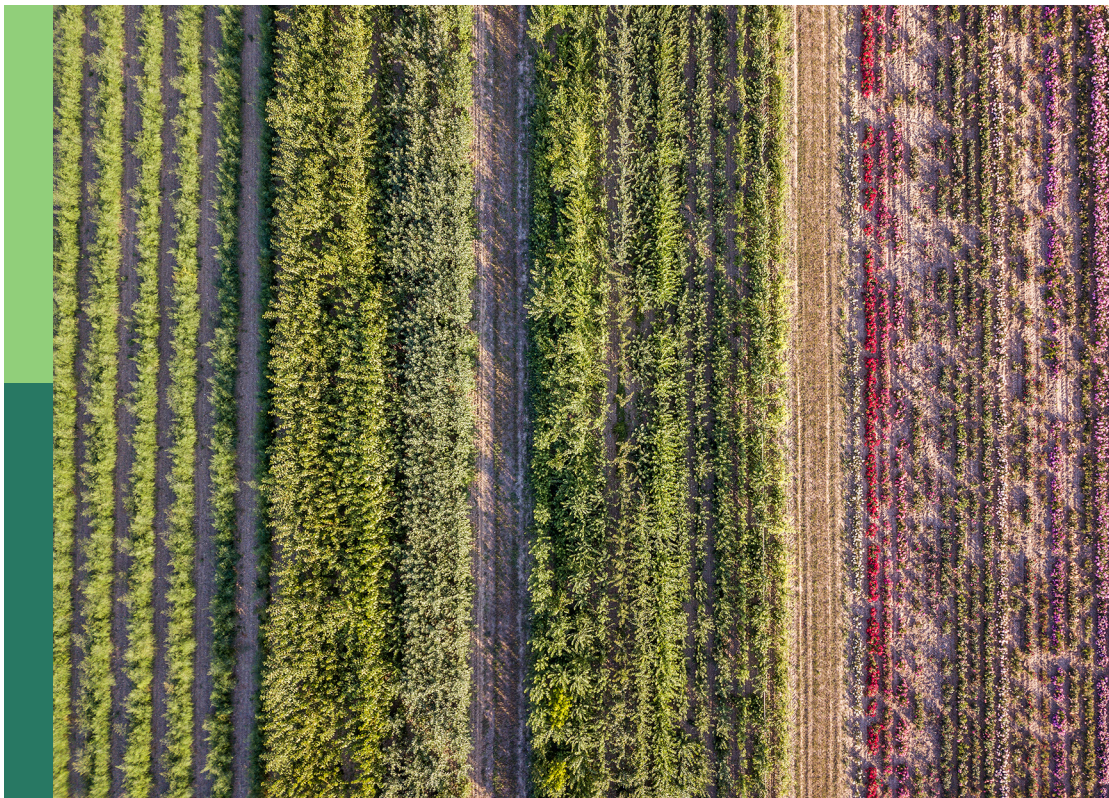
frontiers | Research Topics

Enhancing food security and trade resilience in sustainable agricultural systems

Edited by
Wenjin Long, Catherine Keske and Fuyou Guo

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Enhancing food security and trade resilience in sustainable agricultural systems

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Editorial: Enhancing food security and trade resilience in sustainable agricultural systems

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KEYWORDS

food security, sustainable agriculture, international trade, agricultural policies, food sovereignty

Editorial on the Research Topic
Enhancing food security and trade resilience in sustainable agricultural systems

Food security is a critical global challenge, influenced by complex interactions between agriculture, trade, and market dynamics. As countries navigate the impacts of climate change and economic fluctuations, sustainable agricultural practices become essential for ensuring a stable food supply. International trade agreements, such as the China–Pakistan Free Trade Agreement and the pathways established by the Belt and Road Initiative, significantly shape domestic agricultural economies. Understanding how these agreements affect food access, sovereignty, and production sustainability is crucial for developing resilient food systems.

Despite the recognized importance of these interconnections, there is limited research that comprehensively examines the interplay between trade policies and sustainable agricultural practices in supporting food security. Many existing studies focus on individual aspects, neglecting the integrated nature of these systems. This Research Topic aims to fill this gap by exploring how trade dynamics, local agricultural strategies, and policy frameworks can enhance food security and resilience. By synthesizing diverse case studies and analyses, we aim to identify best practices and effective pathways to strengthen both trade and local agricultural sustainability in various contexts.

This Research Topic welcomes papers that provide insights into the complex relationship between trade and food security within sustainable agricultural frameworks. Contributions are invited on the following subthemes:

- The impact of trade agreements on domestic agricultural markets.
- Strategies for integrating sustainable practices into trade frameworks.
- Case studies illustrating successful agricultural exports and their implications for food security.
- The balance between international trade and food sovereignty.
- Policy recommendations for fostering resilient agricultural systems in a global trade context.
- The impact of emerging technologies on agricultural systems or rural development.

This album is collected around these Research Topics. The six sections and 29 research papers included focus on the systematic role of trade policies and sustainable case practices in food security, overcoming the limitations of a single system or condition on food security. They integrate methods such as spatiotemporal big data analysis, large-scale field surveys, and scenario modeling to explore the impact of trade policies and sustainable practices on food security from multiple scales, perspectives, and time series. Among them, the section of "the impact of trade agreements on domestic agricultural markets" systematically analyzed the impact of free trade agreements on China's agricultural imports and on the agricultural global value chain, and also studied the trade potential of food crops in countries along the Belt and Road and the vegetable exports of China Pakistan free trade agreements to Pakistan; The section of "strategies for integrating sustainable practices into trade frameworks" systematically analyzed the impact of institutional openness on the trade efficiency changes of China's imports of agricultural products from Central Asian countries, the improvement of quality signals, the increased willingness of farmers to pay for cassava planting materials with quality assurance, and the acceleration of cassava variety turnover; The section of "case studies illustrating successful agricultural exports and their implications for food security" systematically analyzed the relevant empirical research on vegetable exports from Pakistan and the empirical analysis of Saudi Arabia's demand for imported raw coffee; The section of "the balance between international trade and food sovereignty" systematically studied the dynamic impact of international price fluctuations on China's soybean market prices, the spatial distribution and influencing factors of China's overseas agricultural land investment projects under the background of food security, as well as Chile's food sovereignty, food security, and international trade; The section of "policy recommendations for fostering resilient agricultural systems in a global trade context" systematically analyzed the solutions to the reduction of rural population in black soil areas, the development goals of wheat in Kenya, and the impact of industrial and commercial capital and urbanization on food security; The section of "the impact of emerging technologies on agricultural systems or rural development" systematically studied the impact of new technologies on agricultural or rural development at different scales, including rural areas, Lanling County, Jiaozuo City, Bihar and China.

The number of submissions for this album exceeded our expectations. We would like to express our academic respect and sincere gratitude to all the authors who submitted the album. Since the establishment of this album, a total of 29 articles have been published, studying relevant cases of agricultural sustainable development and food security in multiple regions and countries including the United States, Pakistan, Africa, Europe, Central Asia, and China, generating positive research results. The album has attracted over 160 authors to submit and publish, and since its release, it has attracted 11,000 downloads, with an overall view count and download count of over 54,000, achieving a wide academic impact.

This album is only a preliminary exploration of interdisciplinary research on sustainable development in agriculture or rural areas. During this submission process, we strongly realized that under the dual pressures of global climate change and food security, interdisciplinary research has become the core path to solving the challenges of sustainable development in agriculture or rural areas. I hope that the publication of this album can serve as a starting point for interdisciplinary research on the intersection of sustainable development in agriculture or rural areas and food security. In the new era, in order to achieve sustainable agricultural development and food security, it is necessary to handle the relationship between ecological environment protection and economic and social development with higher positioning, wider vision, and more refined means, systematically enhance the ability of agricultural or rural ecological environment to support high-quality development, and promote the benign interaction between multiple factors in agriculture or rural areas. We look forward to more scholars continuing to pay attention to and actively participate, making academic contributions to building sustainable agricultural development and food security.

Author contributions

FG: Writing – original draft, Writing – review & editing.

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Does the China–Pakistan free trade agreement benefit the vegetable exports of Pakistan? A gravity estimation

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In the backdrop of criticism that the China-Pakistan Free Trade Agreement has disproportionately favored China, particularly in agricultural trade, there has been a surge in Pakistan's imports, leading to a trade deficit. This study attempts to evaluate the impact of CPFTA 1&2 on the vegetable exports of Pakistan which is an important sector of the agricultural industry. A panel data set of Pakistan's vegetable exports to its trading partners from 2003 to 2021 was analyzed with the extensively used gravity model of trade. The vegetable export data was sourced from the International Trade Centre (ITC) which is based on the Pakistan Bureau of Statistics. The results suggest that the China-Pakistan Free Trade Agreement (CPFTA-I) has a positive association with Pakistan's vegetable exports to China. However, trade liberalization with Afghanistan, Sri Lanka, and Malaysia plays a more substantial role in driving Pakistan's vegetable exports. CPFTA-II has not had a measurable or statistically significant impact on the vegetable exports of Pakistan as this period was highly influenced by COVID-19. The results of colonialism variables show that Pakistan is exporting more to countries with the same colonial history. Moreover, the results of the geographical variable suggest that Pakistan should explore more close markets to expand vegetable exports. Policy implications suggest the need to reduce trade costs, leverage CPEC infrastructure, enrich trade relations with neighboring countries, and involve business professionals in policy negotiations.

KEYWORDS

trade liberalization, China–Pakistan Free Trade Agreement (CPFTA), gravity equation, vegetable trade, CPEC

1 Introduction

Trade liberalization is a crucial element of economic integration that removes or reduces restrictions and barriers to promote international trade. Trade liberalization by creating employment and eradicating poverty increases the country's economic growth (Yameogo and Omojolaibi, 2021). Over the last few decades countries across the globe are actively participating in free trade agreements to accelerate economic and trade activities. Following the same trend of economic integration, Pakistan tied itself to different trade agreements with China, Malaysia, Sri Lanka, Afghanistan, and Iran to promote trade and economic activities (MoC, 2022). Trade advantages can be diverse across nations, upon a country's particular set of interests, economic outlook, and diplomatic relationships (Irshad et al., 2018). In the context of trade liberalization, the China-Pakistan Free Trade Agreement (CPFTA) initially formed in

2006, is still debated, and a popular subject for researchers (Irshad and Xin, 2018; Lateef et al., 2018; Haq et al., 2021; Shah, 2021; Qiu et al., 2022). The impact of free trade agreements, however, on some particular sectors of Pakistan's economy, such as the agriculture sector, has widely drawn criticism (Barbalet et al., 2015; Irshad and Xin, 2018; Qiu, 2020; Butt et al., 2022). These studies discovered several reasons why CPFTA was less effective. These reasons include China's dominant economic position due to its diverse economy, Pakistan's insufficient grounding to exploit the concessions of CPFTA, Pakistan exporting only a few items, and Pakistan's fragile economy and global crises of 2008 occurring shortly after the establishment of CPFTA. Hence it becomes important to study the individual segments of the agriculture sector of Pakistan in the context of the China-Pakistan Free Trade Agreement.

The trade portfolio of China and Pakistan receives handsome contributions from their agriculture sector. China – Pakistan agricultural trade is primarily comprised of raw agricultural products, cotton, and cereals. However, additional trading sectors like vegetables and fruits have emerged over time and trade integration. In 2021, Pakistan's exports totalled USD 3.04 billion and the imports valued at USD 20.7 billion which created a huge trade deficit. In terms of agricultural trade with China, Pakistan's agricultural export was recorded at 4.19 percent of the total exported value to China in 2006. The agricultural exports of Pakistan continued its increase pace and reached 26 percent of the total trade with China in 2021. Vegetable is an important sector of agriculture in Pakistan (Manzoor et al., 2020; Abbas, 2022). As presented in Appendix Table A1, even with its agricultural capabilities, Pakistan's vegetable exports to the world were USD 313 million in 2021, while the imports were USD 946 million on the other hand China's vegetable exports were USD 10077 million and imports were 2,854 USD million (ITC, 2021). Table 1 shows the Pakistan's vegetable trade with China from 2003 to 2021. Though during this period Pakistan's total vegetable trade with China observed 21.6 percent growth. The surging imports of Pakistan have driven the vegetable trade deficit. In the background of the importance of vegetables in the agricultural sector of Pakistan and the trade deficit with China, this study adopts the gravity model of trade to evaluate the impact of China–Pakistan Trade Agreements CPFTA 1&2 on vegetable exports of Pakistan.

TABLE 1 Pakistan's vegetables exports to China (US Dollar Thousand).

Year	Exports	Imports	Trade	Deficit
2003	67	19,824	19,891	−19,757
2004	37	13,689	13,726	−13,652
2005	136	45,741	45,877	−45,605
2006	469	48,563	49,032	−48,094
2007	199	82,296	82,495	−82,097
2008	0	57,420	57,420	−57,420
2009	0	66,765	66,765	−66,765
2010	28	97,310	97,338	−97,282
2011	227	93,258	93,485	−93,031
2012	3,955	35,054	39,009	−31,099
2013	598	30,042	30,640	−29,444
2014	889	67,823	68,712	−66,934
2015	923	63,130	64,053	−62,207
2016	852	107,378	108,230	−106,526
2017	11	87,190	87,201	−87,179
2018	36	43,988	44,024	−43,952
2019	42	58,340	58,382	−58,298
2020	303	112,518	112,821	−112,215
2021	109	71,260	71,369	−71,151

The gravity model of trade hypothesizes that the volume of trade between two countries is positively associated with their economic sizes and inversely related to the distance between them. Trade flow is further influenced by factors including contiguity, colonial links, and the presence of trade agreements. The inclusion of various determinants allows for a comprehensive assessment of the factors shaping Pakistan's vegetable exports. Population size often serves as a proxy for market demand, whilst distance and contiguity capture the geographical barrier and proximity influence trade patterns. Moreover, historical colonial relations can exert lingering effects on trade relationships, further enhancing the depth of analysis.

Compared to the existing research, this study has three notable contributions. First, previous research mainly focused on general or sectoral trade however, to the best of our knowledge, no study focuses on the impact of Pakistan's free trade agreements on the commodity level. To our knowledge, this is the first empirical study using the gravity equation of trade to analyze Pakistan's vegetable exports to China. Second, as discussed earlier, vegetables among the crops of Pakistan hold an important position that requires attention to be placed in the right market to improve the balance of trade and foreign exchange earnings. So, our study contributes by offering detailed insight into vegetable trade which is not covered comprehensively in the existing literature. Third, since earlier studies solely focused on the first phase of CPFTA, a comprehensive study of the trade agreement gives decision-makers the knowledge to make informed decisions. For this reason, this is among the very first studies to take into account both CPFTA-I and CPFTA-II.

The rest of this research is constructed as follows. Section 2 presents a brief literature review. Section 3 describes the material and methods, providing detailed information about the data sources and data structure, the gravity equation of trade, and the estimation techniques involved in the analysis. Section 4 presents the estimated results and discusses each variable under study. All the findings of the study are concluded in section five of this study.

2 Literature review

The primary objectives of the CPFTA were to safeguard the two-sided relationship between China and Pakistan and expand bilateral trade. The tariffs and restrictions were lifted from the 6,711 and 6,418 product lines for Pakistan and China, respectively. The products and product categories for which China removed or reduced barriers included textiles, seafood products, agriculture and livestock, and minerals. Pakistan reduced or removed tariffs on agrarian products such as fruits and vegetables, machinery, meat, and chemicals. However, Pakistan has yet not fully exploited the CPFTA and only enjoyed 3.3 percent of the tariff line (Hussain, 2017). The positive impact of CPFTA is more observable in the imports of

Pakistan from China, which has expanded the trade deficit of Pakistan with China (Xin et al., 2014; Ali, 2018; Baier et al., 2019; Qayyum and Nigar, 2020; Rahamdil et al., 2021; Shah et al., 2022). Since the CPFTA 2006, Pakistan's imports from China rose from USD 2.9 billion to USD 15.17 billion. This trade deficit is mainly caused by those products that were not imported before the implementation of CPFTA (Mukhtar and Hongdao, 2017). Despite the concessions made by China, Pakistan did not achieve all the benefits it hoped for from China because local businessmen and traders were not actively part of the negotiations (Mukhtar, 2019). The backdrop of criticism and the perception that CPFTA 2006 favored China more than that of Pakistan led to the negotiation of the second phase of the CPFTA. The second phase of the China-Pakistan Free Trade Agreement CPFTA-II, spanning from 2019 to 2024, was executed in 2019. The reductions and concessions on the tariff line were expanded in the CPFTA-II. In phase II of the CPFTA China has favored Pakistan by waiving tariffs on 313 export products of the interest of Pakistan (MoC, 2022). The tariff structure of the CPFTA-II is better than that of the CPFTA-I and presents considerable prospects to expand and diversify Pakistan's exports to China. The second phase of the CPFTA is not an independent agreement, instead, its evaluation should be intervened with the China-Pakistan Economic Corridor (CPEC) as the framework of CPEC has notably improved the connectivity between China and Pakistan. The fastest connected route across Khujarab Pass, which is both time and cost-effective, is expected to facilitate and expand bilateral trade (Alam et al., 2023a,b).

The prevailing literature has a contradiction on the effect of the China-Pakistan Free Trade Agreements. For instance, Irshad and Xin (2018) utilized the gravity model of trade and studied the Pakistan-China trade potential from 1992 to 2015. Most of their study results obtained from different techniques like EGLS, PPML Tobit model, etc. are aligned with the theory of gravity however they argue that free trade agreement has a negative impact on bilateral trade. More specifically their results reveal that CPFTA is not successful in achieving its goal of improving the exports of Pakistan. Lateef et al. (2018) preferred the gravity model with the PPML technique and studied the impact of CPFTA on the bilateral agricultural trade between China and Pakistan. Their research argues that although CPFTA has a trade creation effect this agreement has not boosted the agricultural exports of China. Qayyum and Nigar (2020) used various econometric indices to analyze the pre and post-CPFTA trends in the agriculture sector. According to their results, the bilateral trade between China and Pakistan is more tilted towards China. Further, they argue that trade in agricultural products can contribute to reducing the trade deficit of Pakistan. In the same context, Lateef et al. (2017) analyzed the gravity equation with a PPML estimator to evaluate CPFTA. Their research used a large data set of 110 export partner countries of Pakistan from 2001 to 2014. The results show that CPFTA has significantly increased the volume of agricultural trade. Overall the current papers provide a broad picture of CPFTA's effect on the agricultural trade between China and Pakistan and there is an obvious lack of study for certain agricultural commodities. Decision-makers and stakeholders in both China and Pakistan need to know how the CPFTA 1 and 2 impact specific agricultural commodities. This paper will help decision-makers and stockholders to better understand the obstacle and will aid in figuring out where to focus efforts to fully exploit trade liberalization.

3 Materials and methods

In this section, we present how we conducted this study and the tools we used. First, we explain the basic idea of the gravity equation. Second, we describe our derived model for the vegetable exports of Pakistan. Third, we provide the detailed protocol involved in the estimation of our model. Finally, we give information about the data source and summarize the main characteristics of the data.

3.1 Gravity equation

Newton's Law of gravitation serves as the foundation for the gravity model of trade. Tinbergen (1962) and Pöyhönen (1963) introduced the concept of Newton's Law of Gravitation to international trade. The main theme of the model is that trade between countries is directly proportional to the economic masses of the countries and inversely proportional to the trade cost between them. In general, a country's GDP represents its economy or economic size (Markusen, 2013), whereas distance and trade barriers indicate the cost of trade between them. Hence the gravity equation of trade states that "the volume of trade between countries is directly proportional to the GDP of countries and inversely proportional to the distance between them" (Tinbergen, 1962; Linnemann, 1966). The gravity model of trade is widely preferred to measure the trade flow between any two counties or regions (Caporale et al., 2015). Gravity stands as a 'celebrity' in economic modeling, witnessed by its widespread utilization in international trade (Yotov, 2022). Mathematically the gravity equation of trade is expressed as follows in Equation 1:

$$X_{ij} = A\left(Y_i Y_j\right) / D_{ij} \tag{1}$$

Where i and j, respectively, represent exporting and importing countries, X_{ij} refers to the bilateral trade volume between i and j, A is the constant and Y_i represents the GDP of the country i,Y_j represents the GDP of country j, D_{ij} is the cost of transportation and distance between the two countries, i.e., i and j.

The gravity equation is transformed to logarithmic form to get the linear version as follows in Equation 2:

$$LnX_{ij} = \beta_0 + \beta_1 LnY_i + \beta_2 Y_j - \beta_3 LnD_{ij} \tag{2}$$

By adding the stochastic term, we get the final version of the simple gravity model of trade as follows in Equation 3:

$$LnX_{ij} = \beta_0 + \beta_1 LnY_i + \beta_2 Y_j - \beta_3 LnD_{ij} + \varepsilon_{ij} \tag{3}$$

Once we develop the model where the independent variables GDP's of the countries and the distance explains the dependent variable then it is possible to incorporate other control variables that are expected to explain the dependent variable. In Equation 4, γLnX captures all the control variables that possibly affect the bilateral trade.

$$LnX_{ij} = LnA + \alpha Ln\left(Y_i * Y_j\right) - \beta LnD_{ij} + \gamma LnX + \varepsilon_{ij} \tag{4}$$

Anderson and Van Wincoop (2003) incorporated the multilateral resistance term into the model which capture the general equilibrium effect of the trade barriers. The MR gives bilateral trading partners the ability to have their exports influenced by the demand of other countries for their products and alternative suppliers for their imports. The average trade barrier between two trading nations is known as the MR. This indicates that relative adjustments in trade barriers between paired nations relative to other trading partners may result in a reduction in bilateral trade volumes. Structural gravity is another name for the underlying theory of the gravity model, which incorporates the MR term as given in Equation 5:

$$X_{ij} = \frac{Y_i Y_j}{Yw}\left(\frac{t_{ij}}{\prod i \prod j}\right)^{1-\sigma} \quad (5)$$

Where, where Yw represents world GDP, $Y_i$and$Y_j$are the GDP of countries j and i respectively, X_{ij} shows the exports from country i to destination j, tij represents the transaction costs of products export from country i to j, σ is the elasticity of substitution between all products. The basic assumption is to take a fixed value of $\sigma > 1$ to account for a preference for a variation of commodities thus a commodity can be substituted for other similar goods. ÷ $j$is the multilateral resistance term (MRT) (representing the trade costs of country j as a function of all trading partners i and their import demand).÷ i represents the inward multilateral resistance and is, therefore, a function of the trade cost of i (the importer) to all trading partners j. Unobserved trade barriers that are challenging to assess or include in the model are taken into consideration by these two variables. Country-fixed effects for importers and exporters and year-fixed effects are the most widely used and accepted approaches to account for these indicators (Feenstra, 2002).

3.2 The model

We settled our model for Pakistan's vegetable exports. The standard gravity equation is augmented by adding population, binary variable for the trade agreements with the importers, common language, common border (contiguity), common colony, and colonizer.

$$\begin{aligned} LnX_{ij} = {} & \beta_0 + \beta_1 LnGDP_i + \beta_2 LnGDP_j + \beta_3 LnD_{ij} \\ & + \beta_4 Lnpop_i + \beta_5 Lnpop_j + \beta_6 comlan_{ij} + \beta_7 contig \\ & + \beta_8 Comcol + \beta_9 Col + \beta_{10}\text{PAFTA} + \beta_{11}\text{PIFTA} \\ & + \beta_{12}\text{PSFTA} + \beta_{13}\text{PMFTA} + \beta_{14}\text{CPFTA} + \varepsilon_{ij} \end{aligned} \quad (6)$$

$$\begin{aligned} LnX_{ij} = {} & \beta_0 + \beta_1 LnGDP_i + \beta_2 LnGDP_j + \beta_3 LnD_{ij} \\ & + \beta_4 Lnpop_i + \beta_5 Lnpop_j + \beta_6 comlan_{ij} + \beta_7 contig \\ & + \beta_8 Comcol + \beta_9 Col + \beta_{10}\text{PAFTA} + \beta_{11}\text{PIFTA} \\ & + \beta_{12}\text{PSFTA} + \beta_{13}\text{PMFTA} + \beta_{14}\text{CPFTA} \\ & + \beta_{15}\text{CPFTA}_2 + \varepsilon_{ij} \end{aligned} \quad (7)$$

Where the $LnGDP_i$ and $LnGDP_j$ represent the natural logarithm of the GDP of Pakistan and the partner countries, respectively. The GDP of both origin countries and destination countries is expected to have positive signs. LnD_{ij} is the natural logarithm of the distance between the origin country (Pakistan) and destination countries. The coefficient of distance is expected to have a negative sign. $Lnpop_i$ and $Lnpop_j$ is the natural logarithm of the population of origin and destination countries, respectively. Common language is a binary variable used in the study which takes the value of one if the origin and partner countries are sharing an official common language otherwise zero. Common language is anticipated to have a positive impact on trade between countries by reducing the communication gap. The data for the common language is sourced from CEPII. A common border is a binary variable that takes the value of one if the countries sharing the border with the sourced country otherwise zero. Common border (contiguity) is expected to have a positive relation to the trade between them as it reduces the trade cost in terms of distance. The data for the common border is sourced from CEPII. Trade agreement is a dummy variable and takes the value of one if the countries have joined an agreement otherwise zero. In this study, we have added five trade agreements to the model. PAFTA represents the Pakistan trade agreement with Afghanistan, while PIFTA represents the preferential trade agreement with Iran in southwest Pakistan. Three bilateral free trade agreements with China, Sri Lanka, and Malaysia are represented with CPFTA, CPFTA_2, PSFTA, and PMFTA, respectively. However, we will mainly focus on Pakistan's free trade agreements with China. Trade agreements are anticipated to have a positive impact on the vegetable exports of Pakistan.

3.3 Estimation protocol

In line with the previous studies, we employed various econometric approaches to investigate whether our model is consistent with the gravity theory of trade. We preferred Ordinary Least Square (OLS), Fixed effect (FE), and Pseudo Poisson Maximum Likelihood (PPML) to reach reliable results. However, researchers have identified several weaknesses in the specification and estimation techniques of the gravity model of trade.

The estimations of Ordinary Least Square OLS regression drop zero bilateral trade (exports in our case). For instance, in our data, 73% of the data set exhibits positive while 27% are zero trade/exports. OLS outcomes will be only reliable if they fulfill the general required conditions of multicollinearity, homoscedasticity, and error term correlation with any independent variable. if there is heteroskedasticity in the data then the OLS estimations remain biased (Silva and Tenreyro, 2006; Gómez-Herrera, 2013). The gravity equation of trade traditionally estimated with the fixed effects model does not account for exporter and importer invariant variables (Barbalet et al., 2015; Prehn et al., 2016) To address the endogeneity problem in the model recent studies have suggested the fixed effect model as the fixed effect model helps to address the biases arise from the unobserved time-specific effects. By including fixed effects in the model, we essentially capture the country-specific unobserved factors that might influence trade but are not directly included in the model. The fixed effect approach improves the reliability of the estimated coefficient.

In international trade data, it is common to observe zero values indicating no trade between a pair of countries or for a certain product (Sun and Reed, 2010; Philippidis et al., 2013; Timsina and Culas, 2022). For instance, our model is true only if Xij > 0, Xij = 0 indicates

that there is no trade between countries, and the log of zero is not defined. To address the heteroskedasticity and the zero-trade issue literature has widely criticized the OLS, Fixed and Random effects model, and preferred PPML technique (Silva and Tenreyro, 2006; Braha et al., 2018; Brodzicki and Uminski, 2018; Irshad and Xin, 2018; Correia et al., 2020; Yusuf et al., 2021; Santos Silva and Tenreyro, 2022). PPML has several advantages over other estimators and effectively addresses the common issue in trade analysis (Anderson and Yotov, 2016; Yotov et al., 2016). Hence, we rely on the results of estimates obtained from the PPML technique.

3.4 Data

We extracted and compiled data from multiple sources. Vegetable exports are the dependent variable which is the annual export value from the origin country (Pakistan) i to country j which is the destination country. Appendix Table A2 presents the list of Pakistan's vegetable export destinations. This study is based on 2-digit HS classification code 07 within the Harmonized System of Commodity Classification specifically pertaining to "Edible Vegetables Certain Roots and Tuber." Appendix Table A3 presents a detailed description of the products under HS-07. The data spanning from 2003 to 2021 is sourced from the International Trade Centre (ITC) database. Gross domestic product is a measure of the country's economic size. According to the basic gravity equation of trade GDP of both the origin and destination country is expected to positive impact on the exports of vegetables (dependent variable). GDP data in this study is sourced from the World Development Indicator (WDI). Population describes the strength of the country's market. It is expected that the greater the market size the greater will be trade among them. The data on the population of the countries is obtained from the World Development Indicator (WDI). The binary variable Colony has a value of one if the two nations have ever had a colonial connection in the past while the Comcol takes the value of one if the pair of nations were colonized by the same colonial power. The United Kingdom was the only country to have a common colonizer with other countries in the dataset. For the Colony variable, our dataset reveals that the United Arab Emirates, Bangladesh, Bahrain, Brunei Darussalam, Hong Kong, China, India, Kenya, Kuwait, Sri Lanka, Maldives, Myanmar, Malaysia, Qatar, Singapore, Tanzania, and Uganda have historical colonial relations. The data for the history variables Colony and Comcol are sourced from the CEPII database.

Table 2 presents the summary statistics of the data. Exports are often defined as the goods and services that a country sells to other countries. There are 843 observations of exports in our data set. The average value of the exports over these observations is around 3670.79. The standard deviation is relatively high, which explains the significant difference in the exports among countries. The minimum export value is zero which indicates that some countries have no export record for some period.

GDP is the measure of the economic output or total value of goods and services produced within the borders of a country. There are 854 observations of the GDP for Pakistan's vegetable export destination countries. The large standard deviation suggests substantial variability in the economic masses of the destination countries. There are 855 observations for the population of both origin and destination countries. The high standard deviation in the population of the destination countries explains the significant variation in the population of countries. The distance represents the geographical distance between Pakistan and the destination countries involved in trade. The average distance is around 5,092.16 kilometers, with a standard deviation of 3422.59 kilometers. The distance between the trading partners shows high variation. The shortest distance is 373.6 kilometers, while the largest distance observed in our data set is around 15,622 kilometers. CPFTA, PMFTA, PSFTA, PIFTA, and PAFTA are binary variables that represent that represent trade policies. They are crucial indicators that can influence trade with trading partners. Contiguity represents the closeness of origin and partner countries. Contiguity by reducing the trade cost can influence the trade. Common language is a binary variable and is expected to potentially enhance bilateral trade.

TABLE 2 Descriptive Statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
exports	843	3670.696	13975.19	0	165,314
gdp_d	854	1.16E+12	2.88E+12	1.05E+09	2.33E+13
gdp_o	855	2.26E+11	8.43E+10	9.18E+10	3.56E+11
pop_o	855	2.00E+08	1.93E+07	1.67E+08	2.31E+08
pop_d	855	1.11E+08	2.68E+08	297,226	1.41E+09
dist	855	5092.159	3422.593	374.652	15622.2
CPFTA	855	0.018714	0.13559	0	1
PMFTA	855	0.022222	0.147492	0	1
PSFTA	855	0.019883	0.13968	0	1
PIFTA	855	0.022222	0.147492	0	1
PAFTA	855	0.022222	0.147492	0	1
contig	855	0.088889	0.28475	0	1
comlang_off	855	0.266667	0.442476	0	1
comcol	855	0.355556	0.478962	0	1
colony	855	0.022222	0.147492	0	1

"Obs" means observations and "std.dev." means standard deviation.

4 Results and discussion

The objective is to investigate whether the trade agreements between China and Pakistan affect the vegetable exports of Pakistan. In this section, we provide the findings of our study and engage in an in-depth discussion of our results. Through this part of the study, we hope to provide a complete knowledge of the data and the insight it provides into Pakistan's vegetable exports under trade liberalization.

As presented in Table 3, which is calculated based on Equation 6, we compare the results obtained from different methods to reach reliable and robust outcomes. The Hausman test suggests the FE model, as $X^2 = 28.54$ with 5 degrees of freedom, and given the p-value 0.000 we reject the null hypothesis. Despite our reliance on PPML estimation, both the OLS and FE offer support and contribute to the robustness of our findings. The results obtained from the three models are to some degree resembling. We find consistency in the pattern of estimates obtained, as none of the parameters exhibit a change in the sign. We find that overall, the outcomes of each model are in line with

TABLE 3 Gravity estimations for Equation (6) with OLS, fixed effects, and PPML.

Independent variables	OLS	FE	PPML
lnprgdp	1.383***	1.422***	0.474***
	(0.057)	(0.057)	(0.024)
lnpop_d	−1.023***	−1.037***	−0.343***
	(0.058)	(0.058)	(0.028)
lnpop_o	−5.751***	Omitted	−2.089***
	(0.853)		(0.233)
lndistcap	−2.315***	−2.357***	−0.754***
	(0.164)	(0.162)	(0.065)
contig	−2.249***	−2.446***	−0.596*
	(0.617)	(0.61)	(0.275)
comlang_off	−0.043	−0.016	0.018
	(0.214)	(0.211)	(0.073)
colony	2.681***	2.605***	0.396***
	(0.526)	(0.520)	(0.063)
comcol	1.149***	1.187***	0.186*
	(0.224)	(0.222)	(0.075)
PAFTA	7.871***	8.098***	1.472***
	(0.778)	(0.769)	(0.241)
PIFTA	0.513	0.696	0.229
	(0.741)	(0.733)	(0.344)
PSFTA	5.856***	5.942***	1.317***
	(0.538)	(0.532)	(0.089)
PMFTA	4.568***	4.550***	1.011***
	(0.523)	(0.516)	(0.086)
CPFTA	2.321**	2.547***	0.662*
	(0.764)	(0.756)	(0.277)
Constant	77.948***	−33.390***	28.373***
	(15.336)	(2.816)	(4.15)
R-squared	0.621	0.630	0.609
Observations	855	855	855

*, **, and *** represent the significance at 10, 5, and 1% significance levels respectively; the values in the parentheses are standard errors.

TABLE 4 Gravity estimations for Equation (7) with OLS, fixed effects, and PPML.

Independent variables	OLS	FE	PPML
lnprgdp	1.384***	1.424***	0.474***
	(0.057)	(0.057)	(0.024)
lnpop_d	−1.023***	−1.038***	−0.343***
	(0.058)	(0.058)	(0.028)
lnpop_o	−5.722***	Omitted	−2.080***
	(0.855)		(0.233)
lndistcap	−2.315***	−2.358***	−0.754***
	(0.164)	(0.162)	(0.065)
contig	−2.248***	−2.449***	−0.596*
	(0.617)	(0.61)	(0.275)
comlang_off	−0.043	−0.015	0.018
	(0.214)	(0.211)	(0.073)
colony	2.681***	2.602***	0.395***
	(0.527)	(0.520)	(0.063)
comcol	1.149***	1.188***	0.186*
	(0.225)	(0.222)	(0.075)
PAFTA	7.870***	8.103***	1.472***
	(0.778)	(0.769)	(0.241)
PIFTA	0.512	0.698	0.229
	(0.742)	(0.732)	(0.344)
PSFTA	5.856***	5.943***	1.317***
	(0.538)	(0.531)	(0.089)
PMFTA	4.568***	4.549***	1.011***
	(0.523)	(0.516)	(0.086)
CPFTA	2.464**	2.836***	0.708*
	(0.804)	(0.797)	(0.288)
CPFTA_2	−0.776	−1.534	−0.228
	(1.353)	(1.346)	(0.188)
Constant	77.400***	−33.444***	28.193***
	(15.372)	(2.816)	(4.159)
R2	0.621	0.631	0.609
Observations	855	855	855

*, **, and *** represent the significance at 10, 5, and 1% significance levels respectively; the values in the parentheses are standard errors.

the gravity theory of trade as the coefficient of GDP and distance variable have the desired signs (Wang, 2016; Shahriar et al., 2019; Dadakas et al., 2020).

The results obtained from the OLS and FE model are almost similar. Most of the signs of the coefficients are positive and significant except for the common language and population that unexpectedly have a negative coefficient.

Concerning the trade agreements that Pakistan has with the trading partners, the results obtained from various methods show a positive and significant coefficient except the PIFTA which we refer to as the Pakistan trade agreement with the neighbor country Iran. Focusing on the agreement with China the estimated results from different models are somehow similar except the PPML. An increase or improvement of 1 % in the free trade agreement is associated with a 2.3 percent increase in vegetable exports in Pakistan. The results obtained from Equation 7 presented in Table 4 show that the coefficient of CPFTA_2 refers to the second phase of China Pakistan Free Trade Agreement has a negative and insignificant coefficient. The second phase of the CPFTA in conjunction with the CPEC's improved infrastructure is expected to have a trade creation. The negative coefficient could imply that CPFTA_2 has counterintuitive effects on Pakistan vegetable exports. However, statistically, no significance makes it hard to explain. The insignificance can be due to a small sample size, some external factors, and unaccounted variables in the model. Hence, we argue

that COVID-19 started in 2019 as an external factor that led to extensive disruption in the global supply chain resulting reduction in exports.

The OLS coefficient obtained for PAFTA is 7.871 with a standard error of 0.778 suggesting a highly significant and positive effect on the vegetable exports of Pakistan. The positive and significant results obtained from the fixed effect model reinforce the findings obtained from OLS. The coefficient obtained from PPML also confirms the positive association of PAFTA with the vegetable exports of Pakistan, though with a lower magnitude in comparison with OLS and FE estimations. With a standard deviation of 0.538 and an OLS coefficient of 5.856, the PSFTA appears to have had a highly significant and positive effect on the vegetable exports of Pakistan. The positive and significant coefficient obtained from the fixed effect model supports the findings obtained from OLS. The coefficient obtained from PPML also confirms the positive association of PSFTA with the vegetable exports of Pakistan but with a lesser magnitude than OLS and FE estimations. The OLS coefficient of PMFTA is 4.568 with a standard of 0.523, which indicates a highly significant and positive effect on the vegetable exports of Pakistan. The positive and significant results obtained from the fixed effect model underpin the findings obtained from OLS. The coefficient obtained from PPML also confirms the positive association of PMFTA with the vegetable exports of Pakistan, though with a lower magnitude in comparison with OLS and FE estimations. Our results are consistent with the findings of (Alam, 2018). Pakistan's trade agreements with China, Afghanistan, Sri Lanka, and Malaysia show consistently positive and significant coefficients across various estimations. However, the larger, positive, and statistically more significant coefficient of trade agreements with Afghanistan, Sri Lanka, and Malaysia suggests a higher association with Pakistan's vegetable exports.

GDP reflects the production potential of the exporting country and the importing country's purchasing power (Frankel, 1997). The positive and significant coefficient of the GPD explains that the countries with larger economic mass resulting in higher income, have more potential to import products (Ekanayake et al., 2010; Fadeyi et al., 2014; Karemera et al., 2015; Irshad and Xin, 2018; Lateef et al., 2018). According to the outcomes of this study, a 1 % increase in the economic mass of the trading partner countries is associated with a 1.3 percent increase in the vegetable exports of Pakistan. Distance as a proxy of trade cost between countries plays a significant role. In this study, the coefficient of the distance is negative and statistically significant. An increase of 1 % in the distance is associated with a 2.3 percent decrease in the exports of vegetables. Similar results for distance were observed in some research (Shuai, 2010; Fadeyi et al., 2014; Abbas and Waheed, 2015; Salim and Mahmood, 2015; Atif et al., 2017; Lateef et al., 2018). The outcomes suggest that Pakistan should place its vegetable products in the nearest market to surge exports. The negative and significant coefficient of the population of the destination countries expresses that countries having larger populations import fewer agricultural products as a vast number of people are engaged in rural areas in the agriculture sector making the country self-sufficient in the production of agricultural products. Parallel results have been reported by (Yeo and Deng, 2019).

The geographical variable contiguity has a negative and significant coefficient. We quantify the coefficient of the dummy variable contiguity as (exp [0.59]-1*100) which infers that Pakistan's exports to its contiguous countries are comparatively lower. Our findings demonstrate robust alignment with the results reported by (Iqbal, 2016; Iqbal and Nosheen, 2020). Although it looks counterintuitive, there could be various reasons for the negative contiguity coefficient, including infrastructure problems, political or economic barriers, linguistic and cultural differences, and security concerns. The variables representing the colonial relations, Colony and Comcol exhibit positive and statistically significant coefficients. The coefficient is quantified in the same manner as for dummy variables. This implies that colonial ties are likely to exert a meaningful impact on the vegetable exports of Pakistan. The results of the colonial links correspond with the outcomes of (Iqbal and Nosheen, 2020). Generally, a common language facilitates trade with partner countries. However, in our study the coefficient of variable common language is negative. The findings are consistent with the outcomes of (Atif et al., 2017). The negative and significant coefficient of the common language can be supported by the fact that Pakistan is exporting more to the neighboring countries and for these countries the official languages are different. China in the north of Pakistan has Mandarin-Chinese while Afghanistan in the west has Pashtu and Dari as its official languages. Iran in the southwest of Pakistan has Persian as its official language. These facts about the common language make this variable negative and statistically significant.

The aforementioned findings and discussion offer several theoretical and practical implications for understanding the determinants of vegetable exports in Pakistan and broader implications for international trade theories. The consistency of the findings across various estimation techniques reiterates the applicability of the gravity model of trade. The positive coefficients of GDP and distance variables are in line with the theoretical expectation of the model, indicating that economic mass and trade costs significantly influence trade flow. The positive and significant coefficients of the trade agreements highlight the importance of trade agreements in enhancing vegetable exports. The insignificance of certain coefficients such as CPFTA_2 is attributed to external factors like the COVID-19 pandemic. This emphasizes how trade modeling needs to account for exogenous shocks and unanticipated events to provide more accurate predictions and policy recommendations. The negative coefficient of distance and contiguity variables indicates the significance of geographical proximity in facilitating trade. The negative coefficient of language variable challenges the conventional notion that common language facilitates trade and highlights the role of cultural and linguistic factors in shaping trade patterns.

The finding's practical implications include that policymakers should prioritize initiatives aimed at strengthening existing trade agreements and negotiating new agreements to promote vegetable exports. Furthermore, efforts to improve infrastructure, address trade barriers, and enhance market access can help capitalize on trade opportunities. Given the importance of geographic proximity in trade, exports should explore opportunities in neighboring markets and reduce reliance on distant markets. Given the disruptive effects of external factors such as pandemic, exporters should resilience strategies to mitigate risks and adapt to changing market conditions. Collaborative efforts between government, industry stakeholders, and research institutions are essential for implementing evidence-based trade policies."

5 Conclusion and policy implications

The following conclusions can be drawn from the above analysis. First, although the first phase of CPFTA has a positive association with

Pakistan's vegetable exports, there has been a discernible rise in imports from China, resulting in a trade deficit. The free trade agreements with Malaysia, Afghanistan, and Sri Lanka are more efficient in export promotion. Second, the second phase of the CPFTA shows a negative and insignificant association with vegetable exports in Pakistan. However, we argue that this period of the CPFTA-II was mainly influenced by COVID-19, as that period was declared a pandemic by the World Health Organization and borders were restricted aimed prevention of the spread of contiguous disease. The negative association of geographical distance with vegetable exports led us to the conclusion that closer markets are necessary for expanding Pakistan's vegetable exports. Based on the findings of the common official language we conclude that Pakistan is trading more with countries whose official language is different from English. Pakistan is exporting more to countries that have the same historical colonial links. Finally, based on the study findings we give the following policy implications.

Based on these conclusions, several suggestions can be made. First, reduce trade costs, such as simplifying, logistics and transportation routes to reduce transportation costs and transit time. The CPEC infrastructure can aid in the process of connectivity. Aimed expanded exports of perishable goods, in our case vegetables, Pakistan's government should promote the CPEC route in conjunction with the free trade agreements. Business professionals are the key stockholders of the country's domestic and international trade. Therefore, they must be active participants in such policy negotiations in the future. Second, Pakistan needs to enrich trade relations with neighboring countries. Third, expand trade channels and establish more trading partners. Forthcoming research can extend our study by considering more disaggregated commodities to explain the nature of trade under trade liberalization in conjunction with the CPEC.

While this study provides valuable insight into the vegetable exports of Pakistan under trade liberalization, there are a few limitations to note. The focuses of this study are the vegetable exports which may not represent the overall trade relations of Pakistan. Instead of distance actual transportation costs may enhance the model and provide a better understanding. We could not consider political stability in Pakistan which is important in trade relations. This study does not account for the currency exchange rate which is a factor in determining the price and might influent trade flow. To gain a more comprehensive understanding, incorporation of additional variables is required. Further studies could incorporate factors that influence trade such as political stability, exchange rate, security, technological advancement, etc. Future research could enhance the gravity model with more advanced econometric techniques and machine-learning approaches. Researchers could explore alternative techniques that could offer more comprehensive insight into international trade dynamics.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found here: https://www.trademap.org/Index.aspx and https://databank.worldbank.org/.

Author contributions

HK: Data curation, Methodology, Writing – original draft, Writing – review & editing. YC: Conceptualization, Funding acquisition, Supervision, Writing – review & editing. LL: Resources, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2024.1362910/full#supplementary-material

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Food sovereignty, food security, and international trade: evidence from Chile

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Introduction: There is an ongoing debate regarding the role of international trade on food security and food sovereignty. While food security is a concept with a recognized definition and methodologies to assess it, food sovereignty has multiple definitions, and it is not clear how to measure it. Our purpose is to analyze the evolution of cherry and avocado domestic purchases as an illustrative example of the role of international trade on food security and food sovereignty.

Method: Using a descriptive analysis, we analyse export data at country level and household data representative of urban centers.

Results: We found that cherry and avocado exports have increased over the last decades. We found that domestic cherry and avocado purchases have been stable, while the overall fruit and vegetable purchases have been decreasing. Besides, the cherry seasons are showing some signs of expansion. In terms of disparities, households from quintiles 1 and 2, the two lowest income quintiles, increased cherry purchases. Moreover, households from quintiles 4 and 5, the two highest income quintiles, decreased cherry purchases.

Discussion: International trade can also help to increase domestic purchases and decrease purchases disparities, which can be linked to food access and food security. However, the increased of off-season imports of avocado can be linked to a decreased food sovereignty. We expect to contribute to illustrate how international trade, food security and food sovereignty are linked, while the concept of food sovereignty keeps developing.

KEYWORDS

food sovereignty, food security, self-sufficiency, international trade, fruits and vegetables, cherry, avocado, Chile

1 Introduction

The definition of food security has been presented in many articles, and is widely accepted in academic and public policy areas (Gordillo and Mendez, 2013). On the other hand, food sovereignty, in one of its approaches, would be the right of each nation to maintain and develop its own capacity to produce its basic foods, respecting cultural and productive diversity (Patel, 2009). Moving from a macro to a micro scale, according to La via campesina (2009) food sovereignty is "the right of peoples to healthy and culturally appropriate food produced through ecologically sound and sustainable methods, and their right to define their own food and agriculture systems." Although food sovereignty is not a new concept, its definition is not yet consolidated, with multiple approaches (Bustos et al., 2022).

According to FAO (1996), "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life." This definition has

been presented in many articles, and is widely accepted in academic and public policy areas (Gordillo and Mendez, 2013). On the other hand, food sovereignty, in one of its approaches, would be the right of each nation to maintain and develop its own capacity to produce its basic foods, respecting cultural and productive diversity (Patel, 2009). Moving from a macro to a micro scale, according to La via campesina (2009) food sovereignty is "the right of peoples to healthy and culturally appropriate food produced through ecologically sound and sustainable methods, and their right to define their own food and agriculture systems." Although food sovereignty is not a new concept, its definition is not yet consolidated, with multiple approaches (Bustos et al., 2022).

Food sovereignty includes a social pillar of sustainability and sustainable food production (Keske, 2021). For instance, indiginizing food sovereignty enhances the cultural responsibilities and relationships indigenous peoples have with their environment (Coté, 2016). Colson-Fearon and Versey (2022), in the urban context, highlights the importance of community initiatives as a means to achieve food autonomy and address food inequalities. Food sovereignty is associated to local production consumption, which has low environmental costs, while imports make local food production economically infeasible (Keske, 2021). Moreover, out-of-season fruit consumption leads to high environmental costs. Xiong et al. (2023) showed that, in China, cherries from Chile that arrive by plane in October are associated to the highest greenhouse gas emissions, while domestic production in season is associated to the lowest greenhouse gas emissions.

The literature identifies three main differences between the concepts of food security and food sovereignty, understanding in any case the different conceptualizations existing on the latter. First, food security favors a market-oriented global trading system (FAO, 1996), while food sovereignty is frequently associated with positions of food protectionism, and is often anti-free trade (Akter, 2022). While food sovereignty is not explicitly against international trade, there is a strong preference for local markets (Burnett and Murphy, 2017). Food sovereignty implies to shift away from global trade, while make emphasis on smallholder producers and reliance on local communities for food sourcing (Jones et al., 2015). Second, food security is mainly promoted by intergovernmental organizations and is neutral in terms of power relations, while food sovereignty is promoted by non-governmental organizations and civil society actors and points to the asymmetry of power in food markets. Thirdly, food security does not take a single position with respect to different types of food production, while food sovereignty, in general, privileges small-scale agriculture, preferably organic, and mainly using the concept of agroecology (Gordillo and Mendez, 2013). However, Burnett and Murphy (2017) argue that, even for the small farmers, trade is relevant for their regular activities and food security. There is, therefore, no clear role and valuation in the main approaches to food sovereignty with regard to international trade (Bustos et al., 2022).

At the same time the evolving interplay between food security and food sovereignty is increasingly recognized in academic discourse, emphasizing diverse and context-specific aspects. While traditional definitions of food security focus on the accessibility and nutritional adequacy of food (FAO, 1996), contemporary perspectives are broadening to incorporate environmental, socio-cultural, and agency dimensions (Calistri et al., 2013; Lerner and Berg, 2015; Chappell, 2018; del Valle M et al., 2022). This shift aligns with the concept of food sovereignty, which emphasizes social inclusion and participatory governance in food systems, resonating with cultural values and acceptance around food production and consumption (Chappell, 2018). In this context, Young et al. (2023) highlight the importance of involving alternative visions from local food system actors to achieve a sustainable and fair agricultural transformation, arguing that understanding and valuing the diversity of perspectives is crucial for designing effective interventions that respond to the needs and rights of everyone involved in the food system. As an empiric example of local food governance, Kerr et al. (2019) show that participatory agroecological research on climate change adaptation significantly enhances household food security and dietary diversity in Malawi, showcasing the effectiveness of integrating local knowledge and agroecological practices in bolstering resilience against climate challenges. These approaches necessitate a transformation of food systems, advocating for local levers in civil society engagement and recognizing the complexity and diversity of food systems (van Bers et al., 2019; Dupouy and Gurinovic, 2020).

In this context, the purpose of this study is to revisit the role of international trade on local purchases. In particular, we analyze the changes in the domestic market of cherries and avocados in Chile, which, to some extent, can be associated with exports of these fruits. The dataset does not allow us to argue a causal relation between exports and domestic market changes. However, we want to analyze the available data and let the reader judge. We have conducted descriptive analysis regarding the changes in domestic purchases and wholesaler and consumer prices. We analyze domestic purchases in terms of *per capita* purchase by income quintile to show potential purchase inequalities, coverage or the percentage of the population that purchases such products and how long the period, or season of trade lasts.

Therefore, the role of international trade on food security and food sovereignty is unclear. Utilizing data from avocado and cherry, in both cases international trade is relevant. Our study pursues to provide illustrative examples on the role of international fruit trade on food security and food sovereignty. In the coming section, we revise previous evidence on the role of international trade on food security and how sovereignty can be measured. Then, we analyze two waves of household level data. Finally, we discuss our results and identify some areas for future research.

2 Literature review

In this article, our focus is on the association between food exports and domestic food purchases; therefore, we reviewed the evidence on the effect of international trade, particularly food exports, at the consumer level. International trade could play a key role in food security, which is directly linked to Sustainable Development Goal 2 (zero hunger), by allowing production to take place in the most suitable regions and allowing food to flow from countries with abundant food supplies to those with less (Dithmer and Abdulai, 2017). For instance, Miller et al. (2020), classified countries into three trade freedom groups, lowest, middle, and highest, and found that countries with more trade freedom have

scored higher in *per capita* national income, political stability and food security. However, the literature is still scarce, and analyzing the causal links between trade, trade policies, and food security can be challenging due to the multiple dimensions of food security, such as availability, access and utilization (Barros and Martínez-Zarzoso, 2022).

Previous export effect research has focused on the effect of export restrictions on local production. Some of the most cited examples in the literature are the effects of export restrictions on international markets during the global food price crises of 2007–08 and 2010–2011. Then, there is also some evidence about the COVID-19 pandemic, the Russian invasion of Ukraine, as well as some harvest failures (Akter, 2022), but these studies remain descriptive rather than analytical. In these cases, in general, after supply disruptions, exporter countries restricted international trade to mitigate their domestic price increases.

For example, India cut rice exports to Bangladesh in mid-2007 to protect its own domestic market from potential price increases. As a result in changes in the net supply, Bangladesh experienced an increase of 9.0% in the real price of rice, according to Dorosh and Rashid (2013). On the other hand, Fellmann et al. (2014) showed that the effect of grain export restrictions from Russia, Ukraine, and Kazakhstan benefited producers in the rest of the world. In 2010, the latter increased their profits in the short term, as they increased their production in response to higher prices.

Akter (2022) reviewed 13 empirical studies on the impact of export restrictions on local economies. The authors found mixed evidence in the literature on the effectiveness of food export restrictions as an instrument of short-term food price stabilization in local economies among food-exporting countries. When export restrictions lower domestic food prices, they benefit net food buyers at the expense of net food sellers by redistributing the potential economic surplus of high food prices from producers to consumers. However, the net welfare effect generated by such redistribution is very small and disproportionately benefits urban consumers over many small net food sellers.

Baylis et al. (2019) and Giuntella et al. (2020) indicate that trade liberalization increases food security (e.g., China and Mexico) as food products become relatively less expensive after trade liberalization. In addition, Law (2019), examining the Indian case, found that trade liberalization led to a shift in dietary patterns from a grain-based diet to one increasingly based on animal products. Dithmer and Abdulai (2017), studied the impact of trade openness on food security in 151 countries, measured by food energy consumption obtaining positive and significant impacts, as well as improvements in dietary diversity and diet quality. In contrast, Mary (2019) found that a 10.0% increase in food trade openness would increase the prevalence of undernourishment by about 6.0%, using a sample of 52 developing countries and a fixed-effect model with instrumental variables.

There is also evidence of an increase in rural poverty rates with local decreases in food prices, as it causes income losses and decreases agricultural work for most rural households that depend on agriculture for their livelihoods (Ivanic and Martin, 2008; Koo et al., 2021). For example, Diao and Kennedy (2016) reported that maize export bans in Tanzania are expected to lead to a relevant amount of rural households below the poverty line in maize-surplus regions. In this regard, Akter (2022) concluded that food export restrictions, while bringing short-term food security by lowering food prices and thus protecting buyers from inflation, invoke price uncertainty and market instability that restrict long-term food production and agricultural growth.

Despite the mixed results of the literature on the impacts of trade on food security, evidence shows that food prices are the main transmission channels through which increased trade could improve food security if more open trade policies lead to lower food prices at the consumer level. Djuric and Götz (2016) studied the effects of wheat export restrictions on final consumer prices in Serbia during the food crises of 2007/08 and 2011. This is of strategic importance because wheat provides a base for the milling and feed production industries in the country. They suggest that consumers in Serbia experienced welfare losses because the milling and bakery industries transmitted significant changes in wheat prices to end consumers. The study concluded that the effectiveness of implementing an export restriction to dampen domestic food inflation depends on the price behavior of actors along the food supply chain.

Regarding the effects that food export restrictions have on domestic producers, the evidence reveals unintended negative consequences for food producers in most cases (Akter, 2022). Export restrictions prevent domestic producers from taking advantage of high international prices. Also, export restrictions lead to high economic costs in terms of lost income of producers, lost agricultural investments, high implementation costs and high fiscal costs to acquire and maintain larger than normal food reserves (Akter, 2022).

For example, Götz et al. (2013) analyzed the impact on the domestic market of wheat export controls in Russia and Ukraine during the 2007-08 global food crisis. They found that export restrictions caused market instability and pushed producer prices below their long-term equilibrium level. This also discouraged private investors and thus prevented Russia and Ukraine from maximizing their grain potential. Houssa and Verpoorten (2015) studied the impact of Benin's shrimp export ban, triggered by non-compliance with EU food safety rules. The ban had significant improvements in compliance with EU safety standards. In particular, the government updated safety standards provided training on health issues to small-scale actors, strengthened the Competent Authority, and improved laboratories. However, the improvements made were insufficient to allow the country to maintain exports, due to the lack of national capacity building (financial, human, and institutional capacity) with rapidly evolving EU food safety standards.

Previous research used gravity models to analyze the effect on international trade. Adding a perception index of rigor that comprises different dimensions of business requirements, Melo et al. (2014) analyzed the effect that stricter regulations and standards using a stringency index, as perceived by exporters, had on Chile's fresh fruit exports. The stringency index used quantified the impact of multidimensional regulations and standards in a trade gravity model using exporters' perceptions of their rigidity. The selected fruits were grapes, apples, kiwis and cherries in the period from 2002 to 2010. The authors found that a 1.0% increase in the stringency index reduces exports by 0.5%, on average, and also

suggested that the effect is greater if a developed country imposes the standard. Also, Ehrich and Mangelsdorf (2018), analyzed food processing companies from 87 countries, between 2008 and 2013, that are certified with the International Featured Standard (IFS) to study how food standards affect exports. Seven different sectors were considered: egg products, meat, fruits and vegetables, bakery products, dairy products and beverages. Using IFS's 1-year delay as well as IFS certification in neighboring countries as an instrument, the results show that a 1.0% increase in IFS certification increases countries' exports by 0.3% on average. However, the effect remains robust only for high- and middle-income countries and disappears for low-income countries.

More recently, the COVID-19 pandemic led to uncertainty about the availability of food supplies, and despite requests to avoid imposing trade restrictions, more than 20 countries implemented export bans on agri-food products to ensure domestic availability (Koppenberg et al., 2021). For example, countries such as Vietnam, Cambodia and Myanmar declared bans on rice exports, suspended the registration of new export contracts, defined export quotas and temporarily suspended the issuance of rice export licenses (FAO, 2020). As a result, in the Thai market the price of rice increased by around US$100 per ton (more than 20 percent) putting pressure on the budgets of low-income households and making it difficult to pay for nutritious food. The restrictions can cause panic, price increases in international markets and a collapse of food supply chains. Using data from 144 countries, Gilbert et al. (2023) found that 55% of retail items had some active imports supplementing domestic production. Moreover, 83% of the retail price corresponds to value-added at the country of destination. Therefore, international trade helps to provide a more diverse food supply, while consumer prices would depend on the cost levels, infrastructure and institutions underlying each product's entire value chain.

Flexor et al. (2023) argue that food security cannot be solved by the market mechanisms. In Brazil, Flexor et al. (2023) enhance an active role of local governments regarding food security, beyond food production and access to food, while including food diversity and food quality. In this sense, Clapp (2017), away from more extreme positions, argues that food self-sufficiency pursuits of policies to increase domestic food production may make sense both politically and economically.

As presented in the Introduction, there is not an agreement regarding food sovereignty. Therefore, there is not a consensus on the way the need to be measured. Butti Al Shamsi et al. (2018) point out that food sovereignty can be measured through indicators that assess a community's ability to maintain sustainable food systems, the accessibility and availability of nutritious foods, and the autonomy of local producers in decision-making. Sowerwine et al. (2019) suggest that measuring food sovereignty should include community participation in food systems, equitable access to food resources, and the sustainability of agricultural practices, highlighting the importance of qualitative and participatory methods to capture the concept's complexity. Colson-Fearon and Versey (2022) propose that, in urban contexts, food sovereignty can be measured by assessing the impact of urban agriculture initiatives on local food security, social inclusion, and community resilience to food crises.

In summary, most of the studies carried out have focused on how restrictions on food exports by exporting countries affect their own domestic producers, first, and then their consumers and how they affect the domestic market of third countries, mainly through prices. Second, previous research has also focused on the relationship between international trade and food security, and finally, on the effect of higher quality and safety standards driven by developed country markets on exports from third countries. In this context, export restrictions can be linked with a specific period, and then, it is possible to argue a before vs. after effect. To the best of our knowledge, no previous research has provided figures regarding how changes in international trade can be linked to food sovereignty indicators. In this context, our research pursues to provide some figures to the academic debate regarding the role of international trade on food sovereignty and food security.

3 Methodology

The analyzes presented are descriptive in nature. These descriptive analyzes are presented as a combination of descriptive statistical tables and figures that include values as references. Therefore, these analyzes cannot argue causality; however, they can show changes in purchases over time. The choice of cherries and avocados for the study is to show the changes in purchases associated with relevant changes in production. The selection of descriptive analysis in this study is justified by its relevance for exploratory research. This method is recognized for its effectiveness in clearly and accessibly presenting data trends (Babbie, 2020), initial understanding of a subject (Kothari, 2004), and for its value in food security research, particularly in identifying baseline consumption patterns as demonstrated by Headey and Ecker (2013).

3.1 Data

This study works with two databases. First, the *Encuesta de Presupuestos Familiares* (EPF, Family Budget Survey) of *Instituto Nacional de Estadísticas* (National Institute of Statistics of Chile, INE). Every five years, the EPF collects spending information of a representative sample of households, 10-15 thousand households, in the main urban centers of Chile. The data collected are organized according to international classification standards similar to the Consumer Expenditure Survey in the United States and Living Cost and Food Survey in the United Kingdom. For food, the EPF reports expenditure and quantity by type of fruit and vegetable, FV, and its format (e.g., fresh and frozen). In particular, this study works with data on fresh cherries and avocados collected in the wave 7 of the *Encuesta de Presupuestos Familiares*, EPFVII, between November 2011 and October 2012 and in the wave 8 of *Encuesta de Presupuestos Familiares*, EPFVIII, collected between July 2016 and June 2017. Additionally, the EPF data include sociodemographic variables that allow cross-referencing data, for example, in terms of purchases per household income quintile.

Secondly, *Oficina de Estudios y Políticas Agrarias* (the Office of Agricultural Studies and Policies, ODEPA), from the Ministry of Agriculture, publishes a series of databases regarding the marketing of fruits and vegetables at the level of international trade, wholesale markets and prices at the consumer level. Databases vary in

data frequency (calendar year, season, monthly, and daily) and with respect to the start of the data series. However, most of the data can be consolidated on an annual basis since 1994. Wholesale market sales correspond to a sample of markets, and direct sales are not marketed through wholesale markets; therefore, aggregate production marketed in wholesale markets should not be considered an estimate of domestic purchases. In summary, the EPF and ODEPA data provide data on purchases, not consumption, of fruits and vegetables. The EPF databases allow us to cross reference with sociodemographic variables; however, the ODEPA databases allow us to have time series data, in some cases since 1994, regarding prices by quality (first and second) and point in the marketing chain.

We have selected data on avocados and cherries from Chile as illustrative examples since they have experienced relevant changes over the last decades. Moreover, avocados and cherries have been associated to healthy attributes. Avocados have been named a superfood due to their numerous health benefits (Bhuyan et al., 2019). Cherries also have essential vitamins, minerals, carotenoids, dietary fiber, and bioactive food components associated with health benefits (Faienza et al., 2020). Overall, Chile's fresh fruit exports have increased significantly since 1990. Adjusting the export values in 1990 reported by Parodi (2019), US$ 1.4 billion were exported in fresh fruits, while in 2018 exports of these products reached US$ 7.6 billion. Avocados and cherries are two emblematic fruits of this process, with relevant growth in their exports at different times during these three decades. Despite their robust export dynamics, these fruits present some important differences, which makes them interesting to be analyzed: (i) avocado is consumed all year round, while cherries have a seasonal domestic consumption; and (ii) cherry production is destined for export, mainly to China, and given its little relevance, there is no estimate of the production left in the domestic market (iQonsulting, 2023). Additionally, Chile does not import cherries. With this, the domestic cherry market is supplied exclusively by the country's production. On the other hand, avocados face market conditions that make the domestic market attractive (iQonsulting, 2022). Thus, in the 2021/22 season, Chile exported 126.5 thousand tons (iQonsulting, 2022). In 2021, imports reached 71.5 thousand tons, with a domestic market close to 110 thousand tons (iQonsulting, 2022). Avocado imports have been increasing over the years. To illustrate, in 2013 imports were around 3.8 thousand tons, and in 2021 imports, mainly from Peru (March to September), rose to almost 71.6 thousand tons (iQonsulting, 2022).

4 Results

4.1 International trade statistics

Figure 1 shows cherry and avocado exports from Chile and unit values, proxy of price, in US$ per kilogram. In the last decade (2010–2020), cherry exports have grown exponentially. In contrast, avocado exports have increased robustly in the previous decade (2000–10), with significant annual variations in the last decade. In terms of unit values, dollars per kilogram, these have increased steadily in the case of cherries until 2020. In the case of avocados, their prices do not show a clear trend in the period analyzed. According to Guevara et al. (2021), after analyzing the period 2008–2017 for export from Chile using the Balassa index, the avocado price in dollars, has not experienced a relevant increase; in contrast, to other exporting countries that is a sign of a loss of competitiveness. In this regard, it is important to bear in mind that fruit prices in international markets depend mainly on variety, quality, destination markets and timing.

According to data from the *Oficina de Estudios y Políticas Agrarias* (the Office of Agricultural Studies and Policies, ODEPA), from the Ministry of Agriculture, comparing 2000 and 2020, the productive area with cherry trees increased more than ten times (from 3.7 to 39.7 thousand hectares), while the productive area with avocado trees increased two times (from 14.6 to 30.4 thousand hectares). It is expected that the change in production land would lead to an increase in production; however, it may have some lag. Orchards take some time to reach the commercial production level.

4.2 Domestic market statistics

The World Health Organization recommends a minimum consumption of five servings of FV per day per person, which is equivalent to 400 g per day per person. In order to make comparisons easier, the purchase data of cherries and avocados are converted to their equivalent of portions. However, purchased portions overestimate actual consumption because part of the purchases may be wasted (overripening), or fruits and vegetables have portions that are not edible (for example, avocado pit). The overall FV *per capita* purchases have not changed significantly, being close to four portions per person. Therefore, in the period under study, the overall FV purchases at home have remained relatively stable.

In our analyzes, we show the evolution of the cherry and avocado markets in terms of quantity purchased, market coverage, and inequalities in purchases associated with household income. Purchases of cherries, which are equivalent to 0.05 servings per day/person, are marketed mainly in December and January, and do show a significant change in quantity purchased between the EPFVII (2011–12) and the EPFVIII (2016–17). On the other hand, avocado is marketed year round. Its purchases are equivalent to 0.20 servings per day/person, and do not show a significant variation in purchases between the EPFVII (2011–12) and the EPFVIII (2016–17). Also, when comparing the 2011/12 and 2016/17 seasons, exports in tons experienced an increase of 160.7 and 47.2% of cherries and avocados, respectively.

However, a non-relevant variation in the average quantity of cherries and avocados purchased is not an indicator that the distribution of purchases remain the same. Even keeping the average unchanged, it is possible that a greater percentage of the population, coverage, purchase cherries and avocados, or that there is a change in the potential inequalities in purchases associated with income. The EPF data are representative of the urban center spending at the aggregate level (considering the 12 months of data collection). Therefore, the results at the monthly level should be considered as references. As presented in Table 1, in the EPFVIII (2016–17), 12.9 and 46.3% of the population purchased cherries and avocados, representing a decrease of 1.9 and 1.1%, respectively

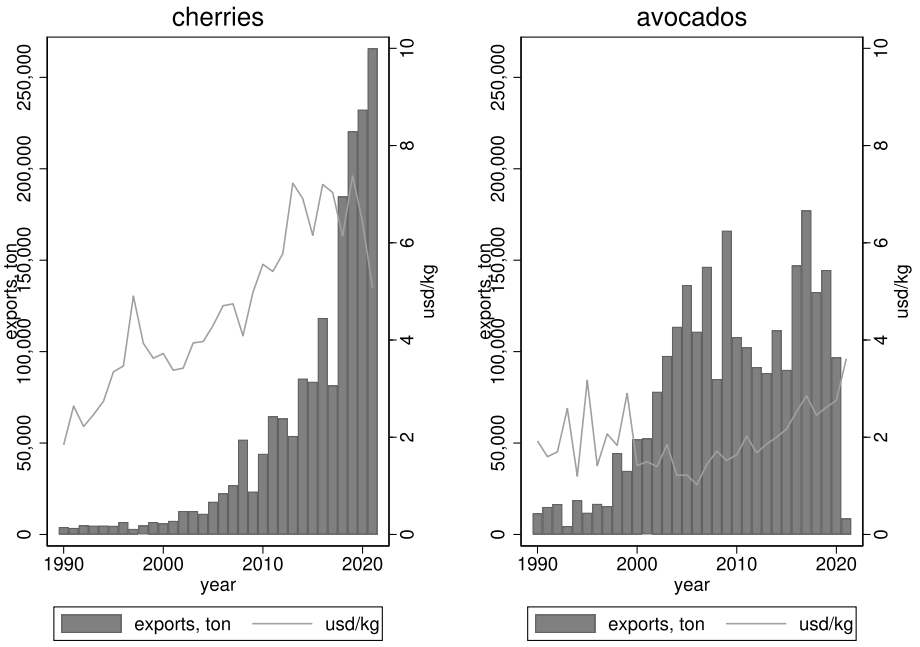


FIGURE 1
Fresh fruit exports.

compared to the EPFVII (2011–12). In the case of cherries, in the EPFVIII (2016–17), purchases in November and January were lower and the maximum coverage was 20.1% in December, which represents a decrease of 5.1% points compared to the EPFVII (2011–12). In the case of avocados, in the EPFVIII (2016–17), coverage varied between 40.2 and 50.0%, while in EPFVII (2011–12), coverage fluctuated between 41.7 and 55.9%.

Figure 2 shows how the different income segments have varied their purchases, in this case of cherries and avocados. The EPF, by including sociodemographic variables, allows data cross-referencing. The graphs above show changes in purchases by household income quintile. Cherry and avocado behave differently. In the case of cherry, households in quintiles 1 and 2 (lower-income households) increased their purchases between 2011–12 and 2016–17 and on the other hand, higher-income households decreased their purchases. In the case of avocado, quintile 4 increased its purchases, while all other quintiles decreased.

With regard to the quantity purchased of these fruits per quintile, EPF VIII shows us that in both cases—cherries and avocados—quintile 5 purchased more than quintile 1. Indeed, while quintile 5 buys 103 g of cherries per household per month and 1,905 g of avocados per household per month, quintile 1 buys 75 g of cherries per household per month and 864 g of avocados per household per month. In summary, comparing income quintiles, the difference in the purchased quantity is 37 and 120% for cherries and avocados, respectively. Comparing 2011–12 and 2016–17, there was a decrease in purchase disparities for cherries, and an increase for avocados.

Now, we analyze domestic prices by qualities. Cherry and avocado fruits are classified into first and second quality. Second quality includes any fruit marketed that is not of first quality. The information used corresponds mainly to ODEPA data for the Lo Valledor Wholesale Market, the main trade market for fresh fruit in Chile located in Santiago.

In Figure 3, the solid line is the first quality and the segmented line the second quality in Lo Valledor. Prices were deflated by inflation as of December 2022. In this way, nominal prices became real prices in December 2022. The results show that cherry prices have remained relatively stable, while avocado prices are on the rise. Also, cherry and avocado prices have cyclical price patterns, beyond the price fluctuations of the season. Finally, the first and second qualities register different prices, and maintain their relatively stable difference for avocado and increase for cherry.

Using real deflated prices as of December 2022 of first quality fruit, in 1994 (base year), the prices of cherries and avocados were Ch$ 2,108.6 and Ch$ 1,335.8 per kilo. In 2002, compared to 1994, prices decreased by 48.9 and 21.7%, respectively. In 2012, compared to 1994 (base year), the price of cherries decreased by 25.9% and that of avocado by 4.7%. In 2022, compared to 1994, the price of cherry decreased by 58.8% and the price of avocado increased by 100.3%. In short, in almost three decades, the price of cherry first quality and avocado have evolved differently. The price of cherries maintains a significant decrease compared to mid-1990. However, the price of avocado shows a relevant increase over the years. In some extent, the price increases of avocado, classified as "superfood," can be a response of the increasing demand in the United States and Europe (Magrach and Sanz, 2020). With regard to the prices of second-quality fruit, the evolution is similar comparing the years 1994 and 2022: cherries price fell by 60.1% and avocados increased by 155%.

For the period 1994–2022, the difference between the price of the first and second quality cherry was Ch$ 419.0 per kilo. In 1994, the difference was $ 881.0, in 2002 Ch$ 245.5, in 2012 Ch$ 386.3 and in 2022 Ch$ 387.8. Thus, although it is true that the price difference

TABLE 1 Descriptive statistics by survey wave.

	EPFVII (2011–12)		EPFVIII (2016–17)		
	Mean	SD	Mean	SD	Difference
Portions FV/day/person	4.08	(4.17)	3.88	(4.01)	0.20
Household size, number of people	3.50	(1.72)	3.29	(1.66)	−0.20**
hline Household income, thousand Ch$	1,295.01	(1,423.898)	1,288.68	(1,336.48)	−6.33
Cherry purchases, population share					
All quintiles	14.73%	(35.44%)	12.86%	(33.49%)	1.87
Quintile 1	11.11%	(31.46%)	10.72%	(30.96%)	0.30
Quintile 5	17.14%	(37.72%)	15.52%	(36.24%)	1.62
Avocado purchases, population share					
All quintiles	47.47%	(49.94%)	46.29%	(49.86%)	1.19**
Quintile 1	38.96%	(48.78%)	35.20%	(47.77%)	3.76**
Quintile 5	56.97%	(49.52%)	50.93%	(50.00%)	6.04**
Observations	10,488		15,184		

A fruit and vegetable portion corresponds to 80 g. Both survey waves are representative for the main urban areas in Chile. The percent corresponds to the proportion of the population share that purchases the fruit under study. The overall purchases statistics are presented in Silva et al. (2021). Standard deviation in parentheses, (**) 5% significance level.

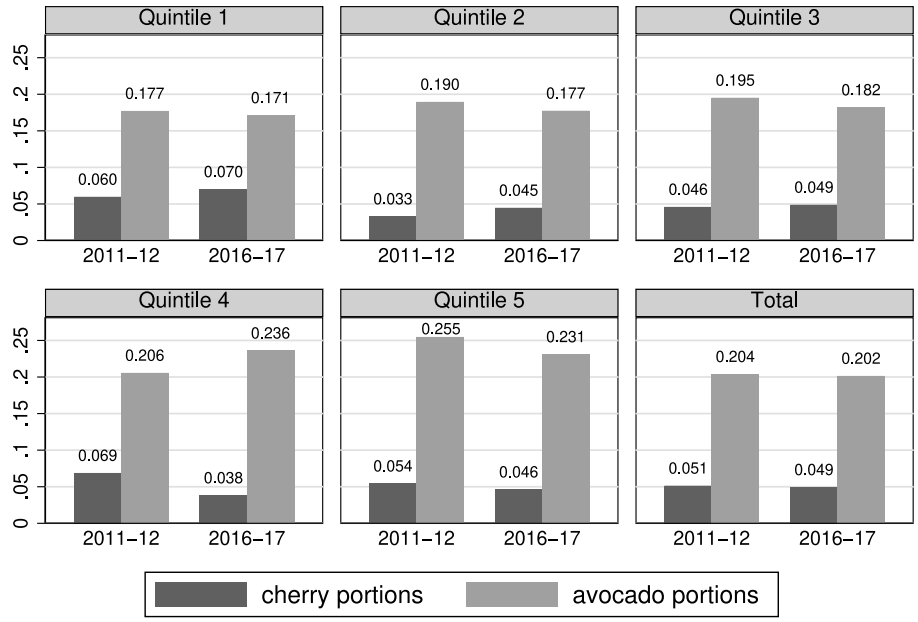


FIGURE 2
Portions of cherry and avocado domestic purchases.

between qualities of the cherries have increased in recent years, this difference is still less than the differences of the mid-90's. In the case of avocado, also in the period 1994–2022, the difference between the price of first and second quality avocado was Ch$ 523.2 per kilo. In 1994, the difference was Ch$ 440.7, in 2002 Ch$ 417.2, in 2012 Ch$ 462.8 and in 2022 Ch$ 746.5. In both, the price difference between qualities in avocado has increased during the studied period.

Using ODEPA data, in the case of cherries, comparing real prices deflated as of December 2022, between 2012 and 2022 of first quality at the wholesale level, the price decreased by 44.5%. On the other hand, at the retail level, the price increased by 176.2%. In the case of avocado, comparing between 2012 and 2022 of first quality at the wholesale level, the price increased by 110.3%. At the retail level, price increased by 151.5%. In summary, in a decade (2012–22), at the first quality (no information is available for the second quality), the price at the consumer level increased more at the wholesale level.

Comparing the difference between first and second quality fruit, in the case of avocado, at the wholesale level the difference was Ch$

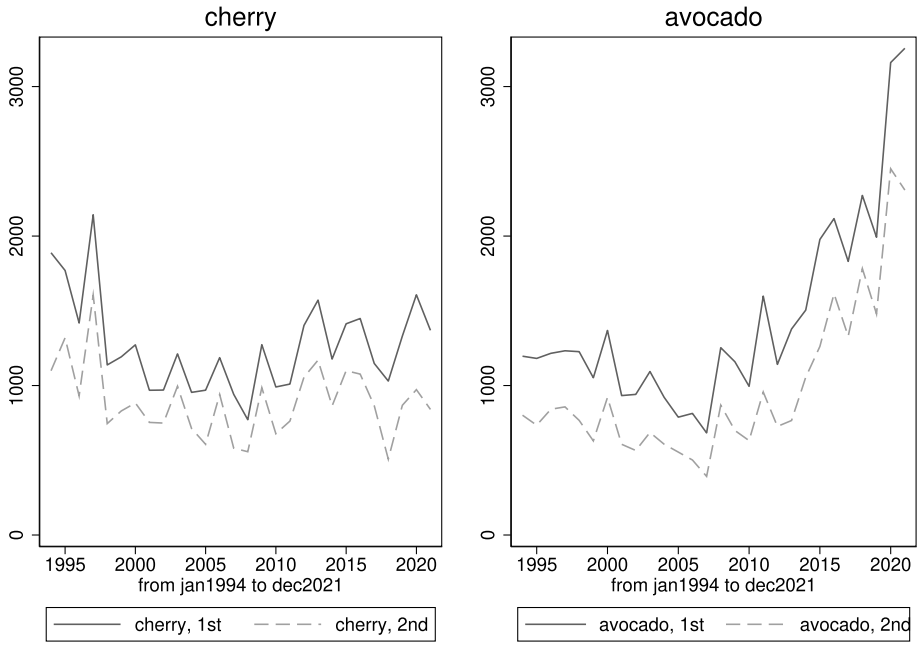


FIGURE 3
Wholesaler price in Santiago.

462.8 in 2012 and Ch$ 746.5 in 2022, which represents an increase of 61.3%. At the retail level, the difference was Ch$ 345.4 in 2012, and Ch$ 520.7 in 2022, which represents an increase of 50.8%. In summary, there is no data to make claims from the evaluation of price margins with respect to qualities for the case of cherry. On the other hand, in the case of avocado, the data show that wholesale prices have decreased, while prices at the consumer level have increased. That is, the price decrease at the wholesale level is not being passed on to the consumer.

Finally, according to ODEPA data from wholesalers, from 1975 to 1991, cherries were marketed only 3 months in the domestic market: from November to January. Starting in 1992, the season starts in October and since 2010, the season ends in February. In summary, in just over three decades, the season expanded from 3 to 5 months a year, although most of the production is still marketed mainly between November and January, which are the months of greatest production for export.

5 Discussion

Previous research has focused on the effect of international trade on food safety standards (Otsuki et al., 2001; Jongwanich, 2009) and the effect of trade restrictions on food exports (Dorosh and Rashid, 2013; Fellmann et al., 2014), and more recently, the effect of imports on domestic food supply (Gilbert et al., 2023). In the best of our knowledge, aligned with the research by Gilbert et al. (2023), our article is one of the few efforts to disentangle the relation between international trade and domestic purchases. We are aware that, based on the available data, is not possible to argue that fresh fruit exports cause a change in domestic purchases. Since exports are a global phenomenon is not possible to have a counterfactual. However, the results show an increase of cherries purchase from households in quintiles 1 and 2, the two lowest quintiles. This seems to indicate that an expansion of cherry production in Chile increased the availability and lower the prices of cherries making them more affordable to lower income households. In the case of avocados, the impact is not as clear because production rose and prices went up over the last ten years, which seems to have impacted lower income households. In this context, we expect that this article can help provide some data to inform the public debate of the role of food export on domestic purchases.

Our article pursues to provide data regarding the role of international trade on food sovereignty and food security. Firstly, as we presented in the literature review section, there is no agreement on how to measure food sovereignty. If we are willing to accept the share of total purchases that is satisfied with domestic production as proxy of food sovereignty, a country that can completely satisfy domestic demand with local production and does not depend on other countries for food supply would have food sovereignty. In our case, Chile used to consume avocado only when they were in season. International trade has opened the possibility to consume them year around; therefore, the domestic market has expanded. In Chile, close to 60% of the avocado production is consumed domestically and the remaining quantity is imported. In a few words, in the case of avocados, Chile has been losing food sovereignty as the population start consuming avocados out of season. In the case of cherries, Chile does not import any cherries and the domestic purchases have increased substantially during the last decade. For cherries, Chile has food sovereignty since all the cherries that are purchased in Chile are produced domestically. Therefore, food sovereignty is linked with eating in season produce;

however, in some cases, people prefer purchasing some products year around. If we are willing to accept that the share of total purchases is a meaningful proxy of food sovereignty, in the last three decades, Chile has been losing food sovereignty in the case of avocado and gaining sovereignty for cherries.

Regarding food security, previous research has linked food security to food access. The FIES questionnaire is an internationally validated instrument to measure food security. In some cases, food *per capita*, also known as apparent consumption, is used as proxy of food security. Food *per capita* is calculated as domestic production minus net exports (imports minus exports). Overall, export development has had some limited effects on the domestic purchases for avocados and cherries during the period under review. The percentage of the population that purchases avocados and cherries in terms of average purchased quantity has remained relatively stable. However, the overall fruit and vegetable purchases are decreasing near to 5.2%. Therefore, cherries and avocados are moving away from the average purchase trend. For the staple cereals in Africa, Grote et al. (2021) state that food security research has focused largely on the availability and stability dimensions, while not relevant attention has been paid to the access and utilization dimensions. In this same way, more research needs to be done in terms of fruit and vegetable access and utilization beyond food availability.

Avocado and cherry production in Chile has been export driven, which takes advantage to sell these products in off-season markets. However, Keske (2021) argue that imports make economically infeasible to local production. The lower prices that would face producers would disincentive domestic production, while it would facilitate economic access to consumers. Therefore, the social pillar of sustainability and sustainable food production of food sovereignty, presented by Keske (2021), may lead to higher prices of off-season products. However, as presented by Lee (2013), trade-oriented food security is relatively unconcerned with sustainability aspects.

Butti Al Shamsi et al. (2018) discuss that the main challenges for food sovereignty include the globalization of food systems, which undermines local autonomy, and the economic and political obstacles faced by small producers. Sowerwine et al. (2019) identify climate change and environmental degradation as significant challenges threatening the sustainability of local food systems, in addition to structural barriers that limit access to resources by marginalized communities. Colson-Fearon and Versey (2022) highlight that, in urban areas, one of the greatest challenges is the limited availability of land for urban agriculture, along with gentrification and the rising cost of living, which can exclude low-income communities from participating in food sovereignty initiatives.

Sowerwine et al. (2019) point out a lack of research on how food sovereignty practices can adapt and withstand climate change and other environmental challenges, as well as the need to study the structural barriers that prevent equitable access to food resources. Colson-Fearon and Versey (2022) identify a gap in research on the role of food sovereignty in promoting social inclusion and equity in urban contexts, particularly on how urban agriculture initiatives can contribute to community resilience.

Our research is built upon previous research by Clapp (2017), in the sense, that food sovereignty and international trade do not need to be treated as opposite concepts. As presented by Silva et al. (2023), in an open-market economy, the production decision of companies and the consumption decision of households are taken separately. In Latin America, most of the fruits that cannot be sold in external markets due to cosmetic imperfections (Balsevich et al., 2003) are eaten in the domestic market. Therefore, trade restrictions may increase domestic fruit supply in the short run, while it would disincentivize investments, and then, would contract fruit production in the long run.

6 Conclusions

Chile's trade opening, for four decades now, has been intensely exploited by the country's agriculture, especially fruit production. Two species of the latter, such as avocados and cherries, are examples of this and have been analyzed in this article. Both fruits have had different dynamics of growth of their exports in the period analyzed, especially in the last decade, and both exhibit different relevance of their domestic markets. In the case of avocado, the domestic market is relevant, but in the case of cherries it is not. Overall cherry prices, for the analyzed period of time, have dropped. This complements the finding that low-income households are purchasing more cherries. On the other hand, avocado prices had no significant trend from 1994 to 2012 and then started mostly and upward trend through 2022. This also coincides with higher avocado purchases from higher income households such as the one in quintile 4. Finally, we found that cherries are expanding the trade season from 3 to 5 months per year, while the trade still focuses in December and January. In the future, based on store innovations and development of new varieties, it is possible that we could see additional expansions of the trade seasons.

In terms of income disparity purchases, households from quintiles 1 and 2, the two lowest income quintiles, increased cherry purchases, while quintiles 4 and 5 decreased cherry purchases. Since food-away-from-home (FAFH) data is unavailable, we do not know whether high income households are purchasing cherries in different formats. However, we do have evidence to support that low-income households are purchasing more cherries than before. In this sense, further research may consider food-away-from-home data to have a more complete measure of total purchases. Finally, in our article, we use the share of total purchases that is satisfied with domestic production as a proxy of food sovereignty. However, previous research has not reached an agreement regarding the most appropriate index to measure food sovereignty. More research is needed to provide indexes that can be followed over time.

This study's descriptive approach has its limitations. While it reveals trends and correlations, it cannot establish causality. The analysis may not capture all influencing factors, potentially leading to an incomplete understanding of the broader context. The focus on cherries and avocados in a specific region also means the findings might not be universally applicable to other fruits or regions in Chile.

Furthermore, this approach does not delve into deeper mechanisms behind the observed trends. Therefore, caution is advised when extrapolating these results to different contexts or agricultural products.

In general, an export boom causes an increase in production that is marketed internally. This could develop consumption habits that are expressed in a demand for the product over longer periods. This increased domestic demand could be met through imports, which has happened with avocado via imports from Peru and more recently from Colombia. Domestic trade periods could also be extended due to the increase in the months in which products are exported, with the consequent availability also on the domestic market. This issue seems to be happening with cherries and that will probably happen more in the future due to the expansion of cultivation to the south of Chile and the incorporation of later maturing varieties that respond to markets other than China.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: www.odepa.gob.cl/estadisticas-del-sector/comercio-exterior and www.ine.gob.cl/estadisticas/sociales/ingresos-y-gastos/encuesta-de-presupuestos-familiares.

Author contributions

AS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing - original draft, Writing - review & editing. AB: Formal analysis, Investigation, Writing - original draft. LR: Investigation, Validation, Writing - review & editing. MV: Investigation, Writing - review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The trade potential of grain crops in the countries along the Belt and Road: evidence from a stochastic frontier model

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This study employs the stochastic frontier model (SFM) to analyze trade potential and efficiency in wheat and maize among Belt and Road Initiative (BRI) countries from 2002 to 2021, encompassing 45 countries for wheat trade and 55 for maize trade. The empirical findings reveal that economic development level, population growth, government efficiency, political stability, and regulatory quality are critical determinants of trade efficiency. Notably, World Trade Organization (WTO) membership exhibits a negative correlation with trade efficiency, potentially reflecting challenges in rule implementation and opportunity utilization among member states. In the context of maize trade, increased arable land area is inversely associated with efficiency, suggesting potential issues in managing large-scale agricultural regions or optimizing land use. The BRI's impact on trade efficiency varies across countries, with Turkey and Hungary showing improved wheat trade efficiency, while Ethiopia and Georgia experienced declines. During the COVID-19 pandemic, effective disease management strategies and diversified trade mechanisms significantly influenced trade efficiency. Furthermore, the study reveals that larger economies do not necessarily outperform small and medium-sized economies in terms of trade potential. These findings contribute significantly to the literature on agricultural trade and offer valuable insights for policymakers, emphasizing the importance of enhancing government efficiency, political stability, and regulatory quality in the context of regional economic development initiatives such as the BRI. This research underscores the need for tailored approaches to trade policy and agricultural management, considering the unique characteristics and challenges faced by different economies along BRI.

KEYWORDS

Belt and Road Initiative, agricultural trade, trade efficiency, maize, wheat, SFM

1 Introduction

Agricultural trade plays a crucial role in promoting regional development and ensuring food security, particularly in the context of China's trade with Belt and Road Initiative (BRI) countries. The BRI, launched in 2013, is a significant effort by China to promote inter-regional economic development, and the initiative aims to facilitate trade and investment in the countries involved, fostering economic development not only in China but also in its partner

countries (Görg and Mao, 2022; Fan, 2023). The initiative supports free trade, connects economies worldwide through regional cooperation, and promotes the close connection of China's foreign direct investment (FDI) and import and export trade with countries along the BRI (Gao et al., 2022). This global initiative lays the foundation for strengthening agricultural trade, which is crucial for the economic stability and development of the countries participating in the BRI.

In the realm of agricultural economics, the trade of grain crops holds a pivotal position, underpinning the global food supply chain and influencing economic stability across nations. Agricultural efficiency is crucial for ensuring food security and generating income (Cai et al., 2024). The significance of grain crops trade extends beyond mere commodity exchange; it is a critical component in ensuring food security, stabilizing food prices, and facilitating the equitable distribution of food resources worldwide. Grain crops, including wheat, maize, rice, and soybeans, represent the backbone of global agriculture, providing essential nutrients to billions of people. Their trade patterns reflect complex interactions between national agricultural policies, global market dynamics, and environmental factors, highlighting the necessity for a nuanced understanding of grain trade's economic and policy implications (Cao and Yuan, 2022; Rathore et al., 2023). In the global agricultural sector, wheat and maize are paramount to the food trade, serving as fundamental staples for billions worldwide. Compared to other corps, the study of wheat and maize's trade potential holds greater significance due to their foundational role in global food security and their substantial impact on the agricultural economy. Data from the Food and Agriculture Organization (FAO) reveal that wheat and maize collectively account for a significant portion of the world's grain trade, underscoring their pivotal role in global food systems. Specifically, the international trade volume for wheat reached approximately 184 million tonnes in 2020, while maize trade was close to 163 million tonnes in the same year, highlighting the massive scale at which these grains circulate globally (Food and Agriculture Organization of the United Nations (FAO), 2021, 2023). This extensive trade volume indicates not just the global reliance on wheat and maize as staple foods but also their importance in the agricultural trade market. Countries across various continents depend on the importation of these crops to meet their domestic food demands, illustrating a global interdependence that underscores the strategic significance of wheat and maize trade. For instance, major wheat-importing countries include Egypt, Indonesia, and Algeria, whereas significant maize imports are seen in countries like Japan, Mexico, and South Korea, reflecting a diverse geographic reliance on these grains (United States Department of Agriculture (USDA), 2021, 2023). Furthermore, The Arab world imports large quantities of wheat and maize through virtual water trade (VWT), which is crucial not only for ensuring regional food security but also for significantly promoting the conservation of water resources and arable land. Egypt, as the main importing country, saves 13.1 billion cubic meters of irrigation water and 2.1 million hectares of crop area annually through these imports, highlighting the central role of these crops in regional resource management.(Lee et al., 2018). Moreover, China's strategic economic investments in wheat and maize imports, amounting to billions of dollars, underscore the critical importance of these crops in meeting the country's growing food demand and ensuring national food security (Shahzad et al., 2019). This global dependence on wheat and maize trade underscores the importance of exploring their trade dynamics, as they influence food security policies, international trade agreements, and national economic strategies more profoundly than many other crops. In conclusion, wheat and maize trade plays a vital role in the global agricultural economy and food security. Understanding the dynamics and implications of their trade is essential for informing policy decisions and ensuring the stability and sustainability of the global food supply.

The literature on grain crops trade encompasses various crucial aspects, including the impact of international trade on introducing nonindigenous organisms into new habitats (Shimono and Konuma, 2008), the influence of genetic and environmental factors on crop yield, particularly for wheat (Brinton et al., 2017), the increasing global production of grain legumes owing to their diverse applications (Sinclair and Vadez, 2012), and the importance of forecasting agricultural commodity prices, such as widely consumed grains in Nigeria, which is essential for informed decision-making within the agricultural sector (Sanusi et al., 2022). Among these areas of study, the trade potential of grain crops, facilitated by the application of advanced econometric models like the stochastic frontier model (SFM), has emerged as a key area of interest. The application of SFM to examine the determinants of agricultural exports in Pakistan revealed potential for increased exports to neighboring countries, the Middle East, and European nations (Atif et al., 2017). Nguyen's (2022) research employed SFM to investigate the "behind-the-border" constraints affecting Vietnam's rice and coffee exports, demonstrating significant impacts on achieving full export potential and indicating opportunities for expanding exports within the Association of Southeast Asian Nations (ASEAN) as well as with the European Union and countries under the Comprehensive and Progressive Agreement for Trans-Pacific Partnership (CPTPP). Abdullahi et al. (2022) utilized the stochastic frontier gravity model to examine the determinants positively influencing China's agricultural exports, the study finds that factors such as China's economic size, the BRI framework, common borders, and linguistic similarities play pivotal roles in enhancing China's agricultural export flows. Kamal et al. (2020) utilized the SFGM to clarify the variation in trade between partner countries, while Abdullahi et al. (2021) focused on the determinants, efficiency, and potential of agri-food exports from Nigeria to the EU using the SFGM. Additionally, Tian (2023) employed the time-varying SFGM to measure China's trade expansion space and other countries' agricultural import dependence. These studies demonstrate the versatility of the SFGM in assessing agricultural trade efficiency across different regions and trade relationships. Furthermore, the SFGM has been employed to explore the prospective efficiency gains in trade arising from the liberalization of agricultural commerce, as investigated by Moon (2022). Building upon the existing literature, this study addresses a significant gap by examining the trade potential and efficiency of wheat and maize within the Belt and Road Initiative (BRI) framework. While the stochastic frontier model (SFM) has been widely employed in various trade studies, research specifically focusing on agricultural commodities in BRI countries remains limited. This paper applies SFM methodology to quantify trade efficiency and potential, identify factors influencing efficiency, and analyze variations among different countries. By concentrating on these key agricultural commodities within the BRI context, this research aims to enhance understanding of their trade dynamics and offer valuable insights for policymakers and stakeholders in the agricultural sector. The findings of this study contribute to the growing

body of literature on agricultural trade within the BRI framework and provide empirical evidence to inform policy decisions in this critical area of international commerce.

Building upon this foundation and addressing the identified research gap, this study makes several noteworthy contributions to the existing body of literature. Firstly, it presents a thorough analysis of the trade potential and efficiency of wheat and maize among the Belt and Road Initiative (BRI) countries by utilizing the stochastic frontier model (SFM) to quantify trade efficiency and identify the factors that influence it. Secondly, the research underscores the importance of economic scale, market potential, government efficiency, political stability, and regulatory quality in enhancing trade efficiency while also examining the intricate relationship between World Trade Organization (WTO) membership and trade efficiency. Thirdly, the study uncovers disparities in the trade potential of wheat and maize across various countries, suggesting that higher domestic production levels may reduce the need for imports; however, international trade remains crucial for global food security. The findings provide valuable insights for developing effective agricultural trade policies and fostering regional economic growth, emphasizing the significance of improving government efficiency, political stability, and regulatory quality to increase trade efficiency. Lastly, by focusing on wheat and maize, this study contributes to a more profound understanding of the trade dynamics of these essential agricultural commodities within the BRI framework, paving the way for further research on the factors that influence trade efficiency.

The rest of the paper is organized as follows: section 2 presents the methodology, detailing the selection of BRI countries for the sample, the choice of agricultural products for analysis, and the construction of the stochastic frontier and trade inefficiency models. Section 3 delves into the results and their implications, exploring the complexities of agricultural trade within the BRI framework. The concluding sections, 4 and 5, summarize the main findings and discuss the implications of the research, highlighting the agricultural trade potential in BRI countries and suggesting ways to enhance cooperation and optimize trade strategies, with an emphasis on the importance of improving government efficiency, political stability, and regulatory quality to significantly boost trade efficiency. Through the application of SFM, this study offers a fresh perspective and methodology for understanding and improving agricultural trade efficiency.

2 The data and methods

2.1 Sample size and data sources

This study covers 45 countries for wheat, and 55 countries for maize. We initially considered all countries participating in the Belt and Road Initiative. However, due to limitations in data availability and consistency from 2002 to 2021, we restricted our sample to countries where reliable and consistent data on agricultural trade, economic indicators, and governance quality could be obtained for the period under study. This study builds upon previous comprehensive agricultural product research by focusing specifically on wheat and maize, two crops of paramount importance in global agriculture and trade. To analyze the efficiency and potential of agricultural trade in countries along the Belt and Road, both wheat and maize were selected due to their significance in global trade and food security. Wheat is a staple food and a major agricultural product in many countries, making it a crucial commodity for trade and food security (Zhang et al., 2022). Additionally, the trade of wheat has been identified as a key component of international agricultural negotiations, such as the Belt and Road Initiative, to enhance global food security (Zhang et al., 2022). With regard to maize, its importance is equally significant. For instance, research conducted in Kupang District indicates the market dominance of Lamuru maize seed farming, showing its economic value and market growth potential (Bria and Joka, 2023). Efficiency in input practices, such as land use, has been identified as a key factor in increasing maize production, potentially mitigating the need for land expansion (Edison, 2021). Additionally, the cultivation of vegetable (sweet) maize varieties as a primary crop has been explored, highlighting the crop's versatility (Sanaev et al., 2020). These findings collectively emphasize the critical role of wheat and maize in agricultural trade dynamics and underscore the necessity to ensure their sustainability and efficiency in trade relations.

The influencing factors in agricultural trade potential analysis in the Belt and Road countries are multifaceted and encompass various dimensions. Cultural and institutional distance, trade facilitation, reduction of tariff barriers, and trade network structure are significant factors affecting agricultural trade between China and the Belt and Road countries (Liu et al., 2020; Fan et al., 2022; Yang and Tsai, 2022; Zhang et al., 2022). The efficiency of China's agricultural exports is also determined by a mix of economic indicators including *per capita* GDP, exchange rate fluctuations, geographic distance, and the landlocked nature of certain regions (Abdullahi et al., 2022; Khan et al., 2024). Additionally, the strategic economic partnerships, exchange rate policy, and the development level of geo-economic relations play crucial roles in shaping agricultural trade dynamics (Muganyi and Chen, 2016; Hu et al., 2020). Moreover, research indicates that the Belt and Road Initiative (BRI) has led to an expansion in the scale of agricultural trade in BRI countries, highlighting the initiative's impact on trade potential (Wang et al., 2022).

This study draws upon a diverse array of reliable data sources to ensure a comprehensive analysis. The World Food and Agriculture Organization (FAO) database provided essential agricultural trade metrics, including yield, population, agricultural land, and GDP figures. To account for geographical factors, information on landlocked countries was sourced from publicly available geographical data. The World Bank's Worldwide Governance Indicators (WGI) database supplied crucial governance metrics, specifically focusing on government efficiency, political stability, and regulatory quality. Additionally, World Trade Organization (WTO) membership status was obtained from the official World Trade Organization (WTO) website. Table 1 presents the names, interpretations, and theoretical rationales of the various variables.

2.2 Model setting

The stochastic frontier model (SFM) is primarily used to analyze and estimate trade efficiency and the potential of agricultural trade flows, considering a combination of both traditional gravity variables

TABLE 1 Variable descriptions and theoretical rationale.

Variable	Interpretation	Theoretical rationale
Yield (hg/ha) (Log of Output)	Natural logarithm of output, representing the level of production	Utilized to transform the production variable into a linear relationship, facilitating the interpretation of elasticity effects
lnpop (Log of Population)	Natural logarithm of population size, reflecting market size or available labor force	Indicates potential demand and supply dynamics in agricultural markets, influencing trade flows
lncorpland (Value, 1,000 ha) (Log of Agricultural Land)	Natural logarithm of the size of agricultural land, denoting agricultural capacity	Agricultural land is a critical input for agricultural production, impacting the volume and efficiency of agricultural outputs
lnGDP (US$, millions) (Log of GDP)	Natural logarithm of Gross Domestic Product, signifying economic magnitude	GDP is indicative of a country's economic capacity, influencing its role in global agricultural trade
interland (Landlocked)	Binary indicator for countries without direct access to maritime routes	Landlocked status affects transportation costs and trade logistics, presenting unique challenges for agricultural trade
Z_Gover (Government Efficiency)	Standardized measure of the efficacy of government administration	Government efficiency is pivotal for creating conducive trade environments through infrastructure development and policy formulation
Z_Political (Political Stability)	Standardized measure of the stability of the political environment	Political stability is essential for sustaining long-term trade relationships and ensuring market confidence
Z_Regulatory (Regulatory Quality)	Standardized measure of the quality and enforcement of regulations	The regulatory framework affects the trade environment by influencing operational costs and legal certainty for businesses
Z_WTO (WTO Membership)	Binary indicator of membership status within the World Trade Organization	Reflects a country's adherence to international trade norms and practices, potentially facilitating agricultural trade

such as the economic size of bilateral countries, population, distance, and whether they are landlocked, as well as inefficiency factors such as government efficiency, political stability, regulatory quality, and free trade agreements. Armstrong (2007) pointed out that in the stochastic frontier model, objective variables that do not change in the short term over time, such as the economic size of bilateral countries, population, distance, and whether they are landlocked, are mainly taken into account, while human factors such as government efficiency, political stability, regulatory quality, and free trade agreements are incorporated into the trade inefficiency model. Furthermore, Romyen et al. (2023) used a copula-based gravity stochastic frontier model (GSFM) to estimate trade efficiency under free trade agreements for Thailand's agricultural exports. Abdullahi et al. (2022) examined the determinants and efficiency of China's agricultural exports with its 114 importing countries using the SFGM, applied to an augmented gravity model. Additionally, Chu (2023) utilized the SFGM to explore the impact of digital trade on China's trade potential and trade efficiency with countries participating in the Belt and Road Initiative.

The selection of variables such as yield, population size, arable land area, GDP, geographical characteristics, WTO membership, government efficiency, political stability, and regulatory quality is based on their relevance to capturing the multifaceted aspects of trade efficiency. Yield and arable land area are used to capture the agricultural capacity of the countries, while GDP and population size reflect economic and market potential. The inclusion of geographical characteristics and WTO membership provides insights into the logistical and regulatory environments that significantly impact trade efficiency. Moreover, government efficiency, political stability, and regulatory quality are incorporated to account for the institutional factors that influence trade performance. Based on these variables, this paper constructs a stochastic frontier model to analyze agricultural trade flows.

$$\ln(\mathrm{IMP})_{it} = \beta_0 + \beta_1 \ln(\mathrm{Yield}_{it}) + \beta_2 \ln(\mathrm{POP}_{it}) + \beta_3 \ln(\mathrm{Corpland}_{it}) + \beta_4 \ln(\mathrm{GDP}_{it}) + \beta_5 \ln(\mathrm{Interland}_{it}) + \mu_i + \eta_t + v_{it} - u_{it}$$

$$u_{it} = \alpha_1 \mathrm{Gover}_{it} + \alpha_2 \mathrm{Political}_{it} + \alpha_3 \mathrm{Regulatory}_{it} + \alpha_4 \mathrm{WTO}_{it} + e_{it}$$

where i represents a given country around the world, this econometric model evaluates the efficiency of imports from country i at time t, encapsulated by the natural logarithm of projected import volumes, ln $(\mathrm{IMP})_{it}$. The model gauges the maximum possible trade value by integrating a host of explanatory variables: ln(Yield) represents the natural logarithm of agricultural output, providing insight into the productivity and potential of crop production; ln(POP) stands for the natural logarithm of population size, which can influence demand within the trade equation; ln(GDP) denotes the natural logarithm of economic size; ln(Corpland) measures the natural logarithm of the amount of arable land, reflecting the capacity for grain crop production; Gov and PolStab are the governance and political stability respectively, indicating how governance quality and political stability can impact trade flows; RegQual indicates the natural logarithm of country i's regulatory quality at time t, a standardized measure of the quality and enforcement of regulations, and WTO signifies World Trade Organization membership, both of which can shape trade policies and conditions. The model also accounts for stochastic disturbances through v_{it}, capturing random shocks, and includes an inefficiency term u_{it}, which adjusts for specific, time-invariant characteristics in trade relations, providing a nuanced understanding of import efficiency and potential across different nations.

3 Empirical results

3.1 Estimated results

The empirical results of stochastic frontier models are presented in Tables 2, 3, to uncover the details and trends of influencing factors. Table 2 presents the estimated results of six stochastic frontier models for wheat. Each model assesses the efficiency of wheat trade based on a variety of variables and assumptions. By comparing the Akaike information criterion (AIC) values across these models, we can evaluate which model most effectively explains the data. Model 6, with the lowest AIC value of 2461.994, suggests it offers the best fit to the data while accounting for model complexity. This model, incorporating both time fixed effects and country fixed effects, provides an in-depth analysis of the factors influencing the efficiency of wheat trade in countries along the "Belt and Road." The slight negative impact of yield variation on trade efficiency (with a coefficient of −0.003 and a significance level of *) suggests that while an increase in yield might reduce dependence on international markets to some extent, it could also slightly decrease trade efficiency due to market saturation and increased costs of storage and transportation. This finding emphasizes the need to consider and balance the relationship between domestic supply and international trade when increasing yield, and to enhance trade efficiency by improving production efficiency rather than merely expanding cultivated areas. The coefficient for population size (lnpop) is 1.7330 (significance level ***), indicating that an increase in the logarithm of population size is positively correlated with wheat trade efficiency. This result may reflect the positive role of larger market size and consumption potential in enhancing trade efficiency. Similarly, the coefficient for GDP (lnGDP) is 1.0484 (significance level ***), indicating that the logarithmic growth of GDP has a positive impact on wheat trade efficiency, emphasizing the importance of economic development level in promoting trade efficiency. Notably, the coefficient for the "interland" (landlocked country) variable is 2.8815 (significance level ***), indicating a significant positive correlation between being a landlocked country and wheat trade efficiency. This may reflect that landlocked countries, facing unique geographical and logistical challenges, have taken effective measures to enhance trade efficiency, or they may focus more on strategies to improve trade efficiency due to geographical constraints.

TABLE 2 The estimated results of stochastic frontier models for wheat.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	9.599*** (1.254)	−8.9550 (5.8600)	11.5190*** (0.7826)	10.7160*** (0.6899)	−13.8880** (5.0444)	−13.6050** (4.1942)
lnYield	−0.7421*** (0.1187)	−0.7651*** (0.1904)	−0.6445*** (0.0782)	−0.5158*** (0.0693)	−0.5610** (0.1764)	−0.003* (0.1261)
lnpop	1.6950*** (0.0844)	2.5390*** (0.4248)	1.3424*** (0.0595)	1.3001*** (0.0619)	2.4412*** (0.3884)	1.7330*** (0.3144)
lncorpland	−0.9723*** (0.0537)	−1.9080*** (0.4287)	−0.6091*** (0.0506)	−0.5578*** (0.0446)	−0.8782* (0.3648)	−0.1436 (0.2725)
lnGDP	0.0893 (0.0586)	1.6550*** (0.1829)	0.0745 (0.0397)	0.0336 (0.0387)	1.2344*** (0.1882)	1.0484*** (0.1553)
interland	0.0381 (0.1250)	1.8500* (0.8973)	0.1733* (0.0792)	0.1383 (0.0757)	2.4924*** (0.7321)	2.8815*** (0.5951)
Z_Gover				−1.1456* (0.4467)		4.0053*** (0.6888)
Z_Political				1.9276*** (0.2709)		2.1957*** (0.3860)
Z_Regulatory				−1.0957** (0.3576)		1.3487* (0.6117)
Z_WTO				0.3948 (0.3229)		−4.0125*** (0.8760)
sigmaSq			6.2202*** (0.3212)	5.8206*** (0.5478)	2.4318*** (0.1773)	5.8599*** (0.7582)
gamma			0.9884*** (0.0032)	0.9869*** (0.0034)	0.9192*** (0.0208)	0.9848*** (0.0040)
Time fixed effects	No	Yes	No	No	Yes	Yes
Country fixed effects	No	Yes	No	No	Yes	Yes
Adjusted R-squared	0.4915	0.7744				
AIC	3368.927	2693.827	3109.474	3035.461	2601.172	2461.994

TABLE 3 The estimated results of stochastic frontier models for maize.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(Intercept)	2.084 (−1.528)	−422.0221 (−245.8374)	6.0087*** (−1.2201)	4.7122 (−1.0532)***	0.0086 (−2.9897)	1.4602 (−2.6194)
lnYield	−0.1539 (−0.1369)	−0.4791 (−0.1675)**	−0.2561* (−0.1023)	−0.0681 (−0.0825)	−0.4687** (0.1472)	−0.2560 (−0.1404)
lnpop	0.2239* (0.1125)	−0.3611 (−0.3252)	0.5652*** (−0.1021)	0.8336 (−0.1084)***	0.2873 (−0.3178)	−0.1086 (−0.2077)
lncorpland	−0.1322* (0.0671)	−0.7349* (−0.2924)	−0.2928*** (−0.0668)	−0.2185*** (−0.0621)	−0.0160 (−0.2187)	−0.7334*** (0.1502)
lnGDP	0.892*** (0.0784)	1.8806*** (−0.2392)	0.6847*** (−0.0744)	0.3831*** (0.0648)	1.0408*** (0.1825)	1.9596*** (0.2771)
interland	0.1442 (−0.1643)	−121.7121 (−72.4592)	−0.2477 (−0.1613)	−0.33213* (0.1340)	0.2131 (−0.4119)	−0.0699 (−0.2332)
Z_Gover				−0.8501* (0.3544)		−1.5334*** (0.4459)
Z_Political				−0.0152 (−0.1732)		0.3837 (−0.1967)
Z_Regulatory				−1.1907*** (0.3206)		0.2334 (−0.4537)
Z_WTO				2.432*** (0.1950)		−1.2546* (0.5063)
sigmaSq			12.253*** (0.8971)	7.0885*** (0.5059)	2.6699*** (0.2186)	4.086*** (0.5242)
gamma			0.9676*** (0.0146)	0.9837*** (0.0046)	0.9600*** (0.0199)	0.9837*** (0.0173)
Time fixed effects	No	Yes	No	No	Yes	Yes
Country fixed effects	No	Yes	No	No	Yes	Yes
Adjusted R-squared	0.4403	0.8702				
AIC	4749.978	3210.461	4659.648	4537.628	3143.644	3134.701

Furthermore, Model 6 also shows that the coefficient for government efficiency (Z_Gover) is 4.0053 (significance level ***), the coefficient for political stability (Z_Political) is 2.1957 (significance level ***), and the coefficient for regulatory quality (Z_Regulatory) is 1.3487 (significance level *). These results highlight the important role of efficient government operations, stable political environments, and high-quality regulation in reducing transaction costs and risks, thereby enhancing trade efficiency. The coefficient for WTO membership is −4.0125 (significance level ***), indicating a significant negative correlation between WTO membership and wheat trade efficiency. This result may initially seem surprising, as WTO members are generally expected to increase their trade efficiency by promoting trade liberalization and providing a more stable and predictable trade environment. However, this negative correlation may reflect the challenges WTO members face in implementing WTO rules and commitments, especially for those countries that may lack the preparation or resources to adapt to rapid trade liberalization. Additionally, this may also indicate differences in trade efficiency among WTO members, where some countries may not fully utilize the opportunities provided by WTO membership due to various internal and external factors. Therefore, the impact of WTO membership on wheat trade efficiency is complex and multifaceted, requiring further research to deeply understand the underlying mechanisms. This includes considering the adaptation process of member countries after joining the WTO, their capacity in implementing trade policies, and how they utilize the WTO framework to enhance their trade efficiency.

By comprehensively considering these variables, Model 6 not only provides an in-depth understanding of the factors affecting wheat trade efficiency in countries along the "Belt and Road" but also ensures the robustness of the analysis results by controlling for time and country-specific fixed effects. This approach allows us to more accurately identify and assess the key factors influencing trade efficiency.

Table 3 presents the estimated results of six stochastic frontier models for maize. Model 6 provides an in-depth analysis of the factors affecting maize trade efficiency by incorporating both time fixed effects and country fixed effects, along with the lowest AIC value (3134.701). In Model 6, the coefficient for cultivated land area (lncorpland) is −0.7334 (significance level ***), indicating that an increase in the logarithm of cultivated land area is significantly negatively related to maize trade efficiency. This may reflect efficiency issues in managing larger agricultural areas or challenges in optimizing land use for trade purposes. The coefficient for GDP

(lnGDP) is 1.9596 (significance level ***), showing that an increase in the logarithm of GDP positively affects maize trade efficiency. This highlights the importance of the level of economic development in promoting trade efficiency, where wealthier economies may have better infrastructure and systems to facilitate trade. Moreover, Model 6 also shows that the coefficient for government efficiency (Z_Gover) is −1.5334 (significance level ***), and the coefficient for WTO membership (Z_WTO) is −1.2546 (significance level *). These results highlight the complex role of governance, regulatory quality, and international trade agreements in influencing trade efficiency. The negative coefficients may indicate that, although these factors are crucial, challenges and efficiency issues need to be addressed to fully leverage their potential in enhancing trade efficiency. Therefore, the impact of these variables on maize trade efficiency is complex and multifaceted, requiring further research to deeply understand the mechanisms behind them. This includes considering how countries can optimize agricultural productivity, manage population growth, and improve governance and regulatory frameworks to enhance trade efficiency.

Tables 2, 3 respectively provide an analysis of the trade efficiency of wheat and maize from 2002 to 2021 under the "Belt and Road" initiative, conducted through six different models using stochastic frontier models. In the analysis of wheat trade efficiency, the results of Model 6 highlight the importance of the level of economic development, population size growth, as well as efficient government operations, stable political environments, and high-quality regulation in promoting trade efficiency. However, the impact of WTO membership on wheat trade efficiency shows a negative correlation, which might reflect the challenges WTO members face in implementing WTO rules and commitments. In the analysis of maize trade efficiency, an increase in the area of cultivated land is significantly negatively correlated with maize trade efficiency, reflecting potential efficiency issues in managing larger agricultural areas or optimizing land use for trade purposes. Additionally, the negative impacts of government efficiency and WTO membership on maize trade efficiency underscore the complex role of governance, regulatory quality, and international trade agreements in influencing trade efficiency. Therefore, the factors affecting the trade efficiency of wheat and maize are complex and multifaceted, necessitating further research to deeply understand the mechanisms behind them. This includes considering how to optimize agricultural productivity, manage population growth, and improve governance and regulatory frameworks to enhance trade efficiency.

Building on the insights from Tables 2, 3 regarding the trade efficiency of wheat and maize, Figure 1 compares the average efficiency of wheat and maize from 2002 to 2021, revealing that wheat's efficiency, though fluctuating, generally exhibits a slight upward trend, peaking at 0.55 before slightly declining to 0.49 by 2021. In contrast, maize's efficiency starts lower, shows some variability, but overall remains relatively stable, concluding at 0.37 in 2021, which is similar to initial value. This indicates that while both crops have seen efficiency fluctuations, wheat has experienced a modest improvement over the period, whereas maize's efficiency has remained stable without a significant long-term increase. Further research would be necessary to examine factors influencing these trends, including shifts in agricultural practices, climate conditions, and technological advancements in farming. Such factors might encompass technological progress in agriculture, global climate pattern changes affecting crop yields, and shifts in market demand or agricultural policy.

3.2 Country-level trade efficiency results

Tables 4, 5 provide a statistical descriptive of country-level trade efficiency scores for wheat and maize over the period from 2002 to 2021. The tables categorize data into several key metrics: overall mean trade efficiency, minimum and maximum efficiency scores observed, mean efficiency up to 2013 (prior to the Belt and Road Initiative, BRI), mean efficiency after 2013 (post-BRI implementation), and mean efficiency during the COVID-19 pandemic years of 2020–2021.

Table 4 presents a comprehensive analysis of wheat trade efficiency scores spanning the period from 2002 to 2021. A notable divergence can be observed between the mean trade efficiency scores prior to and following 2013, suggesting the potential influence of the BRI on the dynamics of trade. Turkey and Hungary, for instance, exhibited a marked improvement in their post-2013 mean efficiency, with Turkey's score increasing from 0.4978 to 0.7585 and Hungary's from 0.2824 to 0.7597, which can be attributed to the enhanced trade facilitation and infrastructure development fostered by the BRI, such as improved rail connectivity and streamlined customs procedures. Conversely, Georgia and Jordan experienced a decline in trade efficiency in the post-2013 era, with Georgia's score dropping from 0.7209 to 0.5534 and Jordan's from 0.7042 to 0.4765, potentially indicating the presence of infrastructural or political obstacles that the BRI has not sufficiently addressed. Furthermore, an examination of the average efficiency scores during the COVID-19 pandemic provides valuable insights into the resilience and vulnerabilities of trade networks in the face of global disruptions. South Africa and Croatia, for example, demonstrated remarkable trade efficiency throughout the pandemic, with scores of 0.7359 and 0.8178 respectively, suggesting the presence of effective pandemic management strategies or well-diversified trade mechanisms that mitigated the impact of the crisis. In contrast, Egypt and Jordan experienced a significant decline in trade efficiency, with scores dropping to 0.3257 and 0.3538 respectively, underlining the detrimental effects of the pandemic on their trade operations, which may have been exacerbated by pre-existing infrastructural or economic vulnerabilities. This disparity in pandemic-era performance highlights the varying degrees of trade resilience across different countries and emphasizes the need for robust crisis management strategies in international trade.

The analysis of wheat trade efficiency reveals a complex landscape of winners and losers in the post-BRI era and during the COVID-19 pandemic. While some countries have significantly benefited from improved infrastructure and trade facilitation, others have struggled to maintain their efficiency levels. This variability suggests that the impact of large-scale initiatives like the BRI and global crises like the pandemic is not uniform and warrants further investigation into country-specific factors that contribute to trade resilience.

Table 5 presents a comprehensive analysis of maize trade efficiency scores spanning the period from 2002 to 2021. A notable divergence can be observed between the mean trade efficiency scores prior to and following 2013, suggesting the potential influence of the BRI on the dynamics of trade. Slovenia and Georgia, for instance, exhibited a marked improvement in their post-2013 mean efficiency, with

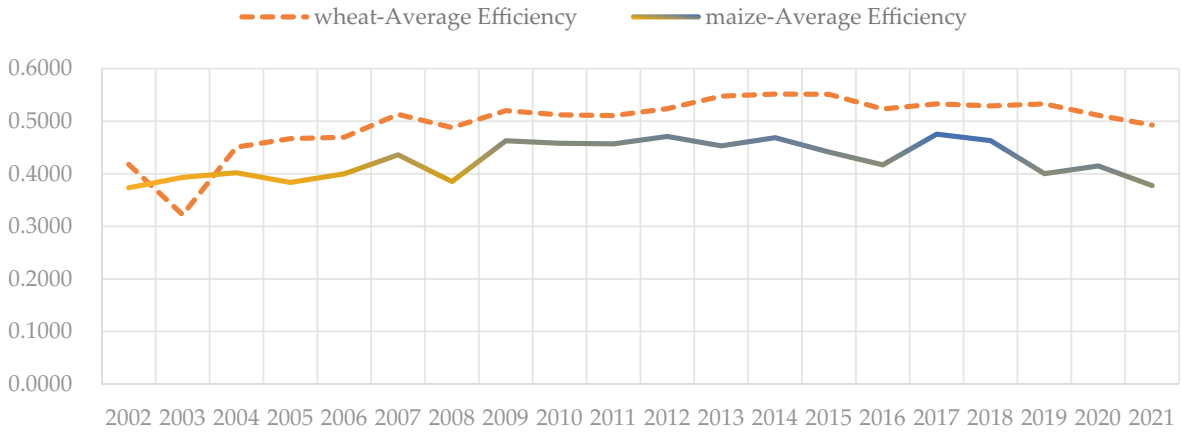


FIGURE 1
Average efficiency of wheat and maize average efficiency from 2002–2021.

Slovenia's score rising from 0.5005 to 0.7207 and Georgia's from 0.4447 to 0.6530, which can be attributed to the enhanced trade facilitation and infrastructure development fostered by the BRI, such as improved port facilities and digital trade platforms. Conversely, China experienced a decline in trade efficiency in the post-2013 era, with its score decreasing from 0.6189 to 0.2597, potentially influenced by a complex interplay of factors, including domestic and foreign policy shifts and fluctuations in the macroeconomic landscape. Furthermore, an examination of the average efficiency scores during the COVID-19 pandemic provides valuable insights into the resilience and vulnerabilities of trade networks in the face of global disruptions. Oman and Qatar, for example, demonstrated remarkable trade efficiency throughout the pandemic, with scores of 0.7780 and 0.7742 respectively, suggesting the presence of effective pandemic management strategies or well-diversified trade mechanisms that mitigated the impact of the crisis. In contrast, Egypt experienced a significant decline in trade efficiency, with its score dropping to 0.2587, underlining the detrimental effects of the pandemic on its trade operations, which may have been exacerbated by pre-existing infrastructural or economic vulnerabilities. The varied responses to the pandemic underscore the importance of adaptable trade policies and robust supply chain management in maintaining trade efficiency during global crises.

Tables 4, 5 provide a detailed analysis of country-level wheat and maize trade efficiency scores from 2002 to 2021. By comparing the data before and after the implementation of the Belt and Road Initiative (BRI), changes in trade efficiency for wheat and maize in different countries can be observed. For example, China's wheat trade efficiency significantly improved after the implementation of the BRI, increasing from 0.5482 to 0.6352, while maize trade efficiency declined, dropping from 0.6189 to 0.2597. This difference may be due to various factors. First, the BRI may have focused more investment and improvements on infrastructure and logistics related to wheat trade, thereby enhancing overall wheat trade efficiency. Second, changes in China's domestic agricultural policies and market demand may have different impacts on the trade of different agricultural products. Wheat, as a major grain crop, may benefit from more stable and prioritized policy support, while maize may be affected by adjustments in domestic supply chains, market demand fluctuations, and changes in international trade policies. Additionally, changes in the global market environment and trade partnerships may also have different impacts on the trade efficiency of different agricultural products. Therefore, although the BRI generally promotes trade facilitation, its specific impact varies significantly between different agricultural products and countries, requiring further in-depth research and analysis.

In comparing wheat and maize trade efficiencies, it's notable that wheat trade generally showed more resilience and improvement post-BRI and during the pandemic. This could be attributed to wheat's status as a staple food crop, which may have led to more consistent demand and prioritized trade facilitation efforts. Maize, often used as animal feed, may be more susceptible to fluctuations in livestock industry demands and alternative feed options. In synthesizing the observations from both tables, it is evident that the BRI's potential to enhance trade efficiency is significant but not uniformly positive across all participating countries. The effectiveness of pandemic response measures, political stability, and existing infrastructure play critical roles in determining the extent of benefits derived from the initiative. Moreover, the COVID-19 pandemic underscores the importance of resilient and diversified trade networks. Future research could focus on identifying best practices from countries that maintained high trade efficiency during the pandemic, potentially informing policy recommendations for enhancing trade resilience in the face of global crises.

3.3 Potential of countries by GDP and yield tiers results

Figures 2, 3 are created by categorizing countries based on their GDP sizes—large, medium, and small—and analyzing the trends and dynamics of trade potential among countries with different GDP levels. This approach aims to uncover the differences in trade potential among countries at various economic levels. In Figure 2, countries of different economic sizes exhibit varying characteristics in terms of wheat trade potential. Large economies such as the Russian Federation, China, and Turkey, despite their significant positions in the global economy, do not significantly outperform medium or small

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TABLE 4 Country-level wheat trade efficiency scores, 2002–2021.

Country	Mean	Min	Max	Mean up to 2013	Mean after 2013	Mean 2020–2021
Israel	0.7276	0.5135	0.8465	0.7774	0.6528	0.5420
Republic of Korea	0.6897	0.4669	0.8176	0.7076	0.6629	0.6197
New Zealand	0.6604	0.3116	0.8003	0.6289	0.7077	0.5975
Bangladesh	0.6583	0.4085	0.8066	0.6231	0.7112	0.6767
Georgia	0.6539	0.3572	0.8273	0.7209	0.5534	0.4395
Morocco	0.6526	0.3528	0.7768	0.6296	0.6871	0.7293
South Africa	0.6433	0.2204	0.7999	0.5988	0.7100	0.7359
Egypt	0.6358	0.2290	0.8022	0.6655	0.5912	0.3257
Armenia	0.6242	0.3535	0.7916	0.6540	0.5794	0.5327
North Macedonia	0.6211	0.2862	0.8156	0.5855	0.6744	0.6308
Jordan	0.6132	0.3222	0.8294	0.7042	0.4765	0.3538
Albania	0.6046	0.3767	0.7786	0.6572	0.5258	0.5230
Turkey	0.6021	0.0417	0.8710	0.4978	0.7585	0.8078
Kuwait	0.5995	0.3962	0.8252	0.6321	0.5508	0.5959
Tajikistan	0.5955	0.1684	0.7692	0.5313	0.6918	0.5566
Czechia	0.5870	0.0725	0.8258	0.5155	0.6943	0.7886
Thailand	0.5837	0.1739	0.8897	0.4593	0.7704	0.7514
China	0.5830	0.2357	0.8992	0.5482	0.6352	0.7896
Slovenia	0.5720	0.1379	0.8728	0.4720	0.7219	0.7149
Myanmar	0.5503	0.1336	0.8011	0.4236	0.7404	0.7624
Poland	0.5430	0.0560	0.8511	0.5214	0.5754	0.5558
Kyrgyzstan	0.5196	0.1567	0.8370	0.6034	0.3939	0.2195
Afghanistan	0.5167	0.1029	0.8879	0.5777	0.4252	0.4479
Oman	0.5156	0.3017	0.9070	0.4565	0.6042	0.6913
Lithuania	0.5144	0.0988	0.8665	0.4307	0.6399	0.6409
Ethiopia	0.5082	0.1796	0.8087	0.6308	0.3244	0.2187
Saudi Arabia	0.4977	0.0005	0.8391	0.3174	0.7682	0.7066
Estonia	0.4920	0.1105	0.8952	0.5243	0.4436	0.2527
Hungary	0.4733	0.0025	0.8416	0.2824	0.7597	0.7447
Romania	0.4651	0.0612	0.8827	0.3437	0.6471	0.6385
Azerbaijan	0.4642	0.3207	0.6858	0.5086	0.3976	0.3687
Russian Federation	0.4607	0.0996	0.9068	0.4806	0.4308	0.2107
Bulgaria	0.4509	0.0779	0.8597	0.3669	0.5769	0.5615
Slovakia	0.4478	0.0209	0.8762	0.5336	0.3193	0.1630
Iraq	0.4213	0.0278	0.7922	0.6121	0.1350	0.1474
Uzbekistan	0.3760	0.0040	0.7551	0.1922	0.6515	0.6725
Croatia	0.3758	0.0033	0.8768	0.1174	0.7634	0.8178
Iran (Islamic Republic of)	0.3753	0.0119	0.8438	0.3774	0.3723	0.5787
Bhutan	0.3279	0.0365	0.8432	0.3505	0.2940	0.1126
Syrian Arab Republic	0.2759	0.0284	0.8718	0.2628	0.2954	0.0329
Belarus	0.2341	0.0005	0.6657	0.2640	0.1894	0.1394
Bosnia and Herzegovina	0.2229	0.0417	0.3228	0.1939	0.2664	0.2250
Republic of Moldova	0.2034	0.0115	0.9354	0.2824	0.0849	0.1519
Kazakhstan	0.1786	0.0020	0.9436	0.1115	0.2793	0.7392
Ukraine	0.1083	0.0039	0.9515	0.1590	0.0322	0.0777

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TABLE 5 Country-level trade efficiency scores of maize, 2002–2021.

Country	Mean	Min	Max	Mean up to 2013	Mean after 2013	Mean 2020–2021
Israel	0.6575	0.3104	0.7960	0.7038	0.5882	0.3838
Albania	0.6475	0.3847	0.8087	0.7039	0.5629	0.4257
Republic of Korea	0.6261	0.3615	0.8094	0.7244	0.4787	0.3652
Malaysia	0.6185	0.3418	0.8200	0.7036	0.4910	0.3476
Saudi Arabia	0.5980	0.3068	0.8102	0.5815	0.6227	0.4819
Morocco	0.5925	0.4263	0.7848	0.6555	0.4980	0.4721
Slovenia	0.5886	0.3092	0.8242	0.5005	0.7207	0.7654
United Arab Emirates	0.5681	0.2080	0.8701	0.6214	0.4882	0.4397
Egypt	0.5505	0.2352	0.7476	0.5984	0.4785	0.2587
Kuwait	0.5448	0.2639	0.7949	0.6331	0.4123	0.2945
North Macedonia	0.5415	0.1981	0.8008	0.6625	0.3601	0.2961
Qatar	0.5371	0.0819	0.8103	0.5553	0.5097	0.7742
Panama	0.5321	0.2297	0.7945	0.6649	0.3329	0.3332
Georgia	0.5281	0.0203	0.8461	0.4447	0.6530	0.5959
Oman	0.5200	0.1090	0.8104	0.4130	0.6805	0.7780
Armenia	0.4987	0.0041	0.8343	0.5629	0.4024	0.3380
Turkey	0.4941	0.0240	0.9029	0.5041	0.4791	0.3562
Iran (Islamic Republic of)	0.4937	0.1914	0.7480	0.4261	0.5952	0.5626
Romania	0.4882	0.0315	0.8449	0.4639	0.5246	0.5836
Bangladesh	0.4784	0.1455	0.8327	0.4862	0.4668	0.4610
Philippines	0.4784	0.0553	0.8202	0.3853	0.6180	0.4697
China	0.4752	0.1594	0.8474	0.6189	0.2597	0.3348
Croatia	0.4635	0.0356	0.8819	0.4289	0.5154	0.5405
Poland	0.4616	0.0564	0.8471	0.5504	0.3284	0.1950
Lithuania	0.4588	0.1483	0.8507	0.3784	0.5794	0.5643
Vietnam	0.4551	0.0829	0.8575	0.2565	0.7528	0.5727
Czechia	0.4466	0.0625	0.8799	0.2705	0.7107	0.6411
Maldives	0.4408	0.0476	0.8730	0.3186	0.6242	0.6879
Slovakia	0.4315	0.0358	0.8760	0.4319	0.4308	0.2979
Hungary	0.4282	0.0199	0.8777	0.3323	0.5720	0.6336
Nepal	0.4184	0.0073	0.8174	0.2508	0.6698	0.6244
Indonesia	0.4152	0.0976	0.8709	0.5000	0.2880	0.1207
Azerbaijan	0.4104	0.0641	0.7484	0.4307	0.3798	0.1474
Belarus	0.4061	0.0970	0.8811	0.5081	0.2531	0.1313
Bosnia and Herzegovina	0.4025	0.0808	0.6263	0.4203	0.3758	0.1714
Bulgaria	0.3825	0.0227	0.8931	0.4807	0.2352	0.1353
Sri Lanka	0.3778	0.0205	0.8713	0.4469	0.2740	0.0447
Thailand	0.3706	0.0325	0.9024	0.3564	0.3918	0.8858
Myanmar	0.3619	0.0099	0.8373	0.2038	0.5991	0.6901
Syrian Arab Republic	0.3580	0.1358	0.7142	0.4165	0.2702	0.1645
Madagascar	0.3528	0.0158	0.8419	0.4664	0.1823	0.0228
Kyrgyzstan	0.3475	0.0293	0.8486	0.4828	0.1445	0.0754
Pakistan	0.3303	0.0602	0.9194	0.3422	0.3125	0.1568
New Zealand	0.3184	0.0086	0.9179	0.0614	0.7039	0.6086
South Africa	0.3126	0.0067	0.9258	0.3362	0.2771	0.0278

(Continued)

TABLE 5 (Continued)

Country	Mean	Min	Max	Mean up to 2013	Mean after 2013	Mean 2020–2021
Russian Federation	0.3076	0.0516	0.8786	0.4537	0.0885	0.0627
India	0.2751	0.0036	0.8940	0.1254	0.4997	0.4820
Ethiopia	0.2618	0.0084	0.8691	0.3893	0.0704	0.0742
Bhutan	0.2592	0.0079	0.7950	0.2088	0.3347	0.3049
Kazakhstan	0.2431	0.0179	0.9122	0.1640	0.3617	0.3165
Iraq	0.2381	0.0004	0.8868	0.0627	0.5012	0.8451
Republic of Moldova	0.2053	0.0103	0.8871	0.2080	0.2013	0.4292
Cambodia	0.1975	0.0038	0.8902	0.0436	0.4283	0.8883
Lao People's Democratic Republic	0.1701	0.0242	0.9286	0.2339	0.0744	0.0799
Ukraine	0.1001	0.0144	0.1999	0.0861	0.1212	0.0574

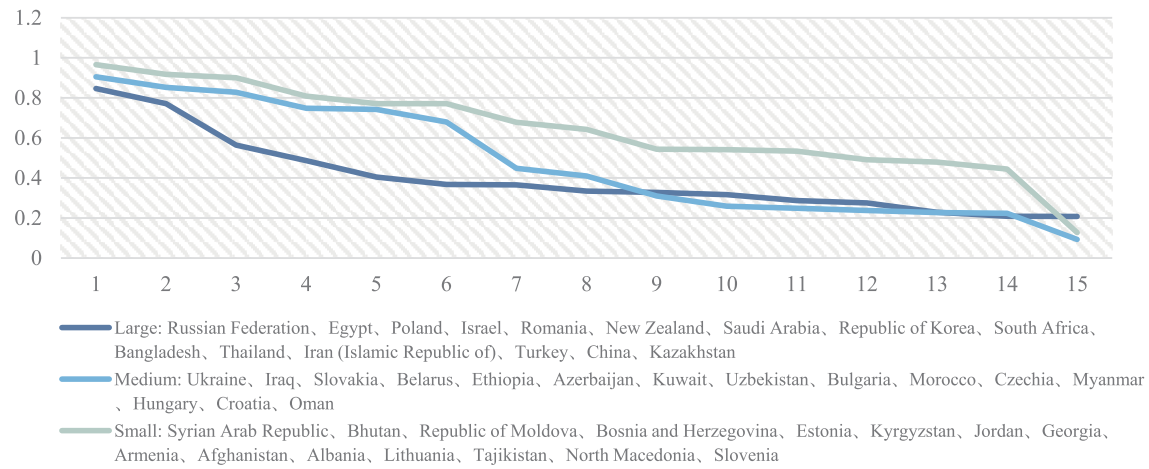


FIGURE 2
Wheat potential of countries by GDP tiers in 2021: large, medium and small.

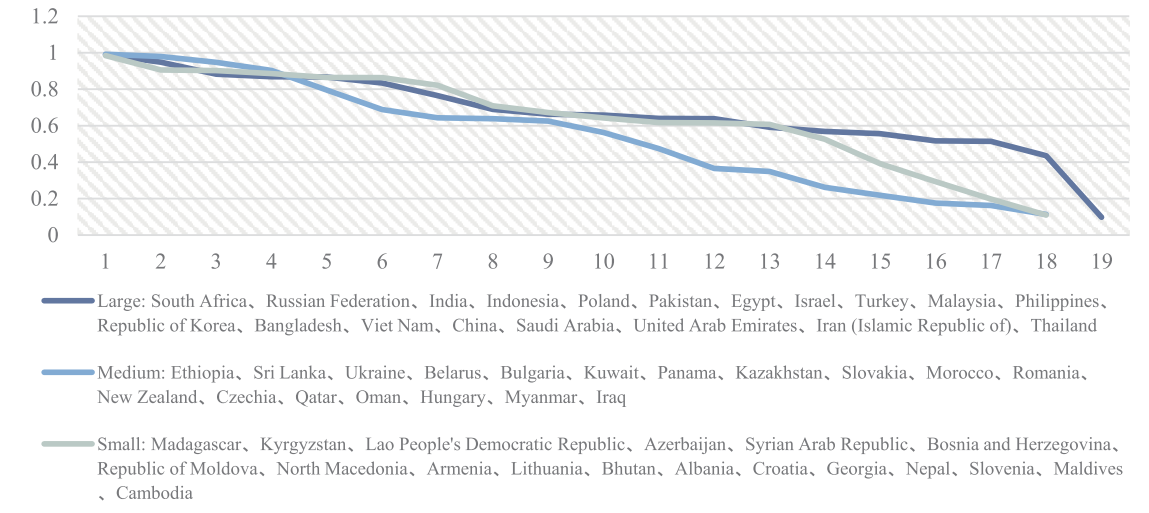


FIGURE 3
Maize trade potential of countries by GDP tiers in 2021: large, medium and small.

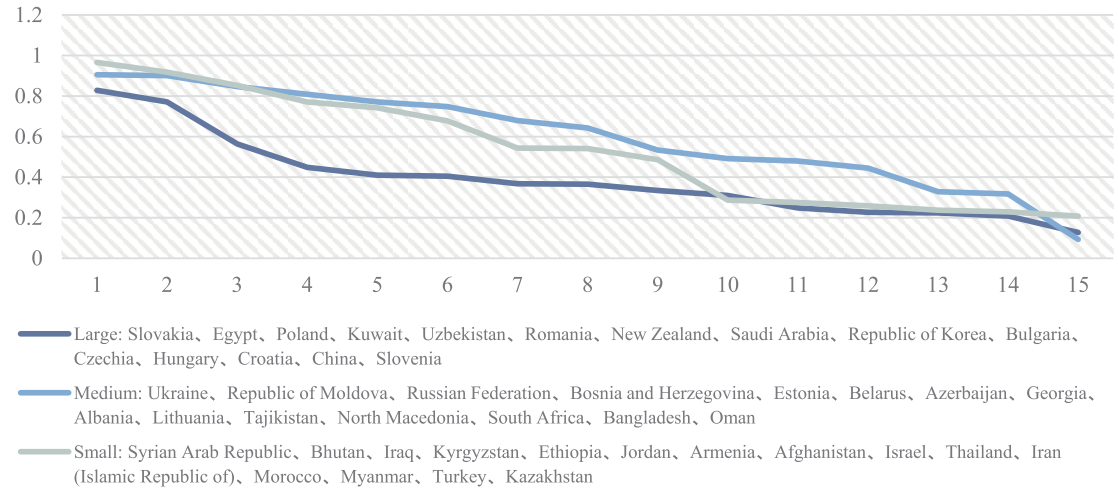


FIGURE 4
Wheat potential of countries by yield tiers in 2021: large, medium and small.

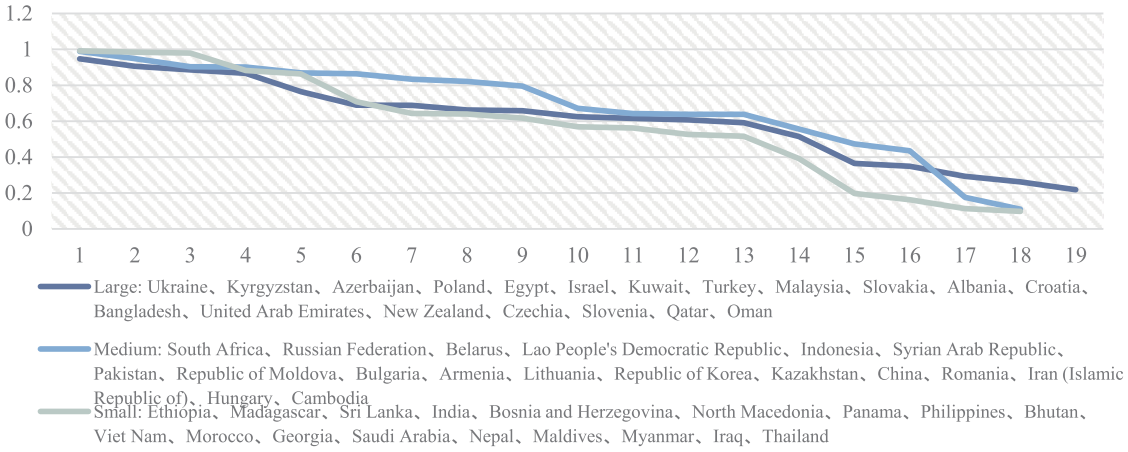


FIGURE 5
Maize trade potential of countries by yield tiers in 2021: large, medium and small.

economies in wheat trade potential. This could be due to these countries having a strong capacity for self-sufficiency and a more diversified economic structure, reducing their reliance on imported wheat. Additionally, varying dietary habits and consumption patterns across countries may also influence the demand for wheat.

In contrast, the analysis of maize trade potential in Figure 3 shows that large economies have a more pronounced potential in the maize market. This may be related to maize's dual role as an important food and industrial raw material (such as for producing feed and biofuels). Larger economies, with their developed livestock industries and industrial demands, have relatively higher needs for maize. Furthermore, the international trade flow of maize might be more active, especially in countries where natural conditions are unfavorable for maize production, leading these countries to rely more heavily on imports to meet their needs. Some large economies might also engage more actively in the international maize market to ensure food security.

Through the analysis of wheat and maize trade potential under the 2021 GDP tier classification, we observe performance differences among countries of varying economic sizes in these two important agricultural product markets. These differences not only reflect the variations in agricultural production capabilities among countries but also their diversity in economic strategies, consumption demands, and other aspects. Understanding these differences is crucial for formulating effective international trade policies and promoting global food security. For large economies, such as China and the Russian Federation, domestic markets should be streamlined to reduce reliance on imports while simultaneously enhancing export capabilities. Furthermore, engaging in international trade agreements and cooperation projects can bolster their competitiveness in the global market. For medium and small economies, including Ukraine and Slovakia, agricultural infrastructure should be improved to increase production efficiency and export capacity. Moreover, governments should provide fiscal support, such as financial incentives and tax benefits, to encourage agricultural production and exports.

Figures 4, 5 analyze the trade potential of wheat and maize, respectively, across countries categorized by yield tiers (large, medium,

and small) in 2021. These figures reveal insights into how yield impacts trade potential across different economic landscapes. In Figure 4, countries with high wheat yields, such as Slovakia, Egypt, and Poland, may have lower wheat trade import potential due to their high domestic production. This aligns with the intuition that countries with high production typically have lower import needs, as they can adequately meet domestic demand.

Similarly, Figure 5 applies this logic to maize. Countries classified with high maize yields, like Ukraine, Kyrgyzstan, and Azerbaijan, indicate excellent production performance, potentially leading to lower maize import potential due to sufficient domestic supply to meet or nearly meet demand.

Figures 4, 5 compare the relationship between production volumes and import potential across different countries for wheat and maize, respectively. Both figures suggest a similar trend: countries with higher production levels tend to have lower import potential. This pattern indicates that increased domestic production can satisfy or even exceed national demand, reducing the need for imports. However, when examining individual countries, variations emerge. For instance, a country with high wheat production might not have a correspondingly high maize production, affecting its import potential for each crop differently. While Slovakia, Egypt, and Poland are highlighted for their wheat production in Figure 4, their maize production and import potential, as shown in Figure 5, may differ. Thus, while the general rule that higher production decreases import potential holds, the specific relationship between production and import potential for wheat and maize can vary significantly from country to country, reflecting differences in agricultural specialization, strengths, and domestic demand for different crops. For high-yield countries, such as Egypt and Poland, export channels should be optimized to ensure their agricultural products can efficiently enter the international market. Additionally, the processing capacity of agricultural products should be enhanced to increase added value and bolster competitiveness in the global marketplace. For medium and low-yield countries, including South Africa and North Macedonia, advanced agricultural technologies should be introduced, and comprehensive farmer training programs should be implemented to improve production levels. Concurrently, through international aid and cooperation projects, these nations can obtain essential financial and technical support to augment their agricultural production capacity and foster sustainable growth in the sector.

3.4 Contrast of wheat and maize potential of different GDP and yield

Figures 6–8 present the contrast in wheat and maize import potential among countries categorized by their GDP size into large, medium, and small groups for the year 2021. These charts reveal the potential advantages and challenges in grain trade for countries of different economic scales by comparing the import potential of wheat and maize.

The analysis of Figure 6 reveals a significant difference between the potential for maize imports and wheat imports among large GDP countries. In these countries, the potential for maize imports is generally higher than that for wheat, which may reflect a high demand for maize, whether as food, feed, or for other industrial uses. This trend may be attributed to agricultural policies, consumption patterns, and demand for biofuels in these economies. For instance, large GDP countries might have more capacity to invest in biofuel projects, thereby increasing the demand for maize.

In Figure 7, the data for medium GDP countries show a more complex difference in the potential for wheat and maize imports. While many countries still show higher potential for maize imports compared to wheat, the difference is less pronounced than in large GDP countries. This could be because medium GDP countries have a greater diversity in agricultural production and consumption habits, and they might be more flexible in balancing domestic and international market supply and demand. Additionally, these countries might be making more trade-offs between wheat and maize to meet their domestic market needs.

The analysis of Figure 8 reveals a unique trend in small GDP countries regarding the potential for wheat and maize imports. In these countries, the potential for wheat imports is generally higher than for

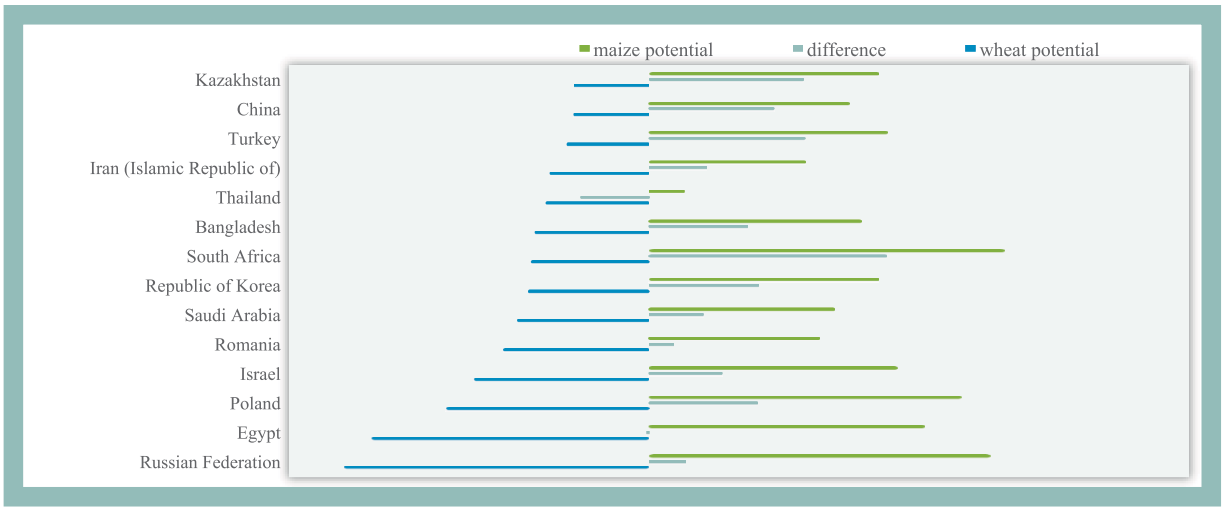


FIGURE 6
Contrast of wheat and maize trade potential of large GDP countries in 2021.

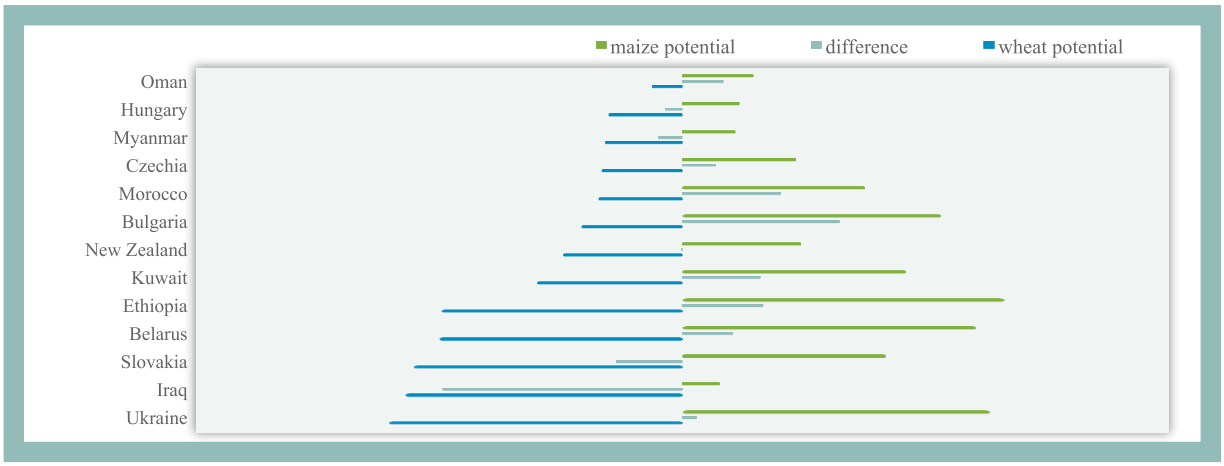


FIGURE 7
Contrast of wheat and maize trade potential of medium GDP countries in 2021.

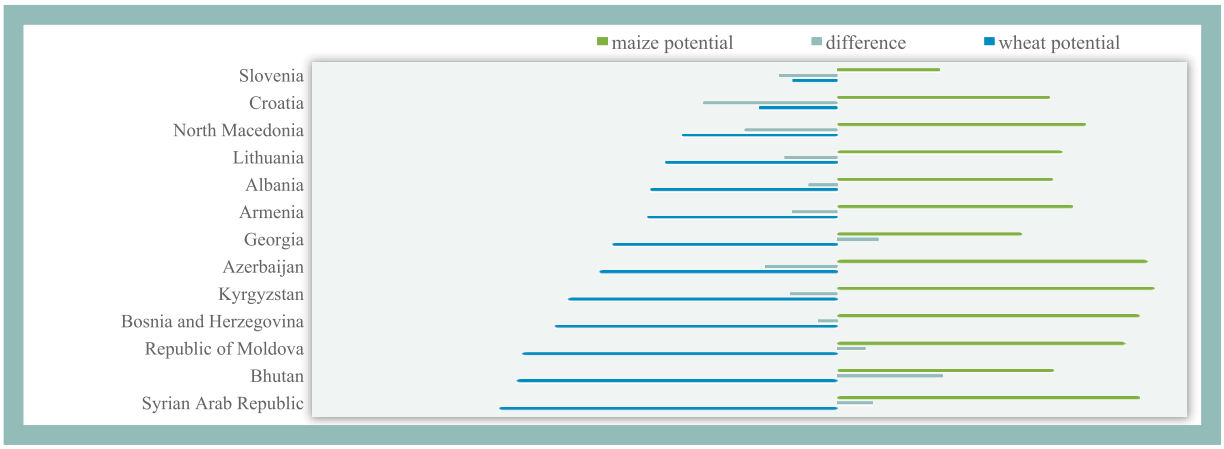


FIGURE 8
Contrast of wheat and maize potential of small GDP countries in 2021.

maize, which may reflect a high dependency on wheat as a staple and basic food. Small GDP countries might focus more on meeting basic food security needs, with wheat being a primary food source in many regions. Moreover, their agricultural policies might be more inclined to support the import of wheat to ensure domestic food security.

Figures 6–8 categorize countries into three groups—large, medium, and small, based on their 2021 GDP, and compare the import potential for wheat and maize among countries of different economic scales. Large GDP countries tend to show a higher demand for the potential of maize imports, possibly related to their agricultural policies, consumption habits, and the demand for biofuels. Medium GDP countries display a greater balance in the potential for wheat and maize imports, reflecting their flexibility in meeting diverse needs. Meanwhile, small GDP countries focus more on wheat imports, likely due to their high emphasis on food security. These trends reveal the complexity of the global agricultural market and the different strategies formulated by economies based on their needs and policies.

Figures 9–11 further explore this dimension by linking grain production capacity to import potential, highlighting the nuanced trade dynamics driven by the production volumes of each country. Figures 9–11 delineate the import potential for two significant grain crops, wheat and maize, across three groups of countries categorized by their yield sizes—large, medium, and small.

Focusing on Figure 9 for countries with large yields, we notice that the import potential for maize generally surpasses that of wheat. This might indicate that in these countries, the production capacity for wheat is relatively high, sufficient to meet most of the domestic demand. Therefore, the demand for maize is relatively higher, possibly due to increased needs for maize in feed, biofuel, and other industrial uses. This trend might reflect the diversified agricultural production demands of these countries and strategic considerations for ensuring food and energy security.

For the medium yield countries depicted in Figure 10, maize's import potential also generally exceeds that of wheat, though the difference is not as pronounced as in the large yield countries. This might suggest a more balanced distribution of wheat and maize production in these countries, but still a higher demand for maize imports. This could be related to the agricultural production

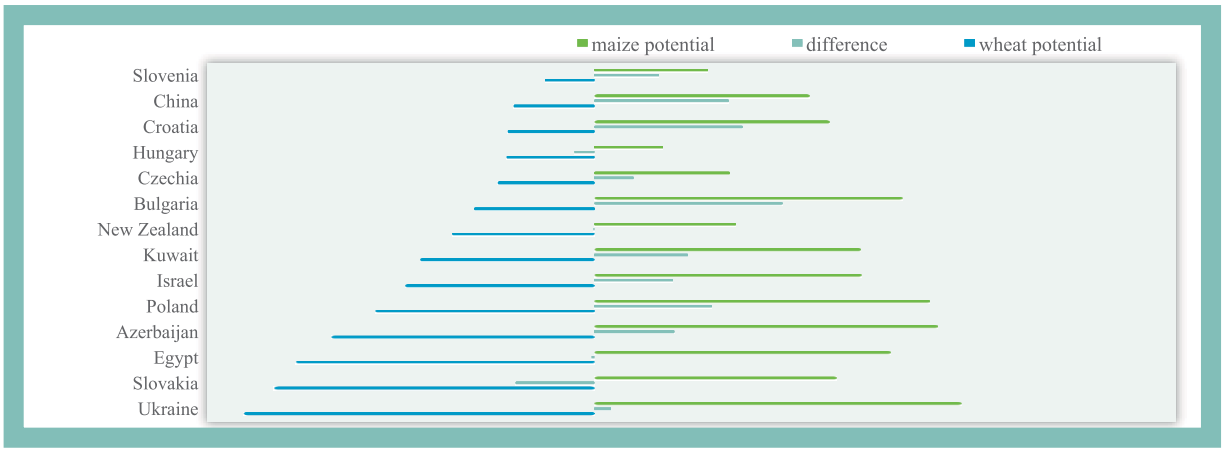


FIGURE 9
Contrast of wheat and maize trade potential of large yield countries in 2021.



FIGURE 10
Contrast of wheat and maize trade potential of medium yield countries in 2021.

conditions, cultivation patterns, and the increased demand for maize as feed and industrial raw material in these countries.

In the small yield countries shown in Figure 11, the import potential for maize similarly tends to be higher than that for wheat. This phenomenon may highlight the challenges these countries face in meeting domestic wheat demands, resulting in a greater reliance on maize imports. This could be due to limitations in agricultural production in these countries, including adverse climatic conditions, constraints on land resources, and limitations in technology and capital, making maize imports a crucial means to supplement domestic production.

Comparing the analysis from Figures 9–11, we observe a clear pattern: regardless of whether the countries have large, medium, or small yields, the import potential for maize is generally higher than that for wheat. This trend might reflect the growing global demand for the diversified uses of maize, alongside relatively stable wheat production. Additionally, this might indicate changes in the global agricultural trade patterns, where maize, as a key agricultural product, plays an increasingly important role in global food security and energy supply.

4 Discussion

This study employs SFM to conduct a comprehensive analysis of wheat and maize trade efficiency among countries participating in the Belt and Road Initiative (BRI). The research assesses and quantifies the trade efficiency of these key agricultural commodities while exploring various factors influencing the trade potential of these nations.

The findings indicate that economic development level, population growth, government efficiency, political stability, and regulatory quality are crucial factors in enhancing wheat trade efficiency. This underscores the significance of institutional quality and economic foundations in promoting agricultural trade. Fu et al. (2023) utilized a time-varying stochastic frontier gravity model to examine the impact of trade facilitation provisions on fresh agricultural product trade in BRI countries. Their findings emphasize the critical role of trade facilitation in improving trade efficiency, aligning with our analysis highlighting the importance of regulatory quality and government efficiency.



FIGURE 11
Contrast of wheat and maize trade potential of small yield countries in 2021.

However, the relationship between economic scale and trade potential is not linear. Large economies such as Russia, China, and Turkey do not necessarily outperform medium or small economies in terms of wheat trade potential. This disparity may stem from the self-sufficiency capabilities and diversified economic structures of large economies, reducing their dependence on wheat imports. Comparative analysis reveals that China and the Russian Federation possess relatively high maize trade potential, potentially reflecting increased demand for feed and strategic considerations for ensuring food security and supporting the livestock industry. The economic and demographic scale of these countries creates a larger market demand for maize, indicating their significant influence on international grain markets.

Contrary to expectations, WTO membership shows a negative correlation with wheat trade efficiency. This finding contradicts the conventional view that WTO membership leads to higher trade efficiency through trade liberalization and a more stable trade environment (Pavcnik, 2002; Abbas, 2014; Siddika and Ahmad, 2022). This result may reflect the challenges WTO members face in implementing rules and commitments, especially for countries that may lack the preparation or resources to adapt to rapid trade liberalization. It highlights the complex effects that international trade agreements can have in practice.

For maize trade, an increase in arable land area is negatively correlated with trade efficiency, highlighting potential issues in managing larger agricultural areas or optimizing land use to promote trade. This suggests that simply expanding cultivated land may not be an effective strategy for improving trade efficiency, and countries should focus on optimizing land use and adopting advanced agricultural technologies.

The impact of BRI on trade efficiency varies significantly among participating countries, with some experiencing improvements while others face declines. For instance, wheat trade efficiency significantly improved in Turkey and Hungary but declined in Georgia. This indicates that the positive effects of BRI on trade facilitation and infrastructure improvement are not uniformly manifested across all participating countries, suggesting that the effectiveness of the initiative is influenced by various factors, including each country's infrastructure level, policy environment, and economic structure. Significant differences in trade efficiency also exist across different sectors (Jiang et al., 2022). While Abdullahi et al. (2022) identified key determinants of China's agricultural export efficiency, finding economic scale and BRI participation as positive influencing factors while highlighting the adverse impacts of income disparities and geographical barriers, the differential impact of BRI on various countries suggests that a one-size-fits-all approach is insufficient. Policymakers should tailor trade promotion strategies to each country's specific circumstances, considering factors such as existing infrastructure, economic structure, and institutional capacity. This may involve targeted infrastructure development investments, capacity-building programs, and policy reforms aimed at enhancing trade facilitation.

Notably, some countries like South Africa and Croatia demonstrated significant trade efficiency during the COVID-19 pandemic. This finding emphasizes the importance of resilience and diversity in trade networks when facing global crises, highlighting the need for robust crisis management strategies and diversified trade mechanisms.

Our analysis of trade potential disparities between countries of different economic scales provides valuable insights for formulating targeted trade policies. Large economies like China and Russia, showing higher maize trade potential, may need to focus on strategies that leverage their market size and demand to optimize trade relationships. Conversely, smaller economies might benefit from specializing in niche agricultural products or value-added processing to enhance their competitiveness in global markets. The negative correlation between WTO membership and wheat trade efficiency warrants further investigation. It suggests the need for a more nuanced approach to trade liberalization, particularly for developing countries. Policymakers and international organizations should consider implementing more gradual and targeted trade liberalization approaches, complemented by capacity-building initiatives to help countries adapt to new trade regimes. The importance of land use efficiency in maize trade highlights the need for agricultural modernization and sustainable farming practices. Countries should invest in research and development of advanced agricultural technologies,

promote sustainable intensification practices, and implement policies that incentivize efficient land use. This may include promoting precision agriculture techniques, improving irrigation systems, and encouraging crop diversification. The resilience demonstrated by some countries during the COVID-19 pandemic underscores the importance of building robust and diversified trade networks. Policymakers should focus on developing crisis management strategies that can maintain trade efficiency during global disruptions. This may involve diversifying trade partners, investing in digital trade infrastructure, and developing contingency plans for supply chain disruptions.

Despite the comprehensiveness of this study, several limitations should be considered. First, the dataset includes only 55 wheat-trading countries and 55 maize-trading countries, which may not fully represent global agricultural trade dynamics. Future research could expand the dataset to include more countries and more recent data. Second, while this study considers multiple influencing factors, incorporating factors such as climate variability, agricultural policies, and technological progress could provide a more comprehensive analysis of agricultural trade efficiency. Third, an in-depth investigation into the specific challenges faced by BRI and WTO members in implementing trade rules and how these challenges affect trade efficiency would be valuable.

5 Conclusion

This paper evaluates and quantifies the efficiency of wheat and corn trade among the countries along the BRI using SFM, and explores various factors that affect the trade potential of these countries. Our findings reveal that the level of economic development, population growth, government efficiency, political stability, and the quality of regulations are key factors in enhancing the efficiency of wheat trade. However, membership in the WTO is negatively correlated with wheat trade efficiency, which may reflect the challenges faced by WTO members in implementing WTO rules and commitments. Research shows that streamlined customs procedures and enhanced logistical efficiency contribute to increasing trade flows between BRI countries. Regarding the efficiency of corn trade, an increase in arable land area is significantly negatively correlated with corn trade efficiency, reflecting potential efficiency issues in managing larger agricultural areas or optimizing land use to promote trade. The implementation of the BRI has yielded varied results, with countries such as Turkey and Hungary have showing significant improvements in trade efficiency, while countries like Georgia have experienced declines, indicating that the positive effects of the BRI in promoting trade and improving infrastructure are not universally reflected in all participating countries. During the COVID-19 pandemic, some countries like South Africa and Croatia demonstrated significant trade efficiency, possibly benefiting from effective pandemic management or diversified trade mechanisms. Based on our findings, it is recommended that governments of participating countries to prioritize government efficiency, political stability, and regulatory quality. Specifically, each country should develop and implement targeted policies aimed at enhancing agricultural infrastructure, optimizing land use efficiency, and promoting trade liberalization through international cooperation. Additionally, the adaptability and enforcement of WTO rules should be strengthened, especially in the face of the rapidly changing global trade landscape, to ensure that the international trade system is effectively harnessed to promote economic development. These recommendations are intended to support policymakers in better utilizing international resources, thereby improving the overall efficiency and competitiveness of agricultural trade. In future research, it is crucial to examine the specific impact of the implementation of WTO rules and commitments on the trade efficiency of different countries. Furthermore, exploring the challenges faced by WTO members in implementing these rules and proposing corresponding improvements to policies and relevant capacity-building plans is essential. Additionally, investigating the significant differences in trade efficiency among different countries following the implementation of the Belt and Road Initiative (BRI) and the reasons behind these differences could contribute to the formulation of targeted trade promotion strategies, aiming to achieve more balanced and sustainable trade growth. Further research on how to enhance agricultural trade efficiency by improving land use efficiency and adopting advanced agricultural technologies and practices to optimize the use of land resources will also be valuable.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.fao.org/food-agriculture-statistics/en/.

Author contributions

TM: Conceptualization, Data curation, Formal analysis, Funding acquisition, Project administration, Resources, Writing – original draft. PP: Formal analysis, Funding acquisition, Methodology, Software, Supervision, Writing – review & editing. XL: Writing – review & editing, Data curation, Investigation, Validation, Visualization. JL: Writing – review & editing, Methodology, Software.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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Coupling of urbanization and grain production: patterns, processes, and mechanisms—a case study from China

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Food security is crucial for national stability and public welfare. Since the 21st century, China's grain production has been significantly influenced by the rapid process of urbanization. In this context, this paper systematically measures the multidimensional coupling patterns and dynamic coupling processes between urbanization and grain production from 2000 to 2022, and preliminarily summarizes the complex coupling mechanisms within the Chinese context. The goal is to provide scientific references for achieving high-quality coordinated development of urbanization and grain production in China. The study reveals the following key findings: (1) The coupling relationship between urbanization and grain production exhibits both regional heterogeneity and temporal variability, demonstrating specific levels of coupling and dynamic processes under distinct spatiotemporal conditions. (2) Between 2000 and 2022, both urbanization and grain production patterns in China underwent significant reconstruction, with the coupling coordination level displaying a long-term spatial pattern of "high in the north, low in the south; high in the east, low in the west." Although there is an overall upward trend in coupling coordination states, spatial imbalances and dimensional heterogeneity persist. (3) Since the beginning of the 21st century, the dynamic coupling processes between provincial urbanization and grain production have primarily manifested as two types: simultaneous increase (with urbanization outpacing grain production) and urban increase accompanied by grain production decrease. Various dynamic coupling types exhibit significant spatial clustering, and the multidimensional dynamic coupling processes reveal notable similarities. (4) The evolution of coupling states demonstrates an overall trend of optimization, with clear bidirectional migration trends observed in coupling dynamics, primarily transitioning from simultaneous increase (urbanization outpacing grain production) to urban increase with grain production decrease, and vice versa. (5) The formation of the complex coupling relationship between urbanization and grain production in the Chinese context is fundamentally influenced by changes in population quantity and structure between urban and rural areas, shifts in land use, economic transformation, regional specialization, technological interactions, and factor mobility. These influences exhibit significant negative effects in the domains of population, land, and economy, while showcasing notable positive effects in terms of technology and factor mobility.

KEYWORDS

urbanization, grain production, coupling, mechanisms, provincial level

1 Introduction

Food security is a key goal of the United Nations' sustainable development agenda. For China, a major developing nation, this issue has significant implications for global food stability and has garnered substantial attention from scholars. Since the founding of the People's Republic of China, the country's grain production capacity has increased dramatically, with a 420% rise in grain output from 1949 to 2022, strengthening its food security foundation. However, in the past two decades, China's grain production has faced serious challenges from various factors, including climate change (Semeraro et al., 2023), globalization (Bentham et al., 2020), geopolitics (Xu et al., 2024), marketization (Ma et al., 2020), industrialization (Ambikapathi et al., 2022), and urbanization (Gu et al., 2017). Among these, urbanization has profoundly shaped the overall landscape of China's grain production and influenced its evolution.

China's urbanization process features distinct phases and has undergone rapid development since the reform and opening-up, resulting in the gradual breakdown of the traditional urban–rural dual structure and a significant transformation in urban–rural relationships (Yang and Wang, 2022). As a crucial factor influencing grain production, urbanization has attracted considerable attention from scholars in geography, economics, sociology, and agricultural studies. Research in this field can be broadly categorized into two main areas. First, studies examining the impact of urbanization on grain production investigate whether it promotes or hinders agricultural output, presenting three primary perspectives: the "suppressive" view, which underscores urbanization's negative effects on essential production inputs like land and labor, leading to increased land scarcity (Huang et al., 2020); the "promotive" view, which emphasizes positive externalities such as technological spillovers and the return of resources, especially the multiplier effect of agricultural innovations (Mok et al., 2020); and the "complex effects" view, which considers regional geographic differences and various driving factors of grain production (Krugman, 1991), acknowledging that different spatial and temporal contexts result in diverse coupling models between urbanization and grain production (Zhu et al., 2021). Second, research on the mechanisms through which urbanization influences grain production can be summarized into six pathways: the transfer of agricultural labor (Yan et al., 2023), encroachment on high-quality arable land (Zhou B. B. et al., 2021), transformation of rural industrial structures (Zhu et al., 2018), advancements in agricultural technology (Benedek et al., 2023), return of rural-oriented resources (Zhu et al., 2023), and changes in agricultural policy (Yang and Zhang, 2021).

It is important to note that provincial regions play a crucial role in spatial governance for coordinating high-quality urbanization and food security in China (Meng et al., 2023). First, provinces exhibit stability, with relatively few changes to administrative boundaries since the founding of the People's Republic. Second, they represent relatively independent natural and cultural geographic units, characterized by noticeable differences in conditions across interprovincial borders, resulting in strong internal homogeneity. Third, provinces combine administrative and cross-administrative features; as political units, they experience significant competition and cooperation among various cities within their borders (Li E. K. et al., 2022). When focusing on the realities of urbanization and grain production, we see that, on one hand, as a vast continental nation, China has experienced rapid urbanization since this concept was integrated into the 10th Five-Year Plan as a national strategy. This has led to the creation of numerous single or dual-centered urban spatial systems at the provincial level, becoming vital engines for regional economic and social development (Chen et al., 2023). On the other hand, since the 21st century, new agricultural policies-such as the abolition of the agricultural tax, direct subsidies for grain, and the establishment of permanent basic farmland-have facilitated the transformation and specialization of agricultural production across provinces. This has emphasized the primary functions of provincial grain production and resulted in three types of grain functional zones: main producing areas, main selling areas, and balanced production-consumption areas (Wang et al., 2024).

After reviewing existing research and theoretical analyses, it is clear that while scholars have extensively examined the impact of urbanization on grain production, notable shortcomings remain. First, analyses of effects and mechanisms often fail to adequately decompose urbanization as a crucial driver of grain production, typically focusing only on the absolute level of population urbanization. Urbanization, however, includes multidimensional aspects of population, land, and economy that are fundamental to understanding its influence on grain production. Second, there is insufficient attention to the provincial spatial scale and a lack of support for decision-making applications. Provinces are essential for studying the relationship between urbanization and grain production, serving as vital governance scales for food security policy. Future research should conduct in-depth analyses of the static and dynamic coupling patterns between urbanization and grain production, delineating regulatory zones and tailored strategies based on major production areas, selling areas, and balanced production-consumption areas. Third, the scientific rigor and timeliness in selecting research periods are often inadequate. Many studies do not sufficiently justify their period selections, with the latest data ending in 2020. Both urbanization and grain production exhibit distinct phase characteristics, making the choice of research periods critical for explaining their coupling mechanisms and developing targeted optimization strategies.

Based on the aforementioned contextual background and research advancements, this paper will conduct an in-depth exploration of the coupling relationship between urbanization and grain production in China's provincial regions within the "Population-Land-Economy" framework. Specifically, the study aims to address the following questions: First, how can the research period be scientifically defined? Second, what complex coupling patterns have emerged between urbanization and grain production in China over the past two decades, and how has this coupling process evolved? Third, what are the objective principles governing the coupling of urbanization and grain production in China within the "Population-Land-Economy" framework? This research seeks to provide scientific support for the coordinated and high-quality development of urbanization and grain production in China during the new era.

2 Theoretical analysis

2.1 Coupling relationship analysis

2.1.1 Static coupling level

At a specific region and point in time, the coupling relationship between urbanization and grain production manifests as a static pattern that can be classified into various types based on the level of coupling

coordination. This degree of coordination reflects the comprehensive and harmonious development of the urbanization subsystem and the grain production subsystem. The overall urbanization level within the "population-land-economy" framework indicates the stage of urbanization in the region (Figure 1) (Cai et al., 2021; Chen et al., 2014). In the early stages of urbanization, limitations in production technology and low resilience to agricultural disasters result in relatively weak grain production capacity, leading to a low-level coordinated state (Ayele and Tarekegn, 2020). During the mid-stages, urbanization advances more rapidly than grain production, with the first-generation technological revolution enhancing grain production capabilities, resulting in a moderate developmental imbalance (Follmann et al., 2021). In the later stages, although urbanization continues to progress, its growth rate slows. At the same time, the second-generation technological revolution fosters rapid advancements in agricultural productivity, promoting a new integrated urban–rural relationship that facilitates the bidirectional flow of resources. This enhances grain production capacity, achieving a high-level coordinated state between urbanization and grain production (Zeng and Chen, 2023).

2.1.2 Dynamic coupling process

Over time, urbanization and grain production systems evolve synergistically through their coupling. In this dynamic relationship, urban areas wield greater influence than rural areas, making urbanization the primary factor affecting grain production, while the latter has only a limited feedback effect on the former (Liu Y. S. et al., 2020). This relationship manifests in changes in grain production levels—whether increases or decreases—corresponding to shifts in urbanization levels, which can be classified into five categories: simultaneous growth (urbanization outpacing grain production), simultaneous growth (grain production outpacing urbanization), urban growth with declining grain production, declining urbanization with increasing grain production, and simultaneous decline (Figure 2). Regions demonstrating simultaneous growth exhibit a mutual reinforcement between grain production capacity and urbanization. In areas with strict resource and environmental constraints, more resources are typically allocated to urbanization, leading to urban growth outstripping grain production. Conversely, in regions where these constraints are less severe, development can ensure sufficient investment in grain production, allowing it to grow faster than urbanization. Regions experiencing urban growth but declining grain production show a negative trend in grain production capacity, indicating an imbalance between urbanization and grain production. This imbalance increases reliance on external food sources and poses food security risks (Ben Hassen et al., 2020). The scenarios of declining urbanization with increasing grain production and simultaneous decline occur within the context of de-urbanization. In this process, the return of skilled urban populations to rural areas promotes the rapid adoption of professional, capitalized, and technological family farming models, significantly enhancing regional grain production capacity (Wang et al., 2021a). However, de-urbanization may also signal an overall decline in regional development, adversely affecting rural areas due to urban downturns, which threatens grain production capacity (Yang et al., 2019). Given the current trends in urbanization in China, it is unlikely that most regions will experience declining urbanization alongside increasing grain production or simultaneous decline.

2.2 Coupling stage division

Since the establishment of the People's Republic of China in 1949, the relationship between urbanization and grain production has shown a coordinated and mutually beneficial progression, which can be divided into three main stages (Figure 3). The first stage (1949–1978) is characterized by slow growth, with urbanization increasing by

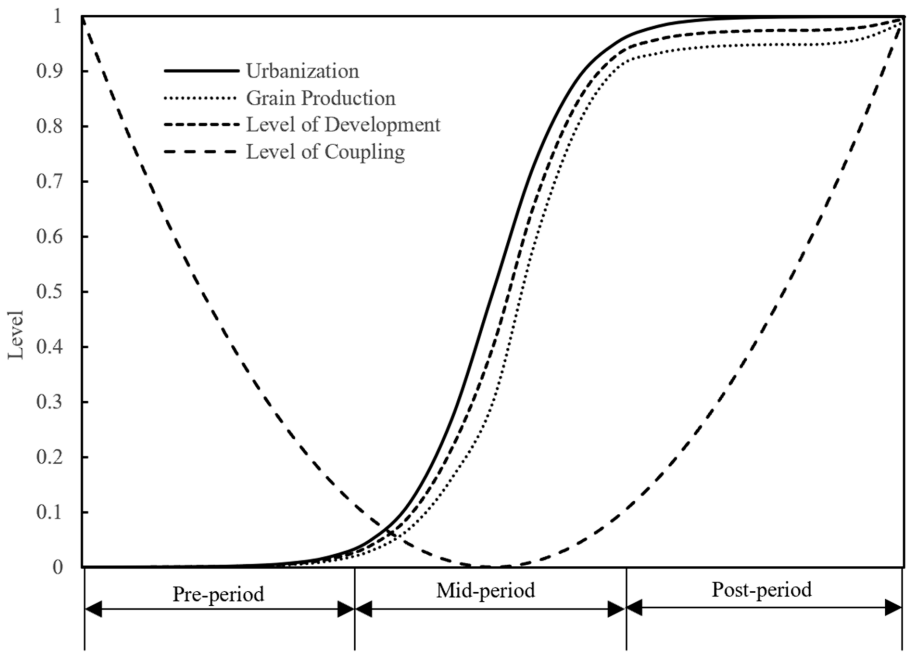


FIGURE 1
Static coupling pattern of urbanization and grain production.

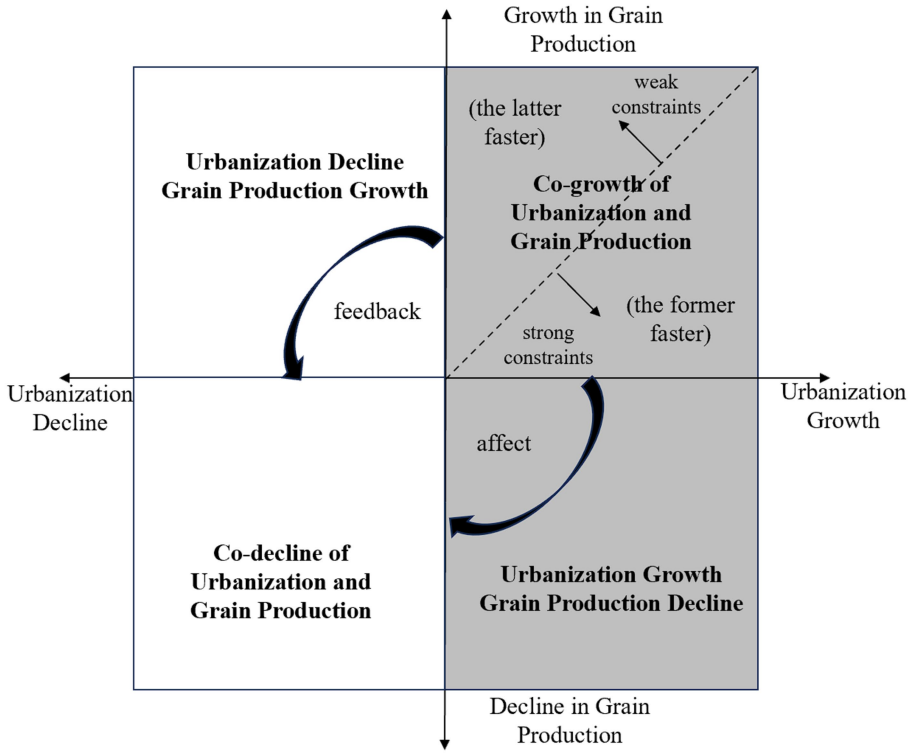


FIGURE 2
Dynamic coupling process of urbanization and grain production.

an average of 0.25 percentage points per year and grain production rising by an average of 6.61 million tons annually. The second stage (1978–2000) represents a period of moderate growth, during which urbanization averaged an increase of 0.83 percentage points per year, while grain production grew by an average of 7.16 million tons each year. The third stage marks a period of rapid growth, with urbanization averaging an increase of 1.32 percentage points annually, and grain production rising by an average of 10.2 million tons per year. This study focuses on the third stage for several reasons: First, China's rapid urbanization process began around 2000, when the urbanization rate was only 36%, indicating it was still in its early stages. Since then, China has progressed through the initial and mid-stages and is now in the later stage of urbanization. Second, during this rapid urbanization phase, cities have significantly exerted a depriving effect on rural resources, making the period since 2000 a time of intense interaction and conflict between urbanization and grain production. Third, despite potential conflicts, China has achieved twelve consecutive years of growth in grain production from 2000 to 2022, with growth rates far exceeding those of the previous two stages. This raises important questions about how these conflicts have been resolved and managed.

3 Data and methods

3.1 Indicator selection

Based on the earlier theoretical analysis, urbanization is a complex process that involves significant changes in population structure, spatial configuration, and economic dynamics. Therefore, this study measures urbanization from three perspectives: population, land, and economy (Table 1). In the population dimension, urbanization reflects important changes in aspects such as urban population size, spatial density, and employment structure. As a result, indicators selected include the urbanization rate, urban population density, and the proportion of non-agricultural workers (Cai et al., 2021). For the land dimension, urbanization is characterized by the expansion of urban built-up areas and the enhancement of urban infrastructure, alongside the growth of green spaces. Relevant indicators include the ratio of built-up area to total land area, per capita urban road area, and the green coverage rate within urban built-up areas (Li et al., 2020). In the economic dimension, urbanization encompasses the transformation of urban industrial structures, regional economic growth, and improvements in citizens' well-being. Consequently, indicators such as the proportion of non-agricultural output, per capita GDP, and disposable income of urban residents are chosen (Liang and Yang, 2019).

The level of grain production refers to the output capacity of the grain production system under specific temporal, natural, economic, and social conditions, as well as varying levels of input factors (Liu and Zhou, 2021). Scholars have conducted extensive research on measuring grain production levels and their spatial–temporal patterns, primarily using two approaches: representative indicators and composite indicators (Liu J. et al., 2020; Liu and Zhou, 2021). This study selects three key indicators—total grain production, yield per unit, and production structure—to characterize grain production capacity (Table 1). There are two main reasons for this selection. First, focusing on total production, yield, and production structure allows us to represent grain production levels from the output perspective,

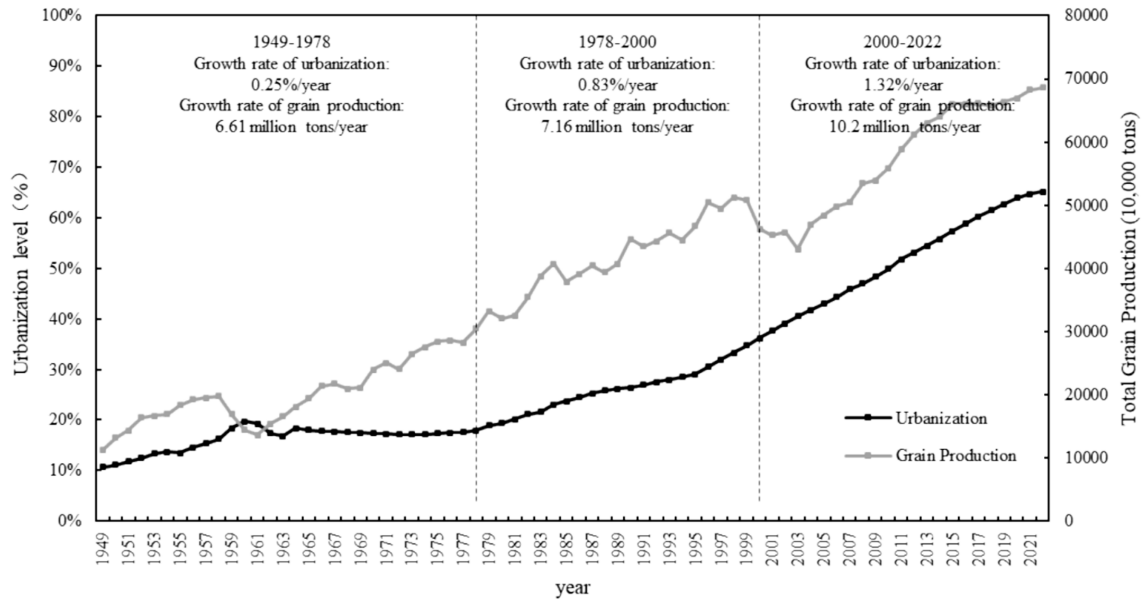


FIGURE 3
Time series evolution of China's grain production and urbanization since 1949.

providing a multidimensional and intuitive view of production characteristics. This method is more scientifically accurate and practical than approaches based solely on input factors. Total grain production serves as a central variable in food security research, reflecting overall output characteristics (Bene et al., 2020). Yield per unit indicates the quality of grain production, which is particularly important for a country like China, where per capita arable land is relatively scarce. In such cases, enhancing yield levels is often more effective than expanding land inputs in an extensive grain production model (Yang et al., 2020). The production structure illustrates the structural characteristics of grain production, especially in the context of urbanization, where the shift towards non-grain agricultural production significantly impacts food security (Liu and Zhou, 2021). Second, calculating grain production levels based on input factors can introduce causal confusion. Factors such as population, land, labor, and technology are causes of grain production levels, and urbanization itself is also a closely linked factor.

3.2 Research methods

3.2.1 Hierarchical combination weighting method

To ensure that weight measurements reflect both the objectivity of the data and the insights of experts, we employ a hierarchical combination weighting method. The indicator system consists of three levels: the goal level, the criterion level, and the indicator level. Based on the nine-point scale principle proposed by Saaty, the weights at the criterion level are generally simpler compared to those at the goal level; thus, we use the Analytic Hierarchy Process (AHP) to calculate these weights (Bene et al., 2020). In contrast, the weights at the indicator level are more complex, so we apply an improved entropy method for their calculation (Zhu et al., 2021). The specific weight results can be found in Table 1, with the relevant formulas outlined below (Equations 1–4):

$$W^{(2,1)} = \left[w_1^{(2,1)}, \ldots, w_n^{(2,1)} \right]^T \tag{1}$$

$$W_k^{(3,2)} = \left[w_{k,1}^{(3,2)}, \ldots, w_{k,m}^{(3,2)} \right]^T, k = 1, 2, \ldots, n \tag{2}$$

$$W^{(3,2)} = \left[W_1^{(3,2)}, \ldots, W_n^{(3,2)} \right] \tag{3}$$

$$W^{(3,1)} = W^{(3,2)} * W^{(2,1)} \tag{4}$$

In this context, $W^{(2,1)}$ represents the weight matrix of the criterion level relative to the goal level, calculated using the Analytic Hierarchy Process (AHP). Here, n denotes the number of variables at the criterion level, and m represents the number of variables at the indicator level. $W^{(3,2)}$ is the weight matrix of the indicator level relative to the criterion level, determined using the improved entropy method, and $W^{(3,1)}$ is the weight matrix of the indicator level relative to the goal level.

3.2.2 Static coupling measurement

The coupling coordination degree reflects the strength of interaction between two systems and their level of coordinated development. However, traditional coupling coordination indices have several shortcomings in practical applications. These include the uneven distribution of the coupling degree C within the [0, 1] range, computational biases resulting from the geometric weighting of the system's development level T, and an excessive dependence of the coupling coordination degree D on T. To address these issues, this paper employs the latest improved coupling coordination index (Wang et al., 2021b). The formula is as follows (Equations 5–7):

TABLE 1 Measurement index system of urbanization and grain production level.

Goal Level	Criterion level	Code 1	AHP weight	Indicator level	Code 2	Entropy weight	Combined weight
Urbanization	Population urbanization	x1	0.3393	Urban population rate (%)	x1_1	0.3385	0.1149
				Urban population density (people/km²)	x1_2	0.4539	0.154
				Proportion of Non-agricultural employment (%)	x1_3	0.2077	0.0705
	Land urbanization	x2	0.3178	Proportion of urban built-up area to total land Area (%)	x2_1	0.4473	0.1422
				Per capita urban road area (m²/capita)	x2_2	0.4093	0.1301
				Urban green space coverage rate (%)	x2_3	0.1434	0.0456
	Economic urbanization	x3	0.3429	Proportion of non-agricultural output (%)	x3_1	0.0508	0.0174
				Per capita GDP (Yuan/capita)	x3_2	0.4776	0.1637
				Per capita disposable income of urban residents (Yuan)	x3_3	0.4716	0.1617
Grain production	Total	y1	0.4203	Total grain production (10,000 tons)	y1_1	1.0000	0.4203
	Yield	y2	0.3235	Grain yield per hectare (tons/hectare)	y2_1	1.0000	0.3235
	Structure	y3	0.2562	Proportion of non-grain crop area (%)	y3_1	1.0000	0.2562

$$C = \sqrt{\left[1 - \frac{\sum_{i>j,j=1}^{n}\sqrt{(S_i - S_j)^2}}{\sum_{m=1}^{n-1} m}\right] \times \left(\prod_{i=1}^{n}\frac{S_i}{\max S_i}\right)^{\frac{1}{n-1}}} \quad (5)$$

$$T = \sum_{i=1}^{n}\alpha_i \times S_i, \sum_{i=1}^{n}\alpha_i = 1 \quad (6)$$

$$D = \sqrt{C \times T} \quad (7)$$

In this context, S represents the score of the subsystem, C is the coupling degree, T is the overall system score, D denotes the coupling coordination degree, and n indicates the number of subsystems. Since this paper focuses solely on the two subsystems of Urbanization and Grain Production, we have $n = 2$. Additionally, based on prior studies, the weights for both systems are set at 0.5. The improved coupling coordination model ensures a more even distribution of C within the [0, 1] range, resulting in higher overall validity of the model. Following the research of Li X. et al. (2022), the values of the coupling coordination degree are categorized into different types based on their magnitude (Table 2).

3.2.3 Dynamic coupling measurement

The dynamic coupling between urbanization and grain production is characterized by their synergistic evolution over a defined time period. By calculating ΔU and ΔF, it is possible to determine the rates of change for both urbanization and grain production. The formula is as follows (Equations 8, 9):

$$\Delta U_{it} = \frac{U_{it} - U_{i0}}{U_{i0}} \times 100\% \quad (8)$$

$$\Delta F_{it} = \frac{F_{it} - F_{i0}}{F_{i0}} \times 100\% \quad (9)$$

In this context, ΔU_{it} and ΔF_{it} represent the rates of change in urbanization and grain production, respectively, for region i in year t. U_{it} and F_{it} denote the levels of urbanization and grain production for region i in year t, while U_{i0} and F_{i0} indicate their levels in the base year for region i. Based on the rates of change, several types of dynamic coupling can be identified.

- When $\Delta U > \Delta F > 0$, this indicates that urbanization is increasing more rapidly than grain production, classified as Type B1.
- When $\Delta F > \Delta U > 0$, it signifies that grain production is increasing more rapidly than urbanization, classified as Type B2.
- Conversely, when $\Delta U > 0 > \Delta F$, it indicates a situation where urbanization is rising while grain production is declining, classified as Type B3, reflecting a disordered developmental relationship.
- When $\Delta F > 0 > \Delta U$ describes urbanization in decline while grain production is increasing, this is classified as Type B4, indicating a disordered relationship characterized by urban decline.
- Lastly, when $\Delta U < 0 \,\&\, \Delta F < 0$, this represents the type characterized by simultaneous declines in both urbanization and grain production, classified as Type B5.

3.2.4 Measurement of coupling type transition

The Markov chain is a statistical mathematical model that describes the transition of a system from one state to another across adjacent time periods, applicable to phenomena exhibiting "memorylessness." Existing research has demonstrated that both urbanization and grain production exhibit a strong degree of "memorylessness" (Yang et al., 2019). By employing a Markov chain, it is possible to quantitatively assess the evolution of the coupling relationship between urbanization and grain production at the provincial level, as well as to forecast their future coordinated development. The formula is as follows (Equations 10–13):

$$P\begin{Bmatrix} X_{t+1}=j\,\middle|\,X_0=i_0, \\ X_1=i_1,\ldots,X_{n-1}=i_{n-1},X_n=i_n \end{Bmatrix}=P\left\{X_{t+1}=j\,\middle|\,X_n=i_n\right\} \quad (10)$$

$$P_{ij}=\frac{N_{ij}}{N_i} \quad (11)$$

$$N=\begin{bmatrix} N_{11} & \cdots & N_{1S} \\ \vdots & \ddots & \vdots \\ N_{S1} & \cdots & N_{SS} \end{bmatrix} \quad (12)$$

$$P=\begin{bmatrix} P_{11} & \cdots & P_{1S} \\ \vdots & \ddots & \vdots \\ P_{S1} & \cdots & P_{SS} \end{bmatrix} \quad (13)$$

In the equation, a total of S coupling states are defined. N_i represents the number of provinces in state i at time t, while N_{ij} indicates the number of provinces transitioning from state i at time t to state j at time $t+1$. P_{ij} denotes the frequency of this transition from state i at time t to state j at time $t+1$. N refers to the state transition matrix, and P represents the frequency transition matrix.

3.3 Data sources

The data for the indicators measuring grain production and urbanization utilized in this study are sourced from the National Bureau of Statistics of China, the China Statistical Yearbook, and various provincial statistical yearbooks. The completeness of the data exceeds 90%, and missing data for specific years were supplemented using linear interpolation. The sources for the driving factor data used in the analysis of driving mechanisms are provided in Table 3.

4 The coupling patterns of urbanization and grain production

4.1 The spatiotemporal evolution of urbanization and grain production levels

Between 2000 and 2022, China underwent a significant restructuring of both urbanization and grain production patterns. Overall, these processes demonstrated a mutually reinforcing relationship; however, notable spatiotemporal heterogeneities were present (Figures 4, 5). In terms of urbanization, all provinces in China showed substantial progress, although provinces in the Northeast, which have a historically earlier onset of urbanization, advanced at a relatively slow pace. Conversely, provinces in North and Northwest China experienced marked increases in urbanization, while the eastern regions—specifically the Beijing-Tianjin-Hebei area, the Yangtze River Delta, and the Pearl River Delta—emerged as leaders in China's urbanization efforts. Within this context of rapid urbanization, China's grain production levels underwent considerable spatial restructuring, primarily evident in the northward shift of the grain production center. Urbanization in southern provinces exhibited a certain negative impact on grain production levels, whereas urbanization in northern provinces did not appear to impede the enhancement of regional grain production. The disparities in grain production levels between northern and southern regions have increasingly amplified the contributions of northern provinces to China's food security. Data indicate that the Northeast's contribution to China's grain production rose from 11.5% in 2000 to 20.9% in 2022, with a peak contribution rate of 49.3% to China's grain production increase recorded between 2000 and 2011. According to the "National Medium- and Long-term Plan for Food Security (2008–2020)" issued by the Chinese government, the majority of key grain-producing areas are situated in northern regions. Due to the emphasis placed on food security functions by northern provinces, along with national policies favoring the elimination of agricultural taxes, the implementation of stringent land protection measures, and subsidies for grain production, China's grain production levels achieved a continuous increase for twelve consecutive years during this rapid urbanization period. Furthermore, significant improvements in grain yield per unit area were observed, regional disparities narrowed, and the excessive trend of non-grain cultivation was preliminarily curtailed, thereby reinforcing the foundations of food security.

4.2 Static coupling measurement

4.2.1 Overall coupling

Between 2000 and 2022, the coupling coordination degree between urbanization and grain production in China's provincial regions exhibited a spatial distribution characterized by the pattern of "higher in the north, lower in the south; higher in the east, lower in the west," with an overall upward trend in the coupling coordination status. In 2000, the development of urbanization and grain production across provinces was primarily marked by low to moderate coupling coordination, with low coupling coordination areas constituting the majority. Moderate coupling coordination zones were predominantly located in eastern coastal provinces as well as inland provinces such as Xinjiang, Heilongjiang, Shanxi, and Hubei. By 2011, high coupling

TABLE 2 Transition frequency matrix of static coupling relationship evolution of urbanization and grain production.

D Value	Coupling type	Type code	Description
(0,0.2]	Marginal coupling coordination	A1	Both urbanization and grain production are at low levels.
(0.2,0.4]	Low coupling coordination	A2	Urbanization is at a moderate level, while grain production remains low.
(0.4,0.6]	Moderate coupling coordination	A3	Urbanization is high, whereas grain production is low.
(0.6,0.8]	High coupling coordination	A4	Urbanization is high, with grain production at a moderate level.
(0.8,1.0]	Extreme coupling coordination	A5	Both urbanization and grain production are at high levels, promoting synergistic development.

coordination areas began to emerge in provinces such as Heilongjiang, Xinjiang, Jiangsu, Henan, and Jiangxi, while the number of moderate coupling coordination areas increased significantly, expanding into the central and southwestern regions. Low coupling coordination areas were found only in Qinghai Province. By 2022, the area of high coupling coordination regions had markedly increased, with regional coupling coordination types primarily consisting of moderate and high coupling coordination, and no extreme coupling coordination areas present. High coupling coordination zones were mainly distributed in the Northeast and central regions, while moderate coupling coordination areas were primarily found in South China and the western regions.

4.2.2 Dimensional coupling

Between 2000 and 2022, the coupling coordination degree among urbanization in terms of population, land, and economy, as well as grain production in China's provincial regions, exhibited significant spatial imbalance and dimensional heterogeneity (Figures 6–8).

(1) The coupling coordination pattern between population urbanization and grain production displayed clear spatial heterogeneity. In 2000, the predominant areas were characterized by moderate and low coupling coordination, with moderate coupling coordination zones mainly located east of the "Hu Huanyong Line," while low coupling coordination zones were primarily found west of this line. High coupling coordination areas appeared only in Guangdong Province. By 2011, moderate coupling coordination zones extended into the northwest, and high coupling coordination zones expanded into the central and northeastern regions. Guangdong, due to a significant influx of migrants and a marked decline in grain production capacity, transitioned from a high coupling coordination area to a moderate one. By 2022, the differentiation in coupling coordination between population urbanization and grain production became even more pronounced, exhibiting an "extreme-high-moderate-low" olive-shaped structure. Heilongjiang, owing to its solid foundation of urbanization and a significant enhancement in grain production capabilities since the 21st century, transformed into an extreme coupling coordination zone. The number of high coupling coordination zones increased significantly as moderate coupling coordination zones diminished, expanding into the northwest, while Qinghai remained in a state of low coupling coordination between population urbanization and grain production.

(2) The coupling coordination pattern between land urbanization and grain production underwent a spatial restructuring process from a "single-core-periphery" model to a "dual-core-periphery" model. In 2000, Heilongjiang served as the core area of high coupling coordination, with the central and eastern regions primarily exhibiting moderate coupling coordination as semi-peripheral areas. The western regions contained both low and moderate coupling coordination zones as peripheral areas. By 2011, the relationship between land urbanization and grain production in the central region showed significant improvement, with the east–west disparity in coupling coordination gradually surpassing the north–south gap. By 2022, the dual-core status of Henan and Heilongjiang was largely established, while the long-standing contradictions between land urbanization and grain production in the western regions, which remained peripheral, became increasingly prominent.

(3) The coupling coordination pattern between economic urbanization and grain production continued to stabilize and optimize. In 2000, with the exception of some western provinces classified as low coupling coordination zones, other regions were predominantly characterized as moderate coupling coordination areas. By 2011, the area of moderate

TABLE 3 Transition frequency matrix of static coupling relationship evolution of urbanization and grain production.

a1. Population urbanization & grain production											a2. Land urbanization & grain production									
a1-1.2000–2011						a1-2.2011–2022					a2-1.2000–2011					a2-2.2011–2022				
	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5
A1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A2	0.00	0.18	0.55	0.27	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.13	0.88	0.00	0.00	0.00	1.00	0.00	0.00	0.00
A3	0.00	0.00	0.58	0.42	0.00	0.00	0.00	0.72	0.28	0.00	0.00	0.00	0.59	0.41	0.00	0.00	0.00	0.75	0.25	0.00
A4	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.91	0.09	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.10	0.70	0.20
A5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

a3. Economic urbanization & grain production											a4. Comprehensive urbanization & grain production									
a3-1.2000–2011						a3-2.2011–2022					a4-1.2000–2011					a4-2.2011–2022				
	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5	A1	A2	A3	A4	A5
A1	0.00	0.50	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A2	0.00	0.21	0.79	0.00	0.00	0.00	0.14	0.86	0.00	0.00	0.00	0.06	0.81	0.13	0.00	0.00	1.00	0.00	0.00	0.00
A3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.56	0.44	0.00
A4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.80	0.00
A5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00



FIGURE 4
Spatial evolution of provincial urbanization and grain production level in China from 2000 to 2022. **(a)** 2000. **(b)** 2011. **(c)** 2022.

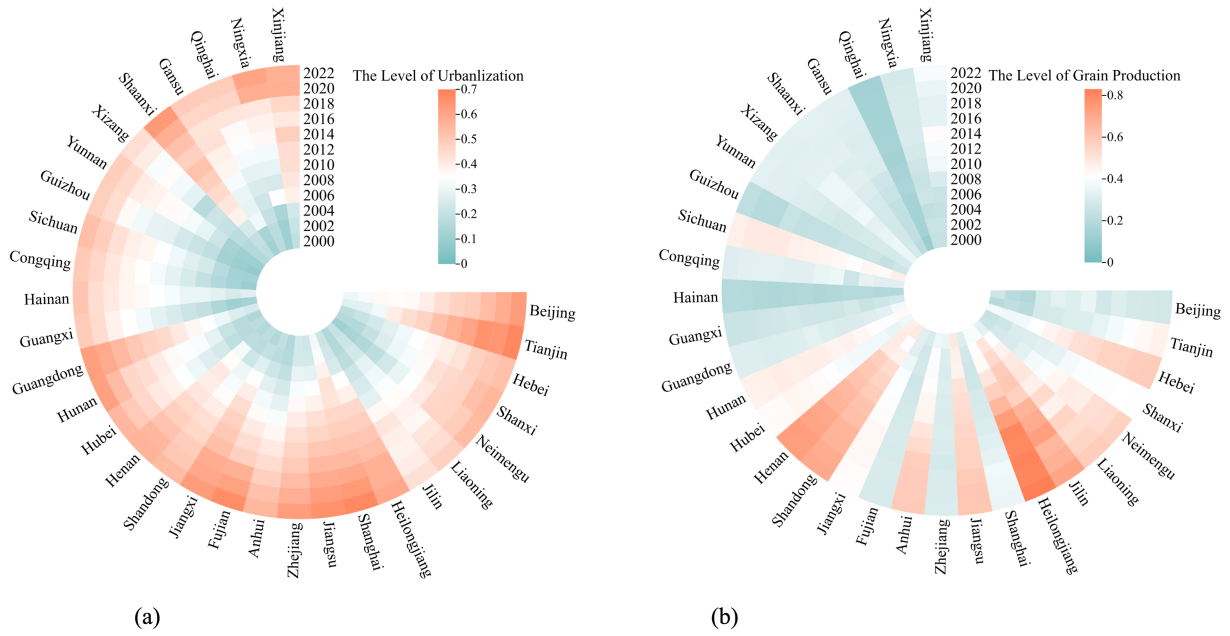


FIGURE 5
Time evolution of provincial urbanization and grain production level in China from 2000 to 2022. **(a)** Time series of urbanization level. **(b)** Time series of grain production level.

coupling coordination zones had further expanded, yet high coupling coordination zones had not yet emerged. By 2022, with the exception of Qinghai, classified as a low coupling coordination area, the coupling relationship between economic urbanization and grain production in other provinces showed significant improvement.

4.3 Dynamic coupling measurement

4.3.1 Overall coupling

Since the beginning of the 21st century, the dynamic coupling process between urbanization and grain production in China's provincial regions has primarily manifested in two types: simultaneous increases in urbanization and grain production (with urbanization outpacing grain production) and urbanization increases coupled with grain production declines. From 2000 to 2011, China's urbanization process accelerated significantly, entering a rapid phase since the reform and opening-up period. The dynamic coupling types exhibited a distinct clustered distribution pattern. Provinces such as Sichuan, Yunnan, Guizhou, and southern coastal provinces like Guangxi, Guangdong, Fujian, and Zhejiang fell into the category of urbanization increasing while grain production declined, while the remaining provinces experienced simultaneous growth in both urbanization and grain production (with urbanization growing faster than grain production). From 2011 to 2022, the pace of urbanization slowed slightly compared to the previous eleven years, resulting in a further decentralization of the spatial distribution of provinces characterized by urbanization increases and grain production declines. Transformations in the dynamic coupling relationship emerged in various regions. For example, Qinghai and Tibet, with their limited agricultural production conditions due to their plateau geography, saw rapid urbanization advancements driven by national strategies such as the Western Development Program. In the Beijing-Tianjin-Hebei region, Tianjin's level of food security for Beijing improved significantly, with grain production capacity increasing by 49%.

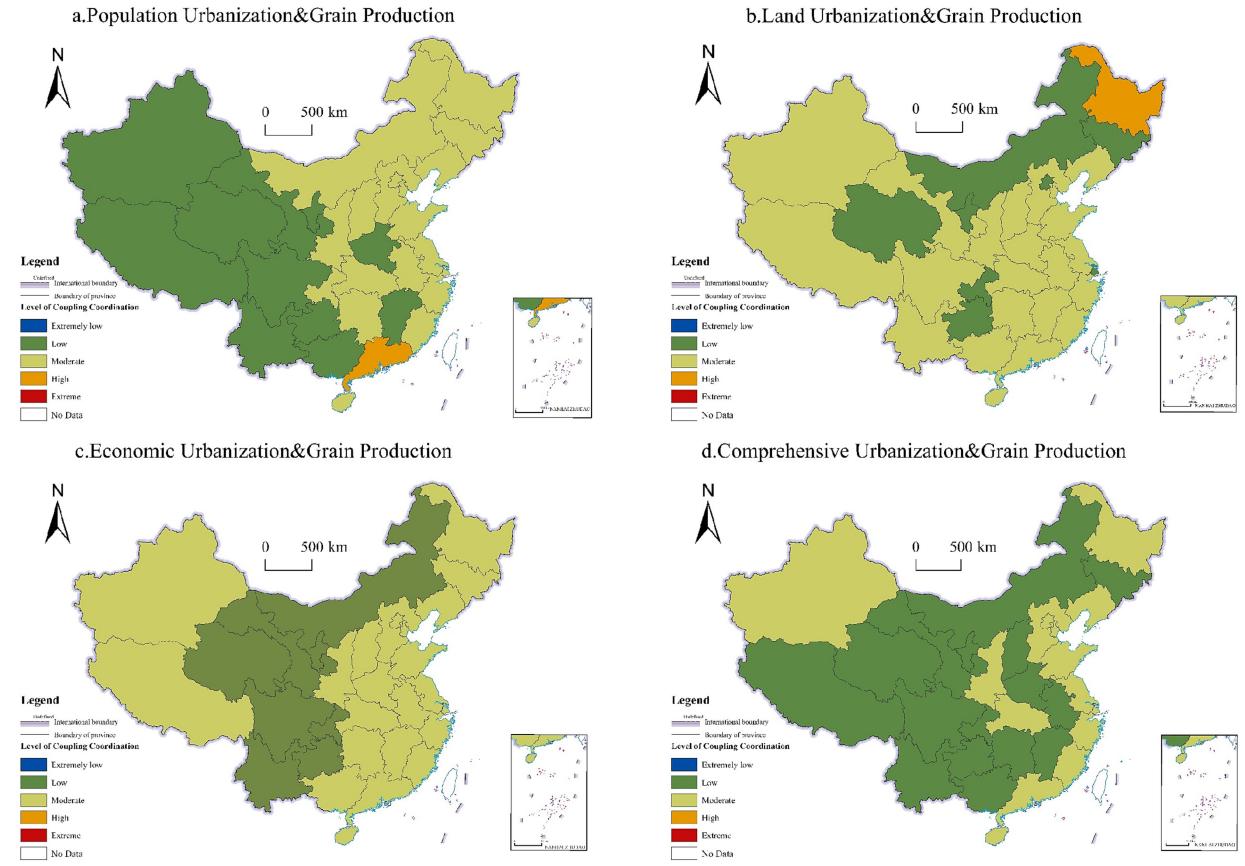


FIGURE 6
Multidimensional coupling pattern of urbanization and grain production in 2000. **(a)** Population Urbanization & Grain Production. **(b)** Land Urbanization & Grain Production. **(c)** Economic Urbanization & Grain Production. **(d)** Comprehensive Urbanization & Grain Production.

4.3.2 Dimensional coupling

From 2000 to 2022, the dynamic coupling processes of grain production with population urbanization, land urbanization, and economic urbanization in China's provincial regions exhibited significant spatial clustering and dimensional similarity (Figures 9, 10).

(1) The dynamic coupling process between population urbanization and grain production displayed four types: simultaneous increases (with urbanization outpacing grain production), simultaneous increases (with grain production outpacing urbanization), urbanization increases with grain production declines, and urbanization declines with grain production increases, with spatial clustering gradually weakening. From 2000 to 2011, the spatial clustering characteristics of dynamic coupling types were pronounced. Provinces in Northeast China, such as Inner Mongolia, Jilin, and Liaoning, were categorized as simultaneous increases (with grain production growing faster than urbanization), where grain production outpaced urbanization. Western provinces such as Xinjiang, Qinghai, Gansu, and Shaanxi, along with provinces in North and Central China, were classified as simultaneous increases (with urbanization growing faster than grain production), where grain production lagged behind urbanization but both exhibited coordinated promotion. Provinces in Southwest China, including Sichuan, Yunnan, and Guizhou, as well as southern provinces like Guangxi, Guangdong, and Fujian, fell into the category of urbanization increasing while grain production declined, indicating a negative effect of urbanization on grain production growth. Notably, Beijing in the Beijing-Tianjin-Hebei region exhibited an urbanization decline with grain production increase type, primarily due to the deconcentration of the population in the central urban area, where the population density decreased from 2,557 people per square kilometer in 2000 to 1,428 people per square kilometer in 2011, while grain production levels increased by 28%. In comparison to the previous eleven years, the spatial clustering of dynamic coupling types weakened from 2011 to 2022, with the emergence of simultaneous increases (with grain production growing faster than urbanization) in Henan and a shift of the urbanization increases with grain production declines type towards the western and central regions.

(2) The dynamic coupling process between land urbanization and grain production closely mirrored that of comprehensive urbanization, although some exceptional provinces were noted. From 2000 to 2011, Tibet exhibited a coupling coordination pattern of urbanization declines with grain production increases, primarily due to the reduction of per capita urban construction land area resulting from the substantial influx of population into cities. In Heilongjiang, grain production increased by 84%, compared to a 67% increase in land urbanization, resulting in a simultaneous increase (with grain production growing faster than urbanization) classification. From 2011 to 2022, the majority of provinces demonstrated simultaneous increases

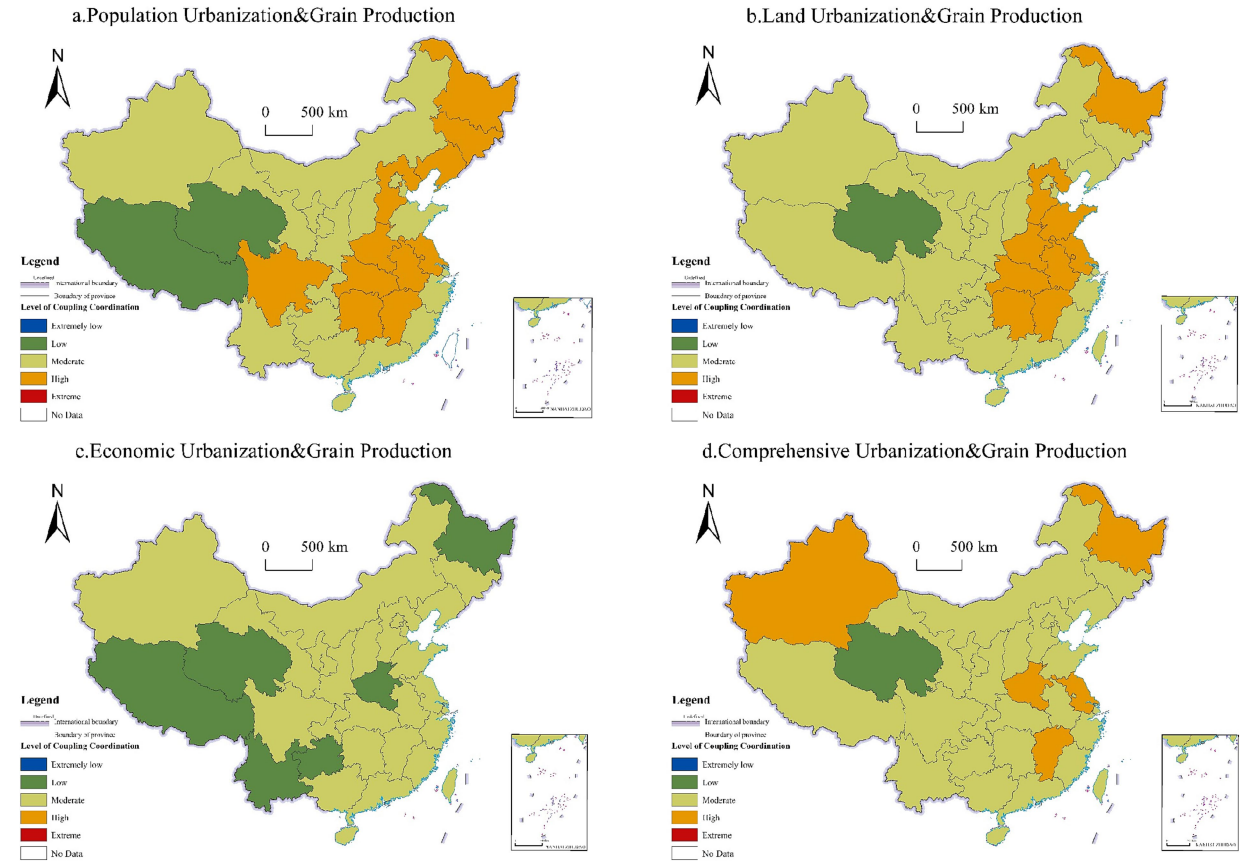


FIGURE 7
Multidimensional coupling pattern of urbanization and grain production in 2011. **(a)** Population Urbanization&Grain Production. **(b)** Land Urbanization&Grain Production. **(c)** Economic Urbanization&Grain Production. **(d)** Comprehensive Urbanization&Grain Production.

(with urbanization outpacing grain production), with only Tianjin exhibiting a simultaneous increase (with grain production outpacing urbanization). This was largely attributed to Tianjin's rapid increase in grain production per unit area and a decline in the trend of non-grain cultivation, with data indicating that grain production in Tianjin rose by 49% while land urbanization increased by only 24%.

(3) The dynamic coupling process between economic urbanization and grain production closely mirrored that of comprehensive urbanization, primarily characterized by simultaneous increases (with urbanization growing faster than grain production) and urbanization increases coupled with grain production declines.

5 The coupling process between urbanization and grain production

5.1 Evolution of static coupling types

The evolution of static coupling types displays an overall "rightward shift," characterized by dimensional heterogeneity and temporal phases (Table 3).

(1) From a dimensional perspective, on one hand, the static coupling relationships among population urbanization, land urbanization, and grain production have experienced varying degrees of degradation, particularly between population urbanization and grain production. From 2000 to 2011, this relationship saw a notable decline, coinciding with a period of extensive quantitative growth in urbanization, marked by a significant influx of agricultural migrant populations into urban areas. For instance, in Guangdong Province, the level of population urbanization increased by 0.17, while grain production levels decreased by 0.06 during the same period. On the other hand, the coupling coordination between economic urbanization and grain production has shown continuous improvement, with no significant negative trends, reflecting the robust development of non-agricultural industries and a complementary division of labor between urban and rural sectors.

(2) From a temporal perspective, since the beginning of the 21st century, the static coupling relationship between urbanization and grain production in China has exhibited distinct temporal phases, which can be broadly divided into two stages. The first stage, from 2000 to 2011, is characterized by a transition from low coupling coordination levels to moderate levels. Provinces experiencing this transition include Shanxi, Inner Mongolia, Chongqing, Sichuan, and Yunnan, which have historically lagged in urbanization and grain production capacity. During this phase, both urbanization and grain production levels in

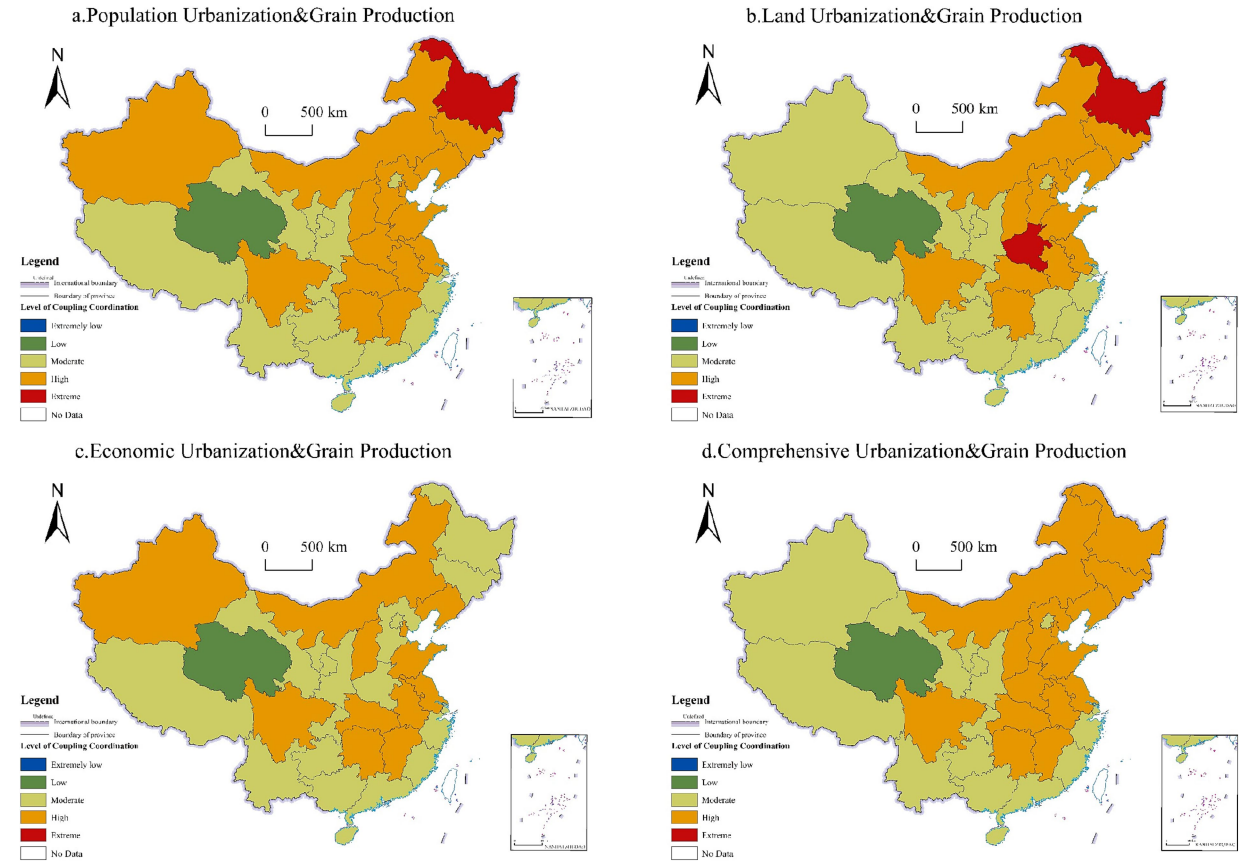


FIGURE 8
Multidimensional coupling pattern of urbanization and grain production in 2022. **(a)** Population Urbanization&Grain Production. **(b)** Land Urbanization&Grain Production. **(c)** Economic Urbanization&Grain Production. **(d)** Comprehensive Urbanization&Grain Production.

these provinces saw significant improvements. The second stage, from 2012 to 2022, is marked by an evolution from moderate to high coupling coordination levels. This transformation predominantly occurred in eastern provinces such as Tianjin, Hebei, and Shandong, where grain production levels ranked among the highest nationally and continuously progressed toward agricultural modernization. In this stage, urbanization processes also advanced rapidly, resulting in a high level of coordinated development between urbanization and grain production.

5.2 Evolution of dynamic coupling types

The evolution of dynamic coupling types exhibits a clear bidirectional trend, characterized by transitional tendencies and dimensional heterogeneity (Table 4).

(1) Overall, the dynamic coupling relationship between urbanization and grain production across multiple dimensions reveals two primary transition pathways: from B1 to B3 and from B3 to B1. The predominant trend is an improvement towards simultaneous increases in urbanization and grain production (with urbanization growing faster than grain production), accounting for approximately 71% of all provinces. This improvement arises from both originally well-coordinated provinces such as Jilin, Heilongjiang, Shandong, Henan, and Anhui in Central and Eastern China (73%) and provinces in Western China, such as Yunnan, Guizhou, and Sichuan, which transitioned from urbanization increases coupled with grain production declines (27%). The secondary trend is a decline towards urbanization increases accompanied by grain production declines, which accounts for about 26% of all provinces. This decline includes both originally disordered provinces, such as Zhejiang and Guangdong in Eastern China (38%), and remote provinces like Tibet and Qinghai experiencing deterioration (62%).

(2) Furthermore, from a dimensional perspective, the complexity of dynamic coupling type transitions exhibits significant variation, with the ranking of complexity across the three dimensions as follows: population urbanization & grain production (8 pathways) > land urbanization & grain production (6 pathways) > economic urbanization & grain production (4 pathways). Compared to the dynamic coupling relationship between economic urbanization and grain production, the first two dimensions show more internal structural adjustments within the simultaneous increases in urbanization and grain production type. Particularly in provinces like Heilongjiang and Henan, where population urbanization is relatively saturated and land urbanization is

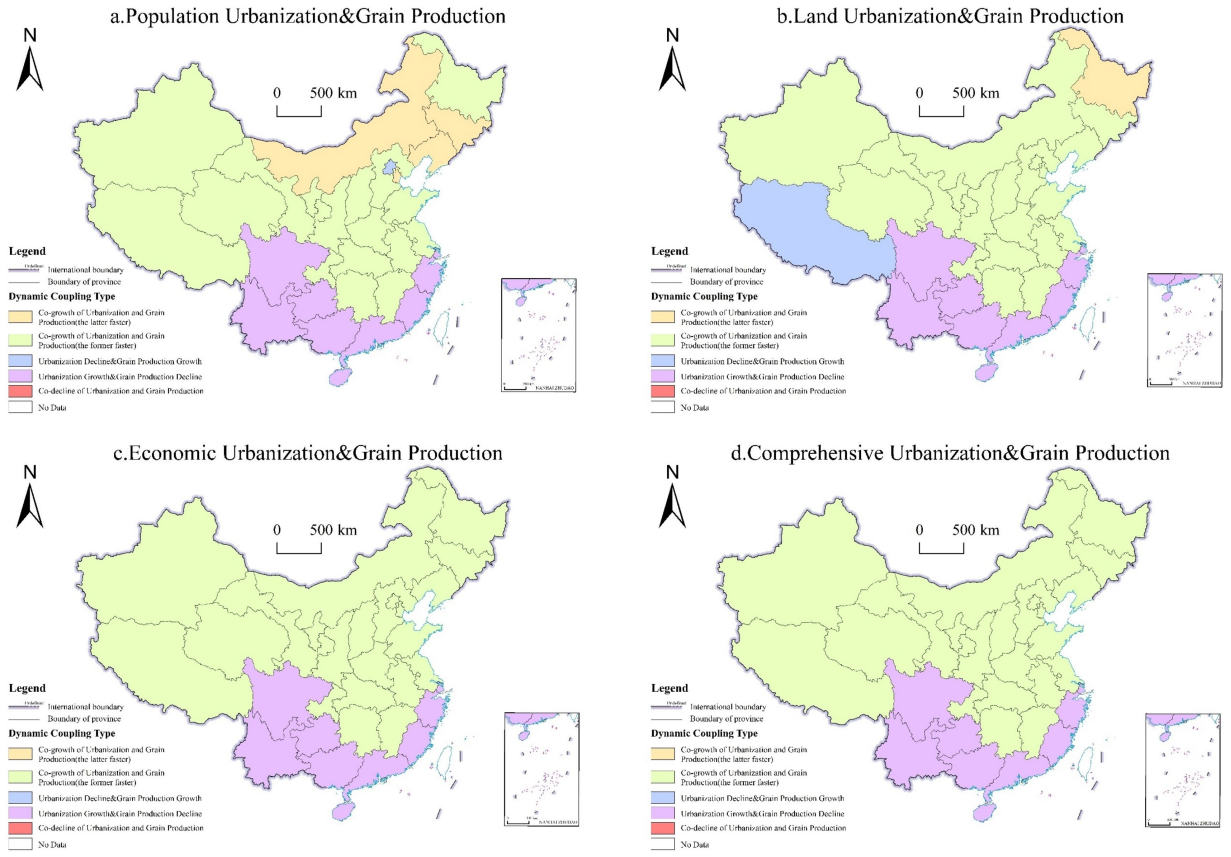


FIGURE 9
Multidimensional coupling process of urbanization and grain production from 2000 to 2011. **(a)** Population Urbanization&Grain Production. **(b)** Land Urbanization&Grain Production. **(c)** Economic Urbanization&Grain Production. **(d)** Comprehensive Urbanization&Grain Production.

overly aggressive, there is a gradual shift towards optimizing existing urbanization. This aims to enhance the efficient use of urban land resources in relation to population urbanization. The stagnation of expansive urbanization processes has allowed certain resources to be redirected towards grain production, resulting in a scenario where grain production growth outpaces urbanization growth.

6 The coupling mechanism between urbanization and grain production

6.1 Analysis of driving factors

Drawing on the theoretical and empirical analyses discussed earlier, this study identifies five driving factors—population, land, economy, technological advancement, and factor mobility—based on the principles of scientific rigor and feasibility to elucidate the coupling mechanism between urbanization and grain production (Table 5).

6.1.1 Population drivers

Two indicators are selected: the total rural population and the number of individuals employed in the primary sector. The former represents the absolute number of people in rural areas, while the latter reflects employment conditions in agriculture (Zhu et al., 2021).

6.1.2 Land drivers

Two indicators are utilized: the area of arable land in rural regions and the proportion of land allocated to grain crop cultivation. The first indicator indicates the total land available for grain production, while the second reflects the actual utilization of arable land (Zhou B. B. et al., 2021).

6.1.3 Economic drivers

This section includes two indicators: per capita agricultural output value and the share of crop output within the total agricultural, forestry, animal husbandry, and fishery sectors. The first indicator signifies labor productivity in crop production and is closely linked to labor earnings, while the second illustrates the role of crop production within the overall agricultural economy (Li X. et al., 2022).

6.1.4 Technological advancement

Two indicators are chosen: per capita total power of agricultural machinery and the application rate of chemical fertilizers per unit area. The first indicator reflects the level of agricultural mechanization, while the second indicates the extent of fertilizer use in agriculture (Zhu et al., 2021).

6.1.5 Factor mobility

This section also utilizes two indicators: reservoir capacity and investment in rural infrastructure. The former signifies investment in

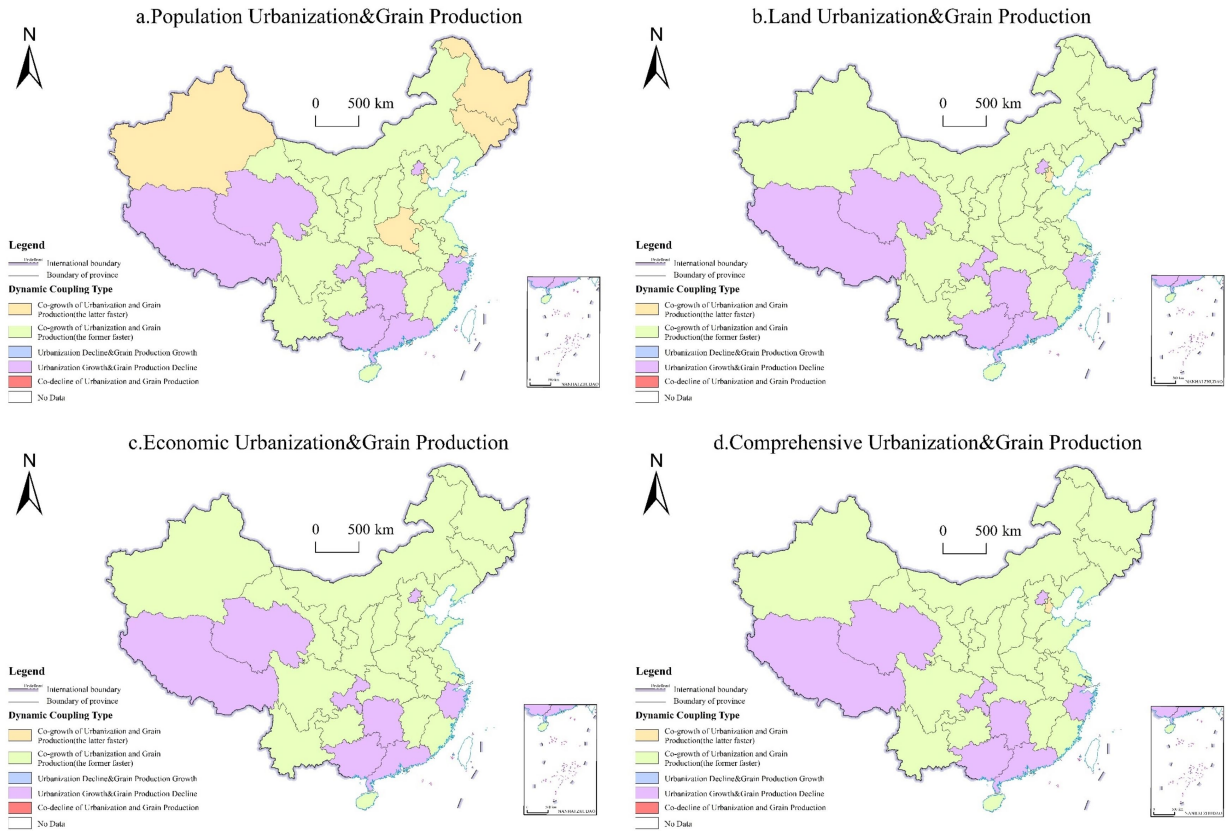


FIGURE 10
Multidimensional coupling process of urbanization and grain production from 2011 to 2022. **(a)** Population Urbanization&Grain Production. **(b)** Land Urbanization&Grain Production. **(c)** Economic Urbanization&Grain Production. **(d)** Comprehensive Urbanization&Grain Production.

agricultural facilities, while the latter represents financial contributions to agricultural development (Zhu et al., 2023).

Additionally, acknowledging that grain production is significantly influenced by natural conditions, particularly climate change, this study includes four indicators: the area affected by agricultural disasters, the area undergoing flood control measures, annual average accumulated temperature, and annual average precipitation. The first two indicators capture the impact of disasters on agricultural production and the effectiveness of disaster management, while the latter two reflect the temperature and precipitation conditions favorable for agriculture (Semeraro et al., 2023). Details of the specific indicators selected are presented in Table 5.

The baseline model is configured as follows (Equation 14):

$$D_{it} = \sum_{j=1}^{10} \alpha_j z_{j,it} + \sum_{m=1}^{4} \beta_m k_{m,it} + u_i + \varepsilon_{it} \quad (14)$$

In this context, D_{it} denotes the degree of coupling and coordination between urbanization and agricultural production for province i at year t. The variable $z_{j,it}$ represents the j-th explanatory variable for province i at year t, with α_j as its corresponding coefficient. The variable $k_{m,it}$ signifies the m-th control variable for province i at year t, and β_m represents its coefficient. Additionally, u_i accounts for individual fixed effects, while ε_{it} is the random error term. To ensure the robustness of the regression results and facilitate comparisons of regression parameters, multiple regression models have been established. Specifically, Models 1 and 2 represent pooled ordinary least squares (POLS) regressions, with and without control variables, respectively. Models 3 and 4 indicate panel regressions with individual fixed effects, also conducted with and without control variables. Finally, Models 5, 6, and 7 examine the degrees of coupling and coordination between urbanization and agricultural production concerning population, land, and economic dimensions.

Initially, the panel data was treated as general cross-sectional data for the POLS regression. The regression coefficients for most variables in Models 1 and 2 were found to be significant, with an average variance inflation factor (VIF) of 4.06, indicating that the selected combination of explanatory variables does not exhibit significant multicollinearity (Figure 11). Subsequently, a panel model regression was performed. F-tests revealed that individual fixed effects are significant, while Hausman tests confirmed that fixed effects are more appropriate than random effects. The regression results indicate that, on one hand, the overall goodness of fit for the models is satisfactory, with R^2 values exceeding 0.5487. However, the goodness of fit for the panel models generally surpasses that of the cross-sectional models, and models that account for control variables exhibit better fit than those that do not, emphasizing the importance of regional heterogeneity and natural environmental factors in influencing agricultural production (Table 6). On the other hand, the driving factors for coupling and coordination between urbanization and agricultural production exhibit dimensional heterogeneity.

Focusing on specific regression results: in the population dimension, the reduction in the absolute rural population in China

TABLE 4 Transition frequency matrix of dynamic coupling relationship evolution of urbanization and grain production.

	b1. Population urbanization & grain production						b2. Land urbanization & grain production				
	2011–2022						2011–2022				
		B1	B2	B3	B4	B5	B1	B2	B3	B4	B5
2000–2011	B1	0.59	0.18	0.24	0.00	0.00	0.75	0.05	0.20	0.00	0.00
	B2	0.50	0.50	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
	B3	0.56	0.11	0.33	0.00	0.00	0.67	0.00	0.33	0.00	0.00
	B4	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
	B5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	b3. Economic urbanization & grain production						b4. Comprehensive urbanization & grain production				
	2011–2022						2011–2022				
		B1	B2	B3	B4	B5	B1	B2	B3	B4	B5
2000–2011	B1	0.77	0.00	0.23	0.00	0.00	0.73	0.05	0.23	0.00	0.00
	B2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B3	0.67	0.00	0.33	0.00	0.00	0.67	0.00	0.33	0.00	0.00
	B4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	B5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

has not hindered the coordinated development of urbanization and agricultural production. This observation aligns closely with the fundamental national context of "more people than land" in rural areas. More importantly, maintaining an adequate number of primary sector employees is crucial. In the land dimension, both the total area of arable land and the proportion of grain crop sowing significantly promote the coordinated development of urbanization and agricultural production. This is primarily because these are fundamental elements necessary for ensuring grain production. The central government of China has placed a strong emphasis on rural land protection and macro-control of economic crop cultivation in recent years. In the economic dimension, higher labor productivity in crop cultivation implies better economic returns for farmers, thereby increasing their willingness to plant. This significantly promotes the coordinated development of urbanization and agricultural production. In fact, Chinese farmers exhibit a high degree of mixed production characteristics, as economic crops generally yield higher returns than grain crops. Consequently, while ensuring grain production, farmers tend to choose economic crops, leading to a decrease in the proportion of agricultural output within the overall agricultural, forestry, animal husbandry, and fishery sectors. In terms of technological progress, advancements in mechanization and fertilizer application have significantly enhanced the coordinated development of urbanization and agricultural production, substantially improving the technological level of agricultural production in China and partially offsetting the negative impacts of urbanization on grain production. According to data from the National Bureau of Statistics of China, the level of agricultural mechanization increased by 110% from 2000 to 2022. In the dimension of factor flow, investments in water conservancy facilities and rural construction have also significantly promoted the coordinated development of urbanization and agricultural production. The water projects constructed and maintained by various levels of government in China are crucial for supporting grain production, especially in regulating the uneven temporal and spatial distribution of precipitation. Moreover, since the implementation of the New Rural Construction Policy in 2005, the Chinese government has allocated special funds annually for rural construction aimed at enhancing water supply, gas services, roads, and bridges. Investments in rural construction grew by 288% from 2005 to 2022. Additionally, amidst global climate change, fluctuations in temperature and precipitation conditions, as well as accompanying natural disasters, pose significant threats to grain production in China. However, the disaster response capabilities in agricultural production are continuously improving. Data from the Statistical Yearbook of China indicate that, in terms of disaster prevention, the area affected by agricultural disasters in 2022 was only 19% of that in 2000. Regarding disaster management, the area of agricultural disaster in 2022 was only 14% of that in 2000.

6.2 Multidimensional coupling mechanisms

Building upon the analysis of the driving factors, the intricate coupling relationship between urbanization and grain production is fundamentally influenced by demographic changes, land use dynamics, economic development, technological progress, and factor mobility. Specifically, population urbanization markedly alters the quantity and composition of agricultural labor; land urbanization exerts significant negative impacts on both the scale and quality of agricultural land; and economic urbanization creates a "push-pull" dynamic that drives transformations in agricultural industrial structures. Furthermore, technological advancements and the return of factors during the later stages of urbanization exert notable positive effects on grain production. However, in contexts characterized by inadequate technology and persistent outmigration, rural areas may continue to experience decline (Figure 12).

6.2.1 Population-driven urbanization and grain production

From a demographic perspective, urbanization is conceptualized as the transition of agricultural populations to urban populations. For

TABLE 5 Driving factors analysis variables.

Variable symbol	Variable description	Unit	Variable category	Variable connotation	Data source
D	Coupling coordination degree of urbanization and grain production	None	Dependent Variable	Coupling Status of Urbanization and Grain Production	Calculated data
D1	Coupling coordination degree of population urbanization and grain production				
D2	Coupling coordination degree of land urbanization and grain production				
D3	Coupling coordination degree of industrial urbanization and grain production				
z1	Rural population size	Ten Thousand	Independent Variable	Absolute number of rural population	China statistical yearbook
z2	Number of employees in the primary industry	Ten Thousand		Employment status in the agricultural sector	
z3	Area of arable land in rural regions	Thousand Hectares		Absolute quantity of arable land in rural areas	
z4	Proportion of arable land used for grain crop cultivation	%		Actual utilization of arable land in rural areas	
z5	Per capita value of crop production	Ten Thousand Yuan/Person		Labor productivity in crop production	
z6	Proportion of crop production value in the agricultural sector	%		Importance of crop production within the overall agricultural economy	
z7	Per capita total power of agricultural machinery	Kilowatt/Person		Level of agricultural mechanization	
z8	Application rate of chemical fertilizers per hectare	Ton/Hectare		Level of chemical fertilizer application in agriculture	
z9	Reservoir capacity	Hundred Million Cubic Meters		Investment in agricultural infrastructure	
z10	Investment in rural construction	Hundred Million Yuan		Financial input in agriculture	China urban–rural construction statistical yearbook
k1	Area affected by agricultural disasters	Thousand Hectares	Control Variable	Impact of disasters on agricultural production	Official website of the national bureau of statistics of China
k2	Area under flood control measures	Thousand Hectares		Agricultural disaster management	
k3	Average ANNUAL ACCUMULATED TEMPERATURE	Celsius		Temperature conditions for agricultural production	European centre for medium-range weather forecasts
k4	Average annual precipitation	Millimeters		Precipitation conditions for agricultural production	

urban areas, the influx of agricultural migrants not only provides a substantial labor force but also generates increased consumer demand, thereby facilitating the development of urban economies of scale. Conversely, this demographic shift poses governance challenges, complicating the provision of essential services such as housing, education, healthcare, and social security, which collectively influence the urbanization process (Zhang and Chen, 2024). In rural contexts, a moderate outflow of agricultural labor can create conditions conducive to large-scale agricultural production, particularly in resource-constrained areas characterized by high population density relative to land availability. This shift also synergizes with the application of modern agricultural technologies (Wang et al., 2021a). However, under an aggressive model of external urbanization, the substantial outmigration of quality young and middle-aged agricultural labor profoundly alters the demographic landscape of rural regions, leading to phenomena such as depopulation, aging, and declining birth rates, all of which pose significant threats to current and future labor supplies for grain production (Liu et al., 2021b; Liu and Zhou, 2021).

6.2.2 Land-driven urbanization and grain production

From the perspective of land use, urbanization is manifested as the expansion of urban land at the expense of rural land. Both urban development and agricultural production exert considerable demand on land resources, leading to significant land-use conflicts, particularly in flat and well-connected areas suitable for both uses (Sui and Lu, 2021). For urban areas, urban sprawl facilitates the expansion of

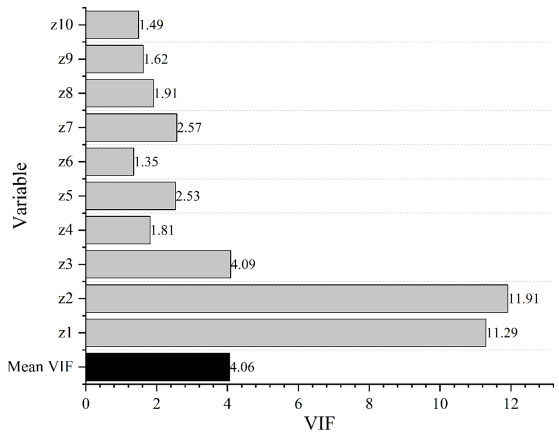


FIGURE 11
The test of multicollinearity.

developmental space and scale, while the marketization of land finance provides necessary funding for sustainable urban growth. Conversely, the encroachment of urban development on land resources diminishes agricultural production capacity, resulting in reduced availability and declining quality of agricultural land. Measures such as unequal compensation for land use fail to effectively counteract the systemic decline of agricultural land due to urbanization (Zhou Y. et al., 2021). Furthermore, in regions suffering from severe rural depopulation, the actual utilization rate of agricultural land is further diminished, resulting in substantial fallow land.

6.2.3 Economic-driven urbanization and grain production

Economically, urbanization reflects a transition in development modes, structural upgrades in industries, and changes in labor division. Regional economic development has shifted from a solely agricultural growth model to a diversified economic framework. Urban centers have established a variety of higher-tier non-agricultural industries, functioning as specialized service hubs for their respective regions. Within these regions, an objective division of labor has emerged between urban and rural areas, with variations in resource endowments leading to distinct labor divisions among different cities. For rural areas, the prosperity of urban economies juxtaposed with the low returns of traditional agricultural practices creates a "push-pull" effect that accelerates the migration of agricultural labor. Additionally, economic urbanization instigates a transformation in agricultural industrial structures, primarily characterized by a shift from low-value traditional grain crops to high-value cash crops, along with the emergence of agricultural ancillary sectors such as rural e-commerce, agricultural complexes, and agro-tourism (Schneider, 2017; Wang et al., 2023).

6.2.4 Technological progress-driven urbanization and grain production

The urbanization process, marked by the agglomeration of resources, objectively facilitates technological advancements in agriculture, significantly enhancing grain production capabilities. On one hand, urban areas benefit from rich human capital and efficient information networks, positioning them as key growth poles for regional technological innovation. During the mid-stages of urbanization, the interplay between urbanization and industrialization—particularly in machinery and chemical sectors—effectively promotes the mechanization of grain production and the application of fertilizers. In the later stages, the interrelation between urbanization and informatization fosters the development of advanced agricultural technologies characterized by automation, digitalization, and high spatial–temporal resolution (Radić et al., 2022). Conversely, agricultural technological advancements enhance the resilience of grain production systems, particularly in managing agricultural disasters, thus providing essential technical support for disaster preparedness, response, and recovery (Haji et al., 2024). Furthermore, modern agricultural technology is increasingly applied within large-scale agricultural production, where urbanization facilitates the emergence of large grain producers, cooperatives, and leading enterprises, creating critical practical avenues for the promotion of these technologies.

6.2.5 Urban–rural factor mobility-driven urbanization and grain production

From the perspective of mobility, the interaction between urban and rural areas is characterized by multidimensional factor flows, where the direction, intensity, and structure of these flows exert complex influences on regional urbanization and grain production. The scope of factor flows encompasses traditional production factors—such as land, labor, and capital—as well as emerging factors like data, technology, and ideas, continuously expanding the breadth of urban–rural interactions (Zhu et al., 2023). In the Chinese context, rural areas characterized by low population density, human capital, and environmental quality exhibit contrasting issues to urban areas suffering from high population density, overloaded infrastructure, and elevated governance costs, creating a symbiotic relationship between rural and urban challenges. The root cause of these issues lies in the excessive concentration of factors in urban areas and the impediments to the free and equitable exchange of resources between urban and rural settings (Fang, 2022). Notably, the impact of factor mobility on grain production is temporally phased; during the early and mid-stages of urbanization, classical economic theories—such as Lewis's dual economy structure theory and Perroux's growth pole theory—illustrate a trend towards unbalanced development (Lewis, 1954; Perroux, 1950), with rural populations and land rapidly concentrating in urban areas, thereby threatening grain production through the swift depletion of traditional rural production factors. In the later stages of urbanization, while urbanization continues to possess growth potential and remains a dominant trend in socio-economic development, traditional production factors such as labor and land are unlikely to fundamentally return to rural areas. However, the economic benefits derived from urbanization can effectively flow back to the agricultural sector; more crucially, the substantial maturation of emerging factors such as data and technology can foster the establishment of a smart agricultural technology system, enriching the qualitative dimensions of grain production. Emerging production factors significantly substitute for traditional factors, thereby amplifying the effects on grain production (Gao and Lyu, 2023). Thus, in the later stages of urbanization, leveraging financial resources to support agricultural revitalization, along with the integration of emerging production factors into agricultural industrialization, can promote the coordinated development of urbanization and grain production. In contrast, adherence to a traditional unidirectional flow of factors could precipitate negative declines in regional grain production levels, ultimately hindering the overall.

TABLE 6 Basic regression and sub-dimensional regression.

	Model1	Model2	Model3	Model4	Model5	Model6	Model7
z1	0.0683* (−1.73)	0.0513 (−1.29)	−0.8325*** (−13.10)	−0.7927*** (−11.96)	−0.6148*** (−8.04)	−0.5218*** (−7.51)	−0.9453*** (−10.49)
z2	−0.1347*** (−3.17)	−0.1074*** (−2.59)	0.1135*** (−2.67)	0.1182*** (−2.78)	0.1105** (−2.25)	0.0580 (−1.30)	0.1354** (−2.34)
z3	0.0026 (−0.10)	0.0192 (−0.63)	0.0883* (−1.73)	0.0960* (−1.87)	0.2613*** (−4.41)	0.1133** (−2.10)	−0.1627** (−2.33)
z4	0.1129*** (−7.36)	0.1089*** (−7.02)	0.1419*** (−6.91)	0.1413*** (−6.84)	0.1464*** (−6.14)	0.1705*** (−7.87)	−0.0377 (−1.34)
z5	−0.0096 (−0.22)	0.0106 (−0.25)	0.1352*** (−4.57)	0.1302*** (−4.37)	0.0733** (−2.13)	0.0933*** (−2.99)	0.3578*** (−8.84)
z6	−0.0171 (−1.16)	−0.0209 (−1.34)	−0.1244*** (−6.42)	−0.1199*** (−6.18)	−0.1286*** (−5.75)	−0.0840*** (−4.13)	−0.0430 (−1.63)
z7	0.2526*** (−10.18)	0.2283*** (−9.26)	0.2208*** (−9.50)	0.2174*** (−9.31)	0.1290*** (−4.79)	0.2584*** (−10.56)	0.3778*** (−11.90)
z8	0.0230 (−1.21)	−0.0279 (−1.35)	0.0895*** (−4.08)	0.0955*** (−4.29)	0.1062*** (−4.14)	0.0770*** (−3.30)	0.1578*** (−5.22)
z9	0.0060 (−0.34)	0.0303* (−1.71)	0.0376* (−1.83)	0.0466** (−2.23)	0.0847*** (−3.51)	−0.0569*** (−2.59)	0.0692** (−2.43)
z10	0.2870*** (−16.22)	0.2328*** (−12.15)	0.0513*** (−2.89)	0.0449** (−2.48)	0.0345* (−1.65)	0.0361* (−1.90)	0.1494*** (−6.08)
k1		−0.1273*** (−5.00)		−0.0126 (−0.66)	0.0102 (−0.47)	−0.0590*** (−2.98)	−0.0551** (−2.14)
k2		0.0664*** (−3.95)		0.1153** (−2.00)	0.0193 (−0.29)	−0.0528 (−0.87)	0.3166*** (−4.04)
k3		0.0712*** (−3.44)		0.0453 (−0.47)	0.1428 (−1.27)	−0.1090 (−1.07)	0.3396** (−2.57)
k4		−0.0510*** (−2.89)		−0.0385* (−1.96)	−0.0449** (−1.99)	−0.0610*** (−2.97)	0.0201 (−0.75)
_cons	0.3740*** (−27.83)	0.3889*** (−25.67)	0.5954*** (−22.26)	0.5514*** (−8.46)	0.4604*** (−6.12)	0.6239*** (−9.12)	0.3021*** (−3.41)
N	713	713	713	713	713	713	713
R-squared	0.5487	0.5822	0.7824	0.7854	0.6493	0.6968	0.8180
Fixed effects			yes	yes	yes	yes	yes
F	85.3544	69.4721	241.6770	174.5934	88.3318	109.6494	214.4554
F test: Prob>F			0.0000	0.0000	0.0000	0.0000	0.0000
Hausman: Prob>chi2			0.0000	0.0000	0.0000	0.0000	0.0000

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

7 Discussion and conclusion

7.1 Discussion

7.1.1 Complexity analysis of the coupled and coordinated development of urbanization and grain production in China

Unlike the "inhibitory effects" and "promoting effects" of urbanization on grain production (He et al., 2022; He et al., 2023; Huang et al., 2020; Mok et al., 2020), the complexity of their interaction is thoroughly demonstrated in this study (Liu and Zhou, 2021). The research on the coupling relationship between urbanization and grain production transcends simple studies of positive or negative effects. It accounts for the superimposition of both effects within specific spatial scales and reveals a spiral upward trend in their coupling and coordination over time (Zhu et al., 2021). This phenomenon has been particularly evident in regional empirical studies in China since the 21st century. Specifically, the complexity can be summarized in five key aspects: (1) the multidimensional interactions of coupling elements, (2) the complex spatial structures of coupling patterns, (3) the intricate evolutionary paths of coupling processes, (4) the multifaceted driving factors of coupling mechanisms, and (5) the regional heterogeneity observed in the study. The most critical aspect is the complexity of the driving factors behind the

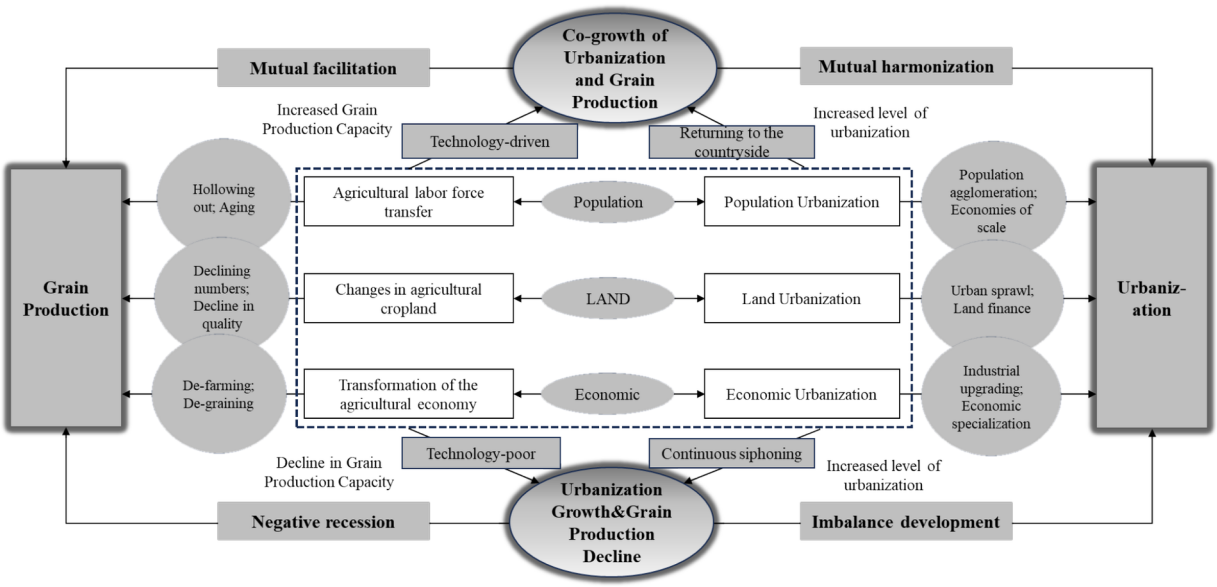


FIGURE 12
The multidimensional coupling mechanism of urbanization and grain production.

coupling mechanisms, which includes both "secondary natural factors" such as population, economy, technology, and the flow of factors, as well as "primary natural factors" such as land, climate, and natural disasters (Krugman, 1991). While the impact of climate change on China's grain production is both significant and complex, this is not the primary focus of the current study. From the perspective of other factors, elements such as population, land, and economy tend to reinforce the "inhibitory effects," while technological progress and the orderly flow of urban–rural factors contribute to the "promoting effects." At the macro level, the coupling and coordination relationship between urbanization and grain production in China continues to improve, revealing a gradual weakening of the "inhibitory effects" and a consistent strengthening of the "promoting effects."

7.1.2 Coupled and coordinated development of urbanization and grain production in the context of China's urbanization policy changes

Since the reform and opening-up period, China's urbanization has followed a clear phased pattern, as illustrated in Figure 3 of this study. The authors divide China's urbanization process over the past 70 years into three stages, each marked by distinct differences in the pace of development. These differences in urbanization speed are largely attributed to the Chinese government's strategic decisions regarding urbanization pathways, which have played a critical role in regulating the speed and stages of development (Chen et al., 2023; Liu and Zhou, 2021). In summary, based on the urbanization strategies and models chosen by the Chinese government, the coupled and coordinated development of urbanization and grain production since the reform and opening-up period can be roughly divided into three stages (Fang et al., 2017; Gu et al., 2017): First Stage (1978–1992): Against the backdrop of rural industrialization, small towns in China developed, albeit at a limited scale. During this period, rural residents could leave agriculture without leaving their hometowns, taking up factory jobs without migrating to cities. This allowed them to engage in industrial production to increase income while maintaining grain production activities. Consequently, the coupling and coordination between urbanization and grain production remained at a low level. Second Stage (1992–2013): As China gradually established its market economy and integrated into globalization, large cities saw rapid development. Agricultural labor migrated long distances to urban areas, which intensified the urban–rural divide. Meanwhile, the improvement of grain production capacity in rural areas was relatively slow, resulting in a medium-level coupling and coordination between urbanization and grain production (Liu and Zhou, 2021). Third Stage (2013–present): The Chinese government has actively promoted a new urbanization strategy, marking a shift away from the previously aggressive urbanization models. Measures have been taken to control the unregulated expansion of urban populations and land, balance urban–rural relations, and encourage the return of resources such as personnel, technology, and capital to rural areas. As a result, the coupling and coordination between urbanization and grain production has reached a medium-high level (Liu Y. S. et al., 2020). Thus, the coupling and coordinated relationship between urbanization and grain production is closely tied to the urbanization model. Through adjustments in national urbanization policies, the Chinese government is steering these two sectors toward a state of high-quality and coordinated development.

7.1.3 Coupling and coordinated development of urbanization and grain production in China: regional patterns and optimization strategies

To facilitate the high-quality coordinated development of urbanization and grain production, it is essential to adopt strategies that are context-specific and temporally relevant (Liu et al., 2021a). This research delineates spatial patterns based on the levels of coupled coordination and the dynamic processes involved in the interaction between urbanization and grain production. Initially, by assessing the current levels of coupled coordination, two primary categories are

identified: moderate coupled coordination and high coupled coordination. Further refinement of these categories is achieved by analyzing the trends in coupling dynamics, particularly referencing the changes in urbanization and grain production from 2011 to 2022. Specifically, if urbanization levels experience an upward trajectory while grain production levels decline, this scenario is classified as a grain production decline type. Conversely, if both urbanization and grain production exhibit simultaneous upward trends, with grain production growth outpacing urbanization, it is categorized as a grain production optimization type. In instances where urbanization progresses more rapidly than grain production, this situation is identified as an urbanization optimization type. Ultimately, the study classifies the 31 provincial units into five distinct types: (1) moderate coupled coordination with grain production decline, (2) moderate coupled coordination with urbanization optimization, (3) high coupled coordination with grain production decline, (4) high coupled coordination with urbanization optimization, and (5) high coupled coordination with grain production optimization (Figure 13). This classification underscores the diverse trajectories and interdependencies that characterize the relationship between urbanization and grain production across different regional contexts.

Based on the identified spatial patterns of coupled coordination between urbanization and grain production, a systematic optimization strategy can be formulated. This strategy aims to harmonize global and local considerations, integrate economic development with grain production, balance developmental levels with quality, and enhance regional specialization while leveraging complementary advantages.

7.1.3.1 Moderately coupled coordination—grain production decline type

This category includes seven provincial units: Beijing, Zhejiang, Guangdong, Guangxi, Chongqing, Qinghai, and Tibet. In this group, Beijing, Zhejiang, and Guangdong are experiencing a persistent decline in grain production levels despite a backdrop of relatively high urbanization. The optimization strategy for these regions should focus on mitigating excessive non-grain crop cultivation while ensuring adequate investments in agricultural technology, finance, and human resources to bolster grain production. Conversely, Guangxi, Chongqing, Qinghai, and Tibet require a coordinated approach to elevate both urbanization and grain production levels, with a particular emphasis on agricultural technological innovation aimed at improving yields in remote and challenging environments.

7.1.3.2 Moderately coupled coordination—urbanization optimization type

This category encompasses nine provincial units: Shanghai, Fujian, Hainan, Guizhou, Yunnan, Shaanxi, Gansu, Ningxia, and Xinjiang. Within this group, Shanghai, Fujian, and Shaanxi exhibit a trend of increasing urbanization alongside relatively low grain production levels, which may lead to new forms of dissonance between urbanization and grain production. Therefore, it is imperative to prioritize high-quality grain production and agricultural modernization within the high-quality urbanization agenda. Meanwhile, Hainan, Guizhou, Yunnan, Gansu, Ningxia, and Xinjiang demonstrate moderate levels of both urbanization and grain production; thus, the implementation of new-type urbanization initiatives could effectively foster high-quality coordinated development in these regions.

7.1.3.3 Highly coupled coordination—grain production decline type

This category is represented by Hunan, which showcases a high level of urbanization alongside moderate grain production levels. Over the period from 2011 to 2022, both total grain production and yield levels have experienced fluctuations, exhibiting an upward trajectory. Future strategies should concentrate on regulating excessive non-grain crop cultivation to stabilize and enhance grain production.

7.1.3.4 Highly coupled coordination—urbanization optimization type

This category includes thirteen provincial units: Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Jiangxi, Shandong, Henan, Hubei, and Sichuan. Among these, provinces such as Jilin, Heilongjiang, Shandong, Henan, and Anhui are significant agricultural producers, where urbanization presents further opportunities for advancement. Future policies should aim to minimize urban encroachment on high-quality arable land, thereby ensuring the sustainability of grain production volumes and reinforcing their status as agricultural powerhouses, essential for national grain security. In other provinces, the constraints of resources and the environment during the high-quality urbanization phase diminish production advantages; hence, it is crucial to enhance the flow of rural–urban factors and implement technological empowerment initiatives to improve regional grain production levels.

7.1.3.5 Highly coupled coordination—grain production optimization type

This category is represented by Tianjin, which exhibits a high level of urbanization coupled with a moderate and consistently improving grain production level. Given the limited availability of arable land, Tianjin's scale advantages in grain production are not pronounced; however, it stands out in high-tech agricultural capabilities. In light of the current context of relatively subdued urbanization growth, Tianjin should focus on developing high-quality urban agricultural zones, positioning itself as a model for high-tech agricultural development and urban–rural integration in the Beijing-Tianjin-Hebei region.

8 Conclusion

This study utilizes China as a representative case from the 21st century to systematically empirically investigate the multidimensional coupling patterns and processes between urbanization and grain production across Chinese provinces from 2000 to 2022. The research aims to identify the driving factors and preliminarily summarize the coupling mechanisms between these two systems.

This study, departing from traditional research on the coupling relationship between urbanization and grain production, contributes novel perspectives and innovations in the following three aspects: (1) Research Perspective: Grain production and urbanization are conceptualized as systems comprising organically integrated multidimensional elements. Unlike prior approaches that treat urbanization as a single entity, this study deconstructs urbanization into three subsystems—population, land, and economy—and investigates the coupling states and interaction mechanisms not only between these two systems but also among the urbanization subsystems and the grain production system, thereby revealing their

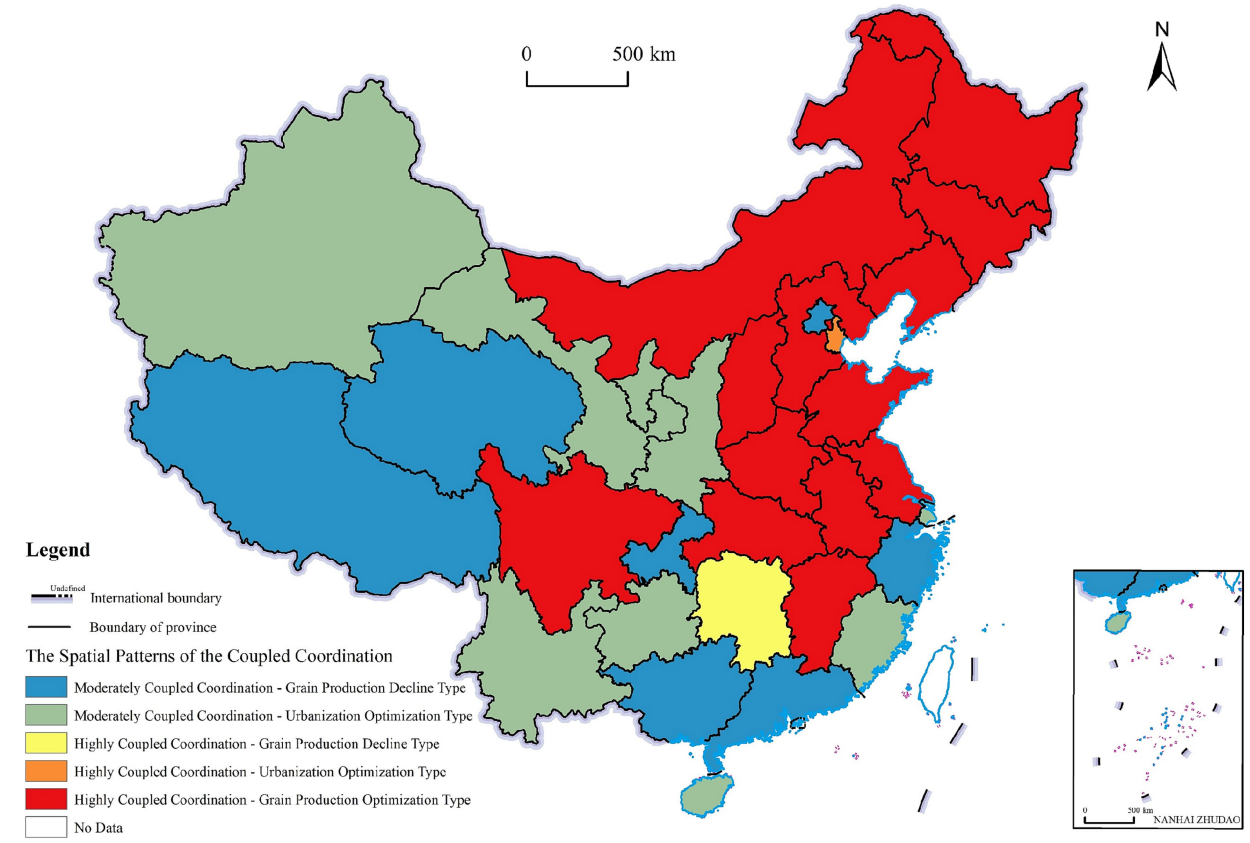


FIGURE 13
The spatial patterns of the coupled coordination between urbanization and grain production.

mechanisms of action more profoundly, building upon the foundational work of scholars such as Liu et al. (2021b) and Zhu et al. (2021). (2) Research Methodology: This study employs a combination of static and dynamic coupling methods to characterize the coupling patterns and processes between urbanization and grain production. This approach not only captures the static coupling state between the two systems but also elucidates the dynamic evolution of these coupling states. Moreover, the coupling coordination degree is calculated using the latest optimized models, ensuring robust applicability to this research (Cai et al., 2021; Zhu et al., 2021). (3) Selection of Research Period: The study selects a more representative period, the third phase (2000–2022), which spans the transition from the initial phase of rapid urbanization to the era of high-quality urbanization in China. This period represents the most significant and complex stage of the coupling relationship between urbanization and grain production (Li X. et al., 2022; Ma et al., 2020). By integrating innovative perspectives, methodologies, and the selection of a representative study period, this study produces findings that are scientifically robust, systematically comprehensive, and highly credible. It reveals the multidimensional, long-term coupling processes and mechanisms between urbanization and grain production in China. At the macro level, the coupling coordination between the two systems has generally improved, whereas at the provincial level, heterogeneous coupling states and differentiated evolutionary processes are evident. These findings highlight the necessity for region-specific and context-sensitive policy recommendations to promote high-quality coordinated development of urbanization and grain production in China. Furthermore, by taking China as a case study, this research offers valuable insights for international reference in similar contexts, systematically uncovering the coupling patterns between national urbanization and grain production in a populous developing country during a period of rapid urbanization (Ambikapathi et al., 2022).

Admittedly, certain aspects of this study require further refinement and exploration in future research. Firstly, this study adopts a narrow definition of "food security"—aligned with the consensus of the Chinese government and academia—that focuses on the production end of key grain crops, particularly total output (production scale), yield per unit area (production quality), and production structure. While emphasizing grain production is essential—particularly under the context of global geopolitical tensions and the substantial food demands of populous nations—the broader concept of "food security" proposed by the Food and Agriculture Organization of the United Nations (FAO), encompassing availability, accessibility, stability, and utilization, warrants further exploration (Erokhin et al., 2022; Xie et al., 2021). Future research will address these dimensions under the broader framework of food security. Secondly, urbanization and grain production should not merely be regarded as simple systems of multidimensional element integration; they embody complex organizational structures characterized by dual dynamics of self-organization and external influences, along with features such as adaptability, synergy, and volatility (Molajou et al., 2023). Future research should leverage the techniques, methods, and theories of complex systems science to

better define the relational dynamics, system boundaries, and external interconnections between urbanization and grain production systems, thereby enhancing the understanding of their mechanisms of action while balancing developmental and security principles to promote orderly interactions. Thirdly, grain production is influenced not only by the complex drives of urbanization but also profoundly affected by global climate change as a natural force (Wheeler and von Braun, 2013). According to the IPCC's Fifth Assessment Report, global climate change represents the most significant environmental challenge facing humanity in the 21st century, with rising temperatures, abnormal precipitation patterns, and extreme climate events—such as droughts, floods, typhoons, and frost—posing major threats to global and regional food security. For developing countries like China, the challenges of food security become particularly complex and urgent within the dual context of rapid urbanization and climate change, necessitating systematic research within the framework of "urbanization-climate change-food security."

Author contributions

XC: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. ShW: Conceptualization, Formal analysis, Funding acquisition, Resources, Writing – review & editing. ZY: Conceptualization, Formal analysis, Project administration, Supervision, Writing – review & editing. KL: Conceptualization, Formal analysis, Project administration, Supervision, Writing – review & editing. SiW: Methodology, Software, Validation, Visualization, Writing – review & editing. MQ: Methodology, Software, Validation, Visualization, Writing – review & editing. XM: Methodology, Software, Validation, Visualization, Writing – review & editing.

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Conflict of interest

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An approach to addressing rural depopulation in the black soil region: insights from the county urban–rural settlement system

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In the context of rural depopulation, spatial reorganization of settlements is widely recognized as a critical strategy to alleviate the human-land contradiction and enhance land use efficiency in the black-soil region. Using Yushu County as a case study, this paper explores an approach to the spatial optimization of urban–rural settlements in the black soil region. Currently, the urban–rural settlement system exhibits a distorted structure characterized by an excess of small settlements and a scarcity of large and medium-sized settlements, while the rank-size curve illustrates the phenomenon of "raising head, craning neck and drooping tail." Rural development potential displays a pronounced high-high and low-low aggregation pattern. In light of this, the consolidation of settlements should be implemented at two scales: administrative villages and towns. In areas with high potential for rural development, merging natural settlements into the central settlement within an administrative village is recommended. In areas with low potential for rural development, the relocation and consolidation of natural settlements should be guided by the ideal service radius of central settlements within a town. This approach could preserve the original social relations to the greatest extent, thus facilitating the effective implementation of rural restructuring strategies.

KEYWORDS

urban–rural settlements, spatiotemporal trajectory, spatial reorganization, black-soil region, Yushu County

1 Introduction

The black soil region, as a major agglomeration of the world's high-quality cropland and a key base for the supply of commercial grains, plays a pivotal role in guaranteeing global grain security and safeguarding the life and health of human beings (Godfray et al., 2010). However, in recent years, with the advancement of urbanization, a large-scale rural population has migrated to central cities, and the black soil region has witnessed a widespread phenomenon of "demographic exodus and rural hollowing" (Zang et al., 2020; Wang et al., 2021), which undermines the urban–rural system and the human-land relations in the black-soil region, posing challenges to the protective utilization of black-soil land. Therefore, it is critical to explore the geographic specificity of the evolution of the urban–rural settlement system and its restructuring pattern. Such an exploration can promote the coordinated development of human-land relations and the efficient utilization of land resources in the black soil region.

Rural settlements serve as critical spatial carriers providing habitation for villagers, and enabling them to engage in agricultural production, and they act as the bond of interaction between villagers and land (Cloke, 2013; Yang et al., 2016). Restructuring rural settlement is naturally regarded as an efficient approach to reshaping the rural human-land relations (Sun et al., 2022). With the advancement of industrialization and urbanization in the 1970s, rural decline has become a common global challenge, such as rural depopulation in Europe, rural sparsification in Japan, and agricultural recession in Korea (Andrzej, 1992; Garcia and Ayuga, 2007; Lobley and Potter, 2004; Yukihiko, 2007). To address these challenges and promote the sustainable development of rural areas, countries began to rely on optimization of rural settlements to stimulate the endogenous development dynamics of rural areas, including Heisei Mergence in Japan, the New Village Movement in Korea (Hong et al., 2022), the Agricultural and Rural Development Act in Canada (Lapping and Fuller, 1985) and the Rural Development Program in Britain (Dwyer and Powell, 2016). In these counties, the spatial optimization of settlement systems roughly complies with three principles derived from Central Place Theory (Christaller, 1966), i.e., market, transportation and administration under the background of special geographic functions. As the practice has proved, rural settlement restructuring is a positive response to rural decline, and it is capable to block the processes of rural socio-economic recession in rural areas by reshaping the spatial structure of the countryside and production-habitation relations (Li et al., 2018; Long, 2014; Zhou et al., 2020).

Similar to developed counties, China also undergoes large-sale outflows of rural population (Hu et al., 2023; Liu et al., 2024), which brings about disorderly village-town system (Sun et al., 2013; Li L. et al., 2020; Li Y. et al., 2020) and severe human-land separation in rural areas, such as homestead hollowing, cropland abandonment, and environmental deterioration (Li et al., 2021; Qu et al., 2021). To revive the countryside, the central government of China issued Rural Revitalization Strategy Planning (2018–2022) in 2017 (Kong et al., 2021), which explicitly proposed the goal of rural revitalization by classification. A prerequisite for the implementation of the plan is to correctly grasp the evolutionary characteristics, patterns and tendencies of rural settlements in the context of rural depopulation (Chen et al., 2022; Zou et al., 2024). Thereafter, scholars have conducted numerous theoretical and empirical studies on rural hollowing, including the life cycle of hollow villages, the spatiotemporal trajectory of hollow villages, identification of hollow villages, factors and mechanism influencing rural hollowing (Li et al., 2022; Gong et al., 2022; Ji et al., 2022; Li T. et al., 2015; Li H. et al., 2015; Wang et al., 2024). With the advancement of urban–rural integration and development, rural hollowing tends to go through five stages: emergence, growth, flourishing, stabilization and disappearance (Liu et al., 2010). The disappearance of rural hollowing is often attributed to external policy interventions, particularly those involving the restructuring rural settlements (Long, 2014; Tu and Long, 2017). Existing patterns in the spatial optimization of rural settlements include the dual-scale coupling relocation (Dong et al., 2022), reconstruction according to social connection (Kong et al., 2021; Ma et al., 2022; Rao et al., 2023; Tian et al., 2016), optimization from social-ecological system perspective (Yao and Xie, 2016; Yin et al., 2023), reorganization o based on mutualism (Tian et al., 2018), and mergence characterized by reclaiming small to fill large (Li et al., 2021). Overall, most existing studies have primarily focused on rural restructuring at the scale of individual settlements, namely their relocation and mergence. These studies often neglect the integrity of the settlement system within geographical or administrative units, as well as the hierarchical associations and coordination between villages and the cities. Theoretically, the rational composition and layout of settlements can effectively ensure the orderly exchange of materials and information between urban and rural areas, which promotes the coordinated development of production, habitation and ecological spaces in rural areas. Furthermore, existing studies have mainly explored the spatial reconfiguration of rural settlements in ecologically fragile areas, grain consumption areas and rapidly urbanizing areas (Gao and Cheng, 2020; Li T. et al., 2015; Li H. et al., 2015; Yao and Xie, 2016; Zhu et al., 2022; Zou et al., 2022), while paying less attention to black soil region. Due to the vastness of China, significant discrepancies in regional functions determine that existing approaches cannot be one-size-fits-all. Compared with other regions, the northeast black soil region serve as "stabilizer" and "ballast" for national grain security in the new era. Therefore, the purpose of rural restructuring is to achieve the efficient and sustainable utilization of the black-soil land through the spatial optimization of settlement systems where the interactions between urban and rural areas enable circular feedback involving technologies, services, and information. This is significantly different from other areas, which are characterized by improvements in ecological systems and increases in construction land quota.

The contributions of this study are twofold. First, we present an empirical case on the spatial optimization of settlements in the black soil region. Second, this study emphasizes the integrity and coordination of the urban–rural settlement system in the process of rural restructuring, which broadens the scope of previous studies that focused on a single scale, namely individual rural settlements. We argue that these approaches might also inform rural restructuring in non-black-soil regions.

The remainder of the paper organized as follows. Section 2 tries to establish a theoretical framework addressing the factors and rules influencing rural restructuring in the black soil region. Section 3 describes the study area, the process of data collection and preparation, as well as the methods of analysis. Section 4 presents the results of the analysis. Section 5 discusses the results and draws the main conclusions.

2 Theoretical framework

The evolution of rural settlements is the combined result of natural and socio-economic factors. In the early stages, the natural geographical environment projects a fundamental influence in restricting or facilitating the formation and expansions of rural settlements (Lin et al., 2020). For instance, topography, involving slope and altitudes, determines suitability for agricultural production and human habitation by influencing temperature, precipitation and light conditions, which further constrains the spatial distribution and expansions of rural settlements (Hill, 2003; Li T. et al., 2015; Li H. et al., 2015; Ma et al., 2018). After entering the era of rapid industrialization and urbanization, farmers' income significantly increased which generates sustainable demand for public

infrastructure and services (Tan and Li, 2013; Wang, 2010). Nevertheless, under the influence of urban-biased development, the disparity between urban and rural areas continues to widen, and rural settlements fail to adequately satisfy developmental aspirations of their inhabitants. Sustainable development of rural areas requires feedback from cities including technology, capital, information, public services (Phillips, 2010; Li L. et al., 2020; Li Y. et al., 2020; Siciliano, 2012; Tu et al., 2024). At this stage, the radiating effect of socio-economic factors in the city on rural settlements increasingly surpasses that of natural geographical factors (Liu et al., 2013). Accordingly, the accessibility of rural settlements to cities begins to project crucial influence on their growth or decline (Huang et al., 2020). Rural settlements with convenient transportation access gain significant developmental momentum in the process of urban–rural interaction, which also stimulates rural inhabitants to construct their dwellings along major roads (Tian et al., 2014).

In a specific geographical unit, settlements often exhibit a distinct rank-size structure. As demonstrated by Central Place Theory, with rapidly socioeconomic development and demographic migration, settlements evolve into various scales defined by functions and population (Christaller, 1966). Settlements with superior geographical and socioeconomic conditions gradually develop into central settlements, towns, even cities, whereas general settlements often evolve into grassroots settlements (Sonis and Grossman, 1984). High-ranked settlements, as economic centers of the area, provide goods and services for surrounding low-ranked settlements. The higher the rank of a settlement, the wider radius of its radiation. Hence, the number of settlements decreases with an increase in their hierarchies, namely grassroots settlements, central settlements, towns and cities, forming a pyramid-shaped structure. The relation between settlement size and rank generally follows a linear regression after they were logarithmically transformed (Giesen and Südekum, 2010). Spatially, the Central Place Theory posits that settlements are distributed according to several principles comprising market, transportation and administration. The market principle applies to spatial layout of settlement system driven by close supply–demand relationships arising from well-established market mechanisms in the area. The others are modifications of the market principle which are suitable for the distribution of settlement systems in densely populated areas and areas with heavily planned economy.

The black-soil region of China is located in the northeast plains suitable for agricultural production and long-term residence, which attracts large-scale in-migration and population settlement. Moreover, affected by the inertia of the planned economy in the old industrial base, the development of the settlement system in the black soil region still remains strongly self-sufficiency. Exchanges among settlements are dominated by public services such as healthcare, transportation, and management. Hence, the principles of transportation and administration might be appropriate for spatial optimization of settlements in the black soil region. Additionally, China's rural society is inherently a society of acquaintance where individuals are 'differentially associated' with the inner circle of family members, the outer circle of extended family, and, further out, the ring of villagers (Fei, 1947). Rural settlements are not geographical nodes integrating agricultural production and people's livelihoods but also fundamental organizational units sustaining dense social networks (Ye et al., 2020). Despite variations in the scale of rural settlement, inter-regional village connections are infrequent in the black soil region of China. Therefore, the spatial optimization of rural settlements should prioritize retaining the original villages as much as possible. Moderate maintaining the integrity of original villages should be regards as a crucial rule guiding rural restructuring in black soil region of China. This is because it can mitigate conflicts between farmers and the government, and ensure the successful implementation of rural restructuring strategies.

3 Materials and methods

3.1 Study area

The focus area of this study is Yushu County (126°1′44″ E-127°5′9″ E-44°30′57″ N-45°15′2″ N) in northeastern Changchun city, a key grain-producing county in the Northeast black-soil region. Yushu County, known as "China's First Grain Silo," consists of 4 sub-districts, 25 towns and 363 administrative villages, covering an area of 4,722 km^2 (Figure 1). In 2010, the Ministry of Agriculture designated Yushu County as one of the country's 50 modern agricultural demonstration zones. Yushu County deviates from the central city of Changchun, resulting in an urban–rural settlement system shaped largely by endogenous socio-economic activities. In recent years, under the influence of agricultural mechanization and modernization, a large-scale exodus of rural population occurs in Yushu County, which triggers the emergency of rural hollowing and drastic transition in the settlement system. Dysfunctions in the countryside's human-land relations, such as idle homesteads and wasted black-soil land, have become increasingly evident.

The data used in this article originate from three main source: First, the statistical data on population was collected from Sixth and seventh Census. Second, the points of interest (POI), including agricultural machinery services, medical facilities, and commercial establishments, were obtained from Tencent map platforms in June 2020. Third, the construction land and transportation routes were collected from very-fine-resolution color aerial photographs taken in June 2020. Referring to Yushu's Comprehensive Plan, we make use of ArcGIS 10.7 to derive the national highways, provincial highways, county highways, township roads and rural construction land.

3.2 Methods

3.2.1 Rank-Size Rule

The Rank-Size Rule is primarily employed to examine the association between the size of settlements and their ordinal order within the entire system, reflecting the rationality of the settlement system in specific region. In essence, with the rapid advancement of urbanization and the implementation of the rural revitalization strategy, urban–rural integrated development has become the dominant trend shaping the future of urban–rural relations. Over time, the village system is expected to gradually integrate with the city-town system, forming a hierarchical settlement system characterized by interaction development among county-level cities, towns, central settlements, and natural settlements. Therefore, this article attempts to utilize the Rank-Size Rule to investigate the

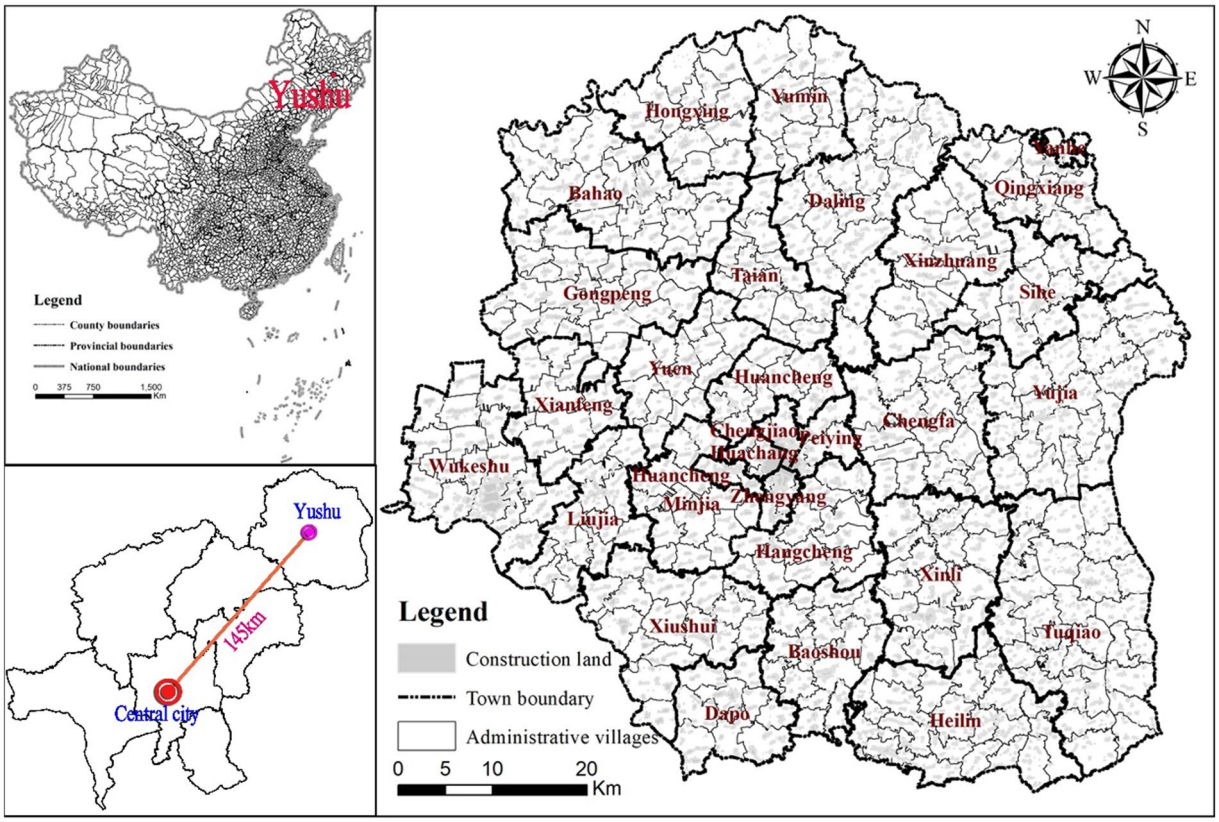


FIGURE 1
Location and administrative divisions of Yushu County.

development level and evolution trend of urban–rural settlement system in the black-soil region.

The formula for the Rank-Size Rule improved by Zipf is as follows:

$$P_r = P_1 r_i^{-q}$$

Where r represents the rank of the population size of settlements in descending order; P_r denotes the population size of the r-th settlement; P_1 represents the population size of the first settlement in the system; q is the Zipf index estimated by a linear kernel model. For simplicity in calculation, a natural logarithmic transformation is typically applied to the equation:

$$\ln(P_r) = \ln(P_1) - q\ln(r_i)$$

where q is a parameter manifesting the hierarchical structure of settlement system. $q = 1$ indicates that settlement system is in a state of equilibrium development, achieving Pareto optimality. $q > 1$ implies that the urban–rural settlement systems tends to be concentrated, with large differences in the size distribution of settlements and a strong monopoly for the first settlement. $q < 1$ indicates a more decentralized size distribution of settlement system, with high-ranked settlements being less prominent and small- and medium-sized settlements being more developed.

3.2.2 Rural development potential index

According to the above theoretical framework and the availability of data, this article incorporates transportation accessibility, the density of agricultural and mechanical establishments, the density of medical facilities, and the density of commercial activities into Rural Development Potential. The weights of four indicators are 0.32, 0.30, 0.28 and 0.10, respectively, obtained from Analytic Hierarchy Process (AHP).

3.2.2.1 Traffic accessibility

Traffic accessibility is an effective indicator identifying village connectivity to external markets and internal space of village. The accessibility of villages to external markets facilitates their socio-economic development by enabling access to external support, such as market information and agricultural production exchange. The accessibility of internal village spaces reflects the ease with which villagers engage in agricultural production, influencing operational costs and farmers' willingness to pursue agricultural activities. In ArcGIS software, travel speeds were assigned as follows: 70 km/h for national highways, 60 km/h for provincial highways, 40 km/h for county highways, and 30 km/h for township roads. Then, the OD cost matrix and travel time for each point in the county reaching all other points were calculated through the tool of Network Analysis. Finally, Kriging was applied to obtain a raster layer of county transportation accessibility, with travel time as the attribute.

3.2.2.2 Kernel density estimation

Kernel density estimation (KDE) is employed to analyze the spatial agglomeration of various service facilities (e.g., agricultural machinery services, medical facilities, and commercial establishments) across the county, and it lays the foundation for examining spatial heterogeneity of rural development potential in Yushu County. The density of agricultural machinery service establishments reflects the service capacity of settlements in the main grain-producing areas to support agricultural production; the density of medical facilities embodies the abilities of settlements to satisfy the basic health demands of residents, particularly under the background of an aging rural population; the density of commercial activities represents the capacity of the settlements to meet the daily necessities of inhabitants. KDE is expressed as follows:

$$F(x) = \frac{1}{nh^2\pi}\sum_{i=1}^{n}\left\{1-\frac{(x-x_i)^2-(y-y_i)^2}{h}\right\}^2$$

where, F(x) represents kernel density function; h is threshold; n is the number of points in the search radius; $(x-x_i)$ denotes the distance from the mean center x to point x_i; d represents the data dimensions.

3.2.3 Weighted Voronoi polygons

Voronoi polygons are a spatial analysis tool for seamless segmentation of planar space in light of a known set of points. The underlying principle is as follows: if the set of known points S = (p1, p2, p3,…pn) in space, and the Euclidean distance between any two points is d(p, pi), then the Voronoi polygon corresponding to each point V(pi) consists of all points in the planar space that are closest to the respective known point. This can be expressed as follows:

$$V_{(P_i)} = \bigcap_{i\neq j}\left\{p|d(p,p_i) < d(p,p_j)\right\}$$

If each point in the plane is assigned a non-negative real weight, Voronoi polygons can seamlessly divide the space according to the weight, generating a weighted Voronoi polygons. Weighted Voronoi polygons are calculated as follows:

$$V_{(P_i)} = \bigcap_{i\neq j}\left\{p|d(p,p_i) < d(p,p_j)\right\}$$

where $d(p, p_i)$ is the Euclidean distance between the point p(x, y) and the point pi(xi, yi); λ_i denotes the weight of point $p(x_i, y_i)$. In this study, pi(x, y) represents the central settlement; λ_i is the rural development potential index of central settlement i; a Voronoi polygon visualizes the functional radius of a central settlement.

4 The evolution of urban–rural settlements in the black-soil region

4.1 Spatio-temporal changes in urban–rural population

In 2010–2020, the urban population of Yushu County grew from 195,200 to 287,000, with an increase of 91,800, or an average annual growth rate of 3.83%. In contrast, the rural population declined from 950,200 to 549,100, with a decrease of 401,100, or an average annual decline of 5.34%. Over the past decade, the magnitude and rate of rural population loss in Yushu County have significantly exceeded those of urban population growth. This reflects the insufficient carrying capacity of county seat and towns to accommodate surplus rural laborers resulting from inadequate non-agricultural industries and public services. Consequently, the county's rural population is compelled to seek employment elsewhere or even relocate entirely. It is worth noting that not all towns in the county have experienced growth, exhibiting a spatial pattern of "global shrinkage and sporadic growth." As shown in Figure 2, during 2010–2020, the county seat of Yushu, Wukeshu Township and Gongpeng Township underwent the demographic growth, whereas the other townships suffered from population outflows. Specifically, the urban population in county seat increased from 142,600 to 239,300, with an increase of 68.08%. The non-agricultural population in Wukeshu Township rose from14,800, to 17,600, with an increase of 18.83%, while in Gongpeng Township, it increased from 7,800, to 8,500, with an increase of 8.20%. Theoretically, townships are hubs supplying public services in rural areas, and play an intermediary role in transmitting market information and agricultural technology between the county seat and surrounding countryside. The shrinkage of township in Yushu County has seriously undermined the countryside's capacity to sustain existing population.

Large-scale population loss has occurred in rural areas of Yushu County, with depopulation rates varying across administrative villages. From 2010 to 2020, almost all administrative villages in Yushu County experienced population loss, with an average loss rate of 41.97%. As shown in Figure 2, the depopulated villages were mainly concentrated along S301, G202 and Tieke Highway, forming a belt-shaped zone of heavily depopulated villages in the southeast-northwest direction. In this zone, the village depopulation rates ranged from 44.46 to 69.06%.This zone is adjacent to the county's growth poles, namely the county seat of Yushu and Wukeshu Township. Influenced by polarization, the rural population continually migrated towards the county seat of Yushu and Wukeshu Township.

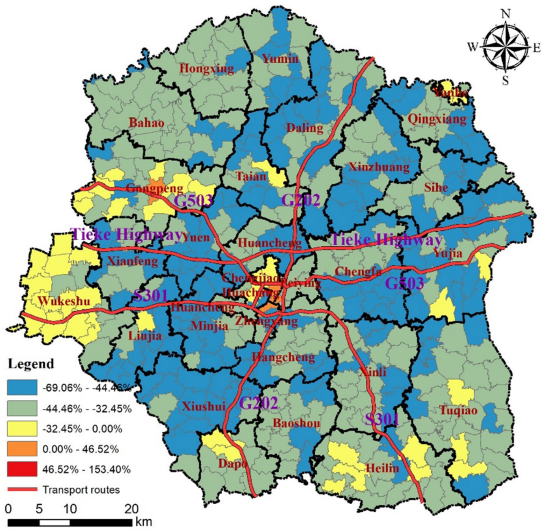


FIGURE 2
Changes in urban–rural population in Yushu County in 2010–2020.

Villages with slight depopulation were scattered across Gongpeng Town, Tai'an Town, Liujia Town, Dapo Town, Hailin Town, Tuqiao Town, Yujia Town, and Yanhe Town. Wukeshu Township depends on product processing industries such as grain and oil, livestock and poultry, has sparked the process of rural industrialization which accommodated the local population of agricultural transfers. The urbanization exhibits the phenomenon of "leaving the land but not leaving the hometown," which to some extent, mitigates the outflow of the rural population. The other villages are distant from the county seat, which restricts the diffusion of technological services from the center towards the countryside. Consequently, the agricultural production in these towns still heavily relies on the large-scale labor force, which delayed the emigration of rural population.

4.2 Changes in the size—hierarchy structure of urban–rural settlements

The size-hierarchy structure of urban–rural settlements in Yushu County demonstrates a tendency towards disorganization in Yushu County. As shown in Figure 3, in 2010, the size-hierarchy of urban–rural settlements exhibited a pyramid-like structure. The ratio of settlements with population sizes of over 6,000, 5,000-6,000, 4,000-5,000, 3,000-4,000, 2,000–3,000 and less than 2,000 was 1.54:1.29:3.08:7.22:45.76:31.11. As of 2020, the number of settlements with population of over 6,000, 5,000-6,000, 4,000-5,000, 3,000-4,000, 2,000–3,000 had decreased by 2, 4, 12, 66, 137, respectively. In contrast, the number of settlements with population of less than 2,000 increased by 221. Consequently, the composition of settlements deteriorated to 1.03:0.26:0.00:0.26:10.54:87.92. Evidently, the urban–rural settlement system in Yushu County formed a distorted structure featuring an excess of small settlements and a lack of large and medium-sized settlements. Large and medium-sized settlements are often critical nodes linking the county seat with the countryside, and play an intermediary role in the disseminating advanced production technologies and market information from the county seat. The underdevelopment of large and medium-sized settlements undermines the demonstration effect of the county seat on the socio-economic development of rural areas, which constrains synergistic development among the county seat, towns and settlements and hampers rural revitalization and retention of villagers in the countryside.

The urban–rural settlement system of Yushu County approximately conforms to the Rank-Size Rule, however, signs of disorganization has begun to emerge. This is evidenced by the following observations. Firstly, in 2010–2020, the goodness of fit (R^2) of rank-size curve for settlement system declined from 0.8031 to 0.7796. This suggests that the settlement system is increasingly diverging from the Rank-Size Rule. Secondly, the Zipf index (q) of the settlement system rose from 0.3976 to 0.4493 during 2010–2020, remaining below 1, which indicates the insufficient development of large settlements within the settlement system. Thirdly, from 2010 to 2020, the rank-size curve of settlement system displayed the morphology of "raising head, craning neck and drooping tail." The population sizes of the first and second settlements, namely, county seat and Wukeshu Township, exceeded their theoretical values, and county seat's population growth outperformed that of Wukeshu Township. During the study period, the population of county seat increased from 142,300 to 239,200, with an increase of 96,900, or 5.32% per annum. In comparison, the population of Wukesu Township increased from 14,800 to 17,600, with an increase of 2,800, or 1.75% per annum. Consequently, the "raising head" phenomenon in the rank-size curve is likely to exacerbate in the future. Additionally, medium-sized settlements remain underdeveloped, with less population than their theoretical value. The rank–size curve of the small settlements exhibited an obvious phenomena of "drooping tail," deviating from the Rank-size Rule. This is because the polarization capacity of medium-sized settlements has decreased, impeding the population migration from small settlements to medium-sized ones (see Figure 4).

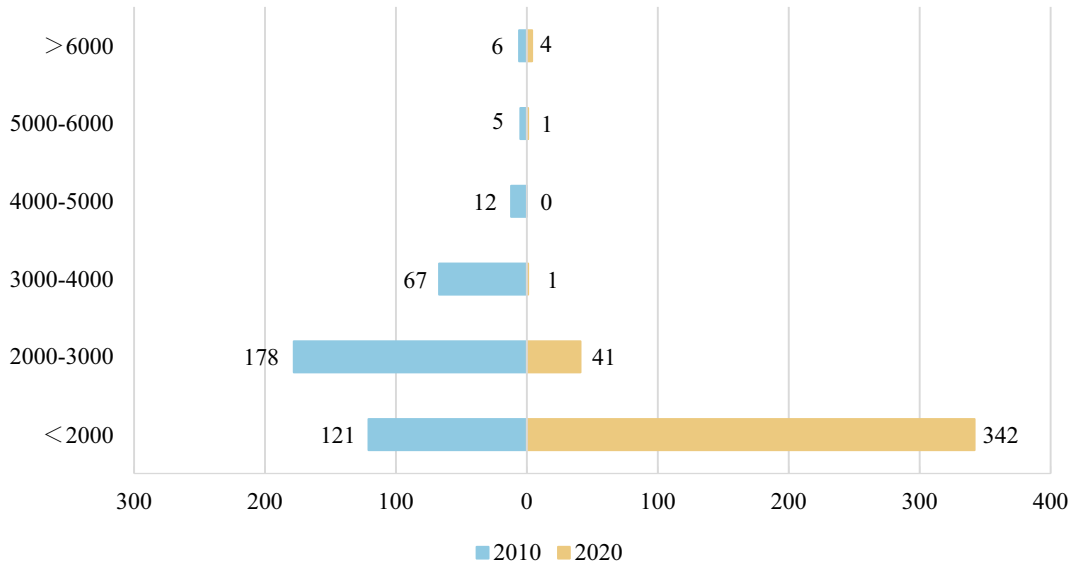


FIGURE 3
Evolution of size-hierarchy structure of urban–rural settlements in Yushu during 2010–2020.

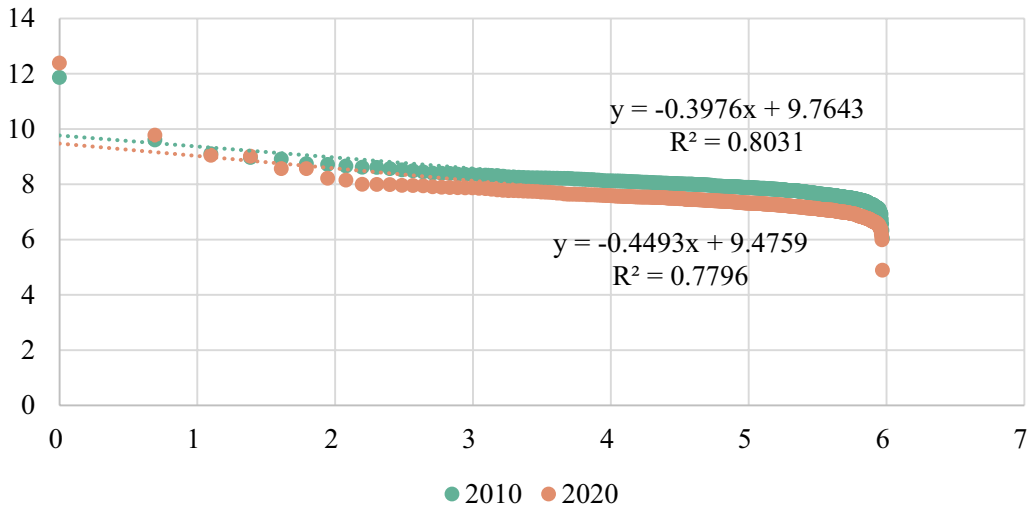


FIGURE 4
Changes in the rank-size curves of settlements in Yushu County during 2010–2020.

4.3 Spatial evolution of urban–rural settlements

Spatial disequilibrium in the distribution of different rank-size settlements in Yushu County has further intensified. As shown in Figure 5, in 2010, Yushu County formed a spatial structure with "a center, triple poles and multiple axis." "A center" refers to the county seat, located at the geometric center of the county which serves as hub for commercial services, agricultural product processing industries, and public services. The "triple poles" denote Wukeshu Township, Gongpeng Township, and Hefa Township which are situated in the western county. The "multiple axis" refer to a star-shaped axis network of medium-sized settlements along S301, G202, G503 and Tieke Highway, including Xiushui Township, Daling Township, and central settlements in Xinzhuang Town along G202, central settlements in Xinli Town along S301, central settlements in Xianfeng Town, Chengfa Township, and central settlements in Sihe Town along Daguang Highway. Overall, in 2010, large and medium-sized settlements were mainly concentrated in the western and southern parts of Yushu County. As of 2020, the spatial structure of "a center and three poles" remained in Yushu County, but the star-shaped network of axises had gradually disintegrated. The medium-sized settlements within the jurisdictions of Daling Town, Xiushui Town, Xinli Town and Sihe Town were downgraded to small-sized settlements. Currently, medium-sized settlements in Yushu County are mainly clustered on the southwest side of the line connecting Bahao Town and Heilin Town. The center of gravity for the spatial distribution of large and medium-sized settlements has started to shift towards the southwestern part of the county.

In the black-soil region of Northeast China, an administrative village usually consists of a central settlement and several natural settlements. To comprehensively reveal the spatial evolution of urban–rural settlements in the county, it is essential to analyze the spatial structure of the urban–rural settlement system from the perspective of urban–rural construction land. In Yushu County, the distribution of settlements is relatively fragmented, exhibiting a spatial mismatch with the spatial patterns of various rank-size settlements. As shown in Figure 6, in 2020, the settlements exhibited a spatial pattern characterized by a combination of a center and multiple cores. A center refers the high-density construction land area formed by the aggregation of the built-up area of Yushu and the settlements at the city's periphery. "Multiple cores" refer to high density construction land areas formed by the aggregations of settlements within the jurisdictions of Wukeshu Town, Gongpeng Town, Bahao Town, Daling Town, Sihe Town, Yujia Town, Tuqiao Town, Xinli Town, Heilin Town, Baoshou Town, Xiushui Town, Minjia Town, and Liujia Town. From the perspective of administrative villages, Yushu County has developed a relatively complete urban–rural settlement system, encompassing large-, medium- and small-size settlements. However, considering the fragmented distribution of natural settlements, the population allocated to the settlements could be decreased, further undermining the integrity of the urban–rural settlement system. Noteworthy, in the northeast part of Yushu County, several high-density construction land areas emerged in Daling Town, Sihe Town, Yujia Town, Tuqiao Town, Hailin Town. But few medium-sized administrative villages existed in the area. The fragmented settlement pattern undermines effects of demographic agglomeration on the socio-economic development of the rural areas, which is not conductive to growth and upgrading of settlements.

Homestead abandonment is another notable feature of the spatial evolution of settlements in Yushu County. From 2010 to 2020, construction land per capita increased from 380.74 m^2/person to 658.97 m^2/person, 4.39 times the standard upper limit of 150 m^2 per capita for urban and rural construction land. More specifically, the proportion of administrative villages with construction land per capita of 0–350, 350–650, 650–1,500, 1,500–2,500 and 2,500–3,500 m^2/person was 2.55, 62.24, 31.88, 2.30 and 0.76%, respectively. More than 90% of the administrative villages had per capita construction land ranging from 350 m^2/person to 1,500 m^2/person. As shown in Figure 7, administrative villages with construction land per capita exceeding 1,500 m^2/person were sporadically distributed across Gongpeng Town, Tai'an Town, Tuqiao Town, Xinli Town, and Huancheng Town. Administrative villages with construction land per capita ranging from 650 m^2/person to 1,500 m^2/person were

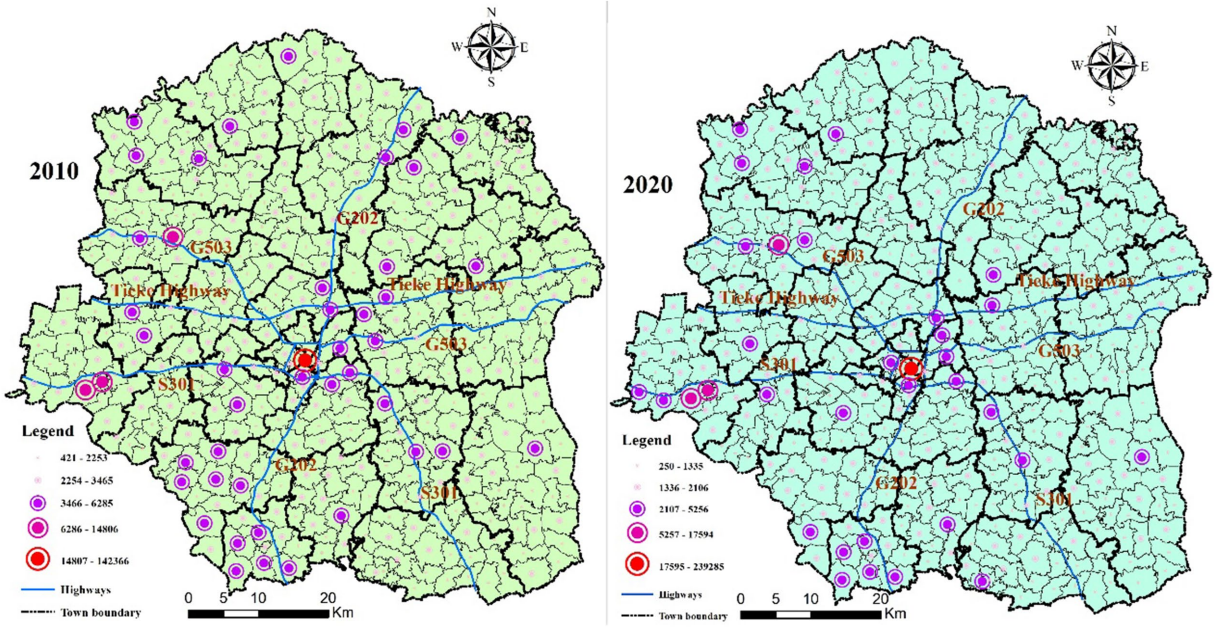


FIGURE 5
Spatial evolution of urban–rural settlements in Yushu County during 2010–2020.

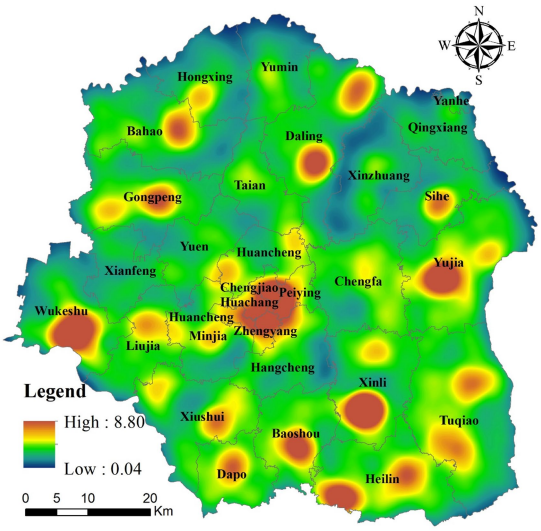


FIGURE 6
Urban–rural settlement density in the Yushu County in 2020.

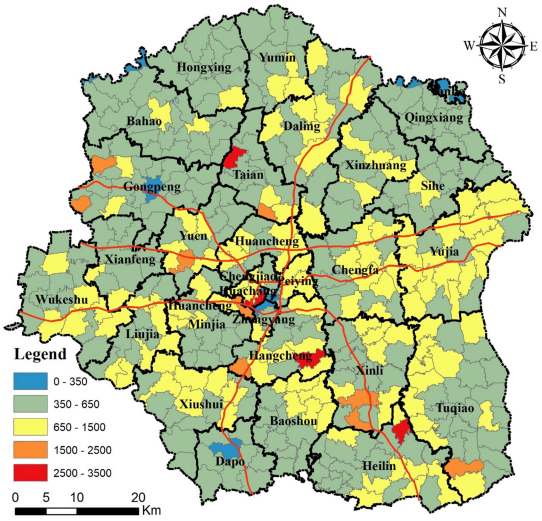


FIGURE 7
Spatial distribution of per capita construction land in the Yushu County in 2020.

mainly concentrated in the towns of Yujia, Hailin, Daling, Xiushui, Tuqiao, Xinli, Liujia, Minjia, Huancheng and Enyu. There are three settlements with construction land per capita of less than 350 m^2/person, namely, Township of Gongeng, Township of Dapo, and county seat of Yushu. Yushu County is a high-quality black-soil catchment area, and unused or abandoned homesteads in rural areas are a significant waste of black-soil land. Additionally, scattered and disintegrated inhabited settlements hinder the implementation of large-scale agricultural operations and the promotion of advanced production technologies. Therefore, reconfiguring urban–rural settlement system is an efficient strategy for achieving the protective utilization of black-soil land.

5 Strategies for reconstructing urban–rural settlement system

Considering the rank-size characteristics of the settlement system, we argue that the reconfiguration of the settlement system in the black

soil region should prioritize increasing the number of large and medium-size settlements by consolidating the population and construction land of low-ranked settlements into relatively high-ranked settlements. More specifically, this process involves two scale: administrative village scale and town scale. In administrative villages with strong potential for socio-economic development, the merger of settlements should be implemented in the administrative village, without disassembling the administrative boundaries. The scattered natural settlements should be integrated into central settlements. With respect to administrative villages with weak socio-economic development potential, settlements should be integrated across administrative villages within the town. Initially, administrative divisions within the town should be reconstructed based on the ideal service radius of central settlements (see Figure 8). Correspondingly, natural settlements should be integrated into the central settlements within the boundaries of the newly defined administrative divisions.

5.1 Identification of rural development potential

Overall, rural development potential in Yushu County was relatively weak, and most administrative villages demonstrated medium or low-level rural development potential. In 2020, administrative villages with high-level, secondary high-level, medium-level, secondary low-level, and low-level potential took up 11.20, 24.22, 26.56, 26.04 and 11.98%, respectively. A total of 64.58% of administrative villages displayed moderate or lower rural development potential. Spatially (Figure 9), the rural development potential gradually decreased from north to south. From west to east, the rural development potential initially increased and then decreased. As shown in Figure 9, in 2020, Yushu County formed five high-potential areas: Daling-Xinzhuang area, Gongpeng-Bahao area, the County seat of Yushu—Chengfa area, Minjia-Liujia areay, and the Dapo-Baoshou

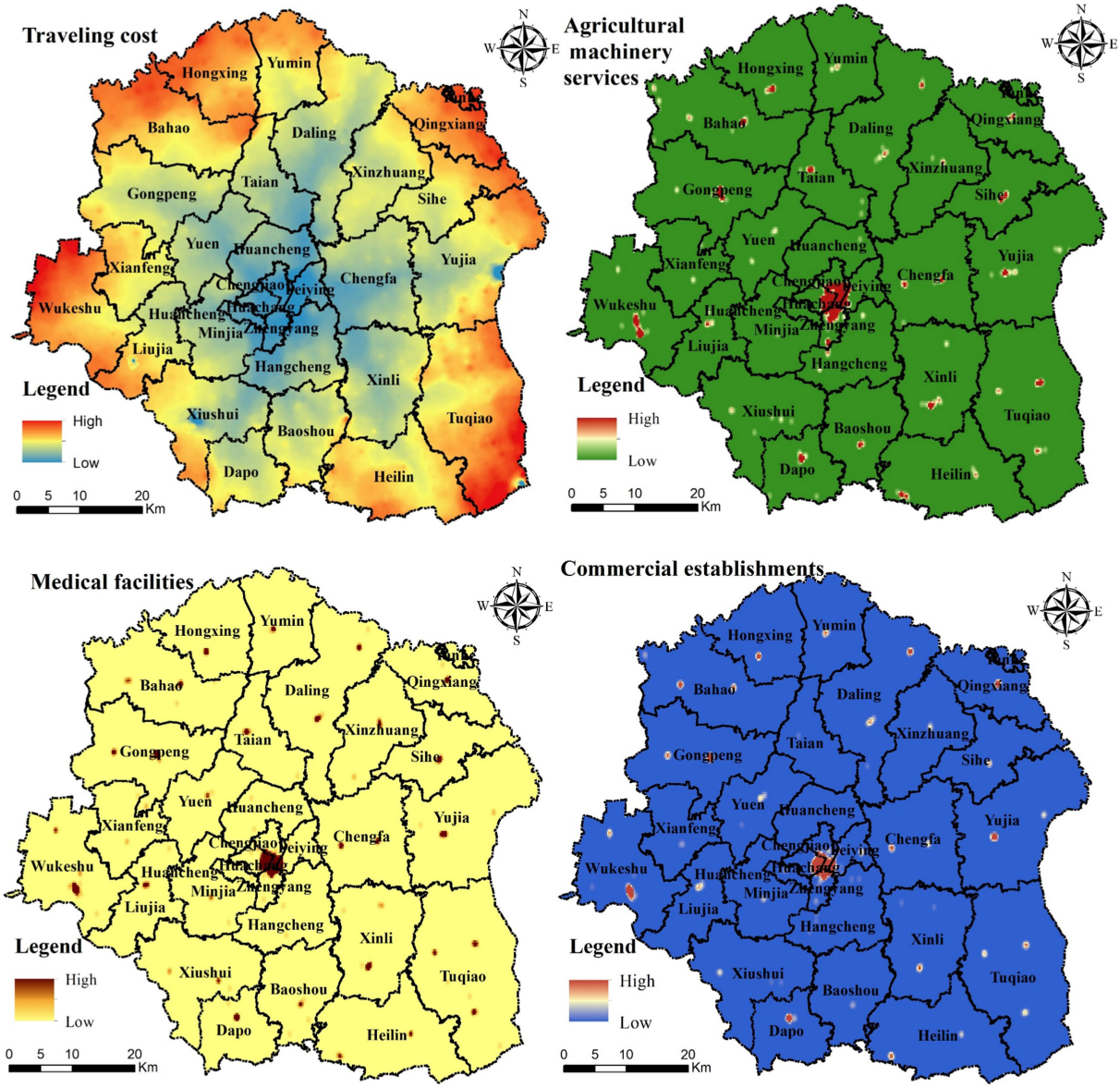


FIGURE 8
Spatial distribution of indicators for evaluating rural development potential in Yushu County.

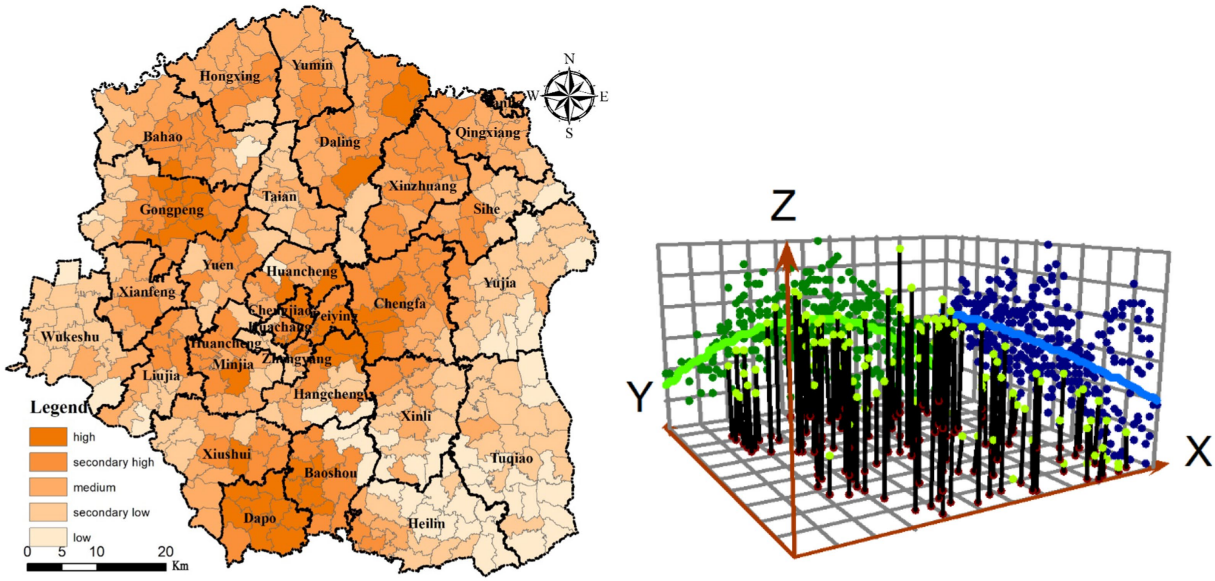


FIGURE 9
Spatial heterogeneity of rural development potential in Yushu County.

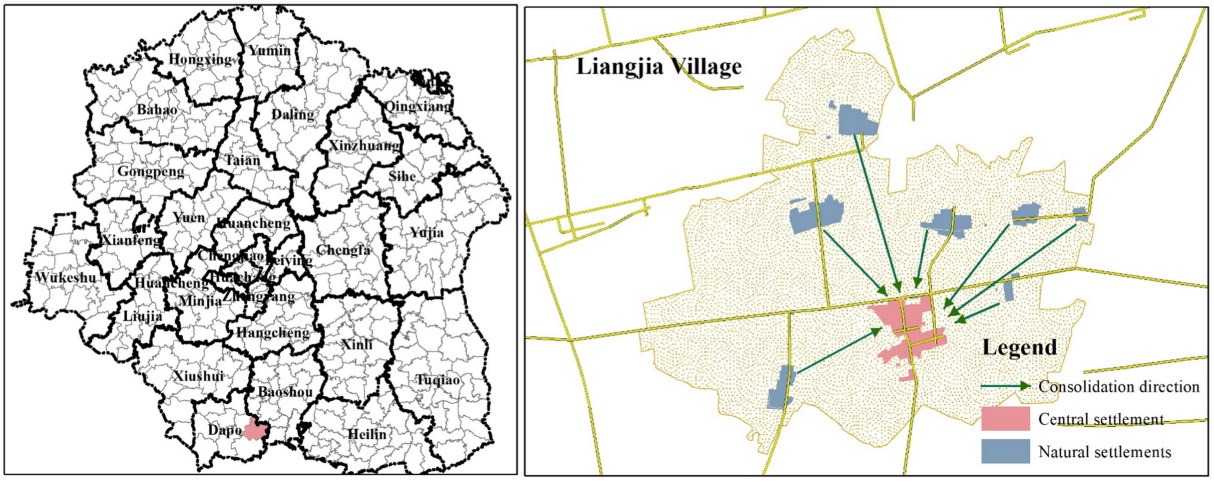


FIGURE 10
Spatial restructuring model of high-potential administrative village.

area. Meanwhile, three low-potential areas were identified, namely Heilin-Tuqiao area, Yujia area and Sihe area.

5.2 Strategies for reconfiguring high-potential administrative villages

According to results of rural development potential analysis, we selected Liangjia villages in Dapo Town to visualize the reconfiguration model of high-potential administrative villages. As shown in Figure 10, the central settlement is located at the geometric center of the administrative village. It is both the center of the transportation network and the hubs of grass-roots management, as well as the settlement with the largest amount of construction land and the most population within the administrative village. The integration of natural settlements into the central settlement offers four key advantages. Firstly, settlement consolidation is conducted entirely within the administrative village, preserving administrative efficiency, local customs and culture, agricultural cultivation radius, and villagers' living habits. Secondly, the central settlement, occupying large built-up area, serves as the seat of the grass-roots management organizations and it is relatively well equipped with public service facilities. In the process of settlement consolidation, idle homesteads in the central settlement can be reutilized in the form of replacement subsidies to resettle the residents from the natural settlements. Furthermore, existing public service facilities could be effectively utilized to satisfy residents' basic

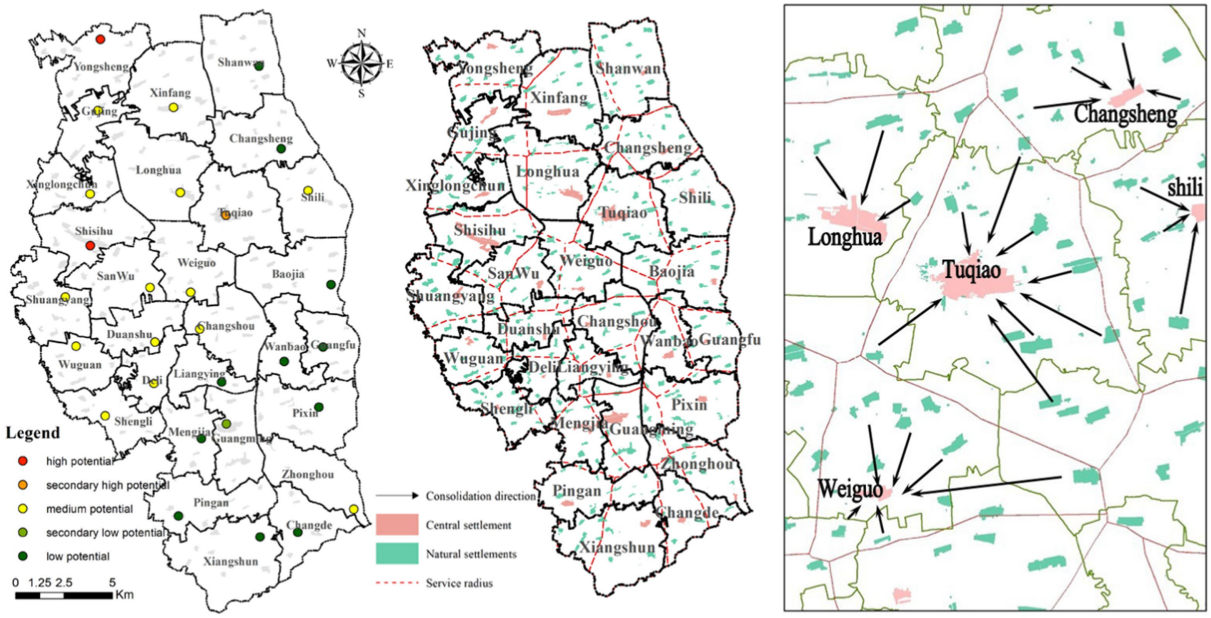


FIGURE 11
Spatial restructuring model of low-potential administrative villages.

demands, thereby reducing construction costs. Thirdly, it is a strategy to implement easily resulting from preserving the original land tenure and acquaintance network. Additionally, it enhances the rural neighborhood relations through the centralized rehabilitation of existing residents. Fourthly, it lays the foundation for consolidating scattered plots of land previously fragmented by dispersed settlements, facilitating land transfer, large-scale operations, and mechanized farming.

5.3 Strategies for reconfiguring low-potential administrative villages

In the light of rural development potential, Tuqiao Town was selected as a case study to illustrate the spatial restructuring pattern of low-potential administrative villages. The administrative villages within Tuqiao Town lacked endogenous development incentives, resulting in insufficient development of central settlements and a disorganized settlement system. Therefore, in Tuqiao Town, cultivating central settlements to increase their size and rank through settlement consolidation is critical. The implementation process involves the following steps. Firstly, the Weighted Voronoi method was employed to determine the ideal service radius of each central settlement according to respective rural development potential. As shown in Figure 11, the service radius of central settlements does not exactly align with the boundaries of the administrative village. For example, central settlements with high rural development potential, such as Tuqiao, Xietou and Longhua, have a spatial radius extending beyond their respective village boundaries, and vice versa. The spatial radius of a central settlement is influenced by the combined effects of its traffic accessibility, ability to provide agricultural and mechanical services, the levels of health care and commercial development, representing the actual served area of each central settlement. Secondly, the spatial radius of each central settlement is taken as the basic unit used for settlement consolidation, instead of administrative division of the village, and the natural settlements within the spatial radius are integrated into the corresponding central settlement. In this process, a central settlement with a large spatial radius may integrate natural settlements beyond its administrative boundary. For instance, the central settlement of Tuqiao would merge several natural settlements from the neighboring villages of Baojia, Weiguo and Changsheng. Finally, settlements with high rural development potential were allocated with more population and construction land, while settlements with low rural development potential experienced reductions in population and construction land to align with their service capacity. This strategy offers two main advantages. On the one hand, it does not alter the number of administrative villages and retains the original grass-roots administrative structure. Existing administrative bodies are familiar with of villages affairs, facilitating the coordination of stakeholders involved in settlement consolidation. On the other hand, although some natural settlements are not subordinate to the targeted administrative villages, they form more intimate association with central settlements in the targeted administrative villages for living and production activities compared to the central settlement in the affiliated administrative villages. In practice, these settlements have already established functional ties to central settlements in the targeted villages, which fosters emotional acceptance among indigenous residents during settlement consolidation. Hence, it facilitates the effective operation and implementation of settlement consolidation.

6 Discussion and conclusions

6.1 Discussion

The black soil regions are global agglomerations of high-quality arable land and critical commodity grain bases, and their sustainable

utilization holds outstanding strategic importance for global grain security. Rural settlements serve as crucial nodes for human-land interactions in the black soil regions, and they provides habitation for farmers and enables farmers to engage in agriculture. Thus, the spatiotemporal trajectories of settlements present a panorama of the human-land relations in the black soil regions. Currently, in process of rapid migration from rural areas to urban, the black-soil region of China has faced serious human-land contradictions, including homestead abandonment, cropland underutilization, and environmental deterioration, which puts spatial optimization of rural settlements at the forefront of rural revitalization. Rural settlement restructuring has received attention from rural geographers, who have proposed innovative modes of spatial optimization of settlements (Lu et al., 2020; Li et al., 2014; Zou et al., 2021). Nonetheless, extant patterns have mainly focused on consolidation or reservation from the perspective of individual settlements, with limited attention to the integrity of the regional settlement system. Settlements are not isolated territorial containers, instead, they maintain interrelationships with towns and cities, requiring feedback that do not confine to the administrative villages. Singular adjustments to individual settlements cannot fully achieve the optimization of human-land relations at the regional scale.

Existing studies on rural restructuring in the black soil region has proposed a reconstruction pattern that consolidates scattered, small natural settlements into the central settlement within an administrative village (Li et al., 2021). However, this pattern overlooks the capacity of public services in the central settlement to accommodate the merged population. If public services in the central settlement fail to support the relocated villagers, they would face the risk of "secondary" relocation. Theoretically, in a given geographical unit, the number of settlements decreases as their population size increases (Christaller, 1966). Blindly consolidating natural settlements into the central settlements may lead to redundant development of large settlements, incurring vicious competition among them. Additionally, other modes mainly focus on rural areas with well-developed market mechanisms, emphasizing the importance of symbiotic relations among settlements in rural restructuring (Gao and Cheng, 2020; Rao et al., 2023; Ma et al., 2024). The direction of settlement consolidation is determined by the frequency of socio-economic connections among settlements (Kong et al., 2021; Ma et al., 2022; Tian et al., 2016). However, this approach does not apply to rural restructuring in the black soil region, which is characterized by a heavily planned economy. Rural settlements in the black soil region do not form intimate economic connections with each other, and villagers tend to seek living and production services in towns and cities. Traffic accessibility still exert a decisive influence on the spatial optimization of rural settlements (Yin et al., 2023). In view of this, rural restructuring in black soil region should consider both administrative village and town scales to determine the direction of settlement consolidation. Areas with high rural development potential could implement a strategy of merging natural settlements into central settlement within an administrative village. In the areas with low potential for rural development, the direction of settlement consolidation is determined according to the ideal transportation and health care service radius of central settlements in the town.

6.2 Conclusion

In the black soil region, population changes presented spatial heterogeneity characterized by "urban growth and rural shrinkage," with the rate of rural shrinkage significantly exceeding that of urban growth. Consequently, the hierarchy-size structure of urban–rural settlements have gradually fallen into a state of disorder. During 2010–2020, the urban–rural settlement system deteriorated from a relatively balanced "pyramid" structure to a distorted one with an excess of small settlements and a deficiency of large and medium-sized settlements. Accordingly, the system started to deviate from the "rank-size" rule, and its rank-size curve demonstrated irrational morphology characterized by raising head, craning neck and drooping tail. The Ziff index of the urban–rural settlement system is less than 1, indicating a weak radiating effect of the county center on the development of settlements in its administrative boundaries.

More specifically, the population size of the first-ranked settlement surpassed its theoretical value simulated by the rank-size rule, whereas the middle-ranked settlements had population sizes below their theoretical values. The population size of low-ranked settlements deviated entirely from the rank-size rule. Noteworthy, in the black soil region, rural settlements are spatially fragmented, and a village consists of a central settlement and several natural settlements. Given the fragmented pattern of rural settlements, the goodness of fit for rank-size curve would be further decrease. Regarding to spatial distribution, the county exposed mismatch between rural residential land and population across various settlement sizes, incurring severe idling and abandonment of rural construction land. Correspondingly, the rural development potential displayed two aggregation patterns, namely high-high pattern and low-low pattern. In the light of the spatial pattern, it is appropriate to optimize the urban–rural settlement system at the scale of administrative villages and towns. In areas with high development potential, the settlement system should be reorganized by consolidation of natural settlements into central settlement within administrative villages. In areas with low development potential, the mergences of natural settlements are suitable for achievement within the town, and their relocation direction could be determined according to functional radius of each central settlement, thereby reshaping the jurisdictional boundaries of administrative villages.

Considering the natural and socio-economic context of the study area, the applicability of the proposed rural settlement restructuring mode is determined by three conditions. First, the rural area is located in a densely populated plains with dispersed settlements. Second, the area lacks a fully developed market economy, with rural settlements exhibiting significant self-sufficiency in both production and consumption. Traffic accessibility and the provision of public services play a decisive role in the distribution of rural settlements. Third, the rural area is geographically distant from regional central cities, with settlement evolution being less influenced by these central cities, thereby showing strong spontaneity and independence.

This paper examines the spatiotemporal characteristics, development trends, and reconstruction patterns of urban–rural settlement system in Yushu, a representative county in the black soil region. However, limited by the availability of data, this study merely employs density of POIs to represent the rural development potential. Weighted Voronoi polygons based on static rural development potential provide an approximate representation of the ideal service radius of central settlements. In the further, we will collect data on the "flow" between central and natural settlements through field research to refine the rural settlement restructuring mode. Moreover, in suburban areas, the central city exerts a profound radiating influence on rural settlements, differing from the study case settlements.

Restructuring modes for rural areas adjacent to central cities deserve further exploration.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

ZM: Writing – original draft, Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing. YT: Methodology, Writing – original draft, Writing – review & editing. JL: Data curation, Writing – original draft, Writing – review & editing. GZ: Conceptualization, Software, Writing – original draft, Writing – review & editing. YL: Conceptualization, Supervision, Writing – review & editing, Project administration, Writing – original draft. XW: Formal analysis, Methodology, Writing – original draft, Writing – review & editing. PZ: Conceptualization, Supervision, Writing – review & editing, Writing – original draft.

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Conflict of interest

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Spatial distribution and influencing factors of China's overseas farmland investment projects under the background of food security

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Since the 21st century, overseas farmland investment has gradually become the focus of research in the field of transnational agricultural investment. Under the background of China's "going out" strategy, exploring the spatial distribution pattern and influencing factors of China's overseas farmland investment activities in different regions of the world and reducing domestic food supply pressure through effective use of overseas farmland resources has become an important path for China to ensure food security. Based on the case data of China's overseas cultivated Land investment in the Land Matrix database, this paper sorted out the utilization status of China's global cultivated land resources, and analyzed the spatial distribution and influencing factors by using spatial analysis method and grey correlation analysis method. The results show that: (1) At present, the host countries of China's overseas cultivated land investment have obvious spatial aggregation, showing the spatial characteristics of "small agglomeration and large dispersion," and have the characteristics of distribution along the border and river; (2) China's overseas farmland investment is affected by geo-economy, resource base, geo-culture and geopolitics, and the degree of impact is weakened in turn. Among them, the average annual import and export value, total water resources and other indicators have a significant impact on the investment choice of Chinese enterprises. Based on this, on the basis of identifying the spatial distribution pattern of China's global overseas farmland investment and development and analyzing its key driving factors, this study proposed the path that overseas farmland investment and development can help improve the resilience of food system with the goal of ensuring the food security of sustainable agricultural system. It provides a theoretical basis for the country to formulate food security strategy based on overseas farmland investment and guide enterprises to invest overseas farmland.

KEYWORDS

China, overseas farmland investment, spatial distribution, influencing factor, food security

1 Introduction

Food security is a national priority. Ensuring national food security is an important foundation for ensuring economic development, social stability and national security (Sun et al., 2017). The problem of population-land mismatch, that is, the imbalance between population distribution and arable land resources, is one of the key issues facing food security.

It means that densely populated areas often lack sufficient arable land resources to ensure food self-sufficiency. Therefore, against the background of rapid global population growth, the food security situation is becoming increasingly severe. Solving the global "people-land mismatch" problem through transnational agricultural investment has become an important development feature of the agricultural field in the process of economic globalization (Zoomers et al., 2017). Making full use of overseas cultivated land resources has gradually become an important means for some countries and international organizations to increase the global supply of agricultural products and ensure their own food security (Jing et al., 2021). According to the 2024 Global Food Crisis Report, in 2023, nearly 282 million people in 59 countries and regions will experience sudden severe hunger, 24 million more than in 2022. The report shows that since 2017, global food insecurity has continued to increase and has become a worrying trend. External factors such as political conflicts, climate change and global economic fluctuations, as well as internal factors such as the level of economic development, natural endowments, scientific and technological levels, and social environment restrict food security. It is impossible for a government to meet the food needs of its people in a short period of time by relying entirely on its own food production (Lu et al., 2018). With the acceleration of global population growth, the contradiction between supply and demand of land and water resources has become increasingly prominent, further intensifying the contradiction between food supply and demand. According to the Food and Agriculture Organization of the United Nations, under the current consumption level to meet the needs of population growth and economic development in 2050, the global demand for arable land will increase from 1.567 billion hm^2 in 2012 to 1.732 billion hm^2. Increasing investment in land and water resources in developing areas is the key to breaking the above constraints on agricultural growth (FAO, 2018). In this context, countries with high food dependence on foreign countries, poor domestic agricultural resource endowment, and scarce arable land, as well as countries with prominent population, resource and environmental conflicts such as India and China, in addition to strengthening domestic agricultural development and improving land productivity to increase food supply, through the investment and utilization of transnational cultivated land, Transferring food crop production activities abroad is an inevitable choice to achieve domestic food supply (Han et al., 2018). Therefore, focusing on countries and regions with good resource endowment and stable investment environment, using their cultivated land resources to alleviate domestic agricultural resource constraints has gradually become a viable option to ensure the stability of domestic grain and important agricultural products and consolidate the foundation of food security (Cheng et al., 2018).

As a populous country with scarce cultivated land and the world's largest food importing country, China has always attached great importance to the issue of cultivated land security and food security by successive governments (Andong et al., 2023; Hules and Singh, 2017). With the development of domestic economy and the improvement of people's dietary structure, the contradiction between supply and demand of agricultural products and resource guarantee has become increasingly acute in China. The use of overseas cultivated land resources to alleviate the constraint of domestic agricultural resources has gradually become a feasible option to ensure China's food security. China's overseas farmland investment began in the early 21st century. Early investments were concentrated in Africa and Southeast Asia, mainly to obtain land use rights, develop agricultural infrastructure and modern planting technology. Subsequently, China gradually expanded its farmland investment in South America, Eastern Europe and other places, covering the planting and production of major agricultural products such as soybeans and corn. In recent years, China has further deepened its agricultural cooperation in countries along the "Belt and Road" and promoted local agricultural development through joint ventures, leasing and other forms, while meeting domestic demand. Overall, China's overseas farmland investment strategy is moving towards diversification and sustainable development.

At present, the distribution of China's overseas farmland investment is mainly concentrated in Africa, Southeast Asia, South America and other countries (Tang et al., 2017; Giovannetti and Ticci, 2016). Due to the limited strategic understanding of cultivated land investment in Africa, Southeast Asia, South America and other countries, foreign investors have strict access rules for cultivated land investment, and Chinese enterprises are at a disadvantage in competition with other countries due to their late start and lack of corresponding supporting facilities (He et al., 2024). Therefore, countries with relatively rich cultivated land resources, relatively high natural resource endowment for grain production, relatively stable national political situation, and relatively perfect policies and regulations have become an important strategic direction for China's overseas farmland investment (Lu et al., 2020). However, what is the spatial distribution pattern of China's overseas farmland investment projects? What factors will affect the choice of host country for China's overseas farmland investment? What are the decisive factors? This series of problems need objective quantitative research and scientific evaluation.

As a matter of fact, investment in overseas cultivated land has been widely debated since it was proposed, involving many aspects such as food sovereignty, civic governance and agricultural structure of host countries (Renqu et al., 2020). As the world's largest developing country and traditional agricultural power, China's food security situation and food security strategy have attracted worldwide attention. The research on China's overseas farmland investment has always been the focus of academic attention (Linyan et al., 2022). Many scholars have discussed the formation mechanism, basic connotation, implementation mode and risk control of China's overseas farmland investment (Linyan et al., 2022). Lu et al. (2020) believes that the distribution of China's overseas farmland investment is obviously unbalanced, and the correlation results show that the factors affecting overseas farmland investment are political stability and interest pursuit and the correlation analysis result shows the trends of overseas farmland investment with political stability and benefits seeking.

Lu et al. (2020) believes that China's overseas farmland investment is noticeably imbalanced, and the current distribution is suboptimal. The most suitable host countries for investment are concentrated in Southeast Asia, as well as along the equator in Africa and Latin America, indicating a need for strategic adjustments. Using panel threshold technology, Renqu et al. (2020) found that the increase of host country resource endowment promoted China's investment in overseas farmland, but the correlation gradually weakened as the level increased. Chen et al. (2017) used Landmatrix data to compare the scale, geographical distribution, utilization and investment mode of China's overseas land investment and pointed

out that China's main investment fields are concentrated in non-food crops, and the investment tends to be in countries with low "transparency index."

An in-depth understanding of the current situation of China's overseas cultivated land investment and a macro grasp of the current distribution of global cultivated land resources are important issues for China to consider in formulating food strategies and promoting the construction of a "new development pattern with domestic and foreign cycles as the main body and domestic and foreign dual cycles promoting each other" (Yu and Cao, 2015). However, most of the existing literatures stay in the macroscopic level of analysis and description, and lack of spatial investigation. In the study of overseas farmland investment, the spatial analysis is very important. By studying the spatial distribution pattern, we can identify the concentration area of investment and the potential problem of unequal allocation of resources. Based on this, this paper analyzes the spatial distribution pattern of overseas cultivated land investment and its influencing factors including geoeconomy, resource base, geo-culture and geopolitics, which plays an important role in enriching the research content of this topic. Different from the existing literature, this paper uses the case data of China's overseas farmland investment to analyze the spatial characteristics of China's overseas farmland investment from a relatively micro level and explore the relevant factors affecting China's overseas farmland investment. The research in this paper can not only enable Chinese "going global" enterprises to accurately grasp the development direction of farmland investment layout in the process of overseas farmland investment, but also provide references for Chinese enterprises to improve the stability of overseas farmland investment projects and reduce risks. It also has important practical value for Chinese enterprises to scientifically carry out overseas farmland investment and safeguard regional food security.

2 Current situation of China's overseas farmland investment

2.1 Spatial distribution of China's overseas farmland investment projects

According to the data of the global Land transaction database Land Matrix, as of September 2024, China has carried out a total of 530 cultivated land investment projects in the world, involving 19.7658 million hectares of cultivated land, of which 61 countries are involved in overseas farmland investment. This paper uses Arcgis to draw the distribution map of China's farmland investment projects in overseas countries (Figure 1) and uses the natural breakpoint method to divide the contracted area and draw the spatial distribution map of China's farmland investment area in overseas countries (Figure 2).

From the perspective of project distribution, investment projects are mainly distributed in Africa, Asia and South America, of which Africa is mainly concentrated in West Africa and South Africa, and Asia is mainly concentrated in Southeast Asia. Investment projects in South America have slightly more investment projects than North America and Oceania, and are mainly distributed in Argentina and Uruguay. European investment projects are mainly distributed in the regions of Russia near the three Eastern provinces, with the least investment projects in North America and Oceania. From the perspective of contracted area, the natural breakpoint method divides the area into five categories. The

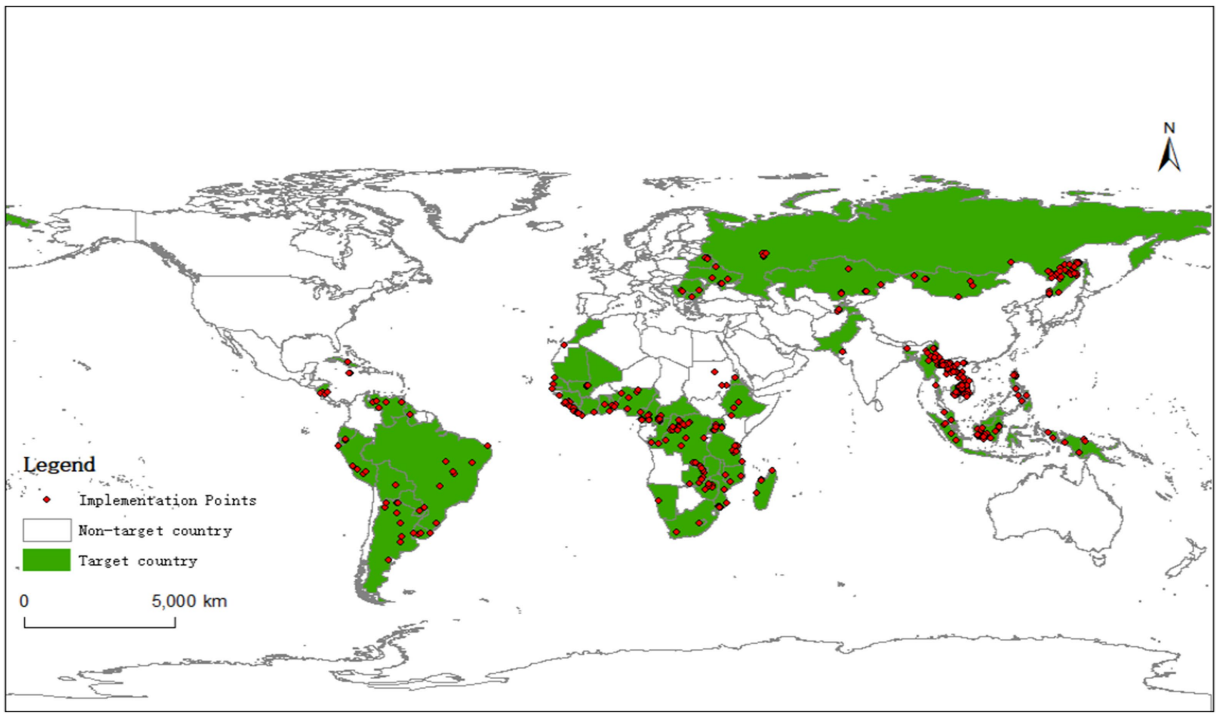


FIGURE 1
Project distribution map of China's investment in cultivated land in various countries.

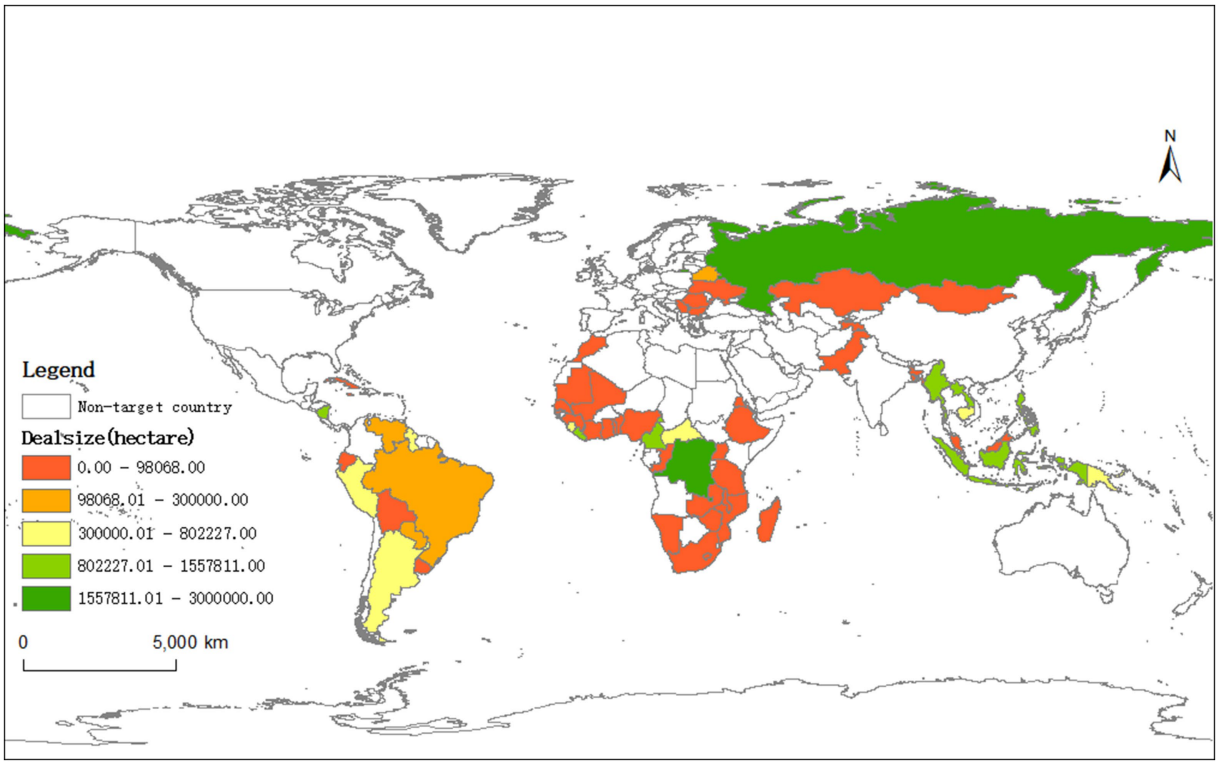


FIGURE 2
Distribution map of contracted area of China's investment in cultivated land in various countries.

first category is the country with the largest investment scale, covering 1,557,800 hectares and above, which represents only Russia and the Democratic Republic of the Congo, indicating that Russia and the Democratic Republic of the Congo are currently the key countries for China's investment. The second category is the contracting area of larger countries, its area between 802,200 hectares to 1,557,800 hectares, representing Indonesia, Cambodia and other countries in Southeast Asia; The third group of countries are countries with average contract area, between 300,000 hectares and 802,200 hectares, representing Guyana, Peru and Argentina in South America; The fourth category is for countries with low contracted area, ranging from 98,100 hectares to 300,000 hectares, representing Brazil and Venezuela in South America; The fifth category is countries with low positive signatories, with an area between 0.004 million hectares and 981,000 hectares, representing Ethiopia, Guinea, Benin, Ghana and other countries in Africa. On the whole, Russia is the country with the largest number of projects and the most contracted area in Europe. The number and contracted area of Southeast Asia projects are larger; There are more investment projects in Africa.

3 Materials and methods

3.1 Estimation of nuclear density

Kernel density estimation is a method to study the spatial distribution characteristics of sample points in a regular region based on their data, and the results can be used to show the agglomeration and dispersion characteristics of sample data sets in a certain region with maps (Derek, 2020). Its calculation formula is as follows:

$$f(x)=\frac{1}{nh}\sum_{i-1}^{n}K\left(\frac{x-x_i}{h}\right)$$

Where: *f(x)* is the estimated nuclear density; h is the bandwidth, that is, the radius of the circle (m); *K* is the kernel function; x-xi represents the distance (m) from the estimate point to the output grid. In this paper, the locations of different types of overseas farmland investment projects are abstracted as point elements, and the kernel density values of each project type are calculated with the area of different types of projects as the weight. Finally, the kernel density map is made with ArcMap component. The level of kernel density values reflects the level of certain attributes of overseas farmland investment projects in a certain region.

3.2 Grey correlation analysis

Grey theory is a systematic scientific theory initiated and developed by Professor Deng Julong in the 1980s. Grey correlation analysis is a quantitative analysis method based on grey theory to study the correlation degree of various factors within the system. The principle of this method is to identify the correlation degree of elements according to the curve proximity degree reflected in the image of each element series. Grey correlation analysis method has low requirement on data sample size, and can better analyze the "small

sample" and "poor information" uncertainty system with "part of information known and part of information unknown." Because of its special investment object, the investment sensitivity of overseas cultivated land investment is large, and the influence of political, economic, cultural, geographical and other factors is prominent, and the above factors have obvious unclear characteristics.

The core idea is to calculate the correlation between different sequences in order to discover the intrinsic relationship between the sequences. The specific steps are as follows:

(1) Data standardization (dimensionless processing)

Since the dimensions of different data may be different, there will be deviations when directly compared. In order to make the data comparable, the data must first be standardized. The purpose of standardization is to convert the data into the same order of magnitude. Common standardization methods include maximum standardization and minimum standardization. After dimensionless processing, each sequence will be converted to the same numerical range, making it suitable for subsequent analysis.

(2) Calculate the difference sequence and gray correlation coefficient

In this stage, the difference between the reference sequence and each comparison sequence is calculated to determine their similarity.

Difference sequence: The difference between the reference sequence and each comparison sequence at the corresponding moment is calculated, which is called the difference sequence.

Gray correlation coefficient: According to the difference sequence, the correlation coefficient of each moment is calculated using the following formula:

$$\zeta_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{o(k)} + \zeta\Delta_{\max}}$$

Among them, $\Delta_{\min}$ and $\Delta_{\max}$ are the minimum and maximum differences in all difference sequences respectively, ζ is the resolution coefficient, which is usually taken as 0.5.

(3) Calculate the gray correlation

Finally, the gray correlation coefficients of each moment are averaged to obtain the final gray correlation. The correlation degree indicates the overall correlation degree between the reference sequence and the comparison sequence. The formula is:

$$r_i = \frac{1}{n}\sum_{k-1}^{n}\zeta_i(k)$$

The greater the correlation r_i, the stronger the correlation between the reference sequence and the comparison sequence, and vice versa.

This paper takes China's overseas host countries as the research area. Although the number of projects involved is large, the number of host countries is small, and the data has obvious "small sample" characteristics. Therefore, this paper regards overseas farmland investment activities as a grey system, and analyzes the influence degree of different factors on overseas farmland investment scale by constructing a grey correlation model between the scale series of overseas farmland investment of host countries and the index series of influencing factors in overseas regions, and calculating the grey relative correlation degree. The idea of grey relative correlation degree is to characterize the relationship between different data series groups by the relative change rate between the starting points. The closer the change rate between two data series is, the greater the grey relative correlation degree will be, and the smaller the grey relative correlation degree will be. Since this method is more conventional, the process of solving grey relative correlation degree will not be described here.

3.3 Data source and index selection

As a transnational natural resource utilization and control issue arising from traditional agricultural investment abroad, overseas farmland investment is influenced by not only resource endowment but also the geographical relationship between the investor country and the host country in the current international political background (Meng et al., 2022). Geographical relationship usually refers to the relationship caused by geographical location, distance, etc. It is a special social relationship between man and land based on the premise of geographical elements (Van den Broeck and Maertens, 2016). The modern state-scale geopolitical relations mainly refer to the geopolitical, geo-economic and geo-cultural relations between countries based on geographical factors such as the geographical weight of countries, the geographical distance between countries and the geographical flow, which has been widely recognized in the academic community (Tabeau et al., 2017). Geopolitics refers to the political interaction between countries due to geographical conditions or geographical factors, and the political relations formed therefrom. Geo-economy is based on the premise of geopolitics to emphasize the interregional relations (mainly refers to the spatial economic relations between regions), its final performance is regional economic integration (Acevedo et al., 2018); Geo-culture refers to the cultural relations between countries formed on the basis of special historical and geographical causes and the development law of ethnic relations (Yun and Yi, 2020). In the study of overseas farmland investment, the four dimensions of resource base, geopolitics, geo-economy and geo-culture are selected as the indicators of grey correlation analysis based on the profound impact of these factors on investment decisions. First, the resource base directly affects the agricultural production potential of the host country, which is an important consideration for the feasibility of investment. Second, geopolitical relations affect the political interaction and stability of countries and determine the security and sustainability of the investment environment (Cotula, 2012). Geo-economy reflects the economic ties and cooperation potential between countries, which is an important guarantee for investment returns and market expansion. Finally, geo-cultural relations affect the cultural adaptability and social acceptance of transnational cooperation and determine the long-term success of investment projects. Through the comprehensive analysis of these four dimensions, we can comprehensively evaluate the investment environment of the host country, and provide scientific basis and strategic guidance for China's overseas farmland investment. Based on the above cognition and the currently available inter-country statistical indicators, and according to the data requirements of grey correlation analysis, this paper takes China's intended project area in each host

country as the initial reference sequence, and constructs grey correlation analysis sequence indicators from four dimensions: resource base, geopolitics, geo-economy and geo-culture (Table 1).

Relevant case data are all from the Land Matrix database, and each index value is finally collected and summarized by the author. Considering the research theme of this paper, the main principles of data summary are as follows: (1) China's overseas farmland investment project refers to the transnational land transaction project whose investment destination is outside China; (2) The number of the earliest years of receiving Chinese investment is calculated from the year of the earliest Chinese investment project known by statistics; (3) The relevant indicators of independent investment are summarized after excluding China's overseas farmland investment projects with partners. The index data of the four dimensions of geographical relations are mainly from FAO database, CEPII database, China Foreign Affairs, China Trade and Foreign Economic Statistics Yearbook and the official website of Confucius Institute Headquarters. The selection of data time points and time period mainly takes into account the diplomatic characteristics of the new era after the establishment of the new Chinese government, the availability of statistical data and the connotation of indicators, and generally takes 2013–2021 as the main data collection period standard.

TABLE 1 Construction table of grey relation analysis sequence index.

Subgoal	Index	Unit	Data time point/year
Resource base	Total cultivated area	hm^3	2021
	Arable land per capita	hm^3	2021
	Proportion of agricultural land	%	2021
	Value of crop production per area	Ten thousand dollars/hm^3	2021
	Total water resources	hm^3	2021
geopolitics	Capital distance	Km	2021
	Duration of diplomatic relations	Year	2021
	Total number of statements, declarations and communiques	time	2013–2019
	Total number of government missions abroad	a	2018
geo-economy	Total annual value of imports and exports	Ten thousand dollars	2013–2019
	Average annual growth rate of total import and export value	%	2013–2019
	Average annual stock of foreign direct investment	Ten thousand dollars	2016–2021
geo-culture	Annual number of inbound tourists	people	2013–2020
	Annual growth rate of inbound tourists	%	2013–2020
	Number of Confucius Institutes	a	2021

4 Results

4.1 Spatial agglomeration characteristics of China's overseas farmland investment projects

4.1.1 Asian region

The cartographic results of the nuclear density estimation method show that the overall distribution of China's overseas farmland investment contract projects in Asia is not balanced, showing a spatial feature of "small agglomeration and large dispersion." From the perspective of agglomeration area, the contract projects of China's overseas cultivated land are mainly concentrated in Vietnam, Cambodia, Malaysia and Indonesia. According to the level of nuclear density, the above concentration areas can be roughly divided into three levels: the first level is the project concentration area with the highest nuclear density, mainly located in Thanh Pho Ha Long, Hai Duong and Thanh Pho Ninh Bing in northern Vietnam; The second level is the project concentration area with high nuclear density, mainly Kampong Thum, Siemreab and Kracheh in central Cambodia. The third level is a project concentration area with average nuclear density values, consisting of two separate clusters, one at the junction of Jambi and Palembang in Sumatra, and the other at Kalimantan Capuas in Central Kalimantan, Indonesia. Investment in Asia is concentrated in Southeast Asia. The geographical proximity and close economic ties between the region and China make investment more convenient and economically beneficial. The rapid economic growth of Southeast Asian countries and close trade relations with China also provide a good market environment for investment. In addition, the promotion of the Belt and Road Initiative has further boosted Chinese investment in the region (Figure 3).

4.1.2 European region

The nuclear density distribution map of China's overseas farmland investment contract projects in Europe shows that there are two obvious clusters and one less obvious cluster in the region, the former one is located in the border of Hungary, Serbia and Romania, and the other one is located in the eastern region of Romania. The latter is in the northern part of Ukraine. In terms of the high and low levels of nuclear density, the above three clusters can be divided into two levels: the first level is the highest concentration of projects, forming two clusters in Romania, mainly located in the Timisoara and Arad regions in the west of the country and Bucuresti, Constanta and Buzau regions in the east; The second level is a project concentration area with average nuclear density values, consisting of an independent cluster, mainly located in the Kiev region of Ukraine. Investment in Europe is concentrated in places such as Russia and Romania. Russia's vast land and rich resources make it one of the key countries for Chinese investment. Eastern European countries such as Romania have also attracted Chinese investment due to their lower land costs and higher agricultural production potential. In addition, Europe's political stability and mature market environment provide security for investment (Figure 4).

4.1.3 South America

A map of the nuclear density distribution of China's overseas farmland investment contracts in South America shows that there is one distinct cluster in the region and three less distinct clusters, the former in Uruguay, the latter in central Brazil, northern Argentina and Costa Rica. From the perspective of high and low nuclear density

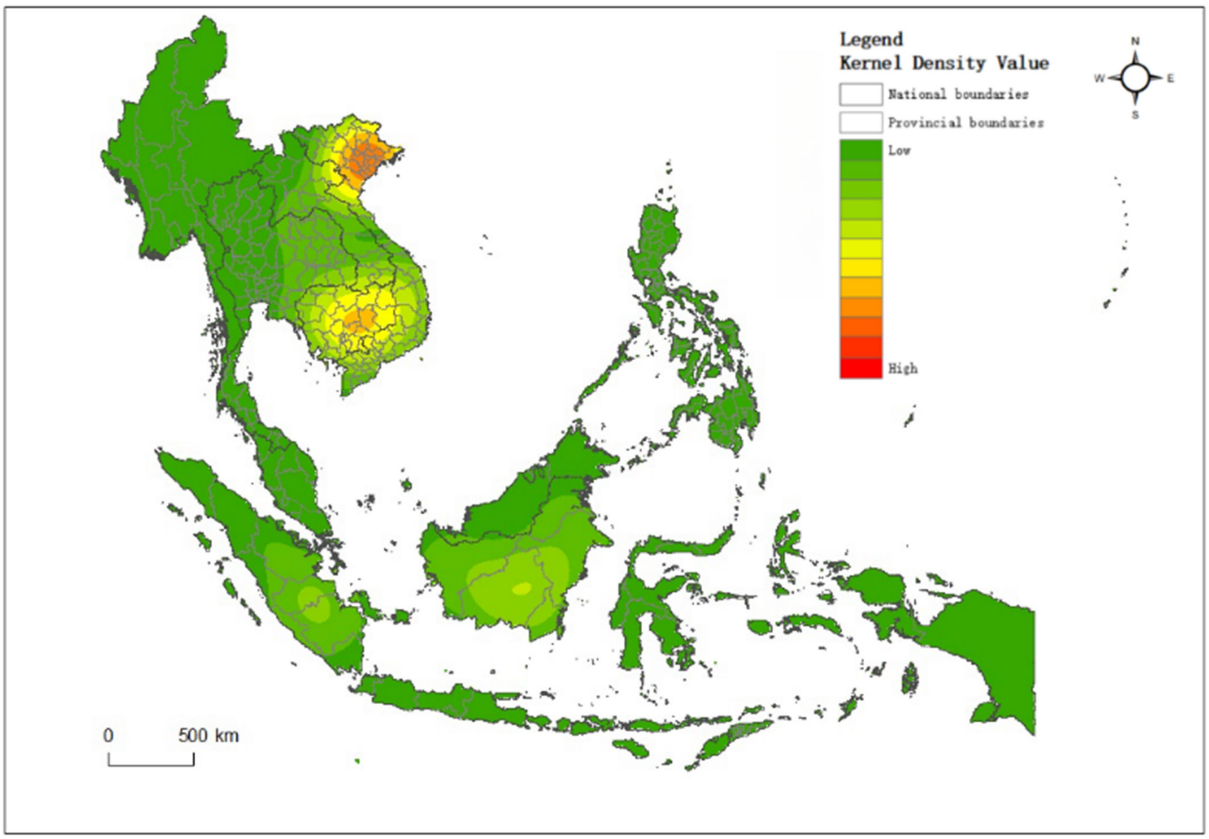


FIGURE 3
Nuclear density distribution of China's overseas farmland investment contract projects in Asia.

values, the above four clusters can be divided into three levels: the first level is the project concentration area with the highest nuclear density value, located in the Paso de los Toros region in central Uruguay; The second is the region with high nuclear density values, located in the Barreiras region in eastern Brazil and the San Salvador de Jujuy region in northern Argentina. The project concentration area with average Grade third nuclear density values is located in the Nueva Guinea region of Nicaragua. In addition, the Talara region in northern Peru, along the Meta River in northern Colombia, and the paranaiba region in central Brazil have also shown signs of agglomeration, but this agglomeration is not yet obvious. In South America, Chinese investment projects are mainly distributed in countries such as Argentina and Uruguay. These countries have abundant agricultural resources and relatively stable political environments, making them ideal targets for attracting investment. South America's economic development potential and trade links with China also support investment (Figure 5).

4.1.4 African region

A map of the nuclear density of China's overseas farmland investment and production projects in Africa shows four distinct clusters in Sierra Leone, Liberia, Ghana, Zambia and the western Democratic Republic of Congo, and five less distinct clusters in Senegal, Ethiopia, Uganda and Mozambique. From the perspective of the high and low levels of the nuclear density value, the above three clusters can be divided into three levels: The first is located on the border of Kenema in eastern Sierra Leone with Guinea and Liberia, the second in Kumasi in Ghana, the third in Bandundu in western Republic of the Congo, and the fourth in Kabew in central Zambia. The second category consists of high concentrations of projects, with the first in the Mboro region on the western coast of Senegal, the second in the Adama region of central Ethiopia, the third in Kampala region of Uganda along the northern shore of Lake Victoria, and the fourth in the Mocuba region of eastern Mozambique. The fifth is located in the Bumba region of the north-western Democratic Republic of the Congo; Level 3 is a cluster of projects with average nuclear density values, located in Souk-EI-Arba-Du-Rharb in central Morocco, Wad Madani in central Sudan, and Douala in central Cameroon. Investment in the African region is concentrated in West Africa and South Africa. This distribution is related to Africa's abundant natural resource endowments, especially arable land available for development. In addition, political instability and low levels of social governance in some African countries make the need for foreign investment more urgent. China's investment in these areas is not only to acquire resources, but also to expand its influence on the international stage (Figure 6).

4.2 Factors influencing the distribution of China's overseas farmland investment projects

As shown in Table 2, the calculated results of the grey relative correlation degree show that the project area of China's overseas farmland investment intention is closely related to the resource base, geopolitics, geo-economy and geo-culture of the host country. Among

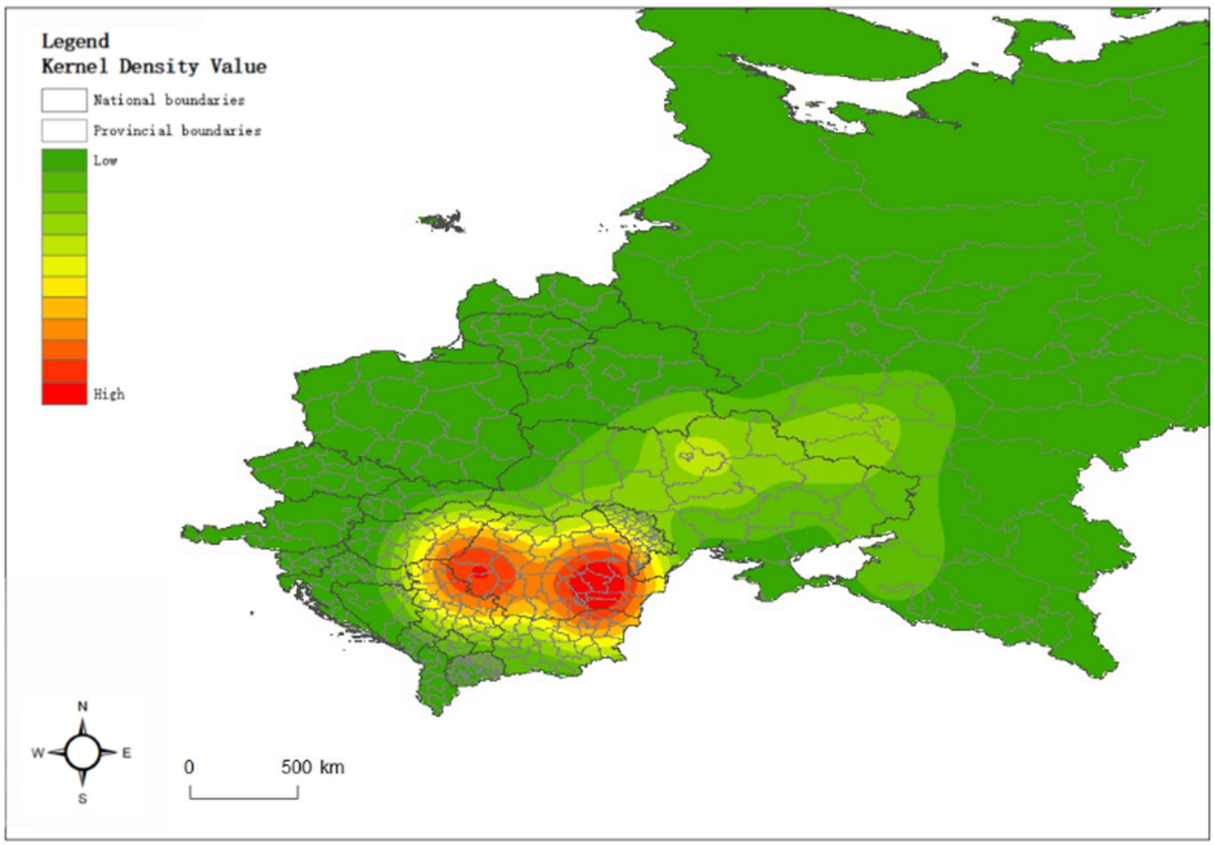


FIGURE 4
Nuclear density distribution of China's overseas farmland investment contract projects in Europe.

the 16 indicators selected in this paper, the grey relative correlation degree value of 11 indicators is above 0.70. The average grey relative correlation of the four dimensions is greater than 0.70, and the importance of the four dimensions is as follows: geoeconomy > resource base > Geoculture > geopolitics.

According to the results of gray correlation analysis, among the four dimensions of resource base, geopolitics, geoeconomy and geoculture, the importance of geoeconomy is the first, and the average gray relative correlation degree of high impact index is as high as 0.7668. China's investment in overseas farmland is not only the investment of funds, but also the sharing of agricultural technology and management experience. This transfer of technology and knowledge can help improve the efficiency of agricultural production in host countries, while also giving Chinese companies a competitive advantage in local markets. The closeness of geo-economic ties determines the depth and breadth of such cooperation. Take Southeast Asia and the Belt and Road countries as an example. Since 2002, after China and ASEAN signed the Memorandum of Understanding between the Government of the People's Republic of China and the Governments of the member States of the Association of Southeast Asian Nations on Food and Agriculture Cooperation and the Joint Statement on China-Asean Food Security Cooperation, Chinese enterprises have significantly increased their agricultural investment in Southeast Asia, and overseas farmland investment activities have also been rapidly developed. With the full launch of China-Asean Free Trade Area in 2010, the economic and trade ties between Southeast Asian countries and China have become closer, the market scale of China in Southeast Asian countries has been expanding, and the convenience of commodity trade has also been improving. All these have laid favorable conditions for Chinese enterprises to implement overseas farmland investment in Southeast Asia. At the same time, the Belt and Road cooperation between China and Latin America and the Caribbean has gradually deepened and made solid progress (Hufe and Heuermann, 2017). Twenty-two countries in Latin America and the Caribbean have signed cooperation documents on the Belt and Road cooperation with China (Yu et al., 2015). China and Latin America have continuously strengthened practical cooperation in agricultural infrastructure construction, cross-border e-commerce, logistics and transportation (Hanif, 2017; Robert and Phil, 2022). In recent years, relying on the opportunity of "Silk Road e-commerce," more and more Latin American agricultural products have entered the Chinese market through cross-border e-commerce, opening up a new channel for Sino-Latin American agricultural trade (Haider, 2022). At the index level, the average annual import and export value and the average annual stock of China's foreign direct investment have a high degree of influence, and the grey relative correlation value of these two indicators is above 0.83, indicating that good trade relations and investment basis have a strong influence on Chinese enterprises to choose the host country of overseas cultivated land investment.

The average grey relative correlation degree of resource base high impact degree index is 0.7703, ranking second. The abundance of natural resources directly affects the attractiveness of agricultural

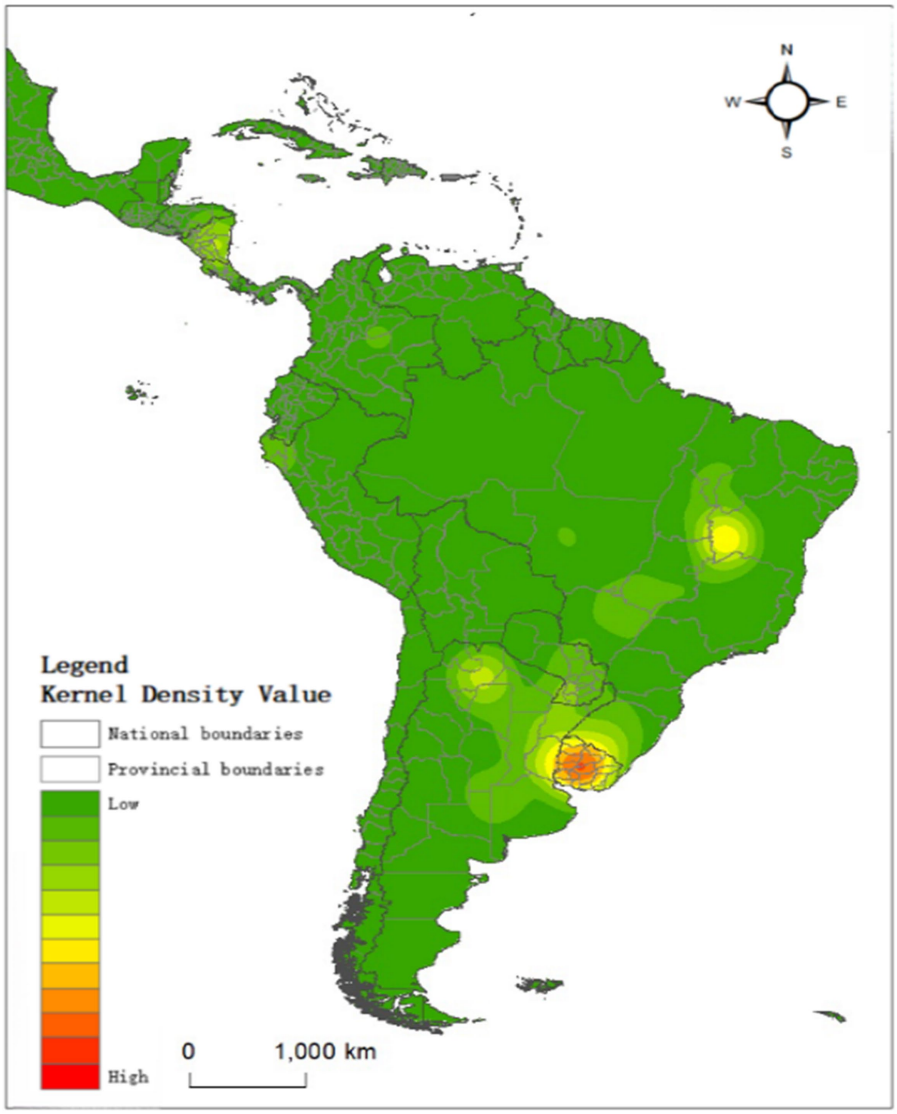


FIGURE 5
Nuclear density distribution of China's overseas farmland investment contract projects in South America.

investment, such as abundant cultivated land resources and water resources, which can provide good growing conditions for crops. The population in Southeast Asia is relatively dense and the per capita cultivated land area is not high, but the region has more reserve cultivated land resources, good solar and thermal conditions, strong output capacity of cultivated land, and some agricultural products have strong complementarity with China. Under good trade conditions, a large number of Chinese enterprises have invested in rice, palm oil and natural rubber projects in the region (Mazzocchi et al., 2018; Azadi et al., 2012). Different from some regions with relatively scarce per capita resources, some countries in South America and Africa are outstanding in terms of per capita cultivated land area and cultivated land potential, especially in terms of arable reserve land and rich water resources (Yu et al., 2015). The photothermal conditions in these areas are good and suitable for the growth of a variety of crops, especially in agricultural products such as soybeans, coffee and fruits, which are highly complementary to the Chinese market (Miao et al., 2024; Suo and Bai, 2024). At the index level, the grey relative correlation values of the four indicators of per capita cultivated land area, total cultivated land area, crop production value per area and total water resources are above 0.70, among which the grey relative correlation values of total cultivated land area are 0.92 and the total water resources area is 0.94, indicating that in terms of resource base, Compared with the total amount of cultivated land, investors may pay more attention to the area of cultivated land and water resources in the selection process of host country.

The average grey relative correlation degree of the geo-cultural high impact degree index is 0.7478, ranking third. There is a long history of cultural interaction between China and many regions, especially in Africa and Latin America, where the Chinese government has actively expanded economic cooperation and cultural exchanges through its "Going out" strategy. In these regions, China has set up a number of Confucius institutes to promote the spread of language and culture, while increasing scholarship support for students from these countries.

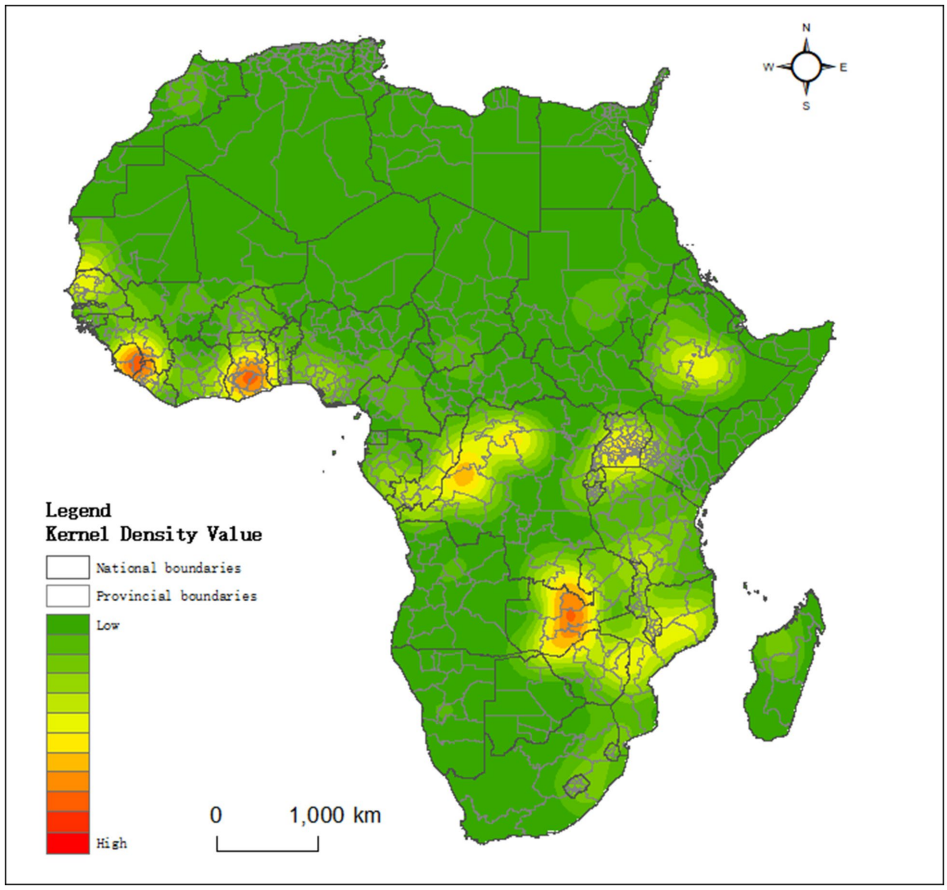


FIGURE 6
Nuclear density distribution of China's overseas farmland investment contract projects in Africa.

Such cultural exchanges not only enhance the trust and friendship between China and the host country, but also provide a good environment for Chinese enterprises to adapt and operate in the local market. Secondly, Southeast Asian countries have a traditional process of friendly exchanges in history. Especially after the reform and opening up, with the development of China's economy, the Chinese government also put forward the policy of "good-neighborly, secure and prosperous neighbors" in its foreign relations with neighboring countries, established a number of Confucius institutes in Southeast Asian countries, and increased financial assistance to students from Southeast Asian countries studying in China. On the one hand, these cultural exchanges enhance mutual trust and friendship between the two sides, and also create conditions for investment enterprises to adapt to local environment and laws (Ji et al., 2023; Raimondi and Scoppola, 2018; Li, 2015). At the index level, among the four geo-cultural indicators selected in this paper, the grey relative correlation values of the average annual FDI stock, the average annual number of inbound tourists and the number of Confucius Institutes all exceed 0.80, and the grey relative correlation value of the number of Confucius Institutes exceeds 0.89. It reflects that good cultural exchanges and friendly exchanges between citizens have an important impact on the choice of host country for Chinese enterprises investing in overseas cultivated land.

Geopolitics has the least influence on overseas farmland investment, and its average grey relative correlation degree is 0.6791. In recent years, with the promotion of the Belt and Road Initiative, China's diplomatic relations with many countries and regions have been significantly strengthened, especially in regions such as Africa, Latin America and Southeast Asia (Bureau and Swinnen, 2018). However, the political environment in these regions is complex and volatile, often with varying degrees of political risk, social unrest and policy uncertainty (Aha and Ayitey, 2017). These adverse risks will have a strong inhibitory effect on the investment activities of overseas cultivated land investment, which has high fixed cost and long recovery cycle (Chavas, 2017). In addition, geopolitics belongs to an extremely complex influence layer, and the influence of China's overseas farmland investment cannot be ignored (Cotula et al., 2011; Fan and Brzeska, 2016). The "balanced diplomacy" policy formed by Latin American and Southeast Asian countries, as well as the strategic intervention of the United States and Japan, makes it difficult to generate a reasonable order in the region. In particular, some Southeast Asian countries have shown uncertainty in their policies toward China, making investment decisions more difficult and making geopolitical factors an obstacle to the development of China's overseas farmland investment in the region. At the level of specific indicators, only the distance between the capital and the total number of declarations, declarations and communiques have grey relative correlation values greater than 0.80, and the values of other indicators are not high. This reflects the weak influence of political atmosphere on the choice of host country for Chinese enterprises to invest in overseas farmland. Despite the increasing number of cooperation mechanisms within the region, geopolitical factors remain

TABLE 2 The grey relative correlation result.

Subgoal	Index	Grey correlation degree	Average
Resource base	Total cultivated area	0.9163	0.7703
	Arable land per capita	0.7116	
	Proportion of agricultural land	0.5371	
	Value of crop production per area	0.7398	
	Total water resources	0.9467	
geopolitics	Capital distance	0.5623	0.6791
	Duration of diplomatic relations	0.4414	
	Total number of statements, declarations and communiques	0.8385	
	Total number of government missions abroad	0.8741	
geo-economy	Total annual value of imports and exports	0.9109	0.7710
	Average annual growth rate of total import and export value	0.5606	
	Average annual stock of foreign direct investment	0.8417	
geo-culture	Annual number of inbound tourists	0.8499	0.7478
	Annual growth rate of inbound tourists	0.4972	
	Number of Confucius Institutes	0.8963	

an important obstacle to China's investment in overseas farmland due to historical issues and competition between countries in the region.

5 Discussions and conclusions

Based on the Land Matrix database, this paper studies the spatial distribution characteristics and influencing factors of global overseas cultivated land investment and development, and mainly draws the following conclusions: (1) From the perspective of regional distribution, Asia has the largest amount of cultivated land, about 579 million hectares, accounting for 39.94% of the total cultivated land in the world. Moreover, most of the projects are located in Indochina Peninsula countries, and have the characteristics of distribution along the border between China and the host country. Myanmar, Cambodia, Malaysia and the Philippines have a better concentration of overseas farmland investment projects; Laos and southern Vietnam are important areas for China's overseas farmland investment; Indonesia's Sumatra Island is the main area for China's overseas farmland investment in the country. It is followed by Europe, which has 20.34% of the global total cultivated land, and Oceania, which has the least cultivated land, only 2.62% of the world's total cultivated land. (2) From the nuclear density distribution map, China's overseas farmland investment projects in countries along the "Belt and Road" show the characteristics of spatial agglomeration distribution, and the distribution of projects in Asia, Africa, Europe and other continents also shows the characteristics of agglomeration distribution, and the distribution of projects in Latin America and Oceania has the highest degree of agglomeration, while Africa has the lowest degree of agglomeration; From the perspective of signed area, the signed area of China to countries along the route tends to be evenly distributed. Specifically, the signed area of Asia, Africa and other continents is concentrated, and only Europe is evenly distributed. (3) In terms of influencing factors, this paper analyzes the influencing factors of China's overseas farmland investment in Southeast Asia by using the grey correlation model and finds that Chinese enterprises' overseas farmland investment activities are closely related to the resource base, geopolitics, geo-economy and geo-culture of the host country, and its significance is as follows: Geo-economy > Resource Base > Geo-Culture > Geopolitics. It can be seen that factors such as political relations between countries, policy stability and international strategic intervention caused by geopolitics have greatly affected the security and sustainability of China's overseas farmland investment. (4) At the index level, the grey relative correlation degree between the average annual import and export value of China and the host country, the average annual stock of China's foreign direct investment, the total amount of water resources, the index of cultivated land area of the host country and the area of China's overseas cultivated land investment project is more than 0.84, that is, the above factors have a strong influence on Chinese enterprises to choose the host country for overseas cultivated land investment.

From the perspective of influencing factors, China's overseas farmland investment strategy shows obvious heterogeneity, mainly in the four dimensions of geo-economics, resource base, geo-culture and geopolitics. In areas dominated by economic factors, China's investment strategies are mainly concentrated in countries and regions with close economic and market connections, such as Southeast Asia and countries along the "Belt and Road." China has strong economic and trade ties with these regions, and the establishment of free trade zones and convenient market conditions have created a good environment for agricultural investment. This type of strategy focuses on efficient investment in capital and technology and pursues rapid economic returns and market share. For regions with better resource endowments (such as South America and Africa), China tends to choose countries with abundant land resources and superior water resources to ensure high yields in crop cultivation. This type of strategy takes resource development as its core goal and emphasizes the full utilization of natural resources to produce agricultural products such as soybeans and palm oil that are in high demand in China to maximize the matching of production capacity and resources. In regions with strong cultural ties, especially Southeast Asia and Africa, China promotes relations with host countries by

strengthening cultural exchanges and educational cooperation. Cultural programs such as Confucius Institutes and scholarships help build a foundation for mutual trust and cooperation. This strategy is particularly effective in areas with high cultural similarities, helping Chinese companies better adapt to local market demands and operating environments. In areas with unstable political environments (such as some African and Latin American countries), China's investment strategy is more cautious. Due to the political risks in these areas, China will pay more attention to risk aversion when choosing investment projects, and may reduce capital investment or choose countries with relatively stable cooperative relations. In addition, China uses the "Belt and Road" cooperation mechanism to balance and strengthen political relations with host countries to enhance the security of agricultural investment. In general, China adjusts its investment strategy according to local conditions to achieve sustainable development of foreign agricultural investment.

Overseas investment in cultivated land is not only a new trend in the utilization and control of transnational agricultural resources, but also an important option for developing countries with weak agricultural foundation to solve the problem of poverty and ensure food security. Through transnational agricultural investment, China has effectively used overseas cultivated land resources and eased the restrictions of domestic agricultural resources. This kind of investment not only optimizes the allocation of land resources, but also promotes the rational distribution of food production on a global scale, thus solving the problem of "mismatch between people and land" to a certain extent and ensuring national food security. According to the distribution characteristics of the three nuclear density grade regions mentioned in the experimental results, we put forward the following suggestions. First, for high-density investment areas, it is recommended to strengthen resource integration and risk management. The government and enterprises should jointly develop detailed investment plans to ensure the efficient use of resources and the sustainability of investment. Second, in medium-density regions, policies should focus on attracting more investment through infrastructure development and policy incentives. The e government can provide tax incentives, financing support and other measures to encourage enterprises to expand investment in these areas. Third, for low-density areas, it is recommended to conduct in-depth market research and risk assessment to identify potential investment opportunities and challenges. And according to the different regions of the world involved in the experimental results, strategies adapted to local conditions can also be adopted, such as Southeast Asia, which offers strong economic ties with China, but fragmented land governance systems pose challenges. China could leverage regional frameworks like the ASEAN-China Free Trade Area to harmonize investment policies and establish dispute resolution mechanisms. Given environmental concerns in this region, investments should focus on crops that align with local ecological conditions and avoid deforestation or overuse of water resources. And China could Strengthen cultural exchanges, such as through Confucius Institutes or scholarships, building trust and facilitate smoother operations for Chinese enterprises. In European Region, Countries like Russia and Romania offer vast agricultural potential. Investments should target modernizing agricultural infrastructure and enhancing productivity while navigating EU regulations. And collaborating with European agricultural research institutions can facilitate knowledge exchange and improve yields in Chinese-operated farms. South America's abundant arable land and water resources make it ideal for large-scale agricultural projects. Investments should focus on high-demand crops like soybeans and coffee that complement China's market needs. To address global criticism of deforestation, especially in countries like Brazil, China should adopt sustainable farming practices and collaborate with international organizations to promote environmental conservation. And Strengthening trade ties through bilateral agreements or participation in regional trade blocs like MERCOSUR to improve market access for agricultural products. About African region, for addressing Geopolitical Risks, China could develop partnerships with local governments to enhance transparency and accountability in land deals, ensuring fair compensation and community benefits. Strengthening diplomatic ties and participating in regional organizations like the African Union can also help manage geopolitical risks. And investments should prioritize improving local infrastructure (e.g., irrigation systems, transportation networks) to support agricultural productivity and foster goodwill among local communities. Providing training in modern farming techniques to local farmers can promote sustainable practices and reduce resistance to foreign investments. Governments and enterprises should pay attention to the resource endowment and market potential of these regions and formulate flexible investment strategies. A comprehensive identification and quantitative measurement of the spatial pattern of China's overseas farmland investment development in the world will not only provide an operational judgment basis for the sound development of China's overseas farmland investment, but also help to scientifically analyze China's investment activities and their rules in the region, optimize China's overseas farmland investment, and formulate corresponding policies for relevant departments. In particular, the establishment of China's overseas cultivated land investment development strategy and policy provides a practical basis, and further promotes resource coordination and cooperation between different countries and regions, and achieves win-win development for maintaining regional food security and agricultural sustainable development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YW: Conceptualization, Funding acquisition, Writing – original draft. FZ: Data curation, Formal analysis, Writing – review & editing. LW: Supervision, Visualization, Writing – review & editing. HJ: Funding acquisition, Supervision, Writing – review & editing. ML: Formal analysis, Resources, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Bridging the gap: challenges and adoption of climate-resilient agriculture technologies in agricultural landscapes across agro-climatic zones of Bihar, India

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How effective are climate resilient agricultural technologies (CRATs) in overcoming barriers faced in agri-food system by farmers across the different agro-climatic zones (ACZs) of Bihar? This study examines the barriers that hinder farmers in Bihar from adopting CRATs amidst the growing impacts of climate change on global agri-food systems. It focuses on key CRATs, including zero tillage/minimum tillage (ZT/MT), laser land leveling (LLL), climate-resilient variety selection (CRVS), crop diversification (CD), site-specific nutrient management (SSNM), crop calendar and timely sowing (CCTS), and direct-seeded rice (DSR), and investigates the factors affecting their adoption. Using descriptive statistics, correlation analysis, and logistic regression, key factors that influence the adoption of CRATs were identified. Descriptive statistics showed moderate levels of soil health awareness

(mean value = 2.70) and climate change awareness (mean value = 2.63). Correlation analysis found that social factors like training received had a positive correlation with the adoption of DSR (correlation coefficient = 0.410). Logistic regression results highlighted that technology awareness significantly influences the adoption of DSR (coefficient = 0.400, p = 0.253), while initial investment costs are major barriers for ZT/MT and LLL (coefficient = 0.400, p = 0.267). Results highlight the need to improve awareness through educational programs, provide technical support, and offer financial incentives to overcome the various barriers farmers faced. Targeted efforts in these areas can significantly increase the adoption of the CRATs, leading to more resilient and sustainable farming systems. Study supports not only the sustainable agricultural development but also align with the United Nations Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 13 (Climate Action), and SDG 15 (Life on Land).

KEYWORDS

climate-resilient agriculture, minimum tillage, laser land levelling, crop diversification, site-specific nutrient management, direct seeded rice, adoption

1 Introduction

India's agricultural sector has transformed significantly over the past six decades, with increased agri-food grain production, diversification into high-value products, and stronger links with the non-farm sector (Mwangi and Kariuki, 2015). However, these advancements are uncertain. While states like Punjab and Haryana have thrived, Bihar state lags in agricultural development despite its rich natural resources. Bihar remains one of India's poorest states, facing significant challenges in poverty, health, and education. The state has the highest rate of malnutrition children under 5 years old (48%) in India and ranks second for underweight 30%-women and 40%-children (Singh and Singh, 2020). Additionally, the Bihar state has a high prevalence of anemia among women and children. A common challenge across the Indo-Gangetic Plain (IGP) is climate change, which adversely affects agri-food production system. Since 1750, greenhouse gases (methane-CH_4, carbon dioxide-CO_2, and nitrous oxide-N_2O) have risen significantly (Pachauri and Meyer, 2014). CO_2-emissions, which represent the largest proportion of greenhouse gases (Sathaye et al., 2006; IPCC, 2014), increased from 22.15 billion metric tons (BMt) in 1990 to 36.14 BMt in 2014 (Abeydeera et al., 2019). The global temperature has been climbing at a rate of 0.15–0.20°C per decade since 1975 (NASA, 2020) and is projected to rise by 1.4–5.8°C by 2021 (Arora et al., 2005). India's rapid industrialization and urbanization are leading to more frequent, prolonged, and intense heatwaves. Changes in urban land cover (ULC) have increased land surface temperature (LST) and air temperatures, impacting the surface climate (Sati et al., 2018). Predictions suggest that by the 2080s, the average yearly temperature will rise by 3.5 to 5.5°C over India. This warming will be less during the monsoon season compared to winter. Rainfall patterns are expected to shift too, with more rain during the monsoon season by 2050 but less during the winter season. These changes are likely to affect agriculture in India, putting at risk the agri-food security (Ravindra et al., 2024).

The Bihar state, highly sensitive to climate, faces challenges due to its geography, unpredictable weather, large rural population, and high poverty levels. Agriculture contributes 21.3% to Bihar's GDP and is a crucial income source (90%) population (Tesfaye et al., 2017). The Bihar government recognizes that climate change is a major threat to the farming community. They aim to make agriculture more resilient to climate changes, ensuring a steady food supply and supporting economic growth. Bihar is prone to weather-related disasters, with northern parts facing yearly floods and southern parts experiencing droughts. Additionally, 27 out of 38 districts are significantly affected by high-speed winds of 47 m/s [Bihar Disaster Management Authority (BSDMA), 2024]. Climate change is causing more frequent extreme weather events, leading to an increase in landslides, flash floods, and droughts. The Bihar state farming was negatively impacted by delayed rice sapling transplantation during the Kharif season. The region, susceptible to natural disasters, is experiencing altered seasonal patterns with late monsoons, reduced monsoon days, elevated temperatures, and prolonged dry spells. These are affecting traditional cropping patterns, posing significant challenges to livelihoods. Despite increased public discussions on climate change impacts in the past two decades, policy reflection has been minimal. The lack of political interest may stem from the challenges of sustainable development-dealing with growing populations and limited resources.

The Eastern Indo-Gangetic Plains (EIGPs), which include Bihar, is an important agricultural region that supports millions of livelihoods and significantly contributes to India's agri-food security. The unique combination of fertile alluvial soils, subtropical climate, and diverse cropping systems makes the EIGPs highly productive but vulnerable to climate change impacts (Ghosh et al., 2018). These climatic uncertainties, including delayed monsoons and prolonged dry spells, coupled with an increase in the frequency of extreme events, including floods and droughts, have increased the farm's stress level (Kumar et al., 2020).

Promotion and adoption of CRATs is thus essential in reducing this kind of stress. Conservation agriculture (CA) technologies such as ZT, LLL can significantly reduce greenhouse gas emissions, improve water use efficiency, and enhance soil health (Jat et al., 2019; Choudhary et al., 2022). Similarly, crop diversification and site-specific nutrient management (SSNM) contribute to increased resource use efficiency, enabling farmers to better adapt to variable climatic conditions (Meena et al., 2021). CA and organic farming practices in India vary in their economic effects, while recent research studies indicate mixed opportunities and challenges for mass adoption (Reddy and Reddy, 2022). The adoption of climate-resilient crop

varieties (CRVs) has also been promising for stabilizing yields in drought- and flood-prone areas (Sharma et al., 2020).

Recent studies underscore the need for targeted interventions to raise awareness and improve access to CRATs among farming community in the EIGPs. Government initiatives, coupled with institutional support through programs such as the Climate Resilient Agriculture Program implemented by the Government of Bihar, are crucial in addressing socio-economic and technological barriers to adoption (Choudhary et al., 2021). These interventions can be scaled up only if they have an appropriate policy framework and investment in farmer training (Verma et al., 2019) and infrastructure (Singh and Sharma, 2020), as argued by Jha et al. (2022). Identifying key challenges and potential solutions contributes valuable knowledge to the global discourse on sustainable agri-food production systems (Prakash et al., 2021). The CRATs can revolutionize farming by improving crop yields, resource efficiency, and resilience to unpredictable weather. Adoption studies help understand the hurdles or challenges farmers face in adopting new technologies, guiding smarter collaboration between farmers and policymakers to ensure effective use of tech tools for farmers' success.

We hypothesized that adoption of CRATs (climate-resilient agricultural technologies) in the agri-food systems of Bihar is significantly influenced by socio-economic factors, technological accessibility, institutional support, and awareness levels among farmers. This hypothesis lead the objectives (i) to identify and analyze the socio-economic, institutional, and technological barriers preventing the adoption of CRATs in different ACZs of Bihar, (ii) to evaluate the effectiveness of various CRATs, such as zero-tillage/minimum tillage, laser land leveling, climate-resilient variety selection, crop diversification, site-specific nutrient management, crop calendar and timely sowing, and direct-seeded rice, in overcoming these barriers, and (iii) to develop targeted strategies and policy recommendations to enhance the adoption of CRATs, focusing on improving awareness through educational programs, providing technical support, and offering financial incentives to the farmers across the diverse ACZs of Bihar. Promote the adoption of CRATs, ultimately contributing to the resilience and sustainability of agricultural systems in Bihar.

2 Methods

2.1 Bihar-eastern IGPs

The EIGPs features diverse agro-climatic and soil conditions. Bihar, situated between 24° 15′ to 27° 31'N latitude and 83° 20′ to 88° 19′E longitude, spans 483 km in length (E-W) and 385 km in width (N-S). It experiences a subtropical sub-humid monsoonal climate with moderate winters and hot, dry summers. The state is divided by the Ganga River into North and South Bihar (SB), with rivers flowing both southward and northward into the Ganga. North Bihar (NB) is categorized into two ACZs (I and II) - Figure 1, while South Bihar is

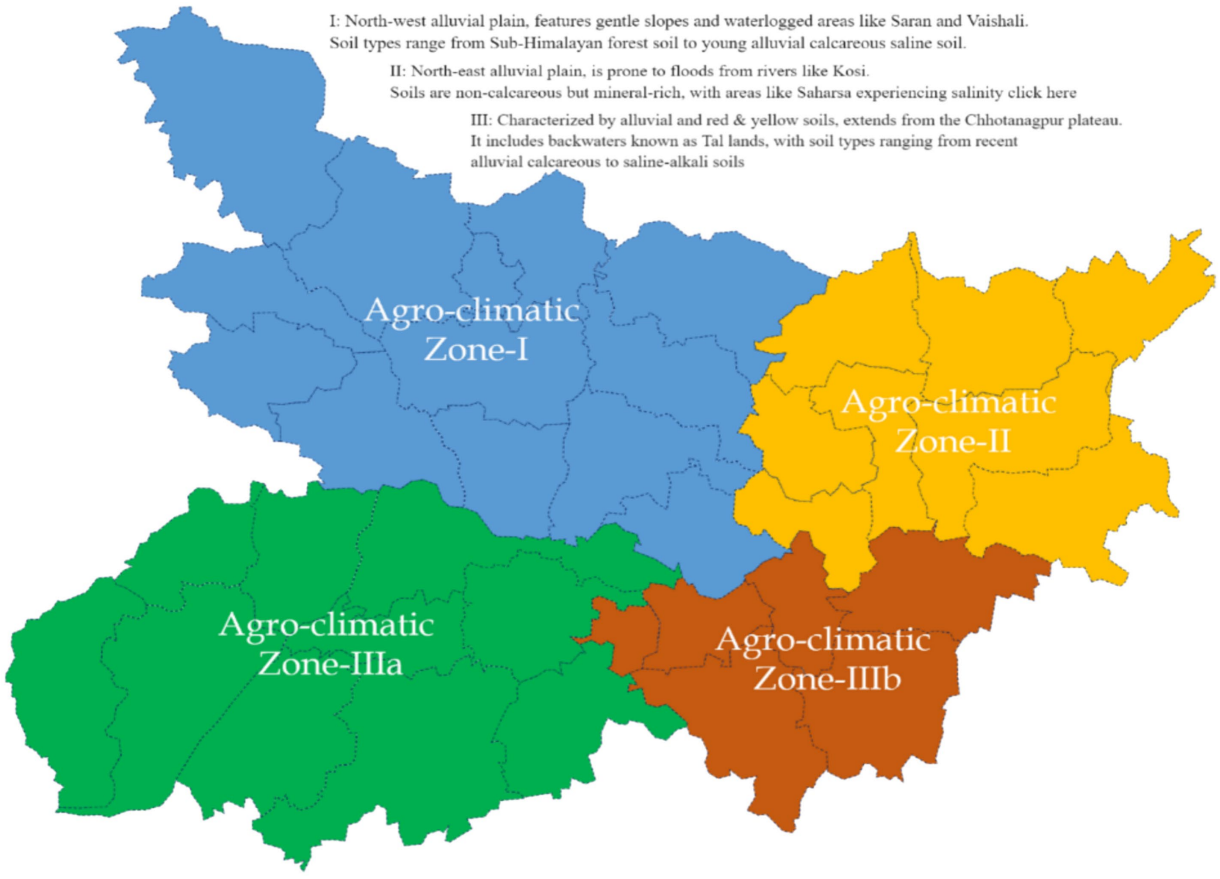


FIGURE 1
Different agro-climatic zones (ACZs) covering the surveyed villages.

represented as ACZs-III, further subdivided into ACZs-IIIa and ACZ-IIIb (Ray et al., 2018; Sahni et al., 2021).

Agro-Climatic Zone I: North-West Alluvial Plains districts which are flood-prone every year, fertile soil, and intensive rice-wheat systems (Mishra et al., 2020).

Agro-Climatic Zone II: North East Alluvial Plains this zone is characterized by moderate rainfall with diversified crops including maize, pulses, and jute (Kumar R. et al., 2019).

Agro-Climatic Zone III: (South Bihar Alluvial Plains): These are further divided into sub-zones ACZ-IIIa and ACZ-IIIb, showing difference in characters. ACZ-IIIa faces water scarcity and supports mixed cropping while the ACZ-IIIb receives modest rainfall and favors rice-pulse systems (Das et al., 2020).

The study area includes seven representative project sites from these ACZs. The SB is the most fertile region for food and non-food grain production, whereas NB faces challenges with floods and droughts. The SB -pan system supports crop cultivation, but NB irrigation infrastructure is inadequate, covering only 50% of arable land. State tube-wells account for 63% of the irrigated land, with the rest coming from canals, tanks, wells, and local sources, many of which are non-operational. Rice, a staple crop, is grown year-round (aghani, summer, and autumn). Rice-producing about 5 million tonnes (Mt) annually. Wheat, initially confined to western Bihar, expanded significantly post-green revolution, yielding 4–5 Mt. annually. Maize thrives in districts like Purnia, Katihar, Khagaria, Saharsa, and Madhepura, producing 1.5 Mt. annually. Pulses are more common in the SB. Bihar ranks 3rd in vegetable and 6th in fruit production nationally. The state's land holdings are divided into three ACZs with distinct rainfall, temperature, and cropping patterns. ACZ-I supports crop rotation despite annual flooding, while ACZs-III sees less frequent rotation. Bihar's agriculture spans kharif (June–October), rabi (October–March), and garma-summer (April–May) seasons, cultivating paddy, maize, pulses, oilseeds, wheat, groundnut, and mung bean.

2.2 Study area

For the survey and assessment, our focus was primarily on the eastern part of the Indo-Gangetic Plain (IGP), specifically the state of Bihar in India. Total 42 villages were chosen across the district (Figure 2; Supplementary Table 1): Vaishali and Samastipur (ACZ-I), Katihar and Purnia (ACZ-II), Nalanda and Nawada (ACZ-III^{a}), and Munger (ACZ-III^{b}). To ensure a comprehensive understanding; random selection of 840 farmers (Supplementary Table 1), disregarding their current level of technology adoption was carried out. The survey was conducted at the beginning of the kharif season and the mid-point of the summer (garma) season. Selection aimed at maintaining gender neutrality. The Climate Resilient Agriculture (CRA) program is being implemented through a multi-stakeholder partnership to address the challenges posed by climate change in agriculture. The Government of Bihar, particularly its Department of Agriculture, plays a pivotal role in formulating policies and driving the implementation of CRA initiatives. Key research and scientific support come from institutions like CIMMYT (International Maize and Wheat Improvement Center) and BISA (Borlaug Institute for South Asia), ICAR-RCER (ICAR-Research Complex for Eastern Region), RPCAU (Dr. Rajendra Prasad Central Agricultural University, Samastipur) and BAU (Bihar Agricultural University). At grassroots level, KVKs (Krishi Vigyan Kendras) serve as field implementation hubs, providing demonstrations and continuous support to farmers. This collaborative approach strengthens the program's ability to build resilience, improve productivity, and enhance livelihoods for Bihar's farming communities. This strategic exclusion was implemented to ensure the independence of our findings from external influences (Figure 2).

2.3 Data collection

A total of 840 farmers were systematically selected from each district, irrespective of their technology adoption status. Specific inquiries related to both dependent and independent variables were posed, and data were meticulously collected through a combination of careful observation. Periodic small-scale farmer meetings were conducted in various sections of the selected block as needed. Data acquisition was accomplished through one-on-one discussions with each farmer. The parameter indexing was established using simple regression models. The ultimate database underwent analysis employing python/probit data analysis. Following set of dependent and independent variables used for study-:

2.3.1 Variables

The study distinguishes variables into three separate dimensions: dependent variables, independent variables, and mediating variables (Figure 3). Dependent variables provide for the measurable outcomes of the CRA-practices adopted; average rice and wheat productivity, economic returns, and the adoption rates of sustainable practices are some of them. The independent variables include CRA-practices, such as zero tillage, laser land leveling, climate-resilient crop varieties, and direct-seeded rice, along with socio-economic factors like age, landholding size, education level, and knowledge of DSR technology, which directly impact the outcomes. The mediating variable offers critical insights into the enabling factors that shape the relationship between these independent variables and the dependent variables, providing a deeper understanding of the dynamics influencing adoption and effectiveness. These include technical factors like soil health awareness and infrastructure elements such as seed availability and access to markets. Further, labor availability, credit access, and the severity of wildlife implications are key components that affect the adoption and effectiveness of CRATs. This classification ensures a comprehensive framework for analyzing the interplay between technological, socio-economic, and environmental factors, emphasizing the pathways to achieving agricultural resilience. The synthesis of social and monetary factors highlights the need for social equity alignment to financial strategies for sustainable agriculture. Techno-financial integration focuses on the role technical changes play in improving the economic feasibility of technologies. Social and technical integration has shed light on the capability-building programs that cost-effective technologies tailored to farmers' economic capacity promote the adoption of CRATs.

2.4 Statistical analysis

The survey data were subjected to comprehensive statistical analysis to identify key influencing factors for adoption of the CRATs. Descriptive statistics were computed to summarize the central tendency, dispersion, and shape of the dataset's distribution. The measures included mean, standard deviation, minimum and maximum values, as well as the 25th, 50th, and 75th, percentiles for

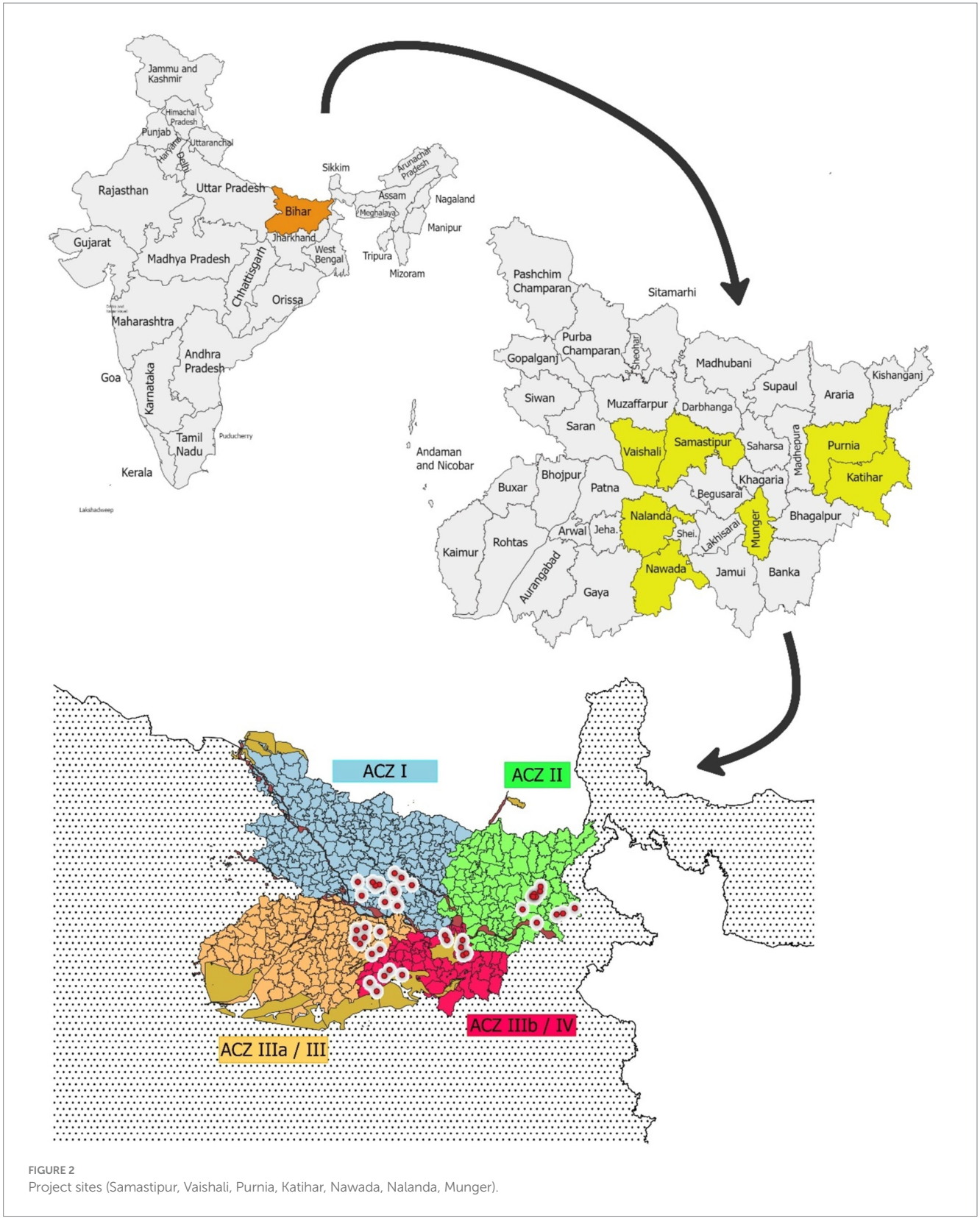


FIGURE 2
Project sites (Samastipur, Vaishali, Purnia, Katihar, Nawada, Nalanda, Munger).

each variable. These statistics provide a foundational understanding of the data distribution and variability among respondents. To explore the relationships between different variables, correlation analysis was performed. The Pearson correlation coefficient was calculated for each pair of variables using the formula Equation 1:

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{\left[n\Sigma x2 - (\Sigma x)2\right]\left[n\Sigma y2 - (\Sigma y)2\right]}} \quad (1)$$

Where,

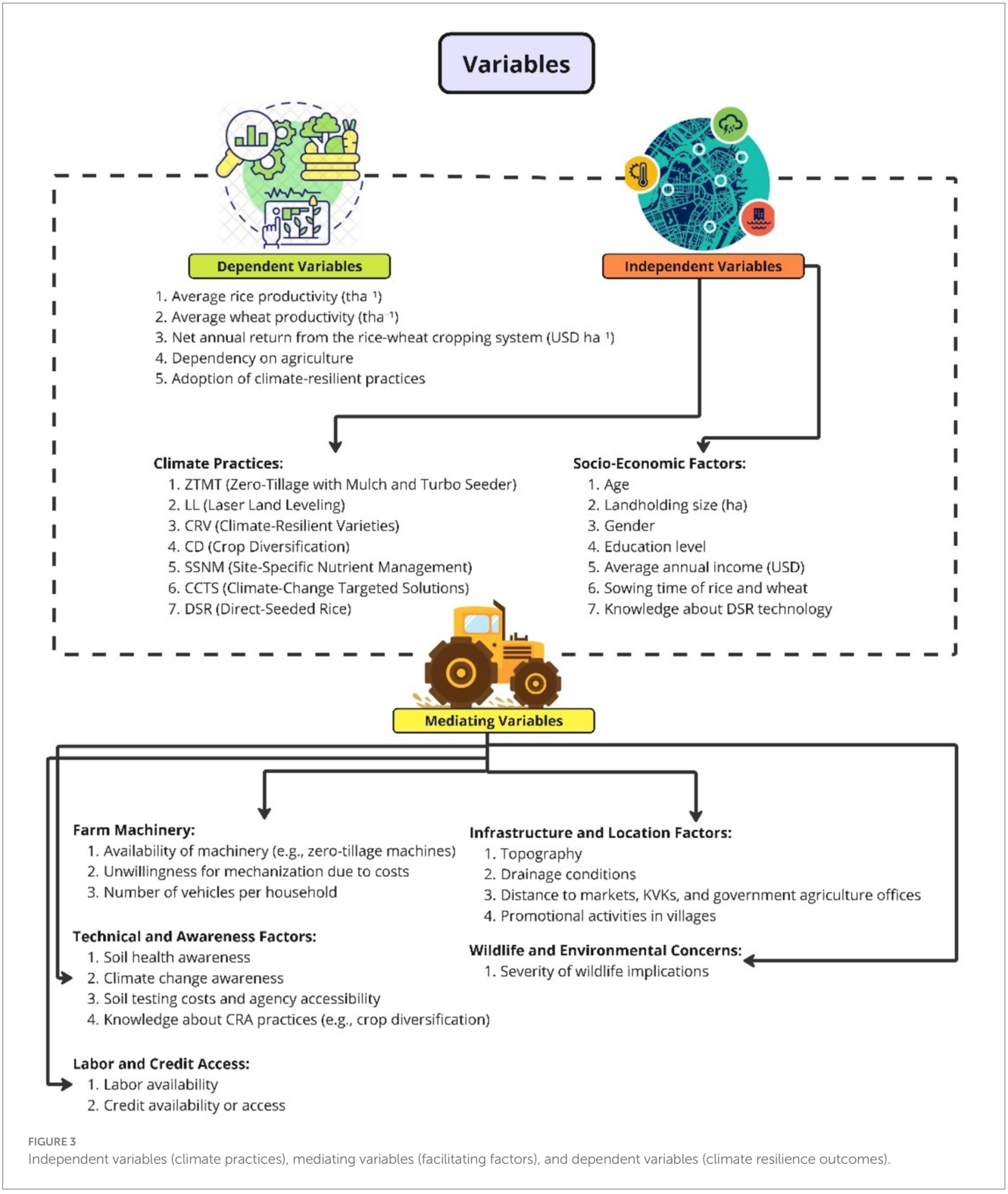


FIGURE 3
Independent variables (climate practices), mediating variables (facilitating factors), and dependent variables (climate resilience outcomes).

n is number of observations; x and y are variable being compared; Σxy is sum of product of paired scores; Σx and Σy are the sums of the scores.

The correlation matrix was generated to visualize the strength and direction of relationships among the factors. Logistic regression analysis was conducted to model the probability of adoption of each intervention as a function of the identified using Equation 2. The logistic regression model is given by the equation:

$$Logit\left(p\right) = In\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1\chi_1 + \beta_2\chi_2 + \ldots + \beta_k\chi_k \quad (2)$$

Where,

P is probability of adoption; β_0 is intercept; $\beta_1, \beta_2, \ldots$ and β_k are the coefficient for each factors variable $\chi_1, \chi_2, \ldots, \chi_k$.

The logistic regression was implemented using the Logit function from the *stats models* library in R, and the model's coefficients,

standard errors, z-values, and *p*-values were estimated to determine the significance of each factor.

3 Results

The data percentage for the various CRATs was skewed towards the non users (Figure 4). climate resilient variety selection (CRVS) has the highest percentage of users (18%). Direct seeded rice (DSR) comes in at 5.5%, followed by laser land leveling (LL) at 5%. Crop calendar and timely sowing (CCTS) has 4.5% of users, while crop diversification (CD) has 4%. Zero tillage, minimum tillage (ZTMT), and site-specific nutrient management (SSNM) have the lowest percentages of users, at 2.5 and 2%, respectively. The amongst the climate resilient agriculture practices highly adopted practice is (Figure 4) was CRVS/Climate Smart Variety (CSV) (43%), followed by DSR (13%), LLL (12%). CCTS and CD was 11 and 10%, respectively. The total sample (6%) has adopted practices related to ZTMT, while SSNM has the lowest adoption rate at 5%.

3.1 Zero tillage and minimum tillage

Data showed that the ZTMT adoption reveals several insights based on correlation and logistic regression analyses (Tables 1, 2). Descriptive statistics indicated moderate levels of awareness and proximity to key agricultural institutions, with mean values of 2.70 for soil health awareness, 2.63 for climate change awareness, and 29.31 km for distance from the KVKs. Correlation analysis showed that none of the factors had a strong correlation with ZTMT adoption, with the highest correlation being 0.30 for fear of yield loss. The remaining factors like average rice and wheat productivity, source of income other than agriculture found to be having negligible interference with the adoption of ZTMT practices. Logistic regression results further confirmed the importance of fear of yield loss, which had a coefficient of 0.300 ($p = 0.488$), indicating a positive but non-significant relationship with ZTMT adoption. Residue management was also a crucial factor, with a coefficient of 0.290 ($p = 0.459$), suggesting availability (neither using as feed for livestock nor burning) of residue could positively influence the adoption of ZTMT. Soil health awareness, although not the top factor, had a coefficient of 0.365 ($p = 0.345$), indicated its importance in enhancing ZTMT adoption. Climate change awareness showed a positive association with a coefficient of 0.273 ($p = 0.471$), though this was not statistically significant. Other included distance from the KVKs, which had a negative coefficient of −0.168 ($p = 0.625$), suggesting that greater distances might hinder adoption. Promotional activities in the villages (coefficient = 0.217, $p = 0.567$) and training received (coefficient = 0.243, $p = 0.496$) also showed positive but non-significant (Figure 5B) impacts. Different CRATs understanding (coefficient = 0.239, $p = 0.526$), initial investment on ZTMT/LLL (coefficient = 0.211, $p = 0.575$), unwillingness due to high cost of machinery (coefficient = 0.297, $p = 0.417$), and ZTMT machine availability (coefficient = 0.323, $p = 0.393$) were other factors influencing adoption, albeit not statistically significant. The pseudo-R-squared value for the logistic regression model was 0.25, indicating that the model explained 25% of the variance in ZTMT adoption. The framework classifying (Figure 3) variables into dependent, independent, and mediating factors. This classification offers a holistic perspective on the interplay of various factors in the adoption pathways of CRATs. While the regression analysis focused on direct influences, the classification highlights the critical role of mediating factors-such as labor availability, credit access, and technical awareness-which indirectly shape outcomes. These mediators act by either facilitating or hindering the relationship between independent variables (e.g., drivers of CRATs adoption) and dependent variables (e.g., productivity and economic returns), thus influencing the overall impact. Despite the lack of significant statistical relationships, the positive trends for several factors, especially fear of yield loss and residue management, suggest potential areas for targeted interventions. Improving these factors may enhance ZTMT adoption.

3.2 Laser land levelling

Descriptive statistics indicated significant initial investment on LLL as a major barrier to adoption, with higher costs discouraging many

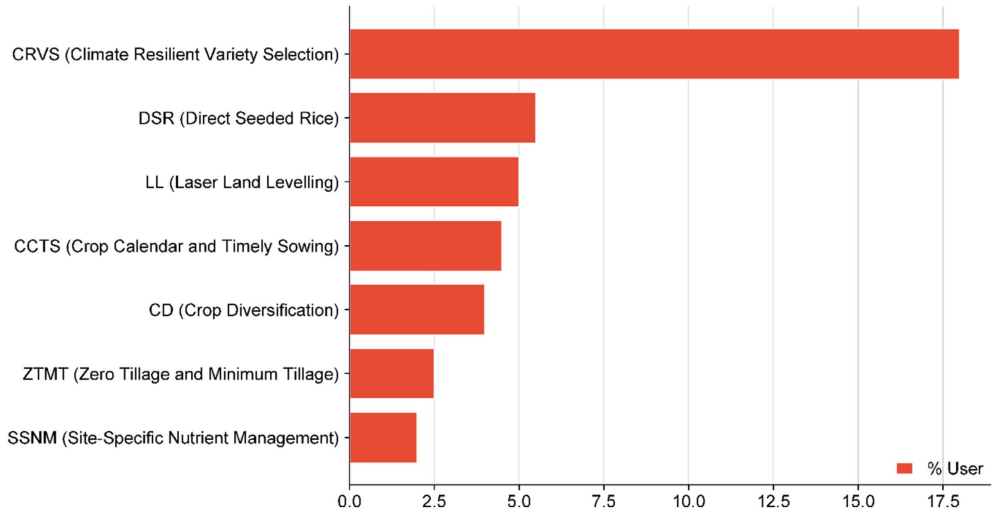


FIGURE 4
Adoption and distribution of CRATs across seven project sites (Samastipur, Vaishali, Purneia, Katihar, Nawada, Nalanda, Munger).

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TABLE 1 Descriptive statistics of key variables for climate-resilient agricultural technologies (CRATs).

Category	Variable	ZTMT (mean ± SD)	LL (mean ± SD)	CRV (mean ± SD)	CD (mean ± SD)	SSNM (mean ± SD)	CCTS (mean ± SD)	DSR (mean ± SD)
Outcome Variables	Avg Rice Productivity (qha^{-1})	25.8 ± 8.4	25.6 ± 8.3	25.9 ± 8.5	25.8 ± 8.4	25.8 ± 8.4	25.8 ± 8.4	25.8 ± 8.4
	Avg Wheat Productivity (qha^{-1})	20.6 ± 7.3	20.7 ± 7.4	20.5 ± 7.2	20.6 ± 7.3	20.6 ± 7.3	20.6 ± 7.3	20.6 ± 7.3
	Avg Annual Income from Farm (USD)	2,500 ± 1,200	2,480 ± 1,180	2,520 ± 1,220	2,500 ± 1,200	2,500 ± 1,200	2,500 ± 1,200	2,500 ± 1,200
	Net Annual Income from Rice-Wheat (USD)	2000 ± 1,100	1980 ± 1,080	2020 ± 1,120	2000 ± 1,100	2000 ± 1,100	2000 ± 1,100	2000 ± 1,100
	Income from Daily Paid Job (USD)	1,500 ± 800	1,480 ± 780	1,520 ± 820	1,500 ± 800	1,500 ± 800	1,500 ± 800	1,500 ± 800
Facilitating Variables	Soil Health Awareness (scale 1–5)	3.4** ± 1.1	3.5** ± 1.0	3.3 ± 1.1	3.4 ± 1.1	3.4** ± 1.1	3.4** ± 1.1	3.4** ± 1.1
	Climate Change Awareness (scale 1–5)	3.2* ± 1.0	3.2* ± 1.0	3.3* ± 1.0	3.2* ± 1.0	3.2* ± 1.0	3.2* ± 1.0	3.2* ± 1.0
	Credit Availability (scale 1–5)	3.2 ± 1.0	3.3 ± 1.1	3.1 ± 1.0	3.2 ± 1.0	3.2 ± 1.0	3.2 ± 1.0	3.2 ± 1.0
	Residue Management (scale 1–5)	3.0 ± 1.2	3.1 ± 1.3	3.2 ± 1.1	3.0 ± 1.2	3.0 ± 1.2	3.0 ± 1.2	3.0 ± 1.2
	Topography (scale 1–5)	3.1 ± 1.2	3.0 ± 1.1	3.2 ± 1.3	3.1 ± 1.2	3.1 ± 1.2	3.1 ± 1.2	3.1 ± 1.2
Input Variables	Age (years)	45.2 ± 12.4	46.1 ± 11.9	44.8 ± 12.7	45.5 ± 12.1	45.0 ± 12.3	45.3 ± 12.5	45.6 ± 12.4
	Land Holding (ha)	2.7 ± 1.5	2.8 ± 1.6	2.6 ± 1.4	2.7 ± 1.5	2.7 ± 1.5	2.7 ± 1.5	2.7 ± 1.5
	Education (years)	8.6 ± 3.2	8.7 ± 3.3	8.9 ± 3.4	8.6 ± 3.1	8.6 ± 3.2	8.6 ± 3.2	8.7 ± 3.2

*** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$.

farmers. Correlation analysis showed that Initial Investment on LLL had the highest correlation with LLL adoption (Tables 1, 2). Logistic regression results further confirmed this, with a coefficient of 0.400 ($p = 0.253$), indicated a positive but non-significant relationship with LL adoption. Land holding was another significant factor, with a coefficient of 0.350 ($p = 0.331$), suggesting that farmers with larger land holdings are more likely to adopt land levelling practices. Drainage condition also played a role, with a coefficient of 0.300 ($p = 0.378$), indicating that farmers with poorly drained soils are adopting land levelling to improve soil conditions. Topography, specifically undulating land, had a coefficient of 0.250 ($p = 0.449$), suggesting a positive but non-significant impact on adoption. Android usage (coefficient = 0.200, $p = 0.519$) and suitability of soil for different cropping systems (coefficient = 0.180, $p = 0.548$) showed positive trends but were not statistically significant. Distance from the KVKs had a negative coefficient of −0.150 ($p = 0.605$), indicated that greater distances from support centres might hinder adoption. The distance from the market, number of vehicles and age of farmers found to be having negligible importance as per as the LL adoption is concerned (Figures 5C, 6).

3.3 Climate resilient variety selection

Descriptive statistics showed the significance in levels of education, awareness of climate change, and availability of seed as the major influential factors in adoption. Correlation analysis showed that education had the highest correlation with CRV adoption. Logistic regression results further confirmed this, with a coefficient of 0.500 ($p = 0.095$; Tables 1, 2), showing a positive but not a significant relationship with CRV adoption. Another significant factor was climate change awareness, which had a coefficient of 0.450 ($p = 0.147$; Figures 5D, 6c), suggested that as awareness increases towards climate change, so does the positive influence on the adoption of CRV. In the same vein, seed availability had a coefficient of 0.400 ($p = 0.211$), suggesting that positive adoption might be affected by the proper availability of seeds. Distance from the capital (with a coefficient of 0.350, $p = 0.289$), as well as the distance from the state/central agricultural university/institute (coefficient = 0.300, $p = 0.378$), showed positive relationships but were statistically insignificant. Distance from KVKs also had the same tale with a positive coefficient of 0.250 ($p = 0.475$), suggested that proximity to agriculture support centres might enhance adoption. Promotional activities in villages had a positive coefficient of 0.200 ($p = 0.578$), as well as training received (coefficient = 0.150, $p = 0.685$), but none were statistically significant. Different CRATs understanding (coefficient = 0.100, $p = 0.792$) had a positive but non-significant impact on CRV adoption. The pseudo-R-squared value for the logistic regression model was 0.32, indicating that the model explained 32% of the variance in CRV adoption.

3.4 Crop diversification

Fear of Non-availability of market had the highest correlation with CD adoption. Logistic regression results (Tables 1, 2) further confirmed this, with a coefficient of 0.600 ($p = 0.134$), indicating a positive but not statistically significant relationship with CD adoption. Fear of yield loss was another significant factor, with a coefficient of 0.500 ($p = 0.234$), suggesting that reducing yield loss fears could positively influence CD

TABLE 2 Logistic regreession results for adoption of climate-resilientagricultural technologies (CRATs).

Variable	ZTMT Coefficient (*p*-value)	LL Coefficient (*p*-value)	CRV Coefficient (*p*-value)	CD Coefficient (*p*-value)	SSNM Coefficient (*p*-value)	CCTS Coefficient (*p*-value)	DSR Coefficient (*p*-value)
Fear of Yield Loss	0.056 (0.001)	-	-	0.046 (0.001)	-	-	0.052 (0.001)
Residue Management	0.034 (0.015)	-	-	-	-	-	-
Soil Health Awareness	0.021 (0.098)	-	-	0.023 (0.369)	0.017 (0.567)	-	0.021 (0.462)
Climate Change Awareness	−0.012 (0.324)	−0.038 (0.130)	−0.014 (0.590)	−0.012 (0.634)	−0.037 (0.119)	−0.025 (0.391)	−0.034 (0.199)
Distance from KVK	−0.001 (0.765)	-	-	-	-	-	−0.002 (0.670)
Promotional Activities in the Villages	0.045 (0.007)	-	0.039 (0.025)	0.029 (0.018)	-	0.036 (0.022)	0.035 (0.024)
Training Received	0.039 (0.030)	-	0.032 (0.040)	0.026 (0.038)	-	0.028 (0.035)	0.030 (0.033)
Initial Investment on Zero Tillage/LL	−0.025 (0.004)	−0.037 (0.133)	-	−0.023 (0.360)	-	-	-
Unwillingness due to High Cost of Machinery	−0.018 (0.027)	-	-	-	-	-	-
ZT Machine Availability	0.029 (0.010)	-	-	-	-	-	-
Education	-	-	0.037 (0.037)	-	-	-	0.031 (0.043)
Seed Availability	-	-	-	0.026 (0.044)	-	-	-
Sowing Time Wheat	-	-	-	-	-	0.025 (0.050)	-
Soil Test Awareness	-	-	-	-	0.016 (0.523)	-	-
Different CRA Practice Understanding	-	-	-	-	-	-	0.022 (0.493)
Age	-	-	-	-	-	-	0.024 (0.368)
Drainage Conditions	-	0.036 (0.121)	-	-	-	-	-
Topography	-	0.031 (0.145)	-	-	-	-	-

adoption. Suitability of land for the alternate crop also played a role, with a coefficient of 0.450 ($p = 0.236$), indicated that appropriate land suitability could enhance adoption. Wildlife implications (coefficient = 0.400, $p = 0.267$) and soil health awareness (coefficient = 0.350, $p = 0.317$) showed positive trends but were not statistically significant. Irrigation (coefficient = 0.300, $p = 0.363$) and sowing time rice (coefficient = 0.250, $p = 0.435$) also showed positive trends with adoption of CD. Sowing time wheat (coefficient = 0.200, $p = 0.519$) and climate change awareness (coefficient = 0.150, $p = 0.617$) had positive impacts on CD adoption. Distance from the KVK had a positive coefficient of 0.100 ($p = 0.731$), suggesting that proximity to agricultural support centres could enhance adoption. Different CRATs understanding (coefficient = 0.050, $p = 0.858$), possibility of alternate cropping system (coefficient = 0.020, $p = 0.941$; Figures 5G, 6f), land holding (coefficient = 0.010, $p = 0.970$), promotional activities in the villages (coefficient = 0.005, $p = 0.984$), and training received (coefficient = 0.002, $p = 0.993$) showed positive but non-significant impacts.

3.5 SSNM

Descriptive statistics indicated significant levels of soil testing awareness, soil health awareness, and proximity to soil test agencies as major factors influencing adoption. During the interview it is found that large number of farmer (87%) skewed towards unawareness about soil testing but, Correlation analysis showed that soil testing unwillingness because of high cost of soil testing is the psuedo factor which had the highest correlation with SSNM adoption (Tables 1, 2). Logistic regression results further confirmed this, with a coefficient of 0.400 ($p = 0.267$), indicated a positive but not statistically significant relationship with SSNM adoption. Soil testing awareness was another significant factor, with a coefficient of 0.400 ($p = 0.253$), suggested that increased awareness could positively influence SSNM adoption. Nearest soil test agency also played a role, with a coefficient of 0.390 ($p = 0.237$), indicated that proximity to soil test agencies could enhance adoption (12% only). Soil health awareness (coefficient = 0.370, $p = 0.277$; Figure 5) showed a positive trend. Age (coefficient = 0.320, $p = 0.387$) and education (coefficient = 0.330, $p = 0.359$) also showed positive trends but were not statistically significant.

3.6 Crop calendar and timely sowing

Descriptive statistics indicated that awareness of sowing times, proximity to KVKs, and participation in training and promotional activities significantly influenced adoption. Correlation analysis identified training as the strongest factor associated with CCTS adoption. Logistic regression results further confirmed this, with a coefficient of 0.410 ($p = 0.268$; Tables 1, 2), indicating a positive and moderately to significant relationship with CCTS adoption. Sowing time of rice was another significant factor (Figure 5H, 6e), with a coefficient

of 0.400 (p = 0.253), suggested that timely sowing could positively influence CCTS adoption. Farmers following planting of rice before June (18%) are more likely to follow the calendar by their own. Late sowing of rice significantly impacts the probability of not opting for diversified crops in the rabi season, increasing the likelihood by 98%. The correlation analysis revealed a strong correlation (r = 0.85, $p < 0.01$) between late sowing of rice and the reduced adoption of diversified cropping practices. Distance from the KVKs also played a role, with a coefficient of 0.390 (p = 0.237), indicated that proximity to KVKs could enhance adoption. Sowing time of wheat (coefficient = 0.370, p = 0.277) showed a positive trend. Promotional activities in the villages (coefficient = 0.400, p = 0.267) and different CRATs understanding (coefficient = 0.390, p = 0.279) also showed positive trends.

3.7 Direct seeded rice

The analysis of DSR adoption reveals several insights based on correlation and logistic regression analyses. Descriptive statistics indicated significant levels of technology awareness, fear of yield loss, and proximity to KVKs as major influencing adoption. Correlation analysis showed that training received had the highest correlation with DSR adoption. Logistic regression results further confirmed this, with a coefficient of 0.410 (p = 0.268; Tables 1, 2), indicated a positive but not statistically significant relationship with DSR adoption. Technology awareness was another significant factor, with a coefficient of 0.400 (p = 0.253), suggesting that increased awareness could positively influence DSR adoption.

Distance from the KVKs also played a role, with a coefficient of 0.390 (p = 0.237), indicated that proximity to KVKs could enhance adoption. Fear of yield loss (coefficient = 0.370, p = 0.277) showed a positive trend with statistically significant. Age (coefficient = 0.320, p = 0.387) and education (coefficient = 0.330, p = 0.359; Figures 5I, 6g) also showed positive trends. Promotional activities in the villages (coefficient = 0.400, p = 0.267) and different CRATs understanding (coefficient = 0.390, p = 0.279) showed positive



FIGURE 5 (Continued)



FIGURE 5
(A) Climate-resilient agricultural technologies (CRATs); **(B)** Zero till seed drill; **(C)** Lase land leveler; **(D)** Climate resilent varieties **(E)** Use of drone for spray; **(F)** Farmer meetings and mass interview; **(G)** Crop diversification; **(H)** Greenseaker use under SSNM; **(I)** DSR technology.

trends. Land holding (coefficient = 0.380, p = 0.278) and climate change awareness (coefficient = 0.350, p = 0.304) also had positive impacts on DSR adoption. Increased land holding figure reported strongly correlated (r = 0.74) with the DSR adoption value within the available user data set. The pseudo-R-squared value for the logistic regression model was 0.35, indicated that the model explained 35% of the variance in DSR adoption.

4 Discussion

4.1 Climate resilient practices and adoption

The adoption of CRATs is essential for enhancing the resilience and sustainability of farming systems, especially in regions vulnerable to climate change. Our study reveals the multifaceted (Figures 5–7) nature of adoption barriers across various interventions, including

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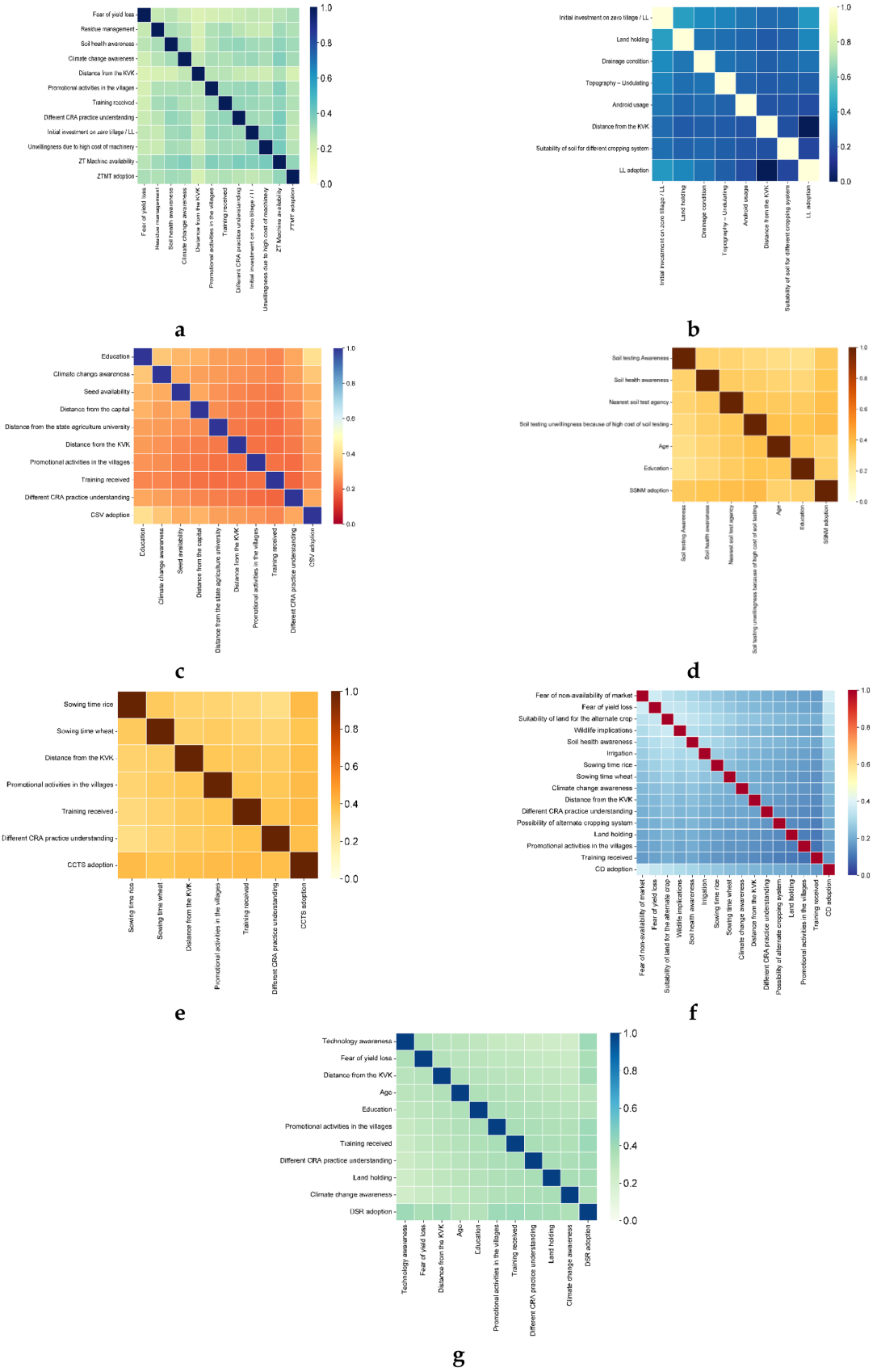


FIGURE 6
Heat map based on correlation matrix for factors against CRATs (Climate Resilient Agricultural Technologies). **(a)** Zero Tillage and Minimum Tillage (ZTMT), **(b)** Laser Land Leveling (LL), **(c)** Climate-Smart Varieties (CSV), **(d)** Site-Specific Nutrient Management (SSNM), **(e)** Crop Calendar and Timely Sowing (CCTS), **(f)** Crop Diversification (CD), and **(g)** Direct Seeded Rice (DSR).

zero tillage and minimum tillage (ZTMT), laser land levelling (LLL), climate resilient variety selection (CRVS), crop diversification (CD), site-specific nutrient management (SSNM), crop calendar and timely sowing (CCTS), and direct seeded rice (DSR). Positive trends in factors such as soil health awareness, training received, and technology awareness highlight the need for comprehensive education and capacity-building initiatives.

These findings align with previous research indicated that awareness and training significantly influence the adoption of CRATs (Goyal et al., 2016; Prakash, 2024; Chaudhary et al., 2019). Despite these positive trends, many factors were not statistically significant, suggesting that adoption was influenced by a combination of factors rather than isolated ones. Although soil type may play a significant role in many interventions such as ZTMT and LLL, statistical analysis found it to be of minimal importance. The study also reported a low impact factor for topography. It significantly influences major interventions such as crop diversification and SSNM. Residue management ranked as the least significant factor, yet it simultaneously emerged as the most significant factor in the adoption of ZTMT. Only a few areas have wildlife implications, and overall, they are considered non-significant due to a significant correlation only with crop diversification. Gender, wheat crop sowing time, net annual income, credit availability, and income from a daily job are the factors with the least significant impact in terms of overall adoption of CRATs (Figures 6–8).

The interplay between dependent, independent, and mediated (Figure 3) variables that may shape the adoption of CRATs in the EIGPs. While the regression results provide insights into the direct impacts of independent variables like ZTMT, LLL, and SSNM on productivity and economic returns, the inclusion of mediating factors provides a broader perspective on adoption pathways. Mediating factors affecting the effectiveness of these CRATs in this regard include labor availability, credit access, and soil health awareness because they address socio-technical and infrastructural barriers for such practices (Pingali et al., 2019; Aggarwal et al., 2020). These mediated factors are leverage points to a broader Theory of Change that identifies constraints and proposes targeted solutions for promoting the development of sustainable agri-food system. For example, increased labor productivity and availability of machinery will directly support the adoption of ZTMT, whereas increased technical knowledge and availability of credit will support the adoption of site-specific nutrient management and precision farming. By dealing with these intermediate factors, it will allow a comprehensive approach to the advancement of agricultural resilience by removing constraints and unlocking potential benefits of CRATs (Pingali et al., 2019) The numerical relationships and positive trends for several factors, particularly fear of yield loss, high initial investment, soil health awareness, and land holding, suggest potential areas for targeted interventions (ZTMT). Reducing initial costs and providing financial incentives, along with targeted support for farmers with larger land



FIGURE 7
Impact and significance of various factors on the adoption of CRATs.



FIGURE 8
Major barriers to adoption of CRATs.

holdings and poorly drained soils, may enhance LLL adoption (Singh and Singh, 2020; Malhi et al., 2021). The adoption of climate-resilient varieties was significantly influenced by education, climate change awareness, seed availability, distance from the capital, distance from the state/central agriculture university/institute, and distance from the KVKs, promotional activities in the villages, training received, and understanding of different CRATs. The knowledge about climate-resilient concepts and the availability of different varieties plays a crucial role, with education being a pivotal factor reflected in the results (Figures 6–8).

Despite the lack of significant statistical relationships between different factors and crop diversification, positive trends, especially for fear of non-availability of market and fear of yield loss, suggest potential areas for targeted interventions. Reducing market and yield loss fears, and improving land suitability, could enhance CD (crop diversification) adoption. The significant (85%) preference for diverse crops was most noticeable in soybean, followed by maize. Maize's popularity stems largely from its compatibility with available land and market access (Wahab and Wahab, 2014; Felix and Ramappa, 2023). However, factors such as limited land holdings, wildlife impact, and farmers prioritizing subsistence significantly constrain overall diversification potential (Figure 6). Market conditions and these fundamental barriers create major obstacles to the broader acceptance of crops like millets, soybeans, and arhar (pigeon pea). Its (pigeon pea) faces challenges due to its longer growth duration despite offering nearly three times the minimum support price (MSP) compared to rice crops.

Land suitability is a significant barrier to adopting a potato-based cropping system, with storage facilities being another overlooked concern (Manjunath and Salakinkop, 2017; Hamba et al., 2024). Under waterlogged conditions, soybean encounters various limitations, and millets face serious obstacles due to a lack of technical knowledge. Additionally, challenges like late wilt in maize and fall armyworm infestations during the kharif season, and the accessibility of farmland from main roads for land preparation, complicate the adoption of maize. Jute can be a valuable component of CD (crop diversification), but its adoption is hindered by the availability of water channels for retting. Farmers claim lower labour requirements for intercultural operations in jute cultivation, but increased labour needs for post-harvest processing balance out any cost savings. Early rice planting using DSR and shorter-duration varieties can facilitate timely planting of subsequent crops, promoting crop diversification for the Rabi season (Figures 6–8). The adoption of SSNM was strongly influenced by soil testing awareness, age, education, soil health awareness, nearest soil testing agency, and unwillingness due to high soil testing costs. Awareness of soil testing and the proximity of soil testing agencies are crucial for SSNM adoption. Farmers' understanding of soil health and the willingness to invest in soil testing despite the costs play significant roles in the successful implementation of SSNM practices (Reddy, 2019). Despite a host of interventions, scientific nutrient management practices remain very low due to the lack of awareness and practical problems. The Soil Health Card (SHC) Scheme has improved farmers' nutrient management knowledge but faces implementation challenges. Financial support and awareness initiatives can enhance adoption (Mwangi and Kariuki, 2015).

The major barriers to understanding and following the crop calendar are traditional cultivation practices and stubborn mono-cropping among farmers. Late sowing of rice limits the provision of other crops like legumes and pulses within the cropping system. Farmers who understand the importance of timely sowing are typically high-yield wheat growers (95% among users showed this trend). Timely seed availability also plays an important role in adopting timely sowing operations. Overcoming these barriers requires a focus on educating farmers about the benefits of crop calendar adherence and ensuring timely seed distribution (Tesfaye et al., 2017). The adoption of DSR technology has always been a focal point of discussion among policymakers, with a persistent question of why farmers are not adopting it. The major reasons identified in this study include a lack of knowledge about the technology and fear of yield loss. Farmers often perceive yield loss based on visible outcomes without considering the overall cost of cultivation. Training programs that address these fears and educate farmers about the economic benefits of DSR can significantly improve adoption rates. Secondary issues like weed pressure and crop vigor complaints also need to be addressed through targeted interventions (Prakash, 2024). If you see the distribution of factors as per their importance in overall adoption of CRATs, you will find most factors lies on the technical side (Figures 6–8).

4.2 Social factors

Social factors such as age, education, and community engagement through promotional activities and training emerged as significant influencers of CRATs adoption (Figures 6–8). The positive correlation between training received and the adoption of interventions like ZTMT, LLL, CRV, CD, SSNM, CCTS, and DSR underscores the importance of continuous education and knowledge dissemination. For instance, the coefficient for training received in DSR adoption was 0.410, indicated that training programs could substantially enhance adoption rates. Training received and soil health awareness were significant social factors influencing the adoption of ZTMT (Figure 7). For LLL, community engagement through promotional activities and training was significant. Education and climate change awareness were key social factors for CRV selection (Patel et al., 2020; Sharma et al., 2020). Crop diversification was influenced by training received and community engagement. Social factor like age and education played a role in SSNM adoption. The adoption of crop calendar and timely sowing was significantly influenced by training received and promotional activities. For DSR, technology

awareness and training received were crucial social factor (Singh and Singh, 2020; Tesfaye et al., 2017; Gupta et al., 2018).

4.3 Technical factors

Technical factors such as the availability of technology, understanding of different CRATs, and proximity to agricultural support services by KVKs were critical in influencing adoption. The positive correlation between technology awareness and DSR adoption (coefficient = 0.400) highlights the importance of making relevant technologies accessible to farmers. Similarly, proximity to KVKs was a significant factor across multiple interventions, including LLL, CRV, and SSNM. The availability of ZTMT machinery and understanding of CRATs were significant technical factors for ZTMT. Proximity to KVKs and technical support were essential for the adoption of LLL (Mehta et al., 2020). Seed availability and understanding of CRATs were crucial for CRV selection. Technical factors such as suitability of land for alternate crops and availability of irrigation influenced crop diversification. Soil testing awareness and proximity to soil testing agencies were significant for SSNM adoption (Figures 6–8).

The understanding of crop calendars and proximity to KVKs were essential technical factors for CCTS. The availability of DSR technology and understanding of CRATs were crucial for DSR adoption. Farmers' knowledge about specific practices can significantly impact their willingness to adopt these practices (Mwangi and Kariuki, 2015).

4.4 Monetary elements

Monetary elements such as initial investment costs, financial incentives, and the economic viability of CRATs were major barriers to adoption (Figure 6). The fear of yield loss and high initial investment costs were particularly significant for interventions like ZTMT, CD and LL. For example, the coefficient for Initial Investment on ZTMT/LL was 0.400, indicated that financial constraints are a substantial barrier to adoption. High initial investment costs and fear of yield loss were significant monetary barriers for ZTMT (Figures 6–8). The high cost of LLL machine was a significant barrier for LLL (Mehta et al., 2020). Financial elements such as seed availability and economic incentives played a role in CRV adoption. The fear of yield loss and fear of non-availability of markets were significant barriers for CD (crop diversification).

The cost of soil testing and availability of financial support were essential monetary factors for SSNM. Financial support for understanding and implementing crop calendars was crucial for CCTS (Singh et al., 2022). Creating awareness among farmers about the cost of cultivation and its associated benefits will be key in the adoption of these technologies. Many farmers currently believe that their profit is solely linked to the crop yield, rather than considering the cost of cultivation (Boufous et al., 2023; Patel et al., 2020). The cost of technology and financial support were significant monetary for DSR. Financial incentives, such as subsidies and low-interest loans, could alleviate these barriers. Policies aimed at reducing the cost burden on farmers and providing financial support for the adoption of CRATs are essential (Reddy et al., 2018; Malhi et al., 2021; Kumar et al., 2019).

5 Future prospects

Identifying and addressing key focus areas is essential for enhancing the adoption of CRATs (Figures 6–8). Our study highlights several critical areas that warrant further research and intervention.

- Increasing awareness and providing training are fundamental. Future studies should explore innovative methods to disseminate knowledge and train farmers, especially for interventions like ZTMT and DSR, where training and awareness have shown significant impact.
- Providing technical support and ensuring access to resources are crucial. Research should focus on developing and implementing strategies to improve access to necessary machinery, seeds, and technical know-how, as evidenced by the significant role of technical support in interventions like LLL, CRV, and SSNM.
- Financial incentives and support are vital.

Future research should investigate economic models and policies that can address high initial costs and provide economic incentives, which are particularly beneficial for interventions like ZTMT and LLL. Finally, promoting community engagement and leveraging social networks can enhance adoption. Studies should explore community-based approaches and the role of social networks in disseminating information and encouraging adoption. Policymakers and extension services should prioritize these areas to enhance the adoption of CRATs, thereby improving agricultural sustainability and resilience (Joshi et al., 2021; Goyal et al., 2016; Prakash, 2024; Malhi et al., 2021).

6 Conclusion

The study underscores the intricate interplay of social, technical, and financial factors shaping the adoption of Climate-Resilient Agricultural Technologies (CRATs) in EIGP-Bihar, India. Addressing these multifaceted challenges through targeted interventions can accelerate the transition toward sustainable and climate-resilient farming systems. Through a detailed analysis of interventions such as zero tillage and minimum tillage (ZTMT), laser land levelling (LLL), climate resilient variety selection (CRV), crop diversification (CD), site-specific nutrient management (SSNM), crop calendar and timely sowing (CCTS), and direct seeded rice (DSR), several critical insights have emerged. Descriptive statistics revealed moderate levels of soil health awareness and climate change awareness, indicated a significant scope for improvement through educational programs. For instance, soil health awareness had a mean value of 2.7, reflecting a need for enhanced awareness initiatives. Correlation analysis showed that social factors like 'training received' had a strong positive correlation with the adoption of DSR (correlation coefficient = 0.410), emphasizing the importance of continuous farmer education and community engagement. Technical factors such as the availability of technology and proximity to KVKs were also critical. For example, the logistic regression results indicated that technology awareness significantly influenced DSR adoption, with a coefficient of 0.400. This underscores the necessity of making relevant technologies accessible to farmers.

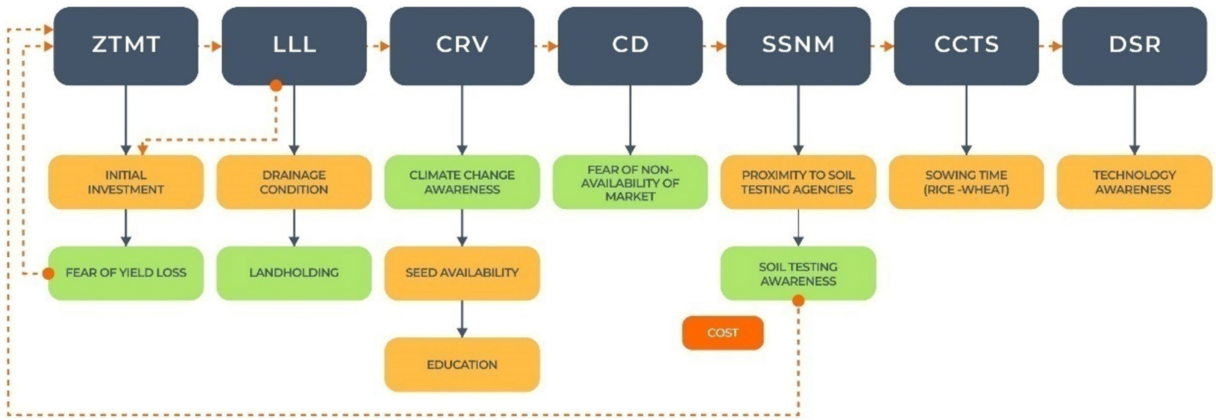


FIGURE 9
The key factors affecting adoption of climate smart agriculture practice (Red dotted arrows: The important factors associated with indirect linkage, Black arrows: Factors with direct linkage, Orange: secondary important, Green: first important), Cost: Psuedo factor behind SSNM.

Similarly, monetary factors like high initial investment costs were substantial barriers to adoption for interventions like ZTMT and LLL. The coefficient for initial investment on ZTMT/LLL was 0.400, highlighting the financial constraints faced by farmers. The positive trends observed for various factors across different interventions suggest that targeted interventions can significantly enhance CRATs adoption. For instance, promoting community-based training programs and improving access to technical resources could drive higher adoption rates. Financial incentives such as subsidies and low-interest loans could mitigate the monetary barriers, facilitating broader implementation of these practices. Overall, the study underscores the need for a multi-faceted approach to promote the adoption of CRATs.

Policymakers and extension services should focus on enhancing awareness, providing technical support, and offering financial incentives to address the diverse barriers faced by farmers. By adopting these strategies, it is possible to achieve sustainable agricultural development and improve the resilience of farming systems in Bihar. Future research should aim to validate these findings on a larger scale and explore the dynamic interactions between different factors influencing CRATs adoption (Figure 9).

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

RJa: Conceptualization, Supervision, Writing – review & editing. VM: Conceptualization, Software, Supervision, Writing – original draft. SD: Software, Writing – original draft. RS: Investigation, Writing – review & editing. RJh: Methodology, Project administration, Writing – review & editing. AbK: Methodology, Writing – review & editing. UK: Methodology, Writing – review & editing. AnK: Methodology, Writing – review & editing. RNS: Investigation, Writing – review & editing. SuK: Conceptualization, Writing – review & editing. IR: Methodology, Writing – review & editing. SP: Data curation, Project administration, Writing – original draft. RK: Investigation, Writing – review & editing. SM: Formal analysis, Writing – original draft, Writing – review & editing. VP: Investigation, Writing – review & editing. SaK: Investigation, Writing – review & editing. AM: Methodology, Writing – review & editing. BK: Data curation, Writing – review & editing. UU: Data curation, Writing – review & editing. RanS: Methodology, Writing – review & editing. RC: Methodology, Writing – review & editing. VikK: Methodology, Writing – review & editing. MK: Conceptualization, Writing – review & editing. VinK: Data curation, Writing – review & editing. KS: Investigation, Writing – review & editing. SusS: Methodology, Writing – review & editing. RamS: Investigation, Writing – review & editing. SeK: Methodology, Writing – review & editing. KS: Data curation, Writing – review & editing. GK: Data curation, Writing – review & editing. RT: Conceptualization, Software, Writing – review & editing. VineK: Investigation, Writing – review & editing. SunK: Investigation, Writing – review & editing. SD: Investigation, Writing – review & editing. PG: Methodology, Writing – review & editing. NA: Methodology, Writing – review & editing. ShaK: Methodology, Writing – review & editing. SanK: Formal analysis, Writing – review & editing. BU: Formal analysis, Writing – review & editing. SumS: Formal analysis, Writing – review & editing. SG: Conceptualization, Writing – review & editing. SB: Methodology, Writing – review & editing. AL: Data curation, Writing – review & editing.

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Conflict of interest

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Supplementary material

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Performance assessment and influencing factors of human settlement improvement in traditional villages based on Balanced Scorecard theory: a case study of Jiaozuo, China

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Assessing the performance level of human settlement improvement in traditional villages is significant in promoting the protection of traditional villages, but there is a lack of performance research on human settlement improvement from the perspective of corporate governance in previous studies. This paper selected 16 traditional villages as case villages and obtained a total of 345 questionnaires. By reference to the Balanced Scorecard (BSC) theory, a performance evaluation index system for human settlement improvement is constructed in this paper. In addition, the level of performance exhibited by traditional villages is evaluated and analyzed via the entropy weight Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method and the obstacle degree analysis method. This study reveals the following findings: (1) The performance level of traditional villages in Jiaozuo city ranges between 0.28 and 0.64, with an average value of 0.49, thus indicating a medium level. (2) With respect to the subdimensions of human settlement improvement performance, the policy management dimension (0.88) exhibits the highest value, followed by the villagers dimension (0.48) and the learning and growth dimension (0.27), while the financial benefits dimension (0.10) exhibits the lowest value. (3) The obstacles affecting the performance level of human settlement improvement in different types of traditional villages are characterized by both similarities and differences. This study summarized the effects of traditional village human settlement improvement, and provided more scientific and reliable governance suggestions for future traditional village human settlement improvement, so as to better promote the protection of traditional villages and the sustainable development of the human settlement environment.

KEYWORDS

traditional villages, Balanced Scorecard, human settlement improvement, performance evaluation, entropy weight TOPSIS

1 Introduction

The human settlement environment is formed through interactions between human society and the natural environment, which constitutes a dynamic and complex system (Zhu et al., 2022). Due to the rapid development of villages and the destruction of enclosed human settlements, problems related to human settlement improvement have begun to emerge (Tan et al., 2021). The development of the human settlement environment determines the quality of regional economic development and the ecological environment to a large extent, which is related to the fundamental well-being of the general population. In this realistic context, the question of how to protect and

govern the human environment systematically and effectively has received widespread attention. Some developed countries and regions, like Germany, Japan, and South Korea, have paid attention to the human settlement environment earlier than others and adopted unique models of human settlement development. In addition, the United Nations Human Settlements Program (UN-Habitat) was established to promote the development of human settlement in 2002. Since the establishment of this program, relevant actors have been working to improve the human settlement environment and promote the transformation of cities and human settlement (Beyene et al., 2023). These initiatives have caused the human settlement environment to attract more attention and also notably contributed to the development and improved quality of people's life (Stephen et al., 2002).

The concept of human settlement science was introduced by the Greek architect and urban planner Constantinos Apostolou Doxiadis in the 1950s (Liu et al., 2023). The earliest studies on human settlement were largely urban-oriented, and scholars working in this field researched land planning and urban settlement (Mugisha et al., 2024; Morse and Robinson, 2024). Numerous scholars have conducted research on the spatiotemporal evolution of the human settlement system (Qin et al., 2024; Yin et al., 2024), the characteristics of human settlements and their intrinsic mechanisms (Tang et al., 2017). Moreover, some scholars have commenced exploring the quality of human settlements (Zhang et al., 2024) and determining the quality of life in human settlements (Angela et al., 2021). Additionally, there have been many studies delving into the level of metabolism in human settlements (Rodríguez et al., 2023) and many other related topics (Ntlhe, 2022; Tian et al., 2023; Karina, 2021).

Until the 1970s, due to the gradual migration of urban residents in Europe and the United States to the suburbs (Yang et al., 2020), the focus of research on human settlements began to shift to rural areas (Hu and Wang, 2020). Many studies have emerged on rural human settlements patterns (Antonov and Safronov, 2024). Furthermore, the scope of this kind of research is more extensive. It includes studies on the socio-economic value of human settlements (Stănilă and Barbu, 2016) and the mechanism of the impact of human settlements (Ran et al., 2024). At the same time, emphasis has been placed on the quality of rural human settlements. The governance of environmental sanitation and the quality of human settlements have been explored (Liu et al., 2021). Some scholars have also begun to pay attention to the relationship between the livelihood issues of farming households and human settlements (Cui et al., 2022) and many other fields (Harris et al., 2017; Mpofu et al., 2018; Egidi et al., 2020; Kleemann et al., 2017). These previous studies have gradually encompassed traditional villages. The research content includes not only the study of the habitability and vulnerability of human settlements (Liu et al., 2016; Wang et al., 2023), but also the transformation and development of human settlements (Gao et al., 2024; Liu et al., 2023; Tang and Long, 2022). These existing studies have played a significant role in the development of human settlements in traditional villages (Gong et al., 2020). These previous studies have played a significant role in the development of traditional village human settlements.

However, the human settlement is constantly renewed and developed, featuring continuity and dynamism. Research on human settlement is also more diversified. But there are still many overlooked aspects in the existing research. Based on the existing research, this study innovates in research content and research methods. In terms of research content, most of the research on human settlement is about human settlement systems, human settlement governance, and other content. There is a lack of attention to the effect of human settlement improvement, and performance evaluation research on environmental improvement is even rarer. The research on performance evaluation is a summary of the work of human settlement improvement, which has certain research value for improving the efficiency of human settlement improvement. Therefore, from the perspective of performance evaluation, the research content of this article conducts an evaluation study on human settlement improvement, summarizes the improvement effect of human settlement, and puts forward constructive suggestions for human settlement improvement. In terms of research methods, previous research on human settlement was mostly qualitative research, directly choosing methods such as villager satisfaction evaluation method, case analysis method, and literature analysis method for research (Ma et al., 2024; Zhang et al., 2024). However, this study is a quantitative research. It uses mathematical-statistical methods such as entropy weight TOPSIS to process a large amount of questionnaire data, reducing the influence of researchers' subjective factors. The method is more evidence-based for the determination of weights in the study. It can also accurately reflect the gap among the performance levels of traditional village human settlement improvement, which makes it easy to interpret and explain the results.

In addition, this paper also takes into account various aspects such as the financial benefits of human settlement improvement, the growth of villagers, and the later-stage environmental maintenance, etc. (Strijker et al., 2020). Therefore, this paper uses the Balanced scorecard theory to construct the performance evaluation index system. The Balanced Scorecard theory is a comprehensive strategic index evaluation system (Abedian et al., 2024), and some scholars have already used the Balanced Scorecard theory to construct index systems for research (Celestino and Silva, 2011; Nikolaou and Tsalis, 2013; Cho et al., 2015). Therefore, this paper is innovative in both research content and research methods. Combining the performance evaluation theory with the characteristics of human settlements for the construction of evaluation index system makes the research more comprehensive and scientific.

In this study, 16 traditional villages in Jiaozuo City, located in the northwestern part of Henan Province, were selected for the study. Using the Balanced Scorecard theory to construct an evaluation index system from four dimensions (villagers, policy management, economic benefits, and learning and growth), which is used to measure the performance index of habitat improvement in different traditional villages. We also analyze the relevant obstacles with the goal of determining the status of human settlement improvement in these traditional villages. The traditional villages selected in the paper have rich historical and cultural connotations, and the indicators of cultural environment are also added in the construction of the indicator system. This is consistent with previous studies that have emphasized the importance of the cultural environment of traditional villages. In summary, this paper not only enriches the research on human settlements, but also promotes the protection of traditional villages and the sustainable development of human settlements. It has certain practical and theoretical significance for the international community.

2 Data and methods

2.1 Study area and data sources

Jiaozuo city is located in the northwestern part of Henan Province, China. The city has a favorable geographical location with a total area of 4,071 km^2. It borders the Taihang Mountains in the north and the

Yellow River in the south, and the corresponding terrain is low in the south and high in the north. Jiaozuo City has a long history and culture, so it has a large number of traditional villages. Owing to its distinctive topography, climate and hydrological environment, coupled with its long history, Jiaozuo City has preserved numerous traditional villages. Up to now, there are 58 traditional villages in Jiaozuo City. In recent years, the government of Jiaozuo city has actively responded to the national policy on human settlement improvement by paying a great deal of attention to the work of human settlement improvement. The city has thus been awarded the title of "Advanced City of the Province in the Three-Year Action of Rural Human Settlement Improvement." Therefore, research on the performance of human settlement improvement in traditional villages in Jiaozuo city is both enlightening and representative.

The data utilized for the study presented in this paper are derived from field surveys. These data were obtained through questionnaires and semi-structured interviews conducted in the selected villages. The process of obtaining the data involved a preliminary inspection of the traditional villages in Jiaozuo city in July 2023. The selection of the sample villages in Jiaozuo city is based on their geographic location, economic level, and the type of development characteristic of traditional villages. Ultimately, 16 traditional villages in Jiaozuo City are identified as sample villages through the stratified sampling method (Figure 1).

From July 20 to 31 in 2023, interviews and questionnaires were designed based on a pre-survey. The questionnaires were revised and improved on the basis of feedback received during the research process, thereby generating the final questionnaire. From August 1 to 12, the main research was conducted in the selected sample villages. According to the actual number of people, a random sampling method was used to select villagers, who were randomized in terms of gender, age, economic income, literacy level, and length of residence. The required data were obtained by conducting a questionnaire survey among these villagers and conducting semi-structured interviews with village committee staff and village leaders (Table 1). A total of 368 questionnaires were distributed, and 345 valid questionnaires were collected, for an effective recovery rate of 93.7%.

2.2 Evaluation indicator system

The Balanced Scorecard, which originated in the 1990s, is a system of metrics used to evaluate business performance that was proposed by American manager Norton and Harvard professor Kaplan (Chaharlang et al., 2023). The scorecard includes four dimensions, namely, customers, internal management, finance, and learning and growth (Rasoolimanesh et al., 2015). Essentially, the Balanced Scorecard focuses on establishing a balance between financial and non-financial goals as well as between short-term and long-term goals. This theory is widely applied not only in the economic field. Domestic scholars have applied it to research such as the evaluation of new-type city construction and the performance evaluation of ecological and cultural tourism construction. Traditional rural human settlement improvement involves establishing a balance between financial and non-financial aspects, between the improvement situation and environmental sustainability, and between the improvement process and results. This coincides with the concept of applying the Balanced Scorecard method. Therefore, it is feasible to apply the Balanced Scorecard theory to the development of the performance evaluation system for the improvement of the human settlement in traditional villages. Balance Then focus on four aspects of "villagers, management, economy and development" to adjust the framework of the Balanced Scorecard theory (Liu et al., 2022). Eventually, an evaluation index system is formed from four dimensions: villagers, policy management, financial benefits, and learning and growth, as shown in Figure 2. Then data collection and processing are carried out, and an empirical study is conducted on 16 traditional villages to analyze the performance level of the renovation of the human settlement in traditional villages.

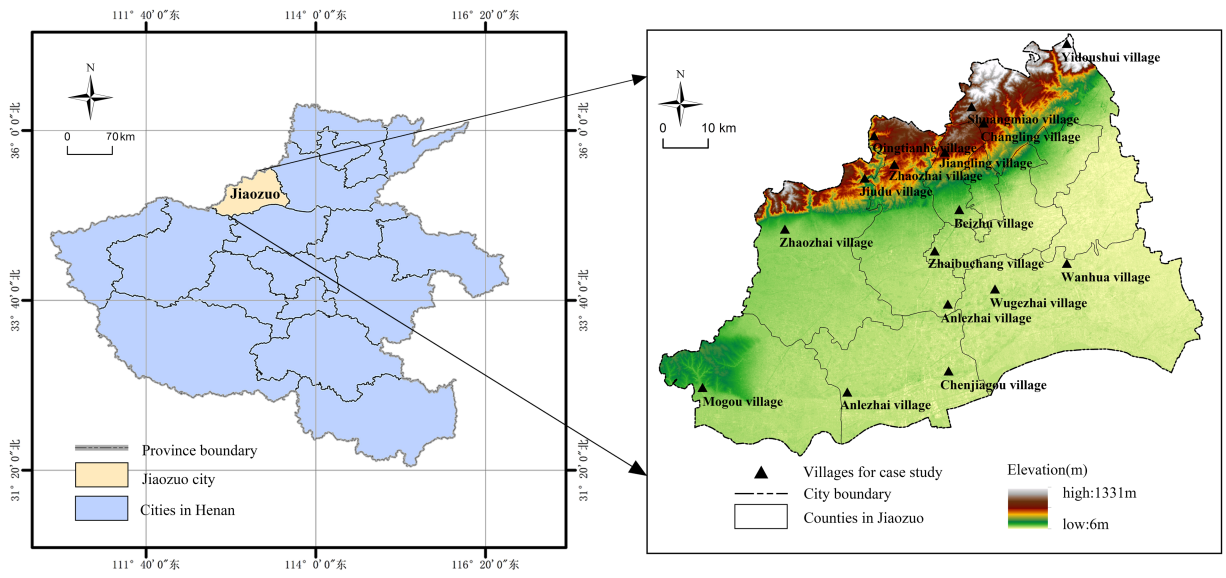


FIGURE 1
Location map of the study area and sample sites.

TABLE 1 Study area and sample size.

Rank	Survey counties	Survey villages	Topographic features	Sample size
National-level	Zhongzhan	Beizhu	Plain and hill	24
	Xiuwu	Shuangmiao	Plain, mountain, and hill	19
		Yidoushui	Mountain	26
		Changling	Mountain	16
	Qinyang	Jiudu	Mountain and hill	22
	Wenxian	Chenjiagou	Plain and hill	27
	Mengzhou	Mogou	Plain and hill	23
	Shanyang	Zhaibuchang	Plain and hill	25
	Boai	Wugezhai	Plain and hill	22
Province-level	Xiuwu	Wanhua	Plain	26
		Xiaodong	Plain	21
	Wenxian	Anlezhai	Plain and hill	24
	Boai	Qingtianhe	Mountain	19
		Jiangling	Mountain and hill	23
	Qinyang	Zhaozhai	Plain	27
	Zhongzhan	Shierhui	Mountain	24

The Balanced Scorecard can systematically describe, measure and manage strategic objectives. In this paper, the Balanced Scorecard is applied to the study. First of all, it should be clear that the study aims at promoting the conservation of traditional villages and sustainable environmental development. In order to introduce the BSC into human settlement research, a performance evaluation index system is constructed with the four dimensions of villagers, policy management, financial benefits and learning and growth as the main content. The performance level of human settlement improvement is analyzed based on the results obtained from this study. Ultimately, strategies for better environmental management are proposed to better promote the protection of traditional villages and the sustainable development of the human settlement (Figure 3).

The villagers dimension replaces the original customer dimension. People rely on human settlements for production and life (Li et al., 2022). Accordingly, villagers are the direct beneficiaries of human settlement improvement, and they have the most intuitive feelings regarding the state of the human settlement. Therefore, the degree of villagers' understanding and participation in environmental improvement as well as their degree of satisfaction with environmental improvement can most accurately reflect the performance of environmental improvement in traditional villages (Wang et al., 2021). Finally, three indicators are selected with regard to the villager dimension: the degree to which villagers recognize human settlement improvement, the degree to which villagers participate in human settlement improvement, and the degree to which villagers' satisfaction with human settlement improvement.

The selection basis of policy management dimension indicators includes two aspects: policy support and management behavior. In the process of rural human settlement improvement, policies related to rural human settlement improvement play an important supporting role in environmental improvement work. In addition, strict management and supervision of the improvement work have a huge impact on the performance of rural human settlement (Wang et al., 2017). Therefore, in the policy management dimension, the number of policies and regulations related to rural human settlement improvement is selected as an indicator to represent the degree of policy support. The implementation efficiency of rural human settlement improvement and the number of post-improvement monitoring and evaluations are selected as two indicators to represent the management behavior in the process of rural human settlement improvement.

The selection of indicators in the financial benefit dimension takes into account two aspects: capital investment and renovation effects. In enterprise management, the financial benefit dimension refers to financial input and output in enterprise performance evaluation. However, this article focuses on the performance evaluation of the human settlement environment renovation in traditional villages. It is necessary to consider the capital investment in the human settlement environment renovation and the environmental situation after the renovation. It can directly reflect the performance of the human settlement renovation in traditional villages. With respect to financial input, two indicators are selected, namely, the amount of funds earmarked for human settlement improvement and the utilization of funds for human settlement improvement. The selection of indicators for governance is extensive. It pertains not only to infrastructure, public service facilities, living conditions (Li et al., 2018), and the level of economic development. It also takes into account factors that represent the cultural environment of traditional villages. Traditional villages have deep historical and cultural heritage, unique architectural features, and traditional customs. Therefore, five indicators are selected on the basis of rural human settlement, namely, the percentage of vegetation cover, water quality status, population resident rate, infrastructure status, and public service facilities. Furthermore, four indicators that can reflect the cultural connotations of traditional villages are added to this list to symbolize the cultural environment of traditional villages. These factors include the abundance of folklore activities, the degree of handcrafted skill transmission, the renovation status of traditional buildings, and the coherence of the overall appearance of the historical environment.

The learning and growth dimension reflects the progress of village committees and villagers in the process of learning relevant knowledge and using relevant technical equipment in the context of human settlement improvement. These factors can reflect the degree of subsequent sustainable development in the human settlement and the degree of importance attached by village committees and villagers to the task of improving the human settlement. Therefore, the learning and growth dimension consists of two aspects, namely, skills upgrades and promotional communication. Three indicators are selected for skills upgrades, namely, technological innovation and application, the number of technicians recruited, and the number of knowledge training sessions conducted. In contrast, two indicators are selected for promotional communication, namely, the number of popular human settlement improvement campaigns and the number of instances of exchange and cooperation between villages and the outside world. These indicators are highly important with regard to the long-term maintenance of the results of human settlement improvement and have significant impacts on the evaluation of human settlement improvement performance.

In summary, according to the performance evaluation framework for traditional village human settlement improvement constructed above and corresponding field research, a performance evaluation

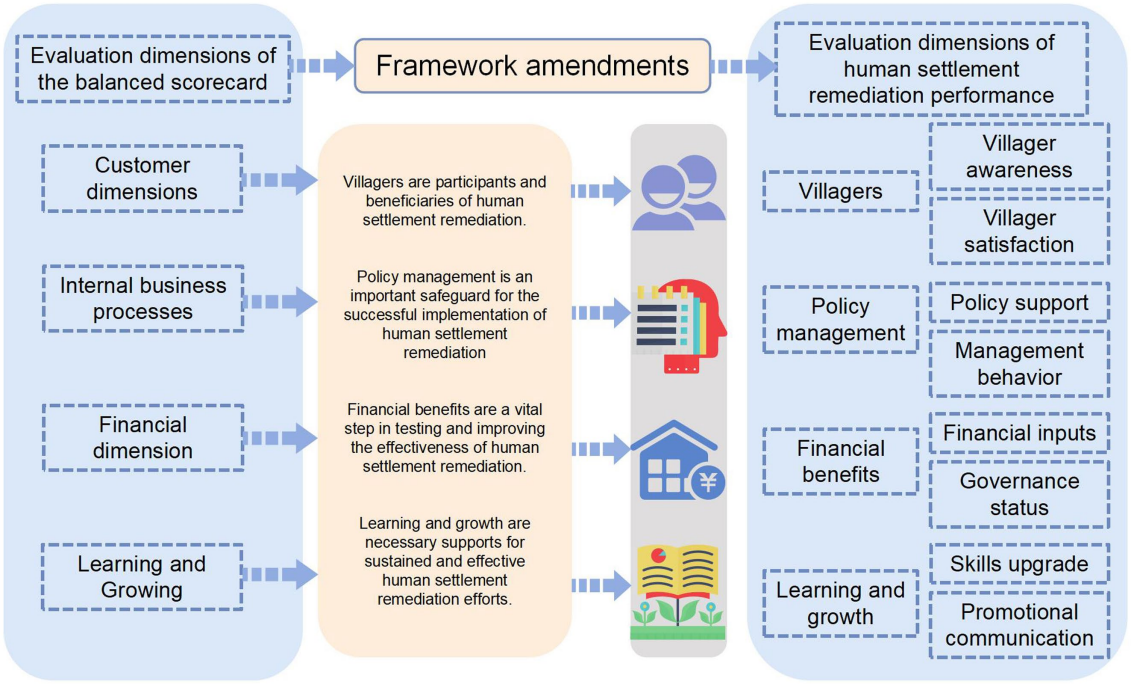


FIGURE 2
Modification of the Balanced Scorecard framework for performance evaluation of traditional village human settlement improvement.

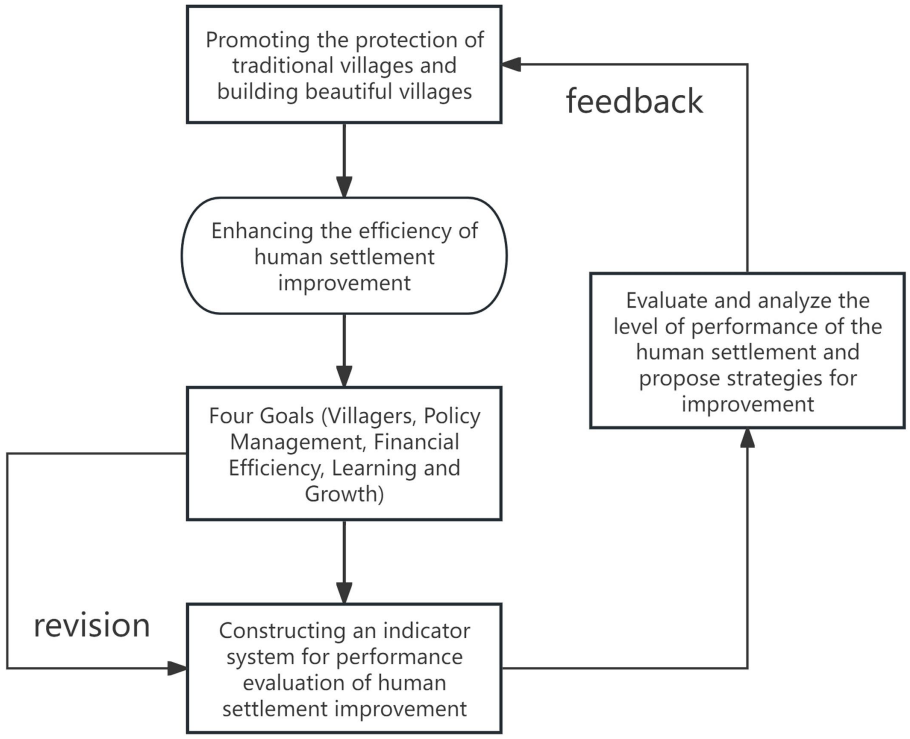


FIGURE 3
The cyclic process of introducing BSC to evaluate traditional village human settlement improvement.

index system for human settlement improvement is constructed in accordance with the principles of scientificity, operability, and referability (Table 2). A total of 22 specific indicators representing the four dimensions of villagers, policy management, financial benefits, and learning and growth, are selected for the evaluation indicator system.

2.3 Methodology specification

2.3.1 The entropy weight TOPSIS method

Use the entropy weight TOPSIS method to evaluate and rank the performance level of the human settlement improvement in traditional villages (Sun and Wang, 2022). First, weight the indicators through the entropy weight method. Then, calculate the weighted distances between each evaluation object and the positive-ideal solution and the negative-ideal solution, thereby determining their superiority-inferiority order. Conducting quantitative research with the entropy weight TOPSIS method and processing a large amount of data determines weights and evaluation results have clear bases. This avoids the influence of researchers' subjective factors and makes the research more universal and scientific. Moreover, many scholars have already used this method in existing research. For example, Jing et al. used this method to evaluate the value of the ancient vernacular dwellings in traditional villages (Jing et al., 2021) used this method to study the protection and renewal strategies of traditional villages (Zhao and Zhang, 2023). To determine the indicator weights using the entropy-weighted TOPSIS method, first, the data should be made dimensionless to eliminate the influence of the magnitude differences between indicators on weight determination. After standardizing the data, calculate the proportion of each indicator value, as well as its entropy value and utility value, and finally use the utility value to determine the objective weights of the indicators. After determining the weights, use the TOPSIS method to rank each evaluation object. The specific calculation steps are as follows:

Step 1: Construct the normalization matrix.

$$Y_{ij} = \left(X_{ij} - X_{jmin}\right) / \left(X_{jmax} - X_{jmin}\right)$$

where Y_{ij} is the standardized value of the jth indicator in the ith traditional village, X_{ij} is the original value of the indicator, $X_j$min is the minimum value of the indicator, and $X_j$max is the maximum value of the indicator.

Step 2: Calculate the weight of each indicator value.

$$P_{ij} = Y_{ij} / \sum_{i=1}^{m} Y_{ij}$$

where m is the number of evaluation subjects.

Step 3: Calculate the entropy value e and the utility value g for each indicator.

$$e_j = -k \sum_{i=1}^{m} P_{ij} \ln P_{ij}; g_j = 1 - e_j$$

Step 4: Determine the indicator weights W.

$$W_j = g_j / \sum_{j=1}^{n} g_j$$

where n is the number of indicators.

Step 5: Construct the weighted normalization matrix.

$$Z = Y \times W$$

Step 6: Determine the positive ideal solution $Z+$ and the negative ideal solution $Z-$.

$$Z_i^+ = \left\{ maxZ_{ij} | j = 1,2,\ldots,m \right\}; Z_i^- = \left\{ minZ_{ij} | j = 1,2,\ldots,m \right\}$$

Step 7: Calculate the distance of each evaluation object from the positive and negative ideal solutions.

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(Z_{ij} - Z_j^+\right)^2}; D_i^- = \sqrt{\sum_{j=1}^{n} \left(Z_{ij} - Z_j^-\right)^2}$$

Step 8: Calculate the relative proximity C_i of each evaluation object to the optimal solution.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

where C_i represents the performance index of traditional village human settlement improvement, the value interval is [0, 1]. The larger the value indicates that the performance level of human settlement improvement is higher, and vice versa is lower.

2.3.2 The obstacle degree analysis method

To further identify the main obstacle factors affecting the level of performance of human settlement improvement, the obstacle degree model was applied to calculate the impact of each indicator on the performance of human settlement improvement (Yang et al., 2021). The calculation formula is as follows:

$$I_j = \left(1 - Y_{ij}\right) G_j / \sum_{j=1}^{i} P_{ij} G_j \times 100\%$$

where $i = 22$; P_{ij} represents the indicator deviation, indicating the gap between a single indicator and the optimal target value; I_j represents the obstacle degree, indicating the degree to which the jth indicator is an obstacle to the improvement performance; and G_j represents the factor contribution, indicating the degree to which the jth indicator influences the performance of environmental improvement.

3 Results

3.1 The performance level of human settlement improvement in traditional villages

On the basis of the preceding discussion, the entropy weight TOPSIS method is used to calculate the comprehensive values of the performance level of 16 traditional villages in Jiaozuo city. Figure 4 ranks the human settlement improvement performance ratings from highest to lowest.

TABLE 2 Performance evaluation indicator system for human settlement improvement.

Target layer	Standardized layer	Factor layer	Indicator layer	Weight
A human settlement improvement performance	B1Villagers	C1Recognition by villagers	D1the degree to which villagers recognize human settlement improvement	0.031
		C2Participation of villagers	D2the degree to which villagers participate in human settlement improvement	0.075
		C3Satisfaction of villagers	D3the degree to which villagers satisfaction with human settlement improvement	0.023
	B2Policy management	C4Policy support	D4the number of policies and regulations pertaining to the human settlement improvement program	0.054
		C5Management behaviors	D5the efficiency of the implementation of human settlement improvement	0.022
			D6the number of post-improvement monitoring assessments	0.037
	B3Financial benefits	C6Financial inputs	D7the amount of funds earmarked for human settlement improvement	0.067
			D8the utilization of funds for human settlement improvement	0.020
		C7Governance status	D9the percentage of vegetation cover	0.042
			D10water quality status	0.040
			D11population resident rate	0.044
			D12the abundance of folklore activities	0.068
			D13the degree of handcrafted skill transmission	0.085
			D14the renovation status of traditional buildings	0.042
			D15the coherence of the overall appearance of the historical environment	0.035
			D16infrastructure status	0.022
			D17public service facilities	0.050
	B4The learning and growth dimension	C8Skills upgrades	D18technological innovation and application	0.045
			D19the number of technicians recruited	0.051
			D20the number of knowledge training sessions conducted of human settlement	0.058
		C9Promotional communication	D21the number of popular human settlement improvement campaigns	0.065
			D22the number of instances of exchange and cooperation between villages and the outside world	0.024

Figure 5 shows the level of human settlement improvement performance in traditional villages and the spatial spread of their ranks. The results reveal that the average level of human settlement improvement performance in the context of traditional villages in Jiaozuo city is 0.49, while the median value is 0.52, thus indicating that human settlement improvement performance in the context of traditional villages in Jiaozuo city is at a medium level overall, although the majority of traditional villages exhibit a high level of improvement performance. The performance level of traditional villages is further divided into three categories based on a cluster analysis conducted with the assistance of SPSS software: high improvement performance level (0.57 ~ 0.64), medium improvement performance level (0.38 ~ 0.56), and low improvement performance level (0.28 ~ 0.37). Traditional villages that exhibit high, medium, and low levels of performance in terms of human settlement improvement account for 31.25, 37.5, and 31.25% of the sample, respectively.

Recalling the above and Figure 4, the level of performance of human settlements in traditional villages has been categorized. There are five traditional villages with high remediation performance, in descending order as follows: Shi'erhui Village (0.64), Mogou Village (0.62), Wanhua Village (0.61), Shuangmiao Village (0.60) and Chenjiagou Village (0.60). All villages of this type are tourist-oriented traditional villages that feature high levels of transportation access, good tourism development, and good economic conditions. Six traditional villages feature medium improvement performance levels, which are listed in descending order as follows: Zhaozhai village (0.56), Jiangling village (0.53), Zhaibuchang village (0.52), Anlezhai village (0.51), Yidoushui village (0.48), and Qingtianhe village (0.43). Five traditional villages feature low improvement performance levels, which are listed in descending order as follows: Beizhu village (0.37), Wugezhai village (0.37), Xiaodong village (0.34), Jiudu village (0.33), and Changling village (0.28). This type of village is characterized by a weak economic base, a low level of government attention, and a weak sense of villager participation.

3.2 Four dimensions of human settlement improvement performance levels

Figure 6 shows the performance level of human settlement improvement in different dimensions of traditional villages. The results regarding the four dimensions of human settlement

improvement performance are 0.88 for the policy management dimension, 0.48 for the villagers dimension, 0.27 for the learning and growth dimension, and 0.10 for the financial benefits dimension. The research results show that the performance level of the policy management dimension in improving the human settlement environment is the highest. Most traditional villages place a high emphasis on improving the human settlement environment, and the management work related to environmental improvement is well-organized, with staff showing a responsible and dedicated attitude. The second-highest dimension is the villagers' involvement, as most traditional villages have improved the village environment and enhanced residents' quality of life after carrying out the human settlement environment improvement, with villagers expressing a high level of satisfaction with the work. The third dimension is learning and growth. In many traditional villages, during the environmental improvement process, the importance of technological innovation and talent utilization is often overlooked. Moreover, there is a lack of knowledge and learning about environmental improvement, leading to insufficient endogenous motivation in the villages. The lowest performance level is in the financial benefits dimension, which highlights issues such as the insufficient funds for environmental improvement in traditional villages.

3.3 The obstacles affecting the level of performance in human settlement improvement

On the basis of the results of our analysis of the performance of different traditional villages, we use the obstacle degree model to explore the factors affecting the performance level of human settlement improvement in depth by obtaining the obstacle degree value for each single indicator across the three types of traditional villages. After these obstacle degree values are organized from high to low, the five most highly ranked obstacles pertaining to each traditional village are identified as the main obstacles that affect the performance of these various traditional villages in the context of human settlement improvement. The main factors influencing the evaluation of the performance of traditional villages in human settlement improvement are then analyzed (Table 3). The results reveal that the obstacles affecting the performance of each type of human settlement improvement are not identical and highlight three common obstacle factors, namely, the degree to which handicrafts are inherited (D13), the degree to which villagers participate in human settlement improvement (D2), and the number of times human settlement improvement publicity is popularized (D21). However, the degrees to which obstacles affect each type of performance differ.

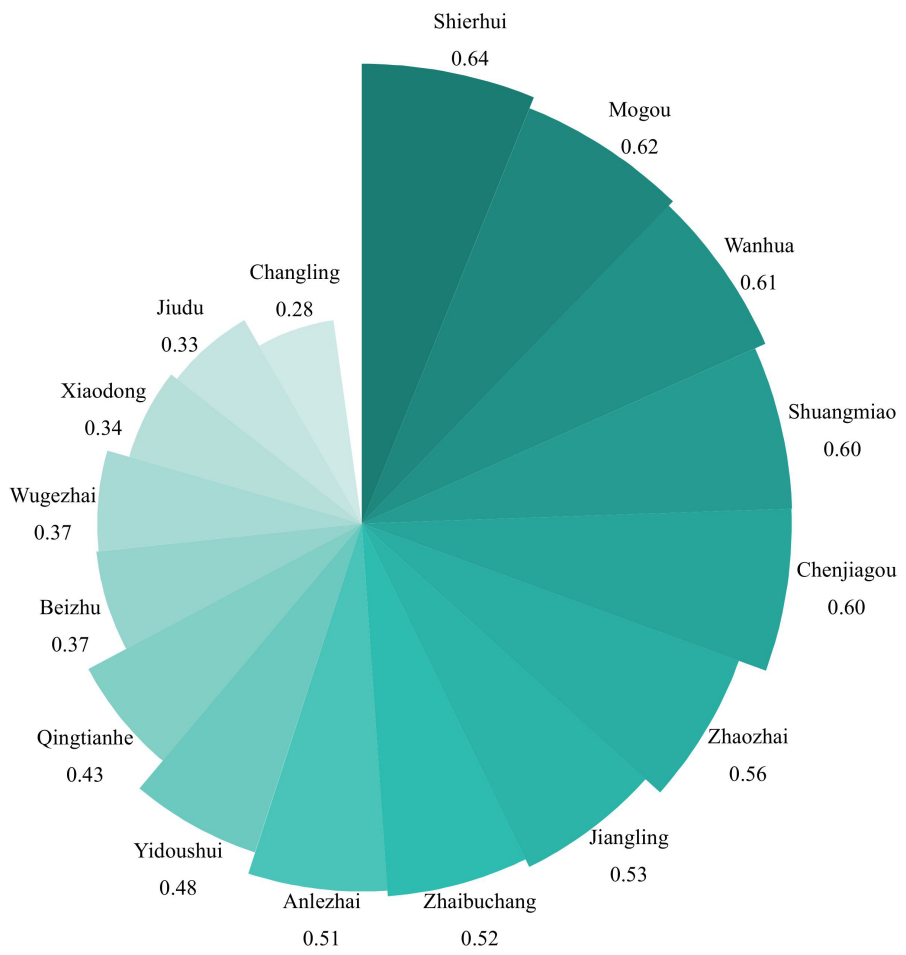


FIGURE 4
Performance level of human settlement improvement in 16 traditional villages.

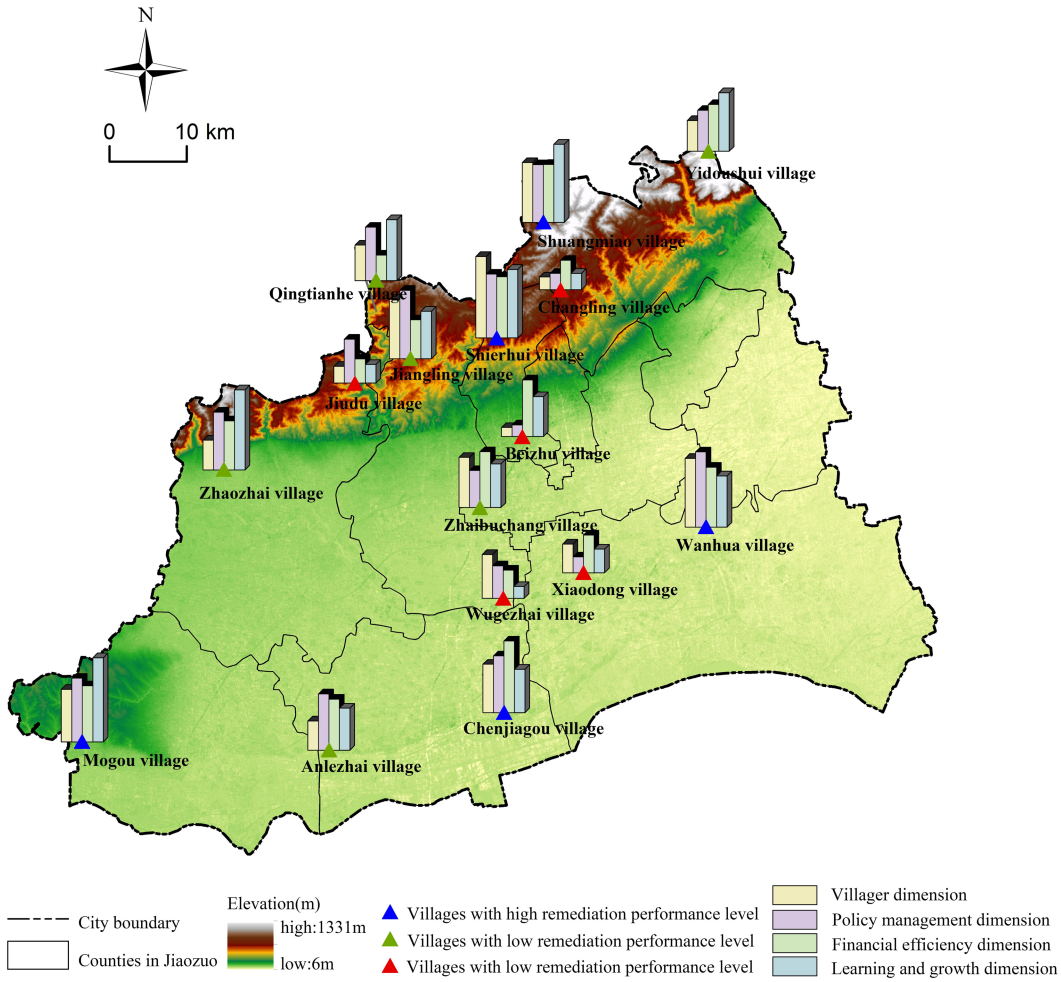


FIGURE 5
Spatial distribution of performance level and grades for human settlement improvement in Jiaozuo traditional village.

4 Discussion

4.1 Analysis of the results of human settlement improvement in traditional villages

According to the field survey, it is found that traditional villages with outstanding improvement performance are all tourist-oriented. In these villages, the economic development is relatively better, and villagers' quality of life is higher. The excellent development of tourism in these villages drives the economic growth of the villages and provides favorable economic conditions to support the improvement of human settlements in the villages (Ma and Tang, 2023). Moreover, tourism development has prompted village committees and villagers to pay more attention to human settlement development. The village committees have strengthened the publicity of human settlement governance, and the villagers have paid attention to the task of protecting human settlements in their daily lives. In addition, the village committees of traditional villages with high remediation performance levels have village rules and regulations to prevent villagers from destroying the environment and to motivate villagers to improve the environment (Zhang et al., 2024). For example, during the "Patriotic Hygiene Activity Month," the village committee leads villagers in the cleaning process to ensure high participation of villagers and enable them to take better care of the hygienic environment in the village. In general, traditional villages that feature a high level of improvement performance benefit from good tourism development, effective management policies, and the extensive participation of villagers in environmental improvement (Cheng et al., 2024).

Traditional villages with a medium level of improvement performance have several issues that reduce their level of human settlement improvement performance (Zhou et al., 2021). According to the field survey combined with the spatial and temporal distribution map in Figure 5, Zhaozhai village, Zhaibuchang village, and Anlezhai village are located in the plains. They have a high degree of road accessibility, making the transportation of installations required for environmental improvement more convenient. However, the development of industries in these villages is relatively limited, and the traditional cultural heritage is relatively weak, which has a certain degree of impact on the improvement of their cultural environment. Jiangling village, Yidoushui village, and Qingtianhe village rely on the Taihang Mountains for their tourism, which can promote better economic conditions, and village committees pay more attention to the governance of human settlements. However, due to their geographical location, the natural environment of these villages is susceptible to damage by bad



FIGURE 6
Performance level of human settlement improvement of traditional villages in villagers, policy management, financial benefits, and learning and growth dimensions.

weather (Wu et al., 2023). In addition, the lack of management of tourists has led to the random disposal of garbage by tourists, which has reduced the level of performance in improving the habitat of the village. In summary, traditional villages with a medium level of human settlement improvement performance are faced with problems such as a weak cultural heritage, incomplete village infrastructure construction, and inadequate management of tourists by village committees.

According to the field survey, traditional villages with low levels of remediation performance have more problems, and the causes are complex. Among these villages, Beizhu village, Wugezhai village, and Xiaodong village are located in the plains and feature a weak cultural heritage, limited industry, and poor economic conditions. Moreover, the government pays relatively less attention to human settlement improvement. The work on human settlement improvement by village committees is unsatisfactory. Simultaneously, villagers in traditional villages featuring low levels of settlement performance rarely participate in human settlement improvement activities and are more dissatisfied with the results of human settlement improvement. Jiudu and Changling villages are located in the Taihang Mountain ravine to the west of Jiaozuo, which is characterized by surrounding mountains, inconvenient access and transportation, and obstacles to the transportation of human settlement improvement equipment in the villages (Cui et al., 2022; Wang and Zhu, 2023). In summary, traditional villages that feature a low level of improvement performance are the result of a combination of poor economic conditions (Stănilă and Barbu, 2016), obstacles to transportation, inefficient village committees, and a weak sense of participation on the part of villagers.

4.2 Analysis of performance level of human settlement by four dimensions

The policy management dimension is ranked highest among the four dimensions of human settlement improvement performance. A well-founded system of policies and effective management can provide important support for villages that exhibit medium and high levels of improvement performance (Beyene et al., 2023), thus enabling them to implement effective and long-term human settlement improvement. Reasonable village rules and effective management not only prevent villagers from destroying human settlements but also stimulate their

TABLE 3 Main obstacle factors for traditional village human settlement improvement performance indicators.

Typology	Form	Order of obstacles				
		1	2	3	4	5
High level of performance	Barrier Factors	D13	D20	D12	D21	D2
	handicap	16.871	9.757	8.553	7.402	6.619
Medium level of performance	Barrier Factors	D13	D2	D12	D14	D21
	handicap	14.953	12.546	10.908	5.729	5.402
Low level of performance	Barrier Factors	D2	D13	D21	D7	D20
	handicap	8.800	8.538	7.959	7.819	6.992

enthusiasm regarding the possibility of participating in human settlement improvement and making improvements in terms of governance efficiency and quality (Liu et al., 2024). In traditional villages that exhibit medium and high levels of improvement performance, the basic government can coordinate all parties, which can not only interact with higher levels of government and promote a fit between the will of that higher-level government and the democratic decisions made at the village level but also take responsibility for implementing policies and maintaining the operation of facilities at the grassroots level. This approach can also mobilize villagers to participate in environmental improvement and establish a good governance environment with a focus on "government management and village participation." In villages that exhibit low levels of improvement performance, the absence of a government management role leads to poorer results in terms of the improvement of the human settlement.

The villagers dimension is ranked second highest among these subdimensions. The enthusiasm of villagers regarding the possibility of participating in environmental management is an important foundation for the implementation of a long-term mechanism for rural environmental management. As "masters" of the village, villagers are not only participants in environmental governance but also beneficiaries of the results of environmental protection (Stephen et al., 2002; Liu et al., 2015). Therefore, the depth of villagers' participation in human settlement improvement is a key factor that impacts the villages' level of improvement performance. According to the survey, 70% of the villagers have a high degree of understanding of human settlement improvement and are very supportive of human settlement improvement in their villages. Among them, a small number of villagers actively participate in the improvement of the human settlement and contribute their efforts to the improvement of the human settlement. In addition, most villagers believe that human settlement improvement has improved the living environment and living conditions, and are very satisfied with the results of environmental improvement. These have largely improved the performance level of traditional village human settlement improvement. Only a very small number of villagers are dissatisfied with the results of human settlement improvement (Wang et al., 2021). The reason is that the villagers are dissatisfied due to the inaction of the village committee or the poor quality of the materials and supplies used in the environmental improvement process.

The learning and growth dimension is ranked third among these subdimensions. According to Figure 6D and the field survey, a few traditional villages have high performance levels in the learning growth dimension. On the one hand, these traditional villages actively publicize human settlement improvement and help villagers learn about human settlement improvement. On the other hand, they actively employ technical personnel related to human settlement and update equipment for human settlement. These actions have greatly improved the efficiency and effectiveness of human settlement improvement (Wang and Zhu, 2023). The majority of villages have neglected the introduction and use of technicians and technical equipment for human settlement improvement. The lack of professionals for scientific and systematic human settlement improvement in traditional villages leads to the result of low efficiency of human settlement improvement. The lack of technology and equipment required for the improvement of human settlement also leads to insufficient endogenous motivation for the environmental improvement in villages (Angela et al., 2021). In this case, it is difficult to improve the performance level of human settlement improvement.

Among these sub-dimensions, the financial benefits dimension was ranked the lowest. In the process of human settlement improvement work, financial investment and equipment allocation are important factors that affect human settlement improvement performance. According to Figure 6C and the field survey, the level of performance of traditional village human settlements in terms of financial benefits is generally low. Among them, some traditional villages indicated that the amount of government funds allocated specifically for their environmental improvement was low. There is no economic support for them to carry out human settlement improvement. The activities of cultural awareness-raising and the renovation of traditional buildings are also difficult to carry out due to funding problems, resulting in poor preservation of the historic environment and landscape. In addition to this, most of the traditional villages indicated that their own industrial development was weak and their level of economic development was relatively low. Thus, it is difficult for the traditional villages themselves to access the funds required to improve the human environment. This issue makes it difficult for these villages to continue to improve the human environment when the amount of funds allocated by the government for this purpose is insufficient (Li et al., 2019; Lin et al., 2023). In summary, low levels of capital investment greatly reduce human settlement improvement performance in traditional villages.

4.3 Analysis of obstacles affecting the level of performance in human settlement improvement

The most notable public barrier with regard to the three types of villages is the degree of handcrafted skill transmission (D13). Among the sample villages selected for this study, 70% of the

traditional villages do not sell specialty products related to village culture. In addition, only a few traditional villages are home to inheritors of the village's intangible cultural heritage, which is a very unfavorable situation with regard to the protection of the cultural environment of traditional villages. The second public barrier in this context pertains to the degree to which villagers participate in human settlement improvement (D2). The number of times villagers participate in human settlement improvement reflects, to a certain extent, the villagers' attitudes toward human settlement improvement, which in turn has a strong effect on human settlement improvement performance (Cui et al., 2022; Wang and Zhu, 2023). According to the field survey, it was found that most of the villagers had low motivation to participate in the improvement of the human environment. As a result, human settlement improvement can only rely on the management of village committees and lacks bottom-up endogenous motivation. This has a significant impact on the level of performance in human settlement improvement (Wang et al., 2021). The third public obstacle in this context is the number of popular human settlement improvement campaigns (D21). In the sample villages selected for this study, most traditional villages ignored the importance of villagers and rarely called on villagers to participate in human settlement improvement (Lin et al., 2023). This situation is not conducive to human settlement improvement on the part of the entire population and, to a certain extent, reduces human settlement improvement performance.

In addition to such public obstacles, the most notable obstacle to high human settlement improvement performance is the number of knowledge training sessions conducted of human settlement improvement (D20). According to the field survey, it was found that traditional villages with a high level of settlement improvement performance did not pay enough attention to the training and learning of human settlement improvement knowledge. The lack of knowledge training for villagers has led to an insufficient knowledge base for villagers to participate in human settlement improvement. This situation is not conducive to their subsequent scientific and effective participation in human settlement improvement and greatly reduces the performance of human settlement improvement. The most notable obstacle in the context of medium human settlement improvement performance is the abundance of folklore activities (D12). According to the field survey, traditional villages at the medium level of improvement performance seldom organize folklore festivals, and there is less promotion of folklore culture. Some traditional villages only organize folk activities during the Spring Festival. This phenomenon greatly reduces the vitality of traditional villages and is not conducive to the sustainable development of the human environment (Zhao and Long, 2020). The most notable obstacle in the context of low human settlement improvement performance is the amount of funds earmarked for human settlement improvement (D7). According to the field research, traditional villages that are characterized by a low level of improvement performance exhibit relatively weak economic development. The amount of government funding provided for the improvement of human settlements in traditional villages is very limited, which makes it difficult to support the comprehensive improvement of human settlements in traditional villages.

4.4 Policy recommendations

According to the above conclusions, the following suggestions are proposed to improve the performance of human settlement improvement, starting from the different performance levels of traditional villages and their specific obstacle factors. Traditional villages with high improvement performance generally have a higher economic level, with the industrial economy mainly focused on tourism development. Therefore, in the subsequent work of this type of traditional villages, more attention should be paid to the planning and management of village tourism development, so as to maintain the development advantages of traditional villages. In addition, based on the obstacle factors, it is clear that the improvement of their human settlement performance is limited by difficulties in inheriting traditional handicrafts and the insufficient knowledge of villagers regarding human settlement improvement. Therefore, for traditional villages with high improvement performance, it is recommended to actively promote the cultural development of the village, and encourage villagers to learn traditional handicrafts to enhance the inheritance of these crafts (Liu et al., 2022). Moreover, training programs should be provided to villagers on improving their living environment. Enriching and strengthening the villagers' knowledge base on human settlement improvement will ensure that they can participate more effectively and scientifically in the work of improving human settlements (Wang et al., 2021).

Traditional villages with medium improvement performance, although they develop tourism, face less-than-ideal tourism development due to weak cultural heritage and poor management by the village committee. According to the obstacle factors, the performance of this type of traditional village's human settlement improvement is also limited by the inheritance of manual skills and the lack of folk activities. For this type of traditional village, it is recommended that the village committee implement grid management for the renovation of the human settlement environment, assigning specific responsibilities for different areas of improvement to enhance the efficiency of the renovation work (Wang et al., 2021). At the same time, efforts should be made to promote the village's traditional culture, actively organize various temple fairs, and increase the variety and number of traditional folk festivals. Constantly enriching the content of cultural development in the village will help enhance its attractiveness, foster the development of the village tourism industry, and positively guide the improvement of the human settlement environment.

Traditional villages with low improvement performance generally suffer from low visibility and low participation of villagers in the improvement of human settlement environments. Moreover, according to the obstacle factors, the low visibility of these villages makes it difficult for them to secure financial subsidies for human settlement improvement, which significantly impacts their ability to carry out such improvements. In view of this type of traditional villages, it is recommended to strengthen publicity and popularize human settlement improvement through comprehensive, multi-channel, and multi-faceted approaches. Not only should the visibility of the village be improved, but efforts should also be made to secure government financial subsidies for human settlement improvement. In addition, traditional villages should use the funds they receive for

human settlement improvement in a rational manner, ensuring that the funds are fully allocated to renovation work. It is also necessary to improve villagers' understanding of and participation in human settlement improvement, encouraging them to pay more attention to the protection of their living environment in their daily lives (Ye et al., 2022).

5 Conclusion

We conducted a study of the city of Jiaozuo, China, which is a city with many national-level traditional villages. We obtained the data through field surveys and used a series of mathematical statistical methods to calculate the data obtained. The results of the performance level of traditional villages in Jiaozuo City were finally obtained. We also analyze the obstacles affecting the performance level of traditional villages in human settlement improvement, so as to better improve the protection of traditional villages and promote the sustainable development of human settlement. The main findings of this study are summarized below.

(1) Levels of human settlement improvement performance in traditional villages in Jiaozuo city range from 0.28 to 0.64, with an overall average value of 0.49, thus indicating a medium level. Levels of human settlement improvement performance among the 16 traditional villages on which this research focused can be divided into three types, namely, high, medium, and low levels of settlement improvement performance, by using the cluster analysis method. In this context, traditional villages that exhibit high levels of improvement performance benefit from their high-level development of the tourism industry, their effective management policies, and the presence of villagers who are deeply involved in the process of environmental improvement. Traditional villages that exhibit medium levels of human settlement improvement performance have a weak cultural heritage, incomplete village infrastructure construction, and incomplete management of tourists on the part of village committees, all of which decrease the level of human settlement improvement performance in these traditional villages. For traditional villages with low human settlement improvement performance, their low performance is due to poor economic conditions, obstacles to transportation, inefficient work on the part of village committees, and a weak sense of participation on the part of villagers.

(2) In terms of the subdimensions of human settlement improvement performance in traditional villages, the value of the policy management dimension (0.88) is the highest, the values of the villagers dimension (0.48) and the learning and growth dimension (0.27) are in the middle, and the value of the financial benefits dimension (0.10) is the lowest. These findings reveal that the government and village committees are providing more effectively environmental governance and management while simultaneously highlighting the problems of financial constraints and unsatisfactory use of funds in traditional villages, which can reduce human settlement improvement performance in traditional villages.

(3) The obstacles affecting the level of human settlement improvement performance in different types of traditional villages are characterized by both similarities and differences. Common obstacles in this context include the degree of handcrafted skill transmission (D13), the degree to which villagers participate in human settlement improvement (D2), and the number of popular human settlement improvement campaigns (D21). However, the degrees of influence exhibited by each obstacle factor differ. In addition to these common obstacles, the most notable obstacle to high levels of improvement performance is the number of knowledge training sessions conducted of human settlement (D20). The most notable obstacle regarding medium levels of improvement performance is the abundance of folklore activities (D12), and the most notable obstacle concerning low levels of improvement performance is the amount of funds earmarked for human settlement improvement (D7).

However, the above research has certain limitations. Firstly, there are deficiencies in the research methodology. Although the Balanced Scorecard theory used in this study is well-established and applied in various fields, its application in the evaluation of human settlement environment improvement performance is relatively rare and still needs further refinement and development. Secondly, there are limitations in data collection. Due to the large number and wide distribution of traditional villages, the sample villages selected are limited and do not cover all regions. Moreover, during data collection, it is inevitable that the differences in villagers' cognitive levels may influence the results. Finally, there are limitations in the research findings. The improvement of the living environment in traditional villages is an ongoing process, and as time progresses, the performance of the improvements may change. In conclusion, research on the performance level of human settlement environment improvement still requires a great deal of exploration and synthesis. It is expected that future studies will pay more attention to the performance of human settlement environment improvement in traditional villages, continuously enriching the research contents on the living environment of traditional villages.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YH: Conceptualization, Funding acquisition, Visualization, Writing – original draft. CY: Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. XM: Investigation, Writing – original draft. YG: Funding acquisition, Methodology, Software, Writing – review & editing.

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The effects and mechanisms of deep free trade agreements on agricultural global value chains

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Introduction: In the context of the growing global trend toward the deep integration of free trade agreements (FTAs), enhanced regional agricultural collaboration has significantly impacted the agricultural global value chains (AGVCs). Clarifying how FTA depth affects a country's AGVC participation is crucial for promoting high-quality agricultural development and deepening international agricultural cooperation.

Methods and goals: This paper constructs and calculates indicators for FTA depth and the AGVC index, employing fixed effects models, PPML models, and other methods, aiming to empirically analyze how the depth of FTAs influences a country's participation in AGVC and the mechanisms involved.

Results: The findings indicate that an increase in FTA depth enhances a country's degree of participation and position within the AGVC. Both the 'WTO+' and 'WTO-X' provision depth indices exert a significant positive influence on increasing participation and position within the AGVC, with the 'WTO-X' provision depth index demonstrating a more pronounced effect than the 'WTO+' provision. Furthermore, the positive effects of increased FTA depth on the integration of developed countries into the AGVC are greater than those on developing countries. Additional analysis reveals that FTA depth promotes trade liberalization and investment facilitation, thereby enhancing countries' participation and position in the AGVC.

Discussion: The findings of this paper provide reliable empirical evidence for understanding the influence of FTA depth on AGVC and offer valuable policy insights for countries actively pursuing deeper FTAs.

Policy recommendations: To further advance the evolution of AGVC, it is recommended that countries actively promote the signing of deeper FTAs to accelerate trade liberalization and investment facilitation. At the same time, developed countries should strengthen agricultural technology research and development, assisting developing countries through technology transfer to jointly build a sustainable GVC; developing countries should enhance agricultural cooperation and improve their negotiating power in FTA discussions.

KEYWORDS

free trade agreements, agricultural global value chain, trade liberalization, investment facilitation, international trade

1 Introduction

Amid prolonged stagnation in multilateral trade talks under the World Trade Organization (WTO), coupled with the rise of anti-globalization sentiments, the prevalence of trade protectionism, frequent geopolitical conflicts, and various uncertainties such as public health crises, the global trade landscape has become increasingly complex and volatile. To promote international economic and trade cooperation, countries worldwide are actively pursuing FTAs that offer greater flexibility in rules and more convenient coordination. From 2003 to 2018, the number of FTAs increased from 113 to 296, with an average annual growth rate of 6.63%. According to the latest statistics from the WTO's RTA (Regional Trade Agreements) database, as of 2024, there are 371 FTAs in force. While the quantity continues to grow, the quality is also improving consistently. Traditional FTAs primarily focused on lowering tariffs and non-tariff barriers. However, the scope of contemporary agreements has expanded to include various areas, such as environmental protection, anti-corruption, competition policy, consumer protection, and cultural cooperation, with the depth of provisions continually increasing. The deep integration of FTAs has emerged as a new trend in global trade, profoundly impacting regional trade enhancement and reshaping global value chains (GVCs). According to the calculated data on the depth of provisions, from 2003 to 2018, the annual growth rates of the coverage index and the bindingness index for "WTO+" were 8.81 and 9.10%, respectively, while the annual growth rates for the coverage index and the bindingness index for "WTO-X" were 11.14 and 11.99%. This indicates that during this period, the depth of provisions in free trade agreements not only increased in quantity but also enhanced the legal binding force and enforceability of the provisions. In comparison, the annual growth rates of the coverage index and the bindingness index for "WTO-X" were greater. This may be attributed to rising external economic uncertainties, which have led countries to prefer signing FTAs that include deeper content to establish a stable and predictable business environment and promote economic and trade cooperation.

Amidst deep integration within GVCs, the global division of labor has shifted significantly, transitioning from inter-industry and intra-industry divisions to intra-product specialization. The 'global production, global sales' model within value chains has rapidly emerged. Agriculture, as a vital component of the GVC, includes not only traditional stages such as production, processing, transportation, and sales but also high value-added sectors like agricultural input supply, seed research and development, and brand building. Developed countries generally dominate the high-end segments of agricultural inputs, seeds, agro-product processing, and branding, while developing countries primarily focus on the production and export of primary agricultural products. Given that agricultural products are perishable, prone to damage, and difficult to store, along with increasingly stringent inspection and quarantine protocols and green barriers, trade in the AGVC faces numerous challenges. In this context, a pressing issue is how to enhance countries' participation and position in the AGVC by deepening FTAs. To this end, this paper focuses on the relationship between FTA depth and GVCs, with a particular emphasis on the agricultural sector. It examines whether an increase in the depth of provisions is beneficial for enhancing a country's participation in and division of labor within the AGVC. Additionally, it explores the underlying mechanisms from the perspectives of international trade liberalization and investment facilitation.

Research findings indicate the following: First, FTA depth significantly enhances a country's participation and position in the AGVC, with deeper agreements yielding more pronounced effects. Second, compared to "WTO+" provisions, "WTO-X" provisions have a more substantial impact on a country's involvement in the AGVC. Third, the effect of FTA depth on enhancing participation and position is more pronounced for developed countries than for developing countries. Fourth, FTA depth primarily improves a country's participation degree and position in the AGVC through two channels: trade liberalization and investment facilitation. This paper aims to reveal the relationship between the depth of FTAs and the AGVC, which has significant theoretical and practical implications for countries formulating strategies, fully leveraging the opportunities presented by FTAs, and improving their positions within the AGVC.

The innovation of this paper lies in two main aspects. First, we break through the traditional assumption of homogeneity in agreements by focusing on the heterogeneity of agreement provisions, distinguishing between shallow and deep provisions, and analyzing the differential impacts of various types of provisions on a country's participation in the division of labor within the AGVC. Second, unlike previous literature that predominantly studies the GVCs of manufacturing and services, we concentrate on the AGVC. We employ methods such as fixed effects models and PPML models to examine the impact of FTA depth on the AGVC and elaborate on the underlying mechanisms of these effects.

2 Literature review

The literature related to this paper can be categorized into three main areas: First, research on the measurement of the depth of FTAs. Scholars such as Vincentvicard (2009), Horn et al. (2010), Dür et al. (2014), and Hofmann et al. (2017) have assessed the depth of FTAs from perspectives such as the degree of integration, content and depth of provisions, and have classified the provisions accordingly. The 'HMS method' introduced by Horn et al. (2010) has been extensively utilized. Second, research on the effects of FTA depth. Researchers have examined how FTA depth affects value-added trade connections, OFDI (outward foreign direct investment) by Chinese enterprises, value chain trade, and a country's involvement in GVCs (Fusacchia et al., 2022; Hanifa et al., 2022; Sun et al., 2020; Zhang et al., 2021; Cheng et al., 2022). They have found that FTAs promote bilateral value chain activities, and this effect intensifies with deeper FTA provisions. Third, research on GVCs. Existing studies have focused primarily on two aspects: the measurement of indicators and influencing factors. Regarding measurement, scholars have assessed the degree of participation in and the position within GVCs from various perspectives, including traditional trade statistics, vertical specialization rates, the KPWW method, the VAX index, upstreamness, and backward decomposition (Hummels et al., 2001; Koopman et al., 2010; Johnson and Noguera, 2012; Fally, 2012; Wang et al., 2013). Concerning influencing factors, researchers have explored the effects of human capital, resource endowments, technological innovation, research and development investment, and institutional quality on the GVC division of labor (Li and Choi, 2021; Wu et al., 2021; Wang and Thangavelu, 2021; Ji et al., 2022; Liang and

Liang, 2021; Chen and Zhang, 2023; Xu et al., 2024; Hong et al., 2020). Some scholars have also explored the impact of FTA depth on GVCs, finding that FTAs enhance bilateral value chain activities, with this effect becoming more pronounced as the depth of FTA provisions increases, particularly benefiting developing countries (Orefice and Rocha, 2014; Laget et al., 2020; Cheng et al., 2022; Lee and Kim, 2022).

While these studies offer substantial theoretical and empirical evidence regarding the relationship between FTA depth and GVCs, several limitations still exist: (1) Most literature concentrates on the impact of FTA depth on the participation of the manufacturing and service sectors in GVCs, with limited research on AGVC; (2) The mechanisms through which FTA depth influences AGVC have not been thoroughly examined, particularly from the perspectives of trade liberalization and investment facilitation. In response, this paper calculates the depth of FTAs and an AGVC index, utilizing fixed effects models, PPML models, and mediation effect models to empirically analyze how FTA depth affects a country's participation in AGVC and its underlying mechanisms. This research contributes to filling the gap in the study of FTA depth's impact on AGVC and provides valuable theoretical and practical insights for countries formulating agricultural development strategies and enhancing international agricultural cooperation.

3 Theoretical analysis and research hypotheses

As technology has rapidly advanced, transportation and communication costs have significantly decreased, leading to a more refined division of labor in agriculture, which has gradually evolved into a GVC characterized by intra-product specialization (Baldwin and Yan, 2021). The segments of AGVC possess their uniqueness, with the two ends being agricultural input supply and seed research and development, as well as agricultural brand building and product marketing promotion. The middle of the value chain consists of agricultural product production and processing, among other segments. However, due to concerns over food security, countries are exhibiting a trend toward diversification in trade barriers for agricultural products. In addition to tariffs, these products also face non-tariff barriers such as sanitary and phytosanitary measures and technical standards. The frequent trade of intermediate products has led to an accumulation of both tariff and non-tariff barriers, resulting in higher trade costs for agricultural products. Against this backdrop, the deepening of FTAs has significantly influenced a country's participation in AGVC's labor division.

3.1 The impact of FTA depth on the AGVC

The deepening of FTAs can significantly enhance a country's participation and position within the AGVC. On one hand, drawing from the Comparative Advantage Theory and the Heckscher-Ohlin model, reducing trade barriers allows countries to better leverage their resource endowments in trade. Agricultural products are highly dependent on seasonal and regional production. The reduction of tariff concessions and non-tariff barriers has facilitated the cross-border flow of agricultural products, lowered the difficulty and costs for agricultural enterprises to enter international markets, and enhanced their participation in the AGVC (Melitz, 2003; Wickrama et al., 2024). The relaxation of sanitary and phytosanitary measures (SPS), in particular, has reduced the trade costs of agricultural products, enhanced the predictability of international markets, and promoted deeper levels of division of labor and cooperation. Trade facilitation measures, such as simplifying customs procedures and enhancing logistics infrastructure, significantly reduce the cost and time of international agricultural product transportation (Wilson and Abiola, 2003). Together, these factors make it easier for countries' agricultural sectors to integrate into global markets, thereby increasing their participation in the AGVC.

On the other hand, deeper FTAs can strengthen a country's position in the AGVC labor division. According to New Economic Geography and Knowledge Spillover Theory, FDI (foreign direct investment) combined with technology transfer can promote technological progress and regional economic growth. The investment protection provisions in deep FTAs can attract foreign investment into the agricultural production and processing sectors, bringing advanced agricultural technologies and management experience, thereby improving production efficiency and product quality. This enhances the position of member countries in the division of labor within AGVC. Agricultural production has a high demand for quality inputs such as seeds, fertilizers, and pesticides. The reduction of tariffs and the elimination of non-tariff barriers lower the import costs of these inputs, improve production efficiency and quality, and, in turn, enhance their added value position within the GVC. Moreover, FTAs encourage stronger cooperation and coordination among countries, concentrating different stages of agricultural production in areas of comparative advantage. By leveraging economies of scale and scope (Helpman and Krugman, 1987), countries can enhance their potential for technological upgrading and productivity improvements in the agricultural sectors, enabling them to ascend the GVC toward higher value-added activities while improving their positions in the AGVC. From this analysis, the following hypothesis is suggested:

> **Hypothesis 1**. The deepening of FTAs can significantly enhance a country's participation and position within the AGVC.

3.2 Differences in the impact of shallow and deep provisions on the AGVC

The provisions of FTAs can be categorized into shallow 'WTO+' provisions and deeper 'WTO-X' provisions, each having significant differences in their impact on the AGVC. 'WTO+' provisions primarily focus on additional tariff reductions, the lowering of non-tariff barriers, and enhancing transparency and consistency in trade rules. These provisions build upon and strengthen the existing WTO rules, representing traditional trade liberalization measures essential for reducing trade barriers in agricultural products. According to New Trade Theory, by streamlining export and import procedures, 'WTO+' provisions facilitate the integration of member countries into GVCs. However, since these provisions concentrate mainly on tariffs and non-tariff measures, their impact is relatively limited, with the primary effect being improved market access rather than deeper AGVC integration. Based on the Melitz model, the influence of these provisions on enhancing productivity, technological advancement, and value-added in the agricultural sector is relatively small, thus having a limited

impact on enhancing a country's position in AGVC (Jordan, 2017; Eum, 2023).

In comparison, 'WTO-X' provisions tackle more complex issues that extend beyond the scope of WTO agreements, such as intellectual property rights, labor standards, competition policy, and agricultural investment protection. These provisions not only influence market access for agricultural products but also have profound effects on the structure of the agricultural industry, technological innovation, and the institutional environment. According to New Economic Geography and the Theory of Knowledge Spillovers, 'WTO-X' provisions can significantly enhance productivity and international competitiveness in the agricultural sector by attracting FDI, promoting technology transfer, and improving institutional quality. The protection of intellectual property rights for seeds, varieties, and technologies in the agricultural sector is strengthened through FTAs, which encourage agricultural innovation and the establishment of high-quality brands, enabling agricultural enterprises to occupy a position of higher added value in the GVC (Grossman and Helpman, 1991). Moreover, based on Transaction Cost Theory, these deeper provisions help create a more stable and predictable business environment, reducing agricultural transaction costs and further boosting the agricultural sector's participation in the AGVC. From this, the following hypothesis is suggested:

> **Hypothesis 2**. Increasing the depth of 'WTO-X' provisions has a more significant positive effect on participation and position within the AGVC compared to increasing the depth of 'WTO+' provisions.

3.3 Mechanisms through which the depth of FTAs affects the AGVC

The depth of FTAs influences a country's participation and position within the AGVC by promoting trade liberalization and facilitating investment.

First, the deepening of FTAs encourages agricultural investment and trade between member countries by fostering trade liberalization and investment facilitation. FTAs have significantly promoted the liberalization of agricultural trade by reducing tariffs and non-tariff barriers, thereby lowering the costs and obstacles associated with agricultural trade. The deepening of FTAs signifies that international trade rules will become more detailed and unified, helping to reduce the implicit costs incurred by both parties in coordinating agricultural trade and promoting the trade of agricultural products among member countries. In terms of investment facilitation, the depth of FTAs has a significant impact. FTAs typically include specific provisions related to investment, such as simplifying investment application and approval procedures, ensuring transparency in investment information and policy regulations, providing clear channels for complaints, and establishing comprehensive dispute resolution mechanisms. These measures have enhanced the transparency and predictability of cross-border investments, directly facilitating the development of agricultural investment (Chi, 2002). Furthermore, Osnago et al. (2019) also pointed out that deeper trade agreements positively affect the growth of FDI.

Second, trade liberalization can effectively enhance a country's participation and position within the AGVC. Agricultural products must comply with strict SPS standards. The liberalization of trade has led to greater coordination and unification of these standards, which helps reduce trade friction caused by discrepancies and encourages countries to engage in the AGVC. According to the Theory of Technology Diffusion, trade liberalization creates favorable conditions for the cross-border dissemination of advanced agricultural technologies and management practices. For instance, advanced agricultural machinery and biotechnology from developed countries can more readily enter the markets of developing countries through free trade. The introduction and application of technology not only enhance production efficiency and quality but also drive the upgrading and structural adjustment of the agricultural value chain, thereby strengthening countries' positions within the GVC. Finally, investment facilitation can also effectively enhance a country's participation and position within the AGVC. According to the Eclectic Theory (Dunning, 1977), investment facilitation promotes outbound agricultural investments, which is a crucial pathway for countries to be involved more deeply in the AGVC. By making outbound agricultural investments, countries can relocate non-competitive production stages abroad, optimize resource allocation, and concentrate on competitive agricultural production activities, thereby increasing the international competitiveness of agricultural products. Furthermore, based on Endogenous Growth Theory, investment facilitation attracts more foreign capital into the country, bringing valuable resources such as funds, technology, and knowledge. The influx of these resources significantly enhances agricultural production efficiency and product quality, thereby promoting the country's position within the AGVC. Building on the above analysis, the following hypothesis is proposed:

> **Hypothesis 3**. Trade liberalization and investment facilitation serve as the primary channels through which FTA depth significantly influences the participation and position of a country in the AGVC.

In summary, compared to the manufacturing and service sectors, AGVC demonstrates greater regional specificity, perishability of products, and an emphasis on primary products in relation to the depth of FTAs. Consequently, FTAs with greater depth can more effectively promote the international circulation of agricultural products, enhance the competitiveness of processing and value-added segments, and facilitate the transition from primary production to higher value-added stages, securing a more advantageous position within GVC. Furthermore, deep FTAs strengthen the participation of agricultural enterprises in the AGVC. Trade liberalization and investment facilitation serve as significant channels for these impacts, with their mechanisms illustrated in Figure 1.

4 Methodology and data

4.1 Econometric model specification

4.1.1 Fixed effects model

To thoroughly explore the effect of FTA depth on member countries' participation degree and division of labor position within the AGVC, this paper constructs the following model:

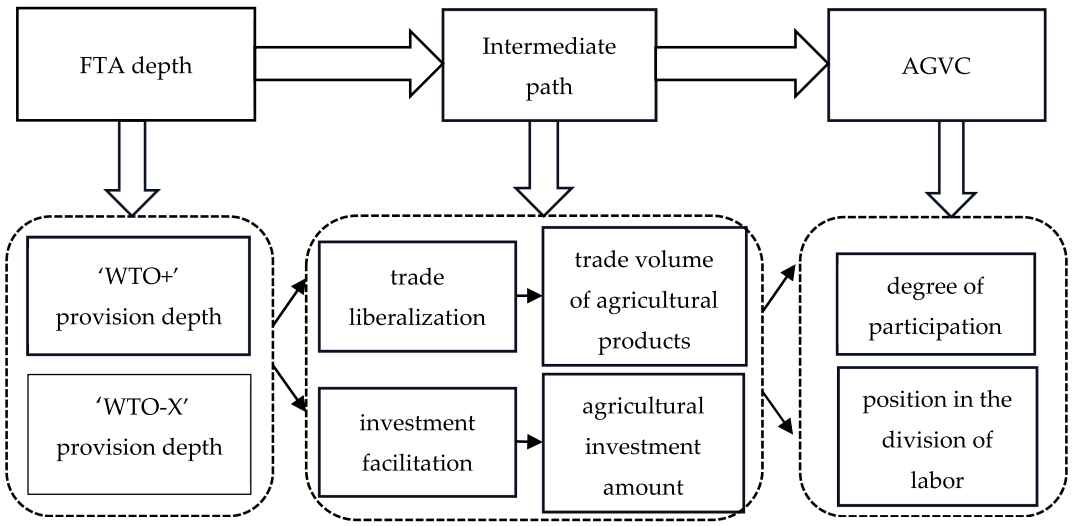


FIGURE 1
Mechanism by which FTA depth affects the division of labor within the AGVC.

$$GVC_Pat_{it} = \alpha_0 + \alpha_1 Depth_{it} + \alpha_2 GDP_{it} + \alpha_3 human_{it} + \alpha_4 material_{it} + \alpha_5 system_{it} + \alpha_6 labsh_{it} + \alpha_7 technology_{it} + \{fix_t\} + \varepsilon_{it} \quad (1)$$

$$GVC_Pos_{it} = \theta_0 + \theta_1 Depth_{it} + \theta_2 GDP_{it} + \theta_3 human_{it} + \theta_4 material_{it} + \theta_5 system_{it} + \theta_6 labsh_{it} + \theta_7 technology_{it} + \{fix_t\} + \varepsilon_{it} \quad (2)$$

Equation 1 employs the AGVC Participation Index as the dependent variable, concentrating on how provision depth affects AGVC participation. Equation 2 utilizes the AGVC Position Index as the dependent variable, investigating the impact of provision depth on the position within the AGVC. Here, i signifies the country, and t indicates the year. Four indices—$cover_p$ (WTO+ coverage), $binding_p$ (WTO+ bindingness), $cover_x$ (WTO-X coverage), and $binding_x$ (WTO-X bindingness)—constitute the explanatory variable, Depth. To more accurately assess the effect of FTA depth on both participation degree and position within the AGVC, this paper integrates several key control variables into the econometric model. These include the level of economic development (GDP), human capital (human), physical capital (material), institutional quality (system), labor compensation rate (labsh), and technological development level (technology). Adding these control variables ensures greater robustness in the empirical results. Additionally, $\{fix_t\}$ represents country fixed effects and year fixed effects, while ε_{it} denotes the random error term.

4.1.2 Examination of the influence mechanism

This paper posits in the theoretical analysis section that FTA depth influences the division of labor in the AGVC through two pathways: trade liberalization and investment facilitation. The impacts of trade liberalization and investment facilitation on participation levels and the division of labor in the AGVC have been widely validated (Wang and Thangavelu, 2021; Morrissey and Filatotchev, 2000; Javorcik, 2004). However, the effect of FTA depth on promoting trade liberalization and investment facilitation warrants further examination. This paper draws on the approaches of Cheng and Dong (2024), Wang et al. (2024), and Ren et al. (2023) to construct the following model for empirical testing of the influence mechanism:

$$GVC_Pat_{it} = \alpha_0 + \alpha_1 Depth_{it} + \alpha_2 control_{it} + \{fix_t\} + \varepsilon_{it} \quad (3)$$

$$GVC_Pos_{it} = \alpha_0 + \alpha_1 Depth_{it} + \alpha_2 control_{it} + \{fix_t\} + \varepsilon_{it} \quad (4)$$

$$freedom_{it} = \beta_0 + \beta_1 Depth_{it} + \beta_2 control_{it} + \{fix_t\} + \varepsilon_{it} \quad (5)$$

$$invest_{it} = \beta_0 + \beta_1 Depth_{it} + \beta_2 control_{it} + \{fix_t\} + \varepsilon_{it} \quad (6)$$

Equations 3–6 are employed to examine the mechanisms through which the depth of FTAs influences the degree of participation and position within the AGVC. Specifically, Equation 3 assesses the impact of FTA depth on participation degree in the AGVC, while Equation 4 explores the effect of FTA depth on position within the AGVC. Equations 5 and 6 are then utilized to evaluate the influence of FTA depth on trade liberalization and investment facilitation. Finally, from a theoretical standpoint, we analyze the mediating effects of trade liberalization and investment facilitation on participation degree and position within the AGVC.

4.2 Variable measurement and selection

4.2.1 Explanatory variable

In this paper, the explanatory variable is FTA depth, which is referred to as 'Depth'. Hofmann et al. (2017) quantified the content of FTAs to measure the heterogeneity of their depth and constructed both a total depth index and a core depth index. Subsequently, the

World Bank released the Content of Deep Trade Agreements database, which employed a similar method to calculate the horizontal depth of FTA provisions, categorizing them into four categories: WTO + AC, WTO + LE, WTO-X AC, and WTO-X LE. Among these, WTO + AC and WTO-X AC assess the coverage of FTAs, while WTO + LE and WTO-X LE consider the legal binding nature of the provisions within the agreements.

Drawing on the methodology developed by Hofmann et al. (2017), this paper quantifies FTA provisions and constructs two types of indicators to measure the depth of the agreements. The first type is the 'coverage index', which measures the number of provisions in a specific trade agreement, while the second type is the 'bindingness index', which evaluates the strength of these provisions concerning dispute resolution mechanisms and legal enforceability. According to Horn et al. (2010), existing FTA provisions are categorized into "WTO+" provisions (14 items) and "WTO-X" provisions (38 items). Among these, 'WTO+' provisions fall within the existing WTO framework, such as tariff reduction, while 'WTO-X' provisions extend beyond the framework of WTO, addressing areas like intellectual property protection. Calculate the coverage index and the bindingness index separately for the two types of provisions using the following methods:

The first step is to calculate the coverage index. FTA provisions are coded 1 if present and 0 if absent. The scores for all provisions are then summed and subsequently divided by the total number of provisions to obtain the coverage index for a given FTA. This paper calculates the 'WTO+ coverage index' ($cover_p$) and the 'WTO-X coverage index' ($cover_x$) by distinguishing between 'WTO+' and 'WTO-X' provisions. The formulas for these calculations are as follows:

$$cover_p = \frac{\sum_{a=1}^{14} wto + provisions_a}{14},\ cover_x = \frac{\sum_{a=1}^{38} wtox\ provisions_a}{38}.$$ Next is the calculation of the bindingness index. If a provision is neither explicitly mentioned in the FTA nor legally binding, it receives a value of 0. If the provision is explicitly stated and legally binding, yet not included in the dispute settlement mechanism, it is given a value of 1. If explicitly mentioned, legally binding, and included in the dispute settlement mechanism, it receives a value of 2. Similarly, the WTO+ bindingness index ($binding_p$) and the WTO-X bindingness index ($binding_x$) are calculated by summing all provisions' scores and dividing by the total number of provisions. The formulas for these calculations are as follows:

$$binding_p = \frac{\sum_{a=1}^{14} wto + provisions_b}{14},\ binding_x = \frac{\sum_{a=1}^{38} wtox\ provisions_b}{38}.$$

4.2.2 Dependent variables

The dependent variables of this paper are the AGVC Participation Index (GVC_Pat) and the AGVC Position Index (GVC_Pos). Drawing on the KPWW method, this paper uses data from the TiVA database for calculating the AGVC Participation and Position indices for 64 economies from 2003 to 2018. The TiVA database was jointly released in 2013 by the Organization for Economic Co-operation and Development (OECD) and the World Trade Organization (WTO), utilizing the World Input–Output Database (WIOD). This database conducts statistical analyses of trade activities from the perspective of value added, thus avoiding issues like double counting that are present in traditional trade statistics. The current TiVA database covers data from 76 economies, 17 countries and regional groups, as well as 45 industries including agriculture, forestry, animal husbandry, fishing, mining, and manufacturing. This paper selects data from six industries within the agricultural sector, including agriculture, hunting, forestry, fisheries, and aquaculture, based on industry codes. It excludes certain economies with significant amounts of missing values and generates a new variable based on country IDs and industry codes. The indices of participation and position in the AGVC presented in this paper more accurately reflect the value-added gains of various countries engaged in agricultural trade, allowing for an assessment of their degree of participation and position within the AGVC.

The formula for calculating the AGVC Participation Index is as follows:

$$GVC_Pat = \frac{IV_{in}}{E_{in}} + \frac{FV_{in}}{E_{in}} \tag{7}$$

In Equation 7, i represents a specific industry, n denotes a particular country, IV_{in} refers to the indirect value-added exports of industry i in country n to other countries, i.e., the value of exports from intermediate product trade. FV_{in} indicates the foreign value-added content in the exports of industry i in country n, i.e., the value of imports from intermediate product trade. E_{in} stands for the total exports of industry i in country n, measured in the terms of value-added. $\frac{IV_{in}}{E_{in}}$ represents the forward participation index (GVC_pat_f), which measures the proportion of indirect value-added exports to total exports for industry i in country n. This ratio directly reflects the degree of forward participation in the AGVC. A higher value indicates greater participation in the AGVC through intermediate product or service exports, and a stronger position in the value chain. $\frac{FV_{in}}{E_{in}}$ denotes the backward participation index (GVC_pat_b), representing the proportion of foreign value-added content to total exports for industry i in country n. A higher value suggests that the country relies more on intermediate products from other countries, indicating a relatively lower position in the GVC. The AGVC Participation Index is calculated by summing the forward and backward participation indices.

The formula for calculating the AGVC Position Index is as follows:

$$GVC_Pos = \ln\left(1 + \frac{IV_{in}}{E_{in}}\right) - \ln\left(1 + \frac{FV_{in}}{E_{in}}\right) \tag{8}$$

Equation 8 illustrates that when the share of indirect value-added exports in total exports surpasses that of foreign value-added content, the AGVC Position Index will be positive. This signifies that a country primarily engages in the AGVC by exporting intermediate products to other nations, indicating a relatively higher standing in the value chain. Conversely, if the proportion of IV is less than that of FV, the AGVC Position Index will be negative. This implies that the country, lacking advantages in areas such as technology and innovation, participates in the AGVC mainly by importing intermediate products or services from other nations, placing it lower in the value chain and

further downstream in labor division, without significant competitive advantages.

4.2.3 Control variables

Leveraging current research (Baier and Bergstrand, 2007; Zhang et al., 2021), this paper integrates variables that influence AGVC as control variables into the model. The specific control variables are as follows: Economic development level (GDP): Measured using each country's GDP (in constant 2015 US dollars). Generally, developed countries tend to occupy upstream positions in GVCs (Mudambi, 2008; Shin et al., 2012). Human capital (human): Represented by the education index from the Human Development Index, which combines both male and female education indices. Human capital is essential for driving economic growth in a country, and increasing investment in it contributes to enhancing the technological complexity of exports (Sun et al., 2024), which in turn affects the country's AGVC participation and position. Physical capital (material): Measured by the ratio of gross fixed capital formation in relation to GDP. Countries with abundant physical capital have greater advantages in global competition, which may influence their participation and position in the AGVC (Ji et al., 2022). Institutional quality (system): Measured by the Worldwide Governance Indicators. High-quality institutions can lower the costs of international trade, minimize resource misallocation, and provide clear social signals (Hou et al., 2020). Labor compensation rate (labsh): Represented by the share of labor compensation in GDP. An increase in labor compensation in a specific industry can attract more talent to that industry, fostering further development and potentially influencing its position in the GVC. Technological development level (technology): Measured by the count of scientific journal articles published in a country. Improvements in technological research and development significantly promote industrial development and upgrading, increasing the added value of products and ultimately helping the country move upstream in the GVC (Xu et al., 2024).

4.3 Data sources and descriptive statistical analysis

Data for measuring the AGVC participation index and position index come from the TiVA database. Data for the FTA depth index is sourced from the World Bank's 'Content of Deep Trade Agreements' database. Control variable data are sourced as follows: economic development level (GDP), physical capital (material), and institutional quality (system) are taken from the World Bank database. Human capital (human) data is derived from the UNDP (United Nations Development Programme) 'Human Development Report'. Labor compensation rate (labsh) data comes from the Penn World Table database, while technological development level (technology) is derived from the World Bank's WDI database. Taking into account the time span of the various data variables, this paper sets the research period from 2003 to 2018.

Considering the significant differences in data among the variables, logarithmic transformations were applied to the two dependent variables, four explanatory variables, and the control variables: economic development level (GDP), physical capital (material), and technological development level (technology). This approach was adopted to reduce data discrepancies, mitigate volatility, and eliminate potential extreme value effects. Table 1 shows that the sample size for this paper is 3,814 observations. Human capital has the largest standard deviation, at 4.449, indicating a relatively dispersed distribution. The standard deviations of GDP, institutional quality, and technological development level are also relatively large, primarily due to significant disparities among countries in these areas.

5 Results

5.1 Basic regression results analysis

Using a two-way fixed effects model, this paper estimates Equations 1 and 2 to examine how the depth of 'WTO+' and 'WTO-X' provisions in FTAs affects the participation and position in the AGVC. Table 2 presents the results. Columns (1), (2), (3), and (4) show the effects of the coverage index and bindingness index of 'WTO+' provisions, as well as the coverage index and bindingness index of 'WTO-X' provisions, on the AGVC participation index, respectively. Columns (5) through (8) correspondingly display the effects of these indicators on the AGVC position index. The results indicate that, across all columns, the coefficients for the respective provision depth indices are positive and at the 5% significance level or higher, suggesting that the increasing depth of FTA provisions significantly enhances a country's participation and position within the AGVC. This finding supports Hypothesis 1.

Further comparison of the impacts of different provision depth indices reveals that, in Columns (1) and (3), as well as Columns (5) and (7), the coefficients of the 'WTO+' provision coverage index are smaller than those of the 'WTO-X' provision coverage index. This suggests that, compared to 'WTO+' provisions, the coverage of 'WTO-X' provisions has a more significant impact on promoting participation and position in the AGVC. Similarly, in Columns (2) and (4), as well as Columns (6) and (8), the coefficients of the 'WTO+' provision bindingness index are also smaller than those of the 'WTO-X' provision bindingness index. This further demonstrates that the depth and bindingness of 'WTO-X' provisions have a more pronounced effect on enhancing a country's position in the AGVC. These results confirm Hypothesis 2, which states that the depth of 'WTO-X' provisions strongly influences the enhancement in a country's participation and position in the AGVC compared to 'WTO+' provisions. This may be because 'WTO-X' provisions encompass broader areas, such as environmental protection, intellectual property, and competition policy, which can more effectively promote institutional improvements and international cooperation in the agricultural sector, thereby further advancing the development of the AGVC.

Regarding the control variables, both physical capital and technological development levels negatively impact participation in the AGVC significantly at the 5% significance level. This could be because countries with higher economic development levels and greater physical capital possess stronger capabilities in autonomous production and technological innovation, leading to less reliance on foreign markets and external resources, thus reducing their

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TABLE 1 Descriptive statistics.

Variable Name	Variable symbol	(1)	(2)	(3)	(4)	(5)
		Observation	Mean	Standard deviation	Minimum value	Maximum value
Participation Index	GVC_Pat	3,814	−1.026	0.563	−3.624	0.381
Position Index	GVC_Pos	3,814	0.086	0.060	0.000	0.398
WTO+ coverage index	$cover_p$	3,814	0.332	0.581	0.000	2.548
WTO+ bindingness index	$binding_p$	3,814	0.448	0.767	0.000	3.132
WTO-X coverage index	$cover_x$	3,814	0.120	0.247	0.000	1.450
WTO-X bindingness index	$binding_x$	3,814	0.123	0.242	0.000	1.380
Economic development level	GDP	3,814	26.255	1.550	22.563	30.601
Human capital	human	3,814	25.467	4.449	8.835	34.925
Physical capital	material	3,814	−1.523	0.298	−2.944	−0.759
Institutional quality	system	3,814	0.625	0.791	−1.198	1.947
Labor compensation rate	labsh	3,814	0.537	0.077	0.199	0.689
Technological development level	technology	3,814	8.816	1.773	3.184	13.183

participation in the GVC. Furthermore, according to the 'smile curve' theory, countries engaged in research and design tend to occupy higher positions in the GVC and obtain greater added value. These countries may strengthen intellectual property protection and restrict the spillover of core technologies, thereby reducing their participation in the GVC (Ming et al., 2015). At the 5% significance level, no significant effect on the division position within the AGVC is demonstrated by any of the control variables. This may be due to the heterogeneous effects of these control variables on different countries: for developed countries, these variables may enhance their division position in the AGVC, while for developing countries, they may exert a suppressing effect. This hypothesis will be further tested in the subsequent heterogeneity analysis.

5.2 Addressing endogeneity with the instrumental variable approach[1]

FTAs may present endogeneity issues (Baier and Bergstrand, 2007), which must be addressed. On one hand, the in-depth development of FTA provisions may facilitate a country's improved participation in the division of labor within the AGVC. On the other hand, to promote the circulation of elements such as products and services and to establish a more stable and predictable business environment, economies may be more inclined to sign comprehensive FTAs to better integrate into the AGVC. Therefore, there may be a reverse causal relationship between the depth of FTAs and a country's participation in the division of labor within the AGVC, leading to endogeneity issues. To address the aforementioned endogeneity issue, this paper draws on relevant literature and employs the average depth of FTAs signed by all other countries in the sample in year t, lagged by two periods, excluding one specific country as an instrumental variable. A two-stage least squares (2SLS) regression analysis is conducted (Cheng et al., 2016). Taking the coverage index of 'WTO+' provisions as an example of the instrumental variable, the calculation formula is as follows:

$$coverp_{it}^{IV} = \frac{\sum coverp_{it-2}}{N_{it-2}} \tag{9}$$

Where $\sum \text{coverp}_{it-2}$ represents the sum of the coverage index of 'WTO+' provisions in the FTAs signed by all other countries in the sample, excluding country i, for year t-2, while N_{it-2} denotes the number of all other countries in the sample, excluding country i, for year t-2. This paper posits that the instrumental variable may influence the depth of FTAs in the current period. If the signing of deep FTAs in the past 2 years has yielded positive outcomes and fostered economic and trade cooperation between countries, there may be a greater inclination to sign additional deep FTAs or strengthen existing agreements in the future. This effect is particularly pronounced when the other countries in the sample are partner countries of country i, leading to a more significant enhancement of FTA depth. On the other hand, the instrumental variable is not related to the degree of

1 The paper also employs the lagged value of the core explanatory variable as an instrumental variable to address the issue of endogeneity, and the results are robust.

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TABLE 2 The impact of different levels of FTA depth on a country's AGVC participation and position.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos
$Cover_p$	0.092** (2.37)				0.021*** (3.14)			
$Binding_p$		0.069** (2.29)				0.016*** (3.26)		
$Cover_x$			0.170** (2.36)				0.031** (2.21)	
$Binding_x$				0.170** (2.40)				0.034*** (2.82)
GDP	−0.165 (−1.59)	−0.158 (−1.53)	−0.182* (−1.73)	−0.180* (−1.69)	−0.019 (−1.27)	−0.018 (−1.23)	−0.019 (−1.17)	−0.020 (−1.31)
Human	0.002 (0.19)	0.002 (0.20)	0.002 (0.21)	0.002 (0.21)	0.002 (1.00)	0.002 (0.98)	0.002 (1.09)	0.002 (1.06)
Material	−0.176*** (−4.69)	−0.176*** (−4.72)	−0.168*** (−4.46)	−0.167*** (−4.44)	−0.012* (−1.88)	−0.012* (−1.92)	−0.010 (−1.54)	−0.010 (−1.54)
System	−0.037 (−0.69)	−0.040 (−0.74)	−0.033 (−0.62)	−0.038 (−0.70)	0.018* (1.66)	0.018 (1.63)	0.018* (1.68)	0.018 (1.63)
Labsh	−0.329 (−1.25)	−0.336 (−1.28)	−0.321 (−1.21)	−0.327 (−1.23)	0.045 (1.10)	0.043 (1.06)	0.046 (1.11)	0.045 (1.09)
Technology	−0.088** (−2.40)	−0.089** (−2.42)	−0.082** (−2.24)	−0.082** (−2.24)	−0.007 (−1.59)	−0.007 (−1.65)	−0.006 (−1.32)	−0.006 (−1.33)
Constant	3.722 (1.47)	3.537 (1.40)	4.131 (1.61)	4.083 (1.58)	0.538 (1.42)	0.519 (1.38)	0.524 (1.28)	0.565 (1.44)
Observations	3,814	3,814	3,814	3,814	3,814	3,814	3,814	3,814
R^2	0.243	0.242	0.241	0.242	0.032	0.034	0.024	0.027
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES

*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$. To minimize intra-group data discrepancies as much as possible, clustered robust standard errors were included in the empirical analysis. The numbers in parentheses indicate clustered robust standard deviations, same as below.

participation and division of labor among various countries in the AGVC during the current period. In addition, this paper examines the issues of insufficient identification and weak instruments related to instrumental variables. The identification test (e.g., the Kleibergen-Paap rk LM statistic) rejects the null hypothesis regarding the lack of relevance of the instrumental variables, while the weak instrument test (e.g., the Kleibergen-Paap rk Wald F statistic) indicates that there are no issues with weak instruments. The results of these tests confirm the validity of the selected instrumental variables, which are presented in Table 3 and Table 4. After introducing the instrumental variables, the regression coefficients of the four core explanatory variables on participation degree in the AGVC and the division of labor remain positive and statistically significant. This indicates that, after accounting for endogeneity, FTA depth continues to have a significant promoting effect on both the degree of participation in and the enhancement of position within the AGVC. These findings are consistent with the baseline regression results and demonstrate strong robustness.

5.3 Robustness test

5.3.1 Lagging the Core explanatory variables by one period

In this paper, the one-period lag of FTA depth is utilized as an instrumental variable in the regression analysis, which incorporates country-year two-way fixed effects. Table 5 displays the results. As shown, Columns (1), (2), (5), and (6) report the regression results of the one-period lag of the 'WTO+' coverage index and bindingness index on participation and position in the AGVC, respectively. The coefficients are statistically significant and positive at the 5% level or higher. Columns (3), (4), (7), and (8) report the regression results for the one-period lag of the 'WTO-X' coverage index and bindingness index, with similarly positive and significant coefficients. These findings confirm the robustness of the baseline regression results.

5.3.2 Changing the regression method

This paper re-estimates Models (1) and (2) using the Poisson Pseudo-Maximum Likelihood (PPML) method to further assess the robustness of the baseline regression results. The PPML method is well-suited for handling zero values in dependent variables and correcting heteroskedasticity, making it particularly appropriate for trade data analysis. Table 6 displays the regression outcomes, indicating that Columns (1), (2), (5), and (6) reflect the impact of the 'WTO+' coverage index and bindingness index on the degree of AGVC participation and division position, respectively, with coefficients that are both positive and statistically significant at the 1% level. Likewise, Columns (3), (4), (7), and (8) present the regression results for the 'WTO-X' coverage index and bindingness index, which display coefficients that are positive and statistically significant at the 1% level. These findings imply that employing the PPML method does not change the conclusions of the baseline regression. The depth of FTAs continues to significantly enhance participation and position in the AGVC, further confirming the robustness of the results.

5.3.3 Modifying the measurement method for Core explanatory variables

To assess whether the conclusions are affected by altering the measurement method for the core explanatory variables, this paper

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TABLE 3 Results of addressing endogeneity issues (AGVC participation).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage
	$cover_p$	GVC_Pat	$binding_p$	GVC_Pat	$cover_x$	GVC_Pat	$binding_x$	GVC_Pat
IV	0.0200***		0.0132***		0.0630***		0.0553***	
	(0.0047)		(0.0034)		(0.0086)		(0.0089)	
$Cover_p$		0.1790**						
		(0.0834)						
$Binding_p$				0.1290*				
				(0.0721)				
$Cover_x$						0.2670**		
						(0.1167)		
$Binding_x$								0.2928**
								(0.1442)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,964	2,953	2,964	2,953	2,964	2,953	2,964	2,953
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM statistic		54.139		59.735		36.070		54.029
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Kleibergen-Paap rk Wald F statistic		80.883		83.085		145.763		85.979
	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}

The values inside [] represent the *p*-values of the LM statistic, and the values inside {} represent the critical values for the Stock-Yogo test at the 10% significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

TABLE 4 Results of addressing endogeneity issues (AGVC position).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage
	$cover_p$	GVC_Pos	$binding_p$	GVC_Pos	$cover_x$	GVC_Pos	$binding_x$	GVC_Pos
IV	0.0200***		0.0132***		0.0630***		0.0553***	
	(0.0047)		(0.0034)		(0.0086)		(0.0089)	
$Cover_p$		0.0285**						
		(0.0134)						
$Binding_p$				0.0227*				
				(0.0119)				
$Cover_x$						0.0403**		
						(0.0202)		
$Binding_x$								0.0452**
								(0.0216)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,964	2,953	2,964	2,953	2,964	2,953	2,964	2,953
idfix	YES	YES	YES	YES	YES	YES	YES	YES
yearfix	YES	YES	YES	YES	YES	YES	YES	YES
Kleibergen-Paap rk LM statistic		56.148		58.185		35.945		52.648
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Kleibergen-Paap rk Wald F statistic		88.161		75.798		142.831		90.443
	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}	{16.38}

Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

recalculates the overall coverage and bindingness indices of FTAs without distinguishing 'WTO+' from 'WTO-X' provisions and re-estimates the Models (1) and (2). Table 7 presents the results. Columns (1) and (2) report the regression results for the overall coverage and bindingness indices on the participation degree in the AGVC, showing coefficients that are positive and significant at the 5% level. Columns (3) and (4) report the regression results for these indices on the division position in the AGVC, with similarly positive and significant coefficients. These findings suggest that even after modifying the measurement method for the core explanatory variables, FTA depth continues to positively affect both participation and position in the AGVC significantly, further confirming the robustness of the baseline regression results.

5.4 Heterogeneity test

To further investigate the variation in the impact of FTA provision depth on the participation of different economies in the AGVC, a subgroup regression analysis was performed. The findings are reported in Tables 8, 9. For AGVC participation, Table 8 shows that the regression coefficients of the 'WTO+' coverage and bindingness indices, as well as the 'WTO-X' coverage and bindingness indices, in Columns (1), (3), (5), and (7) are generally not significant, with only a small number of coefficients reaching the 10% significance level. This implies that the FTA provision depth only affects developing countries' AGVC participation to a limited extent. In contrast, regression coefficients of all core explanatory variables in Columns (2), (4), (6), and (8) are positive and significant at the 5% level or higher. This suggests FTA provision depth greatly enhances developed countries' participation in the AGVC, with 'WTO-X' provisions having a relatively stronger impact. To verify the robustness of these results, a Chow test was conducted to examine the differences in regression coefficients between groups. The results reveal that the *p*-values for all four regressions are significant, indicating that the differences in coefficients between developing and developed countries are statistically significant. These findings suggest that, compared to developing countries, FTA provision depth has a more pronounced effect on boosting developed countries' participation in the AGVC.

Regarding the AGVC position, the results in Table 9 indicate that Columns (1) and (3) present regression results for the 'WTO+' coverage

TABLE 5 Lagging the depth of FTAs by one period.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos
$L.cover_p$	0.091** (2.23)				0.019*** (2.71)			
$L.binding_p$		0.069** (2.20)				0.015*** (2.94)		
$L.cover_x$			0.155** (2.04)				0.026* (1.72)	
$L.binding_x$				0.148** (2.02)				0.029*** (2.25)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	5.359** (2.02)	5.194** (1.97)	5.600** (2.05)	5.418** (1.97)	0.540 (1.40)	0.526 (1.38)	0.506 (1.19)	0.538 (1.33)
Observations	3,322	3,322	3,322	3,322	3,322	3,322	3,322	3,322
R^2	0.233	0.233	0.230	0.230	0.030	0.031	0.022	0.025
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES

Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

TABLE 6 PPML regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos
$Cover_p$	0.077*** (7.21)				0.162*** (8.77)			
$Binding_p$		0.042*** (7.00)				0.088*** (8.59)		
$Cover_x$			0.241*** (7.30)				0.521*** (9.43)	
$Binding_x$				0.304*** (7.56)				0.675*** (15.74)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	2.473*** (3.21)	2.543*** (3.32)	2.329*** (2.96)	2.561*** (3.34)	1.374 (1.35)	1.509 (1.48)	0.986 (0.88)	1.679* (1.68)
Observations	3,814	3,814	3,814	3,814	3,814	3,814	3,814	3,814
R^2	0.407	0.407	0.400	0.404	0.269	0.267	0.247	0.280
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES

Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

index and bindingness index on the position of developing countries in the AGVC, with positive coefficients that are at the 5% significance level. Columns (5) and (7) display the influence of the 'WTO-X' coverage and bindingness indices, where the coefficients show weaker significance, with a few reaching the 10% level of significance. Overall, the regression coefficients for the core explanatory variables show limited statistical significance, indicating that FTA provision depth has only a limited influence on enhancing developing countries' position in the AGVC. Conversely, in Columns (2), (4), (6), and (8), the core explanatory variables' regression coefficients are all statistically significant and positive at the 5% level. This suggests that FTA provision depth significantly enhances the position of developed countries in the AGVC. Comparing Columns (1) and (2), (3) and (4), (5) and (6), (7) and (8), it is evident that the overall regression coefficients for developed countries are larger. The Chow test results show that the p-values for the two groups concerning 'WTO+' provision depth are significant, while the p-values for the two groups regarding 'WTO-X' provision depth are not significant. This could be because 'WTO-X' provisions involve rules that extend beyond the current WTO framework, which are not yet widely reflected in FTAs, and the degree of development is limited. Therefore, the coefficient differences between developing and developed countries are not significant.

In summary, increasing the FTA provision depth has a greater impact on enhancing developed countries' participation and position in the AGVC compared to developing countries. This is due to the fact that developed countries are often the advocates of FTAs and the creators of new trade rules, enabling them to embed their interests more effectively in the agreements. Developed countries, with their advanced agricultural technologies and well-established industrial chains, are better positioned to seize the opportunities presented by FTAs to deepen their participation in the GVC.

5.5 Mechanism test

To further investigate Hypothesis 3 proposed earlier, this paper conducts a mechanism analysis from the perspectives of trade liberalization and investment facilitation.

5.5.1 Examination of the trade liberalization mechanism

First, we analyze the mechanism through which the depth of FTAs affects a country's participation and position in the AGVC via trade liberalization. The regression results are shown in Table 10. Columns (1) to (4) display the effects of the 'WTO+' provision coverage index ($cover_p$) on AGVC participation degree, division position, trade liberalization level, and agricultural trade volume, with all showing positive and statistically significant coefficients. Similarly, Columns (5) through (8) present the regression results for the 'WTO-X' provision coverage index ($cover_x$), which also exhibit positive and significant coefficients. These results indicate that increasing the coverage indices of 'WTO+' and 'WTO-X' provisions in FTAs promotes international trade liberalization, facilitates trade exchanges among countries, and boosts a country's agricultural trade volume. Previous research has confirmed that enhanced trade liberalization benefits the expansion of agricultural trade (Fan et al., 2022; Xin et al., 2024). An increase in agricultural imports enhances a country's backward participation in the GVC. An increase in agricultural exports indicates that the country exports more raw materials or intermediate products, thereby boosting its forward participation. Higher agricultural trade volume signifies more frequent trade activities and stronger connections with the GVC. In particular, the expansion of intermediate product trade can enable a country to integrate more deeply into the division of labor within the GVC (Feyaerts et al., 2019). Additionally, trade liberalization creates favorable conditions for the cross-border transfer of advanced agricultural technologies and management practices, which are crucial for enhancing a country's position within the GVC division (Wang and Thangavelu, 2021). In summary, Hypothesis 3 is validated.

5.5.2 Examination of the investment facilitation mechanism

Next, we analyze the mechanism through which FTA depth influences a country's AGVC participation degree and division position via investment facilitation. Table 11 presents the regression results. Columns (1) to (4) illustrate how the 'WTO+' provision coverage index affects AGVC participation degree, division position, investment facilitation, and agricultural foreign investment, with all coefficients positive and statistically significant. While columns (5) through (8) report the regression results for the 'WTO-X' provision coverage index, they also show positive and significant coefficients, all at the 5% significance level or higher. These results indicate that increases in the 'WTO+' and 'WTO-X' provision coverage indices within FTAs contributes to enhancing investment facilitation and boosting a country's agricultural foreign investment. Investment

TABLE 7 Modifying the measurement method for core explanatory variables.

	(1)	(2)	(3)	(4)
Variables	GVC_Pat	GVC_Pat	GVC_Pos	GVC_Pos
Cover	0.084** (2.42)		0.019*** (3.22)	
Binding		0.065** (2.31)		0.015*** (3.30)
Control Variables	YES	YES	YES	YES
Constant	3.831 (1.51)	3.568 (1.41)	0.559 (1.47)	0.527 (1.40)
Observations	3,814	3,814	3,814	3,814
R^2	0.243	0.242	0.033	0.034
Idfix	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES

Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

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TABLE 8 Heterogeneity test results—the impact of FTA depth on participation in the AGVC.

Variables	Developing country	Developed country	Developing country	Developed country	Developing country	Developed country	Developing country	Developed country
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat	GVC_Pat
$Cover_p$	0.102* (1.70)	0.116*** (3.20)						
$Binding_p$			0.073 (1.65)	0.096*** (3.29)				
$Cover_x$					0.201 (1.56)	0.145**		
$Binding_x$						(2.58)	0.216* (1.74)	0.143*** (2.63)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	−0.243 (−0.07)	13.777*** (5.42)	−0.624 (−0.18)	13.856*** (5.46)	0.915 (0.21)	13.138*** (5.21)	1.169 (0.28)	13.137*** (5.18)
Observations	1,716	2,098	1,716	2,098	1,716	2,098	1,716	2,098
R^2	0.237	0.379	0.236	0.381	0.235	0.370	0.238	0.370
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES
Chow test	9.90		10.04		9.12		9.39	
p-value	0.0000		0.0000		0.0000		0.0000	

The *p*-values for the differences in intergroup regression coefficients are calculated using the estimated results from the Chow test. Significance level: $^*p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

facilitation involves the simplification of cross-border investment processes, making investment activities more convenient, stable, and transparent, thereby reducing investment risks and costs, which in turn fosters the growth of agricultural foreign investments (Chen et al., 2020; Gui et al., 2023; Agyeiwaa-Afrane et al., 2024). Specifically, the increase in foreign investments by agricultural multinational enterprises suggests that a country can transfer segments of the value chain characterized by a lack of comparative advantage, overcapacity, or high pollution through foreign investments (Kastratovic, 2019). This transfer minimizes unnecessary resource waste, optimizes resource allocation, and emphasizes the enhancement of research and development in advanced agricultural technologies, ultimately achieving industrial optimization and upgrading, thereby improving its degree of participation and position within the GVC.

Furthermore, by establishing cooperative research and development institutions with developed countries through foreign investments, a country can closely engage with advanced technologies in collaboration with local enterprises. For agriculture, learning from and adapting advanced technologies for local application can significantly increase national agricultural productivity, facilitate structural adjustment and upgrading of the industry, and enhance the quality of agricultural products, thereby gaining competitive advantages in the international arena and improving participation and position within the GVC. In summary, Hypothesis 3 is validated.

6 Discussion

This paper explores how FTA depth affects member countries' participation and position in the AGVC, as well as the mechanisms through which trade liberalization and investment facilitation play a role in this context. Through theoretical analysis and empirical testing, the paper draws significant conclusions that warrant further discussion.

Firstly, the research findings indicate that an increase in FTA depth significantly enhances member countries' participation and position within the AGVC. This finding aligns with the conclusions of Orefice and Rocha (2014) and Laget et al. (2020), which state that deep trade agreements help intensify GVC divisions. The enhancement of FTA depth not only reduces tariff and non-tariff barriers, promoting trade liberalization, but also improves the institutional environment and lowers institutional transaction costs by encompassing a broader range of 'WTO-X' provisions, such as environmental standards, intellectual property protection, and competition policy (Horn et al., 2010). This creates more favorable conditions for agricultural enterprises to participate in GVCs, thereby enhancing their international competitiveness.

Secondly, the mechanism examination reveals that FTA depth influences a country's participation and position in the AGVC by promoting trade liberalization and investment facilitation. By reducing trade barriers, FTA depth facilitates the cross-border flow of agricultural products and technology, thereby promoting the internationalization of the agricultural sector (Freund and Ornelas, 2010). Investment facilitation improves the investment environment, attracting more foreign direct investment into the agricultural sector. This influx brings advanced technologies,

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TABLE 9 Heterogeneity test results—the impact of FTA depth on the position in the AGVC.

Variables	Developing country	Developed country	Developing country	Developed country	Developing country	Developed country	Developing country	Developed country
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos	GVC_Pos
$Cover_p$	0.019** (2.11)	0.023** (2.47)						
$Binding_p$			0.015** (2.24)	0.018** (2.47)				
$Cover_x$					0.026 (1.13)	0.031** (2.08)		
$Binding_x$							0.033* (1.71)	0.031** (2.20)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	−0.152 (−0.28)	1.358** (1.99)	−0.183 (−0.35)	1.368** (2.00)	−0.173 (−0.25)	1.245* (1.85)	−0.042 (−0.07)	1.251* (1.86)
Observations	1,716	2,098	1,716	2,098	1,716	2,098	1,716	2,098
R^2	0.044	0.040	0.046	0.041	0.030	0.034	0.036	0.035
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES
Chow test	1.56		1.60		1.39		1.35	
p-value	0.0469		0.0378		0.1084		0.1272	

Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

capital, and management expertise, which enhances agricultural productivity and product quality (Blomström and Kokko, 1997). This dual mechanism further explains how FTA depth contributes to the upgrading of the AGVC.

However, this paper has certain limitations. First, the research is primarily based on macro-level data and does not fully account for the variations among different countries and regions within the AGVC. Future studies should incorporate micro-level data, such as firm-level survey information, to explore the effects of FTA depth on agricultural enterprises of various scales and types. It is also possible to focus on the heterogeneity at the product level and explore how FTA depth affects the participation of different categories of agricultural products in the division of labor within the AGVC. Additionally, this paper primarily focuses on the mechanisms of trade liberalization and investment facilitation, without considering other potential mechanisms, such as human capital, technological innovation, and financial development. Future research should verify the influence of these mechanisms. Furthermore, changes in the global economic environment, such as geopolitical risks, the rise of trade protectionism, and global pandemics, may affect the effective implementation of FTAs and the development of the AGVC. Future studies should consider these external environmental factors and assess their potential impacts.

In summary, deepening FTA content, particularly focusing on the negotiation and implementation of 'WTO-X' provisions, is highly significant for improving a country's participation and position in the AGVC. Policymakers should actively promote the integration of FTAs, advance trade liberalization and investment facilitation, and improve the relevant institutional environment to help the agricultural sector integrate more deeply into the GVC and enhance its international competitiveness.

7 Conclusion

Using panel data from 64 countries between 2003 and 2018, this paper employs a combination of theoretical analysis and empirical testing to explore how FTA depth affects a country's AGVC participation and position. The findings reveal the following: (1) An increase in FTA depth significantly enhances a country's AGVC participation and division position. This conclusion remains valid after various robustness checks. (2) Both the 'WTO+' and 'WTO-X' provision depths positively contribute to improving the participation and position of a country in the AGVC. However, the influence of 'WTO-X' provisions is more pronounced than that of 'WTO+' provisions. (3) Heterogeneity analysis shows that an increase in FTA depth positively impacts both developed and developing countries, though the influence is more significant for developed countries. This difference is attributed to variations in economic development levels and resource endowments among countries. (4) Mechanism analysis indicates that FTA depth enhances a country's AGVC participation degree and division position through two main pathways: promoting trade liberalization and facilitating investment.

Drawing from the findings presented above, the following policy recommendations are suggested: (1) Actively promote the signing of deeper FTAs and intensify international cooperation in agriculture. Countries should focus on the deep integration and development of

TABLE 10 Trade liberalization mechanism results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	GVC_Pat	GVC_Pos	Freedom	Sum	GVC_Pat	GVC_Pos	Freedom	Sum
$Cover_p$	0.092** (2.37)	0.021*** (3.14)	0.054** (1.97)	0.621** (2.07)				
$Cover_x$					0.170** (2.36)	0.031** (2.21)	0.112** (1.98)	0.927** (2.02)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.722 (1.47)	0.538 (1.42)	3.979*** (2.93)	−18.573 (−0.97)	4.131 (1.61)	0.524 (1.28)	3.997*** (2.93)	−32.167 (−1.26)
Observations	3,814	3,814	3,663	3,814	3,814	3,814	3,663	3,814
R^2	0.243	0.032	0.063	0.103	0.241	0.024	0.063	0.102
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES

Due to space constraints, the table only displays the results for the provision coverage, while the results for binding force are similar to those of provision coverage. In all regressions shown, the explanatory variable is the provision coverage index. The data for trade liberalization and agricultural trade volumes have been log-transformed. Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

TABLE 11 Investment facilitation mechanism results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	GVC_Pat	GVC_Pos	invest	ofdivalue	GVC_Pat	GVC_Pos	invest	ofdivalue
$Cover_p$	0.092** (2.37)	0.021*** (3.14)	0.021*** (2.65)	0.376** (2.14)				
$Cover_x$					0.170** (2.36)	0.031**(2.21)	0.047*** (2.59)	1.068** (2.13)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
Constant	3.722 (1.47)	0.538 (1.42)	2.087*** (30.80)	5.245 (0.47)	4.131 (1.61)	0.524 (1.28)	1.760*** (2.77)	3.003** (2.21)
Observations	3,814	3,814	3,814	3,814	3,814	3,814	3,814	3,814
R^2	0.243	0.031** (2.21)	0.318	0.029	0.241	0.024	0.348	0.023
Idfix	YES	YES	YES	YES	YES	YES	YES	YES
Yearfix	YES	YES	YES	YES	YES	YES	YES	YES

Due to space constraints, the table only reports the results for provision coverage, while the results related to binding force are similar to those of provision coverage. In all regressions presented in the table, the explanatory variable is the provision coverage index. The data for investment facilitation and agricultural foreign investment volumes are logarithmically transformed. Significance level: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

FTAs, covering not only traditional 'WTO+' provisions but also emphasizing the negotiation and conclusion of 'WTO-X' provisions that encompass broader areas. By enhancing the transparency and clarity of provisions, countries can reduce uncertainties in cross-border production and investment activities, enabling businesses to better predict and mitigate risks. Additionally, an efficient dispute resolution mechanism should be established and improved to ensure swift and fair handling of conflicts between trade partners, thereby ensuring the effective implementation of FTAs and enhancing their role in advancing the AGVC. (2) Accelerate the promotion of trade liberalization and investment facilitation to improve positions within the AGVC. Countries should further reduce trade barriers, simplify customs procedures, improve logistics infrastructure, and eliminate tariff and non-tariff obstacles to foster the development of trade liberalization. Simultaneously, simplifying cross-border investment procedures, enhancing market transparency and stability, and advancing the process of investment facilitation will create a more open and fairer competitive environment for enterprises, increasing their competitiveness in international markets. In the agricultural sector, promoting trade liberalization and investment facilitation will enable countries to integrate more deeply into the AGVC, improving their position and participation. Through strengthened international cooperation and improved resource allocation efficiency, countries and enterprises can more effectively access global markets, capture more value chain profits, and seize growth opportunities, contributing to the overall development and prosperity of the AGVC. (3) Developed and developing countries need to leverage their respective advantages to jointly advance the evolution of the AGVC. During FTA negotiations, it is important to select negotiation topics and terms judiciously. When negotiating with developing countries, greater attention should be paid to the existing terms under the WTO framework, while negotiations with developed countries can focus on deeper 'WTO-X' terms. Developed countries can continue to utilize their advantages in funding and resources to strengthen agricultural technology research and development, further consolidating their position in the AGVC. Additionally, through technology transfer and cooperation, they can assist developing countries in enhancing agricultural production capacity, thereby promoting the formation of a mutually beneficial and sustainable AGVC division of labor system. Developing countries can establish cooperative research and

development institutions with developed countries to learn from their advanced agricultural technologies, knowledge, and management practices, gradually integrating into the upstream segment of the GVC. Furthermore, developing countries should improve their negotiation skills and techniques, collaborating to create synergistic effects that enhance their bargaining power in FTA negotiations and maximize their interests.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HZe: Conceptualization, Funding acquisition, Resources, Writing – original draft, Writing – review & editing. SC: Data curation, Methodology, Software, Visualization, Writing – original draft. HZh: Validation, Writing – review & editing. JX: Resources, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Exploring the evolution of global beef trade network patterns based on complex network analysis

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Introduction: The global beef trade, as a critical component of the meat trade, plays an important role in balancing beef supply and demand worldwide. However, research on the evolution of its network patterns remains relatively limited. This article aims to explore the evolution of global beef trade network patterns and provide insights into its implications for sustainable development.

Methods: Using complex network theory, this paper constructs weighted and unweighted global beef trade networks based on international trade data and conducts an in-depth analysis of the evolution of global beef trade patterns from 2013 to 2022 across the overall, individual, and clustering levels.

Results: The analysis reveals an increasing trend in connectivity, efficiency, and tightness within the global beef trade network. In the unweighted network, the core beef-importing countries are primarily concentrated in Germany, the United Arab Emirates, and the Netherlands. However, in the weighted network, the core importing countries shift to the United States, Japan, and China. Meanwhile, the core beef-exporting countries consistently remain Australia, Brazil, and New Zealand in both network types. Additionally, the analysis identifies clustering and regionalization characteristics within the global beef trade blocks.

Discussion: These findings highlight the evolving dynamics of global beef trade, emphasizing the roles of key countries and the structural shifts in the trade network. The study provides targeted recommendations for promoting sustainable development in the beef trade sector.

KEYWORDS

global beef, trade network, complex network, patterns, sustainable development

1 Introduction

The demand for meat has been increasing along with rising global residents' income and the improvements in dietary structure (Godfray et al., 2018). As a significant segment of the meat industry, beef has experienced growing global demand (Kibona et al., 2022). However, due to resource and environmental capacity constraints, many countries and regions are unable to meet beef production needs independently (Chen et al., 2022). Consequently, international trade has become a vital mechanism for balancing and stabilizing the supply and demand in the global beef market (Caro et al., 2014). In recent years, global beef trade has shown remarkable growth. Using import values as a key indicator, data from the UN Comtrade database indicate that the total import value of the global beef trade increased from USD 39.11 billion in 2013 to USD 66.11 billion in 2022, with an average annual growth rate of 6.01%. This growth highlights the expansion of the global beef trade market over the past decade. It can be said that global beef trade constitutes an essential part of international agricultural trade, and its evolution not only

affects food security and supply chain stability, but also has a link to global economic development and environmental sustainability.

Research on beef trade can be generally categorized into three areas. The first focuses on supply-demand dynamics, product structures and market competitiveness in the beef trade, utilizing statistical data to conduct comprehensive investigations at global or national levels (Reeves and Hayman, 1975; Anderson et al., 2002; Bindon and Jones, 2001; Fields et al., 2018). The second area investigates the impact of factors such as animal diseases, environmental regulations, and food safety on beef trade, mainly employing econometric models to analyze specific influencing factors (Darbandi et al., 2021; Webb et al., 2018; de Waroux et al., 2019; Wilson et al., 2003). The third area introduces advanced technological tools, such as machine learning, to forecast trends and patterns in beef trade by leveraging large datasets and complex algorithms (Batarseh et al., 2019; Jeong et al., 2024).

It is notable that the aforementioned studies have tended to emphasize the independence of individual countries' trade and cannot adequately capture the complex and interconnected relationships in global trade systems. Complex network analysis offers a robust framework for abstracting and simplifying real-world social systems, enabling a more precise investigation of interactions and influences between nodes (Strogatz, 2001; Pagani and Aiello, 2013; Costa et al., 2007). By representing trade relationships as networks, researchers can examine the structural characteristics of these networks, uncover relationships between countries, identify key players in trade, and reveal regional clustering and cooperation patterns. This approach offers a comprehensive understanding of the dynamic and intricate features of the global trade system (An et al., 2018; Hou et al., 2018; Wang et al., 2021). Consequently, complex network theory has gained widespread application as an effective analytical tool in international trade research (Li et al., 2003; Serrano and Boguñá, 2003; Fagiolo et al., 2009; Fan et al., 2014, 2021).

Despite the importance of the global beef trade in the international economy, systematic studies on the evolution of its network patterns remain relatively limited. For example, what are the trends in the evolution of the global beef network structure in recent years? Which countries or regions occupy central roles in the global beef trade network? Does the global beef trade network exhibit regional and clustering characteristics, and if so, how have these evolved? The answers to the above questions are particularly important for countries, especially major beef trading nations. Clarifying the relationships within the beef trade network can help nations adjust their industrial policies, thereby promoting the sustainable development of global beef trade.

To address these issues, this paper conducts an in-depth analysis of the relatively underexplored field of beef trade networks. First, topological structure indicators in complex networks are selected to analyze the overall structural characteristics of the global beef trade network. These indicators provide a quantitative basis for examining the network's topological features and dynamic evolution. Second, both unweighted and weighted centrality indicators are employed to comprehensively identify the countries and regions that play dominant roles in beef trade. Finally, block modeling analysis is applied to identify role similarities and grouping structures within the beef trade network, providing deeper insights into trade relationships between countries. Therefore, this study not only enriches the application of complex network theory in agricultural trade research but also provides a reference framework for analyzing trade networks of other agricultural products.

2 Materials and methods

2.1 Complex network analysis indicators

2.1.1 Whole network analysis

Complex networks are characterized by a variety of metrics that reflect their overall characteristics. In this study, four key indicators—average distance, network density, network diameter and average clustering coefficient—are selected to explore the evolution of the overall characteristics of the global beef trade network (Hao et al., 2018; Bai et al., 2023).

1. Average Distance

Average distance measures the average shortest path length between any two nodes in the network. It is calculated using the following formula:

$$AD = \frac{1}{N(N-1)} \sum_{i \neq j} d(i,j) \tag{1}$$

where AD is the average distance, N is the total number of nodes, $d(i, j)$ is the shortest path length between node i and node j. It quantifies the average number of steps along the shortest paths required to connect any two nodes within the network. A larger average distance indicates poor connectivity and low efficiency, requiring more steps for nodes to reach each other.

2. Network Density

Network density quantifies the proportion of actual connections to all possible connections within the network. For a directed network, this metric is calculated as follows:

$$D = \frac{E}{N(N-1)} \tag{2}$$

where D, E and N represent the network density, actual number of edges, and the number of nodes, respectively. Network density reflects the extent of interconnectedness in trade networks, with higher densities indicating more integrated trade relationships.

3. Network Diameter

Network diameter represents the longest shortest path between any two nodes, and can be expressed as:

$$ND = MAX_{ij} d(i,j) \tag{3}$$

where ND is network diameter, $d(i, j)$ is the shortest path length between nodes i and j. The network diameter provides a measure of

the maximum distance within the network, indicating the longest direct trade connection in the network.

4. Average Clustering Coefficient

The clustering coefficient assesses the degree to which nodes in the network are clustered together. For a directed whole network, the average clustering coefficient is calculated as:

$$C = \frac{1}{N}\sum_{i=1}^{N}\frac{E_i}{k_i(k_i-1)} \quad (4)$$

where C is average clustering coefficient, N is the total number of nodes, E_i is the number of edges between the neighbors of node i, and k_i is the degree of node i. A higher average clustering coefficient indicates that countries tend to form tightly connected trading groups or clusters.

The changes in average distance and network diameter indicate the connectivity and efficiency of the global beef trade network, while network density and average clustering coefficient reflect the tightening and regionalization of the trade network. These structural indicators provide essential support for optimizing supply chain resilience, enhancing trade efficiency, and addressing unexpected external shocks.

2.1.2 Centrality analysis

Centrality is used to identify the most important or influential nodes in a network and serves as a critical structural metric. This article employs the commonly used degree centrality to measure node influence (Freeman, 1979). Degree centrality quantifies the number of direct connections a node has. In an undirected network, degree centrality refers to the total count of edges connected to a node. In directed networks, it is divided into in-degree (number of incoming edges) and out-degree (number of outgoing edges). The calculation formulas are as follows:

$$d_i = d_i^{out} + d_i^{in} \quad (5)$$

$$d_i^{out} = \sum_{j=1}^{N} a_{ij} \quad (6)$$

$$d_i^{in} = \sum_{j=1}^{N} a_{ji} \quad (7)$$

where d_i, d_i^{out}, d_i^{in}, N represent the degree centrality of node i, the out-degree centrality of node i, the in-degree centrality of node i, and the total number of nodes, respectively. a_{ij} is an element of the adjacency matrix, which indicates whether there is a directed edge from node i to node j (1 if yes, 0 if no), so is a_{ji}.

In weighted networks, it is essential it is essential to consider both the number of connections and the weights of those edges. This is measured using the node strength metric, which can be divided into out-strength and in-strength for directed networks. The calculation formulas are as follows:

$$s_i = s_i^{out} + s_i^{in} \quad (8)$$

$$s_i^{out} = \sum_{j=1}^{N} w_{ij} \quad (9)$$

$$s_i^{in} = \sum_{j=1}^{N} w_{ji} \quad (10)$$

where s_i, s_i^{out}, s_i^{in}, N represent strength of node i, out-strength of node i, in-strength of node i, and the total number of nodes, respectively. w_{ij} and w_{ji} stand for weight of the edge from node i to node j, and the weight of the edge from node j to node i.

The application of centrality indicators in the beef trade network identifies core countries or regions involved in beef trade and underscores their critical role in maintaining global trade stability. This analysis provides policymakers with valuable insights to identify dependencies and implement diversification strategies to mitigate supply chain risks.

2.1.3 Block modeling analysis

Block modeling analysis, introduced by White et al. (1976), is a method for studying network position models. As an effective tool, it can identify and understand structural patterns within complex networks. By grouping nodes with similar relationships into blocks, block modeling analysis could reveal the equivalence of roles within the network.

The application of block modeling analysis to the beef trade network identifies role distributions among regional clusters and peripheral countries. This approach facilitates the analysis of regional cooperation and the global competitive pattern, providing decision-makers with valuable insights to help peripheral countries better integrate into the global beef trade network.

In this article, we use the commonly employed CONCOR (CONvergence of iterated CORrelations) algorithm to iterate based on the correlation matrix between nodes until the correlation matrix converges (Breiger et al., 1975). The brief procedural steps are as follows: first, the number of blocks in the overall network is determined using the CONCOR algorithm. Subsequently, a density table and an image matrix between the blocks are derived. Finally, a simplified graph is presented, which more clearly illustrates the structure of each block within the entire network.

2.2 Data description

The HS codes used in this article to determine the classification of beef include HS0201 (fresh beef) and HS0202 (frozen beef). The data were sourced from UN Comtrade database (UN Comtrade Database, 2024). This study employs import value data to characterize trade relationships, as imports are potentially more accurate (Webb et al., 2018). Therefore, the global import trade value is calculated as the sum of the import values of fresh beef and frozen beef. The study covers a decade-long period from 2013 to 2022, with specific focus on the years 2013, 2017, and 2022. These years are selected to analyze the evolving trade network characteristics of beef-importing

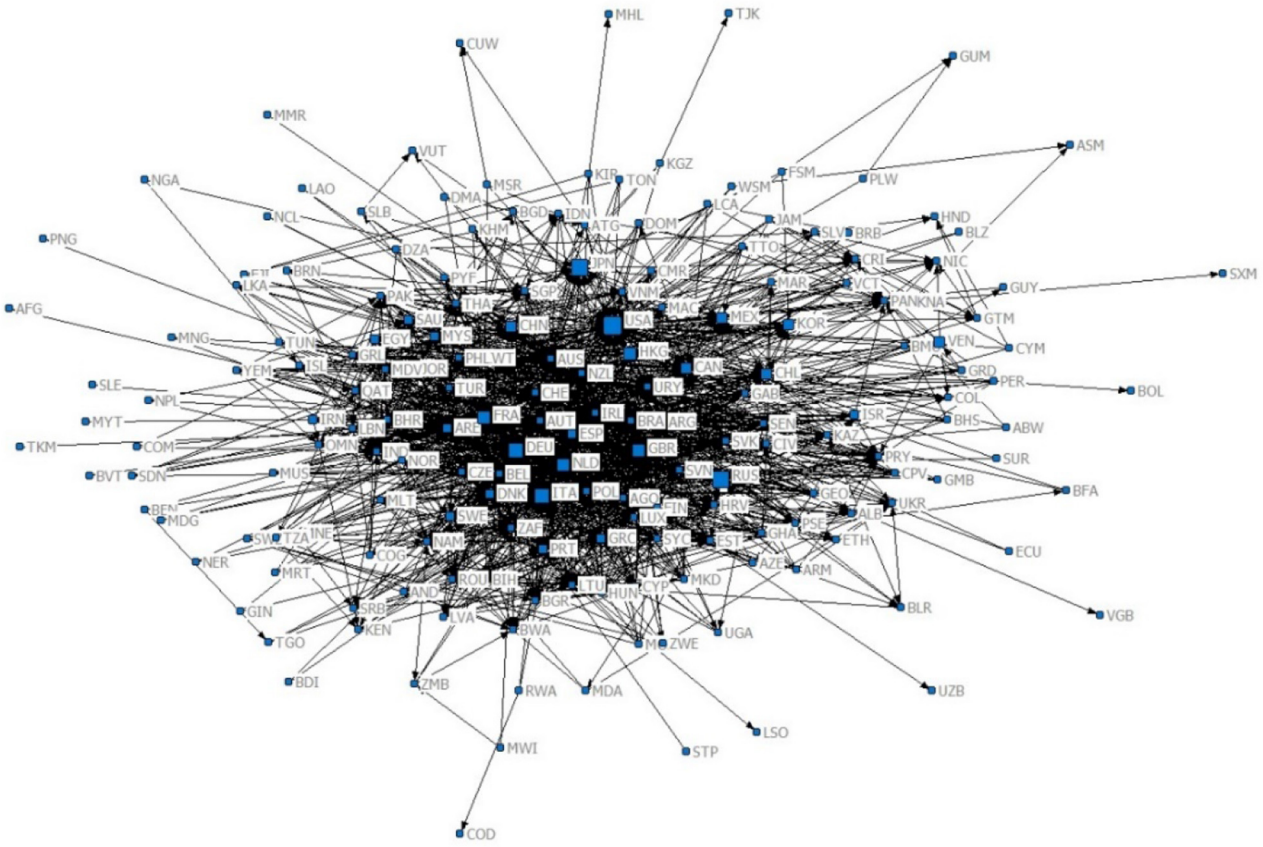


FIGURE 1
Global beef trade network in 2013. The three-letter codes in the figure represent the ISO-defined international standard country (region) codes.

countries. Additionally, the software used in this study is Ucinet 6 and Netdraw.

2.3 Global beef trade network construction

The global beef trade is a typically complex network. In this article, countries or regions are represented as nodes, and import relations as edges to construct a directed complex network of global beef trade. To better understand the global beef trade network, both unweighted and weighted networks are constructed.

In the unweighted network, the trade relations are represented by the adjacency matrix A, where each element a_{ij} indicates whether node i imports beef from node j (1 if it imports, 0 otherwise). In the weighted network, the trade relations are represented by the adjacency matrix W, where each element w_{ij} represents the value of beef trade imported by node i from node j.

It should be noted that the global beef trade network in this article only includes the countries and regions reported in the UN Comtrade database, resulting in minor variations in the number of nodes each year. However, these differences are minimal, and their impact on the comparability of complex network indicators can be reasonably disregarded in this study.

3 Results

3.1 Visualization of the beef trade network

To more intuitively examine the characteristics of the global beef trade network, this study utilizes Netdraw software to visualize the networks for the years 2013, 2017, and 2022 (Figures 1–3). The node size in the figures represents the out-degree centrality value, with larger nodes indicating higher out-degree centrality. Preliminary observations reveal certain changes in the beef trade networks over the years, particularly regarding the central positions of some countries or regions. However, more detailed analysis requires further examination using additional metrics.

3.2 Overall evolutionary characteristics of the global beef trade network

Understanding network connectivity and other structural characteristics is essential for analyzing the beef trade network. To simplify the analysis, this article employs an unweighted network that focuses solely on whether nodes are connected. The overall evolutionary characteristics of the global beef trade network are reflected using the four major topological indicators of the abovementioned complex networks.

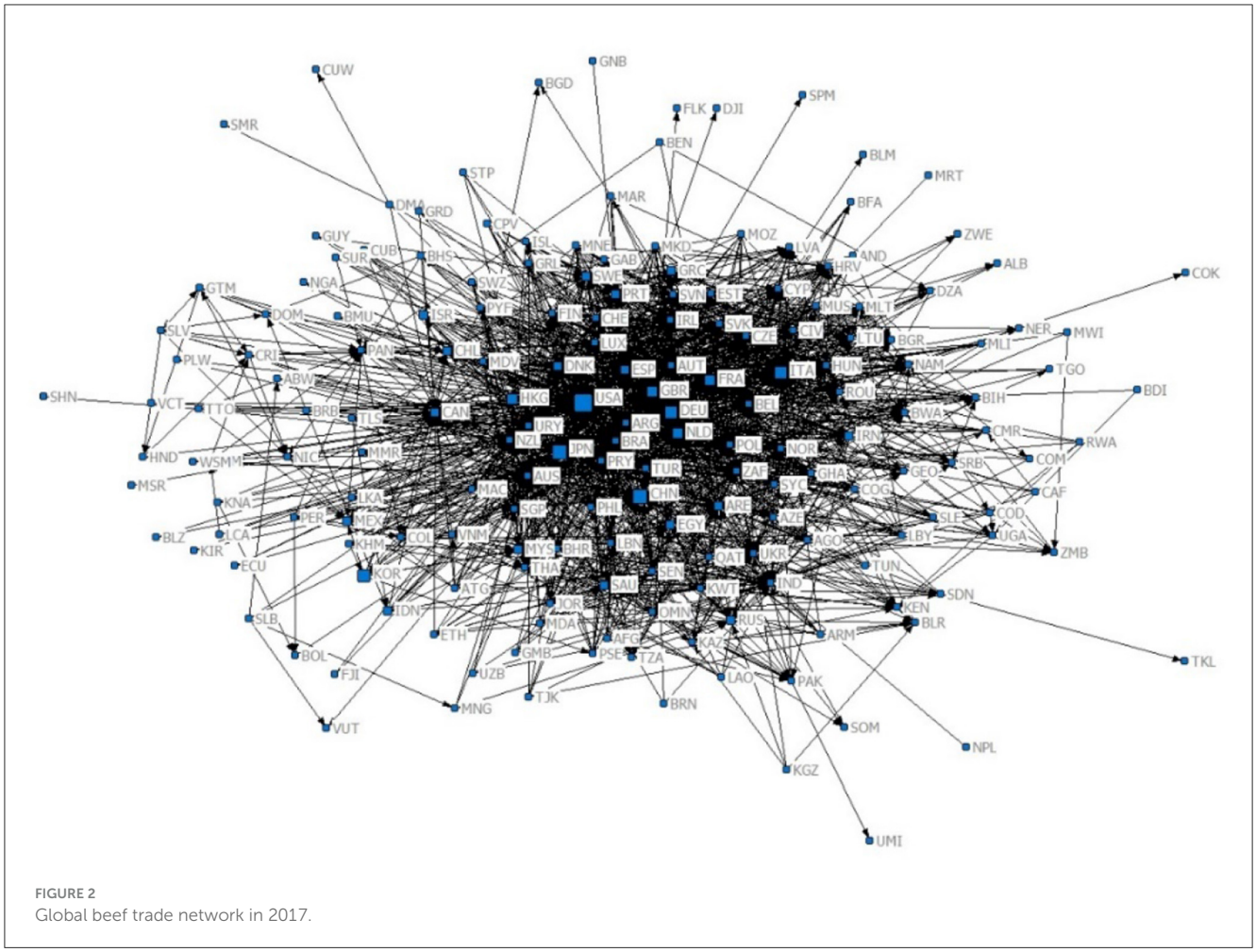


FIGURE 2
Global beef trade network in 2017.

As shown in Figures 4, 5, the average distance exhibited an overall decreasing trend from 2013 to 2022. It reached its lowest point in 2015, followed by a slight increase before declining again after 2019. This overall trend indicates that the connectivity of the beef trade network has increased over the past decade, enabling faster trade between countries or regions. Regarding network density, a significant overall upward trend is evident from 2013 to 2022, despite minor fluctuations during the period. This indicates closer and more interconnected relationships between countries in the global beef trade network. The network diameter decreased from 9 in 2013 to 6 in 2022, demonstrating higher connectivity and efficiency in the global beef trade. The average clustering coefficient showed some fluctuations over the 10 years, but generally exhibited an upward trend, suggesting a tendency toward forming tight trade clusters in the global beef trade network. Notably, possibly influenced by the COVID-19 pandemic, the year 2020 exhibited a higher network diameter and a lower average clustering coefficient.

3.3 Centrality of the global beef trade network

Centrality indicators reflect a country's position in the global beef trade. Out-degree and in-degree metrics indicate the number of countries with which a country engages in beef trade relations, without considering trade value. To more accurately capture the influence of weighted impacts, this article also utilizes out-strength and in-strength metrics in the weighted network, providing a more comprehensive evaluation of the global beef trade centrality. Table 1 lists the top 10 countries or regions based on centrality rankings for the year 2013. It can be seen that countries such as France, Germany, the United Arab Emirates, and the Netherlands ranked among the top for out-degree, indicating they had extensive beef import trade relationships with a large number of other countries. From the perspective of in-degree, the leading positions were mainly occupied by beef-producing countries such as the United States, Australia, New Zealand, and Brazil, suggesting their roles as preferred beef import sources for other countries or regions.

In terms of out-strength, significant changes were observed compared to out-degree rankings. This indicates that the most influential beef-importing countries or regions may vary when trade value weights are considered. Notably, some countries or regions such as the Hong Kong Special Administrative Region of China, emerged as major beef importers in both unweighted and weighted networks. This demonstrates that they not only maintain extensive import connections with a large number of countries or regions but also import substantial trade volumes. However, the countries or regions that ranked in the top 10 for both in-strength and in-degree remain largely unchanged, with only slight

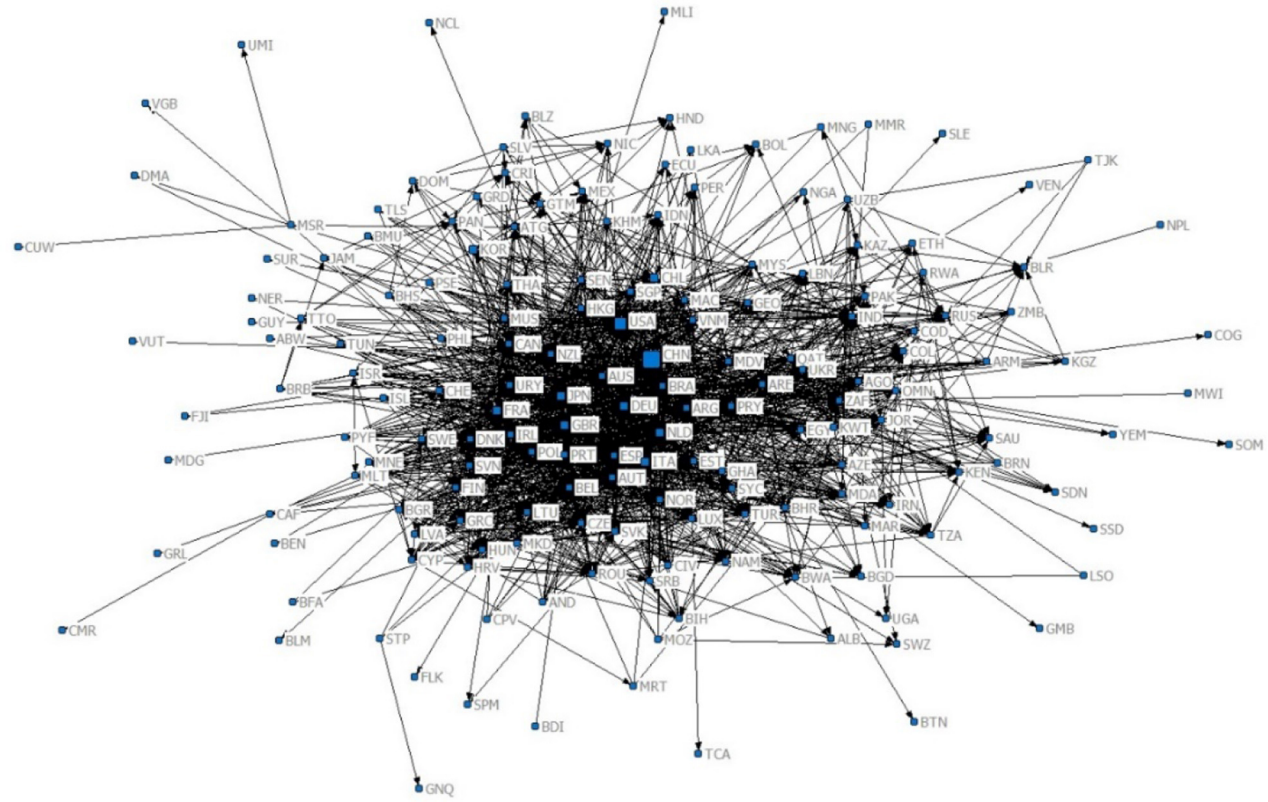


FIGURE 3
Global beef trade network in 2022.

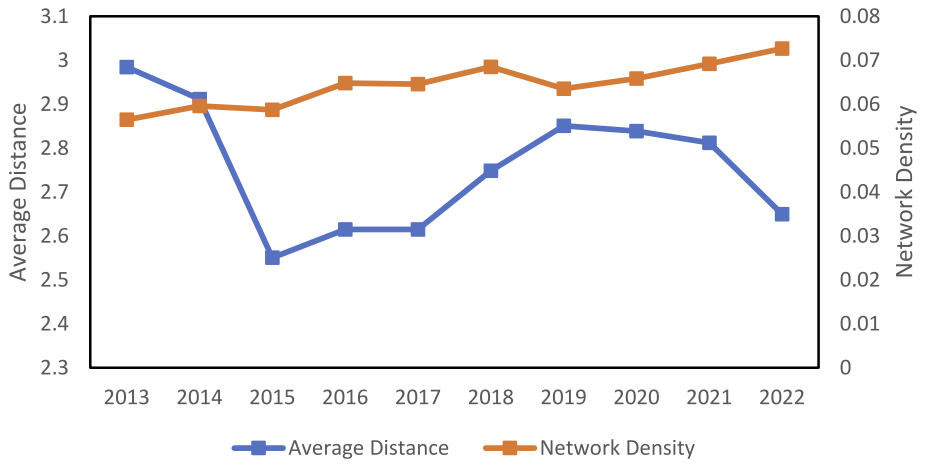


FIGURE 4
Evolution of average distance and network density.

variations in their rankings, showing that these countries or regions consistently serve as important beef import sources regardless of whether trade values are considered.

As shown in Table 2, compared to 2013, the rankings of the top 10 countries or regions for out-degree and in-degree in 2017 changed very little, remaining relatively stable. Specifically, for the out-degree indicator, beef-importing countries or regions were still dominated by countries such as Germany, France, and the Netherlands. For the in-degree indicator, the main sources of beef imports continued to be led by the United States, Australia, and New Zealand, among others. In the weighted network, compared to 2013, the Russian Federation dropped out of the top 10 in terms of out-strength, while China surged from outside the top 10 in 2013 to third place, indicating a rapid increase in China's

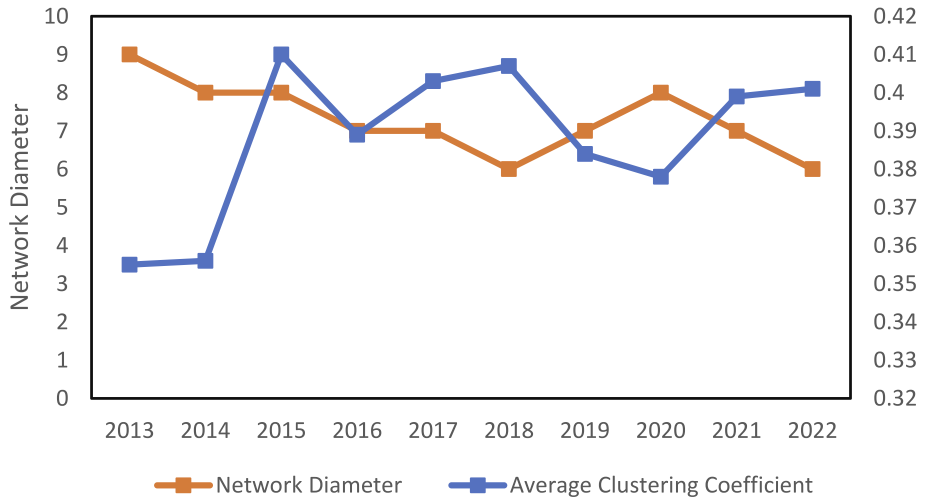


FIGURE 5
Evolution network diameter and average clustering coefficient.

TABLE 1 The top 10 countries (regions) ranked by node centrality in 2013.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
France	47	United States	100	United States	3550425344	Australia	5331096064
Germany	44	Australia	92	Russian Federation	2874125824	United States	4704177152
United Arab Emirates	41	New Zealand	81	Japan	2729087744	Brazil	4542610432
Netherlands	36	Brazil	76	Italy	2655511552	Netherlands	2580094976
Austria	34	Netherlands	75	Germany	2225403392	Ireland	2185708800
Spain	33	France	70	Netherlands	1969199360	Germany	1904731264
Angola	32	Italy	66	France	1869174528	New Zealand	1687826688
Hong Kong	31	Uruguay	62	Hong Kong	1632220416	India	1685328000
Italy	30	Germany	60	United Kingdom	1489831040	Uruguay	1378700032
Denmark/Luxembourg	30	Argentina	60	Republic of Korea	1395684736	France	1275534976

TABLE 2 The top 10 countries (regions) ranked by node centrality in 2017.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
Germany	47	United States	105	United States	5022363136	Australia	5783886848
France	47	Brazil	86	Japan	3117799936	United States	5310192128
Netherlands	43	Netherlands	85	China	3065127936	Brazil	4835801600
United Arab Emirates	41	Australia	85	Germany	2264313600	Netherlands	2514087680
Hong Kong	41	France	76	Republic of Korea	2263236096	Ireland	2103994496
Italy	38	Italy	76	Italy	2166589952	New Zealand	1882374400
Denmark	37	New Zealand	75	Hong Kong	1986669312	India	1646242048
Spain	37	Spain	71	Netherlands	1864500480	Canada	1635460096
Austria	36	United Kingdom	68	United Kingdom	1381266944	Uruguay	1578598016
Luxembourg	34	Germany	65	France	1342759552	Poland	1500094848

TABLE 3 The top 10 countries (regions) ranked by node centrality in 2022.

Country/region	Out-degree	Country/region	In-degree	Country/region	Out-strength	Country/region	In-strength
Maldives	57	United States	94	China	17757921280	Brazil	11161127936
Germany	51	Brazil	82	United States	7899314688	United States	8692796416
United Arab Emirates	49	Netherlands	80	Republic of Korea	4238524928	Australia	7025408000
Austria	45	France	74	Japan	3740416768	Argentina	3995428864
Netherlands	43	Australia	70	Germany	2553453312	Canada	3222881280
United Kingdom	42	Argentina	67	Italy	2546027008	Netherlands	3069270784
Spain	39	Spain	66	Netherlands	2227252224	New Zealand	3034394368
Estonia	37	New Zealand	64	France	2047176576	Uruguay	3014063104
Italy	37	United Kingdom	60	United Kingdom	1533880832	Ireland	2694752000
Portugal/Slovenia	37	Italy	60	Chile	1482933504	India	2568632832

TABLE 4 The number of countries (regions) in each block.

Year	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8
2013	32	11	25	22	44	27	18	8
2017	49	13	24	11	7	28	31	22
2022	26	34	30	30	18	25	6	4

import value and its rising import status. for in-strength, Germany and France dropped out of the top 10 rankings, while Canada and Poland entered the top 10, becoming important sources of beef imports.

From Table 3, it can be seen that for the unweighted network, a significant change in 2022 compared to 2013 and 2017 was that Maldives was ranked first with an out degree of 57. This indicates that the Maldives imported beef from 57 different countries or regions, highlighting a new feature of diversity in import sources. Meanwhile, the top ten in-degree rankings remained relatively stable. For the weighted network, in 2022 compared to 2013 and 2017, China ranked first in terms of out-strength, indicating that China became the largest beef importer globally. In terms of in-strength, Brazil has become the world's largest beef exporter. Additionally, it is noteworthy that the United States occupies a central position in beef trade regardless of imports and exports.

3.4 Block modeling analysis of the global beef trade network

Block modeling is an effective method for identifying the positional roles of nodes within a network. This study primarily focuses on analyzing the overall structure and connection relationships of the network. Therefore, an unweighted network is employed to explore its organizational structure. Based on the R-squared values, this article selects a max depth of splits of 3 and convergence criteria of 0.2, dividing the global beef trade network into 8 blocks. The number of countries or regions included in each block is summarized in Table 4.

In 2013, Block 1 included countries or regions such as the Bahamas and Panama. Many countries or regions within this block were located in the Caribbean and Central America, with many being small island nations. Block 2 comprised countries or regions such as the Democratic Republic of the Congo and Honduras, which were distributed across multiple continents. Most of these regions exhibited relatively small economies. Block 3 included countries or regions like Saudi Arabia and Yemen, which were primarily located in the Middle East, Africa, South Asia, and Southeast Asia. Block 4 encompassed countries or regions such as China, Indonesia, and Fiji, primarily distributed across Asia and Oceania. Block 5 was composed of countries or regions such as Finland and Poland, predominantly located in Europe with higher levels of economic development. Block 6 predominantly consisted of countries in Africa, such as Zimbabwe and Niger. Block 7 featured agriculturally advanced countries or regions such as the United States, New Zealand, Australia, and Brazil, which played significant roles in global agriculture and livestock industries. Block 8 comprised countries or regions such as Lesotho and Malawi, mainly located in Africa, where agriculture played a significant role in their economies.

The blocks in 2017 were formed by reorganizing the blocks from 2013. Specifically, Block 1 and Block 2 in 2017 were mainly composed of countries or regions from Blocks 3 and 4 in 2013. Block 3 in 2017 was primarily derived from countries or regions originally part of Blocks 1 and 4 in 2013. Block 4 mainly consisted of countries or regions from Blocks 1 and 2 in 2013. Block 5 was composed of countries or regions scattered across Blocks 3, 5, and 6 in 2013. Blocks 6, 7, and 8 were primarily formed from countries or regions originally in Blocks 7, 5, and 6 in 2013, respectively. Additionally, some blocks included newly added countries or regions.

TABLE 5 Density matrix of the global beef trade network.

Year	Block	1	2	3	4	5	6	7	8
2013	1	0.046	0.074	0.000	0.006	0.009	0.001	0.151	0.000
	2	0.003	0.000	0.000	0.004	0.000	0.000	0.020	0.000
	3	0.016	0.033	0.138	0.087	0.039	0.018	0.318	0.010
	4	0.013	0.033	0.020	0.041	0.025	0.000	0.268	0.017
	5	0.007	0.023	0.012	0.018	0.192	0.002	0.447	0.037
	6	0.008	0.007	0.016	0.027	0.037	0.013	0.265	0.014
	7	0.019	0.035	0.004	0.013	0.143	0.006	0.255	0.069
	8	0.000	0.000	0.000	0.034	0.003	0.014	0.035	0.000
2017	1	0.046	0.025	0.026	0.009	0.041	0.340	0.045	0.005
	2	0.033	0.013	0.006	0.000	0.011	0.080	0.017	0.021
	3	0.006	0.000	0.013	0.038	0.000	0.125	0.005	0.000
	4	0.000	0.000	0.015	0.164	0.000	0.049	0.000	0.000
	5	0.015	0.000	0.006	0.013	0.024	0.015	0.000	0.000
	6	0.012	0.005	0.019	0.029	0.020	0.347	0.174	0.005
	7	0.009	0.002	0.003	0.006	0.009	0.463	0.202	0.007
	8	0.022	0.007	0.008	0.004	0.019	0.208	0.021	0.013
2022	1	0.037	0.002	0.001	0.021	0.015	0.131	0.000	0.038
	2	0.011	0.070	0.018	0.082	0.170	0.216	0.000	0.000
	3	0.013	0.013	0.020	0.149	0.050	0.308	0.017	0.008
	4	0.019	0.008	0.029	0.470	0.024	0.460	0.000	0.000
	5	0.000	0.003	0.000	0.009	0.003	0.031	0.000	0.000
	6	0.006	0.004	0.007	0.169	0.016	0.202	0.020	0.000
	7	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	8	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In comparison to 2017, the changes in the blocks in 2022 were as follows: the main countries or regions in Block 1 originated from Block 1, Block 3, and Block 4 in 2017. Block 2 mainly included countries or regions from Block 1 and Block 2 in 2017. Block 3 was primarily composed of countries or regions from Block 1, Block 7, and Block 8 in 2017. Block 4 and Block 6 were mainly derived from Block 7 and Block 6 in 2017, respectively. The countries or regions in Block 5, Block 7, and Block 8 were scattered across various blocks from 2017.

To investigate the relationships between different blocks, this article presents the density matrix of the global beef trade network (Table 5). The values on the diagonal of the matrix indicate the degree of intra-block relationships, with higher values indicating tighter internal relationships within the block. The off-diagonal values represent the relationship degree between two blocks, with higher numbers indicating closer inter-block relationships. As shown in Table 5, there were significant differences in the degree of closeness both within and between each block.

To further clarify the relationships among the blocks, an image matrix is derived from the density matrix. Specifically, if the density matrix value is greater than the beef trade network density in the current year, it is assigned a value of 1 in the image matrix; otherwise, it is 0. The image matrix for the 3 years is presented in Table 6.

In addition, a simplified diagram (Figure 6) visually depicts the inter-block relationships. The results showed that in 2013, Block 7 occupied a central position in the beef trade network, establishing close trade relationships with all other blocks except Block 2. Most of the blocks were oriented toward Block 7, indicating that Block 7 had become a major source of beef imports. Moreover, Block 7 exhibited significant internal characteristics, suggesting frequent beef trade activities among the countries within this block. The other seven blocks displayed independent or marginal roles, with close trade relationships established only between one or two other blocks. Blocks 3 and 5 also exhibited strong internal characteristics.

By 2017, the structure of the blocks had shifted to center around Block 6. The previous analysis showed that most of the countries or regions in Block 6 in 2017 originated from Block 7 in 2013. This indicated that the beef network group composed of countries like Brazil, the United States, and New Zealand played a key role in the global beef network, establishing close connections with multiple blocks (Blocks 1, 2, 3, 7, and 8). Additionally, Block 4 displayed internal characteristics, with frequent trade activities

occurring primarily within the block. Block 5 remained isolated, showing no significant beef trade relationships either with other blocks or internally.

TABLE 6 Image matrix of the global beef trade network.

Year	Block	1	2	3	4	5	6	7	8
2013	1	0	1	0	0	0	0	1	0
	2	0	0	0	0	0	0	0	0
	3	0	0	1	1	0	0	1	0
	4	0	0	0	0	0	0	1	0
	5	0	0	0	0	1	0	1	0
	6	0	0	0	0	0	0	1	0
	7	0	0	0	0	1	0	1	1
	8	0	0	0	0	0	0	0	0
2017	1	0	0	0	0	0	1	0	0
	2	0	0	0	0	0	1	0	0
	3	0	0	0	0	0	1	0	0
	4	0	0	0	1	0	0	0	0
	5	0	0	0	0	0	0	0	0
	6	0	0	0	0	0	1	1	0
	7	0	0	0	0	0	1	1	0
	8	0	0	0	0	0	1	0	0
2022	1	0	0	0	0	0	1	0	0
	2	0	0	0	1	1	1	0	0
	3	0	0	0	1	0	1	0	0
	4	0	0	0	1	0	1	0	0
	5	0	0	0	0	0	0	0	0
	6	0	0	0	1	0	1	0	0
	7	0	0	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0

The block modeling for 2022 exhibited a dual-core structure, with Block 4 (comprising countries such as Canada, China, and the United Kingdom) and Block 6 (comprising countries such as Brazil, the United States, and New Zealand) playing crucial bridging roles in the global beef trade network. The relationships among the other blocks were relatively loose, with Blocks 7 and 8 being particularly isolated and playing peripheral roles within the network.

The evolution of the block modeling from 2013 to 2022 reveals that the global beef trade network has transitioned from full participation of all blocks in 2013, to a structure with one isolated block in 2017, and finally to a structure with two isolated blocks in 2022. This indicates an increasing trend toward regionalization and group formation in global beef trade.

4 Conclusion and discussion

The application of complex network theory in international trade effectively reveals both the global and local characteristics of trade network systems, highlighting the interdependencies among various trade entities. This approach represents a significant advancement over traditional economics, which typically focuses on the analysis of individual countries (Cai and Song, 2016; Qiang et al., 2020).

Using global beef trade data from 2013 to 2022, this article constructs a global beef trade network and conducts an in-depth analysis of its evolution from three levels: overall, individual, and clustering.

From an overall perspective, the structure of the global beef trade network has become increasingly complex. Specifically, although the average distance fluctuated between 2013 and 2022, it showed an overall downward trend, with significant decreases during the periods of 2013–2015 and 2019–2022, indicating that the network has become more tightly connected with improved overall connectivity. Network density showed a steady upward trend, reflecting the participation of more countries or regions in the trade network and the increasing closeness of trade relationships. The

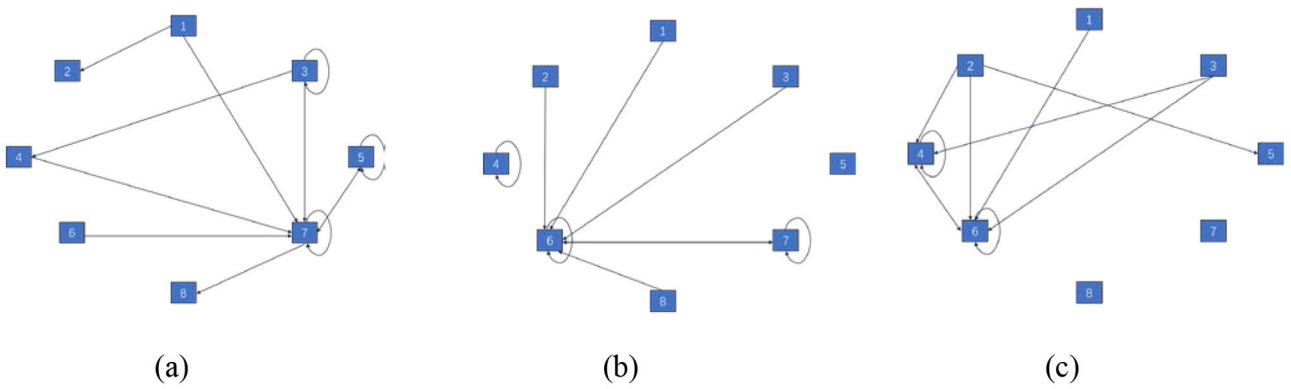


FIGURE 6
Diagram of simplified relationships between blocks. **(A)** 2013. **(B)** 2017. **(C)** 2022.

network diameter decreased from 9 in 2013 to 6 in 2022, suggesting a gradual shortening of distances between the farthest nodes and reflecting enhanced tightness in the network. Furthermore, despite noticeable fluctuations, the average clustering coefficient showed an overall upward trend over the decade, indicating the formation of regional trade clusters and the strengthened localized trade relationships.

These changes in topological indicators reflect the combined influence of globalization, regional cooperation, trade policies, and social demand. Specifically, the increasing demand for beef in emerging markets has led major exporting countries to establish direct trade relationships with more partners. Simultaneously, advancements in modern logistics shortened trade paths, reducing average distance and network diameter while increasing network density. However, a phased increase in average distance during 2015–2019 may be related to global economic fluctuations and trade protectionism. For instance, Sino-US trade friction and adjustments in free trade policies by certain economies may have weakened some direct trade connections. Furthermore, the deepening of regional trade cooperation and the signing of several free trade agreements such as CPTPP and RCEP further strengthened regional ties, driving greater local network tightness. External shocks also had a significant impact on the network structure. For example, the COVID-19 pandemic in 2020 disrupted some trade relationships. However, as supply chains recovered, the network diameter rapidly shortened, demonstrating the resilience of the beef trade network.

From an individual perspective, this study uses degree centrality to measure the position and importance of countries or regions. In the unweighted network, which considers only the number of connections, the evolution of centrality in 2013, 2017 and 2022 showed that countries such as Germany, the United Arab Emirates, and the Netherlands ranked high in out-degree centrality. This highlights their role as key hubs for importing beef from a diverse range of trading partners. In contrast, countries with high in-degree rankings are concentrated in the United States, Australia, and Brazil, which have become significant sources of beef imports for many countries or regions. In the weighted network, which accounts for the value of import trade, significant changes occurred in the out-strength rankings. Countries such as the United States, Japan, and China demonstrate high out-strength centrality, highlighting their role as large-value importers, even though they maintain a limited number of trade partners. Notably, China's rapid expansion in beef imports over the decade has established it as the world's largest importer, significantly reshaping global trade patterns. This growth has been driven by the increasing demand for high-quality beef in China, supported by rising incomes and changes in dietary preferences. Meanwhile, countries such as Australia, Brazil, and New Zealand consistently rank high in in-strength centrality due to their abundant livestock resources and export-oriented production systems. These nations play a pivotal role in stabilizing the beef supply chain and meeting global demand.

From a clustering perspective, block modeling analysis for 2013, 2017, and 2022 reveals distinct trade blocks with varying levels of connectivity and influence. Blocks represented by countries such as Brazil, the United States, and New Zealand have consistently maintained central roles, reflecting their dominant positions in beef production and trade. These countries are characterized by their strong export capacities and stable trade relationships, and form the backbone of global beef trade. Blocks formed by countries such as Canada, China, and the United Kingdom have also gained prominence over time. However, the growing number of isolated blocks reflects fragmented trade integration in certain regions, particularly in parts of Africa, where infrastructural and technological challenges limit participation in global trade. Consequently, the global beef trade network has evolved into a regionalized and clustered competitive structure.

The analysis of the global beef trade network reveals the evolution of trade patterns, enabling countries and regions to better understand their positions within the global beef trade and identify their competitive strengths and weaknesses. In addition, specific recommendations tailored to different countries and regions are essential for promoting the healthy and sustainable development of global beef trade. First, under the current trend of increasing connectivity in the beef trade network, core exporting countries such as Australia and Brazil should enhance cold chain logistics and infrastructure to ensure the stability of exports. Meanwhile, these countries could actively explore emerging international markets to improve supply chain resilience. Furthermore, with the rising demand for premium and environmentally friendly beef, major exporters must adopt sustainable technologies to reduce the environmental impact of production, aligning with global demand for green products. Second, for major importing countries such as China and Japan, efforts should focus on diversifying supply sources and strengthening regional cooperation to mitigate supply chain disruption risks. Additionally, these countries need to establish and enhance beef reserves to safeguard food security during supply chain interruptions. Third, for emerging and peripheral countries and regions, international technical assistance and infrastructure investments are essential to enhance their participation in the global beef trade network. Fourth, countries and regions within regional trade clusters should optimize internal trade policies to boost external market competitiveness, thereby improving overall network connectivity and resilience. The research in this article still has the limitation of not considering the impact of crises on the international beef trade network and their propagation processes, which will serve as a direction for future research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

QW: Writing – original draft, Conceptualization, Formal analysis, Funding acquisition, Methodology. WX: Conceptualization, Formal analysis, Funding acquisition, Investigation, Writing – original draft. RC: Data curation, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The sustainability of China's silk trade: analysis of growth effect and the influencing factors

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Silk and silk products have become one of the world's most vital traded commodities and China is the world's largest producer and exporter of silk products. This study uses statistical data on silk products trade of twenty-nine countries, who are main partners of China's silk trade. The data are mainly from the UN Comtrade database for the years 2002–2022. Utilizing the Constant Market Share (CMS) model, it analyzes the current status of China's silk product export trade. The study decomposes the factors influencing the export growth of silk products between China and other countries. The results indicate that from 2002 to 2022, China's export growth of silk products to other countries was mainly driven by increased export competitiveness. Specifically, silk and satin products and natural silk products have strong export competitiveness, while secondary silk products constrain export growth. In comparison, the dominant factor driving other countries' silk products export to China was the increasing demand in the Chinese market. Market fluctuations caused by the economic crisis and the epidemic have had an impact on the export value of natural silk products and silk and satin products, while secondary silk products, which have the highest value-added, have shown strong competitiveness.

KEYWORDS

silk products, CMS model, export growth, influencing factors, trade fluctuations

1 Introduction

Since ancient times, silk has been known for its unique comfort, luster and charm. It has been the most popular fiber all over the world (Sundari and Ramalakshmi, 2018). The silk industry consists of mulberry cultivation, sericulture, and silk reeling and weaving, which involves agriculture, industry and services, and it occupies a vital position in the industrial sector. There is a sustainable demand for silk due to its wide use in important fields such as the textile industry, medicine and computer science (Furdui et al., 2010; Popescu, 2013). The industry is also of special strategic significance for rural development and poverty reduction (Halagundegowda et al., 2021), because the sericulture and silk industry is highly labor intensive but has high value added (Anitha, 2011; Ashfaq and Aslam, 2006).

Silk and silk products have become one of the most important traded commodities in the world, as well as a key part of international trade in agricultural products. Despite the low production of silk, which accounts for only 0.2% of the global textile fiber market, its trade value is in billions of dollars (Kumaresan et al., 2021). With the economic and social development, sericulture and silk processing industry has been changing from a labor-intensive industry to a capital-intensive industry. The advantages of resources and technology of developed countries and the advantages of labor resources in developing countries are constantly changing the evolution of the production and trade pattern of silk products in the context of deepening economic globalization.

China is the birthplace of silk and has been producing silk for thousands of years, and silk has long been one of China's most representative export commodities. Especially after joining the WTO, China has gradually become the world's largest producer and exporter of silk products. Its natural silk, silk and satin, and secondary silk products trade have accounted for 63.38%, 46.91% and 15.35% of the world, respectively. In addition, China's silk product trade has been in a surplus position in the international silk trade in the long-run, and has become one of China's industries with a monopoly status. However, trade volatility has become a prominent issue in recent years. The complex and volatile global economic landscape coupled with the global financial crisis and subsequent recession in major economies has led to a significant contraction in consumer demand for silk products. Therefore, studying the trade fluctuation and the relevant influencing factors of China's silk products can not only explore the economic law of multilateral trade in silk, but also optimize the world silk industry chain. This study decomposes the factors affecting the trade fluctuations between China and its major trade partner countries of silk products based on data from 2002 to 2022. The heterogeneity of influences across different periods and across various categories of silk products is analyzed.

This paper tries to make up for the shortages identified in the existing research by two aspects of contributions. First, it analyzes the impacts of various factors on the silk trade between China and its trade partners from the perspective of both the silk products as a whole and the heterogeneity across different categories of silk products. The results drawn from the analyses can be applied to the high quality and sustainable development of the silk industry and its segmented products for various silk production and trade countries. Second, a modified Constant Market Share (CMS) model is introduced to quantitatively decompose the influencing factors of trade fluctuations in silk products, as well as the significance and trend of each factor, based on the trade data of Chinese silk products from 2002 to 2022.

The remainder of this article is organized as follows. Section 2 presents the current situation of China's import and export trade of silk products, i.e., the export trade scale, product and market structure of silk products trade. Section 3 is dedicated to the data and methods. The revised CMS model used in this article is introduced, and its theoretical basis and mechanism are analyzed. The empirical results and discussions on the trade fluctuations of silk products trade between China and other countries are presented in Section 4. The last section summarizes the results and proposes policy recommendations.

2 Literature review

2.1 Development of the silk industry and international trade

As a textile product with a long history and unique charm, silk plays an important role in global economic and cultural exchanges (Loewe, 1971). With the deepening trend of economic globalization and the upgrading of the structure of the world's silk industry, the pattern of international silk trade has also undergone significant changes (Shu, 2019). Currently, nearly 70 countries and regions around the world produce silk as well as silk-processed products, the vast majority of which are developing countries, the major ones being China, India, Vietnam, Uzbekistan, Brazil and Thailand (Gu, 2001). China is the world's largest producer and trader of silk, and India is the world's second largest producer of silk and raw silk and the largest consumer of silk (Feng et al., 2009). These countries have good natural conditions for mulberry planting and sericulture as well as advanced production technology and a large number of laborers, which are the main bases for silk production and export (Popescu, 2018).

The international trade market of the silk is complex and dynamically changing. After a long period of low silk prices, silk prices have rebounded to more than 55$/kg, stimulating the recovery of the silk cocoon and raw silk trade in many countries (Popescu, 2018). Madsen (2012) show that technological improvements, such as the introduction of sericulture hybrids, can increase silk production, which in turn affects silk exports. In addition, changes in international market demand, adjustments in trade policies, and geopolitical factors also have a profound impact on silk trade (Popescu, 2018). The trade volume of silk products varies greatly among different types of products. Woven fabrics are more expensive in the export market, while the import price of raw silk and silk yarn is relatively low (Gu, 2001). As the cocoon and silk industry is a more typical labor-intensive industry, the impact of international market fluctuations on the industry is very significant, and the major silk-exporting countries have transformed their export trade mode from quantitative expansion to winning in quality and efficiency (Feng et al., 2009; Zhang et al., 2018).

2.2 Research on the development and international trade of the silk industry in China

Scholars have launched a series of studies on the main factors causing fluctuations in China's silk export trade. From the comparative advantages of China's silk products and international competitiveness, silk is a product with strong competitive advantages in China (Gu and Zhang, 2002). From the analysis of export trade of various products, raw materials such as silk and semi-finished products such as silk satin have strong competitive advantages in the international market, while the competitiveness of women's shirts and other silk products is weaker (Fan and Chen, 2013). The size of the international silk market and the domestic production of raw silk affect China's raw silk export trade, with the reduction in the size of the international silk market being the main reason for the serious difficulties faced by China's silk industry, and oversupply due to the rapid expansion of the size of the domestic silk industry being a secondary reason (Lin et al., 2006). The trade facilitation of the Belt and Road partners has great potential to promote the development of China's silk export trade, and it can effectively promote silk export trade goods to the international market (Ren and Gu, 2019). In addition, the GDP of silk importing countries, the geographical distance between China and silk importing countries, the bilateral real exchange rate and China's accession to the WTO also have a significant impact

on China's silk export trade (Huo and Lin, 2008). Cross-sectional comparisons based on China's major textile export complexity indicators and longitudinal comparisons of China's silk industry export complexity indicators with other silk exporting countries show that China is only a major silk exporting country, not a silk technology powerhouse (Gu and Fang, 2013).

Currently, there are relatively limited studies on China's trade fluctuations in silk products. The existing literature mainly carries out qualitative research and descriptive statistical analysis to analyze the characteristics and development trends of trade in silk products between China and its major trading partners in terms of silk product production, trade product structure, and trade country characteristics (Liu et al., 2006; Feng and Teng, 2012), and only a few scholars utilize the application of econometric models to analyze China's export trade of silk products and its fluctuations from the perspectives of trade competitiveness and development potential (Gu and Zhang, 2002; Fan and Chen, 2013; Wang L. et al., 2017; Huo and Lin, 2008). The existing literature rarely uses the constant market share model to analyze the factors affecting the trade volatility of China's silk products, nor does it systematically analyze the extent to which natural silk products, silk and satin products, and secondary silk products in the silk industry chain affect their respective trade volatility.

2.3 The use of the CMS model to study trade fluctuations

Regression models have been widely applied to analyze the relationship between a single specific variable and export trade volatility by using time series data (Chiou-Wei and Zhu, 2002; Karagöz, 2016; Azar and Ciabuschi, 2017; Ahmadi-Esfahani, 2006). In recent years, for example, gravity models have been applied more to bilateral trade studies (Wang et al., 2022; Masood et al., 2023; Nasrullah et al., 2020; Leng et al., 2020). The trade gravity models often include dummy variables, such as common borders, common language, common religion, etc., as well as institutional indicator variables, such as whether they belong to the same preferential trade agreement or regional integration organization. Such variables that affect export trade volatility are infinite (Widodo, 2010) and most of these variables are not easily and accurately measured, therefore such models can only be used to study the few factors that affect export trade volatility.

The CMS model is one of the main methods used internationally by scholars to study the dynamics of countries' exports and the factors that influence them (Batista, 2008; Merkies and van der Meer, 1988). It was first proposed and applied to the study of world trade by Tyszynski (1951) and refined by Fagerberg and Sollie (1987). In subsequent studies by Jepma (1989), Milana (1988), and Leamer and Stern (2017), The first-level effects were further refined to form a two-level decomposition of the CMS model. The CMS model does not attempt to explain how a particular economic variable affects the volume of export trade; it divides the fluctuations in the volume of export trade into three components, structural effect, competitiveness effect and second-order effect, each with different economic significance (Hatsopoulos and Krugman, 1987; Muhammad and Yaacob, 2008). In addition, the CMS model is able to analyze export volatility comprehensively and accurately with simple and easily available trade data (Wang Z. X. et al., 2017). In a way, the CMS model is a more "macro" analytical framework than other empirically constructed models, making it an important complement to other empirical models used to study the effects of specific variables (Widodo, 2010).

Currently, many scholars utilize the CMS model to study international trade, and most of the studies focus on analyzing the influencing factors of trade fluctuations of specific products, such as aquatic products (Dai et al., 2020), tobacco products (Ruitao et al., 2018), nuts (Aguiar et al., 2017), new energy products (Wang Z. X. et al., 2017). Scholars also take a regional perspective to study the trade between exporting countries and other countries as well as major regions (organizations) in the world, such as the Asian market (Chen and Duan, 2001), the European Union (EU), the North American Free Trade Area (NAFTA), North-East Asia and ASEAN (Widodo, 2010; Abdul et al., 2022), Central and Eastern Europe (CEE) countries (Liu and Xiao, 2018).

3 Current situation of China's silk products trade

The export and import trade value, product structure and market structure of China's silk products are depicted and analyzed in this section.

3.1 Export and import of China's silk products

From 2002 to 2022, the global silk trade exhibited considerable fluctuations. Beginning in 2002, silk trade experienced rapid growth, increasing from US 3.874 billion to US 5.035 billion and reaching its peak in 2008 (Figure 1). Following this peak, the trade volume fluctuated and declined to US 3.507 billion. China, as the largest silk producer and trader worldwide, has consistently maintained a significant position in the global silk market. In 2022, China's import and export of silk products accounted for 32.6% of the global total, highlighting its integral role in the international silk industry.

Similarly, China's silk trade also demonstrated notable volatility during the same period, as shown in Table 1. After joining the World Trade Organization, China's total silk trade surged from US 1.228 billion in 2002 to US 2.130 billion in 2008, achieving an average annual growth rate of 10%. This growth significantly outpaced the global silk trade growth rate of 3.88%. However, the global financial crisis led to a 12.4% decline in China's silk product trade in 2009 compared to the previous year. Although silk exports began to recover in 2010, the growth rate remained modest at 3.92%, below the earlier 10% rate. Subsequently, factors such as the global economic slowdown and regional instability caused the total trade volume to decrease from US 1.799 billion in 2015 to US 1.386 billion in 2019, with an average annual growth rate of −8.62%. Notably, in 2014, India and the European Union surpassed China,

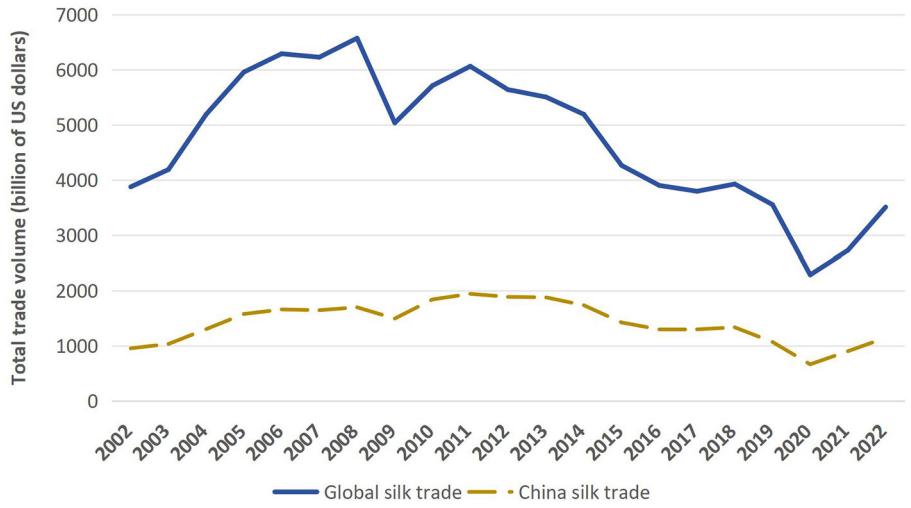


FIGURE 1
Changes of China and Global Trade in Silk Products from 2002 to 2022 (million US dollars). Data source: UN Comtrade database.

marking a significant turning point (Huang and He, 2022). Finally, after reaching a low of US 801 million in 2020, China's silk trade volume rebounded rapidly to US 1.377 billion in 2022.

In spite of the fluctuation of silk product trade, China has maintained a long-term trade surplus position in silk product trade over the past two decades. Silk product import in 2022 accounted for only 16.1% of the total trade value, while the exports accounted for 83.9%. This trade surplus is primarily attributed to China's production volume, quality advantages, and strong demand in foreign markets.

3.2 Product structure of China's silk products trade

Silk products are categorized into three major classes based on the classification criteria of the Harmonized Commodity Description and Coding System. They are natural silk products (cocoon, raw silk, waste silk, non-retail silk, yarn made from non-retail waste silk), silk and satin products, and secondary silk products (women's blouses, silk scarves and shawls, neckties).

As depicted in Figure 2, from 2002 to 2022, silk and satin products and natural silk products, with relatively small profit margins, are the main categories of China's silk products trade. The average annual trade volume of silk satin products is 656 million US dollars, with an average annual growth rate of 10.57%, while the trade of natural silk products showed a similar growth trend, with an average annual growth rate of 7.45%. Comparatively, secondary silk products, which have relatively higher profit margins, grew more slowly, at 4.86%. It is worth mentioning that the global economic crisis in 2008 caused a reduction in the scale of the international silk market, resulting in serious difficulties for China's silk industry.

China's export trade of silk products has declined continuously since 2012, with a large degree of volatility. Between 2013 and 2022, there was a notable decrease in the trade value of silk and satin products, declining from 888 million US dollars in 2013 to 388 million US dollars in 2022. During this period, the trade trends of silk and satin and natural silk products were similar, both showing a decline year by year. The decline in silk and satin products was faster, especially after 2017, with an average annual trade balance of only 28.61 million US dollars.

3.3 Trade market structure of China's silk products

The target markets for Chinese silk products are highly concentrated, with a limited number of import and export trading partners. The main trading partners are India and Pakistan in South Asia, Japan and South Korea in East Asia, and Italy, Germany, and France in Europe. These nations constitute the most significant markets for both imports and exports.

Table 2 displays the top eight countries or regions to which China's silk products were exported in 2022. India stands out as China's largest market for silk, with an export value of 145 million US dollars and accounting for 15.26% of China's total silk export value. For silk and satin products, Italy and Pakistan are the main export destinations, with export values of 108 million US dollars and 54.58 million US dollars, respectively, and accounting for approximately one-third of the total export value. Secondary silk products are mainly sold to developed countries such as the United States, Japan, Germany, and France. The United States, in particular, is China's foremost market for secondary silk products, accounting for 16.88% of the total export value.

The main partner countries and the trade value of China's silk products import are depicted in Table 3. India, Italy, and Uzbekistan are the largest sourcing countries of China's silk product imports, accounting for over 60% of China's total silk product imports. In 2022, the market concentration of silk products

TABLE 1 Overview of China and global trade in silk products from 2002 to 2022 (million US dollars).

Period	Global silk trade	China silk trade	Import of china silk	Export of china silk	Trade surplus
2002	3,874.27	952.20	99.50	852.69	753.19
2003	4,187.89	1,031.87	114.83	917.04	802.21
2004	5,190.43	1,300.96	146.73	1,154.23	1,007.50
2005	5,956.95	1,575.88	146.48	1,429.40	1,282.92
2006	6,289.17	1,658.21	138.03	1,520.18	1,382.15
2007	6,226.35	1,644.39	127.88	1,516.51	1,388.64
2008	6,571.64	1,697.02	147.28	1,549.74	1,402.46
2009	5,034.56	1,492.84	137.23	1,355.61	1,218.38
2010	5,710.91	1,840.18	160.56	1,679.62	1,519.06
2011	6,061.93	1,941.32	169.62	1,771.70	1,602.08
2012	5,637.56	1,886.46	166.24	1,720.21	1,553.97
2013	5,502.45	1,876.61	170.26	1,706.36	1,536.10
2014	5,189.39	1,733.62	144.71	1,588.91	1,444.20
2015	4,262.60	1,421.87	117.49	1,304.38	1,186.90
2016	3,899.53	1,295.15	107.56	1,187.59	1,080.03
2017	3,793.19	1,296.44	110.50	1,185.94	1,075.44
2018	3,925.10	1,333.45	129.49	1,203.96	1,074.46
2019	3,551.53	1,068.31	143.38	924.93	781.54
2020	2,285.19	662.26	155.39	506.86	351.47
2021	2,724.47	900.47	262.77	637.70	374.93
2022	3,507.16	1,144.01	222.07	921.94	699.86

Data source: UN Comtrade database.

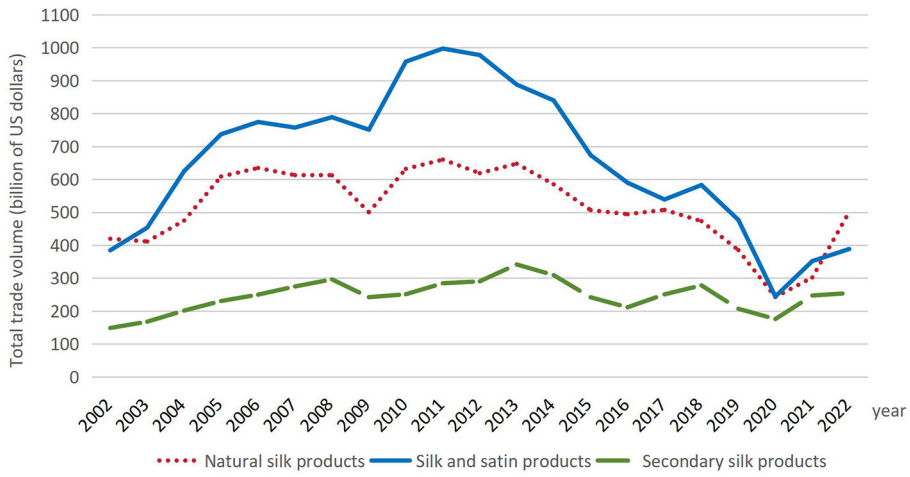


FIGURE 2
Changes in the total trade volume of Chinese silk products during 2002 to 2022. Data source: UN Comtrade database.

imported to China was notably high, primarily centered around India, Uzbekistan, South Korea, and Malaysia. The import value of silk products from each of these countries to China exceeds 10 million US dollars, contributing to a cumulative import share of 42.78%. Italy holds the position of being the largest exporter of silk and satin products to China, constituting 26.44% of the total imports, and is followed by Japan, India, and South Korea, with import values all exceeding 1 million US dollars. The import concentration of China's secondary silk products is the highest, with Italy and France being the key sourcing countries, with

TABLE 2 The top 8 partner countries/regions of China's silk products export in 2022 (million US dollars).

Natural silk products			Silk and satin products			Secondary silk products		
Country/ region	Export volume	Proportion (%)	Country/ region	Export volume	Proportion (%)	Country/ region	Export volume	Proportion (%)
World	956.34	100.00	World	453.42	100.00	World	443.41	100.00
India	145.96	15.26	Italy	107.83	23.78	The United States	74.86	16.88
Italy	74.77	7.82	Pakistan	54.58	12.04	Japan	21.99	4.96
Romania	50.32	5.26	India	39.68	8.75	Germany	17.07	3.85
Japan	46.69	4.88	Sri Lanka	35.30	7.79	France	13.35	3.01
Vietnam	41.04	4.29	Hong Kong, China	30.43	6.71	The United Kingdom	12.70	2.86
Slovenia	20.50	2.14	South Korea	25.11	5.54	Spain	9.28	2.09
Germany	13.83	1.45	Turkey	17.11	3.77	Australia	9.63	2.17
The United States	11.27	1.18	Vietnam	15.18	3.35	Hong Kong, China	8.55	1.93

Data source: UN Comtrade database.

TABLE 3 The top 8 partner countries/regions of China's silk products import in 2022 (million US dollars).

Natural silk products			Silk and satin products			Secondary silk products		
Country/ region	Import volume	Proportion (%)	Country/ region	Import volume	Proportion (%)	Country/ region	Import volume	Proportion (%)
World	130.73	100.00	World	31.57	100.00	World	281.84	100.00
India	17.13	13.11	Italy	8.35	26.44	Italy	72.80	25.83
Uzbekistan	16.25	12.43	Japan	2.57	8.14	France	54.98	19.51
The Republic of Korea	12.18	9.31	India	1.31	4.15	India	1.15	2.02
Malaysia	10.36	7.93	The Republic of Korea	1.22	4.15	Romania	1.11	1.88
Vietnam	2.60	1.99	France	0.27	3.86	Poland	1.04	2.10
Italy	1.77	1.35	Uzbekistan	0.08	0.86	Madagascar	0.70	1.28
Turkmenistan	1.12	0.85	The United Kingdom	0.05	0.26	Morocco	0.53	0.97
Brazil	0.91	0.70	Cambodia	0.05	0.17	Belgium	0.36	0.66

Data source: UN Comtrade database.

import values of 72.8 million US dollars and 54.98 million US dollars, respectively. The combined import share of these two countries reaches 45.34%. This high concentration is attributed to the superior quality and brand premium associated with silk processed products manufactured in Italy and France.

4 Methodology

This section presents the model and data sources.

4.1 CMS model

As can be seen from the analysis in the previous section, the trade volume, product structure and market structure of China's silk products trade have shown tremendous fluctuations. However, descriptive analysis does not explain the causes of trade fluctuations. Silk trade involves a variety of silk product categories and a large number of trading partner countries, and the data presents the characteristics of multi-dimensionality and complexity. Therefore, the constant market share (CMS) model is adopted to explore the influencing factors behind the fluctuation of China's silk trade with other countries in a more comprehensive and in-depth manner from a more macroscopic perspective.

In this paper, the 23 countries that account for more than 90% of China's total exports of silk products are considered as a whole, without taking into account the changes in market demand among the exporting countries. Therefore, this study builds on the model constructed by Jepma (1989) and refers to the model settings of previous scholars (Liu and Xiao,

2018; Wang Z. X. et al., 2017; Bagaria and Ismail, 2019; Capobianco et al., 2017). The model setup of Capobianco constructs the CMS model by dividing the export growth of silk products into two levels and simplifying the second level of decomposition appropriately.

The decomposition formula of the first level model is as follows:

$$\Delta q = \sum_i S_i^0 \Delta Q_i + \sum_i \Delta S_i Q_i^0 + \sum_i \Delta S_i \Delta Q_i \quad (1)$$

Structural effect Competitive effect Second − order effect

Where q represents the export value of silk products from China to other countries or regions, Q_i represents the import value of the i-th category of silk products by China from other countries or regions, and S_i represents the proportion of China's export value of the i-th category of silk products to the total import value of the i-th category of silk products by other countries or regions. The superscript 0 denotes the base (initial) year, and Δ represents the change between the terminal and base years.

At the second level decomposition model, structural effects can be further decomposed into two items:

$$S^0 \Delta Q + \left[\sum_i S_i^0 \Delta Q_i - S^0 \Delta Q\right] \quad (2)$$

Growth effect Commodity effect

The competitive effect can be decomposed into:

$$\Delta S Q^0 + \left[\sum_i \Delta S_i Q_i^0 - \Delta S Q^0\right] \quad (3)$$

Overall competitive effect Specific competitive effect

The second-order effect can be decomposed into:

$$\left(\frac{Q^1}{Q^0} - 1\right) \sum_i \Delta S_i Q_i^0 + \left[\sum_i \Delta S_i \Delta Q_i - \left(\frac{Q^1}{Q^0} - 1\right) \sum_i \Delta S_i Q_i^0\right] \quad (4)$$

Pure second − order effect Dynamic second − order effect

Hence, the decomposition formula of the second level model is as follows:

$$\Delta q = S^0 \Delta Q + \left[\sum_i S_i^0 \Delta Q_i - S^0 \Delta Q\right] + \Delta S Q^0 + \left[\sum_i \Delta S_i Q_i^0 - \Delta S Q^0\right] + \left(\frac{Q^1}{Q^0} - 1\right) \sum_i \Delta S_i Q_i^0 + \left[\sum_i \Delta S_i \Delta Q_i - \left(\frac{Q^1}{Q^0} - 1\right) \sum_i \Delta S_i Q_i^0\right] \quad (5)$$

Growth effect Commodity effect General competitive effect Specific competitive effect Pure second − order effect Dynamic second − order effect

These decomposed effects calculated in above models are depicted in Figure 3.

The definitions of each effect decomposition of the model are shown in Table 4.

4.2 Data

The data for the silk product trades were obtained from the United Nations Commodity Trade Statistics (UN Comtrade) database. Specific categories of products were defined by referring to the HS1996 statistical standard classification codes. The production technology and end-users are very different among different silk products. Meanwhile, different types of silk products also have different tariff policies, trade barriers and market competition situation. We therefore divide the silk products into three categories, they are atural silk products, silk and satin products, secondary silk products. The selected categories include a portion of Chapter 50 (5001–5006) as natural silk products, encompassing silk cocoon (5001), raw silk (5002), waste silk (5003), non-retail silk (5004), non-retail waste silk woven into yarn (5005), and retail waste silk woven into yarn (5006). Category 5007 of Chapter 50 is silk and satin products. A part of products from Chapter 62 are secondary silk products, including women's shirts (620610), scarves and shawls (621410), and ties (621510).

For the segmentation of export markets, 29 countries or regions were selected based on the volume of silk product trade with China. India, the United States, Italy, Romania, Germany, Singapore, Japan, and South Korea are the eight countries with the largest trade values and these countries account for over 90% of China's silk product exports in total. These 29 countries or regions were grouped together as "other countries".

Due to China joined the WTO in November 2001 and started to fully implement its obligations and enjoy corresponding rights in 2002. For the silk trade, this led to a new rule environment and closer integration with the global market, making 2002 a significant starting point for analyzing the changes in silk trade. Therefore, the research period of this paper is 2002–2022 and is divided into four phases:

2002–2009, marked by rapid export growth. Following China's accession to WTO, the process of global economic integration and further opening of national markets has accelerated significantly, and China's trade in silk products has shown an upward trend. 2010–2014, The far-reaching effects of the international financial crisis and the contraction of world trade have led to unstable demand for silk products in the international market, and the scale of China's silk exports has declined, followed by a slow recovery trend. 2015–2019, Export trade continues to shrink stage, Europe and the United States and other major economies, weak economic growth, consumer confidence suffered a setback, the demand for silk and other non-essential goods to reduce the demand for silk, resulting in China's silk products exports continued to shrink. 2020–2022, The epidemic led to the contraction of global silk trade, but the rapid recovery of China's export trade and the development of emerging markets to promote the recovery of China's silk products export trade.

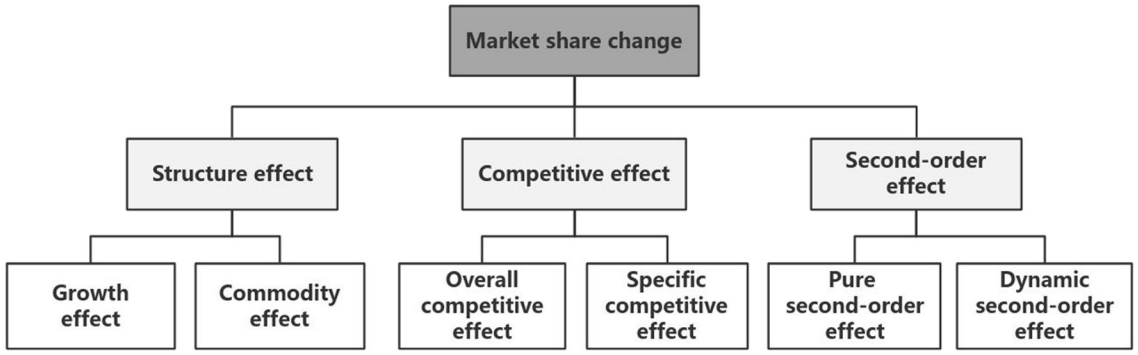


FIGURE 3
The structure of the decomposed effects.

TABLE 4 Decomposition definitions of CMS model specific effect.

Component	Definition
1. Structural effect	Changes in the total import volume of silk products from other countries (China) leading to changes in the export volume of silk products from China (other countries)
Growth effect	Changes in the import demand for silk products from other countries (China) leading to changes in the export volume of silk products from China (other countries)
Commodity effect	Changes in the product structure of silk products exported from other countries (China) have led to changes in the export volume of silk products from other countries (China)
2. Competitive effects	Changes in the export competitiveness of silk products from other countries (China) leading to changes in the export volume of silk products from other countries (China)
Overall competitive effect	Changes in the overall competitiveness of silk products from other countries (China) have led to changes in the export volume of silk products from China (other countries)
Specific competitive effect	Changes in the competitiveness of specific products from other countries (China) leading to changes in the export volume of silk products from China (other countries)
3. Second-order effect	The interaction between changes in the total import volume of silk products from other countries (China) and changes in China's export competitiveness leads to changes in the export volume of silk products from China (other countries)
Pure second-order effect	The interaction between changes in export competitiveness of China (other countries) and changes in the import scale of silk products from other countries (China) leads to changes in the export volume of silk products from other countries (China)
Dynamic second-order effect	The interaction between changes in export competitiveness of China (other countries) and changes in the import structure of silk products from other countries (China) causing changes in the export volume of silk products from China (other countries)

5 Results

5.1 Decomposed effects for the fluctuation of China's silk exports

In this section, the decomposed causes of China's export fluctuations of silk products to other trading partner countries are estimated. From 2002 to 2022, the total growth of China's exports of silk products to other countries is 69.25 million US dollars. In general, the competitiveness effect promotes the export growth most obviously, and the structural effect and the second-order effect have the inverse pulling effect on the exports of silk products.

5.1.1 Structural effect

Overall, from 2002 to 2022, the structural effect exerted a reverse driving force on the growth of China's silk exports, with a contribution rate of −247.52%, resulting in a decrease in export value by 171 million US dollars (as shown in Table 5). Specifically, the Commodity effect had negative contribution values in the first two phases, leading to a decrease in China's silk export value by 17.25 million US dollars and 153 million US dollars, respectively. This indicates that in the initial two phases, China's exports of silk products to other countries were concentrated on products with slower demand growth in those countries, without adjusting the export structure in response to changes in the demand of other countries. In the latter two phases, the export product mix of Chinese silk products has been optimized to some extent, but its contribution to export growth has been limited. In the first three phases, the contribution values of the Growth effect showed a downward trend from year to year. However, under the impact of the COVID-19 pandemic, China's international trade recovered quickly thanks to its strong supply chain resilience, and exports of Chinese silk products were boosted by rapid growth in market demand in other countries.

5.1.2 Competitive effect

The competitive effect is the most significant factor driving the growth of China's silk exports. From 2002 to 2022, the competitive effect contributed to an increase of 715 million US dollars in China's silk product exports, with a contribution rate of 1,032.72%. In the first three phases, the competitive effect showed a declining trend year by year, exerting an increasingly negative impact on export growth. It led to a shift from positive to negative contribution values, causing a decrease in export value by 300 million US dollars in the period from 2015 to 2019. However, under the influence of the COVID-19 pandemic, Chinese silk products demonstrated

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TABLE 5 Decomposition of CMS model results for China's export of silk products to other countries (million US dollars).

Influencing factor	2002–2009		2010–2014		2015–2019		2020–2022		2002–2022	
	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)
Change in export volume	502.92	100.00	−90.71	100.00	−379.46	100.00	415.07	100.00	69.25	100.00
1. Structural effect	132.68	26.38	−80.20	88.41	−99.02	26.09	127.37	30.69	−171.40	−247.52
Growth effect	149.93	29.81	72.92	−80.39	−150.25	39.60	115.85	27.91	21.71	31.35
Commodity effect	−17.25	−3.43	−153.12	168.80	51.23	−13.50	11.52	2.77	−193.10	−278.86
2. Competitive effects	300.90	59.83	61.30	−67.57	−300.49	79.19	259.05	62.41	715.13	1032.72
Overall competitive effect	300.21	59.69	−156.82	172.88	−259.05	68.27	243.56	58.68	376.00	542.98
Specific competitive effect	0.69	0.14	218.12	−240.46	−41.44	10.92	15.50	3.73	339.13	489.74
3. Second-order effect	69.35	13.79	−71.81	79.16	20.05	−5.28	28.65	6.90	−474.48	−55.65
Pure second-order effect	52.91	10.52	2.66	−2.93	34.61	−9.12	59.21	14.26	−178.54	−257.83
Dynamic second-order effect	16.44	3.27	−74.47	82.10	−14.57	3.84	−30.56	−7.36	−295.95	−427.38

strong competitiveness in the international market. From 2020 to 2022, the value of the contribution picked up rapidly to 259 million US dollars, with an upward trend from year to year. During this period, the overall competitive effect became the primary force driving export growth, contributing 243 million US dollars, with a contribution rate of 58.68%, reversing the competitive effect from negative to positive.

5.1.3 Second-order effect

During the period from 2002 to 2022, the second-order effect had a negative impact on the growth of China's silk product exports, resulting in a decrease of 474 million US dollars, with a contribution rate of −55.65%. Specifically, both the pure second-order effect and dynamic second-order effect had negative contributions, with contribution rates of −257.83% and −427.38%, respectively. It indicates that China's silk product export competitiveness did not align well with the import demands and structural changes of other countries. The negative second-order effect offset the export growth brought about by the competitive effect, reducing the growth rate of silk product exports.

5.2 Decomposed effects for the fluctuation of other countries' silk exports to China

Next, we explore the factors affecting the fluctuation of the export of silk products from other trading partner countries to China. From 2002 to 2022, the export growth of silk products from other countries to China was −27.25 million US dollars, of which the total export amount declined by 93.96 million US dollars during the period of 2010–2014, and gradually resumed the growth in the latter two phases. Among the four phases, the structural effect promoted export growth most obviously, while the Competitive effect played a negative pulling role on export growth in general, and the specific decomposition of the model effect is shown below.

5.2.1 Structural effects

As shown in Table 6, from 2002 to 2022, other countries' exports of Chinese silk products decreased by 27.25 million US dollars. The structural effect was the most significant factor influencing changes in other countries' exports of Chinese silk products, promoting an increase in export value with a contribution of 327 million US dollars. As the export value change is negative, it indicates that the increase in Chinese import demand has stimulated the export of silk products from other countries. Specifically, the growth effect directly drove export value growth by 227 million US dollars, being the main contributor to export value growth.

In each of the four phases, the contribution rate of structural effects was positive, showing a fluctuating trend. The main reason for this fluctuation was the impact of economic crises and the COVID-19 pandemic, which led to changes in Chinese import demand across the four phases, consequently affecting export structures.

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TABLE 6 Decomposition of CMS model results for other countries' exports of silk products to China (million US dollars).

Influencing factor	2002–2009		2010–2014		2015–2019		2020–2022		2002–2022	
	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)	Export value	Percentage (%)
Change in export volume	44.71	100.00	−93.96	100.00	11.98	100.00	30.91	100.00	−27.25	100.00
1. Structural effect	83.05	185.75	−76.30	81.20	32.95	275.16	50.87	164.60	327.37	1,201.48
Growth effect	69.86	156.23	−24.25	25.81	24.36	203.43	54.11	175.09	226.97	833.00
Commodity effect	13.20	29.52	−52.05	55.40	8.59	71.73	−3.24	−10.49	100.40	368.49
2. Competitive effects	3.51	7.86	−55.71	59.29	0.21	1.76	−7.01	−22.69	−87.57	−321.39
Overall competitive effect	−18.23	−40.77	−77.34	82.32	−10.15	−84.75	−16.24	−52.54	−113.90	418.04
Specific competitive effect	21.74	48.63	21.63	−23.02	10.36	86.51	9.23	29.86	26.33	−96.65
3. Second-order effect	−41.85	−93.61	38.05	−40.50	−21.19	−176.92	−12.95	−41.92	−267.04	−980.09
Pure second-order effect	1.33	2.98	5.50	−5.85	0.05	0.39	−3.01	−9.73	−107.87	−395.89
Dynamic second-order effect	−43.19	−96.59	32.55	−34.64	−21.24	−177.31	−9.95	−32.18	−159.17	−584.19

5.2.2 Competitive effect

From 2002 to 2022, the competitive effect had a reverse pulling effect on the exports of silk products from other countries, directly leading to a decrease in export value by 87.57 million US dollars, with a contribution rate of 321.39%. Specifically, in the second, third, and fourth phases, the negative pulling effect of the competitive effect on export growth continued to strengthen. The contribution rate of the competitive effect showed a decreasing trend year by year, transitioning from positive to negative, decreasing from 59.29% in the second phase to −22.69% in the fourth phase.

Among these, the overall competitive effect had the strongest negative pulling effect on export growth. In all four phases, the contribution values were negative, indicating that other countries lacked overall competitive advantages in exporting silk products to China. The reason behind this is that in intense market competition, the rising prices of raw materials make it less feasible for other countries to gain a price advantage through human capital.

5.2.3 Second-order effect

From 2002 to 2022, the second-order effect had a negative impact on the exports of silk products from other countries, directly leading to a decrease in export value by 267 million US dollars, with a contribution rate of −980.09%. It indicates that the export competitiveness of silk products from other countries did not align well with the changes in China's import demand and market structure.

Specifically, as shown in Table 6, the dynamic second-order effect had negative contribution rates in all four phases. It further indicates that the interactive impact of the export competitiveness of silk products from other countries and the changes in China's import structure did not promote export growth. It can be observed that the export competitiveness of silk products from other countries had consistently remained in a relatively weak state, unable to adjust promptly according to changes in the import market demand.

5.3 Heterogeneity across different categories of silk products

5.3.1 Exports of different categories of silk products from China to other countries

Due to the different characteristics of different categories of silk products, it would inevitably form the impact on the export structure. Therefore, this section further analyzes the factors influencing China' trade fluctuations of each category of silk products. During 2002–2022, China's exports of silk products to other countries were mainly driven by the growth of silk and satin products, which increased by 72.29 million US dollars, followed by natural silk products, while the export of secondary silk products accounted for the smallest proportion. Overall, the results show that natural silk products and secondary silk products export growth of China mainly depended on the structural effect, while the competitive effect of silk and satin products was the most important

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TABLE 7 Decomposition of CMS model results for China's exports of different categories of silk products to other countries (million US dollars).

Subdivision	CMS decomposition	2002–2009		2010–2014		2015–2019		2020–2022	
		Export	Percentage (%)	Export	Percentage (%)	Export	Percentage (%)	Export	Percentage (%)
Natural silk	Structural effect	21.67	4.31%	88.26	−97.30%	−61.64	16.24%	131.88	31.77%
	Competitive effect	56.09	11.15%	−113.74	125.39%	−87.59	23.08%	56.89	13.71%
	Second-order effect	2.98	0.59%	−16.41	18.09%	10.86	−2.86%	35.45	8.54%
Silk and satin	Structural effect	87.73	17.44%	−215.78	237.88%	−10.42	2.75%	−14.89	−3.59%
	Competitive effect	205.62	40.89%	198.55	−218.88%	−169.58	44.69%	172.24	41.50%
	Second-order effect	60.07	11.94%	−50.22	55.36%	2.83	−0.75%	−11.32	−2.73%
Secondary silk	Structural effect	23.28	4.63%	47.32	−52.17%	−26.96	7.10%	10.38	2.50%
	Competitive effect	39.18	7.79%	−23.51	25.92%	−43.31	11.41%	29.92	7.21%
	Second-order effect	6.29	1.25%	−5.18	5.71%	6.35	−1.67%	4.53	1.09%

factor influencing its export growth. The decomposition of factors affecting changes in China's exports of different categories of silk products to other countries is shown in Table 7.

China's silk products export growth factors are analyzed as shown in Table 7. Structural effect was the main driving force of the export growth of natural silk products, promoting the export growth from 21.67 million US dollars to 132 million US dollars, the contribution rate also increased from 4.31% to 31.77%, indicating that the increase in imports from other countries promoted the expansion of China's exports of silk products, and this effect on the promotion of exports gradually enhanced of the role of competitive effect in the period of 2010–2019 which had a negative impact on the export volume, while the contribution rate reached 125.39% and 23.08%, indicating that the competitiveness of China's natural silk products was insufficient, hindering the export of natural silk products. The second-order effect on exports was generally stable, and the product structure of natural silk exports was more in line with market demand.

Silk and satin products were China's silk trade accounted for the largest category, from the data in Table 8 it shows that the structural effect of silk and satin products contributed to the value of the value of the negative value except for 2002–2009, in particular, the contribution value of −216 million US dollars in 2010–2014, indicating that China's exports of silk and satin products did not expand along with the expansion of the scale of imports from other countries. The competitive effect was positive at all phases except 2015–2019, which was negative, of which the epidemic period of 2020–2022 pushed the export growth of 172 million US dollars, which was the main driving force for the export growth of silk and satin products. And the Second-order effect on exports showed a fluctuating state, the contribution value and contribution rate were negative for many years, indicating that China's export product structure of silk and satin products and the demand for imports from other countries were not adapted to a certain extent.

Secondary silk products were the least important category of China's exports to other countries, with a decrease of 31.52 million US dollars in exports from 2002 to 2022. In the first two phases, structural effects were the main driving force for export growth, pushing up exports by 47.32 million US dollars, but after 2015, structural effect and competitive effect had a negative impact on exports. Although the competitiveness of secondary silk product exports increased significantly during the 2020–2022 epidemic, overall, the contraction of the global silk trade brought about a significant drop in import demand, and the structural effect and competitive effect constrained China's secondary silk products export growth.

5.3.2 Exports of different categories of silk products from other countries to China

In order to better explore the impact of different categories of silk products on the fluctuation of export trade in the world silk trade, therefore, this section we probes into the factors affecting the fluctuation of export trade of silk products from other countries to China by products. Overall, the export value of silk products from other countries to China declined by 27.25 million US dollars from 2002 to 2022, and the export value of both natural silk

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TABLE 8 Decomposition of CMS model results for other countries' exports of different categories of silk products to China (million US dollars).

Subdivision	CMS decomposition	2002–2009		2010–2014		2015–2019		2020–2022	
		Export	Percentage (%)	Export	Percentage (%)	Export	Percentage (%)	Export	Percentage (%)
Natural silk	Structural effect	−0.16	−0.36%	−7.16	7.62%	38.70	323.15%	26.83	86.82%
	Competitive effect	−2.55	−5.69%	4.64	−4.94%	−14.79	−123.50%	−13.87	−44.86%
	Second-order effect	0.02	0.04%	−1.16	1.23%	−26.07	−217.67%	−15.57	−50.38%
Silk and satin	Structural effect	23.09	51.63%	−93.75	99.78%	−22.09	−184.44%	−2.09	−6.75%
	Competitive effect	12.02	26.89%	−66.76	71.05%	2.94	24.57%	−1.04	−3.36%
	Second-order effect	1.85	4.14%	32.19	−34.26%	−1.16	−9.70%	0.11	0.35%
Secondary silk	Structural effect	60.13	134.48%	24.62	−26.20%	16.34	136.44%	26.13	84.54%
	Competitive effect	−5.96	−13.33%	6.41	−6.83%	12.06	100.70%	7.89	25.54%
	Second−order effect	−43.72	−97.79%	7.01	−7.46%	6.04	50.45%	2.51	8.11%

products and silk and satin products were on a downward trend, while the structural effect and competitive effect of secondary silk products drove their export value to grow against the trend. The decomposition of factors affecting changes in other countries' exports of different categories of silk products to China is shown in Table 8.

The contribution value of the structural effect of natural silk products turned from negative to positive and showed a year-on-year growth trend, with a contribution rate of 323.15% in 2015–2019, resulting in an export increase of 38.7 million US dollars, while the contribution value and contribution rate of the competitive effect and the second-order effect show a decreasing trend in the four phases, which indicated that the export growth of natural silk products from other countries mainly originated from the demand of the Chinese market increase, but their products in the Chinese market were not competitive enough, and there was a certain degree of inconsistency between the structure of their export products and the categories of demand of the Chinese market.

The export value of silk and satin products declined by 133 million US dollars, which was the main reason for the decline of its export trade volume. Specifically, the structural effect and competitive effect pushed the export value up by 35.11 million US dollars from 2002 to 2009, while the structural effect became the biggest obstacle to its export growth in the following three phases. The main reason was the shrinkage of demand in the Chinese market due to the global economic crisis in 2008. The competitive effect and the second-order effect remained generally stable after the fluctuation in 2010–2014, indicating that their product categories were generally in line with the Chinese market demand.

The export value of secondary silk products increased by 111 million. Specifically, the structural effect and the competitive effect were the main driving forces of its export growth, and the export value increased by 28.4 million US dollars from 2015 to 2019, with contribution rates of 136.44% and 100.7%, respectively. The contribution value of the structural effect showed an increasing trend, indicating that the silk products of other countries were more competitive in the Chinese market and the demand of the Chinese market was higher. The contribution rate of the contribution value of the second-order effect remained generally stable, indicating that the export product categories of other countries were generally in line with the demand of the Chinese market.

5.4 Conclusion and policy implications

5.4.1 Conclusion

This study presents the evolution of China's export and import of silk products from 2002 to 2022. The CMS model is used to examine the factors contributing to the trade dynamics of silk products between China and other countries. The conclusions are as follows.

During the two decades from 2002 to 2022, China's silk exports growth to other countries were mainly driven by the competitive effect, while structural effect and second-order effect exhibit reverse pull influence. Specifically, China's silk products export was effectively promoted by silk product competitiveness, but the

product structure of China's silk products exported we're not able to adapt to changes in the import demand of other countries.

As for different categories of silk products exported from China to other countries, the export of natural silk products mainly relied on the structural effect generated by the expansion of import demand in other countries. The competitive effect was the main factor promoting the growth of exports of silk and satin products, but the structure of its export products and the demand for imports from other countries there had a certain degree of non-adaptation. The structural effect and competitive effect constrained the export growth of China's secondary silk products, and the export value decreased by 31.52 million US dollars.

For the silk exported from other countries to China, the structural effect is the main factor of export growth, indicating that the rapid growth of China's import demand for silk products promoted the exports of other countries. However, due to the lack of overall competitiveness of silk products in other countries, market fluctuations caused by the economic crisis and the COVID-19 pandemic had a greater impact on their exports. And the export structure of product and the structure of China's import demand were misaligned. It was not conducive to the expansion of exports.

For other countries exporting different categories of silk products to China, the export growth of natural silk products mainly stemmed from the increase in demand in China's market, but the competitiveness of its products in the Chinese market was insufficient. The export value of silk and satin products fell by 133 million US dollars, and the structural effect became the biggest obstacle to its export growth. Secondary silk products were more competitive in the Chinese market and had a higher market demand.

The results of the analysis of the article show that a large part of the fluctuations in the trade of silk products were due to the fluctuations in the world economic situation, and the fluctuation trend was basically the same. China's international competitiveness of silk products had a clear quantitative advantage, especially silk and satin products had a strong export competitiveness advantage, and natural silk products were pressured by the competition in the silk market in neighboring countries, and their export competitiveness advantage had been weakened. The export competitiveness of secondary silk products was weaker, mainly because of the gap in the deep processing of silk with Italy, France and other exporting countries. The growth of other countries' exports of silk products to China resulted mainly from China's expanding market demand, and their export dependence on the international market, resulting in their exports being vulnerable to international trade fluctuations. The market fluctuations caused by the economic crisis and the epidemic had a greater impact on the export value of natural silk products and silk and satin products, while the secondary silk products with the highest added value showed stronger competitiveness, and the structure of exported products was gradually biased in favor of processed silk products.

5.5 Policy implications

Based on the above analysis, we put forward the following policy recommendations from the perspectives of government, enterprises and producers.

First, the government aspect. Governments must establish a favorable macroeconomic environment to support international silk trade. As the world's second-largest economy and a central hub for silk commerce, China should actively advance the Belt and Road Initiative and free trade zone strategies. This entails developing more open and transparent policy frameworks and facilitating access to relevant information channels for member countries' silk industries and import/export businesses. Additionally, optimizing the structure of silk trade is essential. Silk-exporting nations should not only strengthen their comparative advantages in silk product exports but also stay informed about changes in information demand within agricultural markets. Promptly adjusting export product structures can help mitigate the effects of high national market shares and trade barriers.

Second, the enterprise aspect. To enhance international competitiveness and foster export growth in China's silk industry, it is necessary to transition silk raw material exporters into high value-added silk product exporters. This involves bolstering technological innovation in silk fabric production, processing, and design, thereby increasing China's comparative advantages in silk product design and branding. Building on robust product design, enterprises should intensify the brand marketing of pure silk products to establish the international reputation of Chinese silk brands. This will strengthen the position of China's silk industry within the global silk value chain.

Third, the producer aspect. Promoting standardized breeding practices is crucial. Producers should actively comply with the quality inspection standards set by silk enterprises to ensure the stability and consistency of cocoon quality. Establishing stable partnerships with silk companies and signing long-term purchase agreements can help mitigate the impact of market price fluctuations on producers' revenues. Furthermore, producers should adjust their breeding scales and variety structures in accordance with buyers' demands to achieve effective alignment with production requirements.

5.6 Future research

This study still has certain limitations that could be further expanded upon in the future. First, not all of China's partner countries of silk product trade are analyzed. We selected 29 countries and regions, accounting for over 90% of China's silk product exports, as the research objects. Second, the research data in this work are sourced only from the UN Comtrade database and double-check with other databases. Due to the situation where some countries have not reported trade data, there may be slight discrepancies in the data of the total global silk product exports during the model computation process. Finally, more specific analyses could be conducted at the level of China with individual countries or international organizations in the future.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

FL: Supervision, Validation, Writing – review & editing, Visualization, Writing – original draft. MA: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. QL: Funding acquisition, Resources, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Wheat in Kenya: toward self-sufficiency or toward broader development goals

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The conflict between Russia and Ukraine, and the associated disruptions in global wheat supply has resulted in concern for food security throughout sub-Saharan Africa. In Kenya, which depends heavily on wheat imports to meet demand, this concern has intensified calls for self-sufficiency in wheat production. Wheat shortages have led to price hikes that hit all consumers but the urban poor in particular. To decrease reliance on imports, for both food security and for nutrition, Kenya has implemented policy measures to spur increased wheat production. This paper explores the context for increasing wheat production in Kenya to respond to increasing demand, and for addressing the needs of the stakeholders in the sector. Findings suggest that wheat self-sufficiency is unlikely to be achieved soon. Major public and private investments would be required to build the infrastructure, systems, and institutions required to support smallholders to expand and intensify their production. Millers have relied on cheap wheat imports for decades and show limited signs of willingness to support backward linkages with farmers. Critical public infrastructure (e.g., wheat seed systems, extension systems) is ill-equipped to support the growth of the wheat sector. Researchers and policy makers would better serve the interests of smallholder wheat growers by identifying feasible objectives for sustainable and equitable industry growth. We conclude with recommendations for targeted investment and interventions.

KEYWORDS

agricultural development, wheat, Kenya, yield gap, value chains, system approach

1 Introduction: demand and production of wheat in sub-Saharan Africa

The ongoing effects of the Russia-Ukraine war on cereal production and trade has received considerable attention and concern for global food security and particularly for food and nutrition in the Global South. As Erenstein et al. (2022) note, wheat plays an important role in global food/nutrition security, "supplying a fifth of global food calories and protein" (p. 48). In addition, wheat production takes up a significant part of land globally; "By 2018, wheat was cultivated on an estimated 217 million (M) ha of land… making it the most widely grown crop in the world" (p. 48). Of global land production, approximately "29% of the global wheat area is in low and lower-middle income countries (L/LM-ICs), contributing some 25% to the global wheat production" (ibid: 50). Within these low and lower middle-income regions, millions of farmers are engaged in wheat production, sales and consumption. For the period of 2016–2018, global wheat production averaged 750 million tons with Asia (China and India), Europe (Russia, Ukraine and France), and North America as the largest producers. After rice, wheat

is the second most consumed cereal globally. In Asia and Africa, consumption exceeds production and these two regions rely heavily on wheat importation to meet demand (Grote et al., 2021, p. 2).

In sub-Saharan Africa, particularly in urban areas, wheat consumption, spurred in part by inexpensive imported wheat, has grown considerably. Bread, pasta and other wheat products are convenient and quick sources of food compared to maize or rice (Morris and Byerlee, 1993; Kennedy and Reardon, 1994; Boughton and Reardon, 1997; Noort et al., 2022; Minot et al., 2015). As Mason et al. (2015) observe, for women who work outside the home and in urban settings, wheat products (such as bread and pasta) can reduce the time they need to spend on cooking and food preparation.

In the early 1990s, Morris and Byerlee (1993, p. 737) noted that "Over the past 3 decades, dietary patterns in sub-Saharan Africa have undergone dramatic changes. Perhaps the single most remarkable development has been the rapid growth in wheat consumption." The upward trend in wheat consumption across much of the region has continued since then. Wheat products are now thoroughly embedded in diets in African countries. The rising cost of the Ugandan "rolex" snack (rolled chapati stuffed with eggs) due to the Russia/Ukraine war caught the attention of the New York Times in February 28, 2023. Packaged bread, chapati and pasta have become a regular feature of urban diets in particular. Wheat consumption continues to grow and Mason et al. (2015) report that the gap between maize, the dominant staple in sub-Saharan Africa, and wheat consumption is shrinking (p. 582). Demand in sub-Saharan Africa has largely been met with the importation of inexpensive wheat.

Given the demand, and the uncertainties around disruptions in supply chains due to climate events and global conflicts, there has been increased interest in improving wheat production on the African continent to better meet demand and decrease reliance on imports (Gumisiriza et al., 1994; Dorward et al., 2004; Baudron et al., 2019; Anteneh and Asrat, 2020). In neighboring Ethiopia, there has been considerable attention to how to increase wheat production for smallholder farmers through improved access to improved seed varieties, and market and policy interventions (Biggeri et al., 2018; Demeke and Di Marcantonio, 2019; Gabre-Madhin, 2001; Gebreselassie et al., 2017; Minot et al., 2015; Shiferaw et al., 2011; Spielman et al., 2010). Silva et al. point out that "Africa spends 85 billion USD annually on food imports, of which 15% are for wheat imports alone" (p. 1). They argue that decreasing reliance on imports is essential for food and national security and lay out a series of recommendations for a "pathway to wheat self-sufficiency."

While there may be scope for increasing wheat production in Ethiopia, this paper focuses on the plausibility of wheat self-sufficiency in Kenya. The results from Kenya may be more broadly applicable across the continent other than Ethiopia. Our research asks what is inhibiting an increase in production of what in Kenya. To answer this question, we explore the challenges, opportunities and constraints in the wheat sector which have relevance to the crop sector more broadly. Rather than focusing on the potential for technical interventions such as improved seed or agronomic practices, we adopt a systems lens and place wheat value chain stakeholder perspectives through qualitative research at the center of our analysis. Orr et al. (2018, p. 15) argue that components of these systems, such as "policy, institutional and market trends, culture and local circumstances could shape the possible outcomes of interventions to strengthen specific value chains." We adopt this systems approach to explore in depth the myriad factors that contribute to, but also constrain, wheat production in Kenya. Understanding these perspectives is essential for designing policy and other interventions but also for assessing the role that wheat has in rural economies. Others have also argued for this broader approach which goes beyond a focus on farmers to include such stakeholders as "extension agents, agricultural exporters and processors" to gain a fuller picture of how the agricultural system functions and where the challenges are within it (Snapp et al., 2003, p. 349). Indeed, in a study of wheat in Nigeria in the 1980s, Andrae and Beckman (1985) showed how pivotal millers were to both wheat production and consumption.

2 The wheat sector in Kenya

Countries in the northern, eastern and southern regions of Africa possess the agroclimatic conditions to produce spring wheat, and wheat production has featured (with varied levels of enthusiasm) as part of their agricultural development discussions and strategies. In Kenya, wheat is grown primarily in highland areas (1,500 meters and above) and medium and large-scale farmers produce roughly 80 percent of Kenya's wheat. While wheat cultivation has expanded since independence, the area farmed has stayed fairly constant for over the last decade at 120,000 ha in total (FAO, 2015, p. 3). Wheat was first produced in the highlands during the colonial era. As Makanda and Oehmke (1993) note, wheat was central to colonial agriculture and export trade FAO (2015, p. 3). Lord Delamere was instrumental in promoting wheat and planted 1,200 acres of it in 1906. After this, European settlers expanded wheat production on land alienated from Africans. Delamere hired the first wheat breeder in Kenya and established a research station in Njoro. The government took over wheat breeding research in 1911 (Makanda and Oehmke, 1993, p. 4). A focus of wheat research and breeding, from the colonial era onwards, has been on addressing rust varieties which continue to plague wheat production globally. Interestingly, Makanda and Oehmke state that "Kenya was a net exporter of wheat throughout the late 1960's and early 1970's. By the end of the 1970's, Kenya was importing wheat to meet domestic demand" (Makanda and Oehmke, 1993, p. 1). They also observe that "wheat is still one of the seven crops that the government considers as central to achieving the development goals established for agriculture" (Makanda and Oehmke, 1993, p. 2).

Wheat in Kenya is produced entirely as a cash crop and it is the second most important cereal crop in the country "from a food security viewpoint both in terms of quantity and calories consumed" (Monroy et al., 2013, p. 5). The Russia-Ukraine war has dramatically affected the imports the country relies upon to meet demand. The resulting shortages of imported wheat, together with the significant increase in importation costs, led the Kenyan government to ban wheat imports in October 2023 to encourage domestic production by easing competition with cheaply produced imports. Mwangi et al. (2021) reported that Kenya produces, on average, 300,000 metric tons of wheat annually on roughly 140,000 hectares (p. 1–2). It imports about six times what it produces (ibid: 2). Approximately 31% of imported wheat to Kenya comes from Russia, followed by 29% from Argentina.[1] Wheat production in Kenya has been largely stagnant over the past two decades, the reasons for which will be explored in the sections to follow. Briefly however, climate change, low global wheat

1 https://kippra.or.ke/russia-ukraine-conflict-and-wheat-supply-in-kenya/

prices, land fragmentation, insecure leasing arrangements, lack of access to improved varieties and cost of production are the main factors contributing to low production (Figure 1).

There has been very little socio-economic research on wheat in Kenya that assesses the differences in incentives, capacities and circumstances of smallholder, middle-sized farmers, and large commercial farmers. In addition, there has been little inclusion of the perspectives of traders, agrodealers, millers and service providers in the wheat sector. Recently, Mwangi et al. (2021) carried out a study on smallholder wheat in NW Kenya which contributed to understanding constraints faced by farmers. The discussions on the inefficiencies of wheat production in Kenya, especially for smaller-scale production, however, date back at least 20 years. Previous research highlighted wheat production inefficiencies stemming from low yields combined with high costs for inputs (e.g., improved seed, fertilizer) and services (e.g., machinery, transport) (Longmire and Lugogo, 1989; Gitau et al., 2011). No study has been carried out on a country-wide scale or examined all the actors engaged in the wheat sector. In addition, some of the wider impacts of wheat production on the local economy have not been explored. In our results below, a more complete picture of both the constraints and opportunities in wheat emerge as well as an analysis of the overall contribution of wheat, and its byproducts, to the Kenyan economy and rural livelihoods.

Finally, it is also important to situate wheat within the wider political economy of agriculture and food in Africa, as broader interests affect production and investment. As Mason et al. (2015) point out, while demand for wheat increases, it is the interests of millers, bakers and middle to high-income urban consumers that influence national policies more than small-scale farmers or poor urban consumers (Mason et al., 2015). In their analysis of the political economy of wheat in Africa, Byerlee and Morris (1988) suggest that urbanization, increased income, national economic policies, and food aid all aligned to promote greater wheat consumption. They argue that a variety of national pre-structural adjustment policies (exchange rates, consumer subsidies) made wheat products both available and affordable compared to many domestic grain staples. In addition, they contend that different private sector actors also bias policy interventions toward wheat consumption and imports.

> These interest groups include middle-income urban consumers (who often can influence food policy decisions), the wheat-processing sector (which exercises considerable market power in protecting its vested interests), and exporting interests in developed countries, such as grain exporters or milling and shipping industries (which frequently have strong commercial linkages with processors in importing countries). In addition, interest groups in exporting countries also succeed in distorting the policies of these countries toward wheat exports to the developing world. To a large extent, all of these interest groups reinforce each other in promoting wheat consumption (1987, p. 369).

These forces continue to influence policy around wheat production and importation today across the continent. So, while demand has risen significantly, production has not. This paper exposes some of the reasons for this gap.

3 Methodology

This research employed qualitative methods and reviewed relevant policy and trade documents concerning wheat. We focused the research on the major wheat producing counties in Kenya: Narok, Nakuru, Uasin Gishu, Meru and Samburu. We chose these counties based on their production volumes, but also their potential for wheat expansion (Samburu). We carried out key informant interviews with smallholder farmers, medium and large-scale farmers, landowners, traders, agrodealers, private service providers, millers and government officials. We also interviewed seed companies and researchers in the Kenya Agriculture and Livestock Research Organization (KALRO).

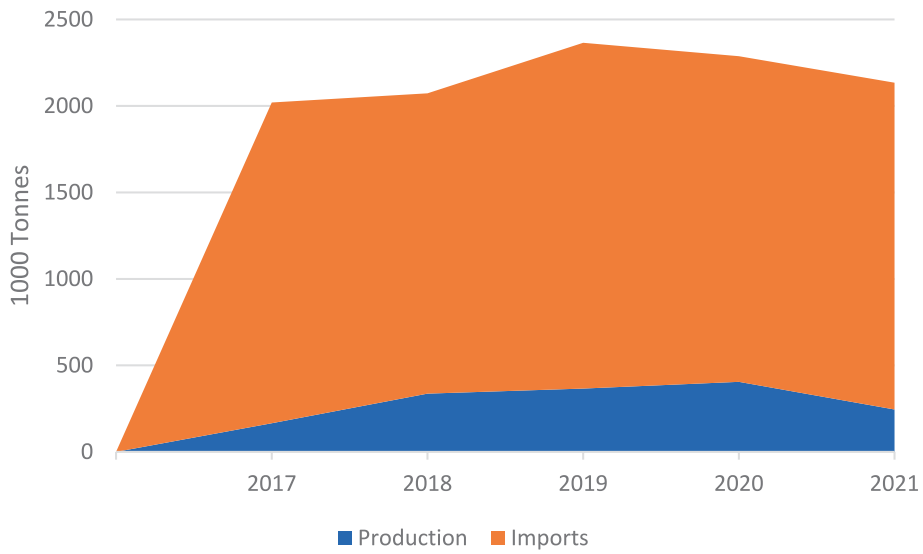


FIGURE 1
Wheat supplies in Kenya 2017–2021. Source: Kenya National Bureau of Statistics-KNBS 2022.

We conducted focus groups in each county, except Samburu where there were not enough farmers available. In total, we carried out 15 focus groups: 5 with women and 10 with men, carried out separately. The lower number of FGDs for women reflects the fact that there are far fewer women wheat farmers, and also that their overall workloads make it hard for them to take the time for focus groups. The FGDs were primarily with smallholder farmers, though medium-scale farmers were included in Narok, Uasin Gishu and Nakuru. The number of participants in the focus groups ranged from 6 to 12 and most of the smallholder farmers cultivated 15 acres or less. In the six counties, we conducted 74 interviews, 13 with women and the remainder with men. The farmers selected came from a list of 2,661 farmers that the Cereal Growers Association provided us (see Table 1 below). While not all wheat farmers are members of CGA, the majority mostly likely are. Working in partnership with the CGA was the most efficient way to find farmers with experience in wheat farming as these data are not collected at the County level.

As a qualitative study of the wheat sector, this study aims to capture the perspectives, opinions and behavior of the relevant actors. It does not focus on gathering quantitative data for statistical analysis or on agronomic data, or specific details on yields, costs, and income except in broad terms that focus on how and why actors engage in the wheat sector. Through thematic content analysis, we assessed data produced from focus groups and key informant interviews across a wide selection of actors and geographical locations.

3.1 Farmer interviews and focus groups

In total, combining focus groups or interviews, we spoke with 143 small-scale, 15 medium-scale and 25 large-scale farmers. The farm size classification for wheat is unique to that crop. Small-scale farmers are defined as those with farm sizes <100 acres. However, the majority of the farmers we spoke with and who defined themselves as small-scale wheat farmers, cultivated around 15 acres or less. Women, due to constraints explored below, usually cultivated 6 acres or less. The farm size classification for wheat farming is specific only to wheat. While small-scale farmers are defined as having <100 acres, most of the farmers we interviewed did not come even remotely close to that number. Rather, they had between 2 and 6 acres. Medium-scale have farms between 100 and 500 acres and large-scale have over 500 acres.

The semi-structured questionnaires covered a several topics, from land size and tenure, reasons for and benefits of farming wheat, yields of wheat, costs of production, use and access to inputs (seed, fertilizer, herbicides, fungicides, machinery, etc.), post-harvest storage and income from sales. We explored the major constraints in wheat production and sales as well as the perceived benefits and opportunities.

All focus groups and interviews were carried out primarily in Kiswahili, with English used with a few stakeholders and took from 1 to 2 h each. Interviews and FGDs were all recorded using digital voice recorders and downloaded into secure folders. Each interview and focus group had at least two note-takers documenting the discussions and notes were compiled and organized by county. We analyzed the data in these documents to expose recurring themes and issues raised around participation in the wheat sector.

TABLE 1 Wheat production in Kenya in all counties.

No	Region	County	Number of farmers	Volumes (in tons)
1	Lower Narok	Narok	462	1,291,735
2	Upper Narok	Narok	72	163,877
3	Nakuru	Nakuru	439	550,591
4	Laikipia	Laikipia	419	121,057
5	Uasin Gishu	Uasin Gishu	1,086	611,841
6	Meru	Meru	151	188,724
8	Machakos	Machakos	1	25,000
9	Elgeyo Marakwet	Elgeyo Marakwet	4	2,315
10	Samburu	Samburu	4	19,620
11	Baringo	Baringo	3	2,020
12	Trans Nzoia	Trans Nzoia	20	–
	Total		2,661	2,976,780

Source: Cereal Growers Association 2023.

3.2 Key informant interviews

In addition to engaging with farmers of all scales, we carried out 31 interviews in total with men and women agrodealers, aggregators, storage facility managers, extension officers, county government officials, traders, landholders (who lease out their land to wheat farmers) and millers. At the national level, we interviewed staff at CGA and in the Ministry of Agriculture. These interviews aimed to gain a deeper understanding of the wider agrarian economy around wheat in Kenya and how wheat contributes to different actors' livelihoods, as well as the challenges in producing, selling or processing wheat. This broad lens on wheat in Kenya revealed both the challenges but also the myriad ways in which wheat contributes to rural livelihoods and the national economy.

4 Results and discussion

Our discussion focuses first on wheat production and the variation in context according to different types of wheat farmers, differentiated by scale and by gender. We then turn to an analysis of post-production factors that affect the benefits farmers obtain from wheat commercialization, as well as the factors that shape other actors' decisions, such as traders and millers. The open-ended questions and our analysis reflect respondents' experiences, opinions and perceptions and are not meant to capture precise quantitative data. We combined content, narrative and thematic analysis of the recorded and transcribed transcripts of all interviews and focus groups to arrive at our results and conclusions.

4.1 Wheat production: "we have no voice, we have no help, we just survive"

4.1.1 Access to land

In Kenya, the competition for land is considerable and, with population growth, land fragmentation (where multiple inheritors

over generations receive increasingly smaller plots) poses numerous challenges, to all agricultural production. For wheat production in particular, access to land is a major constraint that farmers address primarily through leasing land. Indeed, most wheat farmers, independent of their production scale, lease at least part of the land used for the crop's cultivation. For small-scale farmers, this may mean leasing plots at different locations, which in itself poses challenges. Many small and medium-scale farmers we interviewed leased more than one parcel to make it more profitable if climate, pest, disease and low prices at harvest did not get in the way.

Leasing is an opportunity, for both landholder and leasee, but also creates uncertainty. Rarely do landholders agree to lease their land for longer than a year's time. Lease agreements vary by county. All those who leased land remarked upon the tenuousness of leasing. When leasing more than one parcel, the parcels might be quite distant from one another, making various steps in the production and harvesting process more challenging, as one woman farmer in Laikipia explained: "Land leasing agreements are short term and mostly the lands are not centralized; they are in far different places." Leasing for 1 year does not guarantee future leases: "Accessing land can be a challenge because you lease land for 1 year and the following year the owner of the land may decide not to lease it to you."[2] Indeed, throughout the counties covered in our sample, the uncertainty around leasing was a constant concern. One woman's account was not an uncommon one:

> If you are to lease land, you need to lease it early because there is great demand for farmland. We have had disputes before with land leasing because the landowner had leased it to more than 3 people. Because of that, I want to use the written land lease agreement; which will have signature of the two parties entering the agreement and a witness….last year, I had a problem in acquiring land. I first got 7 acres, then after a month I got 3 acres.[3]

In rangeland areas, such as Narok and Samburu, formerly occupied primarily by pastoralists (Maasai and Samburu), and operating under communal land tenure, group ranch titling has given way to individual land titling. The result of this process is highly varied, but in many instances the plot sizes allotted to individual land holders are not sufficient for livestock grazing. So, many Maasai and Samburu community members are now leasing their lands to investors who grow wheat and maize. Investors are increasingly flocking to Samburu country, which is a relatively new area for growing wheat, as the price of leasing is less than in other wheat growing areas like Nakuru or even Narok. For example, leasing land in Samburu runs about 3,000 Kshs per acre, whereas in Nakuru costs are closer to 11,500 Kshs and in Uasin Gishu run as high as 15,000 Kshs per acre. While individual titling, has made leasing land, by both internal and external investors easier, it also leads to the fragmentation that was cited as a problem throughout the counties of this study.

4.1.2 Knowledge and information

Access to information about improved seed varieties, agronomic practices for wheat, chemicals and post-harvest practices for wheat is scarce in Kenya, particularly for small-scale farmers, and for women in particular. Women are less mobile than men due to domestic responsibilities, so they rely on kin, neighbors and friends for information. Getting reliable information on wheat prices is also a major challenge for many small-scale farmers as brokers present them with numerous reasons for offering them the prices they do, such as miller preferences, bushel weight, transport costs, etc. Small-scale farmers have little bargaining power given their constraints so often take what price they are offered.

Due to structural adjustment policies in the late 80s and early 90s, extension services across the continent have declined. Kenya is no different. Overall, extension agents, when they are available, may handle as many as 1,000 farmers or more (Bonilla et al., 2024). A statement by one woman farmer in Laikipia county was reiterated by almost all the farmers we spoke with: "We have never seen extension agents around here so mostly we get information from fellow farmers."[4] At county offices, officials suggested it is difficult to replace agents when they retire, both due to lack of funding but also due to lack of interest by younger people in filling these roles.

Large-scale farmers and agribusinesses often provide services that would usually be supplied by government extension, such as advice on seed varieties, agronomic practices, post-harvest practices, etc. Many small-scale and medium-scale farmers stated that they have participated in several field days hosted by large-scale farmers who provide valuable information on traits (yield expectations, resistance to pests and diseases), seed rate and input requirements, and the importance of crop rotation and zero or minimal tillage.

4.1.3 Obtaining seed

For small and medium-scale farmers, access to quality seed and to the best varieties is a major challenge. For large-scale farmers, who have broader and often global networks, and access to more capital, acquiring the appropriate seeds is not as significant a challenge. Small-scale farmers in particular struggle to find and purchase certified seed. If it is available, they may not have the capital to buy it. In many instances, it is simply not available, and they rely on their own recycled seed, or seed from other farmers. Large-scale farms, such as Kisima Farm in Timau, historically sold untreated commercial grain to small and medium-scale farmers which those farmers used as seed. More recently, Agventure Ltd., which Kisima and other large farms are shareholders of, has been established as a Seed Company and now sells certified dressed seed to farmers. According to both small-scale and medium-scale farmers, large-scale farmers play a crucial role in providing a reliable and accessible source of wheat seed as they have resources (land, finances, and technical know-how) for seed production and storage.

Access to high quality seed is critical for meeting production goals. As an agricultural crop officer in Meru County stated, "most farmers source seed from Agventure because they trust the seed produced."[5] But, for many farmers that we interviewed, the remarks of one woman in a focus group in Meru hold true for other counties: "We are unable to access certified seeds hence we use the already recycled seeds mostly with low yields…. We do not have access to certified

2 15/06/2023.
3 15/06/2023.
4 16/06/2023.
5 19/06/2023.

seeds…you just plant what you can access."[6] Often, farmers are unsure of the varieties they are planting. One farmer in a focus group in Uasin Gishu explained the potential drawback of obtaining seeds from other farmers: "We sometimes buy wheat seeds from farmers in other places without the knowledge that the varieties in those areas will not perform well in our ecological zone."[7]

If farmers do have the capital for purchasing seeds, there may be significant delays in accessing those seeds due to lack of supply. We interviewed medium-scale farmers who had put down cash for seeds but were waiting for months to actually get them. These delays pose critical challenges to production and eventual profits.

The main supplier for wheat seeds is Kenya Seed Company (KSC), followed by KALRO. KSC is unable to meet demand, in part because they cannot find enough outgrowers to produce seed for them. KALRO, who also produce seeds for the market, also noted this impediment. Lack of adequate land to bulk seed, due to fragmentation and also to population growth and expansion of urban areas, is a serious constraint on seed production. At the Cereal Growers Association (CGA), they also underscored that producing and obtaining access to new seed varieties is a major bottleneck in wheat production. Wheat seed is mostly produced in Nakuru and the cost to transport it to other parts of the country raises the overall price of the seed.

For small-scale farmers, the cost of seed is a major concern. Raising enough cash to purchase seed, then the high cost of transportation can be very difficult. Farmers may rely on brokers to access seeds. As a participant in a female focus group discussion explained, "There are men who buy seeds in bulk and come to sell to us. We buy these seeds because it is expensive to buy certified seeds from Nakuru town and transport seed to Elementaita. These brokers sell us the wheat seed in kilos (150 Kshs per kilo – USD $1.08) and most of the time we do not know the varieties they sell to us" (Female FGD in Elementaita, Nakuru County). While 150 Kshs may not seem to be that much, 50kgs are needed for one acre. When buying from brokers, just as with buying from their fellow farmers, farmers may not know the variety of seed they are obtaining.

4.1.4 Inputs and machinery

Achieving higher levels of wheat productivity requires other inputs such as fertilizer, insecticides, herbicides and fungicides. The costs of these inputs is high for small-scale farmers. Most small-scale farmers rely on hiring the equipment necessary for plowing, planting and harvesting wheat from small enterprises or from medium-scale farmers who lease out their equipment. Medium-scale and large-scale farmers own their equipment. A variety of small-scale enterprises have sprung up to provide mechanization services to small-scale farmers. The demand for these services is high and can be difficult to provide if farms are spread out over a wide geographical area and all the farmers need services at the same time. Fuel prices continue to rise so it is costly to travel long distances to service non-contiguous plots across the landscape. While these are challenges, all farmers pointed to mechanization as a major advantage in wheat farming, particularly if compared to maize. As one woman farmer underscored, "you just plant it, apply chemicals and go. You do not have to visit the farm constantly like you do with maize and other crops."[8]

Finally, small-scale farmers also noted that the quality of the chemicals they purchase is often poor. This issue affects farming more broadly, not only wheat. Either the product has been tampered with or is cheaper because of poor quality. Quality products are essential for good harvests. Medium-scale and large-scale farmers have access to, and can afford, better, more reliable products.

4.2 Post-harvest challenges

4.2.1 Drying, storing and transporting harvest

How well the grain has been dried after harvesting greatly influences the price that farmers get. Most small-scale farmers do not have access to commercial driers, nor can they afford to purchase them, so they rely on sun-drying their wheat. Because drying wheat is so critical, small-scale farmers are pushed to sell to brokers quickly at the farm gate and may not be getting the best price. Furthermore, they do not have access to storage where they could hold on to their harvest until the prices go up. Medium-scale farmers also sometimes rely on sun-drying but usually can access driers that they either own or pay to use. Large-scale farmers generally own driers.

Storage facilities are largely absent from most wheat producing areas or are seen to be too expensive to use for small-scale farmers. Medium-scale and large-scale farmers generally have arrangements directly with millers to sell their harvest or transport their crop to aggregators which buy it and sells on to millers.

Finally, for small-scale farmers, hiring transport to bring purchased seed to their farms or to take their harvest to better markets is outside of their ability.

4.3 Wheat sales

Until the recent decline in wheat importation, wheat prices paid to farmers have been low. The high cost of production, combined with low market prices, has driven many small-scale farmers out of the market. However, many of these farmers have stuck with wheat because it provides cash income in a short time period. In October 2023, the Kenyan government temporarily suspended the importation of wheat, ostensibly to protect wheat farmers from depressed prices from cheap imports.

The Cereal Millers Association, the Cereal Growers' Association (CGA), millers' and farmers' representatives together with the government Agriculture and Food Authority discuss, negotiate, and determine the price of wheat which is usually calculated by assessing the cost of production incurred by farmers. However, small-scale farmers may not be aware of these prices or may not be able to bargain successfully with brokers to get them. Millers have considerable influence over the price of wheat nationally and regionally (according to where the miller is located).

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7 07/07/2023.

8 15/06/2023.

4.4 Brokers/traders

Farmers complain about poor prices and unfair practices of brokers/traders, but they rely upon them greatly for selling and transport. Traders will buy unclean wheat from farmers, and clean and store it at their stores which saves farmers' labor and time waiting for their cash. Aggregators usually have equipment to measure moisture content and can assess and grade grain. They also often provide facilities to dry farmers' grain and then sell the grain on to millers. Traders claim that ultimately, the price for grain is determined by millers "as a trader, you first get the prices the millers are buying at, which depends on the market. If the price is good, you offer good prices to the farmers. If not, then you offer low prices" (trader, Meru town).[9]

Traders bear high costs for transportation and the risks on the market as well as stiff competition from other traders. They also often face delayed payments from millers. Many traders have also taken up producing animal feeds so they can buy sub-standard wheat and turn it into livestock feed.

4.5 Millers

There are a variety of companies at different scales and locations involved in milling wheat. According to data from the World Food Program, The Cereal Millers Association (CMA), which has around 35 milling companies, accounts for 40% of millers in Kenya. Small and medium-scale millers are mostly registered under the Grain Mill Owners Association (GMOA). CMA accounts for over 80% of wheat milling capacity.[10] Given the demand for wheat-based foods in Kenya, milling wheat promises significant returns. One respondent began as a trader and then moved into milling, starting his own company. He moved into milling maize and wheat from selling cereals and now mills both flour and animal feeds.

Yet, milling wheat has its own challenges. A miller in Meru explained that he had moved out of wheat due to logistical challenges of getting the wheat from Narok county. Also, he explained that "most of the wheat produced in Kenya is soft wheat and it was difficult to get hard wheat which is sought after for milling. We therefore had to change from wheat milling to milling maize." In addition, the competition among millers is high and traders may sell their wheat to more than one miller, which decreases the amount received by any one miller. Traders may also mix wheat of different quality and moisture content, adding to millers' challenges. Inadequate supply of wheat and fluctuating prices have a bigger impact on small-scale millers. To mill flour and make a profit, large quantities of wheat are needed. Furthermore, some varieties have higher prices than others. For example, one miller noted, "the Asian market wants white and clean wheat like Duma and Korongo. The price difference between white and brown wheat is around 100–300 Kshs ($0.72–$2.17)." Many millers will blend local wheat with imported wheat to meet their production goals and the criteria required by the government that local wheat is purchased before imported.

4.6 The wider context: broader impacts and motivations for farming wheat

Even with the myriad challenges described above, most farmers express continued interest in producing wheat. In part, this is due to recent prices being high because imports have dropped due to the Russia-Ukraine war. While farmers may keep some wheat for their own consumption, wheat is mainly grown as a cash crop. For smallholders, it is attractive for a number of reasons. First, it is a shorter duration crop than maize, the other main cereal in Kenya. And, importantly, it does not require the labor that maize does. So, while the investment in hiring machinery and purchasing chemicals is substantial, there is little need to hire labor. Casual farm labor (*kibarua*) is both costly, often hard to find and hard to adequately supervise. Small-scale farmers stated repeatedly that shorter duration and low labor requirements were the two main reasons to grow wheat. One farmer explained the benefits of wheat: "Wheat is early maturing than maize. So, we can harvest and sell wheat to facilitate us to farm maize".[11] A woman participant in a focus group in Uasin Gishu further elaborated: "you can easily rotate with maize to ensure full land utilization."[12]

While wheat is attractive for many farmers, some also indicated that if another crop came along that was well adapted to their local conditions and had some of the factors that make wheat attractive, they would consider switching. A woman's focus group in Laikipia spelled out these reasons:

> Production of wheat is very low. You use a lot of money for example in preparing land, application of fertilizers and chemicals etc. and get very little from it. The profits are very minimal, and some make losses. Some of us have made small profits in farming wheat, whereas others have never made any profits from wheat farming. We are not able to diversify because the weather in Oljororok is harsh, such that maize and beans would not do well. We can plant peas and groundnuts, however getting labor during harvesting time is a challenge. The advantage of wheat is that it takes a shorter time, and it is a bit tolerant to harsh weather compared to other crops. But if another crop can do better in such kind of weather, we would gladly adopt it.[13]

What is clear from examining the perspectives of farmers from across such a wide diversity of wheat growing areas is that multiple factors shape both the costs and the benefits obtained from wheat. In particular, proximity to markets, road networks, environmental conditions, availability of land and access to services all affect the profits that farmers earn and the decisions they make on how to farm wheat.

9 20/06/2023.

10 https://dlca.logcluster.org/kenya-27-milling-assessment#:~:text=Kenya%20has%20about%2020%20%E2%80%93%2025,%E2809320150%20Mt%20per%20day

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4.7 Women and the wheat sector

Throughout this study, we endeavored to capture the perspectives of women farmers, traders, and small enterprise owners. While there are far fewer women farming wheat, particularly in the medium and large-scale farmer category, there is considerable and growing interest from women small-scale farmers. The constraints they face are similar to men – cost of leasing, costs and availability of seeds and inputs, and low prices offered by brokers. However, these constraints are magnified by the perception that women should work through men, or that they are easy to take advantage of. As one medium-scale woman farmer explained, "all the agreements we do with my husband."[14] It is hard for women to get their husbands to give them the capital to start wheat farming and female-headed households experience even greater challenges to access cash. They rely on borrowing from friends and neighbors, from women's groups or from selling maize and chickens and using the proceeds to invest in wheat farming. In Laikipia County, one woman explained "the men have the money and sometimes it is hard to obtain money from them, so we borrow from our neighbors."[15] One woman summarized: "The biggest challenge facing women is that we do not have many sources of income, compared to men. We rely on farming as the only source of income."[16]

The experiences of women were highly varied. In some, such as in Meru County, women reported that they work and make decisions together with their husbands and they do not perceive gender as a severely constraining factor. In Laikipia County however, women stated "when it comes to farm operations, we help our husbands on their lands, but they do not help us on our lands."[17] And, "wheat is a crop that we grow secretly without our husbands' knowledge…leased land is not my husband's and he will not know how much I harvested."[18]

Access to and use of inputs such as chemicals can also be a challenge for women. They are often advised, for health reasons, to avoid spraying chemicals so they must hire labor instead. It is also harder for women to access information and knowledge of different wheat varieties and agronomic practices as their networks are more local and their movement away from home more limited. Most women turn to fellow farmers for advice. A young woman farmer and agrodealer in Laikipia is making some extra income on providing advice to others. She explained "I have been able to influence other women to join wheat farming. They contracted me to help with the farming. I charge them 1,500 Kshs (USD $11) for a farm visit, depending on the farm location."[19]

Even with all the constraints, there are many women actively engaged in wheat farming and starting small businesses to serve the interests of farmers by supplying inputs, and the machinery to cultivate and harvest wheat. Various opportunities exist for both men and women to engage in enterprises that support farming, and wheat in particular due to mechanization. Leasing out the machinery for wheat cultivation is a growing business and we spoke to a number of women who were engaged in it. One woman interviewed in Narok started off as a wheat farmer and currently cultivates 20 acres. The capital she gets from wheat farming served as her "source capital for my aggregation business."[20] Taking on roles usually dominated by men can be challenging for women as one-woman agrodealer in Nyahururu explained: "There are very many challenges of being a young lady in business. And many people do not believe you can do the farming; they will always ask where my husband is.[21]

4.8 Wider economic benefits

Land leases as income: leasing out land can be an important income generating activity, particularly for those landholders who have land they struggle to farm productively. In pastoralist areas such as Narok and Samburu, where many landholders do not have experience in farming, leasing out land provides valuable cash and also access to crop residues for their livestock. Even medium-scale farmers will lease out land given the demand in any given year. For example, one medium-scale farmer in Narok may lease out 30% of his land depending on demand. What he charges varies by year, "in 2022, we charged 8,000 Kshs (USD $58) per acre and this year, 2023, will charge 10,000 Kshs (USD $72) per acre."[22]

A woman landholder in Meru explained the benefits of leasing out her land:

> I have 2 pieces of land which are in different places. I own 50 acres in Timau and 20 acres in Kiirua. I have leased out land for over 10 years and I lease it out because of the rain patterns we have experienced in this region. Land leasing is a good business, you make some money out of it. At the same time, the tenants are protecting your property.[23]

Wheat byproducts: the grain of wheat is not the only useful and economically important product in the wheat value chain. Wheat straw is an important commodity. In the rangelands, where pastoralists lease out their land, wheat farmers leave the straw for the landlords' cattle. In other areas, farmers collect the straw, bale it and sell it. One farmer said that in a year when wheat prices were particularly low, he made more money from selling straw bales than wheat grain. When farmers own the land they farm for wheat, they may leave the wheat straw as crop residue on their fields to improve soil quality. In Nakuru, a small-scale woman farmer stated that "we leave the straw on the land and charge livestock owners 3,000 Ksh (USD $22) to use the straw for feed, and if they have a herd of cattle, it is 5,000 Kshs (USD $36) per acre. To livestock owners who prefer to buy straw, we charge 300ksh (USD $2) per bale."[24] The price range for straw varies greatly by location, from 90 Kshs per bale to 400 Kshs ($0.65 to $3). A large-scale farmer in Nakuru County reported that they bale and sell straw to farmers who then use it for mulching.

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19 15/06/2023.
20 10/07/2023.
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22 16/06/2023.
23 21/06/2023.
24 21/07/2023.

Because they have storage capacity, they also store and sell straw when prices are higher: "Last year, straw was another cash crop. Last year was very dry, so wheat straw was marketable. I sold the wheat straw and the buyers baled themselves. I sold at 100 Kshs per bale. The money from selling straw last year enabled most farmers to have capital for farming wheat this year."[25]

Wheat bran also has high value for producing animal feed. A miller explained that the profit margins in animal feed are higher than in producing flour. One miller noted that they mixed maize and wheat bran and "sell maize germ at 35 Kshs (USD $0.25) per kilo and 31 Kshs (USD $0.22) per kilo for wheat pollard."[26]

4.9 Wheat's relevance for broader rural development goals

Wheat farming has far-reaching impacts on the Kenyan economy and on individual and household livelihoods, from small-scale to large-scale farmers, to traders, to those actors who make an income from leasing land and machinery to millers. There are also many other stakeholders who rely on wheat for their livelihoods, from small-scale chapati and mandazi (donuts) makers to large-scale bread and bakery item producers and companies.

Kenyan farmers are responsive to markets and when wheat prices rise, many move quickly to enter into or expand their wheat cultivation. There is never a fear that there will be no market for wheat, even if prices rise and fall, as the demand for wheat flour and products continues to rise for urban consumers in particular (Mason et al., 2015). As wheat products are modern convenience foods, they have benefits for working urban women (who do most of the cooking) and their families. While these products may offer limited nutritional benefits in terms of micronutrients, they can offer an important source of fiber and calories.

While successful wheat farming requires capital for seeds, inputs, land leasing and machinery hire, it is also still perceived to be an "easy" crop compared to maize. Not having to hire and supervise labor is seen as a huge benefit. For women, who are more constrained for time due to domestic labor responsibilities, saving time and not having to manage labor are particularly critical (Alkire et al., 2013; Addison and Schnurr, 2016). Also, wheat is seen to be a short duration crop so farmers are able to recoup their costs (if market prices are good) and gain income in a short amount of time compared to maize. While there are undoubtedly many years where small-scale farmers barely cover the costs of production, they are still drawn to the crop as they perceive the risk to be worth it, given the potential benefits of income and the low maintenance quality of cultivation.

As wheat byproducts are important for farmers, breeding efforts should take these factors into consideration. Farmers may use crop residues to improve the organic matter of their soils, or they may or they may sell wheat straw if grain prices are low in the market, providing additional income. Both small and medium scale farmers derive extra income from straw that is sold for livestock feed, or sometimes for crop residues to apply to soils. Thus, when assessing how wheat contributes to rural livelihoods, the byproducts of the crop need also to be considered.

While smallholders contribute only a small part of overall wheat production for Kenya, engaging in wheat cultivation is clearly important for their livelihoods. It supports the growth of small businesses aimed at providing mechanization services to these farmers. So, the ripple effects on local rural economies are important. Women take a keen interest in wheat cultivation for its promise of income. Due to gender norms around land tenure, it is not easy to use their household's land for their independent wheat cultivation. However, if they can find the capital to lease land, wheat offers them a unique opportunity due to its shorter duration and not having to hire labor. A few women we interviewed attested that cultivating wheat has allowed them to move into other enterprises such as trading and providing services to farmers.

Leasing land for wheat provides increased opportunity, and income for landholders. It also is a constraint due to the annual uncertainty about availability and cost. Improvement on leasing contracts could provide better benefits for both landholders and leasees. Improved contracts might also lead to increased numbers of farmers willing to serve as outgrowers. Improved access to seed is clearly a major hurdle to increasing production for small and medium scale farmers. Without addressing this obstacle, production is unlikely to increase.

Access to information, whether on improved seed varieties, agronomic practices or markets is almost entirely dependent on social networks. Small-scale farmers rely on each other and on large-scale farmers for access to knowledge. There is no formal mechanism for knowledge transmission, so access is more *ad hoc*. The lack of extension services and government support for farmers in general is felt keenly by all farmers but is most detrimental for small-scale farmers.

5 Conclusion and policy implications

5.1 Directions for policy

The challenges facing wheat production in Kenya are well known. Stem rust in Kenya has been an ongoing challenge for wheat production since the early 1900s. Mutants of the virus that causes stem rust are common in Kenya as large pathogen populations survive on wheat crops planted throughout the year, with virulence to effective major genes developing shortly after release of resistant cultivars (Fetch et al., 2021). Others have highlighted the high costs of production due to taxes, transport and lack of and cost of inputs. Access to quality seed and difficulties for small-scale farmers to access machinery are also significant challenges (Nyoro et al., 2001; Gitau et al., 2011). In their assessment of the potential for local production to substitute imported wheat, Gitau et al. (2011) noted "Inefficiencies encountered by transporters include high maintenance costs, high fuel prices, poor infrastructure (especially feeder roads connecting production areas and the markets) and roadblocks" (2019: iv). Makanda Oehmke argued that "in the absence of increasing subsidies, wheat self-sufficiency in the next 10 years is not a realistic goal for Kenya. … A realistic goal may be a four-percent annual growth rate for wheat yields, accomplished by increases in the use of non-land inputs, management skills and technical progress" (1993, p. 22).

25 16/06/2023.

26 21/06/2023.

Numerous countries across Africa have the agroclimatic conditions to produce wheat but share challenges like those in Kenya to advance production and productivity goals. In recognition of these challenges, researchers have consistently advocated for public investments to achieve wheat self-sufficiency. In response to the Russia-Ukraine war and its threat to food security across Africa, various authors argued that African countries need to expand their domestic wheat production (Mottaleb et al., 2022; Mottaleb and Govindan, 2023; Silva et al., 2023; Balma et al., 2024). Prior to the war, researchers had been calling for African countries to invest more to address low wheat productivity in the face of rising domestic demand via crop breeding and management practices (Macharia and Ngina, 2017; Tadesse et al., 2019; Zegeye et al., 2020; Shikur, 2022). Various countries (e.g., Egypt, Ethiopia, Afghanistan) have declared wheat self-sufficiency as a strategic agricultural development priority, with major investments proposed in irrigation and price supports (Abdalla et al., 2022; Senbeta and Worku, 2023; Najmuddin et al., 2021).

The calls for wheat self-sufficiently, however, ignore the complexity of wheat value chains in many African countries. Andrae and Beckman (1985, p. 145) study of wheat in Nigeria decades ago illustrates these complexities well. They describe how a variety of interests, from local millers, to importers, to the exporters of wheat from the USA have aligned to make bread the most affordable and widely available staple food in the country. While there have been efforts to increase domestic production, agroclimatic (soils, climate, water availability, etc.) and social challenges (local farmer preferences for guinea corn which is less risky) have limited expansion of wheat production. In sum,

> Imported wheat cannot be substituted on any significant scale by wheat grown in Nigeria. Domestic wheat faces major natural and social constraints which reinforce each other. For wheat to grow well over wide areas, a number of technical and social preconditions must be met. The problems of establishing and maintaining these are staggering and so are the financial and social costs involved (Andrae and Beckman, 1985, p. 156).

5.2 Is self-sufficiency realistic?

Is self-sufficiency in wheat possible for Kenya? Expansion of wheat production in Kenya is certainly possible, however it will be limited by available land due to fragmentation and suitability. Given the huge and increasing demand for the crop, self-sufficiency is unlikely. Public investments in smallholder wheat production however can increase their production, and hence farmer incomes as well, if the challenges they describe can be addressed. Challenges that should and can be tackled include: addressing the lack of extension services, improving access to capital, increasing access to quality seed and inputs; building and improving storage facilities for crops. Researchers have been describing these challenges for decades (c.f. Jayne et al., 2010 for sub-Saharan Africa as a whole).

In the Government of Kenya's new "manifesto," termed the "Bottom Up Transformation Agenda,"[27] agricultural transformation and inclusive growth are at the top of the agenda. The manifesto makes a budget pledge of Ksh.250 billion to be distributed between 2023 and 2027 towars the sector. Budgetary pledges have been made before, such as the countries who signed up to the CAADP Comprehensive African Agricultural Development Programme (CAADP) in which 10 percent of national budgets are to be designated for agriculture. Few countries have fully instituted these commitments. Ultimately, while policies to address the constraints in the wheat sector are important, they need to be implemented to be effective in improving production and the livelihoods of all actors in the wheat value chain.

It is a hopeful sign that agricultural development has such a strong focus in the government's manifesto and budget plan. As so many countries recognize that agriculture is the "backbone" of their economies, this investment is essential. The government has focused on wheat in its Agricultural and Food Authority's Wheat Purchase Programme that requires millers to purchase locally produced wheat before considering imports, and it has imposed a 10% duty on all imported wheat to encourage local wheat production.[28] These are important measures, but they will not entirely address the constraints detailed by stakeholders in the wheat sector. The manifesto's goals of raising productivity, improving finance, increasing extension services and decreasing reliance on imports are all essential but they will require the political will to ensure that this investment in agriculture comes to fruition.

5.3 Recommendations for improving wheat production

In short, productivity can be improved and thus farmers and all who are engaged in the wheat sector can benefit and Kenya can decrease its importation bill. A multi-pronged approach to wheat production is needed. First, wheat breeding, to produce new varieties that improve resistance to disease and pests as well as being adapted to changing climate conditions remains essential and requires investment. Next, access to quality seeds is a major bottleneck that must be addressed with urgency. Extension and finance are already in the plans, but it should be carefully targeted to where there is the greatest need. Irrigation may also provide opportunities for increased production. Another priority must be storage which is an enormous challenge for small-scale and many medium-scale farmers and significantly affects the prices they get for their grain.

While all small-scale farmers experience the same constraints, they are magnified for women whose networks and opportunities are more limited. Women farmers are clearly very interested in and benefitting from wheat production, though they face greater constraints on their time and in raising capital. These women farmers need targeted support, starting with better access to information about wheat farming, access to seeds, prices on the market, agronomic practices and of course, finance. Women farmer groups have addressed some of the constraints around access to knowledge and to inputs and capital. However, these groups are very few and increasing

27 http://www.parliament.go.ke/sites/default/files/2023-09/Budget%20Watch%202023_0.pdf

28 https://kippra.or.ke/russia-ukraine-conflict-and-wheat-supply-in-kenya/#:~:text=The%20key%20policy%20interventions%20that,the%20same%20at%20discounted%20tariffs%2C

and/or strengthening these groups could have important benefits that extend well beyond just wheat production.

This research has demonstrated the importance of applying a broader lens to understanding the wheat sector in Kenya. It details from production to sales and milling the myriad constraints of stakeholders but also the interest and opportunities that exist. It shows the interconnectedness of all actors and how challenges for each group can affect the other. It illustrates the impacts not only on farmer incomes, but on the stakeholders that provide services and supporting enterprises for wheat farmers. It also demonstrates that wheat is not solely about the grain, but also the byproducts produced that can contribute to incomes, but also to the soils on which farmers depend. It is essential to understand these wider impacts to get the full picture of the potential of agriculture to contribute to livelihoods and reduce poverty, as well as to understand the potential for wheat in Kenya. This knowledge is central to designing policies that address specific constraints and opportunities.

Wheat is an important livelihood strategy for many farmers in Kenya, and thus an important crop for Kenya. While urban consumers may drive much food policy, it is the farmers who produce this food who need support. It is impressive what farmers in Kenya already accomplish with so little assistance. It is interesting to think about what successes they could have if they actually received targeted support in their farming.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

KS: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. PM: Data curation, Formal analysis, Investigation, Writing – review & editing, Project administration. CK: Data curation, Investigation, Writing – review & editing, Formal analysis. PR: Conceptualization, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing. JM: Writing – review & editing, Data curation, Investigation. FO: Data curation, Investigation, Writing – review & editing. JD: Writing – review & editing, Conceptualization, Formal analysis, Funding acquisition, Project administration, Writing – original draft.

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Conflict of interest

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Farmers' adoption of smart agricultural technologies for black soil conservation and utilization in China: the driving factors and its mechanism

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Smart agriculture can mitigate the degradation of black soil organic matter to ensure global food security and promote sustainable agricultural development. However, the adoption of smart agricultural technology for black soil conservation and utilization is poorly understood. This study analyzes the influence mechanisms affecting farmers' adoption intentions of one such technology, variable fertilization. We develop a structural equation model by combining the Technology Acceptance Model (TAM), Perceived Value Theory (PVT), and external factors with data from 354 farmers in Youyi State farm in the Sanjiang Plain Area, China. The results revealed that social influence (SI) was the most significant determinant of farmers' adoption intentions (AI), emphasizing the critical role of social networks, particularly information from experienced demonstration households, in shaping decisions. Additionally, both the perceived usefulness (PU) and perceived ease of use (PEOU) of variable fertilization technology (VFT) significantly and positively influenced AI. Among these, PEOU demonstrated a greater overall impact than PU. We propose strategies for demand-driven, incentive-based, and technical support mechanisms to facilitate the adoption of VFT and conclude with recommendations to promote black soil conservation and utilization technologies among farmers.

KEYWORDS

black soil conservation and utilization, smart agriculture, variable fertilization, farmers' adoption, technology acceptance model

1 Introduction

In 2022, the Food and Agriculture Organization of the United Nations (FAO) released its first global report on black soils, emphasizing their value as one of the most important natural resources.[1] Black soils are rich in organic matter and ideal for crop growth. Globally, black soil regions cover approximately 725 million hectares, about 7% of the earth's ice-free land surface. These regions are found in the Russia-Ukraine Great Plain (1.9 million square kilometers), the Mississippi Plain of the United States (2.9 million square kilometers), the Northeast Plain of

1 FAO: https://www.fao.org.

China (1.09 million square kilometers), and the Pampas of South America (0.76 million square kilometers). However, global climate change, natural disasters, population growth, and human activities have led to significant soil degradation. Most black soils have lost at least half of their soil organic carbon (SOC) stocks and suffer from severe erosion. This degradation creates nutrient imbalances and threatens global food production. Black soil must be preserved for environmental protection, sustainable agricultural development, and global food security. A series of international initiatives have highlighted the need to protect healthy black soils to ensure global food production is increased by 60% by 2050 (Rojas et al., 2016).

In the early 20th century, developed countries began experimenting with modern agricultural technologies for more efficient crop production to achieve large-scale food production (Jayaraman et al., 2015; Small, 2016). Since the 1930s, the United States and Russia have pioneered black soil conservation tillage technology to combat famine caused by excessive reclamation and sandstorms (Ao et al., 2022). These efforts included the use of large-scale plowing machinery and conservation tillage technologies, such as reduced tillage and no-tillage (Mitchell et al., 2009). These advancements have increased the net carbon sink of black soils and stabilized grain production. In the 1960s, countries like the Soviet Union, Canada, Australia, and Mexico also adopted conservation tillage technologies (Kassam et al., 2018). China has focused on conservation tillage since the late 1970s and various national departments have developed innovative black soil conservation and utilization technology. Especially smart agriculture technologies, which integrate advanced tools to create interconnected and data-driven farming ecosystems, present substantial potential to enhance black soil fertility, increase agricultural productivity, optimize resource use, and reduce environmental impacts—addressing critical challenges in sustainable agriculture (Rehman et al., 2024).

There is growing academic and practical interest in large-scale black soil conservation and utilization technologies. Farmers play a crucial role in this process, as they are the primary users and protectors of this technology. The effectiveness of black soil conservation and utilization technologies relies on farmers' intentions to adopt them (Adesina and Chianu, 2002). Farmers' adoption of new soil conservation technology is described as a diffusion process, mainly affected by family characteristics, cultivated land characteristics, and the external environment (Rogers, 1995). While it is difficult to change farmers' personal characteristics, their psychological cognitive limitations can be shifted through external influences (Zhang et al., 2020). Therefore, it is essential to consider the conditions and preferences of different farmer groups to improve overall adoption rates (Jansen et al., 2010; Schut et al., 2015). Education about technology is core to adoption, alongside external environmental interventions that affect farmers' behavioral intentions.

China State Farm, dedicated to specialized agricultural production utilizing regional water and soil resources, is crucial for national food security and agricultural modernization. However, the expansion of production scale and mechanization has led to excessive inputs, resource waste, and environmental pollution. The overuse of chemical fertilizers has resulted in the decreased black soil fertility, non-point source pollution, and increased production costs (Du et al., 2021). There is an urgent need to develop smart agriculture and promote high-quality agricultural development. Variable fertilization technology (VFT), which involves precise fertilization based on spatial data such as yield, soil properties, climate, and pest conditions, is a key component of smart agriculture (Miller et al., 2018). As an essential aspect of smart agriculture, it significantly enhances fertilizer utilization, reduces production costs, boosts farmers' income, and provides substantial economic, environmental, and social benefits. The key to enhancing the protection and utilization efficiency of black soil through variable fertilization technology lies in the effective promotion of the technology and the high adoption rate among farmers.

This paper examines the adoption intentions and promotion mechanisms for VFT, using the Youyi State farm in the Sanjiang Plain Area (the largest contiguous reclamation area in China) as the research site. Focusing on farmers as decision-makers in fertilization behavior, the study extends the Technology Acceptance Model (TAM) to investigate the influencing factors and driving mechanisms behind farmers' intention to adopt VFT, integrating both psychological perception factors and external influences. Our findings offer a scientific basis for the comprehensive promotion of black soil conservation and utilization technology, policy formulation, and sustainable agricultural development. The remainder of this paper is organized as follows: Section 2 reviews relevant literature. Section 3 introduces the theoretical framework and hypotheses. Section 4 describes the study area and data methods. Section 5 and Section 6 present the findings on farmers' intentions to adopt VFT and the driving mechanisms behind these intentions. Section 7 provides conclusions and discussion.

2 Literature review

In the 1930s, the United States began developing conservation tillage technology under severe resource and environmental constraints. Such conservation tillage technology has long-term effects on black soil (Voorhees and Lindstrm, 1984). Scholarly research has primarily centered around conservation tillage (straw and no-tillage), soil and water conservation, and black soil health (Ike, 1986; Sturgul et al., 1990). By the late 1970s, conservation tillage had been implemented globally, with the United States, China, Russia, Canada, and Australia leading black soil conservation research (Guan, 2021; Kazeev et al., 2020; Llewellyn et al., 2012; Zhang et al., 2022). With the advent of modern information and communication technologies in agriculture, the "third green revolution" has emerged (De Baerdemaeker et al., 2023). Smart agriculture leverages information technology—such as the Internet of Things, cloud computing, big data, and artificial intelligence—to enable digitalized and information-driven management across the entire agricultural process (Blackmore and Brit Crop Protect, 1996; Trendov et al., 2019). Early research focused on technological innovations in smart agriculture for crop production (Foster et al., 2015; Zhang and Li, 2002). Later, smart technologies such as automatic guidance, sensors attached to the field, and unmanned aerial vehicles were used for variable operations like quality measurement, fertilization, and irrigation (and were gradually applied to black soil conservation and utilization). Today, smart agriculture involves various aspects of black soil conservation, including variable fertilization, vegetation conservation, precision seeding, and water-saving irrigation. Some scholars focus on the physical and chemical properties of black soil, causes of degradation, ecological management, and protection technologies of black soil (Yang et al., 2023; Yu and Zhang, 2004). Other

scholars have found that farmers' psychological expectations about production and management behaviors directly affect the effectiveness of black soil conservation (Chianu and Tsujii, 2005; Guo et al., 2022). Therefore, improving farmers' intentions to adopt black soil conservation and utilization technology and promoting farmers' black soil conservation behavior has become a key issue in academic circles.

Initial research on the factors affecting farmers' adoption of black soil conservation and utilization technology focused on individual characteristics and socioeconomic factors, such as age, gender, education, farmland scale, and income (Hu et al., 2022; Mignouna et al., 2011; Xu and Zhang, 2005; Tey and Brindal, 2012). However, external environmental factors like government policy, trade agreements, market access, and social networks also influence farmers' behavioral decisions (Liu et al., 2021; Wang and Guo, 2020). In Western countries, government policies promoting agricultural environmental protection projects garnered more support from farmers to achieve better black soil conservation results (Burton et al., 2008). Chaudhuri et al. (2021) add that farmers' social networks can also provide information about sustainable practices, promote technology sharing, and address challenges in black soil conservation and utilization.

Farmers' intention to adopt technology is essentially a psychological process of perception, interest, and evaluation (Yang et al., 2023). Therefore, scholars have used psychological models like the Theory of Reasoned Action, Perceived Value Theory (PVT), and Technology Acceptance Model (TAM) to explain farmers' behavioral intentions around black soil conservation and utilization. Caffaro et al. (2020) and Fei et al. (2022) foregrounded the importance of farmers' value judgments about technology adoption, while Jorgensen and Martin (2015) used the Theory of Reasoned Action to explain how perceptions impact farmers' intentions to use irrigation systems. Khoza et al. (2021) extended TAM to determine the perceived risk in adopting conservation tillage technology and found that social processes were central to farmers' decision-making.

TAM explains individuals' acceptance of information technology based on perceived usefulness and perceived ease of use (Davis et al., 1989). However, it does not account for risk perceptions. Therefore, this study expands TAM by incorporating perceived risk factors from Perceived Value Theory (including perceived usefulness, perceived ease of use, and perceived risk). Additionally, research on technology adoption often focuses on internal psychological factors or a single external factor. However, the adoption of black soil conservation and utilization technology is a dynamic process influenced by many internal and external factors (e.g., unstable family interactions, social network coverage, and policy changes). Therefore, we consider both psychological and external factors (i.e., policy support, social influence, and household management characteristics) to better understand the behavioral factors and external environmental interventions that influence farmers' adoption of black soil conservation and utilization technology.

3 Theoretical analysis and hypotheses

3.1 TAM

The Technology Acceptance Model (TAM) was first developed by Davis (1985) based on the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1977) and the Theory of Planned Behavior (TPB) (Ajzen, 1980). TAM considers the mediating role of two variables—perceived usefulness and perceived ease of use—on external variables and the potential use of technology (Marangunic and Granic, 2015). It is widely used to explain and predict users' acceptance of information systems. For TAM, a person's attitude about a technology and their behavioral intention to use it are influenced by the individual's "descriptive beliefs" and "reasoning beliefs," TAM assumes two specific beliefs: "perceived ease of use" and "perceived usefulness." Thus, an individual's behavioral intention is affected by behavioral attitudes, direct and indirect perceived usefulness, and perceived ease of use (Ducey and Coovert, 2016).

3.1.1 Perceived usefulness (PU)

Perceived usefulness considers whether a new technology will improve work efficiency (here, it refers to the perceived benefits of black soil conservation and utilization technology). Mohd et al. (2010) showed a significant positive correlation between PU and behavioral intention—farmers are more likely to adopt black soil conservation and utilization technology if they recognize its economic benefits (if not, their willingness decreases).

While farmers recognize the importance of black soil conservation, most still rely on large-scale fertilization to increase food production. Over time, excessive use of chemical fertilizers adversely affects soil quality through soil acidification. When farmers recognize that black soil conservation and utilization technology can save on fertilizer and improve the black soil quality, they are more willing to adopt new technologies. Therefore, we propose the following hypothesis:

> *H1*: Perceived usefulness has a significant positive impact on adoption intention.

3.1.2 Perceived ease of use (PEOU)

New technologies require time, effort, and money to learn. Therefore, perceived ease of use asks whether people find it easy to adopt new technology. A higher perceived ease of use reduces farmers' anxiety about new technologies (Sorebo and Eikebrokk, 2008), thereby enhancing their willingness to adopt. Farmers are more willing to adopt simple and easy technologies. There is also a positive correlation between perceived ease of use and perceived usefulness, with perceived ease of use indirectly affecting adoption intention through perceived usefulness (Wu and Wang, 2005). Therefore, we propose the following hypotheses:

> *H2*: Perceived ease of use has a significant positive impact on adoption intention.
>
> *H3*: Perceived ease of use has a significant positive impact on perceived usefulness.

3.1.3 External variables

The original TAM model does not explain how external variables affect individual behavioral intentions (Venkatesh and Davis, 2000). Therefore, scholars have advocated expanding TAM to understand how external variables affect an individual's psychological expectations of new technologies. Such insights have been incorporated into the model as influences on perceived

usefulness and perceived ease of use (King and He, 2006). Situational factors like social influence, policy environment and household characteristics also affect behavioral intention and should be included as regulatory factors (Abbasi et al., 2011; Chang et al., 2007). Therefore, this study adds three external variables—social influence, policy support, and household management characteristics— to better explain the factors affecting farmers' intention to adopt black soil conservation and utilization technology.

Social influence (SI) is defined as the degree to which people in the surrounding environment believes that a person should use a new technology (Venkatesh et al., 2003). Individual behavioral intention is influenced by the behaviors of other people in one's social network, with social influence playing a complex role in adoption decisions (Ajzen and Driver, 1991). Social influence significantly shapes perceived usefulness and perceived ease of use (Adnan et al., 2017). The opinions of neighbors, friends, demonstration households, and farm workers influence farmers' perceptions of black soil conservation and utilization technology availability and risk (Li, 2012). We propose the following hypotheses:

> *H4a*: Social influence has a significant impact on perceived usefulness.
>
> *H4b*: Social influence has a significant impact on perceived ease of use.

Policy support (PS) considers government incentives and normative systems. Farmers, as rational economic agents, make decisions to maximize their interests. Therefore, government subsidies for agricultural machinery significantly promote farmers' adoption of new technologies (e.g., conservation tillage) (Guo et al., 2022). Improved government policy support for black soil conservation and utilization technology alleviated farmers' funding and capacity issues, boosting their confidence and promoting adoption intentions. We propose the following hypotheses about the regulatory role of policy environment variables:

> *H5a*: Policy support has a significant impact on perceived usefulness.
>
> *H5b*: Policy support has a significant impact on perceived ease of use.

Household management characteristics (HMC) research shows that the scale of cultivated land management significantly impacts farmers' adoption of new technologies (Xia et al., 2019). Larger farms allow farmers to leverage economies of scale that encourage black soil conservation and utilization technology. Farming income also affects whether farmers can afford technical investments. Therefore, we propose the following hypotheses:

> *H6a*: Household management characteristics have a significant impact on perceived usefulness.
>
> *H6b*: Household management characteristics have a significant impact on perceived ease of use.

3.2 Perceived value theory

Zeithaml (1988) first proposed the Perceived Value Theory to posit that consumers' behavioral intentions depend on the perceived value of products and services. This theory hinges on the trade-off between perceived benefits and perceived risk. Farmers are generally risk-averse and have low awareness and acceptance of new technologies, so any risk farmers perceive significantly affects their adoption intentions (Wang and Wang, 2021). Therefore, we incorporated perceived risk into the influencing factors.

Perceived risk (PR) refers to an individual's attitude about potential risks that may arise from adopting new technologies (Zhang et al., 2012). Perceived risk is a determinant of technology acceptance (Poortvliet et al., 2018). Farmers' perceptions of risk might convince them that adopting black soil conservation and utilization technology is difficult and, thus, inhibit their perceived ease of use (Wang and Wang, 2021). However, a favorable external environment might positively influence farmers' risk perception. Therefore, we propose the following hypotheses:

> *H4c*: Social influence has a significant impact on perceived risk.
>
> *H5c*: Policy support has a significant impact on perceived risk.
>
> *H6c*: Household management characteristics have a significant impact on perceived risk.
>
> *H7*: Perceived risk has a significant negative impact on adoption intention.
>
> *H8*: Perceived Risk has a significant negative impact on perceived ease of use.

4 Materials and methods

4.1 Study area

The Sanjiang Plain is a crucial commercial grain supply base for China. In 2023, its total grain output is projected to reach 2.99 million tons, with the commodity rate surpassing 90%. Moreover, it serves as an essential strategic hub for agricultural modernization. It is a central demonstration zone for black soil conservation and utilization technologies, as well as a leader in research on smart agricultural technologies. This study was conducted at the Youyi State Farm situated in the Sanjiang Plain Area, between 46°28′N and 46°58′N, 131°27′E–132°15′E. It encompasses 11 management areas and 90 operation stations. It is an agricultural organization composed of numerous small farms operated by individuals, who are able to make their own farming-related decisions. The total agricultural output value reached 3.54 billion yuan, reflecting an average annual increase of 22.5% compared to 2020 (Beidahuang Agricultural Reclamation Group Co., Ltd, 2023). Youyi Farm is a model area for black soil conservation and utilization due to its concentrated and contiguous cultivated land, rich black soil resources, and high degree of agricultural mechanization and it serves as a key demonstration site for black soil conservation and utilization technology.

4.2 Data source

The research team conducted a field survey at Youyi Farm in September 2023. The study area encompassed all 11 management areas, with approximately 30 people randomly sampled from each area. The interviews were conducted face-to-face to accommodate farmers of all education levels. The questionnaire collected information in four areas: household characteristics, agricultural production conditions, fertilization conditions, and understanding of VFT. A total of 363 questionnaires were collected; 354 of these questionnaires were valid, resulting in a 97.5% recovery rate. Additional interviews with farm managers and management area leaders provided deeper insights into the farm's black soil conservation and utilization technology measures.

We examined the factors influencing farmers' willingness to adopt VFT using the TAM and PVT frameworks. After consulting existing research (Ajzen and Driver, 1991) and considering the empirical situation, we developed six latent variables: perceived usefulness, perceived ease of use, perceived risk, social influence, policy support, and household management characteristics. The questionnaire utilized a five-point Likert scale ("very disagree," "disagree," "general," "agree," and "very agree"). The management characteristics (i.e., cultivated land area and annual household income) were expressed quantitatively, while the demand degree for precision fertilization was assigned a rating of 1–5. Adoption intention was measured as "unwilling" (0) or "willing" (1). The specific index variables and statistics are presented in Table 1.

4.3 Structural equation model

The structural equation model (SEM) is a multivariate statistical technology that outperforms traditional measurement methods in assessing multiple causal relationships between observed variables, latent variables, and error variables (Wang et al., 2019). Unlike traditional methods, SEM allows both independent and dependent variables to contain measurement errors. The SEM consists of two parts: the measurement model, which reflects the relationship between latent variables and observed variables, and the structural model, which reflects the interaction between latent variables. The following equations were established to explore the relationship between farmers' intention to adopt VFT and various abstract variables:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta \tag{1}$$

$$X = \Lambda_x\xi + \sigma \tag{2}$$

$$Y = \Lambda_y\eta + \varepsilon \tag{3}$$

In Equation 1, η represents the endogenous latent variable, and ξ represents the exogenous latent variable. In this study, the exogenous latent variables are PU, PEOU, PR, and the external variables. The endogenous latent variable is the farmer's intention to adopt VFT. Γ represents the influence of exogenous latent variables on endogenous latent variables; B represents the relationship between endogenous latent variables; ζ is the error vector. In Equations 2, 3, X and Y are the observable variables of ξ and η, respectively. Λ_x and Λ_y reflect the factor loading coefficients of x to ξ and y to η, respectively. σ and ε represent the measurement errors of x and y, respectively.

5 Results

5.1 Descriptive statistics

By investigating and analyzing the individual characteristics of farmers (e.g., age, education, farming experience, cultivated land area, etc.), we can gain a comprehensive understanding of farmers' profiles. This provides a solid foundation for further analysis of the factors influencing farmers' intention to adopt VFT. We found that 81.6% of farmers were willing to adopt VFT. The mean age of farmers was 47 years, with the largest proportion (42.98%) in the age category of 45–55 years. Most respondents were middle-aged. Most respondents had a low level of education: 7.16% had elementary school or below, while 49.86% had only lower secondary school education. However, some farmers (19.56%) had obtained a college or higher degree. The mean farming experience was 23 years, and the average annual household income was 269,900 yuan. Notably, 15.53% of the farmers had an annual household income exceeding 500,000 yuan, indicating that these farmers were large plantation growers with significant agricultural revenue. The mean cultivated land area was 13.45 hectares; 50% of the farmers had fewer than 10 hectares. Most of the farmers owned drylands (69.52%), while 24.21% owned paddy fields. A small number (6.27%) owned both drylands and paddy fields.

5.2 Assessment of measurement model

We first validated the measurement model and then the structural model. We used SPSS 26.0 software to conduct an exploratory factor analysis, obtaining a KMO value of 0.902 ($p < 0.001$), indicating suitability for factor analysis (generally, KMO > 0.5 is considered acceptable). To verify the rationality of the data dimensions, six common factors were extracted through factor rotation, with a cumulative variance contribution rate of 65.524% (>50%), consistent with the scale dimensions shown in Table 1. We performed a Confirmatory Factor Analysis (CFA) to evaluate the scales' reliability and validity, including composite reliability (CR), average variance extracted (AVE), and discriminant validity indicators.

According to Bagozzi et al. (1981), Cronbach's alpha coefficient (>0.6) and CR measure the internal consistency of each dimensional indicator. High CR values indicated high internal consistency, with 0.7 being the minimally acceptable threshold. The square root value of AVE for each construct must be greater than its correlation with other constructs, and AVE values must be higher than 0.5. As shown in Table 2, Cronbach's alpha values ranged from 0.608 to 0.847, and CR values ranged from 0.814 to 0.962, indicating that the construct is reliable. All AVE values were greater than 0.5, suggesting acceptable convergent validity. AVE values were larger than all other cross-correlations for the sample (Table 3). Additionally, the goodness of fit criteria for the structural model were evaluated using Amos 26.0, as indicated in Table 4. The Chi-square value (Chi-square = 1.855, p-value

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TABLE 1 Latent variables, measurement items, and descriptive statistics.

Latent variable	Observational variable	Category coding	Variable description	Mean	Standard deviation
Perceived usefulness	Variable fertilization technology can save input costs.	PU1	1 = very disagree; 2 = disagree; 3 = general; 4 = agree; 5 = very agree	3.70	1.04
	Variable fertilization technology is conducive to increasing production.	PU2		3.65	1.06
	Variable fertilization technology can effectively improve crop quality.	PU3		3.53	1.05
	Variable fertilization technology can effectively improve soil quality.	PU4		3.60	0.97
	Variable fertilization technology can effectively improve the quality of the ecological environment.	PU5		3.41	1.14
Perceived ease of use	I think variable fertilization technology is easy to master.	PEOU1		3.14	1.15
	Under current economic conditions, I can afford the capital investment for variable fertilization technology.	PEOU2		2.82	1.17
	The variable fertilization technology application is very convenient, can save time and effort, and improve efficiency.	PEOU3		3.51	1.13
	I have enough time and energy to adopt variable fertilization technology.	PEOU4		3.23	1.18
	With adequate publicity on the farm, I will be more willing to use variable fertilization technology.	PEOU5		3.60	1.04
	With adequate training on the farm, it will be easier for me to master the principles of variable fertilization technology.	PEOU6		3.68	1.07
Perceived risk	I am worried about the complexity of variable fertilization technology.	PR1		2.97	1.12
	I am concerned about the high cost of modifying agricultural machinery for variable fertilization technology.	PR2		2.93	1.16
	I am worried about the difficulty in leasing agricultural machinery and equipment for variable fertilization technology.	PR3		2.95	1.11
	I am worried that variable fertilization technology will not significantly increase profits.	PR4		2.93	1.13
Policy support	The government's green fertilization policy will encourage me to adopt variable fertilization technology.	PS1		3.79	0.97
	The government's subsidy for the transformation of variable fertilization agricultural machinery and equipment will encourage me to adopt variable fertilization technology.	PS2		4.05	0.97
	The government's preferential policies on capital loans will encourage me to adopt variable fertilization technology.	PS3		3.65	1.14
Social influence	I will refer to the guidance provided by farm managers when deciding whether to adopt variable fertilization technology.	SI1		3.39	1.11

(Continued)

TABLE 1 (Continued)

Latent variable	Observational variable	Category coding	Variable description	Mean	Standard deviation
	Whether I am willing to adopt variable fertilization technology, I will be influenced by my family, friends, and neighbors.	SI2		3.89	1.03
	Whether I am willing to adopt variable fertilization technology, I will be influenced by the demonstration households.	SI3		3.66	1.07
	I will be influenced by the guidance of technicians or expert teams when deciding whether to adopt variable fertilization technology.	SI4		3.84	1.05
Household management characteristics	Cultivated area	CA	hm^2	13.55	12.20
	Annual household income	FAI	yuan	269,900	268,300
	The need for variable fertilization technology	PF	1 = very unnecessary; 2 = unnecessary; 3 = general; 4 = necessary; 5 = very necessary	3.81	1.13
Adoption intention	Are you willing to adopt variable fertilization technology?	AI	0 = unwilling; 1 = willing	0.82	0.39

TABLE 2 Item loadings, CR, AVE and Cronbach's alpha.

Variables	Items	Item loading	CR	AVE	Cronbach's alpha
Perceived Usefulness (PU)	PU1	0.671	0.838	0.510	0.751
	PU2	0.729			
	PU3	0.626			
	PU4	0.751			
	PU5	0.782			
Perceived Ease of Use (PEOU)	PEOU1	0.666	0.862	0.514	0.831
	PEOU2	0.745			
	PEOU3	0.601			
	PEOU4	0.633			
	PEOU5	0.797			
	PEOU6	0.829			
Perceived Risk (PR)	PR1	0.820	0.833	0.561	0.608
	PR2	0.858			
	PR3	0.598			
	PR4	0.690			
Policy Support (PS)	PS1	0.773	0.814	0.594	0.787
	PS2	0.756			
	PS3	0.782			
Social Influence (SI)	SI1	0.742	0.836	0.560	0.847
	SI2	0.727			
	SI3	0.776			
	SI4	0.748			
Household Management Characteristics (HMC)	CA	0.968	0.926	0.808	0.609
	FAI	0.968			
	PF	0.742			

TABLE 3 Correlations and average variance extracted (AVE).

	PS	SI	HMC	PR	PU	PEOU
PS	**0.771**					
SI	0.558	**0.748**				
HMC	0.385	0.366	**0.899**			
PR	0.57	−0.745	−0.027	**0.749**		
PU	0.376	0.642	0.014	0.151	**0.714**	
PEOU	0.224	0.235	0.046	0.071	0.392	**0.717**

The bold value is the square root value of AVE.

TABLE 4 Models evaluation overall fit measurement.

Goodness of fit measure	Recommended values	Model results
Chi-square/degree of freedom (X^2/df)	<5	1.855
Root mean square error of approximation (RMSEA)	<0.05	0.049
Goodness of fit (GFI)	>0.9	0.900
Root mean square residual (RMR)	<0.08	0.042
Normed fit index (NFI)	>0.9	0.900
Comparative fit index (CFI)	>0.9	0.945
Incremental fit index (IFI)	>0.9	0.946
Parsimonious normed fit index (PNFI)	>0.5	0.766
Comparative parsimony correction index (PCFI)	>0.5	0.814
Adjust goodness of fit (AGFI)	>0.9	0.869
Parsimonious goodness fit index (PGFI)	>0.5	0.714

<0.001) and various fit indices met the requirements of model construction, implying that the model has a good fit. The results showed that the model has acceptable internal consistency, reliability, convergent validity, and discriminant validity. Our data fits the hypothetical model well and can be used to analyze the structural model.

5.3 Factors influencing farmers' adoption intentions to use VFT

After we validated the measurement models, we used the structural model to test the hypotheses. We used SEM to analyze the major factors influencing farmers' intentions to adopt VFT. The results from the path analysis of the hypotheses are presented in Table 5 and Figure 1. The results show that PU ($\beta = 0.338$, $p < 0.001$) and PEOU ($\beta = 0.230$, $p < 0.001$) had positive and statistically significant impacts on AI, confirming hypotheses H1 and H2. PEOU directly affects farmers' intention to adopt VFT and indirectly affects AI via PU ($\beta = 0.407$, $p < 0.001$), supporting H3. We did not find a significant impact of PR ($\beta = -0.025$, $p = 0.620$) on AI, leading to the rejection of hypothesis H7. However, PR ($\beta = -0.034$, $p < 0.001$) was found to have a negative significant impact on PEOU and indirectly affect AI via PEOU, supporting H8.

Most external variables significantly affected the farmers' adoption intention through PU, PEOU and PR. Social influence (SI) was found to have a positive impact on PU ($\beta = 0.665$, $p < 0.01$) and PEOU ($\beta = 0.583$, $p < 0.001$) and a negative impact on PR ($\beta = -0.186$, $p < 0.001$), supporting H4a, H4b and H4c. Similarly, policy support (PS) positively affected PU ($\beta = 0.529$, $p < 0.05$) and PEOU ($\beta = 0.179$, $p < 0.001$) and negatively affected PR ($\beta = -0.207$, $p < 0.001$), consistent with hypotheses H5a, H5b and H5c. Finally, household management characteristics (HMC) significantly impacted PEOU ($\beta = 0.049$, $p < 0.001$) and PR ($\beta = -0.090$, $p < 0.001$), supporting H6b and H6c. However, HMC ($\beta = 0.029$, $p = 0.547$) had no significant effect on PU (H6a was rejected). The findings demonstrated that SI had the greatest direct effect on PU and PEOU—positive reputations, delivered through acquaintance networks, significantly affected farmers' perceptions of VFT.

This study also examined the total effects of some explanatory variables on the dependent variables. Table 6 presents a comparison of the effect sizes of the paths from the external variables to AI and from PU, PEOU, and PR to AI. PU (0.34) had the greatest direct impact on AI of all the variables, including PEOU (0.23) and PR (−0.03). However, our study found that the indirect effect value of PEOU on AI through PU was 0.137, and the total effect value of PEOU on AI was 0.367, leading to a higher total effect value than PU (0.338) on AI. The external variables had no direct effect on AI, but they all indirectly affected AI through PU, PEOU, and PR. The external variables displayed multiple paths of impact on AI, so their total effect should not be underestimated. The total effect of SI on AI, through PU, PEOU, and PR, was 0.444—much higher than the total effect of PS (0.075) and HMC (0.031) on AI. In summary, the total effect of all variables on AI was, from highest to lowest: SI, PEOU, PU, PS, PR, and HMC.

TABLE 5 Results of hypotheses testing.

Hypotheses				Std. Estimate	S.E.	C.R.	*p*	Result
H1	AI	←	PU	0.338	0.098	1.999	***	Support
H2	AI	←	PEOU	0.230	0.075	1.450	***	Support
H3	PU	←	PEOU	0.407	0.22	1.688	***	Support
H4a	PU	←	SI	0.665	0.292	2.346	**	Support
H4b	PEOU	←	SI	0.583	0.193	3.940	***	Support
H4c	PR	←	SI	−0.186	0.244	−0.502	***	Support
H5a	PU	←	PS	0.529	0.257	1.406	*	Support
H5b	PEOU	←	PS	0.179	0.168	0.890	***	Support
H5c	PR	←	PS	−0.207	0.214	−0.547	***	Support
H6a	PU	←	HMC	0.029	0.030	0.603	0.547	Reject
H6b	PEOU	←	HMC	0.049	0.032	1.275	***	Support
H6c	PR	←	HMC	−0.090	0.043	−1.173	***	Support
H7	AI	←	PR	−0.025	0.036	−0.496	0.620	Reject
H8	PEOU	←	PR	−0.034	0.044	−1.170	***	Support

*, **, and *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

6 Driving mechanisms for the adoption of variable fertilization technology

While VFT was still in the early stages on the farm, we found that the main factors influencing farmers' intention to adopt VFT were a lack of significant favorability about this technology and a failure to meet their actual needs. Therefore, farmer behavioral intentions and decision-making directly affect the implementation of technology. The large-scale implementation of VFT ought to consider how external dynamic mechanisms affect farmers' behavioral intentions. This section explores three such mechanisms—demand-driven mechanism, incentive-based mechanism, and technical support mechanism—to encourage a more effective implementation of VFT.

6.1 Demand-driven mechanism

Agricultural technology passively accepted by farmers generally leads to issues of technical homogenization. The demand-driven mechanism promotes the application of VFT based on farmers' actual needs. Under this system, problems encountered by farmers are quickly reported to agricultural technology promotion centers, and solutions are developed by research and development (R&D) institutions. Farmers' acceptance of VFT converts theoretical results into productivity. Factors such as farmer skills, knowledge, economic status, and cultivated land area affect psychological expectations of VFT, resulting in variations in PEOU. Farmers with high mechanization levels may prioritize VFT's cost-saving and profit-maximizing features. In contrast, small-scale farmers may exhibit blind conformity; their needs focus on minimizing investment and maximizing benefits, and they are easily affected by social networks.

The demand-driven mechanism includes the R&D system, extension system, and farmer system, where the farmer system determines the operation direction of the R&D and extension systems. The extension system, composed of promotion personnel, connects with the farmer and R&D systems through training, experimentation, and information feedback. The agricultural technology promotion center strengthens testing and demonstration activities to address farmers' technical needs. This approach directly reflects the economic benefits of VFT, improves farmers' awareness, and leverages social networks to spread positive reputations. Extension personnel listen carefully to farmer feedback, provide reliable information for the R&D system, and become a medium of interaction between technological personnel and farmers. The R&D system, composed of universities and research institute personnel, focus on the actual needs of VFT obtained by the extension system, especially whether this technology meets the needs of farmers with varying amounts of land. The R&D system and extension system also carry out technical implementation guarantees according to the technical needs of farmers. The farmer feedback direct promotion personnel and scientific researchers in a bottom-up information transmission path.

6.2 Incentive-based mechanism

State-owned farms depend on both state and market influences. They should leverage advantages in agricultural machinery, technology, scale, and brand management. The incentive-based mechanism formulates benefit distribution policies and behavioral norms to achieve grain production goals and indirectly facilitate new agricultural technologies' effective implementation.

VFT reduces chemical fertilizer use and improves black soil quality but does not generate obvious external benefits for farmers immediately. Farmers' primary concerns are the costs of VFT and agricultural machinery subsidies since adopting VFT may require modifying existing machinery or purchasing costly new equipment. Despite supportive policies, farmers often face long subsidy cycles and insufficient subsidy amounts. Given the unique administrative management of state-owned farms, Beidahuang Group, the parent company of state farms in Heilongjiang, can adjust subsidy policies for

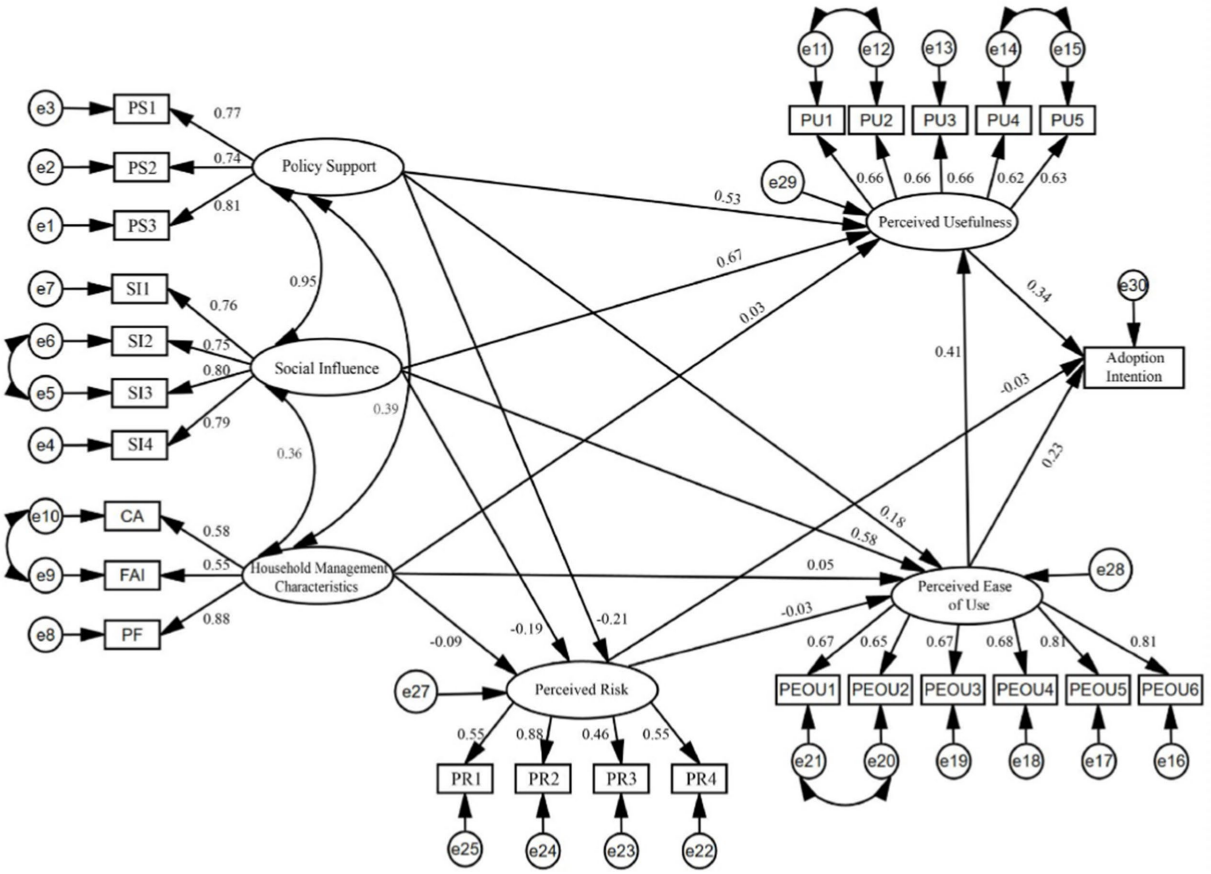


FIGURE 1
Structural equation modeling and path coefficients between variables.

agricultural branches within national policy compliance. It is essential to implement subsidies for purchasing variable fertilization equipment, categorize machinery by modification and purchase to adjust subsidy amounts. Beidahuang Group might also provide low-interest loans for agricultural machinery. It is suggested that demonstration households participating in the pilot projects receive free upgrades for variable fertilization machinery and allocated subsidy funds. Meanwhile, farmers can evaluate promotion personnel and institutions based on service effectiveness. The farm implements an incentive chain for VFT, establishes performance systems and project management systems within the agricultural technology service center, and links promotion personnel's labor performance to technology promotion outcomes.

Policy-driven incentives can significantly enhance farmers' adoption intention, but full policy implementation and large-scale adoption require constraint mechanisms around behavioral norms. During our interviews with farm managers, we learned that farmers could select a unified supply and purchase model for seeds, fertilizers, and other production means implemented by the farm. Hence, there is a need to establish reasonable pricing for seeds, fertilizers, pesticide, agricultural machinery, etc. It is also urgent to establish and improve the management rules and regulations of agricultural technology promotion to ensure that the relevant subsidies for VFT can be implemented to reduce farmers' anxiety about the risk of VFT funds. While the cooperation between farms and agricultural machinery companies is mainly profit-oriented, it should heed fair and just competition, control the quality and price of agricultural machinery, and strictly formulate a matching accountability mechanism. This would promote the effective implementation of VFT and ultimately contribute to a top-down interest transmission path.

6.3 Technical support mechanism

VFT is independently developed by university and research institutions cooperating with farms. The effective transformation of its scientific and technological achievements depends on whether farms and agricultural machinery enterprises have become a community of interest and whether the effectiveness of VFT meets the needs of farmers' agricultural production. The survey revealed VFT issues like imperfect mechanical precision, insensitive signal induction, and equipment blockage due to muddy soil. Therefore, technical personnel promptly communicate with farmers, report to cooperative enterprises, and improve the prescription map. Farms need agricultural machinery manufacturers to address equipment problems effectively.

The promotion process spreads from demonstration households to surrounding regions. Initially, farmers' PU of VFT was low, necessitating effective technology transfer to improve adoption intention. The farm allowed the agricultural technology promotion center personnel to distribute relevant data to the farmers. Technical achievements were publicized through the internet, self-media, and seminars to mobilize farmers to visit the demonstration area. At the

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TABLE 6 Direct and indirect effects on variables.

Variable	Effect											
	PU			PEOU			PR			AI		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
PS	0.529*	0.076*	0.605*	0.179***	0.007***	0.186***	−0.207***		−0.207***		0.075***	0.075***
SI	0.665**	0.237**	0.902***	0.583***	0.006***	0.589***	−0.186***		−0.186***		0.444***	0.444***
HMC	0.029	0.02	0.049	0.049***	0.003***	0.052***	−0.09***		−0.09***		0.031*	0.031*
PR		−0.013***	−0.013***	−0.034***		−0.034***				−0.025	−0.024	−0.049
PEOU	0.407***		0.407***							0.23***	0.137***	0.367***
PU										0.338***		0.338***

*, **, and *** indicate significance at the 5%, 1%, and 0.1% levels, respectively.

same time, the farm mobilized promotion personnel to carry out technical demonstration and training activities and discuss the VFT experience by organizing expert lectures and demonstration household exchange meetings. These events cultivated the habit of providing active and timely feedback to the agricultural technology promotion center.

In summary, the successful implementation and promotion of VFT should prioritize the involvement of the government and the Beidahuang Group. These entities play a crucial role in formulating relevant policies and providing financial incentives to support the black soil conservation and utilization strategy. Additionally, they facilitate the advancement and optimization of VFT in colleges and scientific research institutions. Ensuring reasonable benefit guarantees for VFT will help meet farmers' demand for its adoption. Simultaneously, the agricultural technology promotion center enhances the technical support system and subsidy policies for VFT by collecting and submitting farmers' feedback during its implementation to higher authorities. This feedback loop enables continuous improvement in VFT application. As a result, a two-way technological communication framework is created between the incentive-based mechanism, the technical support mechanism, and the demand-driven system (Figure 2).

7 Conclusions and discussion

This study offers an extended framework to analyze the driving forces behind farmers' adoption intention of VFT using TAM supplemented by PVT and external factors. The SEM was used to predict farmers' intention to adopt VFT through the mediation of PU and PEOU. We found that social influence had the most significant impact, meaning that a social network was necessary to persuade most farmers to adopt VFT. This finding echoes previous work on how farmers benefit from opportunities to communicate and learn from each other (Caffaro et al., 2020; Krishnan and Patnam, 2014). Farmers valued reliable information from demonstration households, relatives, friends, promotion centers and researcher who had already adopted or been familiar with VFT.

When farmers received useful information about VFT, they were more likely to make behavioral intention decisions about it. Perceived usefulness and perceived ease of use both had a significant positive impact on adoption intention (see also Nguyen Khanh et al., 2022; Rezaei et al., 2020). Perceived ease of use had a higher path coefficient than perceived usefulness for the total effect indicating that in the early stage of promotion, farmers' willingness to adopt this technology depended heavily on their perceived ability to use it. If farmers perceived that the technology was difficult or impossible to adopt, their willingness significantly weakened. Therefore, agricultural technology promotion centers should focus on demonstrating how VFT can increase economic benefits and reduce production cost. We also found that perceived risk did not have a direct effect on adoption intention. However, it can indirectly influence adoption intention through perceived ease of use, which aligns with the findings of Wang and Wang (2021). This is likely because the case study farm had full insurance for food crops such as rice, corn, and soybeans in response to natural disasters, as well as an "insurance + futures" planting income insurance project to ensure maximum economic benefits for farmers. Our study also confirmed that policy support significantly impacts adoption intention.

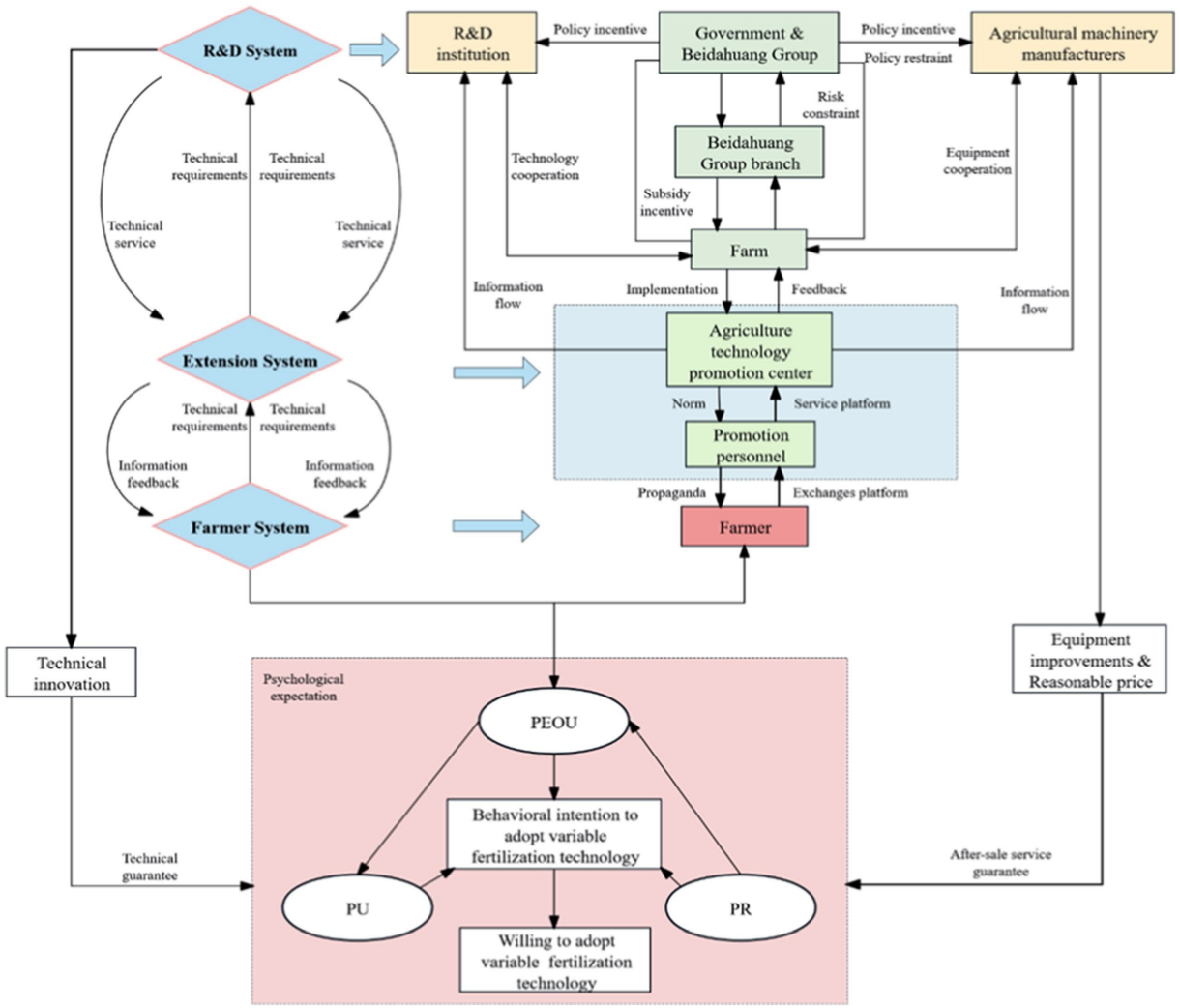


FIGURE 2
The driving mechanisms of the adoption of variable fertilization technology.

We conclude with recommendations for promoting black soil conservation and utilization technology. Firstly, it is necessary to establish technical management mechanisms and implement classification management for the various innovative black soil conservation and utilization technologies (i.e., how each performs in soil and water conservation, water saving and fertilizer saving, variety breeding, tillage methods, and disaster prevention). A diversified subsidy strategy also could be implemented to increase subsidies for agricultural machinery purchases, land fertility protection, crop rotation subsidies, etc. Improving the grain subsidy system and guiding farmers to adjust planting structures according to market demand will reduce production costs and enhance competitiveness. As it becomes increasingly evident that more sustainable approaches are needed to maintain reasonable grain prices and safeguard the benefits of grain farmers. At the same time, preferential policies in finance, credit, and insurance would be strengthened to increase investment in black soil conservation and utilization technology funds, encourage commercial banks to participate in agricultural credit, and jointly establish a low-interest loan system for agricultural machinery, a sound agricultural insurance system, and more comprehensive risk guarantees when implementing black soil conservation and utilization technology.

Second, focusing on the farm-level, a bottom-up information transmission path could usher technical feedback from farmers using black soil conservation and utilization technology to promotion personnel and R&D teams. Farms invite technical R&D experts for demonstrations and guidance, and promotion centers solve farmers' problems by passing technical blind spots on to the R&D team. The promotion center use internet platforms and self-media to release public information on black soil conservation technology knowledge, advantages, models, and implementation measures. Regular online videos, offline exchange meetings, and expert lectures can improve farmers' mastery of black soil conservation and utilization technology. It is best to perform personalized recommendations about black soil conservation and utilization technology based on a farmer's land quality and agricultural production conditions to ensure comprehensive information dissemination. Finally, it is of great necessity to make full use of mechanized state-owned farms, establish a black soil conservation and utilization technology demonstration area, and conduct field tests to share views and experiences of demonstration households. This would form an "acquaintance network" among demonstration households, neighbors, relatives, and friends. Such a network will help farmers conveniently understand the

principles and advantages and enhance their recognition, autonomy, and enthusiasm for black soil conservation and utilization technology.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors without undue reservation.

Author contributions

JY: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft. JL: Conceptualization, Formal analysis, Investigation, Supervision, Writing – review & editing, Data curation. KL: Writing – review & editing. SH: Investigation, Writing – review & editing. YL: Investigation, Writing – original draft. ZZ: Investigation, Writing – original draft.

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Conflict of interest

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Study on the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land—based on the provincial panel data of China from 2013 to 2022

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Industrial and commercial capital going to the countryside can effectively alleviate the shortage of funds for agricultural and rural development, which is the key to promote the modernization of agriculture and rural areas. In order to explore the influence of industrial and commercial capital going to the countryside on the non-grain production of cultivated land, based on the panel data of 30 provinces (except Tibet) in China from 2013 to 2022, this paper systematically uses the two-way fixed effect model, the intermediary effect model and the threshold effect model to test the effect, mechanism and threshold effect of industrial and commercial capital going to the countryside on the non-grain production of cultivated land. The results show that: (1) Industrial and commercial capital going to the countryside can effectively restrain the non-grain production of cultivated land. (2) Industrial and commercial capital going to the countryside can restrain non-grain production of cultivated land by accelerating land circulation and improving the level of scientific and technological development. (3) There is a single threshold effect on the inhibition of industrial and commercial capital going to the countryside. When the level of industrial and commercial capital going to the countryside is higher than the threshold value (29.124), the inhibition on non-grain production of cultivated land is weakened. (4) The inhibitory effect of industrial and commercial capital going to the countryside is heterogeneous, which has a greater inhibitory effect on the non-grain production of cultivated land in central China, major grain producing areas, northern region and areas with low marketization. This study enriches the research on the influence of industrial and commercial capital going to the countryside on the production and use of cultivated land, and provides theoretical reference for guiding industrial and commercial capital to invest in agriculture and promoting the sustainable development of agriculture.

KEYWORDS

industrial and commercial capital going to the countryside, non-grain production of cultivated land, mediating effect, threshold effect, heterogeneity analysis

1 Introduction

With the development of world economy, the transformation of agricultural modernization has become the important task of national development. Capital is the key factor to promote the development of agricultural modernization (Rahmatullah and Kuroda, 2016), but the agricultural industry in most developing countries cannot meet the requirements of attracting capital by itself, and it needs the government to promote and introduce social capital such as industry and commerce (Xudoyberdiyevich, 2021). Whether capital investment in agriculture will promote the development of agricultural industry will have an impact on cultivated land security, and then affect national food security. In order to explore this problem, this paper chooses China as the research subject.

As a country with a large population in the world, China's cultivated land resources only account for 7% of the world's total, so it is a top priority to effectively protect cultivated land food production and ensure food security. Due to the urgent need to develop industry in the early days of the founding of the People's Republic of China, the labor force and property mainly flowed to the cities. The development of agriculture and rural areas lacks modern production factors, and agriculture is caught in the dilemma of productivity involution due to the lack of production factors. However, only relying on the accumulated capital of farmers themselves and the agricultural support of the government can not meet the capital demand of modern agricultural development. It is necessary to rely on external forces to introduce capital, technology and other elements. Traditional agriculture can no longer meet the needs of high-quality development of the times, and modern agriculture must be developed. In view of this, China government began to guide a large number of social capital into agriculture. Since 2013, the China Central Government has issued the No.1 Document of the Central Committee for many times to guide industrial and commercial capital to the countryside, promote rural revitalization and develop modern agriculture. Existing studies have shown that capital flowing into rural areas is the key to promote the transformation from resource agriculture to capital agriculture (Zhang and Ma, 2017) and realize agricultural modernization (Xu et al., 2021); Capital flows into rural areas, which promotes the modernization of agriculture and rural areas by integrating land and labor, optimizing resource allocation (Xie and Yu, 2022). However, capital is born with two sides, and there are many practical difficulties while promoting the development of agriculture and rural areas. For example, increasing income inequality in rural areas (Xie and Liang, 2023), manipulating rural resources (Shao et al., 2024), squeezing out grain land, leading to the non-grain production of cultivated land (Zhou and Zhou, 2022), and so on. The phenomenon of non-grain production of cultivated land has affected the grain security in China, and even seriously threatens China's social stability and economic security. Then, whether industrial and commercial capital going to the countryside will affect non-grain production of cultivated land, and how will it affect non-grain production of cultivated land? Studying this problem is of great significance for guiding capital to flow to rural areas and promoting agricultural modernization.

Scholars have not reached a consensus on the relationship between industrial and commercial capital going to the countryside and non-grain production of cultivated land, and there are two different views. One view is that industrial and commercial capital going to the countryside is not conducive to agricultural production, which will aggravate the non-grain production of cultivated land. As early as 2013, Ma Jiujie pointed out that the profit-seeking nature of industrial and commercial capital makes it very sensitive to changes in the market environment, which increases the uncertainty of agricultural management and will have an impact on grain production (Ma, 2013). In 2018, Ding Dong and Yang Yinsheng pointed out that the profit-seeking nature of capital and the low rate of return on grain cultivation have led to the transfer of a large amount of rural capital to non-agricultural and non-grain management, which is not conducive to grain production (Ding and Yang, 2018). Jiang Guanghui and Hu Hao believed that industrial and commercial capital leased agricultural land to rural areas, which promoted the outflow of agricultural land from farmers and affected grain production (Jiang and Hu, 2021). Subsequently, Zhou Hui and Zhou Xin also pointed out that industrial and commercial capital entering rural areas often joins industries with faster capital appreciation, which will occupy grain land and is not conducive to grain production (Zhou and Zhou, 2022). Another view is that the capital of the countryside capital has a positive role in promoting agricultural production and will inhibit non-grain production of cultivated land. Some scholars believe that it is an inevitable trend for industrial and commercial capital to enter agriculture, which can promote the modernization of traditional agriculture (Liu and Xiong, 2015) and solve the problems of insufficient agricultural investment and factor shortage. Capital going to the countryside helps to improve agricultural production efficiency and increase grain output by optimizing the allocation of agricultural production factors, such as promoting farmland circulation and mechanized substitution (Liu et al., 2018). Jiang Guanghui and Hu Hao's research also pointed out that industrial and commercial capital going to the countryside increased the input of mechanical factors, which was conducive to expanding grain production (Jiang and Hu, 2021).

To sum up, scholars have done some research on the contradiction and coordinated development between industrial and commercial capital going to the countryside and cultivated land non-grain production, but the discussion on whether industrial and commercial capital going to the countryside affects and how to affect cultivated land non-grain production needs to be supplemented and expanded.

The main contributions of this paper are summarized as follows:

From the perspective of research, this paper focuses on the research on the influence of industrial and commercial capital going to the countryside on non-grain production of cultivated land. Through theoretical analysis and empirical test, it is clear whether and how industrial and commercial capital going to the countryside affects non-grain production of cultivated land, which provides some reference for industrial and commercial capital going to the countryside to invest in agricultural production.

In terms of transmission mechanism, the intermediary role played by land circulation and scientific and technological development level in the influence of industrial and commercial capital going to the countryside on cultivated land non-grain production is summarized and analyzed, which enriches the path mechanism of industrial and commercial capital going to the countryside to participate in agricultural production.

In the research method, considering the reverse causal relationship between industrial and commercial capital going to the countryside and cultivated land non-grain production will cause endogenous

problems and lead to research errors. Therefore, this paper adopts the method of instrumental variables, and selects the development level of digital inclusive finance and agricultural carbon emission level as instrumental variables to alleviate this problem and ensure the accuracy of the research results.

2 Theoretical analysis and research hypothesis

The No. 1 Central Document of China in 2024 puts forward specific goals and requirements for consolidating the agricultural foundation and achieving comprehensive rural revitalization, and proposes to "improve the diversified investment mechanism for rural revitalization" and "encourage social capital to invest in agriculture and rural areas." Industrial and commercial capital going to the countryside has played an important role in improving grain production capacity. First, industrial and commercial capital going to the countryside can improve agricultural infrastructure, improve agricultural production conditions, and provide agricultural productive services (Tu, 2014), thereby improving grain production capacity (Xie and Liu, 2014) and land output rate. Second, industrial and commercial capital to the countryside can bring many advanced production factors such as high-quality talents, market information, new business ideas, and high-quality brands into agriculture, promote agricultural industrialization (Tu, 2014), promote high-quality agricultural development, and help improve grain production capacity. Third, industrial and commercial capital going to the countryside to participate in agricultural production activities, by providing capital subsidies as the starting point, encourage small-scale farmers to participate in technical training, increase their own investment, and improve the comprehensive quality of farmers, which is conducive to cultivating new professional farmers, thereby promoting agricultural production efficiency.

The enhancement of grain production capacity is conducive to promoting the extension of the agricultural industrial chain, promoting the integrated development of primary, secondary, and tertiary industries, and curbing non-grain production on cultivated land. On the one hand, the extension of the agricultural industrial chain can bring about economies of scale and increase agricultural value-added income, thereby attracting production factors into agriculture to promote grain production and curb non-grain production on cultivated land; On the other hand, the integration of the three industries can broaden farmers' income channels and promote the development of new agricultural formats, thereby increasing the demand for grain raw materials, promoting grain production and curbing non-grain production on cultivated land.

> Hypothesis 1: Industrial and commercial capital going to the countryside can improve grain production capacity and inhibit non-grain production of cultivated land.

The Investigation Report on Land Circulation of New Agricultural Management Entity Shows that the decentralized and small-scale land management model can not fully meet the needs of the big market and internationalization, and the speed and degree of land circulation are related to the process of realizing agricultural modernization in China. Industrial and commercial capital going to the countryside has played a positive role in promoting land circulation and promoting the scale and intensification of agricultural production: On the one hand, industrial and commercial capital going to the countryside makes farmers' land property gradually capitalized, which increases farmers' property income and reduces farmers' economic dependence on land (Li et al., 2022), and cultivated land is a scarce resource with large demand and high rent. The economic compensation given by capital has a high substitution effect on the income of operating agricultural land (Xu et al., 2002), which promotes land circulation. On the other hand, due to imperfect policies, most of the contracts signed between capital going to the countryside and farmers are short-term contracts, which can reduce the risk of farmers losing land. Industrial and commercial capital going to the countryside can gain the advantage of large-scale production with the support of the government (Zhao et al., 2021), which is not conducive to the agricultural operation of small farmers and forces farmers to transfer their land.

The increase of land circulation is conducive to promoting the large-scale operation of cultivated land, improving agricultural production efficiency, promoting industrial integration and increasing grain output. The land scale formed by large-scale land transfer will increase the planting area and proportion of grain crops (Yang, 2023). First of all, land transfer is conducive to expanding the scale of agricultural land management (Cai et al., 2008), improving the efficiency of agricultural land allocation, thereby improving agricultural production efficiency (Kawasaki, 2010), which is conducive to increasing grain production. Secondly, the land transfer can promote farmers' participation in industrial integration and development (Yan et al., 2018), which is conducive to agricultural industrial agglomeration and can stimulate the improvement of labor productivity, thus increasing grain production. Finally, land transfer can promote the mechanization and standardization of agricultural production. After land transfer, it is connected into pieces, and mechanized production can reduce costs, increase agricultural output, and improve grain production efficiency, which is beneficial to grain production.

> Hypothesis 2: Industrial and commercial capital going to the countryside can accelerate land circulation, improve agricultural production efficiency and inhibit non-grain production of cultivated land.

Industrial and commercial capital going to the countryside has promoted the gathering of science and technology in agricultural production activities and promoted the improvement of agricultural technology level. On the one hand, the introduction of advanced production equipment and advanced management concepts in the process of industrial and commercial capital going to the countryside can promote the development level of agricultural science and technology and the development of new agricultural formats such as smart agriculture and e-commerce platforms. On the other hand, the factor spillover effect caused by industrial and commercial capital flowing into rural areas has solved the problems of shortage of funds, lack of experience and lack of professional talents in the process of agricultural technology development, and promoted the development level of agricultural science and technology.

The improvement of scientific and technological development level is an important way to promote the modernization of agricultural production mode and reduce the risk of agricultural production. First of

all, industrial and commercial capital invested a lot of capital in agriculture for profit, and at the same time increased investment in agricultural science and technology, which promoted the development level of agricultural science and technology (Cao, 2017), promoted the modernization of agricultural production methods and improved the level of grain production. Secondly, the improvement of scientific development level, especially digital technology, can promote information flow, effectively reduce the transaction cost of agricultural production (Qin et al., 2021), reduce the information barriers, and improve the efficiency of resource allocation, thus promoting the intensification of agricultural industry and benefiting agricultural grain production. Finally, the improvement of scientific development level accelerates the mechanization and standardization of agricultural production, alleviates the labor shortage (Deng et al., 2023), reduces the risk brought by traditional planting industry that may miss the season, avoids manual operation errors, promotes agricultural output and agricultural production efficiency (Guo et al., 2024), which is beneficial to grain production and inhibits non-grain production of cultivated land.

> Hypothesis 3: Industrial and commercial capital going to the countryside can reduce the risk of agricultural production and inhibit the non-grain production of cultivated land by improving the level of scientific and technological development.

Due to the differences in agricultural production mode and the popularity of industrial and commercial capital going to the countryside in China, especially in economic development level, grain production capacity, geographical location and marketization degree, the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land may be heterogeneous in different regions. First of all, the difference of economic development level will lead to the difference of infrastructure and services in different regions, and then affect the level of industrial and commercial capital going to the countryside. In areas with high economic development, the original facilities and services are relatively perfect, so the impact of industrial and commercial capital going to the countryside should be small, on the contrary, it will have a greater impact on the non-grain production of cultivated land in areas with low economic development; Secondly, for regions with different grain production capacity, the main grain producing areas are important areas bearing the grain production in China, so the supervision of this area is strict, and the industrial and commercial capital going to the countryside has a great influence on the non-grain cultivation of cultivated land in the main grain producing areas; Thirdly, geographical location will determine the quality of cultivated land. There are many plains in the northern region, and industrial and commercial capital going to the countryside is conducive to greatly promoting the connection of cultivated land in the plain region, thus promoting large-scale production. Therefore, industrial and commercial capital going to the countryside has a greater impact on cultivated land in the northern region; finally, the level of marketization will affect the level of industrial and commercial capital going to the countryside. For areas with higher marketization level, the factors of production flow faster and the demand for capital is less, so industrial and commercial capital has less influence on it. On the contrary, areas with lower marketization level have greater demand for capital and industrial and commercial capital has greater influence on it.

> Hypothesis 4: The impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land is heterogeneous in areas with different economic development levels, different grain production capacity, different geographical locations and different marketization levels.

The mechanism diagram of the influence of industrial and commercial capital going to the countryside on non-grain production of cultivated land is shown in Figure 1.

3 Materials and methods

3.1 Data sources

This study takes the panel data of 30 provinces (regions) in China (except Tibet) as the research object. Considering that the China

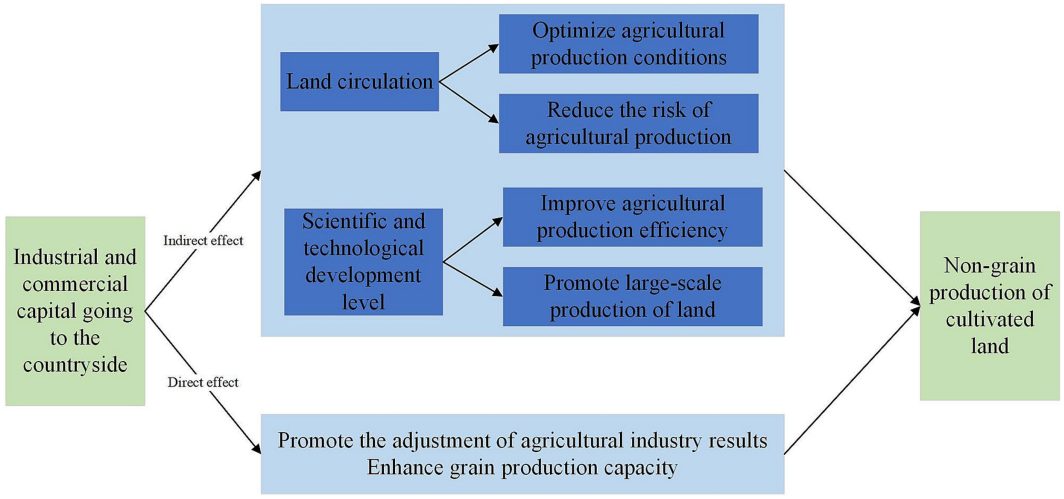


FIGURE 1
Mechanism diagram of industrial and commercial capital going to the countryside.

Central Government officially issued the policy document on industrial and commercial capital going to the countryside in 2013, this paper selects 2013–2022 as the sample interval, and constructs the provincial-level balanced panel data as the total sample. The source of the selected indicators is explained as follows: (1) The non-grain production level of cultivated land is measured by the proportion of grain planting area to the total crop planting area. The corresponding index data mainly comes from China Rural Statistical Yearbook. (2) The level of industrial and commercial capital going to the countryside is measured by the data of agricultural enterprises, which comes from the China Agricultural Research Database (CCAD) of Carter Enterprise Research of Zhejiang University. (3) The indicators of intermediate variables and control variables mainly come from China Statistical Yearbook, China Rural Statistical Yearbook and the website of National Bureau of Statistics. For individual missing data, this paper uses linear interpolation to fill in to ensure data integrity.

3.2 Variable selection

(1) Explanatory variable: The explanatory variable of this study is the non-grain production level of cultivated land. Non-grain production of cultivated land refers to the use of cultivated land to produce crops other than grain crops (except rice, wheat, potatoes, soybeans and corn). Referring to the research of Wang et al. (2023), this paper selects the non-grain planting structure to measure the non-grain production level of cultivated land, that is, the proportion of non-grain crop planting area to the total crop planting area is symbolized as Dec. The specific calculation formula is as follows:

$$R_A = \left(1 - \frac{N}{T}\right) * 100\% \quad (1)$$

In Equation 1, N represents the area of grain crops, T represents the total sown area of crops, and R_A represents the level of non-grain production of cultivated land.

(2) Key explanatory variable: The key explanatory variable of this paper is the industrial and commercial capital going to the countryside. Industrial and commercial capital going to the countryside in this paper refers to the participation of industrial and commercial capital outside the countryside in agricultural and rural production activities. According to the research of Huang et al. (2023) and Jia et al. (2024), this paper uses the number of agricultural-related enterprises to represent the level of industrial and commercial capital going to the countryside, symbolized as Cap. The main business income of large-scale agricultural processing enterprises is used as an alternative indicator of the key explanatory variable, with the symbol Proc.

(3) Mediating variables: The intermediate variables of this study are land circulation level and scientific and technological development level. Scientific and technological development is conducive to promoting the reform of agricultural production mode, land transfer can accelerate agricultural large-scale production, and both intermediary variables affect agricultural production. This study uses technology market transaction volume and land transfer area to represent scientific and technological development level and land transfer indicators, with symbols Tech and Tran, respectively.

(4) Control variables: Referring to the research of Gao and Du (2022), this study controlled the variables of rural characteristics, market characteristics, and government characteristics. The three rural characteristic variables include energy and power level (*Dies*), urbanization level (*Urba*), agricultural product price level (*Price*), farmers' income level (*Inco*), and farmers' education level (*Educ*). Market characteristic variable and government characteristic variable are replaced by economic development level (*Agdp*) and financial expenditure level (*Fina*) respectively. Descriptive statistics of each variable are shown in Table 1.

3.3 Model setting

(1) Benchmark regression model.

Referring to the research of Tang and Chen (2022), this paper uses a double fixed effect model to test the impact of industrial and

TABLE 1 Descriptive statistics.

Variables	Observations	Average value	Standard error	Minimum value	Maximum value
Dec	300	34.474	15.143	2.9246	64.4875
Cap	300	92.189	69.806	3.2810	445.2470
Dies	300	0.172	0.185	0.0192	1.0442
Inco	300	1.436	0.597	0.5108	3.5717
Educ	300	0.047	0.027	0.0138	0.1999
Agdp	300	6.256	3.105	2.1952	19.0206
Fina	300	0.260	0.110	0.1050	0.7534
Urba	300	61.387	11.385	37.8855	89.5344
Price	300	103.102	5.930	86.4000	123.300
Mtran	300	16.473	14.425	0.2711	68.9731
Tech	300	0.654	1.135	0.001	7.9475

commercial capital going to the countryside on non-grain production of cultivated land. The specific function model is shown in Equation 2.

$$Dec_{i,t} = \partial + \beta_1 Cap_{i,\ t} + \sum \varphi_i Control_{i,t} + \gamma_t + v_i + \varepsilon_{i,t} \quad (2)$$

In Equation 2, i and t represent region and year respectively, *Dec* represents the level of non-grain production of cultivated land, *Cap* represents the level of industrial and commercial capital going to the countryside, *Control* represents a combination of control variables, including energy and power level (*Dies*), farmers' income level (*Inco*), farmers' education level (*Educ*), economic development level (*Agdp*), fiscal expenditure level (*Fina*), urbanization level (*Urba*), and agricultural product price level (*Price*), r_t is the year fixed effect, v_i is the province fixed effect, and ε is the random error term.

(2) Mediating effect model

This paper refers to Wen and Ye's (2014) mediation effect theory and test method, constructs a mediation effect test model, conducts empirical tests on the two mediating variables of land transfer level and scientific and technological development level, and explores the transmission mechanism of industrial and commercial capital going to the countryside on non-grain production of cultivated land. The specific function model is shown in Equation 3.

$$\begin{cases} Dec_{i,t} = \partial_0 + \beta_1 Cap_{i,t} + \sum \eta_i Control_{i,t} + \gamma_t + v_i + \varepsilon_{i,t} \\ Mtran_{i,t} \ / \ Tech_{i,t} = w_0 + \mu_1 Cap_{i,t} + \sum \vartheta_i Control_{i,t} + \gamma_t + v_i + \varepsilon_{i,t} \\ Dec_{i,t} = \theta_0 + \lambda_1 Cap_{i,t} + \tau_2 Mtran_{i,t} \ / \ Tech_{i,t} + \sum \phi_i Control_{i,t} + \gamma_t + v_i + \varepsilon_{i,t} \end{cases} \quad (3)$$

In Equation 3, the coefficient β_1 represents the total impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land; the coefficient μ_1 represents the impact of industrial and commercial capital going to the countryside on the level of land transfer/level of scientific and technological development; and λ_1 represents the direct impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land after controlling the mediating variables of land transfer level/level of scientific and technological development.

(3) Threshold regression model

In order to further explore whether there is a threshold effect of the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land, this paper draws lessons from the research of Wang (2015) and constructs a threshold regression model of the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land. The specific function model is shown in Equation 4.

$$\begin{aligned} Dec_{i,t} = {} & \partial_3 + \sum \varphi_i Control_{i,t} + \beta_3 Cap_{i,t} I\left(q_{i,t} \le o\right) \\ & + \beta_4 Cap_{i,t} I\left(q_{i,t} > o\right) + \gamma_t + v_i + \varepsilon_{i,t} \end{aligned} \quad (4)$$

In Equation 4, *Dec* represents the non-grain production level of cultivated land, *Control* is the combination of control variables, *Cap* is the threshold variable of the level of industrial and commercial capital going to the countryside, o is the threshold value, I is indicator function, if $q_{i,t} \le o$ is true, the function value is 1, otherwise it is 0, and other variables have the same meaning as Equation 2.

4 Results

4.1 Benchmark regression results

First, based on the results of the LM test, F test, and Huasman test, it was preliminarily determined that the fixed effect model would be used for regression analysis. Secondly, after adding time fixed effects and individual fixed effects to the regression in turn, it was found that both the time fixed effects and individual fixed effects of the sample were significant, which determined that this paper used a double fixed effects model. Finally, the benchmark regression model was tested on the total sample, and the results are shown in Table 2.

From the columns (1) to (3) in Table 2, it can be seen that with more and more fixed effects, the estimation coefficient value of industrial and commercial capital going to the countryside is getting larger and larger, which shows that the non-grain production of cultivated land is greatly affected by time and region, so it is verified that it is more reasonable to use the double fixed model. After introducing fixed year effect and fixed province effect in turn, the estimation coefficient of industrial and commercial capital going to the countryside is always significantly negative at the level of 1%, indicating that industrial and commercial capital going to the countryside can significantly inhibit the non-grain production of cultivated land, and the research hypothesis 1 has been verified. Specifically, for every one percentage point increase in the level of

TABLE 2 Benchmark regression model test.

Variables	(1)	(2)	(3)
	Dec	*Dec*	*Dec*
Cap	−0.014***	−0.015***	−0.016***
	(0.00462)	(0.00479)	(0.00494)
Dies	8.817***	8.191***	7.116**
	(2.856)	(2.901)	(3.038)
Inco	−5.694***	−9.179***	−9.271***
	(1.424)	(2.081)	(2.647)
Educ	39.62***	36.75***	35.35***
	(12.36)	(12.93)	(12.88)
Agdp	1.380***	1.430***	1.406***
	(0.278)	(0.287)	(0.289)
Fina	9.682**	12.61**	12.96**
	(4.889)	(5.480)	(5.611)
Urba	0.250***	0.045	0.048
	(0.0615)	(0.109)	(0.156)
Price	0.019	−0.021	−0.022
	(0.0190)	(0.0284)	(0.0281)
Constant	12.13***	30.44***	35.39**
	(4.416)	(8.312)	(17.43)
Year		Yes	Yes
Province			Yes
Observations	300	300	300

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

industrial and commercial capital going to the countryside, the level of non-grain production of cultivated land will be reduced by about 1.6%. The reason may be that the factors of production brought by industrial and commercial capital going to the countryside can effectively improve the level of agricultural production, increase grain output and curb non-grain production of cultivated land. Accordingly, the relevant departments of China Central government should speed up the improvement of relevant policies on industrial and commercial capital going to the countryside, and actively encourage and guide social capital to go to the countryside in an orderly manner.

From the results in column (3) of Table 2, it can be seen that most of the control variables have a significant impact on the non-grain production of cultivated land. The specific results are as follows: the level of energy power has a positive impact on the non-grain production of cultivated land at the level of 5% significance, with a coefficient of 7.116, indicating that the improvement of energy power level makes the non-grain production level of cultivated land rise. The possible reason is that the development of electricity and energy makes it convenient to engage in agricultural activities, and farmers are more inclined to produce economic crops with high economic value, which leads to the decline of grain production and the increase of non-grain levels. Farmers' income level has a significant negative impact on non-grain production of cultivated land, with a coefficient of −9.271, indicating that the increase of farmers' income can significantly reduce non-grain production of cultivated land. The possible reason is that the opportunity of long-term investment in agricultural production increases with the increase of income, and improving agricultural production mode is conducive to increasing grain production and reducing the level of non-grain production in cultivated land. The education level of farmers has a significant positive impact on the non-grain production of cultivated land, with a coefficient of 35.35, indicating that the non-grain production level of cultivated land has also improved significantly with the improvement of farmers' education level. The possible reason is that with the development of society, farmers' educational level and cultural level have improved significantly, and their ability to accept new things has also improved significantly. High-quality farmers are more willing to develop in cities, thus changing their identity from farmers to citizens, resulting in a decrease in agricultural labor input, which is not conducive to grain production. The level of economic development has a significant positive impact on the non-grain production of cultivated land, with a coefficient of 1.406, indicating that the non-grain production level of cultivated land will increase with the development of social economy. The possible reason is that with the economic development, more and more farmers give up agricultural production with little economic benefit and engage in other industrial production activities; with the economic development, industrial expansion is increasing, rural land is occupied, agricultural production is threatened, and grain output is reduced. The level of fiscal expenditure has a positive impact on the non-grain production of cultivated land at a significant level of 5%, with a coefficient of 12.96, indicating that with the increase of fiscal expenditure, the non-grain production level of cultivated land will also increase. The possible reason is that with the increase of financial expenditure, the subsidies to agriculture will also increase, which leads to the phenomenon that some capital going to the countryside to rent farmland to obtain agricultural subsidies, which hinders normal agricultural production activities and is not conducive to grain production.

4.2 Endogeneity and robustness test

4.2.1 Endogeneity test

There may be two endogenous problems in the study of the influence of industrial and commercial capital going to the countryside on non-grain production of cultivated land. One is the problem of missing variables. Although the factors that affect industrial and commercial capital going to the countryside and non-grain production of cultivated land are included in the econometric model as much as possible, there are inevitably missing variables, which lead to the correlation between the missing variables and disturbance terms, thus generating endogenous problems. The second is the two-way causal problem. Industrial and commercial capital going to the countryside and non-grain production of cultivated land will interact with each other, resulting in a two-way causal problem. Based on this, in order to alleviate the possible endogenous problems, on the one hand, considering that the development level of digital inclusive finance (*Incl*) is closely related to industrial and commercial capital going to the countryside and non-grain production of cultivated land, the conditions that instrumental variables are related to endogenous explanatory variables and have nothing to do with random disturbance terms are met; On the other hand, agricultural carbon emissions (*Carb*) can reflect agricultural production activities from the side, which is related to industrial and commercial capital going to the countryside and has nothing to do with random disturbance. Therefore, the development level of digital inclusive finance and agricultural carbon emissions are selected as instrumental variables, and the two-stage least square method is used for regression analysis. The regression results are shown in Table 3.

According to the regression results in Table 3, the estimation coefficients of digital inclusive finance development level and agricultural carbon emissions in the first-stage regression results are significantly positive, and both of them have passed the test of unidentifiable and weak instrumental variables, which shows that the instrumental variables selected in this study are reasonable; The estimation coefficients of the level of industrial and commercial capital going to the countryside in the two-stage regression results are −0.138 and −0.303, respectively, which are significant at the level of 1%, indicating that the conclusion that industrial and commercial capital going to the countryside can significantly inhibit the non-grain production of cultivated land after dealing with endogenous problems through instrumental variables is still valid.

4.2.2 Robustness test

In order to ensure the reliability of the empirical results, this paper adopts the replacement of core explanatory variables and econometric models to test the robustness, and the results are shown in Table 4.

Referring to the research of Shao et al. (2024), this paper makes an empirical analysis by replacing the level of industrial and commercial capital going to the countryside with *Cap*, the main business income of large grain processing enterprises, and the results are shown in column (2) of Table 4. After replacing the core explanatory variables, the estimation coefficient of industrial and commercial capital going to the countryside is significantly negative,

TABLE 3 Endogenous test.

Variables	(1)		(2)	
	One-stage regression	Two-stage regression	One-stage regression	Two-stage regression
	Cap	*Dec*	*Cap*	*Dec*
Cap		−0.138***		−0.303***
		(−3.14)		(−2.88)
Incl	14.988***			
	(6.63)			
Carb			0.071***	
			(3.73)	
Control variable	Yes	Yes	Yes	Yes
Constant	237.226***	74.008***	200.622***	124.275***
	(4.33)	(3.60)	(3.19)	(3.19)
Unidentifiable test (LM statistics)	39.331***		13.706***	
Weak instrumental variable test (Cragg-Donald Wald F statistic)	43.907(16.380)		13.931(8.96)	
Observations	300	300	300	300
R^2		0.121		−0.760

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

TABLE 4 Robustness test.

	(1) Benchmark model	(2) Replace the core explanatory variables	(3) Unconditional panel quantile model	
			25%	95%
Variables	Explained variable: *Dec*			
Cap	−0.016***		−0.080**	−0.113***
	(0.00494)		(0.0375)	(0.0416)
Proc		−0.005***		
		(0.00164)		
Control variable	Yes	Yes	Yes	Yes
Constant	30.77***	36.51***	−14.02	−77.40
	(11.23)	(10.82)	(27.39)	(84.80)
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	300	300	300	300
R^2	0.388	0.383	0.914	0.776

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

which is consistent with the estimation coefficient of industrial and commercial capital going to the countryside in the benchmark regression model, indicating that industrial and commercial capital going to the countryside will significantly inhibit the non-grain production of cultivated land.

Quantile regression econometric model can estimate the regression coefficients of the explained variables under different quantiles, and it is not easily affected by extreme values, so the regression results have a robust advantage. Unconditional quantile regression does not depend on the choice of control variables, and the estimation results are more accurate. Because the data used in this study is provincial panel data, the year effect and provincial effect must be controlled, so this study uses the unconditional quantile fixed effect model proposed by Borgen (2016) to test the robustness, and the results are shown in column (3) and column (4) of Table 4. It can be seen that the estimation coefficients of industrial and commercial capital's level of going to the countryside are negative at 25 and 95%, and both of them have passed the significance test, which is consistent with the test results of the benchmark regression model, indicating that the research results are robust.

4.3 Analysis of intermediation effects

Based on the previous theoretical analysis and empirical test, it can be concluded that industrial and commercial capital going to the countryside will significantly inhibit the non-grain production of cultivated land, while land is the basic element of agricultural production, and science and technology is an important driving force to promote agricultural efficiency, so there may be a transmission mechanism of "industrial and commercial capital going to the countryside—land circulation/scientific and technological development level—non-grain production of cultivated land." Based on the test method of intermediary effect, this study conducted a step-by-step test on two intermediary variables, land circulation and the level of scientific and technological development, and the regression results are shown in Table 5.

From the columns (1) and (4) of Table 4, it can be seen that industrial and commercial capital going to the countryside has a significant negative impact on the non-grain production of cultivated land. On this basis, the intermediary effect between land circulation and the level of scientific and technological development is further tested. From columns (2) and (3) of Table 4, the regression coefficient of industrial and commercial capital going to the countryside to land circulation is positive and significant, which means that industrial and commercial capital going to the countryside will accelerate land circulation. After introducing the intermediary variable of land circulation, the estimation coefficient of industrial and commercial capital going to the countryside is not significant, so it can be judged that industrial and commercial capital going to the countryside has a complete intermediary effect on the non-grain production of cultivated land through land circulation, and has formed the "industrial and commercial capital going to the countryside-(promoting) land circulation-(reducing) non-grain production of cultivated land." From the columns (5) and (6) of Table 4, it can be seen that industrial and commercial capital going to the countryside can significantly improve the level of scientific and technological development. After the introduction of intermediary variable, the estimation coefficient of the impact of industrial and commercial capital going to the countryside on cultivated land non-grain production is still significantly negative at the level of 1%, indicating that the level of scientific and technological development plays a partial intermediary role in the process of industrial and commercial capital going to the countryside affecting cultivated land non-grain production, forming a negative transmission path of "industrial and commercial capital going to the countryside-(improving) the level of scientific and technological development-(reducing) cultivated land non-grain production," and the research hypothesis 3 has been verified. Referring to the research method of He et al. (2019), the Sobel method and Bootstrap method are used to further verify the two intermediate variables: land circulation and the level of scientific and technological development. The Sobel test requires strict sample data, and the Bootstrap method can overcome the shortcomings of stepwise regression method. From Table 4, the results of stepwise regression passed the Sobel test and Bootstrap test, which further verified the establishment of the transmission mechanism of land transfer and scientific and technological development level.

4.4 Threshold effect regression analysis

In order to further explore the relationship between industrial and commercial capital going to the countryside and non-grain production of cultivated land, this paper selects industrial and commercial capital going to the countryside as the threshold variable for research. Through Bootstrap self-help method, 1,000 samples were randomly selected for single-threshold and double-threshold tests. From the test

TABLE 5 Intermediary effect test.

Variables	Land circulation			Scientific and technological level		
	(1)	(2)	(3)	(4)	(5)	(6)
	Dec	*Mtran*	*Dec*	*Dec*	*Tech*	*Dec*
Cap	−0.016***	5.654***	−0.006	−0.016***	0.008***	−0.023***
	(0.00494)	(0.633)	(0.00554)	(0.00494)	(0.0009)	(0.0054)
Mtran			−0.002***			
			(0.000480)			
Tech						1.069***
						(0.3308)
Constant	30.77***	3,461**	36.75***	30.77***	−0.685	31.50***
	(11.23)	(1,437)	(11.10)	(11.23)	(2.095)	(11.028)
Sobel test (*p-value*)	0.0008(The land transfer mechanism is effective)			0.0026(The scientific and technological level mechanism is effective)		
Ind_eff test(p-val)	0.006 (Indirect effect established)			0.002 (Indirect effect established)		
Year	Yes			Yes		
Province	Yes			Yes		
Observations	300	300	300	300	300	300
R^2	0.388	0.635	0.418	0.388	0.750	0.412

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

TABLE 6 Threshold effect test.

Threshold variable	Threshold number	*F* value	*p* value	BS times	Critical value		
					1%	5%	10%
The level of capital going to the countryside	Single threshold	24.99*	0.077	1,000	38.819	28.360	23.207
	Double threshold	8.14	0.637	1,000	39.912	25.211	20.497

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

results in Table 6, it can be seen that the *F* value of the single-threshold capital going to the countryside index is 24.99, which is significant at the level of 10%, and it has passed the single-threshold test; Secondly, the double-threshold test shows that the F value of the index of industrial and commercial capital going to the countryside is 8.14, but it does not pass the significance test, indicating that there is no double threshold. Therefore, this study judges that there is a single threshold effect of industrial and commercial capital going to the countryside. Further, the estimated threshold values of industrial and commercial capital going to the countryside index is tested. As shown in Table 7, the threshold value of industrial and commercial capital going to the countryside index is 29.124.

Introducing industrial and commercial capital to the countryside as a threshold variable into the benchmark regression model, the results are shown in Table 8. When the level of industrial and commercial capital going to the countryside is lower than 29.124, the level of industrial and commercial capital going to the countryside has a negative impact on the non-grain production of cultivated land at a 1% significance level. Specifically, the level of industrial and commercial capital going to the countryside increases by 1, and the level of non-grain production of cultivated land decreases by 12.04%; When the level of industrial and commercial capital going to the countryside is higher than 29.124, the level of capital going to the countryside has a negative impact on the non-grain production of cultivated land at a significant level of 1%. Specifically, the level of industrial and commercial capital going to the countryside increases by 1 and level of non-grain production of cultivated land decreases by 1.4%. Therefore, with the improvement of the level of industrial and commercial capital going to the countryside, the inhibitory effect on non-grain production of cultivated land will be greatly reduced. Therefore, it is necessary to continuously strengthen the supervision and guidance of capital to prevent the profit-seeking nature of capital from adversely affecting grain production.

TABLE 7 Threshold estimates.

Threshold variables	Threshold estimate	95% Confidence interval
λ_1	29.124	[28.315, 30.075]

TABLE 8 Regression of threshold panel model.

Variables	*Dec*	Standard error	*T* value
Dies	6.356**	2.806	2.27
Inco	−5.378***	1.364	−3.94
Educ	36.767***	11.707	3.14
Agdp	1.084***	0.272	3.99
Fina	3.995	4.896	0.82
Urba	0.298***	0.060	4.95
Price	0.013	0.018	0.71
Cap≦29.124	−0.1204***	0.022	−5.38
Cap > 29.124	−0.014***	0.005	−3.12
Constant	13.569***	3.699	3.67
Observations	300		
R^2	0.413		

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

4.5 Further analysis results

Considering China's vast territory, different regions have different economic development levels due to differences in resource endowments and government system implementation. Therefore, the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land in regions with different economic development levels may be different. Therefore, according to the regional division standards of the National Bureau of Statistics, and referring to the research of Wang et al. (2022) and Ren and Cheng (2024), this study divides the total sample into three regions: eastern, central, and western. The impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land in the eastern, central, and western regions is examined, respectively. The results are shown in column (1) of Table 9. The results show that the inhibitory effect of industrial and commercial capital going to the countryside on non-grain production of cultivated land in the central region is the strongest, followed by the western region, and finally the eastern region. The reason why the impact on the eastern region is small and the effect is not obvious may be that the eastern coastal region has a developed economy, complete infrastructure, high agricultural production level, and sufficient original capital, so the impact of industrial and commercial capital going to the countryside on agricultural production is small. The central and western regions are relatively remote in geographical location, relatively backward in economic development, and lack modern elements in agricultural development. The capital and technology brought by industrial and commercial capital going to the countryside will significantly affect agricultural production activities and help promote grain production. Therefore, the central and western regions show a significant inhibitory effect.

Considering the fragmentation of agricultural resources in China, the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land in areas with different grain production capabilities may be different. Based on the above analysis, referring to the research of Meng et al. (2024) and Zhang and Li (2024), the total sample was divided into main grain-producing areas and non-main grain-producing areas, and the impact of industrial and commercial capital going to the countryside in areas with different

TABLE 9 Heterogeneity test of economic development level and grain production capacity.

Variables	(1)			(2)	
	Dec				
	Eastern Region	Central Region	Western Region	Major grain-producing areas	Non-major grain-producing areas
Cap	−0.005	−0.033**	−0.020*	−0.019***	−0.016
	(0.00573)	(0.0129)	(0.0101)	(0.00601)	(0.0101)
Constant	71.72***	−49.24	−19.39	−0.763	22.23
	(14.95)	(42.10)	(15.16)	(18.17)	(14.50)
Control variable	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
Observations	130	60	110	130	170
R^2	0.599	0.538	0.719	0.247	0.608

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

TABLE 10 Heterogeneity test regression of geographical location and marketization environment.

Variables	(1)		(2)	
	Dec			
	Northern region	Southern region	Market-oriented high-level areas	Market-oriented low-level areas
Cap	−0.030***	−0.019**	0.005	−0.031***
	(0.00701)	(0.00810)	(0.00845)	(0.00808)
Constant	−54.89**	61.13***	40.14***	1.697
	(21.57)	(13.09)	(15.03)	(23.26)
Control variable	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Observations	140	160	169	131
R^2	0.541	0.403	0.461	0.418

*** means 1% significance level, ** means 5% significance level, * means 10% significance level.

grain production capabilities on non-grain production of cultivated land was examined, and the results are shown in column (2) of Table 9. The results show that for the main grain-producing areas, the estimated coefficient of industrial and commercial capital going to the countryside is −0.019, which passes the significance test at the 1% level. For non-main grain-producing areas, the estimated coefficient is −0.0164, but does not pass the significance test. The main grain-producing areas bear most of China's grain production and transportation, and the government strictly supervises the capital going to the countryside in this area, so the industrial and commercial capital to the countryside can effectively improve the level of grain production. The level of agricultural production capacity in non-main grain-producing areas is relatively low. Capital tends to invest in areas with high profits, so it will have little impact on non-major grain-producing areas.

Considering that the northern and southern regions of China have a large span, and there are certain differences in living customs and concepts, which may have different effects on industrial and commercial capital going to the countryside and non-grain production of cultivated land, this study divides the total sample into northern and southern regions according to the traditional north–south dividing line (Qinling-Huaihe line) and with reference to Yang et al. (2024) and Jiang et al. (2024), and investigates the effects of industrial and commercial capital going to the countryside on non-grain production of cultivated land in different geographical locations. The results are shown in column (1) of Table 10. It can be seen that industrial and commercial capital going to the countryside has a significant inhibitory effect on the non-grain production of cultivated land in both northern and southern regions, but the inhibitory effect in the northern region is better. The possible reason is that the northern region has a superior geographical location and many plains, and industrial and commercial capital going to the countryside to facilitate agricultural production, with low cost, which is conducive to increasing grain production and has the strongest inhibitory effect on non-grain production of cultivated land.

Considering the different degree of marketization in different regions of China, it will affect the effect of industrial and commercial capital going to the countryside on the non-grain production of cultivated land. Based on the above analysis and referring to the research of Xing and Liu (2024) and Fan et al. (2011), the total sample

is divided into high-level areas and low-level areas, and the influence of industrial and commercial capital going to the countryside in different market-oriented areas on cultivated land non-grain production is investigated. The specific results are shown in column (2) of Table 10. The influence of available industrial and commercial capital to the countryside on cultivated land non-grain production in areas with high degree of marketization is not significant. The possible reason is that the high degree of marketization reflects the relatively good economic environment and the free flow of production factors, and the resource allocation in this area is more effective, and capital has little influence on it. Industrial and commercial capital going to the countryside has a significant inhibitory effect on non-grain production in areas with low marketization level. The possible reason is that the degree of marketization is low and the factors needed for agricultural production cannot be allocated in time. However, industrial and commercial capital going to the countryside can effectively alleviate the shortage of agricultural production funds, thus improving agricultural production level, benefiting grain production and restraining non-grain production of cultivated land.

Finally, the impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land is significantly heterogeneous. Judging from the heterogeneity of economic development level, industrial and commercial capital going to the countryside has the strongest inhibitory effect on non-grain production of cultivated land in the central region, followed by the western region and finally the eastern region; Judging from the heterogeneity of grain production capacity, industrial and commercial capital going to the countryside has a significant impact on the non-grain production of cultivated land in the main grain producing areas, but has a poor effect on the non-grain producing areas. From the perspective of geographical heterogeneity, industrial and commercial capital going to the countryside has a significant inhibitory effect on the non-grain production of cultivated land in both northern and southern regions in China, but the inhibitory effect in the northern region is better; Judging from the heterogeneity of market-oriented environment, industrial and commercial capital going to the countryside has a significant inhibitory effect on non-grain production of cultivated land in low-level market-oriented areas, but has no significant impact on high-level market-oriented areas.

5 Conclusion and policy implications

5.1 Main conclusions

Ensuring the safety of cultivated land is the basis of realizing grain security, agricultural modernization is an important way to realize grain security, and grain security is a major event related to the national economy, people's livelihood and social security of all countries in the world. The development of modern agriculture needs a lot of capital investment, and the industrial and commercial capital going to the countryside is the key to the development of modern agriculture. In order to study the influence of industrial and commercial capital going to the countryside on cultivated land non-grain production, this paper takes the balanced panel data of 30 provinces in China (except Tibet) from 2013 to 2022 as the total sample, and analyzes the influence and mechanism of industrial and commercial capital going to the countryside on cultivated land non-grain production by using the two-way fixed effect model. The main conclusions are as follows:

First, industrial and commercial capital going to the countryside has a significant negative impact on non-grain production of cultivated land, which shows that industrial and commercial capital going to the countryside can effectively curb non-grain production of cultivated land. After controlling the endogenous problems, replacing the core explanatory variables and replacing the robustness test of the econometric model, this conclusion still holds.

Secondly, industrial and commercial capital going to the countryside to inhibit the non-grain production of cultivated land by promoting land circulation and improving the level of scientific and technological development, forming a path mechanism of "industrial and commercial capital going to the countryside-(promoting) land circulation/(improving) the level of scientific and technological development-(reducing) non-grain production of cultivated land"; The threshold test shows that when the level of industrial and commercial capital going to the countryside is higher than the threshold (29.124), the inhibitory effect on non-grain production of cultivated land will be significantly reduced.

5.2 Policy implications

This study puts forward the following policy suggestions to ensure grain security, implement farmland protection and encourage capital to go to the countryside: First, improve the policy of industrial and commercial capital going to the countryside, guide industrial and commercial capital to invest in the countryside through tax incentives, fund subsidies and other measures, and strengthen supervision to prevent non-grain production of cultivated land. Secondly, establish a linkage mechanism between the government and industrial and commercial capital, increase investment in agricultural infrastructure, and form an investment-driven effect. Thirdly, optimize agricultural insurance policies, reduce agricultural production risks and attract industrial and commercial capital investment. In addition, strengthen land circulation and technology promotion, improve agricultural production efficiency and promote industrial structure upgrading. Finally, considering regional differences, formulate differentiated policies and coordinate development in various regions, especially in the central and western regions and major grain-producing areas, so as to achieve balanced development of agricultural modernization throughout the country.

5.3 Research limitations and future research directions

Future research can be conducted in three different ways. First, micro-farmer survey data can be used for in-depth analysis. This study uses balanced panel data from 30 provinces (except Tibet) from 2013 to 2022, which may not be able to fully and thoroughly study the specific impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land at the micro-farmer level. Secondly, the level of non-grain production of cultivated land can be measured from multiple aspects such as output structure, planting income, and planting scale. This study only uses planting structure to measure the level of non-grain production of cultivated

land, which cannot fully reflect the actual situation of non-grain production of cultivated land. Future research can consider combining indicators of these dimensions to obtain more accurate evaluation indicators of the level of non-grain production of cultivated land. Finally, long-term follow-up research can be conducted in the future to observe the long-term trend and impact of industrial and commercial capital going to the countryside on non-grain production of cultivated land, and provide more accurate reference for the formulation of relevant policy recommendations.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1907997.html.

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Accelerated cassava varietal turnover in Tanzania, a direct result of cassava seed system interventions

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Cassava is a vital food security crop grown in the tropics primarily for its starchy tuberous roots that play a significant role in calorie intake in Africa. The cassava seed system has been historically neglected resulting in the widespread propagation of poor quality and diseased planting materials (stems/cuttings). Recently there have been ongoing efforts to modernise cassava breeding and improve seed delivery in Tanzania which have resulted in the creation of a functional and commercially sustainable cassava seed system. This system comprises a decentralized network of seed producers in a hierarchy from early generation to community-based seed with different quality assurance requirements at each level. Seed entrepreneurs are registered on a 'SeedTracker^{TM}' database where volumes of seed produced can be tracked for each variety. In this study, we analysed SeedTracker^{TM} data and household survey data to determine the Weighted Average Varietal Age (WAVA) of improved cassava varieties in Tanzania. We used total seed (cuttings) produced as weights for WAVA estimations. Results showed changes in WAVA from 11.3 years in 2018, 13.6 years in 2019, 13.5 years in 2020, 10.6 years in 2021, 11.4 years in 2022 to 10.1 years in 2023. This suggests that there is an accelerating turnover rate of improved cassava varieties. The findings of this study are useful to cassava seed system actors such as policymakers, quality assurance agencies, breeders, and seed businesses. This study also serves as an indicator of the positive impacts being achieved through cassava seed system interventions in the country. Furthermore, it validates the adopted cassava seed system model and suggests that the model could be readily adapted to other crop systems where varieties are being routinely monitored.

KEYWORDS

varietal turnover, Cassava seed system, WAVA, seed renewal frequency, adoption

Introduction

More of the tropical root crop cassava (*Manihot esculenta* Crantz) is produced in Africa than any other continent, however, yields in Africa are significantly below those of the other two major cassava-producing continents—Asia and South America. Tanzania is one of the largest cassava producers in Africa, however, yields are low at 6.5 t/ha [FAO (Food and Agricultural Organisation of the United Nations), 2023] which is well below its estimated potential yield of 25 to 30 t/ha (Lebot, 2019). Intense disease pressure, combined with the slow adoption of improved cassava varieties, has prevented farmers in Tanzania from achieving the potential yields. Cassava Brown Streak Disease (CBSD) and Cassava Mosaic Disease (CMD), both transmitted by the whitefly—*Bemisia tabaci* (Genn.)—significantly reduce yields when susceptible varieties are planted (Thresh et al., 1994; Hillocks et al., 2001; Ndyetabula et al., 2016; Chikoti and Tembo, 2022; Mkamilo et al., 2024). The diseases also cause important losses when farmers recycle stem cuttings of disease-tolerant improved varieties over extended periods (Shirima et al., 2019). The combined effect of CBSD and CMD on cassava yield in Africa causes an estimated financial loss of more than 1 billion USD annually (Patil et al., 2015; Legg et al., 2011).

To achieve the potential yields in cassava, farmers need to adopt the latest improved varieties and take advantage of the genetic gains resulting from enhanced disease resistance and increased yield. An effectively functioning seed system is crucial for the rapid adoption of the latest improved varieties and the swift phase-out of outdated ones. In the U.S., replacing maize hybrids typically takes 3 to 4 years; however, in developing countries, this process is typically much slower. For instance, in 2017, the 15-year-old maize cultivar SC513 was still widely cultivated in eastern and southern Africa (Atlin et al., 2017). The situation is even more challenging for vegetatively propagated crops in developing countries, as farmers often have restricted access to high-quality planting materials (Spielman et al., 2021). Slow rates of varietal turnover negatively impact yields over time, as farmers miss out on genetic advancements from breeding programs that address current biotic and abiotic stresses (Nuthalapati et al., 2024). Key factors contributing to slower varietal turnover in the developing world include issues within seed systems, such as limited commercialization of crop varieties, regulatory obstacles in seed production, and inadequate seed delivery systems.

Varietal turnover, defined as the rate at which farmers replace old cultivars, is a crucial mechanism for farmers to maintain yield gains and mitigate the impacts of evolving biotic and abiotic stresses (Witcombe et al., 2016; Veettil et al., 2018; Boddupalli et al., 2020; Delaquis et al., 2024). Varietal turnover played a key role in The Green Revolution. The yield boost characterizing The Green Revolution was not a one-time event in the 1960s but a sustained increase in productivity due to successive generations of improved varieties (Evenson and Gollin, 2003). Regular adoption of new varieties is also critical to combating resistance breakdowns, as demonstrated by the rapid loss of resistance to blackleg disease of rapeseed within just 3 years (Sprague et al., 2006).

The cassava seed system in Tanzania consists of four seed classes: pre-basic, basic, certified, and quality-declared seed (QDS). The Tanzania Agriculture Research Institute (TARI) primarily produces and sells pre-basic and basic seed through its national breeding programme and seed business unit. Meanwhile, seed companies and registered farmers manage the production and sale of certified and QDS seed classes. The registered farmers, known as Cassava Seed Entrepreneurs (CSEs) in Tanzania, form a decentralized network of suppliers across all cassava-producing districts (Legg et al., 2022).

Seed production across all classes is regulated by the Tanzania Official Seed Certification Institute (TOSCI), the government body responsible for seed quality assurance in Tanzania. TOSCI has set various regulations, guidelines, and tolerances for disease incidences according to each seed class. Seed inspectors from TOSCI use SeedTracker™, an ICT platform for electronic field registration, inspection and certification of cassava seed production fields at all levels of the seed system. SeedTracker™ enables the collection and storage of detailed data which is useful for estimating varietal turnover rates, and which is gathered through the routine work of TOSCI seed inspectors.

To evaluate the efficiency of Tanzania's cassava seed system and assess the impact of interventions done in the country, it is crucial to understand the adoption rate of improved cassava varieties and the varietal turnover rate. Currently, there are no reliable estimates of these metrics for cassava in Tanzania. To address this, we analyzed 6 years of data (2018–2023) obtained through SeedTracker™ (2018–2022) and a household survey (2024) to determine the varietal turnover rate by using the Weighted Average Varietal Age (WAVA) method. Additionally, we used the household survey data to estimate the adoption rate of improved cassava varieties and seed renewal frequency among the interviewed farmers. The findings of this study provide an assessment of the impact of cassava seed system interventions in the country and offer valuable insights for seed system actors and policymakers in Tanzania and elsewhere in sub-Saharan Africa.

Methodology

Data sources

To determine the cassava varietal turnover rate in Tanzania's cassava seed system, this study employed the WAVA method using seed volumes as weights. Two key assumptions were taken, first, we assumed all seeds produced were planted, and second, we assumed farmers applied a uniform cassava seed rate of 10,000 stem cuttings per hectare. WAVA estimations were done utilizing six years of data (2018–2023) from two different sources. The first source was SeedTracker™ (www.seedtracker.org), which provided 5 years of data (2018–2022). SeedTracker™ data for the period of this assessment were collected by TOSCI seed inspectors.

The second source was a 2024 household survey ($n = 326$) conducted across twelve regions in Tanzania's Lake and Coastal Zones, the country's primary cassava-producing areas (Figure 1), but which recorded information for varieties planted in 2023. These regions collectively accounted for over 70% of Tanzania's total cassava production in 2018/2019 [National Cassava Development Strategy (NCDS), 2020–2030]. The survey employed a combination of purposive and random sampling techniques. At the regional

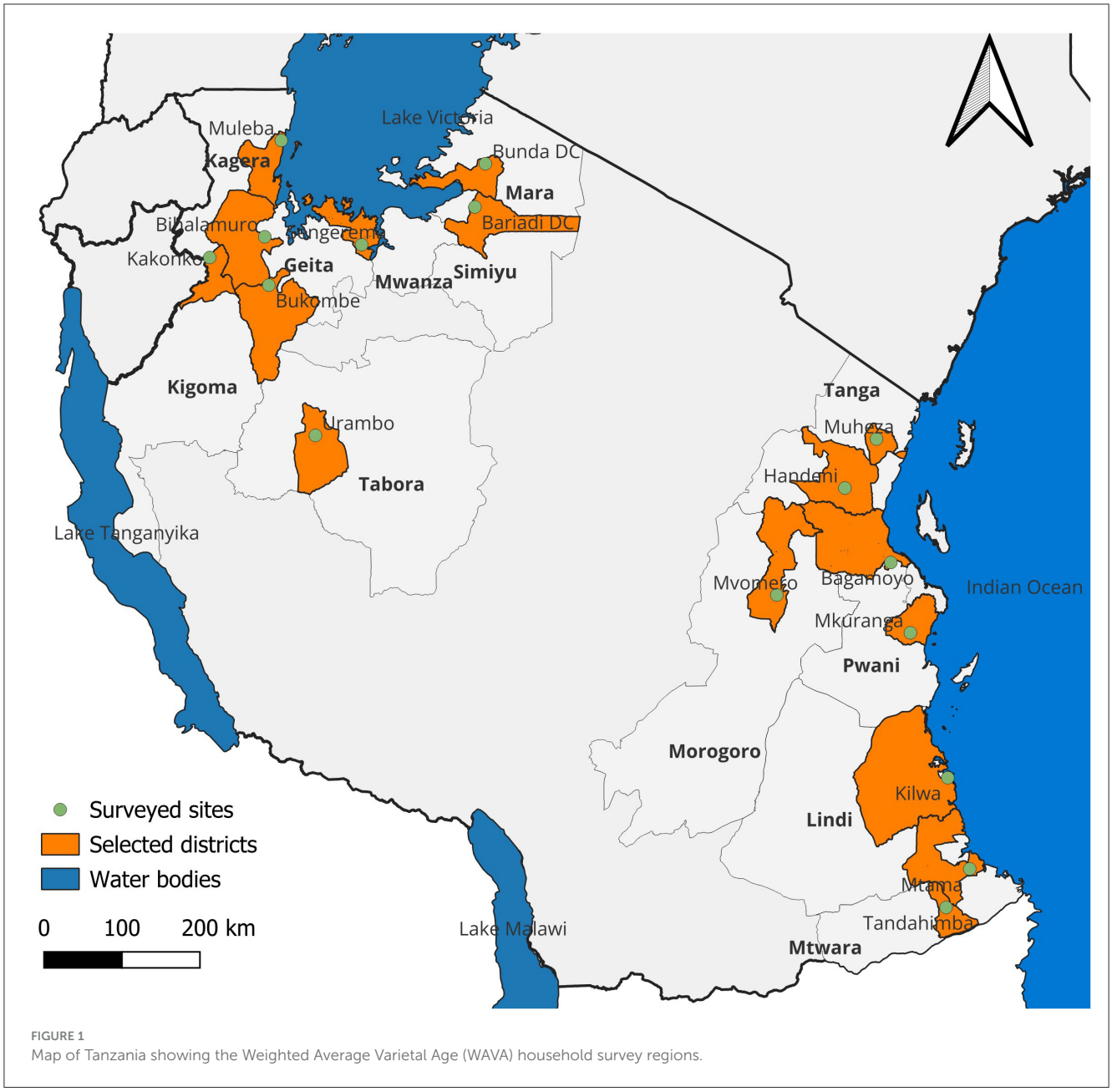


FIGURE 1
Map of Tanzania showing the Weighted Average Varietal Age (WAVA) household survey regions.

level, purposive sampling was conducted in collaboration with Regional Agriculture Officers and key seed system stakeholders to identify districts where Cassava QDS farmers were located. Although the survey targeted cassava root farmers, it was reasoned that proximity to Cassava QDS farmers would positively impact the adoption of improved varieties and increase the likelihood of encountering root farmers cultivating these varieties.

At the village level, random sampling was used to select twenty cassava root farmers. These farmers participated in a questionnaire survey which asked, among other questions, which variety they plant for the current season and what was the area under cultivation of the variety (see Supplementary Questionnaire survey tool). Surveyors also inspected the cassava farms to assess farm area under cassava cultivation and to identify the cultivated cassava varieties. The questionnaire tool is provided as Supplementary Data. Statistical analyses were done using Microsoft Excel and R. Results from the household survey were used to validate the WAVA estimations made using SeedTracker™ data.

Empirical WAVA method

The empirical strategy used to estimate WAVA follows the approach of Brennan and Byerlee (1991). This strategy has been widely used to determine varietal turnover across a wide range of crops such as wheat (Krishna et al., 2014), maize (Abate et al., 2017; De Groote and Omondi, 2023), soybean (Nuthalapati et al., 2024), and potato (Sharma et al., 2024).

$$A_t = \sum_{i=1}^{n} P_{it} \quad (t - y_i) \tag{1}$$

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TABLE 1 Weighted Average Varietal Age (WAVA) for cassava in Tanzania in 2018 (SeedTracker™ Data).

Variety	Year of Release	2018			
		Age	Seed volume	% seed volume	WAVA
Chereko	2014	4	50,000	5.6%	0.2
Kipusa	2014	4	4,300	0.5%	0.0
Kiroba	2004	14	610,100	68.8%	9.6
Kizimbani	2014	4	5,700	0.6%	0.0
Mkombozi	2009	9	16,000	1.8%	0.2
Mkumba	2012	6	0	0.0%	0.0
Mkuranga1	2014	4	171,100	19.3%	0.8
Mumba	2003	15	30,000	3.4%	0.5
TARICASS4	2020	N/A	N/A	N/A	N/A
TOTAL			**887,200**		**11.3**

TABLE 2 Weighted average varietal age (WAVA) for cassava in Tanzania in 2019 (SeedTracker™ data).

Variety	Year of Release	2019			
		Age	Seed volume	% seed volume	WAVA
Chereko	2014	5	27,000	1.2%	0.1
Kipusa	2014	5	47,397	2.0%	0.1
Kiroba	2004	15	1,475,000	63.1%	9.5
Kizimbani	2014	5	0	0.0%	0.0
Mkombozi	2009	10	476,000	20.4%	2.0
Mkumba	2012	7	0	0.0%	0.0
Mkuranga1	2014	5	40,975	1.8%	0.1
Mumba	2003	16	270,847	11.6%	1.9
TARICASS4	2020	N/A	N/A	N/A	N/A
TOTAL			**2,337,405**		**13.6**

A_t = Weighted Average Varietal Age in year *t*.

P_{it} = Proportion of the quantity of seed volume in the seed system (total of cuttings planted for all seed classes) for a given variety '*i*'.

y_i = Year of release of variety '*i*'.

Results

WAVA estimations

There are currently twenty-five officially released cassava varieties in Tanzania (TOSCI). However, data from SeedTracker™ indicates that only nine of these varieties hold significant economic importance within the formal cassava seed system based on the seed volumes produced (Tables 1–5). Among these, Kiroba, released in 2004, is the oldest popular variety in Tanzania's cassava seed system. Between 2018 and 2020, Kiroba accounted for over 60% of the total seed produced. However, by 2022, its share had declined to 32.2% (Table 5).

The latest cassava varieties released in 2020 include TARICASS1, TARICASS2, TARICASS3, TARICASS4, and TARICASS5. Among these, data show that only TARICASS4 has gained significant importance within the cassava seed system, driven by strong demand in the Lake Zone. Just 4 years after its release, TARICASS4 constituted 38% of the total seed volume planted in 2023, highlighting its success as a variety and the efficiency of the cassava seed system pipeline in the speedy delivery of new varieties from breeders to farmers.

Cassava seed production was highest in 2020 in which about 4 million cuttings of different varieties were produced across all seed classes (Table 3). Production was least in 2018 when less than a million cuttings were produced (Table 1). According to the SeedTracker™ data, the average figure for cassava seed production for the 5 years (2018–2022) is about 2.7 million stem cuttings. The weighted average varietal age (WAVA) of cassava in Tanzania over the years 2018 to 2022, as calculated from SeedTracker data, was as follows: 11.3 years in 2018, 13.6 years in 2019, 13.5 years in 2020, 10.6 years in 2021, and 11.4 years in 2022. For 2023, the WAVA calculated from household survey data was 10.1 years (Table 6).

TABLE 3 Weighted average varietal age (WAVA) for cassava in Tanzania in 2020 (SeedTracker™ data).

Variety	Year of Release	2020			
		Age	Seed volume	% seed volume	WAVA
Chereko	2014	6	45,000	1.1%	0.1
Kipusa	2014	6	50,000	1.2%	0.1
Kiroba	2004	16	2,849,700	69.8%	11.2
Kizimbani	2014	6	18,000	0.4%	0.0
Mkombozi	2009	11	240,000	5.9%	0.6
Mkumba	2012	8	326,000	8.0%	0.6
Mkuranga1	2014	6	486,500	11.9%	0.7
Mumba	2003	17	40,000	1.0%	0.2
TARICASS4	2020	0	28,000	0.7%	0.0
TOTAL			**4,083,200**		**13.5**

TABLE 4 Weighted average varietal age (WAVA) for cassava in Tanzania in 2021 (SeedTracker™ data).

Variety	Year of Release	2021			
		Age	Seed Volume	% seed volume	WAVA
Chereko	2014	7	282,000	7.3%	0.5
Kipusa	2014	7	59,000	1.5%	0.1
Kiroba	2004	17	1,153,000	29.8%	5.1
Kizimbani	2014	7	0	0.0%	0.0
Mkombozi	2009	12	502,500	13.0%	1.6
Mkumba	2012	9	663,000	17.2%	1.5
Mkuranga1	2014	7	959,800	24.8%	1.7
Mumba	2003	18	0	0.0%	0.0
TARICASS4	2020	1	245,700	6.4%	0.1
TOTAL			**3,865,000**		**10.6**

Figure 2 illustrates the combined WAVA of cassava in the seed system of Tanzania for each of the 6 years from 2018 to 2023.

Adoption of improved cassava varieties

A total of 326 households participated in the household survey, collectively cultivating 267 hectares of cassava. About 22% of this area was planted with improved cassava varieties, while the remaining 78% consisted of local landraces. The average cassava farm size was 0.8 hectares. Among the surveyed farmers, 73 households (22%) were female-headed, while 253 households (78%) were male-headed. Overall, 25% of the respondents had adopted at least one improved variety of cassava. Chi-square analysis revealed that there was no significant difference in adoption rates between male-headed and female-headed households ($\chi^2 = 1.784$, $p = 0.18$) (Table 7).

In the Coastal Zone, Kiroba was the dominant variety, accounting for 67% of the area under improved varieties, followed by Mkuranga1 at 10% (Table 8). In the Lake Zone, TARICASS4 led with 60%, followed by Mkumba and Mkombozi at 12% each (Table 8). TARICASS4, Mkumba, and Mkombozi were very popular among farmers in the Lake Zone, while Kiroba and Mkuranga1 were favored in the Coastal Zone.

Seed renewal frequency

This refers to the frequency at which farmers renew their seed stock with fresh seed to ensure that they are using seed with optimal genetic and physical quality. Frequent seed renewal is important for preserving the vigor and health of the crop. The seed renewal rate varied more between adopters and non-adopters of improved varieties than between different zones. A clear distinction was noted between adopters and non-adopters of improved varieties. The majority of adopters of improved varieties (60.7%) sourced new planting materials every 1 to 3 seasons (1 to 3 years) while the rest (39.3%) did so at intervals greater than three seasons. In comparison, only a small portion of non-adopters (38.4%) acquired new planting materials within 3 years or less while 61.7% sourced

TABLE 5 Weighted average varietal age (WAVA) for cassava in Tanzania in 2022 (SeedTracker™ data).

Variety	Year of Release	2022			
		Age	Seed Volume	% seed volume	WAVA
Chereko	2014	8	113,500	4.8%	0.4
Kipusa	2014	8	14,000	0.6%	0.0
Kiroba	2004	18	765,500	32.2%	5.8
Kizimbani	2014	8	4,000	0.2%	0.0
Mkombozi	2009	13	116,000	4.9%	0.6
Mkumba	2012	10	197,500	8.3%	0.8
Mkuranga1	2014	8	927,700	39.0%	3.1
Mumba	2003	19	51,000	2.1%	0.4
TARICASS4	2020	2	191,500	8.0%	0.2
TOTAL			**2,380,700**		**11.4**

TABLE 6 Weighted average varietal age (WAVA) for Cassava in Tanzania in 2023 (household survey data).

Improved Variety	Year of Release	Age in 2023	Area (ha)	Seed (stem cuttings)*	% Proportion	WAVA
TARICASS4	2020	3	22.30	222,982	38%	1.15
Kiroba	2004	19	15.05	150,543	26%	4.92
Mkumba	2012	11	4.49	44,920	8%	0.85
Mkombozi	2009	14	4.25	42,492	7%	1.02
Mkuranga1	2014	9	2.93	29,340	5%	0.45
Chereko	2014	9	1.82	18,211	3%	0.28
Kibaha	2003	20	1.82	18,211	3%	0.63
Pwani	2012	11	1.82	18,211	3%	0.34
Rangimbili	2009	14	1.21	12,141	2%	0.29
TARICASS3	2020	3	1.21	12,141	2%	0.06
TARICASS1	2020	3	0.81	8,094	1%	0.04
TARICASS2	2020	3	0.40	4,047	1%	0.02
		Total	**58.13**	**581,331**	**WAVA**	**10.1**

*Seed rate = 10,000 stem cuttings per hectare.

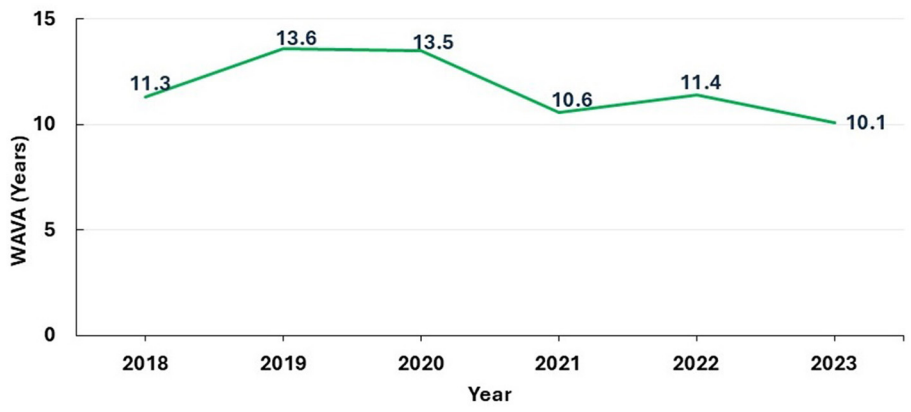


FIGURE 2
Weighted Average Varietal Age (WAVA) for cassava in Tanzania (2018-2023).

TABLE 7 Adoption rate of improved cassava varieties amongst male-headed and female-headed households.

Sex	Adopted	Not Adopted	Total	Adoption Rate (%)
Male	68	185	253	27%
Female	14	59	73	19%
Total	**82**	**244**	**326**	25%

new planting materials after more than 3 years of recycling seeds (Figure 3).

Discussion

Weighted Average Varietal Age (WAVA) requires three data points: varietal identity, year of release, and either the area planted or the seed volume produced for each variety as weights. This study represents the first instance of using SeedTracker™ data to estimate WAVA. Although household surveys provide a more direct and reliable method for estimating varietal turnover by allowing investigators to physically identify varieties and measure their cultivation areas, this study demonstrates that both approaches (utilizing SeedTracker™ data from 2018–2022 and the household survey of varieties planted in 2023) can be effectively used for assessing varietal turnover within a seed system such as that of cassava in Tanzania. SeedTracker™ has proven to be a cost-effective tool for determining varietal turnover due to the fact that data are collected as part of the normal field inspection routine of certification officers. This underscores the importance that digital tools can play in reducing the cost of agricultural interventions and expediting improvements in practice.

However, the household survey revealed that only about half of the twenty-five released cassava varieties were present in the fields of surveyed farmers. Overall, these differed somewhat from the SeedTracker™ data, as three varieties being produced by seed producers and recorded through SeedTracker™ were not grown by household survey farmers, while six improved varieties recorded in the household survey (Kibaha, Pwani, Rangimbili, TARICASS1, TARICASS2, and TARICASS3) were not recorded in SeedTracker™. The discrepancy may arise because the household survey did not cover all the cassava-growing zones in Tanzania. Also, farmers receive improved varieties directly from the national breeding programs when newly released varieties are being promoted. Nevertheless, the combined results indicate that the Lake Zone is largely responsible for driving an accelerated varietal turnover rate in the country.

This study has revealed a declining trend in the weighted average varietal age of cassava in Tanzania over six consecutive years (2018–2023). The trend reflects an accelerated turnover of cassava varieties, characterized by new adopters embracing the most recent improved varieties and former adopters transitioning to newer releases. This dynamic is supported by a robust and geographically extensive cassava seed system in Tanzania, comprised of more than 600 CSEs, which facilitates access to the newly released improved varieties (MEDA, 2022). The weighted average varietal age of cassava in Tanzania of 10.1 years in 2023 is lower than other crops in the region, such as maize, where the average varietal age is 14 years in Eastern Africa, 15 years in Western Africa, and 16 years in Southern Africa (Abate et al., 2017). These results indicate that Tanzania has benefited from interventions and investments in the cassava seed system.

Moreover, the study has found that the adoption rate of improved cassava varieties in Tanzania's major cassava producing regions is 25%. This is higher than a previous report by Walker and Alwang (2015) that estimated an adoption rate of just 14% of improved cassava varieties in sub-Saharan Africa with an average age of 14.1 years. These findings underscore the importance of continuing interventions and programmes aimed at creating and supporting a sustainable cassava seed system in the country. Literature shows that adopting improved crop varieties can increase yields by over 80%, boost farm income, enhance household consumption, promote property ownership, and ultimately reduce poverty (Asfaw et al., 2012; Walker and Alwang, 2015; Manda et al., 2019; Yabeja et al., 2025). Therefore, to better understand the long-term effects of the adoption of improved cassava varieties in Tanzania, we recommend further studies on its impact on farmers' income and nutrition.

It is important to note that in many vegetatively propagated crops (VPCs), including cassava, subjective traits such as taste significantly influence farmers' preferences. Ethnic groups in Tanzania that rely on VPCs as staples often prefer specific varieties due to their taste and cookability, which are closely linked to traditional food processing and preparation methods rather than disease resistance or yield. This phenomenon partly explains the lack of adoption in 75% of the interviewed farmers. Other factors such as insufficient local supply of high-quality improved cassava seed, poor access to information and misinformation about the improved varieties also contribute to the low adoption rates (Asfaw et al., 2012). More studies need to be conducted to identify the specific challenges associated with adopting improved crop varieties in the country.

Additionally, we noted that preferences for improved cassava varieties differed greatly between the Coastal Zone and the Lake Zone. The top three varieties in the Lake Zone are virtually absent in the Coastal Zone, and vice versa. This difference may be due to the adaptation and performance of varieties in different agroecological zones, as well as distinct uses for cassava in these areas. Farmers in the Lake Zone tend to cultivate less sweet, late-maturing varieties best suited for preparing "*Udaga*", a traditional starchy meal made from a mix of maize and cassava flour, popular in the Lake Zone. In contrast, farmers in the Coastal Zone, especially on the northern coast, primarily cultivate cassava for fresh consumption; frying, and selling in urban markets where there is high demand for cassava snacks. When other things remain constant, it is expected that the two zones will have different popular varieties based on farmer and market preferences. We recommend further studies to assess farmers' preferences as well as market preferences in traits such as cookability, sweetness, flour conversion rate and starch content. Understanding these preferences is crucial for developing policies that support strategic breeding for specific market segments and ensuring the rapid uptake of market-preferred varieties.

Also, it has been noted that the use of clean seeds and the practice of frequent seed renewal are essential in mitigating yield

TABLE 8 Improved cassava varieties in the Coastal and Lake Zones.

Improved variety	Coastal zone (ha)	% in coastal zone	Lake zone (ha)	% in lake zone
TARICASS4	0.61	3%	21.69	60%
Kiroba	14.85	67%	0.20	1%
Mkumba	0.00	0%	4.49	12%
Mkombozi	0.00	0%	4.25	12%
Mkuranga1	2.23	10%	0.71	2%
Chereko	0.81	4%	1.01	3%
Kibaha	1.82	8%	0.00	0%
Pwani	1.82	8%	0.00	0%
Rangimbili	0.00	0%	1.21	3%
TARICASS3	0.00	0%	1.21	3%
TARICASS1	0.00	0%	0.81	2%
TARICASS2	0.00	0%	0.40	1%
Total	**22.14**		**36.00**	

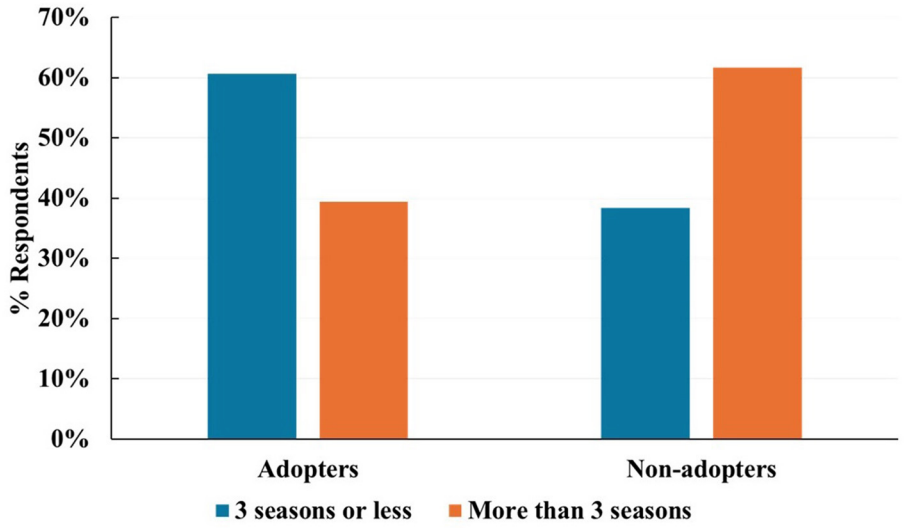


FIGURE 3
Seed renewal frequency among adopters and non-adopters of improved cassava varieties in Tanzania.

losses due to diseases and seed degeneration in cassava cultivation. Clean seeds that are free from pathogens and pests ensure healthy crop establishment and vigorous growth, reducing the incidence of disease outbreaks and subsequent associated yield penalties (Akanbi et al., 2024; Yabeja et al., 2025). Frequent seed renewal refreshes the genetic vigor and health of the crop, preventing the accumulation of viral and bacterial infections that can decimate yields over successive planting cycles (Thomas-Sharma et al., 2017; Shirima et al., 2019; Onofre et al., 2021). It is therefore advised to recycle clean cassava seed for a maximum of three seasons when planting during the long rains in Tanzania (Shirima et al., 2019). The current study revealed that a significantly higher proportion of adopters of improved cassava varieties in Tanzania (60.7%) renew their seed frequently (every 3 years or less) compared to non-adopters (38.4%). This is unsurprising, as early adopters of improved varieties are also more likely to have access to information highlighting the benefits of high quality seed and are typically more commercially focused.

Conclusion

This study successfully estimated the Weighted Average Varietal Age (WAVA) for cassava in Tanzania using SeedTracker™ data as well as household survey data. Both datasets provided broadly comparable results, although they each applied a slightly different approach to WAVA estimation. The most recent weighted average varietal age of 10.1 years (2023) is comparably lower than

other more commercialized crops in the region, which highlights the positive impact of interventions and investments in the cassava seed sector. With an adoption rate of 25% and the declining trend of varietal age for improved cassava varieties, there is progress, but also a need for continued support and development of the cassava seed system. Further research into the impacts of improved cassava variety adoption on farmers' income and nutrition could provide valuable insights. Additionally, the study revealed a quicker seed renewal rate for adopters of improved varieties, which is essential for maintaining crop health and productivity. We recommend that seed system actors should ensure that farmers who adopt improved varieties also receive training in good agronomic practices, so that the benefits from the adoption of the technology are maximized. Addressing the preferences and practices of the 75% of farmers who are yet to adopt improved varieties is crucial. Factors such as access to the supply of high-quality seeds, as well as taste and suitability for traditional food preparation methods, play significant roles in farmers' varietal adoption. Tailored policies to support strategic breeding for specific market segments and enhancing farmer education will therefore be vital for the sustainable adoption of improved cassava varieties in Tanzania, as well as in other countries in sub-Saharan Africa where cassava is important.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author/s.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/ participants OR patients/participants legal guardian/next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

JM: Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. MN: Data curation, Investigation, Writing – review & editing. JoN: Formal analysis, Writing – review & editing. MA: Data curation, Investigation, Writing – review & editing. JaN: Data curation, Investigation, Writing – review & editing. NM: Data curation, Investigation, Writing – review & editing. AM: Data curation, Investigation, Writing – review & editing. DM: Data curation, Investigation, Writing – review & editing. PK: Data curation, Resources, Software, Writing – review & editing. JL: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing.

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Estimating the demand for imported green coffee in Saudi Arabia using the Almost Ideal Demand System

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Introduction: Understanding the demand for imported green coffee in Saudi Arabia is crucial for stakeholders in the coffee trade. This study examines how demand varies by country of origin, focusing on Ethiopia, Brazil, India, and other exporting nations such as Colombia, Vietnam, and Kenya. Given the growing coffee consumption in Saudi Arabia, analyzing consumer preferences and market dynamics can provide insights for importers, exporters, and policymakers.

Methods: This study employs the Almost Ideal Demand System (AIDS) model to estimate demand elasticities for green coffee imports. The analysis considers income and price elasticities to determine the classification of coffee imports as necessities or luxury goods, as well as cross-price elasticities to assess substitution and complementarity relationships between different origins.

Results: Findings indicate that Ethiopian coffee dominates the Saudi market and is considered a luxury good with high income elasticity. In contrast, Brazilian and other coffees exhibit characteristics of necessities, with relatively stable demand. Indian coffee is highly price-elastic but maintains a smaller market share. Cross-price elasticity estimates reveal that Ethiopian and Indian coffees act as substitutes, whereas Ethiopian coffee complements imports from other sources.

Discussion and conclusion: Projected trends suggest continued growth in Ethiopian, Brazilian, and Indian coffee imports, while imports from other origins may decline. These findings have practical implications for importers and marketers, who can refine sourcing and promotion strategies, and for exporters, particularly from Ethiopia and Brazil, who can strengthen their market positioning. Policymakers may leverage these insights to ensure stable coffee import flows through targeted trade policies. This study contributes to the coffee demand literature by emphasizing the role of origin differentiation in shaping market dynamics in Saudi Arabia's green coffee sector.

KEYWORDS

green coffee, almost ideal demand system, Saudi Arabia, import demand, differentiated demand

1 Introduction

Coffee is one of the most widely consumed beverages in the world, with an estimated daily intake exceeding 2.25 billion cups [Daviron and Ponte, 2005; International Coffee Organization (ICO), 2012]. Its importance extends beyond cultural preferences, playing an important role in the economies of numerous coffee-producing countries, particularly in the developing world. In these regions, coffee is a major source of export revenue,

contributing at least 10% of total export income in many cases (Feleke and Walters, 2005). The global coffee industry supports the livelihoods of over 25 million households and spans over 10.3 million hectares of cultivated land (Pohlan and Janssens, 2010).

Estimating differentiated demand is critical in empirical research, particularly in markets where consumers make choices based on product characteristics beyond price and income considerations. Traditional aggregate demand models often assume homogeneity among goods, failing to account for consumer preferences, quality perceptions, and brand differentiation variations. Bresnahan (1987) emphasizes that differentiated product markets require models that accommodate substitution patterns and price sensitivity differences across varieties. The Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980) and other structural demand models provide a flexible framework for analyzing these variations, ensuring that empirical findings reflect the actual heterogeneity in consumer behavior. Differentiated demand estimation is instrumental in understanding market segmentation, informing policy decisions, and guiding industry strategies in response to shifting consumer preferences (Nevo, 2001).

Differentiated demand models have been widely applied in agricultural and food markets, where products from different sources exhibit distinct attributes influencing consumer choices. For example, Moschini et al. (1994) estimate a differentiated demand system for milk, considering variations in fat content and organic labeling. Brown and Schrader (1990) analyze egg consumption, distinguishing between conventional and free-range varieties. Davis and Stewart (2002) apply a differentiated demand model to beef, examining the impact of branding and country of origin on consumer preferences. Similarly, Bouamra-Mechemache et al. (2008) investigate cheese demand, capturing variations across regional varieties and processing methods. These studies demonstrate that treating agricultural products as homogeneous can lead to inaccurate policy implications and market assessments.

Analyzing demand through a differentiated model is particularly valuable for coffee, where consumer preferences vary based on origin, flavor profile, and production methods. Different exporting countries produce coffee with unique sensory attributes and perceived quality levels, significantly influencing purchasing decisions. Studies have shown that consumers differentiate between Arabica and Robusta varieties (Teuber, 2010) and between organic and conventional production methods (Liu et al., 2019).

Recent research further highlights the importance of differentiation in coffee markets. Marescotti et al. (2016) examine the role of geographical indications in Latin American coffee markets, showing how origin-based branding affects consumer demand. Grieco (2022) analyzes the European coffee market, emphasizing how country-of-origin effects shape consumer preferences and pricing strategies. Storer (2017) discusses the emergence of direct trade and single-origin coffees, illustrating how differentiation strategies influence market segmentation and pricing. These studies reinforce the argument that treating coffee demand as homogeneous can lead to misleading conclusions, as intrinsic quality attributes and external market signals drive consumer preferences. Without accounting for these differences, aggregate demand models risk oversimplifying consumer behavior, leading to misinformed trade policies and marketing strategies. Using a differentiated demand approach, researchers can better capture these dynamics, providing insights essential for industry stakeholders, policymakers, and exporters in shaping supply chain decisions.

Previous studies have extensively examined coffee demand at both household and national levels, aiming to understand key consumption drivers, price sensitivity, and socioeconomic factors. Research across various regions has consistently shown that consumer preferences are influenced by income levels, price fluctuations, and product characteristics (Capps et al., 2023; Yohannes and Matsuda, 2016; Bussolo, 2006). For instance, Capps et al. (2023) highlight the income elasticity of coffee demand in the United States, demonstrating how consumption responds to economic conditions. Similarly, Yohannes and Matsuda (2016) analyze household coffee consumption in Japan, finding that consumers exhibit significant sensitivity to price changes. These studies underscore the importance of accounting for income and price elasticities when analyzing coffee demand, particularly in markets where preferences for different coffee origins and varieties play a crucial role in shaping consumption patterns.

Saudi Arabia's coffee market has transformed significantly over the past six decades, reflecting consumer preferences, trade policies, and economic development shifts. Coffee consumption is both culturally significant and increasing rapidly, making accurate demand estimation crucial for guiding import decisions and trade policies. For instance, Saudi consumers may prefer Ethiopian coffee for its distinct flavor, whereas Brazilian coffee is often considered a more affordable option. A demand model based on country of origin accounts for these differences, enabling a detailed analysis of how price and income changes affect the demand for coffee from each exporting country. This approach provides a clearer understanding of market dynamics and supports more targeted policy decisions, benefiting importers, policymakers, and the coffee industry.

According to the Saudi Ministry of Environment, Water, and Agriculture, total coffee imports have grown significantly over the past six decades. In 1961, Saudi Arabia imported 3,740 tons of coffee, valued at $2.41 million, with 100% of imports comprising green coffee. By 1973, imports had more than doubled to 8,411 tons ($9.20 million), with green coffee maintaining a dominant share (84.19% in volume, 81.95% in value). By 2000, imports had increased substantially to 23,331 tons ($66.99 million), with green coffee comprising 91.37% of total volume and 72.63% of total value. In 2009, total imports reached 33,276 tons ($114.98 million). While green coffee still accounted for the majority (90.40% in volume, 75.07% in value), its share had started declining, indicating an emerging demand for processed coffee products. By 2021, total coffee imports surged to 101,318 tons, valued at $470.90 million, yet the share of green coffee fell to 65% in volume and 53% in value, signaling a growing preference for processed, specialty, and instant coffee. Over the past six decades, green coffee has accounted for 81.05% of total import volume and 69.32% of total import value, underscoring its historical significance while reflecting a gradual shift toward value-added coffee imports.

Given coffee origins' diversity and distinct market characteristics, a differentiated demand system is necessary to capture these variations. This study employs the Almost Ideal Demand System (AIDS) model (Deaton and Muellbauer, 1980) to estimate price and income elasticities for green coffee

imports from key suppliers such as Ethiopia, Brazil, and India. By applying this framework, the analysis identifies distinct price and income elasticities for Saudi Arabia's demand for green coffee from different origins, contributing to the broader literature on coffee consumption and providing valuable insights into consumer preferences in a growing market. The observed decline in green coffee's share relative to total imports underscores the importance of considering differentiation in coffee demand as consumer preferences shift toward premium, single-origin, and processed coffee varieties, driven by economic and cultural changes.

While many studies on coffee demand focus on aggregate consumption patterns, they often overlook distinctions between coffee types or their countries of origin. Traditional demand models provide useful insights into overall market trends. Still, they fail to capture origin-specific consumer preferences shaped by factors such as quality, flavor, and perceived value. Few studies have adopted a differentiated approach, where each exporting country's coffee is treated individually to assess its unique demand elasticity. This study addresses this gap by analyzing Saudi Arabia's demand for green coffee imports through a country-of-origin framework, using the Almost Ideal Demand System (AIDS) model to estimate price and income elasticities for key suppliers such as Ethiopia, Brazil, and India. This approach extends previous research by providing a more precise analysis of demand differentiation, allowing for a deeper understanding of Saudi consumer preferences and their implications for importers, exporters, and policymakers.

Recent studies highlight the importance of analyzing demand with respect to country of origin. For instance, Alamo and Malaga (2012) examined U.S. retail coffee demand by considering origin, blend, and roast preferences, while the Specialty Coffee Transaction Guide offers pricing benchmarks for differentiated coffees, emphasizing the role of geographical indications in specialty coffee markets. In the Saudi context, understanding how price and income changes affect demand for coffee from different suppliers is essential for designing effective trade policies and market strategies. This study's findings provide valuable insights for stakeholders by revealing how sensitive Saudi consumers are to price variations in coffee imports. The high elasticity of Ethiopian coffee, for example, suggests that it is perceived as a premium product, meaning even small price reductions could significantly boost demand. In contrast, Brazilian coffee, which exhibits lower price sensitivity, may be better positioned as an affordable, stable choice in the market.

These results have important policy and business implications. Importers and retailers can use elasticity estimates to optimize sourcing, pricing strategies, and product positioning. At the same time, exporters may tailor their trade negotiations and supply chain decisions based on the relative price sensitivity of their coffee in Saudi Arabia. Policymakers can leverage these insights to support stable trade agreements and adjust tariffs to ensure consistent access to preferred imports. As Saudi Arabia's coffee market continues to expand, accounting for differentiated demand dynamics will be essential for fostering a balanced, competitive, and sustainable trade environment.

The remainder of this paper is organized as follows. Section 2 presents material and methods, including the conceptual, data, and empirical framework. Section 3 discusses the findings, their implications for policymakers and market participants, and a comparison with previous research. Finally, Section 4 concludes the study by summarizing key insights and suggesting directions for future research.

2 Materials and methods

This study examines the behavior of Saudi importers of green coffee from various nations using the Almost Ideal Demand System (AIDS) model. This section describes the AIDS model, its assumptions, techniques for estimating parameters, and derived elasticities.

2.1 AIDS conceptual framework

The Almost Ideal Demand System (AIDS), introduced by Deaton and Muellbauer (1980), is widely used in economic studies focused on demand systems due to its flexibility and consistency with consumer theory. The model offers several advantages: it is an arbitrary first-order approximation to any demand system, satisfies the axioms of choice, allows for aggregation over consumers, and accommodates non-linear Engel curves. The AIDS model is derived from the expenditure function, which represents the behavior of importers in relation to a set of goods (Yang and Koo, 1994).

Let n represent the number of the goods considered, $(p_{1t}, p_{2t}, \ldots, p_{nt})$ are the prices of these goods at time period t, and $(q_{1t}, q_{2t}, \ldots, q_{nt})$ quantities consumed at time period t, then the total expenditure on amounts imported during the time period t is$m_t = \sum_{i=1}^{n} p_{it}q_{it}$. The demand equations of AIDS can be expressed in terms of the budget shares:

$$w_{it} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \ln(p_{jt}) + \beta_i \ln\left(\frac{m_t}{P_t}\right) + \varepsilon_{it}, \quad i = 1, 2, \ldots, n, \quad t = 1, 2, \ldots, T \tag{1}$$

where $w_{it} = \frac{p_{it}q_{it}}{m_t}$ is the expenditure share of good i, ε_{it} is the disturbance term, and $\ln P_t$ is the translog price index given by:

$$\ln P_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln(p_{it}) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \gamma_{ij} \ln(p_{it}) \ln(p_{jt}) \tag{2}$$

The model to be estimated is given by the system of equations summarized in Equation 1.

2.2 Theoretical restrictions of the AIDS model

The Almost Ideal Demand System (AIDS) model is grounded in the principles of consumer theory, ensuring that its predictions align with rational economic behavior. To achieve this, the model must satisfy several theoretical restrictions. These restrictions are not merely mathematical constraints but are essential for ensuring the model's consistency with the axioms of consumer choice. Below, we discuss these restrictions in detail.

2.2.1 The adding-up restriction

The adding-up condition ensures that the total expenditure on all goods equals the consumer's budget. Mathematically, this is expressed as: $\sum_{i=1}^{n} w_{it} = 1$, where w_{it} represents the expenditure share of good i at time t. This condition implies that the sum of the expenditure shares across all goods must equal one, reflecting the consumer's budget constraint. For the AIDS model, this condition is satisfied if the following restrictions on the model's parameters hold:

$$\sum_{i=1}^{n} \alpha_i = 1, \quad \sum_{i=1}^{n} \beta_i = 0, \quad \sum_{i=1}^{n} \gamma_{ij} = 0 \quad \forall j. \tag{3}$$

These restrictions ensure that the model accurately reflects the allocation of the consumer's budget across different goods.

2.2.2 The homogeneity restriction

The homogeneity restriction ensures that the demand functions are homogeneous of degree zero in prices and income. This means that if all prices and income change by the same proportion, the quantities demanded remain unchanged. Mathematically, this restriction is expressed as:

$$\sum_{j=1}^{n} \gamma_{ij} = 0 \quad \forall i. \tag{4}$$

This restriction ensures that the model is free from "money illusion," meaning that consumers respond to real changes in prices and income rather than nominal changes. It is a crucial condition for ensuring that the model's predictions are consistent with rational consumer behavior.

2.2.3 The symmetry restriction

The symmetry restriction ensures that the compensated (Hicksian) cross-price effects between goods are symmetric, reflecting the consistency of consumer preferences. Mathematically, this restriction is expressed as:

$$\gamma_{ij} = \gamma_{ji} \quad \forall i, j. \tag{5}$$

This condition implies that the effect of a price change for good i on the demand for good j is the same as the effect of a price change for good j on the demand for good i. The symmetry restriction is derived from the assumption that the consumer's utility function is well-behaved and that the substitution effects are consistent.

2.2.4 The negativity restriction

The negative condition ensures that the Slutsky substitution matrix is negative semi-definite, which is a necessary condition for the demand functions to be consistent with utility maximization. Mathematically, this condition requires that the own-price elasticities are non-positive:

$$e_{ii} \leq 0, \tag{6}$$

where e_{ii} represents the own-price elasticity of demand for good i. This condition ensures that the law of demand holds, meaning that an increase in the price of a good leads to a decrease in its quantity demanded, all else being equal.

2.3 AIDS model elasticities

The AIDS model enables the computation of expenditure (income) elasticities (η_i) and Marshallian (uncompensated) price elasticities (Θ_{ij}). The income elasticity is calculated as:

$$\eta_i = 1 + \frac{\beta_i}{w_i} \tag{7}$$

The own- and cross-price elasticities can be calculated using the following equation (Gravelle and Rees, 2004; Nicholson, 2005):

$$\Theta_{ij} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i}\left(\alpha_j + \sum_{k=1}^{n} \gamma_{kj} \ln p_k\right), \quad \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{8}$$

Equation 8 can be simplified as:

$$\Theta_{ij} = -\delta_{ij} + \frac{\gamma_{ij} - \beta_i(w_j - \beta_j \ln(\frac{m}{P}))}{w_i}, \quad \delta_{ij} = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases} \tag{9}$$

2.4 Estimation of the AIDS model

The Almost Ideal Demand System (AIDS) model is estimated using a system of equations derived from the budget share (Equation 1). However, due to the adding-up condition, the system of equations is singular, as the sum of the expenditure shares equals one, and the sum of the disturbance terms equals zero. To address this issue, one equation is dropped from the system, and the parameters of the omitted equation are recovered using the theoretical restrictions (Equations 3–6). This approach ensures that the estimated model is theoretically consistent and empirically robust.

The system of equations in Equation 1 is non-linear due to the presence of the translog price index $\ln P_t$. To simplify the estimation, Deaton and Muellbauer (1980) propose using the Stone price index as an approximation:

$$\ln P_t^s = \sum_{i=1}^{n} w_{it} \ln(p_{it}), \tag{10}$$

where $\ln P_t^s$ is the Stone price index. Substituting this into Equation 1 yields the Linear Approximate Almost Ideal Demand System (LA-AIDS):

$$w_{it}^s = \alpha_i^s + \sum_{j=1}^{n} \gamma_{ij}^s \ln(p_{jt}) + \beta_i^s \ln\left(\frac{m_t}{P_t^s}\right) + \varepsilon_{it}^s, \quad i = 1, 2, \ldots, n, \quad t = 1, 2, \ldots, T. \tag{11}$$

The LA-AIDS model can be estimated using the Zellner (1962) Seemingly Unrelated Regression (SUR) method, which accounts

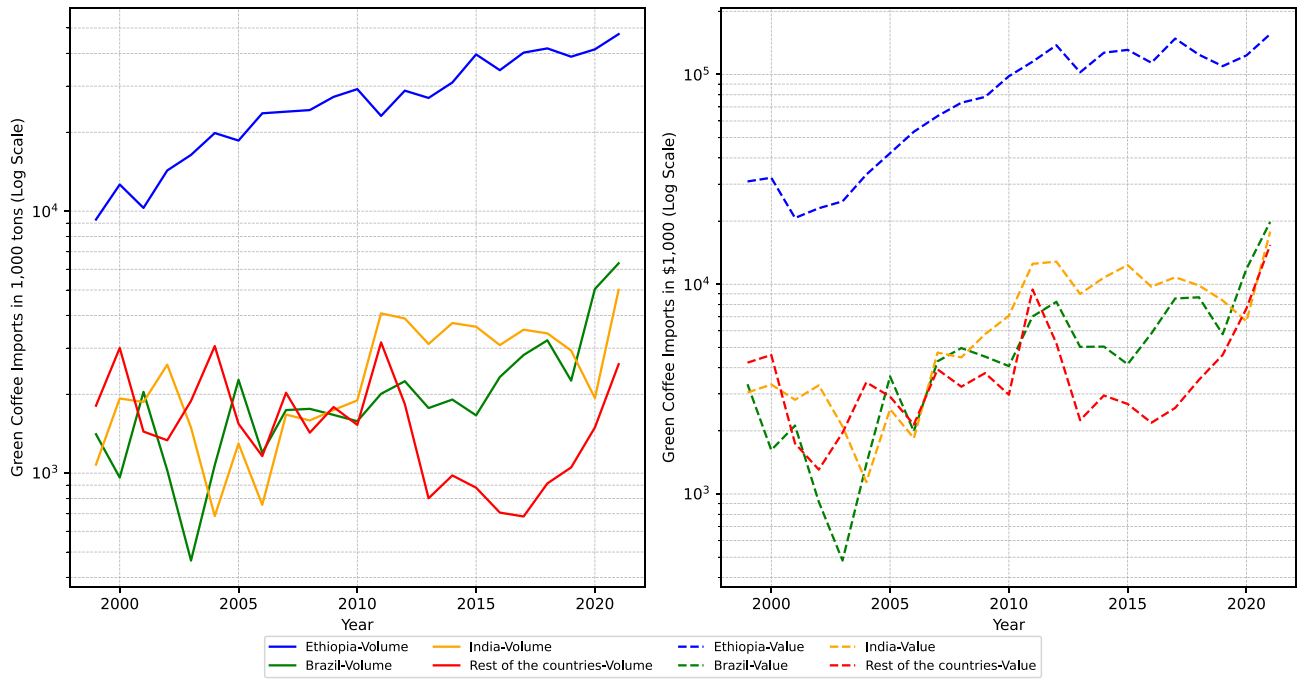


FIGURE 1
Historical trends in Saudi Arabia Green Coffee imports in volume **(left)** and value **(right)** between 1999 and 2021.

for the correlation between the disturbance terms across equations. However, using the Stone price index introduces a simultaneity bias, as the budget shares w_{it} appear on both the left-hand and right-hand sides of the equation. To mitigate this issue, lagged budget shares are often used in the Stone price index:

$$\ln P_t^s = \sum_{i=1}^{n} w_{it-1} \ln(p_{it}). \tag{12}$$

Alternatively, the nonlinear AIDS model can be estimated directly using Nonlinear Seemingly Unrelated Regression (NLSUR) or Maximum Likelihood (ML). These methods provide consistent and efficient estimates, avoiding the issues associated with the Stone price index.

In this study, the AIDS model is estimated using the R software, specifically the `micEconAids` package, which provides a straightforward way to perform econometric estimation of the AIDS model (Henningsen and Hamann, 2008). The package includes the `aidsEst` function, which allows for estimating the model parameters, elasticities, and hypothesis testing.

2.5 Empirical model and data description

This study employs the Almost Ideal Demand System (AIDS) model to explore and assess Saudi Arabia's demand for green coffee imported from major producing nations (Ethiopia, Brazil, and India). Additionally, it includes data from secondary coffee-producing countries (Colombia, Vietnam, and Kenya, aggregated as the rest of the countries). Secondary data on the quantities of green coffee (q_i) imported from these countries and their respective values (m_i) are from the Food and Agriculture Organization (FAO) from 1999 to 2021. Based on this data, we calculated the year-on-year import prices ($p_i = \frac{m_i}{q_i}$) and the expenditure shares ($w_i = \frac{m_i}{\sum_k m_k}$).

2.5.1 Data description

Figure 1 displays the historical trends of green coffee import volumes (left panel) and values (right panel) for Saudi Arabia's coffee imports from Ethiopia, Brazil, India, and other countries. We employed a logarithmic scale to account for the significant disparity in import figures–where Ethiopia's imports are more than tenfold those of other countries. The data reveal that Saudi Arabia's imports of Ethiopian green coffee from 1999 to 2021 exhibit a consistent positive linear trend. In contrast, imports from other countries show no clear pattern over time. Furthermore, the import volumes of these other varieties are relatively similar, with no significant differences observed.

Table 1 provides descriptive statistics for the quantities, values, prices, and budget shares of green coffee imports in Saudi Arabia from 1999 to 2021. The data reveal significant variations in import patterns across different origins, reflecting Saudi Arabia's preferences and market dynamics for green coffee.

From 1999 to 2021, Saudi Arabia imported an average of 27,111 tons of Ethiopian green coffee annually, with an average price of $3,003 per ton. Ethiopia dominates Saudi Arabia's green coffee imports, accounting for 85% of the total expenditure on imported green coffee. The expenditure on Ethiopian coffee has grown at a substantial annual rate of 9.1%, significantly outpacing the growth rate of import prices, which stood at 2.6%. This strong demand has

TABLE 1 Descriptive statistics for green coffee imports in saudi Arabia (1999–2021).

Variable	Mean	SD	Min	Max	Unit
Quantities (volume)					Tons
q_1 (Ethiopia)	20,123.45	12,345.67	9,289.00	47,382.93	Tons
q_2 (Brazil)	1,987.65	1,234.56	464.00	6,322.40	Tons
q_3 (India)	2,345.67	1,234.56	686.00	5,007.59	Tons
q_4 (Others)	1,543.21	987.65	683.35	2,605.25	Tons
Values (expenditure)					USD
m_1 (Ethiopia)	65,432.10	40,123.45	20,700.00	155,705.00	USD
m_2 (Brazil)	6,543.21	4,123.45	482.00	19,822.00	USD
m_3 (India)	7,654.32	4,567.89	1,141.00	17,814.00	USD
m_4 (Others)	5,432.10	3,456.78	1,308.00	15,391.00	USD
Prices					USD/Ton
p_1 (Ethiopia)	2,500.00	1,234.56	1,515.40	4,982.72	USD/Ton
p_2 (Brazil)	1,800.00	987.65	895.61	3,498.01	USD/Ton
p_3 (India)	2,000.00	1,234.56	1,271.11	3,557.40	USD/Ton
p_4 (Others)	1,700.00	987.65	979.78	5,907.69	USD/Ton
Budget shares					Proportion
w_1 (Ethiopia)	0.75	0.10	0.60	0.85	Proportion
w_2 (Brazil)	0.10	0.05	0.05	0.15	Proportion
w_3 (India)	0.08	0.04	0.03	0.12	Proportion
w_4 (Others)	0.07	0.03	0.02	0.10	Proportion

Subscript 1 refers to Ethiopia, 2 to Brazil, 3 to India, and 4 to the rest of the countries. Values are rounded to two decimal places.

led to a yearly increase of 6.5% in the volume of Ethiopian green coffee imported.

In contrast, the average quantity of Brazilian green coffee imported by Saudi Arabia is 2,120 tons, with an average price of $2,330 per ton. Brazil's share of Saudi Arabia's green coffee expenditure is relatively smaller, at 5%. However, the expenditure on Brazilian coffee has grown at an annual rate of 10%, which is higher than the growth rate of import prices (4%). This has resulted in a yearly growth rate of 6.1% in the volume of Brazilian coffee imports, indicating a steady demand for this origin.

Indian green coffee imports show a similar trend, with an average annual import volume of 2,476 tons and an average price of $2,695 per ton. Saudi Arabia spends an average of $7,079 thousand on Indian coffee, representing 5% of the total expenditure on imported green coffee. The expenditure on Indian coffee has grown at an annual rate of 8.8%, surpassing the growth rate of import prices (3.4%). Consequently, the volume of Indian coffee imports has increased by 5.4% annually.

Imports from other countries, including Colombia, Vietnam, and Kenya, average 1,613 tons annually, with an average price of $2,653 per ton. These countries collectively account for 4.8% of Saudi Arabia's total expenditure on green coffee imports. However, the growth rate of expenditure on these imports (3.6%) is lower than the growth rate of import prices (6.5%), leading to a 3% annual decline in import volumes. This suggests a shift in consumer preferences toward coffee from Ethiopia, Brazil, and India.

Table 1 highlights the relative significance of Saudi Arabia's demand for green coffee from different origins. Ethiopian coffee holds the largest market share, accounting for 85% of total expenditure, followed by Indian coffee (6.9%) and Brazilian coffee (5%). Coffee from other countries, including Colombia, Vietnam, and Kenya, collectively represents 4.8% of total expenditure. These findings underscore the dominance of Ethiopian coffee in Saudi Arabia's green coffee market while revealing steady demand for Brazilian and Indian varieties. The declining imports from other countries suggest a potential shift in consumer preferences toward higher-quality or more competitively priced coffee from major suppliers.

2.5.2 Empirical model for Saudi Arabia's imports of green coffee

To estimate the model given by Equation 1 under the theoretical restrictions given Equations 3–6, we construct the empirical model presented in Equation 13. It assumes that p_{1t}, p_{2t}, p_{3t}, and p_{4t} represent the import prices of green coffee ($/ton) at time t from Ethiopia, Brazil, India, and other countries (Colombia, Vietnam, and Kenya), respectively. w_{1t}, w_{2t}, w_{3t}, and w_{4t} represent the distribution of budget shares on imported goods from the specified nations at time t. m_t indicates the total expenditure on imports from these countries and represents the entire budget at time t. By replacing the variables in the AIDS model (1) with

the variables under study, the empirical model can be formulated as follows:

$$w_{1t} = \alpha_1 + \gamma_{11}\ln(p_{1t}) + \gamma_{12}\ln(p_{2t}) + \gamma_{13}\ln(p_{3t}) + \gamma_{14}\ln(p_{4t}) + \beta_1 \ln\left(\frac{m_t}{P_t}\right) + \varepsilon_{1t}, \quad (13a)$$

$$w_{2t} = \alpha_2 + \gamma_{21}\ln(p_{1t}) + \gamma_{22}\ln(p_{2t}) + \gamma_{23}\ln(p_{3t}) + \gamma_{24}\ln(p_{4t}) + \beta_2 \ln\left(\frac{m_t}{P_t}\right) + \varepsilon_{2t}, \quad (13b)$$

$$w_{3t} = \alpha_3 + \gamma_{31}\ln(p_{1t}) + \gamma_{32}\ln(p_{2t}) + \gamma_{33}\ln(p_{3t}) + \gamma_{34}\ln(p_{4t}) + \beta_3 \ln\left(\frac{m_t}{P_t}\right) + \varepsilon_{3t}, \quad (13c)$$

$$w_{4t} = \alpha_4 + \gamma_{41}\ln(p_{1t}) + \gamma_{42}\ln(p_{2t}) + \gamma_{43}\ln(p_{3t}) + \gamma_{44}\ln(p_{4t}) + \beta_4 \ln\left(\frac{m_t}{P_t}\right) + \varepsilon_{4t}. \quad (13d)$$

To simplify the AIDS model, one equation is dropped, and it is assumed that the constant in the price index (Equation 2) is normalized to zero. The system of equation in Equation 13 is estimated by the Nonlinear Seemingly Unrelated Regression (NLSUR) method.

3 Results

The Almost Ideal Demand System (AIDS) model was applied to estimate the parameters and demand elasticities for green coffee imports in Saudi Arabia. The results provide insights into how Saudi importers respond to price and income changes across different coffee origins, examining own-price, cross-price, and income elasticities. Additionally, we evaluate the significance of each type of coffee based on consumer perceptions, test the consistency of the estimated demand model, and predict import trends through 2030.

3.1 Parameter estimates

Table 2 provides the estimated parameters of the AIDS model, which are fundamental to understanding the sensitivity of Saudi demand for green coffee from various countries. These parameter estimates are used to calculate elasticities, helping to identify how price and income changes affect coffee demand from each origin. The estimates reveal positive and statistically significant intercept values for Ethiopian and Brazilian green coffee, indicating that these coffee types have substantial baseline shares in Saudi Arabia's import market. The estimated coefficients for Ethiopian coffee, in particular, underscore its dominant role in Saudi Arabia's green coffee imports, as reflected by its high intercept value. In contrast, the intercept for Indian coffee is lower and not statistically significant, suggesting a smaller baseline share and less market penetration compared to Ethiopian and Brazilian coffees.

3.2 Elasticities

Table 3 presents the calculated own-price and cross-price elasticities based on the parameter estimates. The own-price elasticity of demand for Ethiopian green coffee is –1.029, indicating a significant elasticity; a 10% increase in price would reduce demand by ∼10.3%, showing Saudi consumers' high sensitivity to price changes for Ethiopian coffee. In contrast, Brazilian green coffee has a price elasticity of –0.629, indicating a lower sensitivity and suggesting that Saudi consumers view it as a more stable product in their consumption choices. Indian coffee shows high price elasticity at –1.635, reflecting strong responsiveness to price changes.

TABLE 2 Results of ILLE method to coefficients of the almost ideal demand system.

Countries	α_i	γ_{i1}	γ_{i2}	γ_{i3}	γ_{i4}	β_i
Ethiopia	0.486***	0.023	–0.047	0.079*	–0.055*	0.095***
Brazil	0.170**	–0.047	0.041	–0.034	0.040**	–0.030*
India	0.025	0.079*	–0.034	–0.044	–0.001	0.009
Others	0.319***	–0.055*	0.040**	–0.001	0.016	–0.074***

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

TABLE 3 Marshallian price elasticities and income elasticities.

Saudi demand	Θ_{i1}	Θ_{i2}	Θ_{i3}	Θ_{i4}	η_i
Ethiopia	–1.029***	–0.074	0.090*	–0.101**	1.114***
Brazil	–0.629	–0.092	–0.654	0.966**	0.409
India	1.077*	–0.514	–1.635***	–0.052	1.125***
Others	–0.386	1.076**	0.039	–0.187	–0.543

*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

3.3 Predictions

Table 4 summarizes the projected demand for green coffee imports in Saudi Arabia through 2030 based on observed import prices and expenditure growth rates. Ethiopian, Brazilian, and Indian coffee imports are projected to grow annually by 6.2%, 5.3%, and 4.3%, respectively, reflecting an increasing preference for these origins. In contrast, imports from other countries (Colombia, Vietnam, and Kenya) are expected to decline at an annual rate of 4%, suggesting a shift in consumer preferences.

3.4 Consistency with economic theory

The estimated AIDS model parameters were tested for consistency with economic theory by evaluating adding-up, homogeneity, symmetry, and negativity restrictions, as shown in Table 5.

The results indicate that the model satisfies the adding-up, homogeneity, and symmetry conditions, supporting its consistency with economic theory. However, the negativity condition is only partially met, suggesting limitations in the model's ability to capture consumer behavior fully.

TABLE 4 Prediction of Saudi's green coffee imports.

Years	Ethiopia	Brazil	India	Others
2021*	47,383	6,322	5,008	2,605
2022	50,342	6,657	5,223	2,501
2023	53,486	7,010	5,447	2,401
2024	56,825	7,381	5,681	2,305
2025	60,374	7,772	5,924	2,213
2026	64,144	8,184	6,179	2,125
2027	68,150	8,618	6,444	2,040
2028	72,405	9,074	6,720	1,958
2029	76,927	9,555	7,009	1,880
2030	81,731	10,062	7,309	1,805

*Base year.

TABLE 5 Results of likelihood ratio tests for theoretical restrictions.

Restriction	Log-Likelihood	Null Hypothesis	χ^2	p-value
Symmetry	186.968	$\gamma_{ij} = \gamma_{ji}$	2.2845	0.5455
Homogeneity	188.101	$\sum_{j=1}^{n} \gamma_{ij} = 0$	7.3401	0.062
Symmetry and homogeneity	191.774	$\gamma_{ij} = \gamma_{ji}$ and $\sum_{j=1}^{n} \gamma_{ij} = 0$	9.6245	0.1414

4 Discussion: implications for Saudi Arabia

The results of this study align with and extend previous research on differentiated demand in agricultural markets, particularly in the context of coffee. The dominance of Ethiopian coffee in Saudi Arabia's imports, characterized by its high income elasticity (1.114), is consistent with findings from other studies that highlight the importance of origin-specific attributes in shaping consumer preferences. For instance, Marescotti et al. (2016) and Grieco (2022) have shown that geographical indications and country-of-origin branding significantly influence consumer demand, particularly for premium products like Ethiopian coffee. The high price elasticity of Ethiopian coffee (−1.029) further supports the notion that consumers perceive it as a luxury good, as observed in studies by Teuber (2010) and Liu et al. (2019), which emphasize the role of quality and flavor profiles in driving demand for specialty coffees.

Brazilian coffee, with its lower price elasticity (−0.629), aligns with findings from studies such as Capps et al. (2023)and Yohannes and Matsuda (2016), which suggest that more affordable, stable products are often treated as necessities in consumer demand models. This is particularly relevant in markets like Saudi Arabia, where Brazilian coffee serves as a reliable, everyday option. Similarly, the high price elasticity of Indian coffee (−1.635) reflects its niche position in the market, consistent with research by Alamo and Malaga (2012), who found that price sensitivity varies significantly across coffee origins and types.

The substitutive relationship between Ethiopian and Indian coffees, as well as the complementary relationship between Ethiopian coffee and imports from other countries (Colombia, Vietnam, and Kenya), underscores the importance of origin-specific differentiation in consumer preferences. These findings are in line with studies by Bouamra-Mechemache et al. (2008) and Davis and Stewart (2002), which highlight how consumers differentiate between products based on attributes such as flavor, quality, and branding. The projected growth in imports from Ethiopia, Brazil, and India, coupled with declining imports from other countries, further supports the argument that Saudi consumers are increasingly prioritizing quality and origin-specific characteristics, as noted in the Specialty Coffee Transaction Guide and research by Storer (2017).

From a policy perspective, these findings emphasize the need for targeted trade policies that ensure stable access to preferred coffee origins. The high elasticity of Ethiopian coffee suggests that even small price reductions could significantly boost demand. In contrast, the stability of Brazilian coffee imports highlights the importance of maintaining competitive pricing and supply reliability. These insights are particularly relevant for policymakers and importers, as they align with the broader literature on trade policy and consumer behavior in agricultural markets (Feleke and Walters, 2005; Daviron and Ponte, 2005).

5 Conclusion

This study examined the demand for imported green coffee in Saudi Arabia using the Almost Ideal Demand System (AIDS) model, focusing on the differentiated demand for coffee from Ethiopia, Brazil, India, and other countries. The primary objectives were to estimate price and income elasticities and to understand how consumer preferences vary by origin. The findings reveal that Ethiopian coffee, with its high income elasticity (1.114), is perceived as a luxury good, while Brazilian coffee, with lower price elasticity (−0.629), is considered a necessity. Indian coffee, despite its high price elasticity (−1.635), occupies a smaller market share, indicating a niche position. The results also highlight the substitutive relationship between Ethiopian and Indian coffees and the complementary relationship between Ethiopian coffee and imports from other countries. These findings underscore the importance of origin-specific attributes in shaping consumer preferences and have significant implications for importers, exporters, and policymakers.

These insights have significant implications for importers, exporters, and policymakers. Importers should prioritize sourcing Ethiopian coffee due to its high demand elasticity and premium status, while maintaining Brazilian coffee as a stable, affordable option, and promoting Indian coffee as a competitive alternative in price-sensitive segments. For exporters, Ethiopian producers should emphasize the unique flavor profiles and premium quality of their coffee to appeal to affluent Saudi consumers, while Brazilian exporters should focus on maintaining supply stability and competitive pricing. Indian exporters could explore opportunities to increase market share through competitive pricing strategies. Policymakers should consider reducing tariffs or implementing trade agreements to ensure stable access to preferred coffee origins, particularly Ethiopia and Brazil, which would support

consumer welfare and foster a competitive and sustainable trade environment.

While this study provides valuable insights, it is important to note that the findings are based on historical data and certain theoretical assumptions, which may not fully capture all market dynamics. Future research could build on these findings by incorporating additional data sources, exploring the impact of emerging trends such as sustainability and ethical sourcing, and refining the model to account for external factors like climate change and geopolitical shifts. Such efforts would further enhance our understanding of the evolving coffee market in Saudi Arabia and beyond.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

EA: Writing – review & editing, Project administration, Conceptualization, Writing – original draft. BC: Writing – review & editing. AK: Writing – original draft. MA: Conceptualization, Data curation, Software, Validation, Writing – original draft. AA: Writing – review & editing, Project administration, Resources, Investigation. YK: Writing – review & editing, Conceptualization.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evolution of grain trade patterns among RCEP member countries and the potential impacts of agreement signing

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Introduction: Trade plays a pivotal role in maintaining global grain security. However, the grain trade network (GTN) within Regional Comprehensive Economic Partnership (RCEP) member countries remains unclear. Analyzing grain flow characteristics and the agreement's potential impacts are essential to fostering resilient economic and trade cooperation within the world's largest free trade area.

Methods: This study constructed a trade network analysis framework incorporating complex network topology, competition intensity, interdependence intensity, and robustness. It examined the grain trade patterns and coopetition relationships from 2000 to 2020. Building on this, the study created the "Five Forces" model to analyze evolutionary mechanisms in the GTN and explored the potential impacts of trade agreements through trade diversion and creation effects.

Results: (1) The GTN has grown increasingly complex and interconnected, with key nodes exhibiting trends toward homogenization. By 2020, Australia, Viet Nam, Myanmar, Thailand, and Cambodia collectively accounted for 95.70% of total exports, emerging as major grain exporters in the GTN. (2) The GTN exhibits high competition and low interdependence. Populous countries with constrained arable land resources, such as China, Philippines, Malaysia, South Korea, and Indonesia, face intense import competition. Concerns over external supply security have led to diversified trade behaviors among member countries, fostering a trade pattern characterized by low interdependence (87.23%). (3) The robustness of the GTN has significantly improved due to the complexity of network structures and the homogenization of key node positions. Countries such as Thailand and Australia, with high Betweenness centrality values, play crucial roles in maintaining stability. Meanwhile, Viet Nam and China, as major import–export countries, are exerting growing influence in the GTN. (4) The evolution of the GTN is shaped by the interactive effects of five key forces: resource endowments, domestic demand, economic conditions, geopolitical relations, and important events. Differentiated tariff reduction commitments and reduced non-tariff measures are expected to generate trade diversion and creation effects. Such policy measures may reallocate intra-regional trade flows and expand trade volumes while intensifying import competition.

Discussion: From a complex network perspective, this study provides valuable policy insights for RCEP member countries to leverage their strengths and participate more effectively in agricultural trade.

KEYWORDS

grain trade network, coopetition relationships, evolutionary mechanisms, trade agreement, RCEP member countries

1 Introduction

Grain trade has remained a focal point of sustained attention across various sectors (Chen and Zhang, 2022). Recently, the rise of unilateralism and backlash against globalization have introduced significant uncertainties to global trade (Gong et al., 2022). Influenced by factors such as health crises (Alabi and Ngwenyama, 2023), regional conflicts (Liu L. et al., 2023; Liu H. et al., 2023), and trade policy changes (Yang et al., 2022), the vulnerability of grain trade systems has become increasingly evident (Zhang et al., 2021a,b), impacting the achievement of the global Zero Hunger goal (SDG 2) by 2030 (FAO, 2023).

In the context of rising anti-globalization sentiments, participating in regional trade agreements has become one of the key strategies for countries to address risks in grain trade (Zhang and Gong, 2022). Existing research has shown that trade agreements such as Association of Southeast Asian Nations (ASEAN), North American Free Trade Agreement (NAFTA), and Transatlantic Trade and Investment Partnership (TTIP) have facilitated the integration of regional agricultural markets, contributing to the agricultural development of member countries (Greenville and Kawasaki, 2018; Zahniser et al., 2015; Bureau et al., 2014). The world's largest free trade agreement, the Regional Comprehensive Economic Partnership (RCEP), was signed in 2020. The member countries of RCEP represent a significant global population aggregation district (24.64% of the world's population) and a major grain production area (27.17% of global grain production) in 2022. Agricultural trade is one of the key traditional areas of cooperation among RCEP member countries. The agreement includes provisions for agricultural trade, such as tariff reduction, rules of origin, trade facilitation, negative list, and trade remedy, with the overarching goal of maximizing trade liberalization and facilitation within the region (Zuo et al., 2024).

The Customs Unions Issue argues that trade agreements lead to trade diversion and trade creation effects, with agricultural products subject to higher tariff rates being more sensitive to these impacts (Viner, 2014; Hoekman and Nicita, 2011). Currently, scholars have conducted extensive research on trade promotion effects of RCEP provisions from a commodity trade perspective (Wei, 2024; Zainuddin et al., 2020). However, studies on grain trade tend to focus on unilateral or bilateral relations based on value quantity, with limited research exploring the overall intra-regional trade pattern. On one hand, scholars have analyzed the bilateral grain flow characteristics among RCEP member countries, such as examining trade structures with between China and other countries (Chen and Wang, 2021). On the other hand, there are studies discussing the post-signing impacts of the agreement on individual countries, such as analyzing each country's involvement in agricultural value chains (Cui et al., 2025) and forecasting the potential rice export markets for Vietnam (Chakradhar and Thao, 2024). However, there remains a lack of research on multilateral trade relations, and the potential impact of RCEP on the overall grain trade pattern remains an area with considerable room for exploration.

Investigating the complex characteristics of grain flows among RCEP member countries is a fundamental prerequisite for analyzing the potential impact of RCEP on regional GTN. Complex network analysis methods provide a solid foundation for addressing this issue. Currently, there is relatively abundant research based on complex network methods from the "cooperation relationship" perspective (Liu L. et al., 2023; Liu H. et al., 2023), exploring global trade patterns in different food types (Duan et al., 2022; Sun et al., 2018; Burkholz and Schweitzer, 2019; Zhang et al., 2022). However, research on trade from the "competition relationship" perspective remains mostly focused on energy (Zhang et al., 2014; Chen et al., 2016) and key minerals (Zhu et al., 2023; Li et al., 2022). Research indicates that, within the increasingly complex global trade network, trade relations between countries exhibit both interdependence and competition, and trade networks dominated by core countries are gradually evolving into a "robust but fragile" structure (Puma et al., 2015). That is, when major exporting countries restrict exports, it is more likely to trigger supply disruptions and exacerbate competition risks for importing countries. For grain, which is also a strategic resource, existing studies mostly analyze global trade patterns from a cooperation perspective based on trade value quantity (Wang and Dai, 2021). In the field of regional grain trade, research is mostly limited to areas such as the Belt and Road (Miao et al., 2024; Zhang et al., 2021a,b), the European Union (Bojnec and Fertő, 2009), and the China-Pakistan free trade agreement (Khan et al., 2024), while there is relatively limited attention to the grain trade network within RCEP, the world's largest free trade area. Therefore, considering the unique role of regional grain trade in ensuring global grain security, it is necessary to reveal the structural characteristics, coopetition relationships, robustness, and evolutionary mechanisms of the RCEP regional trade network, serving as a basis for exploring the potential impacts of RCEP.

In summary, there are still the following gaps in the research on the grain trade pattern among RCEP member countries: (1) Due to the limited time since RCEP's implementation, the coopetition relationships and robustness of the GTN among member countries have not been fully explored. Specifically, how competition within the GTN is shaped by similar geographical environments remains unclear; (2) Due to the relatively small number of member countries, traditional quantitative methods used to reveal the evolutionary mechanisms of complex networks have shown limited effectiveness, and further investigation is needed to effectively uncover the evolutionary mechanisms of the GTN within the world's largest free trade area; (3) The impact of tariff and non-tariff barrier reductions under RCEP on the cooperation and competition of the GTN still requires further exploration.

Therefore, this study approaches the issue from the perspective of multilateral trade relations, focusing on major grains (rice, wheat, and maize), and attempts to answer the following questions: (1) What are the characteristics of the GTN among RCEP member countries and their competition and interdependence from the perspective of physical quantity? (2) What are the evolutionary mechanisms of the GTN? (3) What are the potential impacts of RCEP on the GTN? To address these questions, this study applies complex network method, constructing the GTN among RCEP member countries based on FAO trade matrix data from 2000 to 2020, revealing the evolution characteristics of the grain trade pattern. On this basis, competition intensity index and interdependence index are introduced to clarify the coopetition relationships between countries, and the network's robustness is simulated and analyzed. Furthermore, this study creates the "Five Forces" model to analyze the evolutionary mechanisms of the

GTN. Finally, the potential impacts of RCEP on reshaping the GTN are explored based on trade diversion and creation effects. This study aims to clarify the grain trade pattern within the region before the agreement was signed, thereby firmly establishing a baseline for measuring the direction and magnitude of subsequent changes. It aims to provide a theoretical perspective and practical basis for promoting regional grain trade cooperation and ensuring the security of the regional trade network.

2 Data and methodology

2.1 Data source and processing

The RCEP member countries include the ASEAN countries (Brunei, Cambodia, Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand, Myanmar, and Viet Nam) along with China, Japan, South Korea, Australia, and New Zealand, totaling 15 countries. This study focuses on three key grains: rice, wheat, and maize. The trade data is derived from the FAOSTAT Detailed Trade Matrix dataset (http://faostat.fao.org, accessed 10 January 2024), while grain import/export volumes and production data are obtained from the FAO Food Balance Sheets. The analysis covers the period from 2000 to 2020. Notably, for Brunei, Cambodia, Myanmar, Laos, and Viet Nam, certain years have missing import data; in these cases, export volumes from other countries to these countries were used as Supplementary data. Additionally, trade data for China excludes Hong Kong, Macau, and Taiwan. As shown in Figure 1, this study constructs the GTN based on import volume data and analyzes the trade network structure, coopetition relationships, and network robustness of RCEP member countries using Gephi, Python, and MATLAB. Furthermore, the "Five Forces" model is created to uncover the evolutionary mechanisms of the network. Finally, the potential impacts of RCEP are evaluated based on trade diversion and creation effects.

2.2 Research methods

2.2.1 Complex network analysis

According to graph theory, the RCEP member countries GTN is defined as follows:

$$N = (V, L, W, W', T) \tag{1}$$

In the formula (1), V represents the set of all nodes (i.e., countries), L is the set of all edges (i.e., the trade links between two countries), W and W' represent the function sets of all node attributes (i.e., the number of trade links each country possesses) and all edge attributes (i.e., the total trade volume between two countries), respectively. T denotes the set of years for each trade network. In this context, RCEP member countries are treated as nodes, trade relationships between countries are treated as edges, and the grain trade volume (t) is the weight of the edges (Wasserman and Faust, 1994).

Based on the construction of the trade network, the following indicators are used for network feature analysis (Table 1).

2.2.2 Competition intensity index

Due to differences in import volumes and import structures, the competition intensity between grain-importing countries varies. Therefore, drawing on the competition intensity index

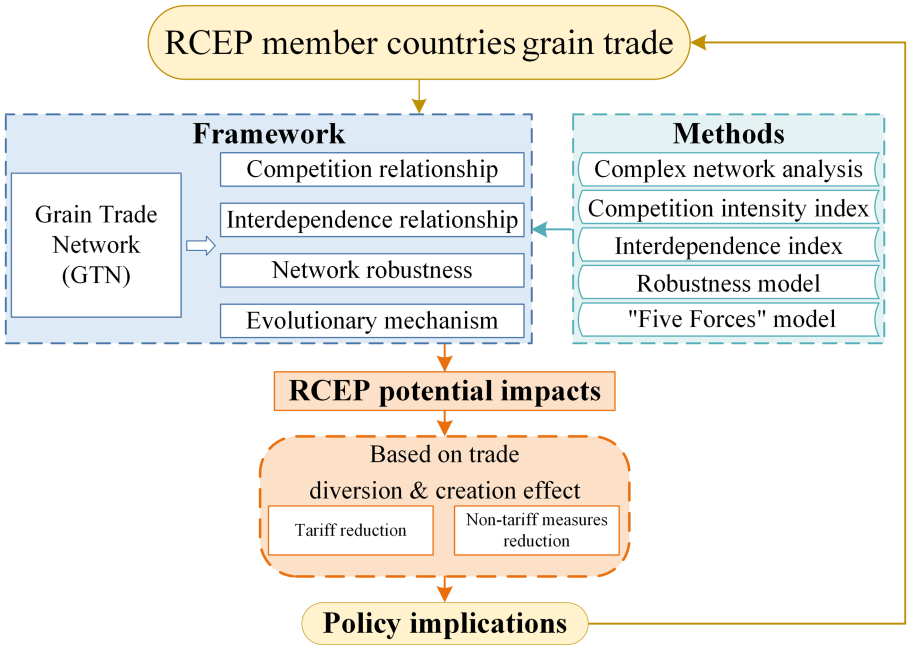


FIGURE 1
Research framework for the RCEP member countries GTN.

TABLE 1 The RCEP member countries GTN analysis method and its geographical significance.

Indicator	Formula	Definition	Geographic significance
Degree (*K*)	$K_i^{in/out} = \sum_{j=1}^{N} a_{ij}$ $K_i = \sum_{j=1}^{N} a_{ij} = \sum_{j=1}^{N} a_{ji}$	It refers to the number of nodes that have direct connections with node K_i, including indegree and outdegree	It reflects the level of activity in inter-country trade. Generally, the higher the degree value, the more foreign trade connections a country has
Weighted degree (*W*)	$W_i^{in/out}(n) = \sum_{j=1}^{N} W_{ij} a_{ij}$ $W_i = \sum_{j=1}^{N} S_{ij} = \sum_{j=1}^{N} S_{ji}$	It refers to the total weight of connections between a node and all the nodes it is linked to, categorized weighted indegree and weighted outdegree	It represents the volume of imports and weighted outdegree represents the volume of exports
Density (*d*)	$d = \frac{M}{N(N-1)}$	It refers to the ratio between the actual existing connections and all possible connections that could exist	It reflects the degree of closeness of connections within the network. A higher density indicates stronger connections between trade countries
Average clustering coefficient (*ACC*)	$ACC = \frac{1}{N} \sum_{i=1}^{N} \frac{2M_i}{k_i(k_i-1)}$	It refers to the likelihood of a connection existing between nodes, with values ranging from 0 to 1	The larger the value, the better the connectivity between trade countries
Average path length (*APL*)	$APL = \frac{2}{N(N-1)} \sum_{i \geq j}^{N} d_{ij}$	It refers to the average number of steps in the shortest paths between all potential pairs of nodes that could be connected in the network	The smaller the value, the higher the trade efficiency
Betweenness centrality (*BC*)	$BC_i = \frac{1}{N^2} \sum_{i,t} \frac{n_{si}^i}{g_{si}}$	It refers to the indicator that measures the intermediary bridging role of a node within the entire network	The larger the value, the higher the country's overall importance
Closeness centrality (*CC*)	$CC_i = \frac{N-1}{\sum_{j=1, j \neq i}^{N} d_{ij}}$	It refers to the extent to which a node can quickly reach or be reached by all other nodes in the network	The larger the value, the greater the country's ability to operate independently in the trade network
PageRank (*PR*)	$PR(i) = c \sum_{i \in B_i} \frac{PR(j)}{N_j}$	It refers to a measure of a node's importance based on the significance of the nodes to which it is directly connected	The larger the value, the higher the country's local importance
Authority	$x_i(k) = \frac{x'_i(k)}{\| x'(k) \|}$	It refers to the extent to which a node is pointed to by multiple Hubs nodes	The larger the value, the higher the Authority of the node
Hubs	$y_i(k) = \frac{y'_i(k)}{\| y'(k) \|}$	It refers to the extent to which a node points to multiple Authority nodes	The larger the value, the higher the Hubs of the node

proposed by Glick and Rose (1999) and Zhang et al. (2014), this study measures the competitive level between countries. The formula is as follows:

$$S_{ij} = \sum_{c} \left\{ \left(\frac{M_{ic} + M_{jc}}{M_w} \right) \times \left[1 - \frac{|(M_{ic}/M_i) - (M_{jc}/M_j)|}{(M_{ic}/M_i) + (M_{jc}/M_j)} \right] \right\} \times 100 \quad (2)$$

In the formula (2), S_{ij} represents the trade competition intensity between grain-importing countries v_i and v_j. M_{ic} and M_{jc} represent the grain trade volumes imported by countries v_i and v_j from the common importing source c, respectively. M_i and M_j represent the total grain imports of countries v_i and v_j, while M_w denotes the total regional grain imports. The larger the value of S_{ij}, the greater the import competition intensity between grain-importing countries v_i and v_j, indicating more intense competition. Due to the widespread nature of grain trade, import competition exists between nearly all countries. As supported by existing studies (Wang and Fan, 2023), this study sets a threshold of 0.1. If $S_{ij} \geq 0.1$, the competition intensity between grain-importing countries v_i and v_j is maintained as S_{ij}, indicating the presence of import competition with intensity S_{ij}. If $S_{ij} < 0.1$ then $S_{ij} = 0$, indicating no import competition between countries v_i and v_j.

2.2.3 Interdependence intensity index

The interdependence index can be used to characterize the interdependence relationship between countries in grain trade. Drawing on the Grubel-Lloyd index (Grubel and Lloyd, 1975), the formula for constructing the interdependence index of grain trade is as follows:

$$RaGL_{ij} = \left[1 - \left(\frac{\left|RE_{i\to j} - RI_{i\to j}\right|}{RE_{i\to j} + RI_{i\to j}}\right)\right] \quad (3)$$

In the formula (3), $RE_{i\to j}$ and $RI_{i\to j}$ represent the grain export volume of country i to country j and the grain import volume of country i from country j, respectively. The value of $RaGL_{ij}$ represents the grain trade interdependence index between countries i and j. The larger the value of $RaGL_{ij}$, the stronger the interdependence in grain trade between the two countries. When $RaGL_{ij} \geq 0.5$, it indicates a high level of interdependence. When $0.2 < RaGL_{ij} < 0.5$, it indicates a medium level of interdependence. When $RaGL_{ij} \leq 0.2$, it indicates a low level of interdependence. When $RaGL_{ij} = 0$, it indicates a one-way dependence.

2.2.4 Robustness

Robustness refers to the ability of a network to maintain its structure and function, either fully or partially, after nodes or edges are subjected to external attacks. When assessing the vulnerability of the trade network, network efficiency (E) is a good indicator of the network's topological performance, particularly the connectivity between nodes and overall efficiency. It is widely used in evaluating the network's robustness (Crucitti et al., 2003). Network efficiency is defined as the average of the reciprocal of the distances between all pairs of nodes in the network. The formula is as follows:

$$E = \frac{1}{n(n-1)} \sum \frac{1}{d_{ij}} \quad (4)$$

In the specific evaluation, the objects of simulated attacks are typically nodes and edges. The attack methods are generally divided into random attacks and targeted attacks. Random attacks generate random sequences using MATLAB to attack nodes or edges sequentially, calculating the new trade network efficiency by the formula (4) until there are no remaining nodes or edges in the network. Since countries with large trade volumes or important positions inevitably impact the trade network once they implement import–export control measures, targeted attacks are also considered. Referring to existing studies (Karakoc and Konar, 2021; Gutiérrez-Moya et al., 2021), targeted attacks on nodes are conducted based on five indicators: Degree, Betweenness centrality, Closeness centrality, Hubs, and Authority. Targeted attacks on edges are conducted by the weight of the edges. These nodes or edges are sequentially removed according to their indicator values. The updated trade network is then obtained, and its network efficiency is recalculated until all nodes or edges are removed. The robustness of the trade network is analyzed based on the changes in network efficiency.

2.2.5 "Five forces" model

Existing studies have explored the evolution mechanisms of trade network from natural, economic, political, policy, and cultural perspectives (Nie et al., 2021). Building on these studies, this research incorporates the geographical attributes and development characteristics of RCEP member countries and comprehensively considers factors such as resource endowments, domestic demand, economic conditions, geopolitical relations, and important events to analyze their impact on this regional trade network. Accordingly, we create the "Five Forces" model, which is defined as follows:

(1) Resource endowment: Within the region, there is significant heterogeneity in arable land endowment, which is closely linked to domestic grain supply capacity. The region includes countries with abundant arable land, such as China and Australia, as well as those with relatively scarce land resources, such as South Korea and Japan. Additionally, differences in cropping patterns and yield levels vary across countries. According to the Factor Endowment Theory, disparities in resource availability serve as a key driving force behind international trade. Therefore, it is necessary to explore the relationship between domestic supply capacity and trade links from the perspective of arable land resource endowment. We define this driving force as the "potential difference force" in the evolution of the GTN.

(2) Domestic demand: Population size differences serve as a fundamental factor driving variations in grain demand. The RCEP region includes populous countries such as China, Indonesia, and Japan, each with a population exceeding 100 million, as well as countries like Australia, which have abundant arable land but relatively small populations. These disparities in population size lead to differences in domestic demand, where shifts in population size drive changes in demand, subsequently influencing import volumes. This dynamic acts as the "reconstructing force" in the evolution of the GTN.

(3) Economic conditions: Changes in economic development levels are a key driver of shifts in grain demand. The RCEP region includes rapidly developing countries such as China and Viet Nam, where economic growth has led to rising demand for animal-based food products, thereby increasing grain consumption and import demand. This dynamic serves as the "propelling force" in the evolution of the GTN.

(4) Geopolitical relations: RCEP member countries are naturally proximate, and under the influence of the First Law of Geography, the cost advantages of trade serve as the initial "traction force" in the formation of the trade network. Additionally, this region represents a geostrategic intersection of great powers, where geopolitical competition among major nations shapes interregional relations and further provides traction for the evolution of the GTN.

(5) Important events: The impact of important events on trade networks has been widely recognized. Therefore, it is essential to analyze how both intra-regional and extra-regional events influence the evolution of the trade network. This influence is referred to as the "disturbing force" in the evolution of the GTN.

3 Results

3.1 Topology characteristics of the trade network

The RCEP member countries GTN has become increasingly complex, with closer ties between countries. From 2000 to 2020, the

number of network edges increased from 94 to 144, representing a rise of 53.20%, which indicates a significant growth in network complexity. The network density increased from 0.448 to 0.686, representing a 53.13% growth, while the average path length decreased from 1.582 to 1.270, reflecting a 19.72% reduction. During the study period, trade cooperation within the China-ASEAN Free Trade Area and the Greater Mekong Sub region deepened progressively, fostering a more integrated trade network and a more diversified range of trade partners.

The dominance of major countries in the GTN is significant, but the dominance effect has decreased (Table 2). Regarding weighted indegree (Figure 2 and Supplementary Figure S1), in 2000, South Korea, Indonesia, Malaysia, Japan, and Philippines ranked among the top five, collectively contributing 88.90% of total imports. South Korea alone accounted for 37.05%, with imports reaching 7.71×10^6 tons. By 2010, the combined import proportion of the top five countries had declined to 72.02%. By 2020, China, Philippines, Thailand, South Korea, and Malaysia emerged as the top five countries in terms of weighted indegree, with their combined import proportion reaching 71.42% and consistently remaining above 70%.

Regarding weighted outdegree, in 2000, China, Australia, Thailand, Viet Nam, and Myanmar ranked among the top five, collectively accounting for 99.46% of total exports. By 2010, the combined export proportion of the top five countries had slightly declined. By 2020, Australia, Viet Nam, Myanmar, Thailand, and Cambodia held the highest weighted outdegree, with their combined export proportion reaching 95.70%.

Countries with overall importance and local importance are primarily major grain exporters, and the role of core trade nodes has become increasingly homogenized. From an overall importance perspective (Supplementary Figure S2A), in 2000, Thailand, Indonesia, Australia, Singapore, and Malaysia exhibited the highest Betweenness centrality. By 2010, Japan and China had entered the top five. In 2020, Thailand's rank fell to fourth, Australia rose to first, and Viet Nam, China, and Japan secured positions in the top five. The Betweenness centrality values of the top five countries exhibited a stepwise decline, reflecting a trend toward homogenization of trade roles among countries with significant overall influence. From a local importance perspective (Supplementary Figure S2B), in 2000, Indonesia, Malaysia, Australia, Singapore, and Thailand achieved the highest PageRank scores. By 2010, Australia had surged to first place. In 2020, Singapore, Australia, Malaysia, Philippines, and Viet Nam ranked among the top five. Known as the "Crossroads of the East," Singapore has leveraged its port advantages to become the most influential player among neighboring countries. Australia, Viet Nam, and Thailand, as major exporting countries, occupy significant positions in the trade network.

3.2 Competition relationships among RCEP member countries

From 2000 to 2020, the scale of grain trade among RCEP member countries expanded substantially, accompanied by a rise in the number of competition relationships in trade. The overall competition intensity increased, but the growth rate was moderate. The evolution of competition intensity can be categorized into three stages (Supplementary Figure S3): (1) From 2000 to 2007, competition intensity in grain trade fluctuated, remaining near its initial level. (2)

TABLE 2 Characteristics of the RCEP member countries GTN core node.

Year	Rank	ISO3	Indegree	Weighted indegree (10^3 t)	Proportions of weighted indegree (%)	ISO3	Outdegree	Weighted outdegree (10^3 t)	Proportions of weighted outdegree (%)
2000	1	KOR	5	7710.38	37.05	CHN	12	10912.58	52.43
	2	IDN	11	4565.44	21.94	AUS	12	7088.90	34.06
	3	MYS	9	3387.13	16.28	THA	14	1402.80	6.74
	4	JPN	6	1671.72	8.03	VNM	9	1251.97	6.02
	5	PHL	7	1173.40	5.64	MMR	4	43.90	0.21
	Total	/	/	20811.84	88.93	/	/	20811.84	99.46
2010	1	IDN	10	3984.37	25.90	AUS	12	9245.38	60.09
	2	PHL	8	2362.79	15.36	VNM	9	2978.34	19.36
	3	VNM	8	1635.80	10.63	THA	14	2345.42	15.25
	4	MYS	11	1626.68	10.57	CHN	11	266.75	1.73
	5	JPN	8	1469.76	9.55	KHM	6	231.11	1.50
	Total	/	/	1538.48	72.02	/	/	15384.82	97.93
2020	1	CHN	10	3798.80	23.84	AUS	13	6727.75	42.21
	2	PHL	11	3067.89	19.25	VNM	14	3770.42	23.66
	3	THA	10	1937.38	12.16	MMR	12	2975.58	18.67
	4	KOR	8	1409.95	8.85	THA	14	1250.98	7.85
	5	MYS	11	1168.83	7.33	KHM	10	527.71	3.31
	Total	/	/	15936.94	71.42	/	/	15936.94	95.70

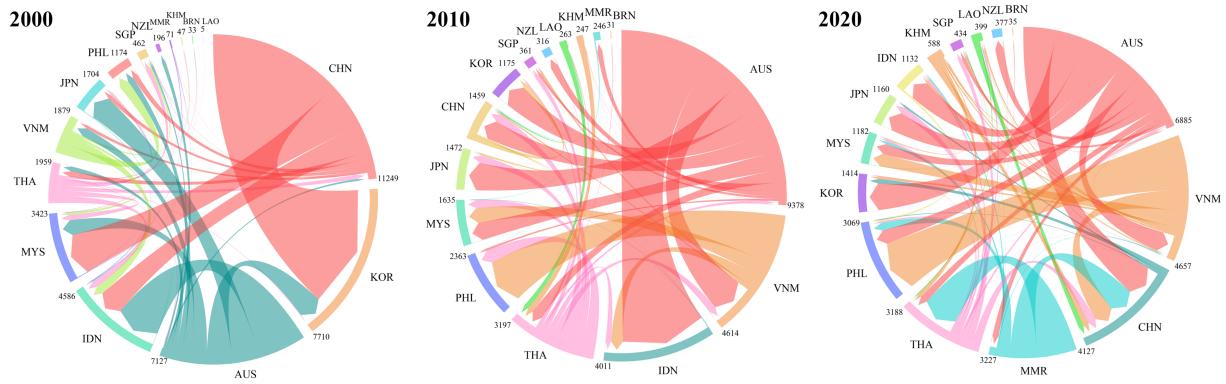


FIGURE 2
Grain trade flow of the RCEP member countries. Note: Countries are ranked by the total trade volumes and plotted clockwise in descending order. The size of the out bar indicates the total trade volumes (unit: 10^3t).

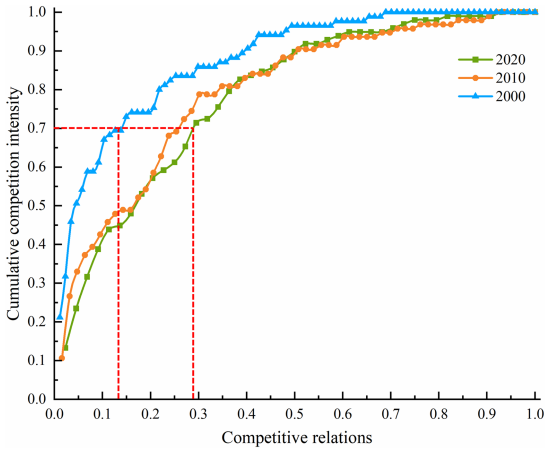


FIGURE 3
Cumulative distribution of the competition intensity between RCEP member countries.

From 2008 to 2012, competition intensity in grain trade steadily rose, peaking at 750.19 in 2014, representing a 52.14% increase compared to the early stage. (3) From 2013 to 2020, competition intensity in grain trade fluctuated before gradually declining. With member countries diversifying their trade partners, competition intensity eased. It began to decline gradually in 2017, reaching 515.45 in 2020, which approached the competitive level observed at the beginning of the period. Overall, competition intensity rose by 2.70% over the study period.

The main competition is concentrated among a few major importers, and the cumulative distribution of competition intensity among RCEP member countries follows the "key minority rule" (Figure 3). Using 70% cumulative competition intensity as the standard, 70% of the competition intensity in intra-regional grain trade comes from 15 to 30% of the competition relationships. This indicates that intense competition mainly occurs between a small number of major grain importers, while most countries experience relatively low levels of competition. This suggests that the competition intensity among member countries is unevenly distributed, with the majority concentrated in a few competition relationships.

From the perspective of single country competition (Figure 4A and Supplementary Table S1), the top five countries in terms of competition intensity shifted from South Korea > Indonesia > Malaysia > Japan > Thailand in 2000 to China > Philippines > Malaysia > South Korea > Indonesia in 2020. In terms of competition intensity as a percentage (Figure 4B), South Korea's competition intensity initially declined and then increased, with its proportion of total competition intensity dropping from 19 to 10%. Indonesia's competition intensity remained stable initially before decreasing, with its proportion falling from 17 to 10%. Malaysia and Viet Nam maintained competition intensity proportion between 9–15% and 7–11%, respectively. Japan and Thailand's competition intensity remained relatively stable, with proportion of 8 and 6% in 2020, respectively. Thailand's competition intensity consistently remained low, with its proportion falling to 6%. China's competition intensity proportion steadily increased, rising from 4 to 17%, making it the leader. The proportion of other RCEP member countries in grain trade competition increased overall, rising from 23 to 32%.

From the perspective of inter-country competition (Table 3), in 2000, the top ten grain competition intensities primarily involved Indonesia, South Korea, Malaysia, and other ASEAN countries. By 2010, a pattern emerged where Indonesia and China became the primary competitors with other countries, signifying a notable shift in the main competition relationships. By 2020, competition between China and ASEAN countries dominated the top ten competition relationships.

3.3 Interdependence relationships among RCEP member countries

From 2000 to 2020, the number of interdependence relationships among countries increased steadily, from 66 pairs to 94 pairs, representing a 42.42% growth and resulting in a more complex and interconnected interdependence pattern (Supplementary Figure S4). From the perspective of interdependence differentiation (Table 4), the proportion of high and medium interdependence relationships declined from 15.15 to 12.77%, while low interdependence relationships rose from 84.85 to 87.23%. Low interdependence relationships dominate, with the proportion of high and medium interdependence relationships

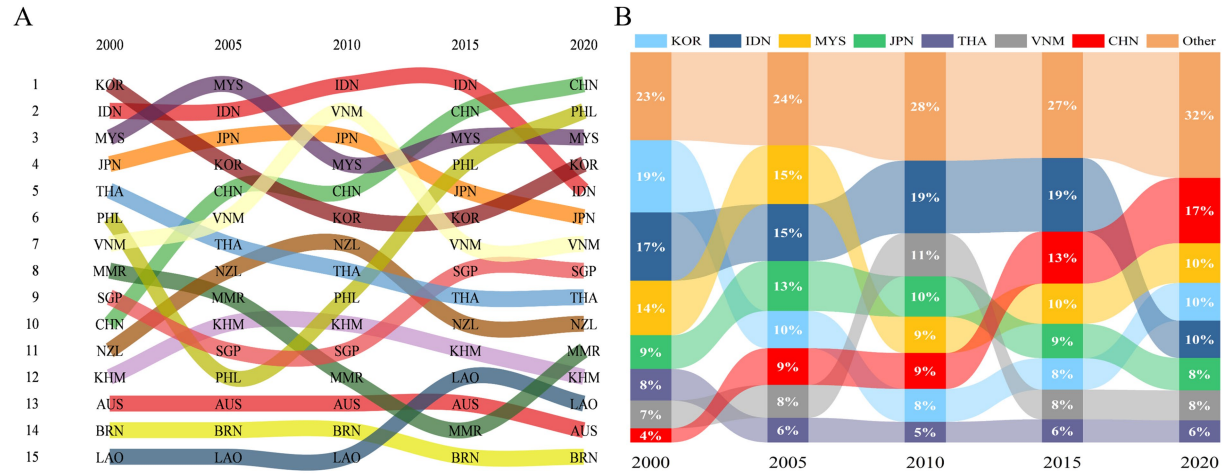


FIGURE 4
The changes of RCEP member countries competition intensity. **(A)** Rank. **(B)** Regional proportion.

TABLE 3 Top ten country pairs ranked by competition intensity.

Rank	2000	2010	2020
1	MYS-KOR	IDN-VNM	CHN-MYS
2	KOR-THA	IDN-KOR	CHN-PHL
3	IDN-KOR	IDN-JPN	MYS-PHL
4	IDN-MYS	IDN-CHN	CHN-THA
5	IDN-JPN	IDN-NZL	CHN-SGP
6	PHL-KOR	IDN-MYS	CHN-IDN
7	KOR-VNM	IDN-MMR	KHM-PHL
8	IDN-PHL	IDN-THA	IDN-KOR
9	IDN-VNM	JPN-VNM	JPN-KOR
10	IDN-THA	IDN-KHM	CHN-KOR

TABLE 4 Grain trade interdependence of RCEP member countries.

Interdependence level	2000		2010		2020	
	Relations	Number (Proportion)	Relations	Number (Proportion)	Relations	Number (Proportion)
High (0.50–1.00)	CHN-NZL, CHN-THA, KHM-SGP, VNM-THA, MYS-SGP, MYS-IDN	6 (9.09%)	KHM-VNM, MMR-THA, KOR-NZL, KOR-JPN, SGP-IDN, KOR-KHM, KOR-IDN	7 (9.72%)	KHM-VNM, JPN-VNM，JPN-NZL, THA-LAO, MYS-IDN, THA-VNM	6 (6.38)
Middle (0.20–0.50)	JPN-SGP, JPN-IDN, THA-LAO, THA-AUS	4 (6.06%)	THA-AUS, THA-LAO, KHM-AUS, SGP-MYS	4 (5.56%)	THA-AUS, JPN-MMR, MYS-PHL, KHM-AUS, LAO-VNM, KOR-NZL	6 (6.38%)
Low (0.00–0.20)	MYS-NZL, IDN-PHL, MMR-SGP, IDN-THA, MMR-AUS, etc.	56 (84.85%)	CHN-VNM, JPN-MYS, KHM-SGP, JPN-NZL, IDN-PHL, etc.	61 (84.72%)	VNM-AUS, THA-KHM, SGP-PHL, CHN-JPN, CHN-THA, etc.	82 (87.23%)

steadily declining, remaining relatively stable between Thailand-Laos, Cambodia-Viet Nam, and Malaysia-Indonesia. This reflects the low interdependence in grain trade among RCEP member countries, highlighting the diversification of trade behavior in choosing grain import sources. Coupled with the increasing competition intensity within the region, this trend illustrates a decentralization of cooperation

and a rise in competition, indicating that competition relationships outweigh cooperative ones. This can be attributed to the fact that although member countries exhibit diversified trade behaviors, their import volumes remain highly concentrated among the region's major grain-exporting countries. These exporting countries maintain dominant positions in weighted outdegree and have limited import volumes, resulting in significant imbalances in trade scales among countries. This highlights a "high competition, low interdependence" competitive-cooperative dynamic.

3.4 Robustness of the trade network

Results of random node attacks (Figure 5) reveal that in 2000, the GTN completely collapsed (network efficiency dropped to 0%) when 86.67% of the nodes were attacked. By 2010 and 2020, the percentage of nodes required to be attacked for the network to fully collapse increased to 93.33%. Targeted attacks results demonstrate that the decline in network efficiency occurs more rapidly compared to random attacks. However, the ranking of indicators influencing the rate of efficiency decline has remained relatively consistent over the years. As trade relations have grown closer, under targeted attacks, the percentage of nodes required to cause the network's complete collapse rose from 66.67 to 86.67%. The slope of the network efficiency decline curve has gradually aligned with that of the random attack scenario, exhibiting an overall roughly uniform downward trend. In 2020, the centrality measures ranked as follows: Betweenness centrality > Degree > Hubs > Closeness centrality > Authority > Random attacks. This indicates that countries with high Betweenness centrality, such as Thailand and Australia, serve as key nodes in the GTN. Overall, the current robustness of the GTN under targeted attacks closely resembles that under random attacks. Diversified trade behaviors have partially enhanced the network's robustness, strengthening its capacity to withstand shocks.

Results of random edge attacks (Figure 6) indicate that in 2000, 2010, and 2020, the proportion of edges attacked that reduced the network efficiency to below 1% were 96.00, 97.33, and 98.11%, respectively. Under targeted attacks, the proportion of edges attacked that reduced the network efficiency to below 1% were 40.89, 49.78, and 63.11%, respectively. The proportion of attacked edges required to collapse the GTN reflects an upward trend, suggesting that the growing tightness of trade connections enhances the network's robustness against potential disruption risks.

Table 5 presents the results of targeted attacks on single countries, revealing that during the study period, the impact of member countries on network efficiency has become increasingly similar, while the influence of core countries still varies significantly. Currently, Viet Nam, China, Thailand, and Australia exert the highest influence on

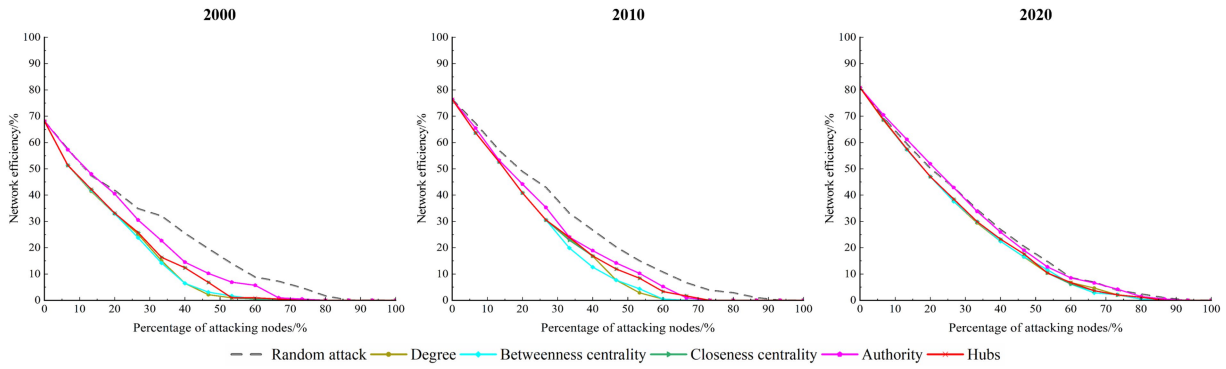


FIGURE 5
The change curve of the RCEP member countries GTN efficiency under node attack.

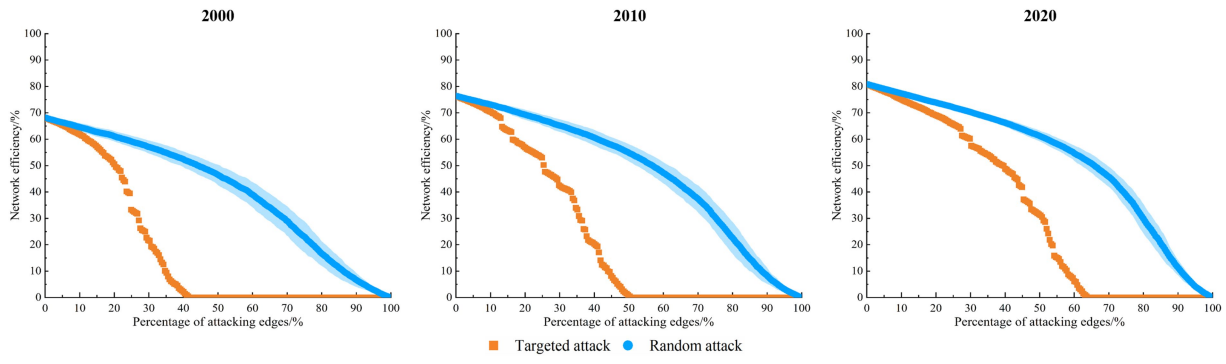


FIGURE 6
The change curve of the RCEP member countries GTN efficiency under edge attack.

TABLE 5 The changes in the network efficiency of the RCEP member countries GTN under deliberate attacks on a single country.

2000			2010			2020		
BC rank	ISO3	Reduction rate (%)	BC rank	ISO3	Reduction rate (%)	BC rank	ISO3	Reduction rate (%)
1	THA	24.63	5	SGP	17.50	2	VNM	15.31
3	AUS	16.53	1	THA	16.63	3	CHN	15.01
2	IDN	15.95	2	AUS	15.70	4	THA	15.01
4	SGP	15.60	3	JPN	15.07	1	AUS	15.01
6	CHN	15.25	7	IDN	14.65	6	MYS	14.42
5	MYS	14.78	4	CHN	14.54	5	JPN	14.13
9	VNM	14.68	6	MYS	14.33	9	MMR	14.13
10	JPN	13.97	9	VNM	13.93	7	IDN	13.84
8	NZL	13.50	8	KOR	13.61	11	PHL	13.24
7	PHL	13.27	10	PHL	12.78	8	KOR	13.24
12	MMR	11.99	11	KHM	12.46	12	KHM	13.24
11	KOR	11.76	12	MMR	12.16	10	SGP	12.85
13	KHM	11.35	13	NZL	11.95	13	NZL	12.37
13	LAO	9.36	14	LAO	9.71	14	LAO	11.38
13	BRN	6.28	14	BRN	9.10	15	BRN	6.76

BC rank refers to the ranking of countries based on their Betweenness centrality.

overall network efficiency, with each surpassing 15%. Viet Nam and China, as major importers and exporters, have become increasingly critical to the entire GTN. Despite its declining influence, Thailand remains one of the most important countries in the GTN. This finding further underscores the critical role of countries with high Betweenness centrality in maintaining the stable operation of the GTN.

3.5 Evolutionary mechanisms of the trade network

3.5.1 Resource endowments

Resource endowments serve as the "potential difference force" driving the evolution of the RCEP member countries GTN. This is mainly reflected in differences among countries in cropland area per capita and grains production, which influence their roles in the trade network. In physics, potential difference force refers to the force that drives an object from a region of higher potential energy to one of lower potential energy due to a potential energy gradient (Kellogg, 1953). According to Factor Endowment Theory, "potential difference" in economics essentially reflects differences in factor endowments among countries. Variations in resource endowments across countries influence grain production scale and domestic supply levels, creating a resource potential difference. During the study period, countries with limited arable land per capita, including South Korea, Japan, and Malaysia, struggle to meet domestic grain demand. As a result, these countries consistently ranked high in weighted indegree, with high competition intensity. Conversely, countries with abundant arable land per capita, such as Australia and Thailand, are major players in the global grain export market. They rank high in weighted out-degree but experience relatively low import competition intensity. At the same time, differences in resource potential drive varying patterns of resource flows between countries, leading to different types of interdependence. When the disparity in grain production is significant, one-way dependence emerges. For example, in 2020, Cambodia, which had the highest per capita grain production, exhibited a one-way dependency relationship with South Korea and Singapore, which ranked the lowest. In contrast, when countries have similar per capita grain production levels, they tend to develop a high level of interdependence. This is evident in the relationships between Thailand-Laos, as well as Thailand-Viet Nam.

3.5.2 Domestic demand

Domestic demand serves as the "reconstructing force" driving the evolution of the RCEP member countries GTN. This is mainly reflected in how changes in population size and per capita consumption demand influence the scale of grain imports, reconstructing the GTN. According to Demand and Supply Theory, when domestic grain consumption demand exceeds domestic supply, it drives an increase in grain imports. In the short term, a significant rise in grain imports by a single country can lead to noticeable changes in the GTN, with China being the most typical example. Between 2000 and 2020, China's annual per capita grain consumption rose from 282.15 kg to 441.75 kg, a 56.56% increase, transitioning from an export powerhouse to a net grain importer. Similar populous countries include Indonesia and Philippines. The reliance of these countries on grain imports has rapidly increased, reconstructing the grain trade pattern and intensifying competition among major importers. For example, the import competition intensity between China and Philippines ranked 10th and 6th, respectively, in 2000, and rose to 1st and 2nd by 2020.

3.5.3 Economic conditions

Economic conditions serve as the "propelling force" driving the evolution of the RCEP member countries GTN. This influence is

primarily reflected in income levels, foreign exchange reserves, and price levels. These factors collectively contribute to the rise in per capita grain demand, thereby driving the increase in total grain demand. According to Bennett's Law, the consumption of animal-based foods increases with higher income levels (Bennett, 1941), which in turn drives the demand for feed grain and triggers a rise in grain imports. Additionally, foreign exchange reserves serve as a crucial foundation for supporting grain imports. For example, in China, from 2000 to 2020, per capita disposable income surged 5.98 times, while foreign exchange reserves increased 18.43 times. As a result, feed grain consumption increased by 1.2 times, and import volume surged 10.28 times. Similarly, international grain prices significantly shape grain imports and exports. For instance, during the low-price period of 2016, China's imports increased by 32.83% compared to the previous year. In contrast, Australia's exports decreased by 34.66%, triggering structural changes in the GTN. During the same period, China and Indonesia experienced rapid economic and population growth. With the rising demand for grain imports, competition for grain imports has become increasingly intense.

3.5.4 Geopolitical relations

Geopolitical relations serve as the "traction force" driving the evolution of the RCEP member countries GTN. This impact is primarily reflected in the "traction" created by political relations, geo-economic linkages, and geographical distance. These factors not only foster the formation of trade relationships but also potentially intensify regional competition in grain imports. On the one hand, the First Law of Geography suggests that countries geographically close to each other are more likely to engage in trade interactions. On the other hand, economic cooperation policies effectively lower regional grain trade barriers and promote trade facilitation (Hayakawa and Kimura, 2015). Owing to the closer geographical distance, RCEP member countries demonstrate high trade intensity, reflected in a network density of 0.686 in 2020—far exceeding the global GTN density (0.141) of the same period (Nie et al., 2021). Following China's accession to the WTO and the signing of the "China-ASEAN Comprehensive Economic Cooperation Framework Agreement," intra-regional trade connections rapidly increased, strengthening the network's robustness. In addition, geographic proximity and tariff changes resulting from joining trade organizations further highlight the advantage of lower grain transportation costs within RCEP. This advantage not only drives the tightening of the regional trade network but also intensifies import competition among countries, such as those with high import competition intensity, which are often neighboring countries (e.g., China-Philippines, Indonesia-Malaysia, Malaysia-Philippines).

3.5.5 Important events

Important events serve as the "disturbing force" driving the evolution of the RCEP member countries GTN. These disruptions heighten trade uncertainty, compel adjustments in trade partners, and propel the evolution of the GTN. According to System Resilience Theory, external shocks prompt adaptive adjustments in complex systems. In the realm of resource flows, significant events can disrupt existing grain trade relationships between countries. For example, the 2008 global financial crisis led to soaring grain prices, causing some countries to struggle with the high costs of grain (Headey, 2011). As a result, total intra-regional trade volume dropped to its lowest point, and the average path length of the network increased. At the same time, some countries enacted export restrictions or outright bans to protect domestic grain supply, reducing trade fluidity and increasing dependence on fewer sources, thereby intensifying overall import competition. On the other hand, to reduce the risk of reliance on a single country, member countries often seek new or additional trade partners. This will strengthen the network's robustness. For instance, despite the grain export restrictions during the COVID-19 pandemic in 2019 (Laborde et al., 2020), the network's robustness against targeted attack improved. Due to the diversification of import sources, trade volumes remained stable or even increased, while overall competition intensity slightly decreased. This highlights the pivotal role of important events in driving the evolution of the GTN.

The above content explains the impact mechanisms of the "five forces" on the evolution of the GTN from the perspective of individual factors. In fact, as shown in Figure 7, the interaction between the "five forces" varies, with their primary roles differing during different stages of trade network evolution.

In the early stages of trade network formation, disparities in resource endowments played a pivotal role in shaping regional trade relationships. For instance, in 2000, countries with abundant arable land resources, such as Australia and Thailand, established strong trade ties with countries like South Korea, which faced land resource constraints. This dominant influence continued throughout the evolution of the network. On the basis of the initially established trade patterns, the heterogeneity of countries within the region—especially regarding economic development and changes in domestic demand—collectively fueled the evolution of the trade network. For example, China's rapid economic growth prompted significant shifts in food consumption patterns and demand, resulting in increased reliance on external grain imports. Notably, this growing dependency on grain imports from RCEP member countries has driven the evolution of the trade network and intensified competition between China and other major grain importers.

Undoubtedly, the low-cost trade effect driven by geographic proximity has continued to play a crucial role in maintaining the stability of the network structure, contributing to its robust characteristics. The influence of geopolitical relations and important events on trade network structure changes has been widely acknowledged. For example, the signing of "China-ASEAN Comprehensive Economic Cooperation Framework" significantly facilitated the tightening of trade network, while the 2008 global financial crisis disrupted grain trade relations within the region, leading to a decline in network density. Following the global financial crisis, the diversification of trade partners among member countries somewhat enhanced the robustness of the network. Despite disruptions caused by the COVID-19 pandemic, the trade network has maintained a relatively stable structure. Looking ahead, the signing of RCEP is expected to influence the future evolution of the GTN in a significant way.

4 Potential impacts of RCEP signing on the trade network

The RCEP provisions on agricultural trade encompass tariff reductions, rules of origin, investment facilitation, negative list,

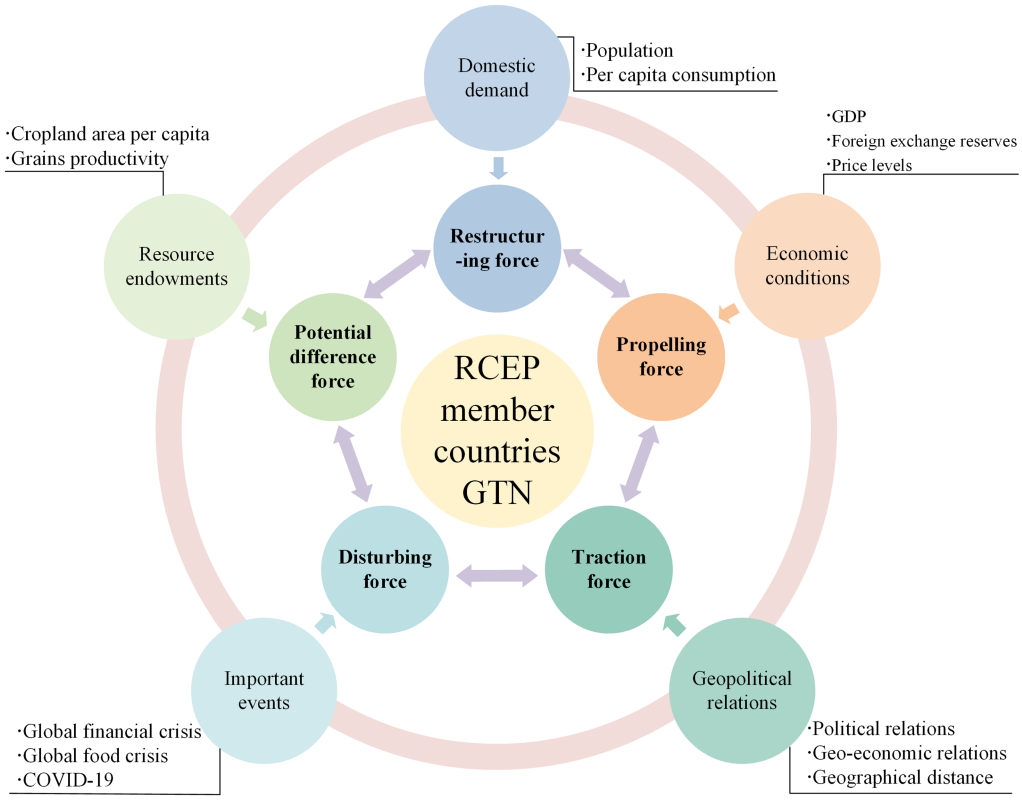


FIGURE 7
Evolutionary mechanisms of the RCEP member countries GTN.

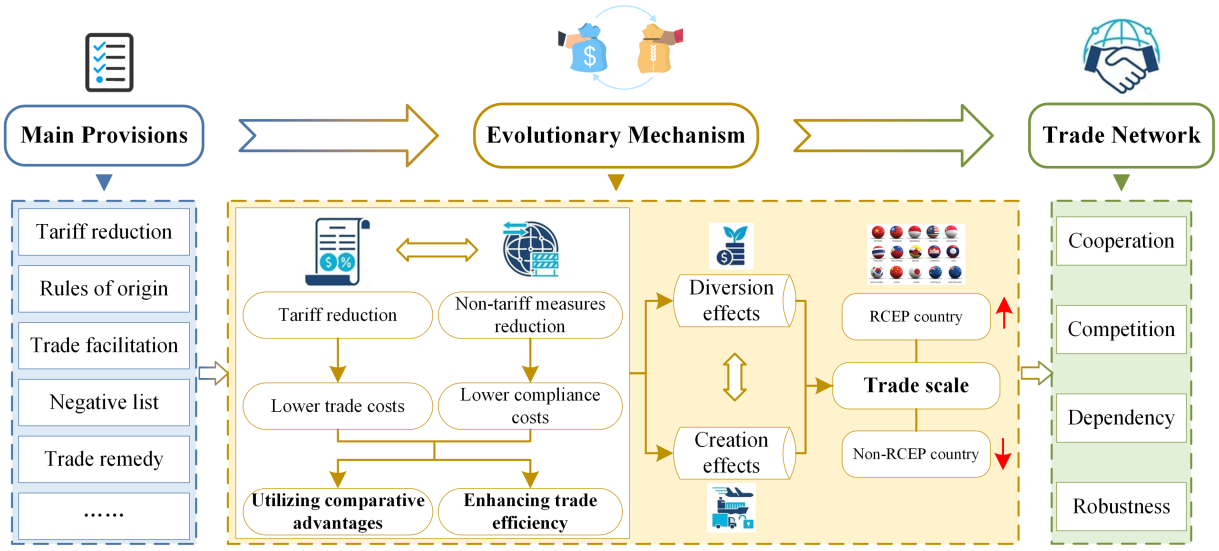


FIGURE 8
Conduction path of the potential impacts of RCEP signing on the GTN.

and trade remedy. These measures are expected to generate trade diversion and creation effects, reshaping existing grain trade patterns (Xu et al., 2025). Therefore, this study analyzes the potential impact of RCEP on the GTN based on two key provisions: tariff reduction and non-tariff measures reduction. On this basis, it identifies the conduction path through which these provisions influence the trade network (Figure 8) and explores the differentiated effects of RCEP.

TABLE 6 RCEP Schedule of Tariff Commitments on grain.

Type	ISO3	Base rate (%)	Year 5 (%)	Year 10 (%)	Year 15 (%)	Year 21 and subsequent years (%)
No tariff reduction commitments	KOR	110.33	110.33	110.33	110.33	110.33
	CHN	50.00	50.00	50.00	50.00	50.00
	MYS	13.33	13.33	13.33	13.33	13.33
	IDN	10.00	10.00	10.00	10.00	10.00
Gradual tariff reductions	LAO	5.00	3.33	2.33	1.67	1.67
Immediate tariff exemptions	VNM	1.67	0.00	0.00	0.00	0.00
	THA	0.33	0.00	0.00	0.00	0.00
	PHL	0.33	0.00	0.00	0.00	0.00
Zero-tariff maintenance	AUS, JPN, SGP, NZL, MMR, KHM, BRN					

This table is summarized from http://fta.mofcom.gov.cn/rcep/rcep_new.shtml (accessed 7 September 2024).

4.1 Tariff reduction

Against the backdrop of widespread tariff reductions, grain trade within the RCEP region will grow increasingly interconnected, with import sources gravitating toward RCEP member countries. As imports become more concentrated, intra-regional competition is expected to intensify. According to RCEP Schedule of Tariff Commitments, the region's grain tariff reduction policies fall into four categories based on benchmark rates (Table 6): (1) No tariff reduction commitments (e.g., South Korea, China, Malaysia, and Indonesia, maintaining rates of 110.33, 50.00, 13.33, and 10.00%, respectively). (2) Gradual tariff reductions (e.g., Laos reducing tariffs from 5 to 1.67% over 21 years). (3) Immediate tariff exemptions (e.g., Viet Nam, Thailand, and Philippines eliminating tariffs outright). (4) Zero-tariff maintenance (e.g., The tariff levels of Australia, Japan, Singapore, New Zealand, Myanmar, Cambodia, and Brunei have consistently remained at 0.00%).

The reduction or elimination of grain tariffs will substantially lower trade costs, thereby stimulating trade among member countries (Wei, 2024; Liu and Wang, 2024). As a result, grain imports previously sourced from non-RCEP countries are likely to shift toward major intra-regional producers offering comparative advantages, such as lower tariffs and shorter transportation distances. This shift is expected to expand the scale and density of intra-regional grain trade, reduce external trade volumes, and increase interdependence, thereby homogenizing the network. As grain import sources concentrate in major exporting countries, competition among importers will intensify.

Meanwhile, the export destinations of major grain-exporting countries may undergo a partial redistribution of trade flows due to some countries maintaining their existing grain tariff levels (Huang and Li, 2024). Some countries, such as South Korea, China, Malaysia, and Indonesia, have retained their current grain tariff levels to safeguard national grain security. These countries have neither reduced tariffs nor eased market access thresholds and have no tariff reduction plans for the next 20 years. Consequently, grain trade volumes previously destined for these countries may be redistributed within the region, potentially altering the roles of key grain importers.

4.2 Non-tariff measures reduction

The reduction of non-tariff measures in the grain trade among RCEP member countries will encourage the formation of new trade links. The impact of non-tariff measures on grain trade is characterized by mixed effects. While ensuring product quality, non-tariff measures inevitably increase compliance costs, leading to a reduction in the export supply of producing countries (Wickrama et al., 2024). Hoekman and Nicita (2011) highlights that a 10% increase in non-tariff measures could lead to an average trade volume decline of 1.7%. Nevertheless, the reduction of non-tariff measures within RCEP has undeniably fostered a more efficient and integrated regional market. It has significantly reduced potential barriers, enhanced trade efficiency, and highlighted the comparative advantages of grains among member countries (Ratna and Huang, 2016).

For example, in the context of trade facilitation, some less-developed countries in the region incur high customs clearance costs. These measures are expected to significantly enhance the efficiency of grain clearance, reducing both fixed costs (e.g., passing health inspections, acquiring certificates, and meeting marketing requirements) and variable costs (e.g., delays caused by customs inspections) (Crivelli and Gröschl, 2016). This will promote trade among member countries by lowering costs and simplifying procedures.

4.3 Conduction path and unique effects of RCEP's potential impact

The reduction of tariff and non-tariff measures (such as rules of origin, trade facilitation, negative list, and trade remedy) impacts the formation of trade links by influencing trade costs and compliance costs, leading to changes in the structure of the trade network. Specifically, the reduction of trade tariff within the region will lower grain trade costs, thereby highlighting the price competitiveness of grain. This, in turn, triggers the formation of new trade relationships and promotes the substitution of trade links between member countries for those between the region and non-member countries.

Compared to regional free trade agreements such as the CPTPP and ASEAN, RCEP has distinct advantages. On one hand,

it includes both China and Japan, making it the first bilateral free trade agreement between the two countries, which helps reduce the tariff levels on grain trade between China and Japan, significantly weakening trade barriers between them. On the other hand, RCEP enforces more open and unified rules of origin, with lower restrictions on origin certification standards, thereby reducing hidden barriers to a greater extent. Specifically, the more substantial reduction in tariffs and non-tariff measures under RCEP, compared to other agreements, will lead to price effects that further promote the tightening of the GTN within the region.

5 Conclusion and discussion

This study examines the dynamics of grain trade within the world's largest free trade agreement zone. It investigates the characteristics of grain flow among RCEP member countries, explores the mechanisms driving the evolution of the GTN, and assesses the potential impacts of the agreement on the grain trade pattern. The main contributions are as follows: (1) This study characterizes the GTN among RCEP member countries from a trade network perspective for the first time, systematically uncovering its cooperation relationships as well as its robustness. (2) The "Five Forces" model is created to analyze the evolution mechanisms of complex networks, providing a multi-dimensional framework for understanding the RCEP member countries GTN. This model addresses the limitations of quantitative approaches in analyzing regional trade network evolution and offers methodological advancements for studying trade network with relatively small numbers of nodes. (3) The study adopts an innovative perspective, analyzing the potential impacts of RCEP on the GTN through the lenses of trade diversion and creation effects. The main findings include the following aspects.

(1) Under the influence of multiple factors, the GTN among RCEP member countries has grown more complex and interconnected, with both the number of network edges and density increasing by over 50%. Australia, Viet Nam, Myanmar, Thailand, and Cambodia serve as the primary exporters in the region, contributing 95.70% of total exports, while China, Philippines, Thailand, South Korea, and Malaysia are the main importers, accounting for 71.42% of total imports. Significant differences in trade scale persist among countries, and the network exhibits a typical major-country dominance effect, with grain-exporting countries serving as key nodes. However, the Betweenness centrality of these key nodes has declined stepwise, signaling a trend toward greater homogeneity in the trade status of member countries. Compared to the global GTN (Wang and Dai, 2021), the geographically proximate, bloc-based free trade zone offers more favorable conditions for establishing trade connections (Chaney, 2014). Currently, the network density and average clustering coefficient are 4.67 times and 1.36 times higher than global averages, respectively, while the average path length is only 63.44% of the global level (Figure 9). These findings indicate that the regional GTN is characterized by tighter trade links, shorter network distances, and higher transmission efficiency.

(2) The grain trade within RCEP member countries exhibits a distinct "high competition" characteristic. During the study period, regional competition intensified, though the increase was only 2.70%. The primary competition in the regional grain trade is concentrated among a small number of major grain-importing countries, with 70% of competition intensity arising from competition relationships ranging between 15 and 30%. Due to variations in resource endowments and demand scale,

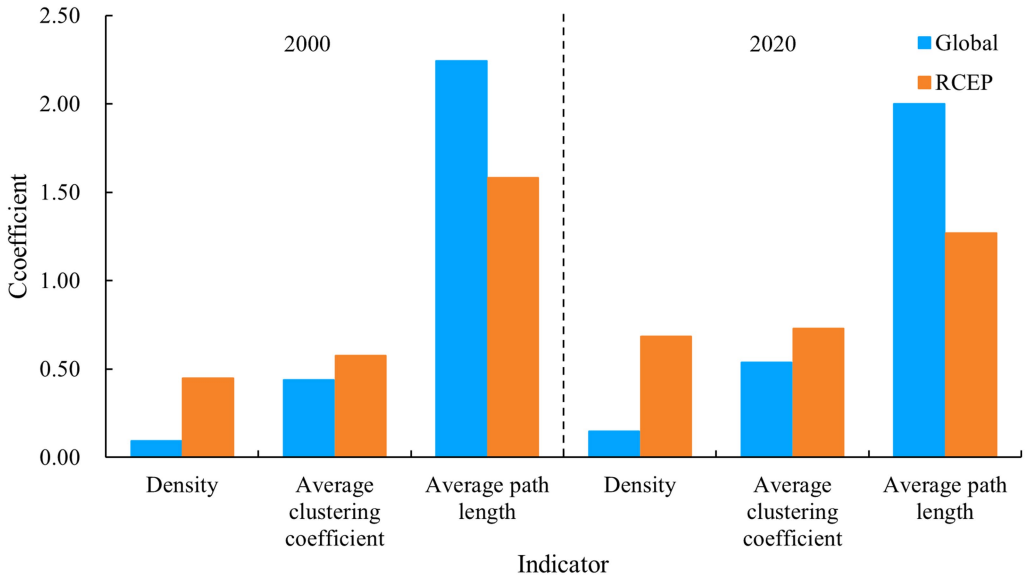


FIGURE 9
Comparative analysis of GTN characteristics: Global and RCEP member countries.

grain-importing countries with large populations and significant land constraints, such as China, Philippines, Malaysia, South Korea, and Indonesia, face greater competition intensity. Unlike the global grain trade (Wang and Fan, 2023), where competition is decelerating, grain import competition within the region continues to rise because member countries' import sources are heavily concentrated among a few major exporting countries. Currently, the average competition intensity in regional grain trade is 2.08 times higher than the global level (Supplementary Figure S5), underscoring the high concentration of grain import sources within RCEP member countries.

(3) Due to the immense trade scale imbalance implied by the dominance of large countries, grain trade cooperation among RCEP member countries exhibits a pronounced "low interdependence" characteristic. Growing concerns about external supply security have driven the diversification of trade behaviors among member countries, contributing to a more complex interdependence pattern. Throughout the study period, low-interdependence relationships consistently prevailed, with their proportion rising from 84.85 to 87.23%. Considering the competition intensity in regional grain trade, competition relationships among RCEP member countries outweigh cooperative ones.

(4) With the increasing complexity of the GTN structure and the homogenization of trade positions among member countries, the robustness of the GTN has significantly improved. Currently, under both random and targeted attacks scenarios, 93.33 and 86.67% of nodes, respectively, must be attacked to cause a complete network collapse. The network efficiency decline curves are gradually aligning, presenting a near-uniform decline. Countries with higher Betweenness centrality, such as Thailand and Australia, are pivotal in maintaining the stability of the trade structure. Meanwhile, the influence of major trade countries, such as Viet Nam and China, has been steadily deepening. Compared to the global trade network of wheat (Ma et al., 2023), one of the three major primary grains, the homogenization of trade positions among RCEP member countries enhances the robustness of the regional GTN against disruptions. In the random attacks scenario, its robustness is comparable to the global level, with network collapse occurring when the node failure rate reaches 90%. However, in the targeted attacks scenario, its robustness far exceeds the global level. The global trade network collapses when the node failure rate reaches 40%, whereas the RCEP network remains intact under similar conditions.

(5) The evolution of the GTN among RCEP member countries results from the combined influence of resource endowments, domestic demand, economic conditions, geopolitical relations, and important events. The increased trade connections driven by export powerhouses significantly contribute to the network's complexity, the intensification of cooperation relationships, and enhanced trade network robustness. Following the agreement's implementation, the differentiated tariff reduction commitments among member countries are expected to redistribute trade flows. Meanwhile, the reduction of non-tariff measures will enhance the efficiency of trade links, which is expected to generate trade diversion and creation effects. While the agreement strengthens intra-regional trade links and boosts the scale of trade within the region, the intensity of import competition will further increase, thereby reshaping the grain trade pattern. The findings of the above study are also supported by simulation results from previously published research. Taking Viet Nam, a major grain exporter, as an example, on one hand, if import partners reduce their rice import tariffs by 1%, the per capita consumption of Vietnamese rice in those countries will increase by 0.01 USD, generating a trade creation effect. On the other hand, due to high tariff barriers set by the South Korean government to protect its domestic rice industry, South Korea is not an ideal destination for Vietnamese rice exports. This portion of the export volume will be redistributed to other member countries that have committed to tariff reductions, generating a trade diversion effect (Chakradhar and Thao, 2024). For China, a major grain importer, it is expected that, 10 years after the formal implementation of RCEP, rice imports from non-RCEP member countries will decrease by 5.65%, with some of the import volume shifting to within the region. Specifically, China's rice imports from Australia are expected to increase the most (7.23%), and the import competition pressure within the region will also rise (Liu and Wang, 2024).

This study emphasizes the importance of effectively leveraging the RCEP agreement to address the "high competition, low interdependence" nature of grain trade relations among member countries. Transitioning from "highly competition relationships" to "strong cooperative relationships" is identified as a critical issue for ensuring the stable development of grain trade within the RCEP region. It is recommended that countries facing significant import competition pressure—such as China, Philippines, Malaysia, South Korea, and Indonesia—enhance agricultural production cooperation with countries in the Indo-China Peninsula. These countries, endowed with abundant arable land and favorable water and heat conditions, possess substantial potential for yield improvement. By supporting these high-potential agricultural producers to capitalize on their resource endowment advantages, the region can increase its overall grain supply and mitigate the intense import competition within the member countries.

Undoubtedly, RCEP member countries have extensive trade interactions with non-member countries and also participate in multiple free trade agreements across the Asia-Pacific region and globally, which may result in the "Spaghetti bowl phenomenon" (Sorgho, 2016). Looking ahead, it is necessary to quantitatively analyze the trade network evolution mechanism of RCEP member countries from the perspective of an open system linking both intra-regional and extra-regional dynamics (Guo et al., 2023), and simulate the global economic effects of the agreement's signing (Xu et al., 2025). On the other hand, the RCEP member region serves as a geostrategic intersection of great powers, and

geopolitical conflicts among these powers may impact the implementation process of the agreement. Assessing the potential supply risk in the regional GTN (Sun et al., 2022) and proposing response strategies is also an important avenue for future research.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: http://faostat.fao.org.

Author contributions

ML: Conceptualization, Methodology, Writing-original draft, Formal Analysis. YinW: Data curation, Methodology, Writing-review & editing, Funding acquisition. CZ: Conceptualization, Funding acquisition, Methodology, Writing-review & editing. YanW: Data curation, Formal analysis, Writing-review & editing. JY: Methodology, Visualization, Writing-review & editing. YH: Methodology, Visualization, Writing-review & editing. YiW: Methodology, Visualization, Writing-review & editing.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1565092/full#supplementary-material

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Can the integration of agriculture and tourism foster agricultural green development? An empirical analysis based on panel data from 30 provinces in China

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The integration of agriculture and tourism, grounded in agricultural resources, not only offers new development opportunities for the agricultural sector but also steers it towards a greener and more sustainable trajectory. Using panel data from 30 provinces in China from 2011 to 2022, this study quantifies the levels of agriculture and tourism integration (ATL) and agricultural green development (AGD) in each province. Then, the study applies the fixed effects model, the spatial Durbin model, and the panel smooth transition regression (PSTR) model to empirically assess the impact of ATL on AGD, as well as its spatial spillover effect and its nonlinear characteristics. The findings are as follows: (1) Over the study period, both AGD and ATL exhibited steady growth, with marked spatial agglomeration effects; (2) ATL positively influenced AGD, suggesting that the integration of agriculture and tourism contributes to the green development of agriculture; (3) The impact of ATL on AGD exhibited significant spatial spillover effects, meaning that integrated agricultural-tourism development in one region can enhance AGD in its neighboring provinces; (4) The effect of ATL on AGD demonstrated nonlinear characteristics, with the influence of ATL on AGD intensifying as ATL increased. Based on these findings, the study proposes several policy recommendations, including strengthening top-level policy design, improving regional coordination mechanisms, and enhancing human capital cultivation, to foster deeper the integration of agriculture and tourism and to further accelerate the green development of agriculture.

KEYWORDS

integration of agriculture and tourism, agricultural green development, spatial spillover effect, non-linear effect, impact

1 Introduction

Since the reform and opening up, China has made significant strides in agricultural development. Statistics show that the country's total grain output increased from 430.7 million tons in 2003 to 706.5 million tons in 2024, marking 21 consecutive years of growth. Despite these achievements, the green development of China's agriculture still faces serious challenges. During the rapid modernization of agriculture, issues such as the excessive consumption of fossil energy, overuse of pesticides, and improper disposal of agricultural waste have led to severe agricultural

non-point source pollution and carbon emissions (Li and Guan, 2023). Non-point source pollution from farmland has surpassed industrial point source pollution, becoming the largest source of environmental contamination in many regions of China.

To address these concerns, the report from the 18th National Congress of the Communist Party of China emphasized the importance of promoting green development and establishing a scientifically sound agricultural development model. The 19th National Congress report further highlighted the need to enhance green development and strengthen efforts to control agricultural non-point source pollution. In 2021, the Ministry of Agriculture and Rural Affairs unveiled the "14th Five-Year Plan for the National Green Development of Agriculture," which explicitly called for accelerating the creation of a green, low-carbon, and circular agricultural system, improving the management of agricultural non-point source pollution, and promoting carbon reduction and sequestration in agriculture and rural areas. In December 2024, the Ministry issued the "Guiding Opinions on Accelerating the Comprehensive Green Transformation of Agricultural Development and Promoting Rural Ecological Revitalization," recognizing the acceleration of green transformation in agriculture as a critical task to promote rural revitalization and strengthen China's agricultural power. In the new stage of development, transitioning agricultural production modes and achieving green development are considered essential to ensuring national food security and maintaining social and economic stability (Zhou et al., 2023).

On a practical level, since the 18th National Congress, China's agricultural development has made considerable progress in achieving green transformation, even in challenging circumstances. This progress is evidenced by the widespread adoption of green production methods, improved resource conservation and efficiency, and increased capacity for producing high-quality agricultural products. According to the China Agricultural Green Development Report, the country's agricultural green development index increased from 73.46 in 2012 to 77.90 in 2022, marking a 6.04% rise (Luo et al., 2024). Nevertheless, China's agricultural green development still faces several pressing issues, such as inadequate material and technical infrastructure, insufficient exploitation of scientific and technological innovation potential, and an underdeveloped policy and institutional support system. Therefore, there is an urgent need to identify new elements, models, and drivers to accelerate the process of agricultural green development.

The primary objective of green agricultural development is to harmonize "green" and "development," shifting agriculture from a model characterized by high resource consumption and significant environmental costs to one marked by high productivity, efficient resource use, and minimal environmental impact (Liu et al., 2020). Research on green agricultural development generally focuses on two key areas: (1) the measurement of green development levels (Oenema, 2020; Sun, 2022) and (2) the factors influencing green agricultural development (Liu et al., 2020; Luo et al., 2024; Schmidt-Traub, 2020; Wang et al., 2024a).

In terms of measurement, Hall and Kerr (1991) introduced the "Green Index" concept and developed an indicator system for evaluating green development. Building upon this, Huang et al. (2017) constructed an indicator system based on the DPSIR model to assess agricultural green development levels and regional disparities across China. Methodologically, techniques such as principal component analysis (Zhang et al., 2022), analytic hierarchy process (Zhang et al., 2018), entropy method (Zhao and Yu, 2019), and entropy-weighted TOPSIS (Li et al., 2023) are commonly used to evaluate green development levels in agriculture.

Regarding the factors influencing green agricultural development, existing studies have identified several key determinants, including the role of the internet (Wang et al., 2024a), digital inclusive finance (Guo et al., 2022), agricultural green technology (He and Liu, 2022), agricultural insurance (Hou and Wang, 2022), and policy factors such as low-carbon strategies (Luo et al., 2024; Chen and Chen, 2021; Sun, 2022). Other important factors include agricultural industrial agglomeration (Zhang et al., 2022) and urbanization (Ge et al., 2023; Li and Li, 2019), which also significantly impact the green development of agriculture.

In recent years, the scale of agricultural tourism, or leisure agriculture, has expanded rapidly as an important form of rural industry convergence. According to data from the Ministry of Culture and Tourism, in 2019, the total number of rural leisure tourists in China reached 3.2 billion, with the total consumption (output value) of rural tourism amounting to 850 billion yuan (Wang et al., 2023). While this indicator declined between 2020 and 2022 due to the COVID-19 pandemic, the output value of rural tourism exceeded 900 billion yuan in 2023 (as shown in Figure 1). By the end of 2022, a total of 388 national leisure agriculture and rural tourism demonstration counties had been established nationwide, along with 1,973 "Beautiful Leisure Villages of China" and 1,597 national-level key villages and towns for rural tourism. According to the United Nations World Tourism Organization, China became the country with the largest number of "Best Tourist Villages" in 2024. The integrated development of agriculture and tourism has become a crucial strategy for advancing rural revitalization in China.

With the deepening integration of agriculture and tourism, the development effects of this integration have garnered significant scholarly attention. A review of literatures reveals that most studies focus on the economic and social impacts of industrial integration on rural development. Economically, scholars argue that establishing effective linkages between agriculture and tourism can create new market opportunities and consumer demand, thereby fostering the high-quality development of both sectors (Chang et al., 2019; Fleischer and Tchetchik, 2005; Rogerson, 2012; Gao et al., 2014). Although agricultural products required for tourism represent only a portion of total agricultural output, tourism plays a vital role in ensuring the quality and safety of agricultural products and promoting broader economic growth (Huang et al., 2014; Renting et al., 2009). Additionally, numerous empirical studies have examined the impact of ATL on rural and regional economic growth (Schilling et al., 2012; Streifeneder, 2016). In terms of its social effects, the integrated development of agriculture and tourism helps strengthen the connection between urban and rural areas while contributing to the preservation of natural and cultural heritage (Gao and Wu, 2017; Joo et al., 2013). Environmentally, scholars assert that tourism provides

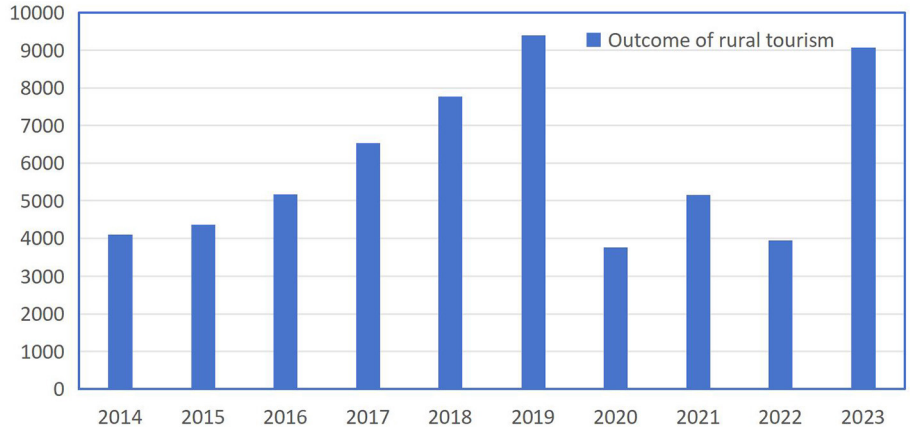


FIGURE 1
Change of total output value of rural tourism in China from 2014 to 2023.

farmers with an alternative source of income, which supports the green development of agriculture. This integration encourages the reallocation of part of the agricultural labor force and provides funding for the adoption of innovative technologies such as fertilizers. As a result, farmers can expand production without increasing tillage frequency or cultivating new land, thereby indirectly mitigating environmental degradation (Jiang, 2022; Kaswanto, 2015; Wang and Zhou, 2021).

However, few studies have explored the impact of agriculture and tourism integration on agricultural green development. Luo and Wei (2022) are among the few to analyze the environmental effects of rural industrial integration, particularly its impact on polluting production practices, providing preliminary evidence of its environmental implications. As a significant form of rural industrial integration, the connection between agriculture and tourism draws upon agricultural ecological resources, inherently influencing agricultural production methods and enhancing the green development of agriculture. Consequently, utilizing empirical analytical tools to examine the impact and characteristics of agriculture and tourism integration on agricultural green development is crucial for advancing both agricultural and tourism integration and promoting green agricultural development.

Against this backdrop, this study seeks to explore the following aspects: (1) measuring the levels of agricultural green development (AGD) across 30 provinces in China with panel data from 2010 to 2021; (2) quantifying the levels of agriculture and tourism integration (ATL) to better understand the dynamics between agriculture and tourism; (3) employing panel data and econometric models to assess the impact of agriculture and tourism integration on agricultural green development, including its spillover effects and non-linear characteristics; and (4) proposing specific policy recommendations to strengthen the role of agriculture and tourism integration in promoting green agricultural development.

The marginal contributions of this study are as follows: First, it expands the research scope regarding factors influencing agricultural green development. While previous studies have predominantly focused on technological and policy factors, this study innovatively introduces industrial integration as a significant variable, which also has an important reference value for exploring the road of agricultural green development. Second, it deepens the understanding of the impacts of agriculture and tourism integration by examine its ecological effects. In the past, a large number of studies focused on the impact of the integration of agriculture and tourism on rural economic development, farmers' income increase, farmers' local employment and the price of agricultural products. Through empirical analysis, this study explores the ecological implications of agriculture and tourism integration on agricultural green development, providing valuable insights for future research on the ecological outcomes of rural industrial integration.

2 Theoretical analysis and hypothesis

The integration of agriculture and tourism has significantly advanced the application and promotion of agricultural technologies, such as intelligent greenhouses, precision agriculture, and other technical innovations. These developments have enhanced the intelligence and precision of agricultural production, thereby fostering the growth of green agriculture (Wang et al., 2023). Moreover, this integration promotes the diversification and efficiency of agricultural development by leveraging the synergies between agriculture and tourism resources. Through this process, agricultural resources are utilized more fully and efficiently. To meet the demands of tourists, agricultural producers increasingly prioritize the quality and safety of their products, adopting green and organic production methods. This includes reducing the use of fertilizers and pesticides, which, in turn, mitigates agricultural non-point source pollution. Additionally, the integration of agriculture and tourism facilitates the extension and expansion of the agricultural value chain, such as the processing of agricultural products and the development of rural tourism offerings, further advancing the green and sustainable development of agriculture (Ayyildiz and Koc, 2024).

Building on existing research, this study develops a theoretical framework to examine the impact of agriculture and tourism integration on agricultural green development, with a focus on its spatial spillover effects and non-linear characteristics.

2.1. Influence mechanism of agriculture and tourism integration on agricultural green development

(1) The integration of agriculture and tourism can foster advancements in agricultural technology. The integration and evolution of agriculture and tourism have facilitated the spatial agglomeration of business units, the flow of talent, and the exchange of technologies (Wang et al., 2024b). Concurrently, the advanced technology and management expertise of tourism enterprises are disseminated to agricultural stakeholders, enhancing agricultural production and management capabilities (Ndhlovu and Dube, 2024). Furthermore, as agricultural resources are integrated and the "tourism" functions of agricultural products and activities (e.g., agriculture, animal husbandry, folk customs, leisure, vacation, and popular science education) are expanded, agricultural businesses increasingly introduce advanced agricultural technologies and management practices. This process plays a crucial role in enhancing agricultural technology levels.

(2) The integration of agriculture and tourism promotes the optimal allocation of resources. Under traditional agricultural management models, resource allocation primarily relies on limited capital, abundant land, and primary labor, resulting in relatively low efficiency in the allocation of agricultural production factors (Amsden and McEntee, 2011). However, the integration of agriculture and tourism facilitates the market-oriented flow and full interaction of capital, technology, talent, information, and management between the two sectors. This interaction promotes the optimal allocation of production factors at a higher level and significantly improves the efficiency of agricultural resource allocation (Soleimannejad et al., 2021). Moreover, new business models emerging from this integration create numerous non-agricultural employment and entrepreneurship opportunities for rural labor. Additionally, it encourages the moderate-scale and intensive management of agricultural land resources, thus leveraging economies of scale to achieve lower costs and higher efficiency (Ammirato et al., 2020).

(3) The integration of agriculture and tourism fosters the optimization and upgrading of agricultural industrial structure. The integration of agriculture and tourism has enriched rural tourism development, creating a diverse range of rural tourism products and services (Valdivia and Barbieri, 2014). For example, new types of businesses have emerged, such as national agricultural parks, leisure farms, rural camps, rural museums, citizen agricultural parks, and rural homestays. Driven by demand, these developments have led to adjustments in the allocation of agricultural production factors, optimizing the structure of agricultural production, quality, and variety. This shift in agricultural supply, aligned with changing market demand, enhances the efficiency of agricultural production and operations (Arru et al., 2019; Collins et al., 2024). The integration of agriculture and tourism fosters the development of agricultural versatility, meets the diverse needs of consumers for agricultural and tourism products, and drives improvements in agricultural technical efficiency and technological progress.

(4) The integration of agriculture and tourism enhances farmers' awareness of green environmental protection. With the rise of rural tourism, there has been growing demand among tourists for green, organic, and healthy agricultural products (Ndhlovu and Dube, 2024). This demand has prompted farmers to place greater emphasis on environmental protection and sustainability throughout the production process. Farmers are increasingly adopting green agricultural practices, such as organic farming techniques, reducing the use of fertilizers and pesticides, and improving the quality and safety of agricultural products (Ayyildiz and Koc, 2024; LaPan and Xu, 2024). In order to attract tourists, farmers are motivated to improve the agricultural production environment and enhance the green quality of their products, thus establishing a virtuous cycle of green production. The mechanism of agriculture and tourism integration on agricultural green development is illustrated in Figure 2.

Based on the above analysis, Hypothesis 1 is proposed: The integrated development of agriculture and tourism has a significant positive effect on the green development of agriculture.

2.2. Spatial spillover effects of agriculture and tourism integration on agricultural green development

The flow of tourism exhibits strong network diffusion effects. A distinctive feature of the tourism industry, compared to other sectors, is its cross-regional management. Given China's vast geographic expanse and significant regional variations in crop production cycles, the cross-regional operation of agriculture and tourism integration becomes both feasible and advantageous. This cross-regional interaction not only helps to expand market scale but also deepens the vertical division of labor within the agricultural system, facilitating economies of scale (Grillini et al., 2025). Furthermore, the seasonal nature of crop production enhances the mobility of agro-tourism visitors, fostering more efficient information and technology exchange between regions. Consequently, the integration of agriculture and tourism can influence the allocation of production factors, the agricultural industrial structure, and technological progress in neighboring areas through cross-regional operations, thereby impacting the green development of the agricultural system.

Based on the above analysis, Hypothesis 2 is proposed: The integration of agriculture and tourism has a spatial spillover effect in promoting agricultural green development.

2.3 Non-linear threshold characteristics of agriculture and tourism integration on agricultural green development

The process of integrating agriculture and tourism leads to the realization of agro-ecological premiums. However, in the early stages of this integration, the agro-ecological premium is relatively modest, and agricultural production predominantly relies on traditional methods (Grillini et al., 2025). During this period, the focus of agricultural production is primarily on enhancing efficiency, with little emphasis on actively reducing harmful

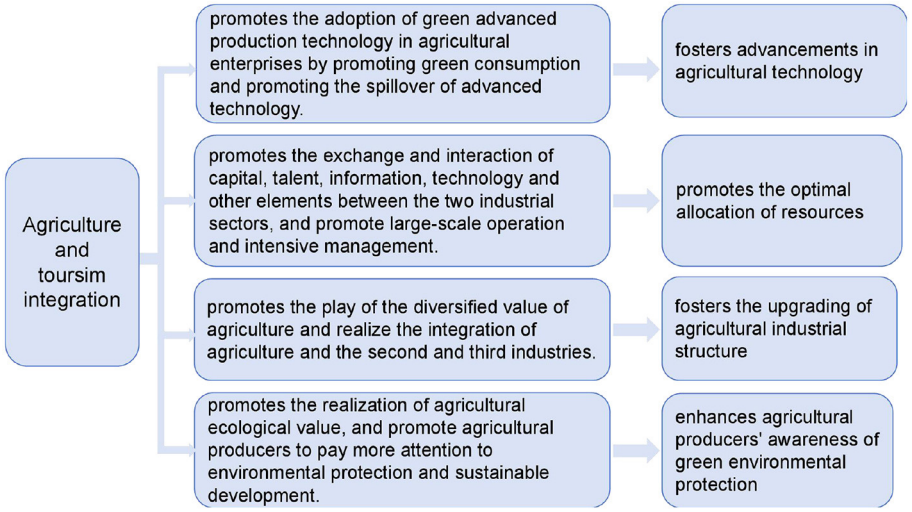


FIGURE 2
Mechanism of agriculture and tourism integration on agricultural green development.

environmental inputs such as fertilizers and pesticides. As a result, the integration of agriculture and tourism at this early stage did not significantly promote the green development of agriculture. As the integration progresses, the full agro-ecological premium becomes realized (Grillini et al., 2025). This shift encourages agricultural producers to prioritize green and sustainable agricultural practices, reducing the use of harmful inputs, and aiming for more substantial agro-ecological benefits (Bigiotti et al., 2024). Therefore, as the level of the integration of agriculture and tourism improves, its impact on the green development of agriculture is likely to intensify.

Based on the above analysis, Hypothesis 3 is proposed: There are threshold characteristics in the influence of the integration of agriculture and tourism on agricultural green development.

3 Methods and data

3.1 Variable selection

3.1.1 Explained variable

The agriculture green development (AGD_{it}) is the explained variable in this study. Based on researches of Xiong and Zhou (2024), Lu et al. (2024), and He et al. (2021), and adhering to the principles of comprehensiveness and representativeness, this study constructs an indicator system for measuring the level of agriculture green development. The system is structured around four dimensions: conservation of resources, environmental friendliness, ecological sustainability, and efficient output. Indicators for measurement for AGD are shown in Table 1.

The TOPSIS method with entropy is used to measure AGD in the study. In practice, there are many comprehensive evaluation methods. According to the different weights determined, there are subjective and objective weighted evaluation methods. In this study, the objective weighting method is used to determine the weight through the principle of information entropy, which can evaluate the research object objectively and accurately. To compare different methods, the entropy method is improved, and a time variable is added to make the analysis results more reasonable. The evaluation model of the improved entropy method is as follows:

(1) Index selection: with r years, n provinces, and m indicators, $x_{\theta ij}$ is the j-th index value of province i in the θ-th year.

(2) Standardization of indicators: Because different indicators have different dimensions and units, it is necessary to standardize them:

Standardization of the positive index:

$$x'_{\theta ij} = x_{\theta ij} / x_{\max} \tag{1}$$

Standardization of the negative index:

$$x'_{\theta ij} = x_{\min} / x_{\theta ij} \tag{2}$$

(3) Determine the index weight:

$$y_{\theta ij} = x'_{\theta ij} / \sum_{\theta} \sum_{i} x'_{\theta ij} \tag{3}$$

(4) Calculate the entropy of the *j-th* index:

$$e_j = -k \sum_{e} \sum_{i} y_{ij} \ln (y_{\theta ij}),\ k > 0, k = \ln (rn) \tag{4}$$

(5) Calculate the weight of each indicator:

$$w_j = g_j / \sum_{j} g_j \tag{5}$$

(6) Calculate the comprehensive score of the AGD level of each province:

$$AGD_{\theta i} = \sum_{i} (w_j x' \theta ij) \tag{6}$$

TABLE 1 Evaluation index system of agricultural green development.

First-level indicators	Secondary indicators	Measuring indicators	Unit	Attribute
Conservation of resources	Arable land replanting index	Total sowing area/cultivation area of crops	–	–
	Water-saving irrigation rate	Water-saving irrigation area/effective irrigation area	%	+
	Total mechanical power of arable land area per unit	Total power of agricultural machinery/arable land area	KW/hectare	–
	Agricultural water efficiency	Agricultural water consumption/total agricultural output	Ton/1 billion	–
	The intensity of pesticide application	Pesticide usage/arable land area	Ton/hectare	–
Environmental friendliness	Fertilizer application intensity	Agricultural fertilizer usage/arable land area	Ton/hectare	–
	The application strength of agricultural film	Agricultural film usage/total sowing area of crops	Ton/hectare	–
	Agricultural CO_2 emission intensity	Agricultural CO_2 emission intensity/total agricultural yield	Ton/1 billion	–
	The area of nature reserves	Nature reserve/jurisdictional area	%	+
Ecological protection	Forest coverage	Forest area, wetland area/Jurisdiction	%	+
	Wetland coverage rate	Wetland area/Jurisdiction	%	+
Efficient output	Soil erosion control rate	Soil erosion control area/Jurisdictional area	%	+
	Disposable income	Disposable income	Yuan	+
	The proportion of agricultural output	Agricultural output value/Total output value agriculture, forestry, animal husbandry and fisheries	%	+
	Land productivity	Agricultural output value/Crop sowing area	10 billion/Ton	+

3.1.2 Explanatory variable

The integration of agriculture and tourism (ATL_{it}) is the core explanatory variable, which is evaluated by coupling cooperation degree model. This requires selecting appropriate indicators to assess the development levels of both agriculture and tourism. A review of the literature reveals that agriculture and tourism integration refers to the process of establishing a distinct agricultural tourism brand based on regional characteristics of agricultural resources and integrating agricultural endowments with thematic or resource-based tourism. Key manifestations of agriculture and tourism integration include branded agricultural tourism towns centered on geographically indicated agricultural products, key tourism villages, leisure agriculture initiatives, and rural tourism demonstration counties, all of which encapsulate the defining features and elements of agriculture and tourism integration.

To enhance the specificity and rationality of agriculture and tourism integration measurement, this study uses publicly available data that reflect the development of agriculture and tourism integration, rather than generic indicators such as tourism revenue or agricultural output from statistical yearbooks. Based on the research of Yang et al. (2023), several indicators were selected to measure the levels of both distinctive agricultural development and rural tourism development with the entropy-weighted TOPSIS method. Indicators for the measurement are shown in Table 2.

The coupling cooperation degree model is used to evaluate ATL. The construction process of coupling coordination degree model of characteristic agriculture and rural tourism to evaluate ATL is as follows:

① Standardize the data of evaluation index:

When the evaluation index is a positive index:

$$y_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_j} \tag{7}$$

When the evaluation index is a negative index:

$$y_{ij} = \frac{x_{\max} - x_j}{\max x_j - \min x_j} \tag{8}$$

② Calculate the information entropy:

$$h_j = -k \sum_{i=1}^{m} p_{ij} \, In \, p_{ij} \left(\text{Where } p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}, k = \frac{1}{Inm}\right) \tag{9}$$

Define the weight of the j-th indicator as:

$$w_j = \frac{1 - h_j}{\sum_{j=1}^{n}(1 - h_j)} \left(\text{where } w_j \in [0,1], \text{and} \sum_{j=1}^{n} w_j = 1\right) \tag{10}$$

③ Calculate the development level of agriculture and tourism industry, respectively. The agricultural comprehensive evaluation function was determined and established according to the linear weighting method:

$$A(x) = \sum_{j=1}^{n} w_j M_{ij} \tag{11}$$

In the Formula (11), j is the number of evaluation indexes of agricultural development level, w_j is the weight of indexes,

TABLE 2 Measurement index system of agriculture and tourism integration.

First-level indicators	Secondary indicators	Attribute	Source of data
Characteristic agriculture	The number of geographical indications of agricultural products (s)	+	Ministry of Agriculture and Rural Affairs
	The number of "one village, one brand" project brands (s)	+	Ministry of Agriculture and Rural Affairs
	The output value of special agricultural products (billion yuan)	+	Ministry of Agriculture and Rural Affairs
	The number of advantageous agricultural products with local characteristics (s)	+	Ministry of Agriculture and Rural Affairs
	Orchard area (thousand hectares)	+	Yearbook of China's Rural Statistics
Rural tourism	The number of key townships of rural tourism in the county (s)	+	Ministry of Culture and Tourism
	The number of famous towns and villages in national characteristic landscape tourism (s)	+	Ministry of Housing and Urban-Rural Development
	The number of A-level scenic spots (s)	+	China Tourism Yearbook
	The number of demonstration counties for leisure agriculture and rural tourism(s)	+	Ministry of Culture and Tourism
	Rural tourism and leisure agricultural income (billion yuan)	+	Ministry of Culture and Tourism

and M_{ij} is the standardized value of the j-th agricultural index in the i-th year. The higher the value of $A(x)$ is, the higher the level of comprehensive agricultural development is, and vice versa. Similarly, the comprehensive evaluation function of tourism industry is established:

$$T(y) = \sum_{i=1}^{n} w_j N_{ij} \tag{12}$$

The interpretation of each indicator in Formula (12) is similar to Formula (11). The larger the value of $T(y)$ is, the higher the development level of tourism is, and vice versa.

④ The coupling coordination model of agriculture and tourism industry is established as follows:

$$C = \sqrt[2]{\frac{A(x) \cdot T(y)}{(A(x) + T(y))^2}} \tag{13}$$

$$D = \beta \cdot A(x) + \gamma \cdot T(y) \tag{14}$$

$$ATL = U = \sqrt{C \cdot D} \tag{15}$$

In Formula (13), C is the coupling degree, $C \varepsilon [0, 1]$. The greater the value of C is, the more ideal the degree of integration of the two industries is, and vice versa. The coupling degree C only reflects the interaction and cross state of agriculture and tourism industry, and cannot accurately reflect the actual integration and development level of the two industries. In order to avoid the illusion that the development level of the two subsystems is not high but the coupling degree of them is high, the coupling coordination degree U is used to represent the integration level of agriculture and tourism (ATL). The larger the U value, the better the coupling coordination. Generally speaking, the greater the value of coupling coordination degree is, the higher the degree of integration between industries is Su (2020). In Formula 15, β and γ are undetermined coefficients, and D is the comprehensive coordination index of agriculture and tourism industry. In view of the interactional relationship between agriculture and tourism industry system in the process of integration, this paper follows the view of Wang (2018), making $\beta = \gamma = 0.5$.

3.1.3 Control variables

Based on the current state of agricultural development, this study selects six control variables: financial support for agriculture (Fsa), agricultural industry structure (Ais), human capital (Huc), industrialization level (Ins), urbanization rate (Urb), and the level of economic development (IGDP). These variables are defined and measured as follows:

Fiscal support for agriculture (Fsa): This is measured by the proportion of local government expenditures on agriculture, forestry, and water resources relative to total local budget expenditures. Increased fiscal support for agriculture enhances the external environment for agricultural development, which significantly impacts agricultural green development (Zhang et al., 2022).

Industrialization level (Ins): Studies have shown a strong correlation between industrialization and agricultural green development. The level of industrialization is quantified by the proportion of the added value of the secondary industry in relation to the total GDP (Li et al., 2023).

Agricultural industry structure (Ais): This is represented by the proportion of the added value of crop production relative to the total added value of agriculture, forestry, animal husbandry, and fisheries. A higher proportion of crop production generally indicates a more concentrated agricultural production structure, which may have a positive influence on agricultural green development (Sun, 2022).

Human capital (Huc): This variable is measured by the proportion of college graduates per 100,000 rural residents. In general, higher levels of education among agricultural producers facilitate the acquisition of production skills and the rational use of chemical inputs, which is expected to positively influence agricultural green development.

Urbanization rate (Urb): The urbanization rate is calculated as the proportion of the urban population relative

TABLE 3 Descriptions of the variables and their specific measurements.

Variable	Variable name	Unit	Calculation method	Data source
Explained variable	Agricultural green development (AGD)	_	Calculated by entropy power TOPSlS method	Shown in Table 1
Explanatory variable	The integration of agriculture and tourism (ATL)	_	Calculated by coupling cooperation degree model	Shown in Table 2
Control variables	Financial support for farmers (Fsa)	%	lt is expressed in the proportion of agricultural, forestry and water conservancy expenditure to local expenditure in the total local budget	China's rural economy
	Agricultural industry structure (Ais)	%	Represented by the proportion of the added value of the planting industry to the added value of agriculture, forestry, animal husbandry and fishery	China Statistical Yearbook
	Human capital (Huc)	%	Expressed by the proportion of college students per 100,000 people in rural areas	
	Industrialization level (Ins)	%	It is expressed by the proportion of the added value of the secondary industry to the total output value.	
	Urbanization rate (Urb)	%	Expressed by the proportion of urban population in each province to the resident population	
	The level of economic development (IGDP)	—	Represented in the logarithm of GDP per capital	

to the total permanent population in each province. As the agricultural production model shifts from extensive to intensive practices, the increased use of pesticides and fertilizers, aimed at boosting yields, contributes to higher agricultural carbon emissions, hindering progress in agricultural green development.

Regional economic development level (IGDP): This is represented by the logarithm of per capita GDP, adjusted for inflation. Descriptions of all variables and their specific measurements are shown in Table 3.

3.2 Empirical model specification

3.2.1 Fixed effects model

The fixed effects model is capable of controlling unobservable factors that remain constant over time, effectively addressing errors caused by omitted variables in the model. In this study, the panel model with fixed effects is established as the benchmark regression model, which is formulated as follows:

$$AGD_{it} = \alpha_0 + \beta_1 ATL_{it} + \sum_{k=1}^{n} \lambda_k \, Col_{it,\,k} + \mu_i + \nu_t + \xi_{it} \quad (16)$$

In the above formula, *AGDit* and *ATLit* represent the explained variable and the core explanatory variable, respectively. Subscripts *i* and *t* denote province and year, respectively, while *Colit, k* refers to a set of control variables.

3.2.2 Spatial Durbin Model

When both the explained variable and explanatory variables exhibit spatial correlation, it is necessary to construct a Spatial Durbin Model (SDM). Considering the potential spatial dependence between the explained variable AGD and the explanatory variable ATL, the following SDM is constructed:

$$AGD_{it} = \alpha_0 + \rho W AGD_{it} + \beta ATL_{it} + \gamma Cit, k + \theta WATL_{it} + \xi W \sum_{k=1}^{n} C_{it,\,k} + \mu_i + \nu_t + \varepsilon_{it} \quad (17)$$

In the above formula, ρ represents the spatial correlation coefficient, W is the spatial weight matrix, the geographical distance spatial matrix (W) is used in the spatial econometric model. The calculation formula is, d_{ij} is the direct distance between two provincial capitals and other variables are defined as in Formula (17).

3.3.3 Panel smooth transition regression (PSTR) model

The promotion effect of agriculture and tourism integration on AGD may also show non-linear characteristics, so the panel smooth transition regression (PSTR) model is used to test the non-characteristic characteristics of agriculture and tourism integration on AGD. The specific model is set as follows:

$AGD_{it} = \beta_{01} ATL_{it} + \beta_{02} Fsa_{it} + \beta_{03} Ais_{it} + \beta_{04} Huc_{it} + \beta_{05} IGDP_{it+} \beta_{06} Ais_{it+} \beta_{07} Urb_{it+} (\beta_{01} ATL_{it+} \beta_{02} Fsa_{it} + \beta_{03} Ais_{it} + \beta_{04} Huc_{it} + \beta_{05}\ IGDP_{it+} \beta_{06} Ais_{it+} \beta_{07} Urb_{it}) \cdot g\ (q_{it}; r, c) + \mu_i + \varepsilon_{it}$

Where $g(q_{it};\ r,\ c)$ represents the conversion function, and the formula for the conversion function is as follows:

$$g(q_{it}; r, c) = \left\{ 1 + \exp\left[-r \prod_{j=1}^{m} (q_{it} - c_j) \right] \right\}^{-1}, \quad r > 0, c_1 \leq c_2 \leq \cdots \leq c_n, r > 0, c_1 \leq c_2 \leq \ldots \leq c_n \quad (18)$$

In Formula (19), the explained variable is AGD_{it}, the explanatory variable and the conversion variable are both ATL_{it},

TABLE 4 Description of variables.

Variables	Samples	Mean	Median	Std. dev	Max	Min
AGD_{it}	360	0.665	0.692	0.115	0.824	0.468
ATL_{it}	360	0.661	0.689	0.121	0.853	0.376
Fsa_{it}	360	0.109	0.101	0.065	0.179	0.084
Ais_{it}	360	0.516	0.515	0.583	0.865	0.303
Huc_{it}	360	0.028	0.025	0.008	0.064	0.010
Ins_{it}	360	0.404	0.398	0.075	0.792	0.254
Urb_{it}	360	0.554	0.542	0.139	0.895	0.211
$IGDP_{it}$	360	1.092	1.116	0.505	2.316	−0.143

and the other variables are interpreted as above. In Formula (20), q_{it} is the conversion variable; r is the slope parameter, which determines the conversion speed; c is the position parameter, which determines the threshold condition of parameter conversion; m is the number of positional parameters. In the PSTR model, the variable estimation coefficient is composed of the linear part β_0 and the non-linear part $\beta_1{}^*g(\cdot)$. When $g(\cdot) = 0$, the model is in a low regime; When $g(\cdot) = 1$, the model is in a high regime. At the same time, as the value of the conversion function moves smoothly between [0, 1], the estimated coefficient will monotonically shift between β_0 to $\beta_0 + \beta_1$, centered on c (González et al., 2005).

3.3 Data source and variable characteristics

3.3.1 Data source

Data of 30 provinces in China from 2011 to 2022 are used in this study to conduct the empirical analysis. Considering the lack of data from Hong Kong, Macao, Taiwan and Tibet Autonomous Region, the above four provinces are not included in the analysis. The data mainly are drawn from the National Bureau of Statistics, the Ministry of Culture and Tourism, the Ministry of Agriculture and Rural Affairs, the provincial statistical bureau and statistical bulletins. All data measured in monetary units are deflated at the 2011 price level. Some missing data values are supplemented by mean difference, linear interpolation and moving average method. Z-score standardization method is used to convert variables to dimensionless numerical values, eliminating the impact of units. In addition, R language and GeoDa software are used for quantitative analysis.

3.3.2 Variable characteristics

The descriptive statistical results of each variable are shown in Table 4.

Using provincial panel data, this study calculates the levels of AGD and agriculture tourism integration for each province from 2011 to 2022. The average annual values of AGD and agriculture and tourism integration over the study period are presented in Figure 3.

Overall, AGD demonstrated steady improvement from 2011 to 2022, with an average annual growth rate of 3.819%. In recent

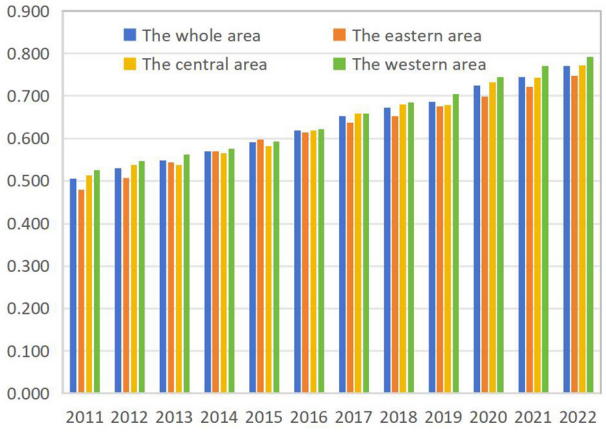


FIGURE 3
The mean value of AGD from 2011 to 2022 in China.

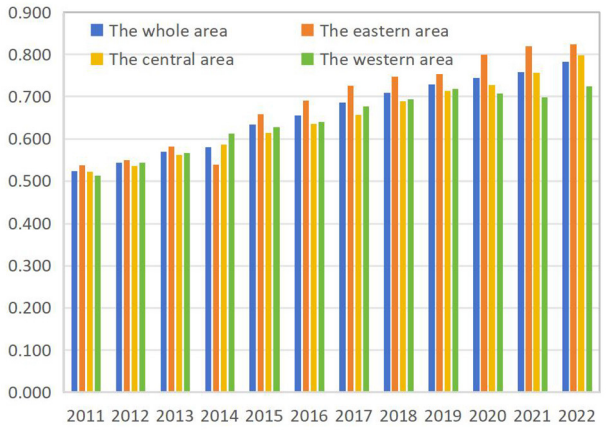


FIGURE 4
The mean value of ATL from 2011 to 2022 in China.

years, the central government's increasing emphasis on sustainable agricultural development had significantly contributed to this progress. During the study period, the average annual growth rates of AGD in the eastern, central, and western regions were 3.836%, 3.860%, and 3.834%, respectively. Notably, the eastern region consistently exhibited a higher agricultural green development growth rate compared to other regions. This can likely be attributed to its stronger economic foundation, which facilitates the adoption and dissemination of advanced green production technologies.

The annual average value of agriculture and tourism integration across the entire study area also showed an upward trend, with an average annual growth rate of 3.722%. This growth was primarily driven by the substantial role of rural industrial integration in promoting income generation and employment, an area that has received strong support from governments at various levels. Regionally, the eastern region had the highest average agriculture and tourism integration, while the western region exhibited relatively lower average agriculture and tourism integration, as illustrated in Figure 4. The eastern region benefited from a robust economic foundation, well-developed transportation

TABLE 5 Full sample estimation results.

Variables	FE	RE	POLS
ATL_{it}	0.512***(5.969)	0.206***(5.418)	0.337***(4.315)
Fsa_{it}	1.311***(8.165)	1.234***(7.136)	1.128***(8.191)
Ins_{it}	0.021**(3.118)	0.017**(3.042)	0.014**(3.139)
Huc_{it}	0.148***(6.136)	0.117***(5.854)	0.094***(4.176)
$IGDP_{it}$	0.213*(1.998)	0.206(0.418)	0.274**(3.143)
Ais_{it}	0.020***(4.418)	0.028**(3.136)	0.015*(2.418)
Urb_{it}	−0.348***(-3.649)	−0.198*(-2.143)	−0.144**(-2.842)
N	360	360	360
R^2	0.734	0.695	0.611

***, **, and * represent $P < 0.01$, $P < 0.05$, and $P < 0.1$ respectively, and the T-value is in parentheses.

infrastructure, and comprehensive public services. These factors, coupled with higher levels of regional economic development and stronger market demand, had fostered a higher degree of agriculture and tourism integration. In contrast, the western region lacked some of these driving forces, resulting in comparatively lower levels of agriculture and tourism integration.

4 Results and discussion

4.1 Benchmark model estimation results and analysis

4.1.1 Estimation results of fixed effect model

As shown in Table 5, the regression coefficient of ATL on AGD is 0.512 ($P < 0.05$), indicating a statistically significant positive impact of ATL on AGD. This relationship underscores the alignment of ATL with the principles of "agriculture-oriented development" and ecological sustainability, with agriculture and rural areas serving as foundational pillars. The integration process fosters the transition toward more intensive and environmentally friendly agricultural production and operations.

Throughout the deepening of ATL, resources and elements originally confined to agriculture, tourism, and related sectors are synergistically combined, giving rise to innovative business models such as "agriculture + tourism + sports," "agriculture + tourism + wellness," and "agriculture + tourism + education." These new models unlock synergies between tourism and agriculture, facilitating the transformation of traditional agricultural practices into more ecologically sustainable forms. By injecting fresh momentum into rural development, expanding the functional scope of agriculture, and fostering novel economic growth patterns, these models generate new sources of value creation, ultimately driving the advancement of AGD.

4.1.2 Robustness and eogeneity test

(1) Robustness test

To ensure the robustness of the benchmark regression results, several methods were employed for endogeneity and robustness testing:

First, using the lag term of ATL for regression: At the time level, considering the lag effect of ATL on AGD, the first-order lag term and second-order lag term of ATL are used as the core explanatory variables for regression.

Second, changing the number of bootstrap iterations:Panel data analysis typically assumes that disturbance terms are independent across individuals and uncorrelated over time within the same individual. However, to account for potential heteroscedasticity and autocorrelation, cluster-robust standard errors at the provincial level may be less accurate in small samples. Therefore, the bootstrap method, which provides more reliable estimates, was applied. The number of bootstrap iterations was set to 500 to ensure robustness.

Third, changing the sample size: Municipalities directly under the central government, such as Beijing, Shanghai, Tianjin, and Chongqing, often experience more pronounced benefits from national policies. These municipalities are better positioned to accelerate economic decision-making, implement urban renewal strategies tailored to local conditions, and unlock untapped urban potential. To account for this, the samples of these four municipalities were excluded, and the fixed effects model was re-estimated.

Under the three robustness tests, ATL can significantly increase AGD, which proves the robustness of the baseline regression results.

(2) Endogeneity test

In order to alleviate the possible endogeneity problem of the model, IV-2SLS method was used to deal with it. The density of highway network is used as the instrumental variable, and the selection of the instrumental variable needs to meet two conditions of correlation and externality: First, the development level of the integration of agriculture and tourism is often closely related to transportation infrastructure, so the integration level of agriculture and tourism can be characterized by the density of highway network to a certain extent, so the condition of correlation between independent variable and instrumental variable is satisfied. Secondly, the density of highway network does not directly affect the green development of agriculture, so the exogenous conditions of instrumental variables are satisfied.

The results of columns (1) and (2) in Table 6 show that: in the first stage, instrumental variables and ATL has positive correlation, and the higher the density of highway network, the better the historical infrastructure conditions, and the more conducive to the subsequent integrated development of agriculture and tourism; In the second stage, the effect of ATL on AGD is still significantly positive at the level of 1%, and all pass the validity test of instrumental variables.

4.2 Estimation results and analysis of spatial panel model

4.2.1 Identification of spatial model

Before estimating the model, the spatial correlations between ATL and AGD over the years were tested. The calculated Global

TABLE 6 Robustness and eogeneity tests.

Variables	Instrumental variable method		Alternate explanatory variable		Bootstrap iterations was set to 500	Changing the Sample Size
	First stage	Second stage	One-phase lag	Two-phase lag		
ATL		0.498*** (3.593)	0.546*** (3.354)	0.324*** (5.113)	0.417** (2.917)	0.696*** (3.323)
IV	0.643*** (4.593)					
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Year	√	√	√	√	√	√
Province	√	√	√	√	√	√
Adj R^2	0.932	0.795	0.694	0.637	0.593	0.621
N	360	360	330	300	360	324
Unidentifiable test	12.984***					
Weak instrumental variable testing	209.462					

*** and ** represent $P < 0.01$ and $P < 0.05$ respectively, and the *t*-value is in parentheses.

TABLE 7 Test results of the spatial model.

Spatial correlation test	*LM-lag*	*Robust LM-lag*	*LM-error*	*Robust LM-error*
	9.414***	17.312***	0.576	5.811**
Wald statistic and LR statistic test	*Wald-spatial lag*	*LR-spatial lag*	*Wald-spatial error*	*LR-spatial error*
	23.785***	11.094***	14.091***	5.676**

*** and ** represent $P < 0.01$ and $P < 0.05$ respectively, and the *t*-value is in parentheses.

TABLE 8 Estimation results of Spatial Durbin Model.

Variables	Two-ways fixed effect model	Time fixed effect model	Spatial fixed effect model
ATL_{it}	0.475**(2.997)	0.172*(2.315)	0.237**(3.352)
Fsa_{it}	1.245**(3.186)	1.128(1.191)	1.170(0.966)
Ins_{it}	0.026**(1.969)	0.025(0.139)	0.043*(2.118)
Huc_{it}	0.135**(3.326)	0.173**(3.176)	0.209**(2.765)
$IGDP_{it}$	0.201***(4.180)	0.274*(3.143)	0.274*(2.195)
Ais_{it}	0.014*(2.496)	0.005(0.989)	−0.001*(2.383)
Urb_{it}	−0.314***(-3.379)	−0.165**(-2.760)	−0.209**(-2.894)
W^*ATL_{it}	0.175**(3.097)	0.081*(2.035)	0.137**(2.954)
Adj R^2	0.920	0.763	0.587
ρ	0.321***(3.841)	0.206***(3.635)	0.215**(2.819)
Log L	193.143	155.043	119.758

***, **, and * represent $P < 0.01$, $P < 0.05$, and $P < 0.1$ respectively, and the *t*-value is in parentheses.

Moran's I values for both variables were positive and statistically significant at the 1% confidence level across all years, indicating substantial spatial correlations for both ATL and AGD. This suggests that spatial factors must be incorporated when analyzing the relationship between these two variables.

To determine the most appropriate spatial econometric model, the two-step procedure proposed by Elhorst (2003) was applied. The results revealed that both the Wald and LR statistics were significant, suggesting that the Spatial Durbin Model (SDM) is the most suitable model for fitting the sample data. The test results are presented in Table 7. Additionally, a Hausman test was conducted, yielding a test statistic of 32.675 ($P < 0.000$), which supports the use of the fixed effects model as the more appropriate specification.

4.2.2 Results of the SDM

Based on the above estimations, the fixed effects Spatial Durbin Model (SDM) is identified as the optimal model for this study. The estimation results are presented in Table 8. As shown in Table 8, in the two-ways fixed effects SDM, the regression coefficient of ATL on AGD is 0.475, indicating that for every unit increase in ATL, AGD increases by 0.475 units. In contrast, the ATL coefficient in the fixed effects panel model is 0.237. This indicates that the impact of ATL on AGD is greater in the two-ways fixed effects panel model than in the spatial effects panel model. This discrepancy suggests that the two-ways fixed effects model may overestimate the positive effects of ATL on AGD when spatial factors are ignored. Furthermore, the spillover coefficient (ρ) is positive and significant, indicating that AGD in one region has a positive spatial spillover effect on AGD in neighboring regions.

Due to the presence of spatial spillover effects, the coefficient of ATL cannot be interpreted as the marginal effect on AGD in a straightforward manner. Therefore, it is necessary to decompose the estimated results to more accurately reveal both the direct (local) and indirect (spatial spillover) effects of ATL on AGD. The results of the spatial effects decomposition are presented in Table 9.

Regarding the direct effects, the direct (local) effect of ATL on AGD is estimated at 0.471 ($P < 0.05$). This suggests that for every unit increase in a region's ATL level, the level of AGD in that region improves by 0.471 units. In terms of indirect (spillover) effects, the indirect effect of ATL on AGD is 0.245 ($P < 0.05$), as

TABLE 9 Decomposition results of spatial effects.

Variables	ATL_{it}	Fsa_{it}	Ins_{it}	Huc_{it}	$IGDP_{it}$	Ais_{it}	Urb_{it}
Direct effect	0.471** (3.056)	1.215* (2.016)	0.016* (2.118)	0.095** (3.187)	0.193** (2.914)	0.021** (2.587)	−0.246** (−2.653)
Indirect effect	0.245** (3.125)	0.055 (1.027)	0.003 (0.735)	0.011* (2.295)	0.016** (3.021)	0.010* (2.769)	−0.021** (−3.191)
Total effect	0.716* (2.159)	1.270* (1.986)	0.019* (1.992)	0.106* (2.131)	0.209** (3.125)	0.031** (2.860)	−0.267** (-2.983)

** and * represent $P < 0.05$ and $P < 0.1$ respectively, and the t-value is in parentheses.

TABLE 10 Estimates for different regions.

Variable	Eastern area	Central area	Western area	Variable	Eastern area	Central area	Western area
ATL_{it}	0.466** (2.738)	0.524** (3.153)	0.480** (3.074)	$W*ATL_{it}$	0.332* (2.154)	0.362* (1.971)	0.277* (2.041)
Fsa_{it}	1.262* (2.003)	1.231* (1.995)	1.339* (2.421)	$W*Fsa_{it}$	0.063 (0.874)	0.043 (1.615)	0.105 (1.241)
Ins_{it}	0.016* (1.984)	0.033* (2.068)	0.036* (2.241)	$W*Ins_{it}$	0.132 (1.030)	0.081 (1.287)	0.039 (1.144)
Huc_{it}	0.181** (3.154)	0.149** (3.086)	0.164 (1.663)	$W*Huc_{it}$	0.281* (2.116)	0.149* (2.089)	0.141 (1.093)
$IGDP_{it}$	0.232* (2.132)	0.215** (3.221)	0.109** (3.042)	$W*IGDP_{it}$	0.081* (2.276)	0.073** (2.901)	0.109* (2.324)
Ais_{it}	0.072* (2.415)	0.015** (3.064)	0.009* (2.255)	$W*Ais_{it}$	0.102* (2.098)	0.015* (2.917)	0.009 (0.982)
Urb_{it}	−0.332* (-2.132)	−0.215** (-2.875)	−0.209** (-2.691)	$W*Urb_{it}$	−0.053* (-2.132)	−0.103** (-3.210)	−0.096** (-2.943)
$Adj\ R^2$	0.8984	0.8473	0.8265	ρ	0.221** (2.841)	0.287** (2.605)	0.185** (2.675)
$LogL$	163.622	185.732	149.736				

** and * represent $P < 0.05$ and $P < 0.1$ respectively, and the t-value is in parentheses.

shown in Table 9. This finding indicates that a one-unit increase in ATL in a given region results in a 0.245 unit increase in AGD in neighboring regions.

As agricultural tourism infrastructure continues to develop and differentiated business models are implemented, regions that are first to overcome transformation challenges and bottlenecks are more likely to attract consumer preference. These regions thus draw more consumers, both locally and from surrounding areas, creating new consumption growth centers and demonstration effects (Madaleno et al., 2019). In response to competitive pressures, neighboring regions are likely to leverage their local tourism resources to develop unique business models. Thus, the integration of agriculture and tourism in one region not only directly stimulates the development of rural industries within that region but also promotes innovation and catch-up in neighboring areas. The integration of agriculture and tourism drives the upgrading of agricultural structures and the transformation of economic development models within a region (Zhong et al., 2022). This transformation impacts labor distribution, agricultural industrial layouts, capital flows, and land transfer mechanisms in neighboring areas, improving ecological environmental protection and agricultural development. In turn, this fosters AGD. Additionally, the development of ATL encourages the spatial diffusion of tourism flows and production innovation, thereby advancing the integration of agriculture and tourism in neighboring regions.

4.2.3 Analysis of spillover effects in different regions

Given the potential regional differences in the impact of ATL on AGD, this study further divides the research area into eastern, central, and western regions for analysis. The Spatial Durbin Model (SDM) with two-ways fixed effects was employed for estimation, and the results are presented in Table 10. The analysis shows that the estimation results for the eastern, central, and western regions are generally consistent with those for the full sample: both the direct (local) effects and spatial spillover effects are significant. This indicates that the findings from the overall analysis are relatively robust.

TABLE 11 Decomposition results of spatial effects in different regions.

Variables	Eastern area	Central area	Western area
Direct effect	0.451**(2.975)	0.513**(2.997)	0.465**(3.091)
Indirect effect	0.335**(3.031)	0.291**(3.115)	0.226**(2.606)
Total effect	0.786**(2.786)	0.804**(3.113)	0.691**(2.867)

** represents $P < 0.05$, and the t-value is in parentheses.

At the same time, considering the direct (local) effect of ATL on AGD and the spatial spillover effect, the difference of spillover effect between different regions was analyzed. The decomposition results of spatial effects are shown in Table 11. The direct (local) effect in the central and western regions is greater than that in the eastern region, and the direct (local) effect in the central region is the strongest. This result may be due to the fact that the central region has a good resource base for the integration of agriculture and tourism, but its AGD level is not so high, as shown in Figure 3. Therefore, the marginal effect of the integrated development of agriculture and tourism on the green development of agriculture is more prominent. In terms of spatial spillover effect, the spillover effect (regression coefficient 0.335, $P < 0.05$) of ATL on improving AGD in eastern China was greater than that in central and western China. This is mainly due to the economic foundation and infrastructure conditions, the tourism flow, information flow and factor flow in the eastern region can operate conveniently and

TABLE 12 Non-linear test results of the panel smooth transformation model.

Model	Number of positional parameters	H_0: $r = 0$; H_1: $r = 1$		H_0: $r = 1$; H_1: $r = 2$	
		LM	LM_F	LM	LM_F
Model 5	$m = 1$	19.471***	6.839**	6.914	1.642
	$m = 2$	24.404***	4.004**	4.532	0.994
Model 6	$m = 1$	14.728**	5.569**	5.674	0.585
	$m = 2$	21.303**	6.045**	6.343	0.711
Model 7	$m = 1$	15.831***	4.976**	4.056	0.899
	$m = 2$	20.882***	4.085*	3.880	0.512
Model 8	$m = 1$	13.654***	6.176**	3.154	0.765
	$m = 2$	19.764***	4.543*	3.543	0.438

***, **, and * represent $P < 0.01$, $P < 0.05$, and $P < 0.1$ respectively.

efficiently. Therefore, the spillover effect in the eastern region is more prominent.

4.3 Non-linear effect estimation results and analysis

With ATL as the transformation variable, Model 5 to Model 8 were constructed for the whole region, the eastern region, the central region and the western region to test whether there were differences in the influence of the integration level of agriculture and tourism on the improvement of AGD in different regions. Non-linear tests were performed on the models before model estimation (Table 12). When the number of positional parameters $m = 1$ and $m = 2$, all models rejected the null hypothesis that $r = 0$, indicating that the constructed non-linear relationship model was reasonable. According to the principle of panel smooth transfer model, the number of model conversion functions can be obtained as 1, that is, $r = 1$.

Secondly, the conversion mechanism and the number of optimal positional parameters were selected according to AIC and BIC criteria (González et al., 2017). In each model, the number of positional parameters corresponding to the minimum AIC and BIC values is the ideal number of positional parameters. It is verified that the number of positional parameters of each model is 1. On the basis of the above tests, the results of model estimation combined with the data of various provinces over the years are shown in Table 13.

First, for the whole study area, when the conversion function $g(\mathrm{ATL}_{it}; r, c) = 0$, the coefficient of the integrated development of agriculture and tourism is 0.065 (β_{01}), indicating a low-mechanism state. When the conversion function $g(\mathrm{ATL}_{it}; r, c) = 1$, the impact of ATL rises to 0.441 ($\beta_{01} + \beta_{11}$), signifying a high-mechanism state. The influence of this integration on AGD transitions smoothly between these two mechanisms, with a threshold value of 0.723 ($e^{-0.318}$) demarcating the shift from low to high mechanism. As the integration level changes, the effect on AGD gradually increases from 0.065 to 0.441, suggesting that the integration of agriculture and tourism not only contributes to AGD improvement but also enhances its impact as the level of integration increases.

Analyzing the trend in AGD from 2011 to 2021, growth was relatively slow from 2011 to 2013, followed by an acceleration of growth after 2014. Although China had already proposed the vigorous development of rural tourism in 2010, early efforts primarily focused on the simple "farmhouse music" model, resulting in a relatively low level of integration. When the integration level of agriculture and tourism is low, the ecological premium of agriculture is not fully utilized, and agricultural producers pay more attention to the increase of output, and seldom consider the environmental pollution caused by agricultural production and the conscious reduction of the input of harmful environmental factors such as pesticides and fertilizers.

However, as leisure agriculture and rural tourism began to play a more significant role in integrating agricultural functions and rural industries, policy support for industrial integration was significantly strengthened, ATL improved as a result, highlighting its role in promoting AGD. In 2014, eight provinces surpassed the threshold value of 0.730, while by 2019, 18 provinces had crossed this threshold. This trend confirms that ATL has a non-linear effect on AGD improvement: as the level of integration increases, its effect on AGD becomes more pronounced. When the level of agro-tourism integration is high and agro-ecological resources can create more ecological value, agricultural producers will take the initiative to reduce the input of harmful environmental factors in agricultural production, so as to make agro-tourism integration develop in a sustainable direction.

Second, from a regional perspective, in the eastern region, once the level of ATL surpasses the threshold value of 0.693 ($e^{-0.366}$), its impact on AGD steadily increases. Both the linear and non-linear coefficients for the influence of ATL on AGD in this region exceed the national average. This can be attributed to the favorable natural resources and climate conditions in the east, as well as a strong demand for tourism, which stimulates the integrated development of agriculture and tourism. As integration levels rise, the agricultural ecological value becomes more apparent, encouraging agricultural producers to focus on sustainable agricultural practices. This heightened ecological awareness leads to a stronger emphasis on agricultural ecology and a more sustainable development approach, thereby improving AGD. Hence, the effect of ATL on AGD in the eastern region is more substantial than the national average.

In contrast, the western region has the highest threshold, suggesting that overcoming this threshold is more challenging compared to other regions. In this region, only when the threshold value of 0.730 ($e^{-0.314}$) is surpassed does the integration of agriculture and tourism begin to positively influence AGD. This can be explained by the weaker economic foundation and limited access to advanced agricultural technologies in many western provinces. Additionally, the natural resource and climatic conditions in this region are less conducive to the widespread development of agricultural tourism. Consequently, during the early stages of integration, the effect of ATL on AGD is minimal. However, once the threshold value of 0.730 is exceeded, the creation of agro-ecological capital generates more ecological value, prompting agricultural producers to prioritize sustainable development.

TABLE 13 Estimated results of panel smooth transformation model.

	Coefficient	Model 5	Model 6	Model 7	Model 8
Slope parameter	r	1.432	2.769	3.236	3.586
Location parameter	c	−0.318	−0.366	−0.335	−0.314
Linear part coefficient	β_{01}	0.065***	0.072***	0.074***	0.055
	β_{02}	0.110***	0.175***	0.032**	0.072**
	β_{03}	0.003**	0.004**	0.004**	0.002
	β_{04}	0.026*	0.021	0.019**	0.020
	β_{05}	0.052**	0.089**	0.023	0.024
	β_{06}	0.001	0.003	0.002	0.001
	β_{07}	−0.165**	−0.209**	−0.085	−0.089
Non-linear part coefficient	β_{11}	0.376**	0.393**	0.265**	0.236**
	β_{12}	1.191***	0.999**	1.120**	1.035**
	β_{13}	0.024**	0.015	0.005	0.031
	β_{14}	0.139**	0.157**	0.135**	0.111
	β_{15}	0.154**	0.143**	0.185**	0.105**
	β_{16}	0.004***	0.005	0.002	0.002
	β_{17}	−0.318***	−0.353***	−0.299***	−0.275***
Composite coefficient	$\beta_{01}+\beta_{11}$	0.441	0.465	0.339	0.291
	$\beta_{02}+\beta_{12}$	1.301	1.174	1.152	1.107
	$\beta_{03}+\beta_{13}$	0.027	0.019	0.009	0.033
	$\beta_{04}+\beta_{14}$	0.165	0.178	0.154	0.131
	$\beta_{05}+\beta_{15}$	0.206	0.232	0.208	0.129
	$\beta_{06}+\beta_{16}$	0.005	0.008	0.004	0.003
	$\beta_{07}+\beta_{17}$	−0.483	−0.562	−0.384	−0.386

***, **, and * represent $P < 0.01$, $P < 0.05$, and $P < 0.1$ respectively.

As harmful environmental inputs are reduced and agricultural practices become more eco-friendly, AGD begins to improve, and the positive effect of ATL on AGD becomes more significant.

5 Conclusions, limitations, and policy recommendations

5.1 Conclusions

Based on panel data from 30 provinces in China from 2011 to 2022, this study employed fixed effects models, SDM and PSTR model to explore the impact of the integration of agriculture and tourism on agriculture green development (AGD) and its spatial spillover effects and non-linear characteristics. The key findings are as follows:

(1) Over the study period, both agriculture and tourism integration and agricultural green development levels exhibited steady increases, with average annual growth rates of 3.823% and 2.144%, respectively. Overall, agricultural green development and ATL levels in the eastern region were found to be higher than in the central and western regions.

(2) Agriculture and tourism integration has a significant positive effect on agricultural green development. This conclusion is consistent with that of Jiang (2022). Rooted in ecological sustainability and supported by agriculture and rural areas, this integration promotes agricultural intensification and environmentally friendly production management, which in turn contributes to the advancement of agriculture green development.

(3) The impact of agriculture and tourism integration on agricultural green development reveals substantial spillover effects. The agriculture and tourism integration coefficient in the fixed effects model is higher than that in the spatial effects model, suggesting that neglecting spatial spillover effects may lead to an overestimation of the positive impact of agriculture and tourism integration. The estimation results across the eastern, central, and western regions align with those for the entire study area: agriculture and tourism integration has both direct (local) and spatial spillover effects on agricultural green development. Notably, the direct effects are stronger in the central and western regions, while the spillover effects are more pronounced in the eastern region.

(4) The relationship between agriculture and tourism integration and agricultural green development is non-linear, with a single threshold value identified in the whole region and across the three regions. This conclusion is different from the study of Wang et al. (2024a,b), whose study showed a double threshold effect of agriculture and tourism integration on agricultural eco-efficiency, and this difference may be due to the different scale of the study area. When agriculture and tourism integration exceeds this threshold in the study area, the regression coefficient for agriculture and tourism integration increases, indicating that higher levels of integration positively influence agricultural green development. Among the three regions, the eastern region has the lowest threshold value, whereas the western region has the highest. In western China, the effect of agriculture and tourism integration on agricultural green development does not pass the significance test until it crosses this threshold. This finding suggests that enhancing the integration of agriculture and tourism is key to fully leveraging its potential to promote green agricultural development.

5.2 Limitations

Although this paper demonstrates the impact of the integration of agriculture and tourism on the green development of agriculture through quantitative models, and analyzes its non-linear characteristics and spillover effects, it still has the following shortcomings: First, although the impact mechanism is theoretically analyzed in this paper, the empirical test of the mechanism is not carried out, and the impact mechanism can be further tested through empirical analysis in the future; Second, limited to the availability of data, this paper uses provincial panel data for research, and the spatial scale of sample measurement is large, so the accuracy of the results may be affected. In the future, the quantitative analysis can be carried out through smaller scale sample data such as municipal panel data.

5.3 Policy recommendations

The findings of this study provide valuable insights for promoting the integration of agriculture and tourism and maximizing its role in fostering agriculture green development:

(1) Optimize and Improve Policy Framework and Strategic Design

The integration of agriculture and tourism needs strong support and scientific planning from the government. It is important to coordinate short-term planning and long-term planning while scientifically evaluating the development potential of the integration of agriculture and tourism and the environmental carrying capacity of each region. This ensures the rationality and feasibility of the project development. The integrated development of agriculture and tourism in different regions should give full play to local resource endowments and actively explore an integrated development model based on ecological protection such as sustainable use of mountains, rivers and lakes.

To play a leading role, the government should focus on expanding the depth and breadth of the agricultural value chain and building a modern agricultural industrial system. At the same time, the government should increase financial investment in the project of integrating agriculture and tourism, and ensure that the funds are used for infrastructure construction, environmental improvement, cultural excavation and inheritance. By setting up special funds or providing financial subsidies, the investment threshold and risk of agricultural and tourism integration projects will be reduced. Enterprises and individuals engaged in agricultural and tourism integration projects will be given tax incentives to reduce operating costs and improve profitability. In addition, it is necessary to establish a scientific and reasonable performance evaluation index system to comprehensively evaluate the economic benefits, social benefits and ecological benefits of agricultural and tourism integration projects to ensure the sustainable development of industrial integration.

(2) Promote Regional Coordination Mechanisms for Development

On the first hand, the government should introduce relevant policies to encourage and support cross-regional cooperation on the integration of agriculture and tourism, such as providing tax incentives, financial support and land policy inclining, so as to reduce cooperation costs and improve cooperation benefits. Establish a cross-regional coordination organization for the integration of agriculture and tourism, which is responsible for overall planning and coordinating resources of all parties, and solve the problems of cross-responsibility and poor coordination among departments. On the other hand, increase the investment in trans-regional transport infrastructure, improve the capacity and comfort of roads, and ensure that tourists can easily reach each rural and tourism integration area. Meanwhile, we should integrate agricultural resources in different regions through cross-regional cooperation to form scale effects and complementary advantages.

(3) Strengthen and Prioritize Human Capital Development

Advancing the integration of agriculture and tourism requires the support of a highly skilled workforce. Policies and initiatives should be designed to attract and nurture talent in line with the specific needs of agriculture and tourism integration and industrial development. Special attention should be given to developing foundational technical skills, as well as middle- and senior-level management and operational expertise. In addition, rural vocational and technical education should be strengthened to improve agricultural techniques and enhance the professional skills of local workers, thereby elevating the quality of rural tourism services.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CC: Conceptualization, Data curation, Investigation, Software, Writing – original draft. JW: Formal analysis, Project administration, Supervision, Writing – review & editing. WJ: Conceptualization, Formal analysis, Investigation, Supervision, Validation, Writing – original draft. AX: Resources, Software, Validation, Visualization, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Agrifood systems' resilience for sustainable food security amid geopolitical tensions: a systematic literature review

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Introduction: This study examines the resilience of the agrifood systems amid geopolitical tensions with a primary focus on the Ukraine-Russia war and its increased effects on global food security, climate change, and post-pandemic recovery. The study explores different resilience elements, scenarios, and behaviors of agrifood systems, highlighting how geopolitical conflicts disrupt resource availability and economic stability. Further, it explores the existing Resource Nexus and its influence on sustainable food and nutrition security amid geopolitical tension. Much research focuses on agrifood systems' resilience in the context of climate change and pandemics, repeatedly overlooking the impacts of geopolitical tensions and related policies enacted for sustainable food security.

Methods: Focused on geopolitical tension as an influence on food security, 76 articles were systematically reviewed to identify key resilience elements and scenarios enacted based on countries' development, discovered major vulnerability indicators, and Resource Nexus of agrifood systems.

Results: This review leads to the identification of four key resilience scenarios of the agrifood system amid geopolitical tensions: fragility reduction, robustness building, adaptive strategies, and transformative change over time. In general, the reduction of agrifood system fragility was more prevalent compared to the other three scenarios. There was a decline in the agrifood system's performance due to the existence of some policies that increased the system's instability over time. The study further identifies that the impact of enacted resilience policies on sustainable food security is not uniform. It often influences positive or negative outcomes depending on its feedback nature at different operational levels of the agrifood system. During geopolitical tensions, food, energy, and finance are the most affected sectors, followed by other interconnected resources such as land, water, food (LWF), and water, energy, and food (WEF).

Discussion: In the presence of effective policies and scenarios, the agrifood system experiences improved resilience and sustainability that contribute to the beneficial relationship between resources, and all pillars of food security.

KEYWORDS

agrifood, resilience, resilience elements, food security, geopolitical tensions, resource nexus, sustainability, Ukraine-Russia war

1 Introduction

Sustainable food security is fulfilled when the society has physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for active and healthy life (Batt, 2024; Capone et al., 2014; Ejiohuo et al., 2024; FAO, 2023; Hasan et al., 2024; Mbow et al., 2019; Mishra, 2024; Mohamed, 2017). It is highly distressed by several factors including climate change and geopolitical tensions through disrupting the operation and processes of agrifood systems (Aminetzah et al., 2022; Murphy et al., 2023). According to Fernandois and Medel (2020), geopolitical tensions are all risks posed by tensions between states that affect a peaceful course of relations, which can be composed of threats plus realizations such as riots, wars, or terrorist acts. It imposes challenges that impact sustainable food and nutrition security and continues to expand globally, affecting production, processing, and the whole supply chain of agrifood products such as grains, oilseeds, and tea in the global market (Zhou et al., 2020; Zurek et al., 2022). This situation is weakening agrifood system resilience worldwide, hindering progress toward the UN's Sustainable Development Goals (SDGs), including SDG 1 (no poverty), SDG2 (zero hunger), and SDG 12 (responsible consumption and production) (Nguyen et al., 2023; Wudil et al., 2022). Similarly, extensive consequences of degraded agrifood system resilience are expected to worsen and deepen in the coming decades (FAO, 2022). There is a pressing need for vulnerable societies to understand what, how, and when agrifood systems resilience is important for maintaining food security in the face of geopolitical tension.

The complex nature of the effects of geopolitical tensions on food security creates confused challenges to all levels of the agrifood system operation, due to the interconnected and unequal distribution of the impacts. It influences the implementation of strategies or elements that lead to different outcomes (e.g., fragility reduction, robustness building, adaptation, and overtime transformation changes) (Nieuwborg et al., 2023; Stone and Rahimifard, 2018). The effects of the geopolitical tension on agrifood systems are also stimulated by other global challenges such as climate change and human diseases. However, very little research conducted into the resilience of the agrifood systems, our understanding of what, how, and when agrifood systems resilience policies are effective in maintaining food security is only just developing.

Addressing the gap requires investigation of the previous research on the consideration of the underlying drivers, and how they affect the agrifood system's resilience. Currently, there exists a wealth of insightful perspectives from domestic and international sources regarding the impact of geopolitical tension on food security (Ben Hassen and El Bilali, 2022; Mhlanga and Ndhlovu, 2022; Trollman et al., 2023; Xu et al., 2023) with a focus on the Russia–Ukraine conflict. The conflict between Russia and Ukraine impacted global food security through market disruption of key global commodities such as grains, oilseeds, and fertilizers (Arreyndip, 2025; Bas, 2025). Export and import bans were enacted on the world's largest food and related commodities suppliers including Russia and Ukraine (Babets et al., 2024; Tsolko, 2025), leading to inflation of food prices and increased vulnerabilities of the countries that are over-depending on the global market commodities from conflicting or other affected countries, especially developing countries. Different initiatives were introduced to reduce vulnerabilities and facilitate global food security in the most affected countries, the Black Sea Grain Initiative and the Grain From Ukraine program were expected to mitigate this global food crisis (Ivashova and Komarov, 2024; Kacperska et al., 2025; Kormych et al., 2024), but still challenges remain in securing trade routes and stabilizing agricultural production amid ongoing geopolitical conflicts (John, 2025).

While many research documents are available to provide evident trends and background of the field, most of the presented study resources are sometimes irrelevant, lack critical information, overlook targeted key policies, neglect temporal and geographical scales, and provide outdated conclusions. Nevertheless, few studies empirically assessing the link between these variables have yielded mixed results (Al-Maadid et al., 2017; Pondie et al., 2023). For instance, Zhou et al. (2020), described that food security is not negatively driven by the armed conflict only, diversified governance of agrifood systems and resources can also impact the current global food security situation. This implies that there are interactions between these long-term geopolitical conflicts and other drivers concerning food security status (Zurek et al., 2022), and it is necessary to conduct empirical research on the food system's resilience, considering both resilience policy behaviors and existing key resources.

This study employed a systematic literature review (SLR) to examine the influence of the various agrifood systems' resilience elements on sustainable food security in the context of geopolitical tensions. The SLR is a replicable and transparent research method (Harper et al., 2021), which reduces bias in addressing the challenge dynamics and is ultimately intended to improve the reliability and accuracy of conclusions. By understanding the influence of the implemented resilience elements and other food dynamics on the resilience of agrifood systems, policymakers, and practitioners can develop strategies to mitigate the risks posed by geopolitical tensions and build more sustainable food security. Eventually, this study contributes to the existing body of knowledge on the resilience and resource nexus in food systems.

2 Methodology

This paper follows the guidelines proposed by the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) which provides six steps as shown in Figure 1.

2.1 Study context identification

This stage focused on the identification of the general research idea and the objectives. The study context was identified through the existing ongoing global situation on geopolitical tension and food security. It discovered the resilience elements and policies enacted by vulnerable countries to enhance their food security and the resilience of different agrifood systems. The study used a systematic literature review extracting information from studies

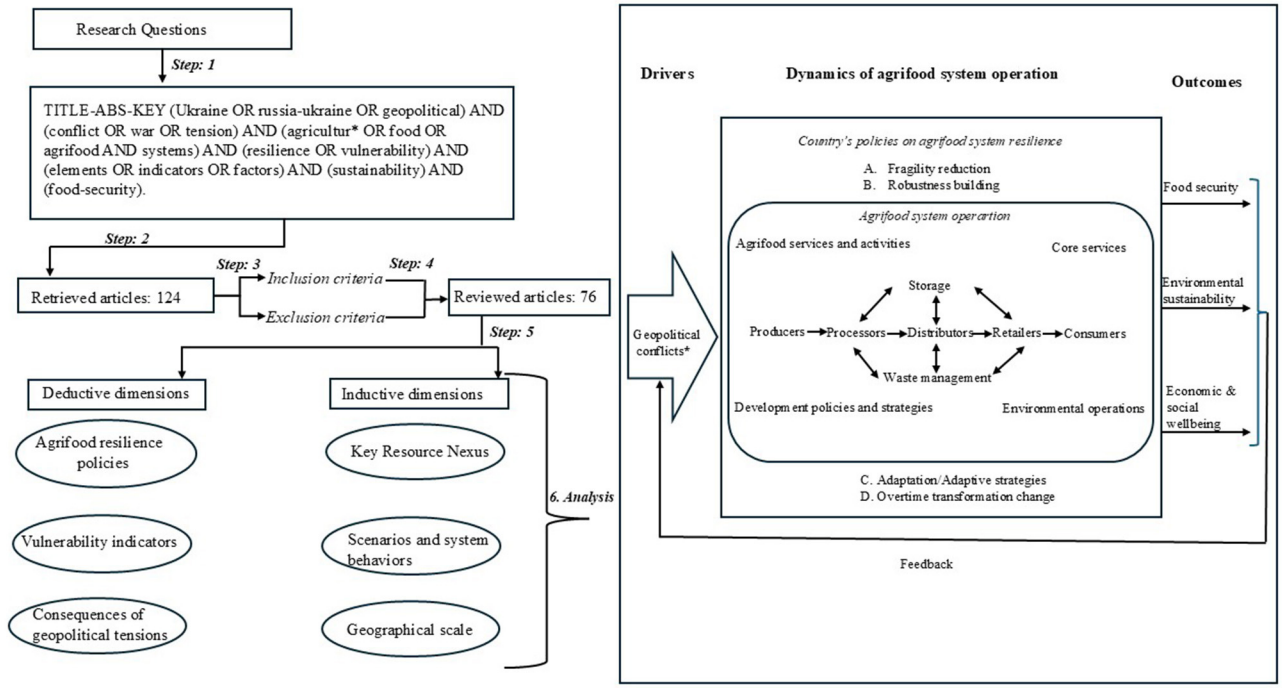


FIGURE 1
Methodology summary. This methodology facilitates the review of 76 (61.29% of the total retrieved articles) with achieved different dimensions: deductive, such as; agrifood resilience, vulnerability indicators, and consequences of the geopolitical tensions*, as well as inductive dimensions: key resource nexus, scenarios and system behaviors and geographical scale. Additionally, shows the dynamics of agrifood system operations, with the found outcomes, such as; food security, environmental sustainability, and economic and social well-being (Zurek et al., 2022).

about tensions, food security, and others related to the topic published from 2013–2023. understanding of the study's context from the identified challenge facilitates three research questions which are; (*i.*)*What are the major vulnerability indicators of the agrifood system that distress global food security in the era of geopolitical tension? (ii.) What are the key agrifood system resilience elements and how do they differ between developed and developing countries amidst geopolitical tensions? (iii.) How do geopolitical conflicts influence agrifood resilience and resource interlinkages?* Most scholars define the Agrifood system's resilience as the ability to tolerate experienced shocks and disasters and adapt to changes while maintaining its core functions (Miles and Hoy, 2023; Murphy et al., 2023).

In the context of existing conflicts, the agrifood system resilience is influenced by the diversification of the food sources and markets of the commodities, the cooperation between key stakeholders improves resilience by ensuring the continued functioning of the food supply chain (UNEP et al., 2023). These factors improve adaptability to changing situations (FAO, 2021) and reduce the vulnerability of the agrifood system to the effects of geopolitical tensions (Hobbs, 2021). Referring to Figure 1, illustrated different identified internal and external factors that affect the agrifood system's resilience mechanisms. However, the major internal drivers include agricultural practices, technology adoption, and governance structures, while external drivers encompass factors such as climate change, economic policies, pandemics, and other related geopolitical tensions. In the era of geopolitical tension, most countries introduce different policies to facilitate the performance of the agrifood systems. Implemented policies for fragility reduction, robustness-building, adaptation, and change in overtime transformation were considered in most cases.

Furthermore, the performance of the agrifood system involves a feedback system between drivers and outcomes that leads to a decision-making process, it enables the system's components to adjust and adapt to changing conditions. Therefore, it is necessary to employ resilience policies at the national and global scale to ensure the efficient operation of the agrifood system and attain satisfactory results that can address the existing challenges.

2.2 Study materials search

The searches of documents were conducted in Scopus, extracting data from 2013 to 2023. The search strategy shown in Table 1 includes the keywords that form target papers focusing on agrifood system resilience and vulnerability elements or indicators or factors for the sustainability of food security during geopolitical tension, especially the Russia-Ukraine armed conflict. Furthermore, the Scopus search retrieved 124 reports related to the search terms, including publications in different languages. The search result was limited to publications in English due to our language skills. Then, followed by the screening, duplicate removal, and reports inclusion and exclusion criteria on title and abstract publications that provide insights into the relationship

TABLE 1 Document review process.

Date	Search string	Database	Documents
August 2023	TITLE-ABS-KEY (Ukraine OR russia-ukraine OR geopolitical) AND (conflict OR war OR tension) AND (agricultur* OR food OR agrifood AND systems) AND (resilience OR vulnerability) AND (elements OR indicators OR factors) AND (sustainability) AND (food-security).	Scopus	124

between agriculture and food systems resilience and food security in the context of geopolitical tension. The criteria involve lack of clarity, language, duplicate documents, and lack of other eligibility criteria as shown in Figure 2. In this study, the PRISMA meta-analysis was employed to determine the resilience of the agrifood system amid geopolitical conflicts, it is among the most suitable methodology to ensure inclusiveness, transparency, and independence in analyzing existing research articles. By following a given structured framework to obtain suitable documents for reviewing, the study can generate realistic perceptions from the findings on the existing impacts of geopolitical conflicts on agrifood systems, ultimately supporting informed policy and sustainability strategies. The screening was narrowed to include only those available publications that addressed the resilience of agrifood systems for sustainable food security during the Russia-Ukraine conflicts. After all, 76 documents were approved for the study review.

2.3 Data extraction and content analysis

2.3.1 Resilience elements and scenarios

Data extraction and content analysis were conducted to disclose enacted agrifood system policies and elements for resilience and grouped them into different scenarios. The content analysis of the retrieved documents was performed using MAXQDA which identifies resilience elements and other useful information mentioned in each scientific publication. This is a qualitative data analysis tool that facilitates the organization, coding, and analysis of different data from mixed-method research (Kirsten et al., 2025). It analyses various types of qualitative information, including text, audio, video, images, and survey responses.The study follows system-thinking steps to discover key resilience scenarios and elements of the agrifood system by reviewing approved documents. Thereafter, each scenario is composed of various enacted resilience elements or policies effective in mitigating risks and building the resilience of the agrifood system. To assess the resilience of the agrifood system amid geopolitical conflicts, the study developed different Resilience scenarios from the combination of study findings as shown in Table 2. These scenarios were designed to capture different pathways through which agrifood systems can respond to and recover from external shocks. Three resilience categorization studies provided guidance and references. First, Nieuwborg et al. (2023) described different categories of resilience in the aviation industry during the COVID-19 pandemic. The major discovered types are fragility, robustness, adaptation, and transformation. Another framework from Hillmann and Guenther (2021) suggests categories for organizational resilience: resilience behavior, resources and capabilities, response, and organizational growth. Finally, the framework (Stone and Rahimifard, 2018) proposes redundancy, robustness, adaptability, and flexibility as the main categories of resilience in agrifood resources. The resilience categorization frameworks from these three different research studies and sectors were considered as the roadmap to show the broadest range of resilience scenarios

Four scenarios were derived from the three study frameworks consulted. The study adopted four resilience scenarios for the agrifood system in the context of geopolitical tension, guided by the following principles: fragility reduction, robustness building adaptation, and changes in overtime transformation as shown in Table 3.

These scenarios were based on the intentions of different countries they want to achieve after implementing different policies to address the effects of geopolitical conflicts on the global market trend of the agrifood key commodities for food security.

2.3.2 Geopolitical tension consequences analysis

This study employed a PESTEL breakdown on the consequences of geopolitical tensions in the agrifood system. It stands for Political, Economic, Social, Technological, Environmental, and Legal factors. Moreover, this framework provides a wide range and regular approach to studying the different external factors that influence agrifood system resilience amid geopolitical conflicts. Given that agrifood systems are governed by multiple archetypes represented by political, economic, social, technological, environmental, and legal dimensions, PESTEL allows for a holistic evaluation of how these factors interact and contribute to vulnerabilities or resilience policies, strategies, and plans. This study explored major vulnerability indicators of agrifood systems that affect food security in geopolitical tension. These indicators were associated with the four identified pillars of food security which are availability, accessibility, stability, and utilization (FAO, 2022).

2.3.3 Resource nexus concept

All Resource Nexus systems were qualitatively developed to model and explore interactions across and between sectors. Four research studies were used to generate the Matrix that described and evaluated the direct and indirect resource nexus effects in response to geopolitical tension. The first study by Brouwer et al. (2024) provided a background on the Resource Nexus concept. Moreover, it described the Resource Nexus as the interlinkages and interdependencies between the environmental resources. Besides, the study mapped different environmental resources in a Resource Nexus approach, where Water, Biota, Climate, Space, Material, and Soil were identified as key resources. In addition, Food, Sea, Waste, Energy, and Land were identified as other important resources derived from these key environmental resources. Apart from that, Hoff (2011) developed a resource nexus model to help find the optimal combinations of WEF (Water-Energy-Food) nexus system policy options and parameters that lead to the system's best

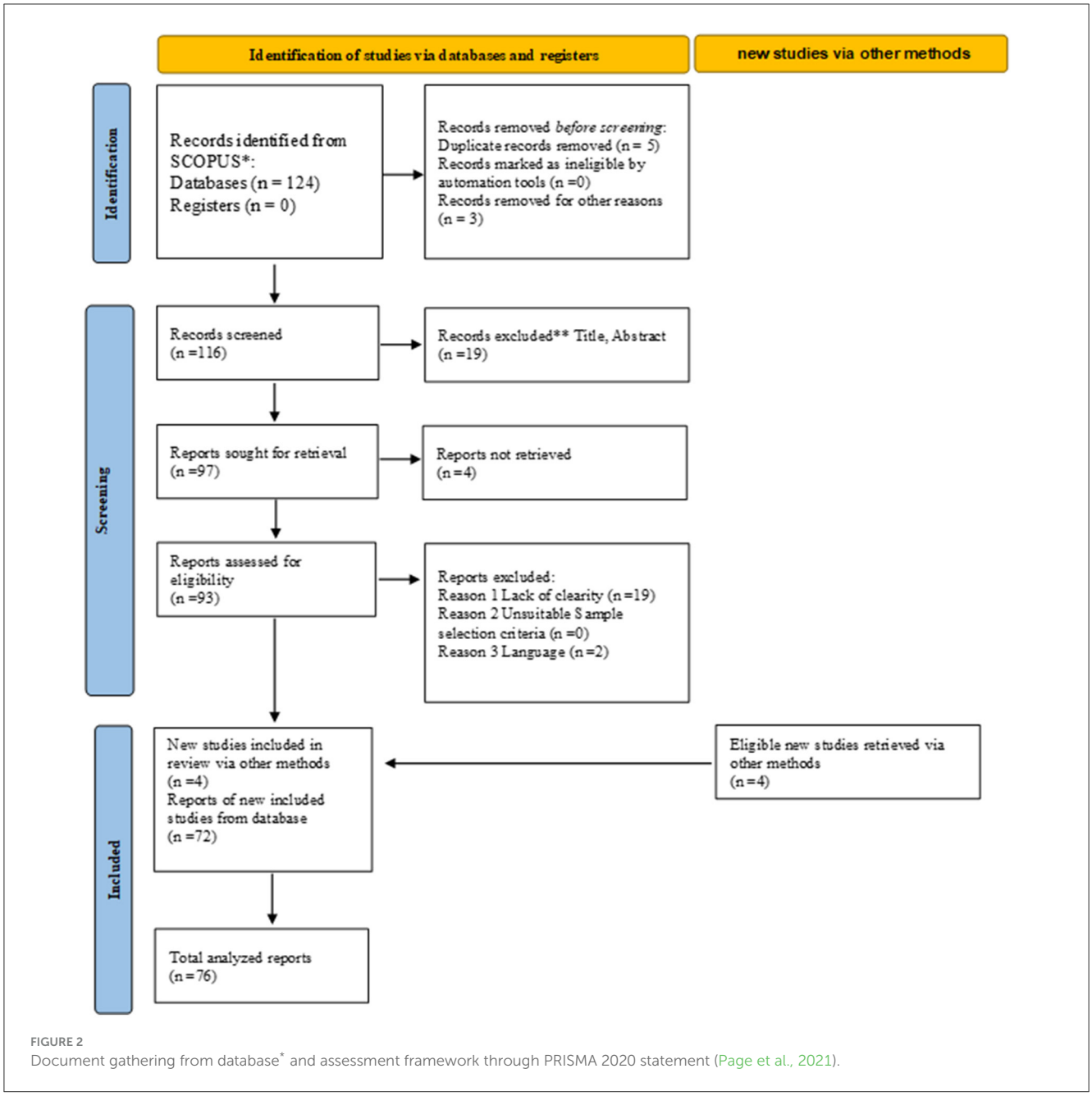


FIGURE 2
Document gathering from database* and assessment framework through PRISMA 2020 statement (Page et al., 2021).

TABLE 2 Development of study's resilience scenarios from previous studies.

Targeted theme	Resilience aspects/scenarios				References
Organizational resilience	Resilience behavior, resources, and capabilities		Response	Organizational growth	Hillmann and Guenther, 2021
Agrifood resources resilience	Redundancy	Robust	Adaptive	Flexibility	Stone and Rahimifard, 2018
Aviation industry amid COVID-19 pandemic	Fragility	Robustness	Adaptation	Transformation	Nieuwborg et al., 2023
Agrifood system amid geopolitical tension	Fragility Reduction	Robustness Building	Adaptation/Adaptive Strategies	Overtime transformation Changes	Study's system thinking

TABLE 3 Agrifood system resilience elements categorization check and boundaries.

Resilience scenario	Elements categorization check	Boundaries
Fragility reduction	Does the proposed resilience policy or element address immediate risks?	- Reduce current vulnerabilities to prevent system collapse. - Address short-term food security and supply chain risks. - Involves reactive policies or interventions rather than proactive adjustments. - Either mentioned or discussed in the reviewed reports as a fragility reduction element.
Robustness building	Does it reinforce the immediate stability and productivity of the agrifood system?	- Maintain current productivity and stability during a crisis. - Focuses on hard infrastructures technological solutions and inputs. - Prevent immediate disruptions but does not involve long-term system shifts - Either mentioned or discussed in the reviewed reports to build the robustness of the system.
Adaptative strategies	Does it implicate flexible, short-to-medium-term adjustments of the agrifood system?	- Focuses on flexibility and learning-based responses to evolving crises. - Involves short-term to medium-term adjustments that help cope with uncertainties - Encourage diversification and innovation to adapt to new conditions. - Either mentioned or discussed in the reviewed reports contributing to the adaptive system.
Overtime transformational changes	Does the implemented policy or element drive the long-term structural transformation of the agrifood system?	- Focuses on structural reforms and paradigm shifts in the agrifood systems. - Involves long-term policy changes, institutional reforms, and social restructuring. - Aims at building a resilient, sustainable, and equitable agrifood system. - Either mentioned or discussed in the reviewed reports as transformative changes element.

performance. Other scholars describe a framework for integrating the quantitative WEF nexus simulation model with an optimization tool, which gives policymakers the ability to negotiate the best policy options based on the WEF nexus simulator (Karnib, 2017). Then Karthe et al. (2021) provided Resource Nexus's understanding of the sustainable recovery of tourism amid COVID-19 where they highlighted that Resource Nexus can serve as a paradigm for promoting tourist sustainability. Moreover, instead of focusing on a single dimension, the study examines environmental resources holistically, considering possible synergies and trade-offs between different sustainable development goals (SDGs) as indicated in Table 4. Other insights acquired from Khairulbahri (2022), using the system archetypes the study proposes a qualitative analysis of the nexus dynamics in the Pekalongan coastal area, Indonesia. This study helped us integrate specific resilience elements into the renowned and less recognized nexus elements of the agrifood system during geopolitical tension. The resource nexus modeling ideas from these four different research studies were considered as guidance to show the general concept of resilience and resource nexus in agrifood systems. The study adopted and described the four most mentioned resource nexus resilience scenarios in the agrifood system in the context of geopolitical tension.

2.4 Results presentation

This study developed different data presentations based on a proposed research question. Results were presented based on the identified major consequences of geopolitical tensions on agrifood systems following the PESTEL breakdown arrangement. Also, through a literature review, the study identified the major agrifood system vulnerability indicators that affect global food security in the era of geopolitical conflicts. Moreover, it explores the possible interrelation of the agrifood system's resilient elements and resources. Finally, it presents different implemented agrifood systems resilience elements based on context-sensitive perspectives with a specific focus on; the occurrence of the resilience elements based on the specific scenarios and country development.

TABLE 4 Sustainable development goals and their meanings.

Sustainable development goals (SDGs)
SDG1: End poverty
SDG2: End hunger, achieve food security
SDG3: Ensure healthy lives and promote wellbeing for all at all age
SDG4: Ensure inclusive and equitable quality education
SDG5: Achieve gender equality and empower all women and girls
SDG6: Ensure availability and sustainable management of water
SDG7: Ensure access to affordable, reliable, sustainable, and modern energy
SDG8: Promote sustained, inclusive, and sustainable economic growth
SDG9: Build resilient infrastructure, promote inclusive and sustainable industrialization
SDG10: Reduce inequality within and among countries
SDG11: Make cities and human settlements inclusive, safe, resilient, and sustainable
SDG12: Ensure sustainable consumption and production patterns
SDG13: Take urgent action to combat climate change and its impacts
SDG14: Conserve and sustainably use the oceans, seas, and marine resources
SDG15: Protect, restore, and promote sustainable use of terrestrial ecosystems
SDG16: Promote peaceful and inclusive societies for sustainable development
SDG17: Strengthen the means of implementation and revitalize the global partnership

Source: United Nations (2024).

3 Results

3.1 Summary list of resilience elements from the review

The selected 76 papers were retrieved from 39 different sources, including articles, books, reviews, and conference papers. It covered documents published from 2013 to 2023. The largest number

of documents was published on topics such as *Sustainable Food Systems (8) Sustainability (8), Food Security (4), Agriculture and Resources Economics (3), and other sources related to policies on Marine, Land use, Nature, and Resources(2), and 1 document from the environment, Global Change, and Circular Economy*. The reviewed publications include papers that shed light on agrifood systems resilience categorization, food, health, and environment security in the context of geopolitical tensions, especially in African and Middle Eastern countries. The sustainable food systems governance on interdisciplinary viewpoints, and highlights sustainability and supply chain management. Publications cover four continents (America, Europe, Asia, and Africa), with more articles from America. Dominant Corresponding Author's Countries are USA (29), Australia (22), UK (22), China (18), Ukraine (13), Germany (10), and other <10 from South Africa, India, and Italy.

A summary of the resilience elements discovered in our review is presented in Table 5. From the systematic literature reviews, we extracted thirty-three (33) resilience elements that were implemented in agrifood systems during the era of Russia-Ukraine geopolitical conflict. The resilience elements refer to coping strategies or policies that individuals or systems use to manage crises, difficulties, and urgency (Rutter, 2012). There were four resilience scenarios or aspects or categories adopted from the studies of Hillmann and Guenther (2021), Stone and Rahimifard (2018), and Nieuwborg et al. (2023) in which the elements were grouped: fragility reduction, robustness building, adaptation or adaptive strategies, and overtime transformational change.

3.2 Geopolitical tension consequences influencing agrifood systems change: a PESTEL breakdown

The study has identified various outcomes influenced by geopolitical conflicts that affect the resilience of the agrifood system. The key influencing factors reflect the PESTEL approach, which includes Political, Economic, Societal, Environmental, and Legal/Regulatory consequences referring to Figure 3. The study revealed that geopolitical conflicts between parties significantly impact the agri-food system. It has identified 24 specific consequences (Figure 3) affecting it. Considering its nature and particular sector of influence, these consequences are fitted into a specific PESTEL category. The economic category is the most dominant, comprising 41% of all identified consequences, including instability of agrifood systems, which is affected by trade disruptions and market shocks, which were the most observed factors, causing food fraud and difficulties in investment flows. However, 31% of the observed consequences are related to societal aspects like food insecurity, and humanitarian-related disasters. Moreover, 16% of the environmental consequences include the devastation of the environmental infrastructures, natural resources, and biodiversity. The political, technological, and legal/regulatory categories were less affected by 7, 3, and 2% respectively. Factors such as the destruction of foreign relations, diplomatic strategies, government policies, and international partnerships drastically impact the agrifood system.

3.3 Major agrifood system vulnerability indicators and global food security in the era of geopolitical conflicts

During geopolitical conflicts, agrifood systems were experiencing challenges in managing sustainable food security. Based on the total number of word occurrences in the evaluated studies, Food availability was mentioned as the most vulnerable aspect of the system. It is affected by two major factors, including the country's reliance on global commodities importation (grains and energy products) from conflicting parties which was mentioned 28 times. Also, the dependence of global economic development on the trade of grains and energy products from the conflicting countries was mentioned 24 times. Apart from that, the increased trend of income consumers spending mentioned on food 19 times as among food security vulnerability indicators, it was highly associated with reduced food utilization, especially in developing countries. Besides, the influence of economic and political instabilities of countries was mentioned 16 times as the vulnerability indicator for food accessibility. Finally, referring to Figure 4 food instability was detected as the least affected pillar of food security.

3.4 Implementing resilience elements in agrifood systems: context-sensitive perspectives

3.4.1 Resilience elements based on specific scenarios

One of the studies revealed that 33 different elements significantly influence the resilience of the agrifood systems during geopolitical tensions (Figure 5 and Table 5). These elements were systematically aligned into four categories/scenarios, including fragility reduction, robustness building, adaptation/adaptive strategies, and overtime transformation changes. These scenarios were then reflected as the outcomes of implementing certain policies over a specific period.

Furthermore, the scenario that proposed to reduce the fragility of the agrifood systems was identified as the most dominant and commonly experienced by 45% in the era of geopolitical conflicts. It is composed of 15 resilience elements, comprising the implementation of export and export restrictions to some countries to protect and govern the sustainability of the local producers, to cope with increased tariffs and quotas in other countries leveraging processed food products. Then followed by 24% of adaptive strategies were dominated by elements that focused on modifying the agrifood system and making it resilient to the consequences of geopolitical tensions. It is made of various elements like food testing, traceability, and statistical reporting, also implementations of research and technologies innovation, regional farmers/producers' cooperation, capacity building, crop substitution, as well as subsidies, intensive modernization, and mechanization. Whereas 15% of the overtime transformation changes scenario is composed of 5 resilience elements including agrifood systems governance and policy reforms, Conflict Resolution, Social safety net/access to resources,

Resilience scenario	Elements/Strategies	Occurrence	Category	Descriptions	References
Fragility reduction	Trade Restrictions	72	Economic	To protect domestic consumers and global food security from the effects of tensions between countries i.e. Russia-Ukraine conflict, most countries such as the European Union, the United States, and their allies-imposed trade restrictions such as import and export bans on Russia.	Hellegers, 2022
	Economic sanctions	61	Economic	The International Food Policy Research Institute recommends that both the sanctions on Russia and export restrictions to protect domestic consumers be designed to protect global food security and that consequences for third parties be assessed.	Hellegers, 2022
	Over-reliance global commodities	18	Economic	Very few African countries produce fertilizers in a minimally significant amount, they mostly depend on imports for this commodity, thus making local prices very respondent to variations in international prices.	Rogna, 2023
	Tariffs and Quotas	17	Economic	To reduce the fragility of their food systems and maintain food availability, some countries introduced tariffs and quotas, and others are categorically against tariffs, considering them an obstacle for local agricultural producers on the way to fulfilling international obligations.	Rudyk et al., 2023
	Storage and stockpiling	16	Societal	To counter food insecurity, the establishment of an independent global buffer stock to create a food reserve has been proposed, but there are numerous obstacles to practical implementation, especially in the identification of appropriate price triggers.	Trollman et al., 2023
	Market diversification	13	Economic	To minimize the global impact of the food crisis, it is important to diversify the domestic and international markets of the highly demanded food crops.	Neik et al., 2023
	Change food pattern/food assistance	12	Societal	As food prices rise, households shift their diets toward staple grains that become more dominant, while consumption of more micronutrient-dense animal-source foods, fruits, and vegetables declines. This is likely to result in child stunting, which can often lead to lifelong costs to the child and the economy.	Dyson et al., 2023
	Domestic and Regional Markets	10	Economic	As a result, some countries like Turkey are expected to mitigate the food crisis through a range of measures focusing on domestic markets, e.g., increasing domestic production, export bans, and aid to vulnerable groups, including the large population of Syrian migrants.	Al-Saidi, 2023
	Flexible Supply chain and Collaboration	10	Economic	The government's interest in private entities' supply chains increased by creating a risk management culture through a contractual agreement between a public agency and a private sector entity to market trend information, skills and assets, risks, and rewards to deliver services or facilities to the public.	Tukamuhabwa et al., 2017
	Leveraging Processed food products	8	Technological	When food prices rise, people reduce their consumption of more expensive nutritious foods, such as fruits, vegetables, meat, and dairy. And they maintain calorie consumption by buying more processed foods or cheap staple foods.	Xu et al., 2023
	Diverse Local food agricultural production	6	Environmental	Most of the developing countries are trying to produce various products as an alternative to reduce reliance on specific products and suppliers.	Tukamuhabwa et al., 2017
	Cross-border lending	6	Economic	The financial capacity of countries to protect themselves against such global threats as the war in Ukraine remains rather limited, thus, making them highly vulnerable and borrowing from other foreign countries.	Pryiatelchuk and Novak, 2022
	Diverse food sources/dependence on imported global commodities.	4	Environmental	To minimize the global impact of the food crisis, it is important to diversify the import/export sources of food crops.	Karoliina et al., 2023; Neik et al., 2023

(Continued)

TABLE 5 (Continued)

Resilience scenario	Elements/Strategies	Occurrence	Category	Descriptions	References
	Early warning systems/risk management	2	Technological	Governments develop and put in action preparedness plans (e.g., including critical data sharing among different ministries) for food safety incidents and natural disasters.	Galanakis, 2023
	International Companies negotiations	1	Political	Most of the food companies in Ukraine are now in the third round of negotiations with suppliers and retailers for the fourth wave of price increases which will further affect consumer behavior on food expenditures.	Mukhtar, 2023
Robustness building	Food/inputs price management (Negotiation)/subsidies	18	Political	Food subsidies are one of the policies that are considered to protect consumers from rising food prices, especially when there is insufficient local production and food must be supplemented by imports with fluctuating prices.	Gebeltová et al., 2023
	Decreasing food waste	9	Social/Environmental	Efforts to reduce food waste along the value chains from retailers to private homes could thus reduce short-term pressures on global markets.	Pörtner et al., 2022
	Increase the use of synthetic agro-inputs	5	Environmental	Countries develop an application plan that optimizes synthetic agricultural input use.	Halecki and Bedla, 2022
	Controlling local currency value	3	Economic	To conserve and attract foreign currency, countries like Egypt continued devaluating their currency after the outbreak of the Russia-Ukraine war while increasing the interest rate.	Abay et al., 2023
	Resource mobilization	2	Economic	The mobilization of strategic stocks was prioritized by most of the countries as an important tool for countries to buffer spikes in commodity prices.	Berkhout et al., 2022
Adaptation/Adaptive strategies	Intensive Modernization and Mechanization	31	Technological	To minimize the negative consequences of Russia's military invasion of Ukraine and restore the Ukrainian economy's agricultural sector after the war, it is necessary to introduce innovations and modernize agricultural production.	Skydan et al., 2023
	Crop switching/substitution	13	Environmental	During the Ukraine conflict countries like the United States switched from cultivating crops that depended on the external market to crops such as corn that have more value in the domestic market.	
	Research, Innovation and Policy communication	13	Technological/Political	Collaborative networks between farmers, private and government research institutions, agronomists, researchers, and industry professionals in breeding programs drive knowledge and technology transfer through active dialogues and participatory research.	Neik et al., 2023
	Capacity building	11	Social	Knowledge and skills, both about food (or FSP) and "democratic" skills such as collaboration and tolerance, are essential prerequisites for food democracy	Pungas, 2023
	Food demands stability	10	Social	As their populations grow, several African and MENA nations are dependent on imported grains like wheat to meet their food and fertilizer needs. But if the conflict continues, there will be shortages in the supply of these goods, driving up the cost of food	Chepeliev et al., 2023
	Food testing and and traceability, statistical reporting	6	Legal	Further development in traceability and testing facilities is essential to eliminate the risk of contamination because of food fraud	Chepeliev et al., 2023
	Modern Market	4	Technological	Organized an online farmers' market on a popular online platform for groceries and other agricultural products to expand the reach of local farms	Tortajada and Lim, 2021
	Farmers' Cooperative andassociations	3	Social	Farmers began to unite, and the public union "Agro-producers of Occupied Territories" was created, one of the main tasks of which was to speed up work on demining agricultural lands.	Skydan et al., 2023

(Continued)

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TABLE 5 (Continued)

Resilience scenario	Elements/Strategies	Occurrence	Category	Descriptions	References
Overtime Transformational Change	Agrifood systems governance and Policy reforms/food democracy	26	Political	To cope with the global food crisis, governments and international organizations should actively act. Each country needs to reassess the risks and difficulties of its national food security from multiple dimensions of food security and restructure and improve its food system so that it remains resilient in the long run and ensures food security in the face of rising climatic, conflict-related, and economic risks.	Xu et al., 2023
	Social safety net/access to resources	19	Social	A large amount of humanitarian aid from domestic and international sources is collected and processed to be sent to countries in need like Ukraine, as well as distributed domestically.	Kovács et al., 2022
	Sustainable agriculture	13	Environmental	Diversification of agricultural practices, such as intercropping spatially or temporally, mixed farming with crop and livestock, adding organic material or beneficial microbes in the soil, and reduced tillage has contributed to biodiversity conservation, improved soil fertility, enhanced nutrient cycling, and water regulation, and improved pest control, decreasing the environmental burden without compromising crop yield.	Neik et al., 2023
	Conflict resolution	9	Legal	Promoting democracy, dialogue, and trust building should also be considered key to avoiding armed conflict and food security.	Nguyen et al., 2023
	Domestic renewable energy production	4	Environmental	Countries focus on improving energy sufficiency through implementing renewable energy infrastructures for domestic energy production. This was important because dependence on electricity was continuing to increase in society.	Karoliina et al., 2023

This table shows four main resilience scenarios which are; fragility reduction, robustness building, adaptive strategies, and overtime transformational change. Additionally, each scenario is made up of several elements strategies, or policies implemented to improve the resilience of the agrifood systems amid geopolitical conflicts.

sustainable agriculture, and domestic renewable energy production. Finally, 15% of the robustness-building scenario which includes countries controlling local currency value, decreasing food waste, resource mobilization, increased use of synthetic agricultural inputs, and others focused on price management of food and agro-inputs products.

The study found trade restriction through export and import bans of the global commodities were the most frequently identified strategies with a frequency of 72. Followed by the implementation of economic sanctions against some countries, which was 61. On the other hand, the least frequently applied strategies were international companies' pricing and trade negotiation, resource mobilization, and the implementation of early warning and risk management strategies, which were identified only 1, 2, and 2, respectively.

3.4.2 Agrifood system resilience elements amid geopolitical tension for developed and developing countries

Based on the total number of resilience elements found in each scenario, the study found that compared to other resilience scenarios 15 resilience elements were employed to foster the reduction of the agri-food system's fragility (Figure 6). The study identifies that developing and developed countries prioritize measures that ensure food security. Furthermore, with a focus on specific resilience elements in each scenario, in the fragility reduction scenario, developing countries are highly executing tariffs and quotas, as well as increased foreign lending, whereas developed countries implemented policies that focus more on economic sanctions and diversifying food sources. Moreover, the study reveals that 80% to 90% of developing countries focus on initiatives such as diversification of local agricultural production, and domestic storage, respectively, while only 20 to 10% of developed countries have implemented these measures. Furthermore, developing countries have focused more on resource mobilization ideas to build the robustness of the system. The study found that about 80–90% of developed countries focused on building the robustness of the agrifood system through the reduction of food waste, increased use of synthetic agricultural inputs, and price management of crucial agrifood commodities.

Furthermore, to enhance over time transformation changes developed countries tend to focus on investing more in renewable energy and improving the governance and policy reforms within the agrifood systems. Conversely, during times of geopolitical tension, developing countries tend to prioritize social safety nets and sustainable agriculture initiatives to bring about gradual transformational changes within the agri-food system (Figure 6). On the other hand, the adaptation scenario consists of 8 resilience elements where developed countries play a dominant role in implementing food testing, traceability, and record-keeping (Figure 6). This influences regional cooperation between stakeholders, capacity building, and a shift from the production of one crop to another. Nonetheless, most of the developing countries propose adaptive strategies such as modern markets, intensive modernization, and mechanization strategies. They also implement initiatives that stabilize food demand to strengthen their adaptation.

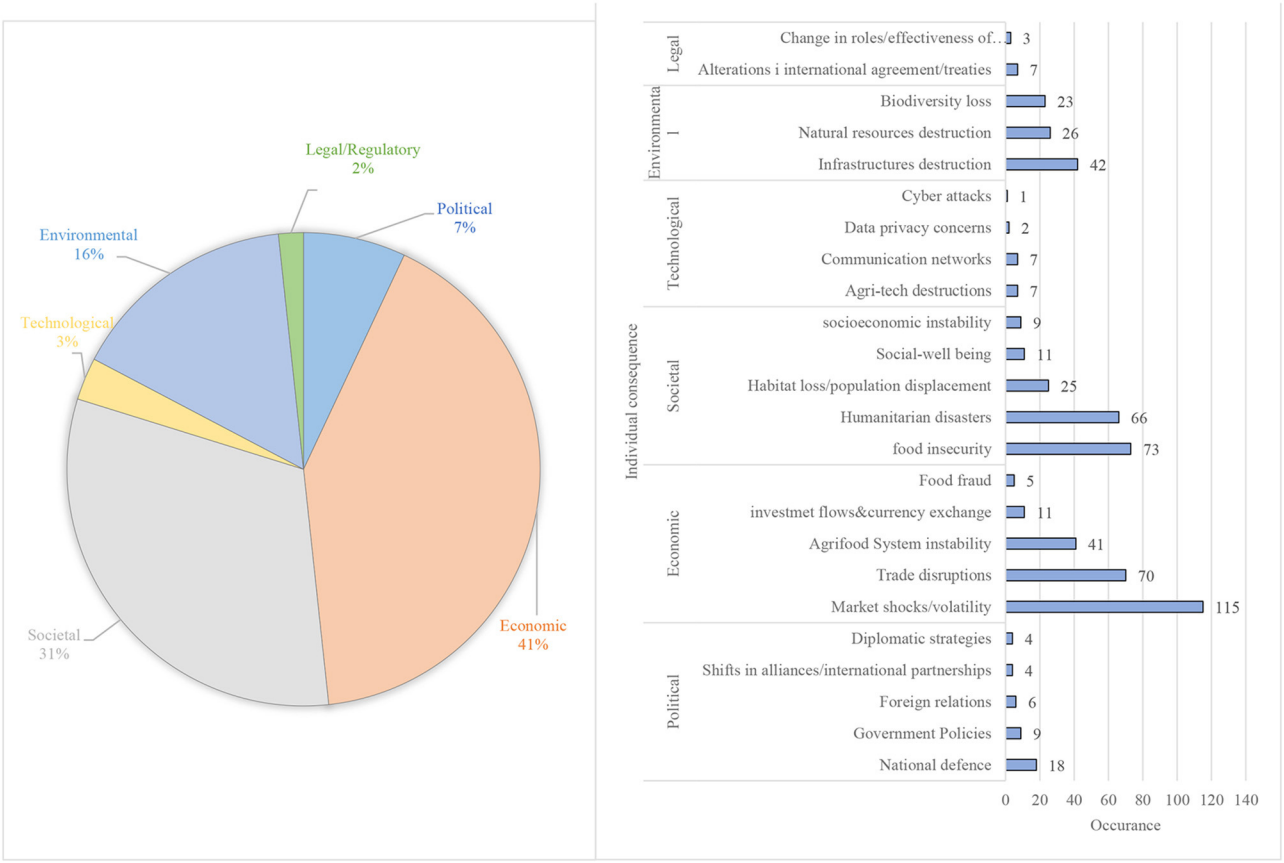


FIGURE 3
The prevalence of geopolitical consequences based on PESTEL breakdown.

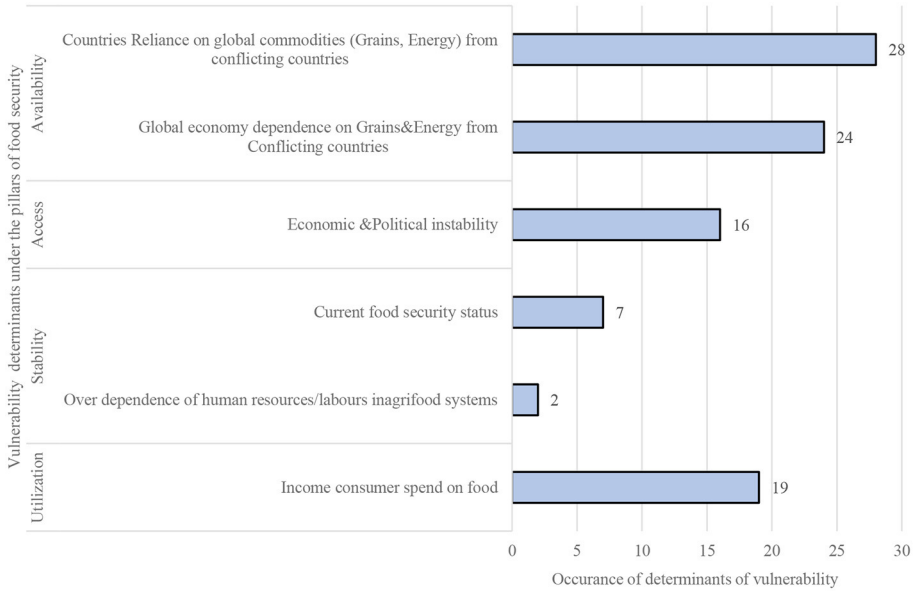


FIGURE 4
Indicators of vulnerability under the pillar of food security during geopolitical conflicts.

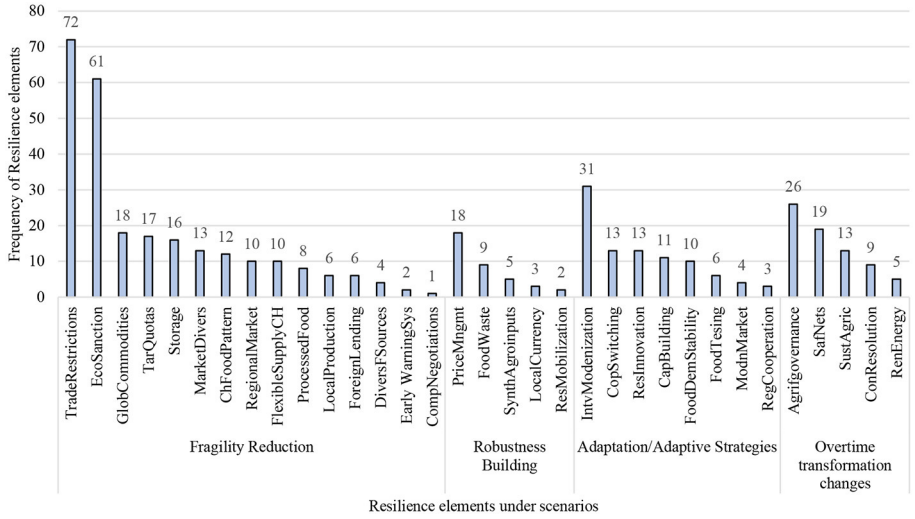


FIGURE 5
Occurrence of agrifood resilience elements based on specific scenarios during geopolitical tension.

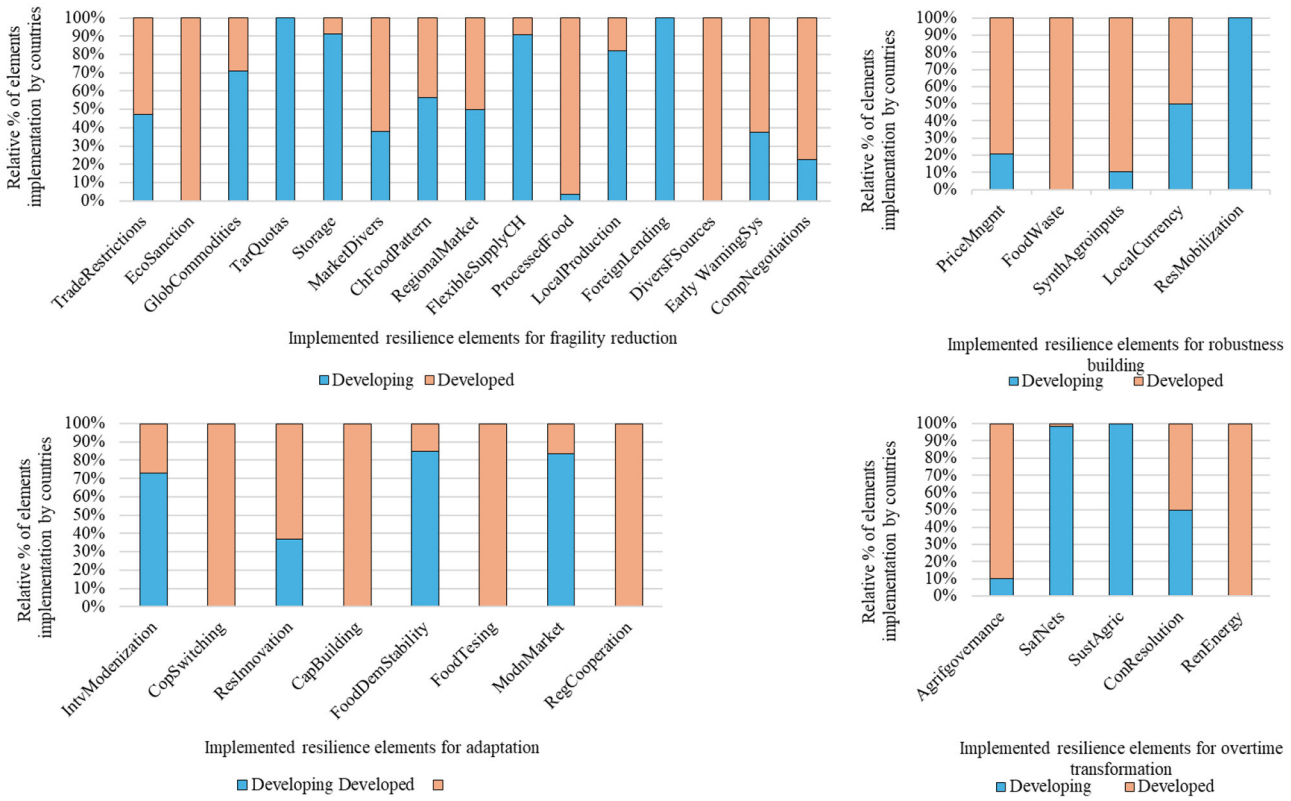


FIGURE 6
Resilience elements implemented during geopolitical tension for fragility reduction, robustness building, adaptation, and overtime transformation change of the agrifood systems.

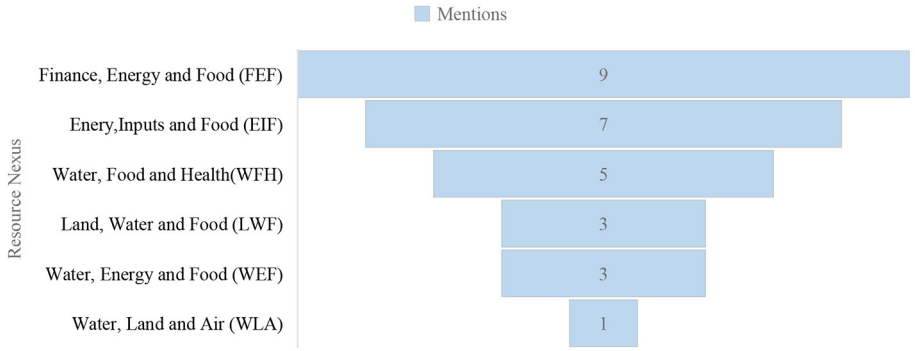


FIGURE 7
Occurrence of Resource Nexus in the documents.

3.5 Exploring the agrifood system resilience elements, and resource nexus in the context of geopolitical conflicts

The Resource Nexus and its related terms in the geopolitical tensions occurred 28 times. The Finance-Energy and Food Nexus (FEF) appeared as a dominant and most mentioned Resource Nexus in 9 statements. The Agroinputs, Energy, and Food sub-nexus (AEF) followed them, which occurred 7 times. Moreover, the study explored Water, Food, and Health interlinkage (WFH) stated 5 times. However, Land, water, and food (LWF), and Water, Energy, and Food (WEF) occurred 3 times while the least stated Resource Nexus was Water, Land, and Air (WLA) by 1 (Figure 7). Based on study findings, economic consequences are directly linked with FEF Nexus that financial crisis, sanctions, and increased transportation influence the agri-food systems' fragility as shown in Figures 8, 9. These factors were found to be interconnected in the study. Additionally, the primary FEF Nexus directly influences various other sub-nexuses.

4 Discussion

4.1 Addressing major agrifood system vulnerability indicators to enhance global food security in the era of geopolitical conflicts

The agrifood system faces distinct challenges due to geopolitical conflicts, as emphasized by this study. To make well-informed policies and be prepared for crises, it is crucial to acknowledge and comprehend indicators of food security vulnerability. This was proven through the study's systematic thinking approach. Still, the research systematically identifies how the four pillars of food security were directly affected by various socioeconomic influences that led to the vulnerability of the global agri-food system. Geopolitical conflicts disrupt agricultural production and distribution, leading to challenges in food availability, accessibility, stability, and utilization (FAO, 2022; von Cramon-Taubadel, 2022), making it difficult for stakeholders to plan and invest in agriculture for sustainable development of the agrifood system (OECD/FAO, 2023; UNEP et al., 2023). Moreover, societies in developing countries are often more vulnerable to food insecurity because they have less disposable income and are more likely to live in areas that are prone to conflict and natural disasters (UNEP et al., 2023; UNICEF, 2023). Empirically, food crises were highly experienced from 2020 to 2023, whereby wheat, energy, and fertilizer were highly scarce in the global market due to trade restrictions imposed by different countries (Vos et al., 2023). Most of the low-income countries depend on wheat, fertilizer, and oil products from Russia and Ukraine, which makes them more susceptible to hunger, undernourishment, and food insecurity due to imposed trade restrictions and sanctions.

Food utilization in the least developing countries has previously been observed as a major threatened pillar of food security for the social wellbeing and functioning of food systems (Gebel and Gundert, 2023; Morrissey et al., 2020; Nichols et al., 2013). Recently, in most of the developing countries, food availability was unexpectedly threatened by the economic consequences of geopolitical tension. However, vulnerability indicators for food availability were directly associated with the enacted economic sanctions and trade disruptions that enhanced the decrease of sufficient quantity of quality food to the global market (FAO, 2023; OECD/FAO, 2023; UNCTAD, 2023). An increase in reliance on imports and global economic dependence on global commodities from conflicting countries have heightened food availability challenges. According to (Pryiatelchuk and Novak, 2022), food availability becomes increasingly limited by reduced imports, and food access is restrained by higher prices, lack of inputs, and the destruction of productive assets and infrastructure. Similarly, unnecessarily higher prices disrupt the global market and worsen the situation in sub-Saharan Africa, which is the most vulnerable (Ouko and Odiwuor, 2023). Several countries at the beginning of the geopolitical tension with the emerging financial, imposed export bans on some of the food items to address rising domestic food shortages. For example, India has banned wheat exports which has a significant impact on neighboring and vulnerable nations. Economically and politically powerful countries enforce export limits for their self-interest, prices rise, worsening food poverty (Dyson et al., 2023; FAO, 2022).

Likewise, geopolitical tensions pose additional effects to food accessibility and stability, due to the unpredictable economic and

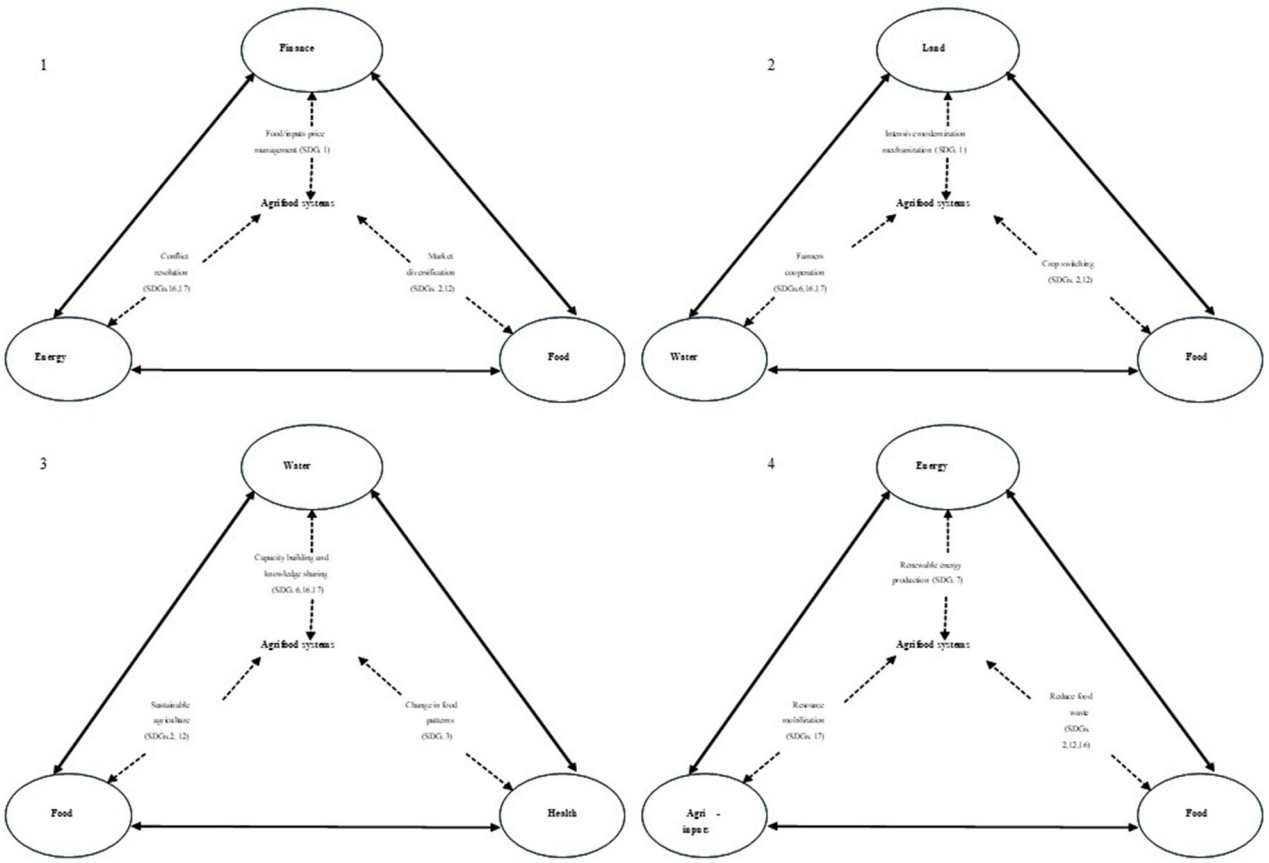


FIGURE 8
Agrifood systems resilience elements integrated into the most mentioned Resource Nexus during geopolitical conflicts.

political situation of the conflicting and non-conflicting countries. For instance, economic instability influences job losses and poverty (Gebel and Gundert, 2023; Morrissey et al., 2020; Nichols et al., 2013; Pryiatelchuk and Novak, 2022), which can make it difficult for susceptible society to afford food. Moreover, economic sanctions disrupt the food supply chain through increased costs of production and transportation due to increased prices of the agrifood commodities in the global market.

Furthermore, food utilization challenges have been linked with the consumer's purchasing power, rising food prices make people spend all their income on food, leading to social unrest. Compared between countries, consumers from richer countries spend a much smaller fraction of their income on food than those from poor countries (Hellegers, 2022). However, the amount of income spent on food is influenced by many factors, such as the cost of food and services, and preferences (Karonen and Niemelä, 2022; Muhammad et al., 2017).

Conclusively, the relationship between vulnerability indicators of the agrifood systems amid geopolitical tensions with the four pillars of food security is significant, because geopolitical tensions impact involve food insecurity, which also harms human health, economic development, and social stability (Ben Hassen and El Bilali, 2022; International Monetary Fund, 2022; Kemmerling et al., 2022). It is important to increase awareness of the possible impact of geopolitical tensions on food security to make applicable adaptive initiatives.

4.2 Agrifood system resilience: a comparative analysis of developed and developing countries in the context of geopolitical conflicts

In the context of geopolitical conflicts, the resilience of agrifood systems varies significantly between developed and developing countries influenced by economic status, institutional framework, and trade dependencies. Developed countries implemented policies enabling them to mitigate food risks while recovering more efficiently from geopolitical shocks. Conversely, developing countries face greater vulnerability due to over-dependence on key agrifood commodities such as wheat, oilseeds, and fertilizers from the global market, making them more susceptible to disruptions in food production and distribution. The study's comparative analysis aims to identify the dominant resilience scenarios and the major elements implemented between developed and developing countries' responses to geopolitical conflicts. Also, to examine the effectiveness of each implemented

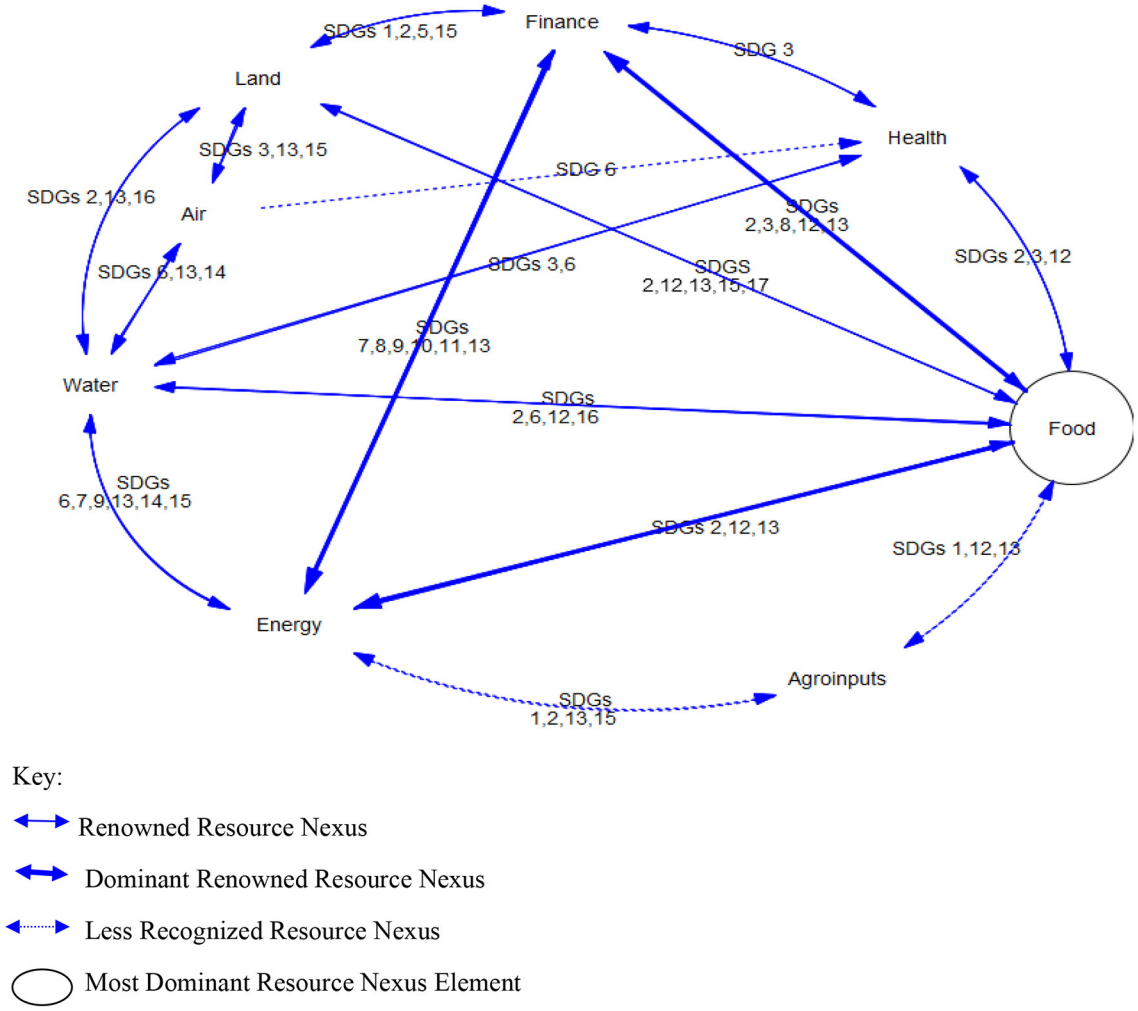


FIGURE 9
Resource Nexus and SDGs for agrifood system resilience in the context of geopolitical conflict modified from Karthe et al. (2021).

resilience policy in influencing the stability of the agrifood system, and highlight policy gaps that can inform global food security strategies.

However, the impact of the implemented resilience elements on sustainable food security varies according to the characteristics of certain specific resilience scenarios. The nature of the elements or policies determines the scenario's behavior, enhancing the positive or negative growth of the agrifood system.

There was no statistical evidence, only the empirically significant effect of agrifood resilience elements on the sustainability of food security amid geopolitical tensions. The resilience elements that influence the effective performance of the agrifood system were found in different scenarios such as fragility reduction, robustness building, adaptation or adaptive strategies, and overtime transformation changes. In general, the fragility scenario showed negative behavior and increased food instability over time amid geopolitical tension.

In this study, the fragility reduction scenario was more dominant than other scenarios. This was due to the large number of policies or elements implemented to reduce the fragility of the agrifood system during geopolitical tension. Somewhat surprisingly, some of the elements related to the fragility scenario appeared, although (not significant) non-beneficial to the agrifood system progress than robustness, adaptation, and transformation-related scenarios. To reduce the fragility of the agrifood system amid geopolitical conflicts, developed countries primarily focus on economic sanctions and diversification of food sources, meanwhile developing countries rely more on tariffs quotas and foreign lending. Furthermore, resilience elements such as economic sanctions, export restrictions, tariffs, and quotas were determined to distress more developing countries in safeguarding their growers, consumers, and markets (WTO, 2022). These elements raise food crises which increase the vulnerability of most of the developing countries due to a rise in the price of food and fuel. Various scholars correspond with the study findings, Araujo-Enciso and Fellmann (2020) highlight the long-term vulnerability of smallholder farmers and poor consumers to poverty traps, even when short-term price fluctuations are manageable. Imposing economic sanctions on Russia causes adverse effects on the economy of most developing countries that import agricultural commodities from Russia (Jagtap

et al., 2022; Mukhtar, 2023; Neik et al., 2023; Nguyen et al., 2023). Conversely, some studies differ from the study findings in that some of the implemented policies such as economic sanctions and export restrictions were enforced to protect susceptible domestic consumers from food insecurity (Abay et al., 2023; FAO, 2021; Hellegers, 2022; Sheahan and Barrett, 2017). Moreover, to avoid negative behavior from the implemented policies, Policymakers stabilized food markets and food security through focusing on short-term initiatives, consequently in the end these initiatives may not solve the intended problems with agrifood systems.

The study reveals that the robustness-building scenario was less implemented in both developed and developing countries. It was dominated by resilience elements that strive to increase the local currency values, reduce food waste, increase the use of synthetic agricultural inputs, commodities price management, and resource mobilization for sustainable food security. In this scenario, the developed economies rely on reducing food waste while developing economies focus on resource mobilization. Robustness differs from fragility because it has a sort of absorptive capacity to shocks. Implementing robustness-building mechanisms can result in suboptimal outcomes for the food system. Hence, several developed and developing countries have refrained from implementing it. In the adaptive strategies: developed economies rely on crop switching and regional cooperation, meanwhile developing economies rely on stabilizing food demand. Generally, the study findings highlight how sometimes erroneous it is to count only upon some scenarios as worthwhile to agrifood system resilience amid geopolitical tensions. This suggests that policymakers, governments, and stakeholders should prioritize the collective implementation of acknowledged measures to reinforce the resilience of agrifood systems in times of geopolitical tensions.

4.3 Exploring agrifood system resilience and resource nexus amid geopolitical conflicts

This study discovers different types of Resource Nexus and its Subsets that are directly or indirectly influenced by geopolitical tensions. The most mentioned resource nexus is Food, Energy, and Finance (FEF). Various scholars described that the geopolitical tensions supercharging a three-dimensional crisis of food, energy, and finance with devastating impacts on the world's most vulnerable people, countries, and economies balancing the three core needs is an uphill task that requires joint efforts of the international community (Guterres, 2022; Ouko and Odiwuor, 2023). The other identified nexus are Agroinputs-Energy-Food (AEF), Water-Health-Food (WHF), and Land-Water-Food (LWF). This situation happens to increase the growing importance of understanding the nexus between water, energy, food, and land in academic research (Khairulbahri, 2022).

This study showed that the disturbed nexus of food, finance, energy, water, land, health, and agricultural inputs (fertilizers and agrochemicals) might have far-reaching effects on the resilience of the agrifood system, owing to increased global interest. Influences such as increased food costs, lower resource availability, investment uncertainty, food insecurity, and other socioeconomic issues were considered among the experienced consequences. These factors collectively make the agrifood system's resilience susceptible to different global shocks that endanger global food security.

Moreover, the synergies of two more resilience elements tend to stimulate the efficiency of any Resource Nexus and enhance the resilience of the agrifood system. It indicates that a disturbance in a single resource and its related policy can increase adverse effects across all levels of the agrifood system (Folke et al., 2002; Khairulbahri, 2022). Human Rights (2022); Kitenge (2023) and Onyeaka et al. (2022) portrayed that hunger and severe food insecurity in Eastern Africa are worsening due to the negative influence of the Russia-Ukraine conflict on food, energy (oil and gas), and fertilizer prices. Furthermore, in different nexuses, the resilience elements needed to achieve the same resource may vary. For instance, the FEF Nexus, achieving SDGs 2 and 12 requires enhancing food resources through market diversification. This also influences the function of other elements like commodity price management (Finance) and conflict resolution (Energy). In other Resource Nexus such as AEF, WHF, and LWF, achieving food security necessitates implementing different elements other than that from the FEF nexus. For example, reducing food waste, promoting sustainable agriculture, and crop switching are essential. Moreover, disturbances to the food supply chain caused by geopolitical conflicts affect the efficiency of various resource nexuses and make food production more expensive (OECD/FAO, 2023). Nevertheless, to sustain food security in the era of geopolitical tensions, the key resilience elements that should be considered are those that improve resource nexus efficiency, through strengthening market diversification, investing in agricultural innovation, promoting sustainable land management, empowering smallholder farmers, enhancing cross-sectoral coordination, etc.

In conclusion, change in Resource Nexus efficiency has an obvious influence on food security, public health, and economic stability (Ben Hassen and El Bilali, 2022). It is relevant for policymakers, researchers, and stakeholders to focus on the resilience of the agrifood system through sustainable management of the available resources that will finally achieve maximum efficiency.

4.4 Bridging the gaps: agrifood system's vulnerability indicators, resilience differences, and resource nexus solutions amid geopolitical conflicts

This study found that the resilience of agrifood systems amid geopolitical tension, in both developed and developing countries, is deeply dependent on the addressed six major vulnerability indicators that facilitate the effectiveness of the four pillars of food security (availability, accessibility, stability, and utilization), through the application of worthwhile resilience policies, and the consistent resource nexus. Major vulnerability indicators, including the overreliance of countries on global commodities from conflicting nations, economic and political instability, and the proportion of consumer income spent on food, have significantly aggravated food insecurity in developing countries

compared to developed countries where they have strong economic and institutional capacity. The experienced vulnerabilities affect susceptible agrifood systems and Resource Nexus, which are more exposed to global shocks.

Moreover, the study identified that the food-energy-water (FEW) and land-water-food (LWF) nexuses under the support of finance, and community health factors are crucial in enhancing agrifood resilience. The existence of geopolitical conflicts between major producing countries of the key global commodities hinders the efficiency of these resource nexuses, intensifying food insecurity by limiting the availability and accessibility of important agricultural inputs, such as fertilizers, and irrigation resources (Bas, 2025; Quitzow et al., 2025; Rudloff et al., 2024), which in turn distresses the agrifood system's productivity and elevates food crisis in vulnerable countries. Furthermore, the extent to which the resource nexus overlaps or should be integrated for effective operation and sustainability of the agrifood system is a key consideration in policy design and implementation. However, employing different resilience policies to facilitate robustness, adaptive, and transformative agrifood systems amid geopolitical conflicts will significantly impact attaining resource nexus efficiency and food security (Aungkulanon et al., 2024; Nadia et al., 2024). For instance, during geopolitical conflicts, countries enact policies such as food and inputs price management, resource mobilization, and implementing sustainable agricultural practices (Stanberry and Fletcher-Paul, 2024) to facilitate an effective adjustment of the devastated resources. Consequently, some of the policies disclosed positive promising results under sustainable resource management and ensured the resilience of the agrifood system, while others exhibited worse reactions. A holistic approach that promotes regional cooperation and sustainable resource management can enhance Resource Nexus efficiency and strengthen resilience capacity in both developed and developing economies in the context of geopolitical conflicts.

Conclusively, the study responds to the proposed three research questions, where it highlights that the connection between identified agrifood system's major global vulnerability indicators, enacted resilience elements, and prioritized Resource Nexus determines how agrifood systems respond to the consequences of geopolitical shocks to enhance resilient agrifood system for sustainable global food security. A well-designed agrifood system's resilience context that integrates findings from the research questions dimensions can better inform policies, strategies, and plans to sustain global food security and mitigate the long-term consequences of an existing geopolitical conflict. Addressing these challenges through adaptive governance, cross-sectoral collaboration, and strategic resource allocation will be essential for strengthening agrifood system resilience in an increasingly uncertain geopolitical landscape.

5 Conclusion

This study proposed based on the increased interest in exploring the resilience behaviors of the agrifood system, observing the interlinkage between resources, and their influences on sustainable food and nutrition security amid geopolitical tension. The findings declared that compared to developed countries, most developing countries employed policies focused on reducing the fragility risks of agrifood systems. Moreover, the reduction of agrifood system fragility is more prevalent compared to the other three scenarios, there was a decline in the performance of the agrifood system due to the existence of some elements that increased the system's instability over time. However, the impact of the implemented resilience elements on sustainable food security varies following the characteristics of certain specific resilience scenarios. The nature of the elements or policies determines the scenario's behavior, enhancing positive or negative growth of the agrifood system. Based on their specific outcomes, resilience elements have been designated into four unique scenarios, namely fragility reduction, robustness building, adaptive strategies, and overtime transformation changes. We found that the impact of agrifood system resilience elements on sustainable food security is not uniform and varies depending on the specific scenario; it can influence either valuable or devastating impacts across all levels of the agrifood system.

Furthermore, this study shows that the impact of agri-food resilience concepts on food security is not uniform and varies depending on the specific agri-food resilience scenarios recognized at each level of the agri-food system. It identifies food availability as the most important pillar of food security in times of crisis in the region, due to the increasing dependence on imports and the dependence of international trade on goods from conflicting countries. At the same time, the most common resource relationship during the crisis in the region was food, energy, and finance (FEF), while other relationships included land, water, food (LWF), and water, energy, and food (WEF). Generally, this means the main factors to consider are those that contribute to the relationship between resources, food availability, accessibility, sustainability security, and use. At a time of increasing geopolitical tensions, this research demonstrates the need to reflect on increased knowledge and interest in the resilience of agri-food systems and Resource Nexus.

This study is limited to specific geopolitical tension and armed conflicts between countries and was only conducted in the agrifood sector. However, despite this limitation, this study makes an important contribution because it provides a thorough analysis of the present understanding regarding the resilience of agrifood systems and the impact of geopolitical tensions. This research paper contributes to the existing body of knowledge on the resilience and resource nexus in food systems. Future research should focus on determining the characteristics and behavior of the identified resilience scenario under the influence of existing Resource Nexus efficiency.

6 Limitations of the study

Although the review covers a wide geographical range, the dominance of articles from Western and Chinese perceptions may introduce a geographical bias, potentially limiting the applicability of findings to regions with lower representation in the dataset (e.g., Africa and South America). There is a need for future research to address this gap by incorporating more diverse regional perspectives.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AM: Conceptualization, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Funding acquisition, Investigation, Software, Validation. TL-K: Investigation, Resources, Software, Visualization, Writing – review & editing, Methodology, Validation. KM: Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – review & editing. EG: Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declare that no Gen AI was used in the creation of this manuscript.

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Improved quality signaling boosts farmers' willingness to pay for quality assured cassava planting materials: evidence from experimental auctions in the Lake Zone of Tanzania

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Cassava (*Manihot esculenta* Crantz) is a key staple food in the Lake Zone of northwestern Tanzania and a critical food security crop in Sub-Saharan Africa. However, rather than purchasing quality assured cuttings of improved varieties from trusted sources, many farmers rely on free or almost free cassava cuttings from unregulated sources to establish their plots. This study uses Vickrey's method to examine farmers' willingness to pay for cassava cuttings by exploring two aspects in two rounds of experimental auctions: Round 1, the impact of asymmetric information between buyers and sellers, and Round 2, the influence of enhanced quality signaling using quality assurance labels. Cassava farmers (n=200) placed bids on three products: P1, a farmer-sourced landrace; P2, an improved variety called TARICASS4 sourced from a quality declared seed (QDS) producer; P3, the TARICASS4 variety, also sourced from a QDS producer, but with a quality assurance label. In Round 1, the mean bids per cutting did not differ between treatments, and were TSh 24.5 (USD 0.0091) for P1, TSh 23.4 (USD 0.0087) for P2 and TSh 24.6 (USD 0.0091) for P3. This changed in Round 2, where the mean bids per cutting were TSh 11.5 (USD 0.0043) for P1, TSh 20.0 (USD 0.0074) for P2, and TSh 32.7 (USD 0.012) for P3. Despite P2 and P3 being the same variety and sourced from QDS producers, bidders in Round 2 placed a premium price on P3 because of the added quality assurance label. Relative to bids for the local landrace in Round 2, bids were almost double for the improved variety, and almost triple for the improved variety with certification labeling. These results confirm that providing product information and enhancing quality signaling can significantly boost farmers' willingness to pay for cassava seed, thereby increasing demand. This will have the important consequence of enhancing the commercial viability and therefore sustainability of the cassava seed system.

KEYWORDS

cassava, willingness to pay, seed system, Vickrey method, gender

Introduction

Cassava (*Manihot esculenta* Crantz.) is an important crop for food security and income generation in the tropical belt of Sub-Saharan Africa, and one of the crops best adapted to the anticipated future environmental shocks associated with anthropogenic climate change (Jarvis et al., 2012). However, average yields in Africa of 8.2 h/ha (FAOSTAT, 2023) are far below the estimated potential of 25–30 t/ha (Lebot, 2019). Some of the key factors causing this deficit include an overreliance on informal sources for cassava planting materials among smallholder farmers (Kilwinger et al., 2021) coupled with high disease pressure (Legg et al., 2006; Mbanzibwa et al., 2009; Winter et al., 2010; Legg et al., 2011; Ndyetabula et al., 2016) and the minimal use of agro-inputs like fertilizers (Nweke, 1994; Kelly, 2006; Fermont et al., 2010). The most important cassava diseases in Africa are the viral diseases—cassava mosaic disease (CMD) and cassava brown streak disease (CBSD). Both diseases have the greatest impact on seed quality, as the causal viruses are readily propagated from one crop cycle to the next through infected cassava cuttings (Legg et al., 2015).

The traditional reliance on informal planting material (= seed) sources hinders farmers' access to quality planting materials of improved varieties, preventing them from benefiting from the potential genetic gain of new improved varieties developed by existing cassava breeding programs in Sub-Saharan Africa. To address this bottleneck and increase farmer access to high quality seed, formal cassava seed systems have been established in several countries, most notably Nigeria and Tanzania (Legg et al., 2022). These systems are made up of networks of cassava seed entrepreneurs (CSEs) who are producing near disease-free seeds of high-yielding improved varieties whose quality is assured through regular inspection by seed regulators. In Tanzania, the CSE network includes > 600 seed producers at pre-basic, basic, certified and Quality Declared Seed (QDS) levels and delivers high quality seed of improved varieties from breeders to farmers (MEDA, 2022; Legg et al., 2022; Liani et al., 2023). Currently, the Tanzania Official Seed Certification Institute (TOSCI) regulates seed quality across all seed classes (Msami et al., 2025). However, efforts are being made to empower QDS producers to declare the quality of their seed using guidelines from TOSCI. Like most vegetatively propagated crops (VPCs), cassava has botanical seeds, however, in the context of this paper we refer to cassava cuttings as "seed" because they are used as planting materials instead of the botanical seeds as is the norm for grain crops.

Currently, the cassava seed business is constrained by imperfect markets characterized by a relatively low volume of buyers (root producing farmers) of quality planting materials of the improved varieties coupled with a low frequency of "seed" replacement in cassava farming (MEDA, 2022; Delaquis et al., 2018; Wossen et al., 2020). This is probably due to a general lack of awareness amongst many smallholder farmers of the availability of cassava planting materials from quality and regulatory-compliant sources and the potential benefits of planting improved varieties (Abdoulaye et al., 2014; Wossen et al., 2017; Yabeja et al., 2025). These characteristics are at least partly attributable to the predominance of informal seed exchanges and the nature of cassava being a vegetatively propagated crop (Delaquis et al., 2018; Almekinders et al., 2019; Wossen et al., 2020).

Previous estimations of willingness to pay (WTP) for cassava seeds in Tanzania were done using contingent valuation theory (Maggidi, 2019), which is an approach that relies on the hypothetical nature of non-market products (Bamwesigye et al., 2020). While measures of stated WTP obtained from approaches such as survey questionnaires, key informant interviews, and focus group discussions remain popular (Borghi et al., 2007; Hite et al., 2008; Maggidi, 2019), their results are often viewed as unreliable. Alternatively, revealed preference methods, such as auctions, can be employed to reliably mimic purchasing decisions and scenarios to determine consumer demand for products or their attributes and reveal their WTP for a product (Vecchio, 2013; Banerji et al., 2016; Delaquis et al., 2024; Wossen et al., 2024). While experimental auctions are somewhat complex, they are trusted to prompt bidders to disclose their true willingness to pay for a product (Lusk and Shogren, 2007).

Therefore, for the first time in Tanzania, we used the Vickrey Second Price Auction (SPA) sealed-bid experimental auction method (Vickrey, 1961) to elicit farmers' willingness to pay for cassava seed and investigated how asymmetric information and enhanced quality signaling through TOSCI quality assurance labels influence farmers' willingness to pay for cassava cuttings in the Lake Zone of Tanzania. Additionally, we performed group comparisons of bidders from male-headed households (MHH) vs. female-headed households (FHH) and male bidders vs. female bidders to assess the gender implications in willingness to pay for cassava seed. Our study presents the first evidence of farmers' willingness to pay for quality cassava seeds in Tanzania using experimental auctions. The results of the study will be useful in improving marketing strategies of the CSEs involved in the cassava seed business in Tanzania, and the results will be relevant more broadly for cassava seed business development elsewhere in Sub-Saharan Africa.

Methodology

Study area and sampling procedures

The study was conducted in 10 villages spanning six districts from four regions of the Lake Zone of Tanzania, including Mara (Bunda District), Geita (Chato and Bukombe Districts), Kagera (Muleba and Biharamulo Districts) and Kigoma (Kakonko District) (Table 1, Figure 1). Pre-testing of the pre-auction tool and optimisation of the auction protocol were done in Magu District, Mwanza Region. The study locations were purposively selected in consultation with the regional and district agricultural officers, based on the presence of CSEs and/or historical dissemination of improved cassava varieties by cassava seed system actors.

Using simple random techniques, 20 cassava farmers representing the heads of households in each village were selected by their local Village Agriculture Extension Officers (VAEOs) to participate in the interviews and auctions. However, we encountered challenges in achieving equal representation of female-headed households (FHHs) compared to male-headed households (MHHs) given the apparent patriarchal nature of societies in the Lake Zone. Nonetheless, by expanding participation beyond just the heads of households, some MHHs chose to send

female representatives to the auctions, which consequently led to an increase in the number of female bidders.

Cassava is typically planted in the short rainy season, which usually starts in October in the Lake Zone. To leverage the strong demand for cassava planting materials at the start of the planting season, all auctions were conducted in October 2024 in all 10 villages, each involving the selected 20 cassava farmers. All auctions were conducted in Swahili—the most widely spoken language in Tanzania, ensuring clear communication and engagement.

TABLE 1 Study area.

Region	District	Ward	Village
Mara	Bunda	Salama	Salama Kati
Geita	Chato	Iparamasa	Imarabupina
Geita	Chato	Iparamasa	Kinsabe
Geita	Bukombe	Busonzo	Busonzo
Geita	Bukombe	Busonzo	Nampalahala
Kagera	Muleba	Ngenge	Ngenge
Kagera	Muleba	Ngenge	Rwigembe
Kagera	Biharamulo	Kabindi	Chebitoke
Kigoma	Kakonko	Nyabibuye	Nyabibuye
Kigoma	Kakonko	Nyabibuye	Rumashi

Experimental design

The auction experiment consisted of three parts (i) a pre-auction interview, (ii) two rounds of cassava cutting auctions preceded by a practice round involving bars of soap instead of cassava cuttings, and (iii) post-auction phone interviews. In the pre-auction interviews, we collected demographic, household, and farm characteristics data, as well as information on farmers' usage of quality seeds. The auctioned cassava cuttings were presented as P1, a farmer-sourced local landrace; P2, an improved variety called TARICASS4 sourced from a Quality Declared Seed (QDS) producer; P3, the "TARICASS4" variety, also sourced from a QDS producer but with a quality assurance label as shown in Table 2. In post-auction phone interviews, we contacted farmers who had zero bids for any of the products in either round of auction and asked why they were not willing to pay for any of the products.

The Vickrey Second Price (SPA) auction method (Vickrey, 1961; Barrot et al., 2010; Delaquis et al., 2024; Wossen et al., 2024)

TABLE 2 Attributes of the auctioned cassava cuttings (planting materials).

Attribute	P1	P2	P3
Variety	Local landrace	TARICASS4	TARICASS4
Source	FSS	QDS	QDS
Quality Signaling	No TOSCI label	No TOSCI label	TOSCI label

TARICASS4 is an improved disease-resistant variety.
QDS, Quality Declared Seed; FSS, Farmer Saved Seed.

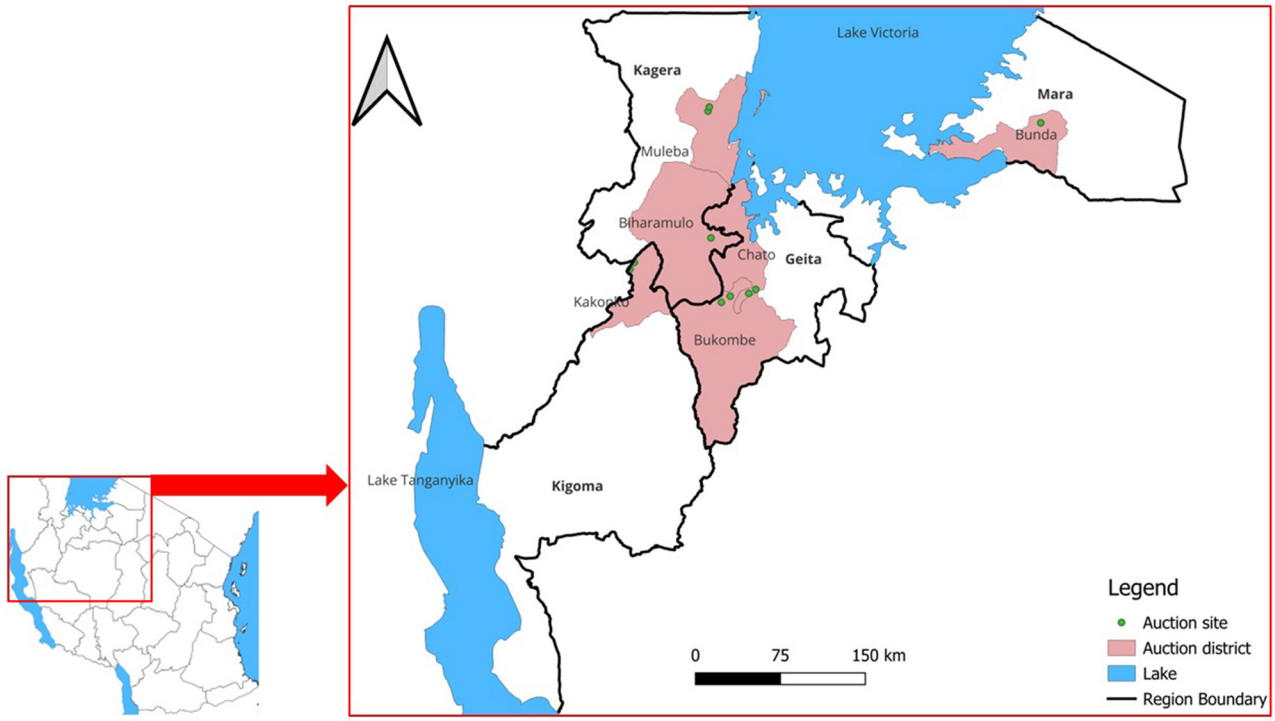


FIGURE 1
Map of the Lake Zone of Tanzania showing auction sites.

was used to simulate cassava seed purchasing decisions in two scenarios: first, mimicking a situation in which there is information asymmetry between the buyer and the seller; and a second situation in which we provided information and used improved quality signaling in the form of quality assurance labels placed on the auctioned cassava cuttings. In all scenarios, the farmer who placed the highest bid was selected as the winner of the auction and would buy the seed at the second highest price.

To prevent the windfall effect that could distort participants' willingness to pay (Banerji et al., 2016; Delaquis et al., 2024), we did not offer endowments or participation fees. Instead, participants were asked to bring their own money to purchase cassava seeds. Participation was not hindered because cassava cuttings are relatively inexpensive, and this was a high-demand planting season. However, light refreshments such as snacks and drinks were provided during the auctions. Auction venues were selected for their central locations within the village, either in village office meeting rooms or schools, to ensure easy access for all participants.

Before conducting auctions for cassava cuttings, a practice auction round was done using three slightly different soap bars to explain the general principle of the experimental auction method used to elicit farmers' willingness to pay for cassava cuttings of different attributes (Lusk and Shogren, 2007, p. 62; Briz et al., 2017; Delaquis et al., 2024). Although the soap bars presented did not have equivalents in the attributes of the cassava seed to be auctioned, they proved to be a useful tool to describe the auction process to farmers who were mostly unfamiliar with second price sealed-bid auctions.

To test for the effect of seed quality misperceptions resulting from information asymmetry and the absence of proper quality signaling (quality assurance labels), two rounds of auctions were conducted. The first round of the cassava seed auction, termed the "*Pre-reveal auction*", was conducted without revealing information about the sources of cassava cuttings, or names of the varieties and without presenting the quality signal (TOSCI quality assurance label) to the farmers. They were allowed to inspect the 20 cassava stem cuttings from each product type (P1, P2, and P3) displayed on the table and then they were asked to bid on the cuttings based on what they could physically observe, mimicking the prevalent situation in the informal cassava seed exchanges in the Lake Zone of Tanzania. Bids for each product were discreetly placed and recorded by the bid recorder who ensured no farmer knew what the other was bidding until the results were presented at the end of the round. This was done to make sure that farmers wrote down what they actually were willing to pay for the products and to reduce the chance of farmers trying to haphazardly bid higher than everyone else just to win the round–a behavior which would have distorted the real price that the farmers were willing to pay under normal circumstances.

In the second round of the auction ("*post-reveal auction*"), farmers were provided with complete information about the auctioned cassava cuttings, including names of the varieties presented, sources of the cuttings, and the TOSCI quality assurance label was displayed on the appropriate bundle of cuttings. The second round of the auction was run immediately after the pre-reveal auction. The farmers' bidding behavior in this round assumes that farmers are now acting on the "*objective quality information*" provided. In this round too, bids for each product were discreetly placed and recorded by the bid recorder who ensured none of the farmers knew what the other was bidding until results were revealed at the end of the round. This was done to make sure that farmers wrote down what they were truly willing to pay for the products and to reduce the chance of farmers engaging in haphazard bidding just to win, as described above.

Data collection and analysis

Data collection was done using Microsoft Excel. The data collected at the village and district levels proved insufficient for analysis. Each auction included only 20 farmers to ensure maximum engagement, however, this number is below the minimum sample size of 30 recommended by the Central Limit Theorem (CLT) for achieving accurate and generalisable results. To address this limitation, data from all districts were aggregated at the zonal level, resulting in a combined sample size of 200 farmers. This larger sample size was considered adequate for ensuring reliability and generalizability of the findings (Kwak and Kim, 2017; Zhang et al., 2023). A descriptive analysis of pre-auction information and analysis of bidding data was done using the SPSS and R statistical packages. WTP estimates were calculated for each round, and comparisons were made.

Results

Socio-demographics of cassava farmers involved in the study

Two hundred farmers participated in the experimental auctions from the four regions where the study was conducted. Among them 151 were men and 49 were women. However, considering the gender of the heads of households represented, 188 were male-headed households (94%) and 12 were female-headed households (6%). The majority (72%) of the farmers were adults aged 36–50 and mature adults aged 51–65 (Table 3). Most had only received primary education (82.0%), with only 4.5% having received tertiary education. Most farmers had more than six years of experience in cassava cultivation. More than 95% of farmers had cassava farms of <2 ha (Table 4).

Auction bidding

In the first round (pre-reveal of information), the mean bids per cutting were TSh 24.5 (USD 0.0094) for P1, TSh 23.4 (USD 0.0089) for P2, and TSh 24.6 (USD 0.0094) for P3, however there was no statistically significant difference in the mean bids among the products ($p = 0.92$). This changed in the second round (post-reveal of information), in which mean bids per cutting were TSh 11.5 (USD 0.0044) for P1, TSh 20.0 (USD 0.0076) for P2, and TSh 32.7 (USD 0.013) for P3 (Figure 2) which varied significantly between products ($p = 1.97\times10^{-7}$). Results show that in the first

TABLE 3 Socio-demographics of cassava farmers involved in the study.

Age			Farming Experience			Education		
Age	Frequency	Percent	Years	Frequency	Percent	Level	Frequency	Percent
18–35	43	21.5%	<3	16	8.0%	Illiterate	10	5.0%
36–50	85	42.5%	3–5	35	17.5%	Primary	164	82.0%
51–65	60	30.0%	6–10	35	17.5%	Secondary	17	8.5%
>65	12	6.0%	>10	114	57.0%	Tertiary	9	4.5%
Total	200	100.0%	Total	200	100.0%	Total	200	100.0%

TABLE 4 Cassava farm size among farmers involved in the study.

Land size (ha)	All farms		Cassava farm	
	Frequency	Percent	Frequency	Percent
Very small farms (<1.0)	26	13%	142	71%
Small farms (>1.0-2.0)	83	41.5%	49	24.5%
Medium farms (>2.0-4.0)	58	29%	6	3%
Large farms (>4.0)	33	16.5%	3	1.5%
Total	200	100%	200	100%

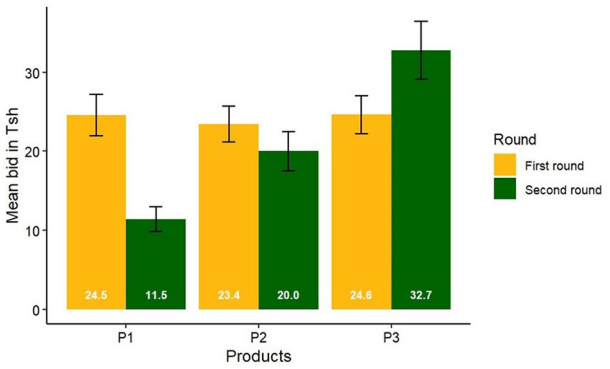


FIGURE 2
Mean bids before information sharing in the first round (Round 1) and after information sharing in the second round (Round 2).

round one participant bid 0 for P1 and another person bid 0 for P3; none bid 0 for P2. In the second round 38 participants (19%) bid 0 for P1 and 22 (11%) bid 0 for P2; none bid 0 for P3. Considering the results from both rounds, only P3 in round 2 resulted in significantly higher bids than P2 in round 2 or all of the treatments in round 1. The demand curve (Figure 3) shows an increase from 30% (round 1) to about 40% (round 2) of farmers willing to pay at least TSh 25 (USD 0.0096) for the premium product P3. The vertical distance among the three curves, evident from the round 2 results, illustrates the discount or premium farmers are willing to pay for various products of differing quality. The difference encompasses the unobservable and observable quality premiums. In round two, the vertical distance of the demand curve for P3 was greater compared to round one, signifying farmers were acting on the objective information provided when placing their bids.

Bidding behavior by the gender of the head of household (HH)

In the first round, the mean bids per cutting for bidders from female-headed households (FHH) ($n = 12$) were TSh 9.0 (USD 0.0034) for P1, TSh 9.3 (USD 0.0036) for P2, and TSh 13.4 (USD 0.0051) for P3 while the mean bids per cutting for bidders from male-headed households (MHH) ($n = 188$) were TSh 25.5 (USD 0.0098) for P1, TSh 24.3 (USD 0.0093) for P2 and TSh 25.3 (USD 0.0097) for P3 (Figure 4). In the second round, the mean bids per cutting for bidders from FHH were TSh 3.5 (USD 0.0013) for P1, TSh 7.2 (USD 0.0028) for P2 and TSh 11.8 (USD 0.0045) for P3 while the mean bids per cutting for bidders from MHH were TSh 12.0 (USD 0.0046) for P1, TSh 20.8 (USD 0.008) for P2, and TSh 34.1 (0.013) for P3. Bids were significantly higher among bidders from MHH compared to the bidders from FHH across all products in round 1 ($p = 0.03$) and round 2 ($p = 0.02$).

Bidding behavior by the gender of the bidder

The mean bids per cutting for female bidders ($n = 49$) in the first round were Tsh 20.9 (USD 0.0077) for P1, Tsh 19.7 (USD 0.0073) for P2, Tsh 22.7 (USD 0.0084) for P3 while in the second round the mean bids were Tsh 8.3 (USD 0.0031) for P1, Tsh 18.1 (USD 0.0067) for P2, Tsh 29.5 (USD 0.0110) for P3. On the other hand, the mean bids per cutting for male bidders ($n = 151$) in the first round were Tsh 25.8 (USD 0.0095) for P1, Tsh 24.6 (USD 0.0091) for P2, Tsh 25.3 (USD 0.0093) for P3 whereas in the second round the mean bids were Tsh 12.5 (USD 0.0046) for P1, Tsh 20.6 (USD 0.0076) for P2, Tsh 33.8 (USD 0.012) for P3 (Figure 5). While mean bids for male bidders were higher than those of female bidders across all products and rounds, the observed differences were not statistically significant ($p > 0.05$).

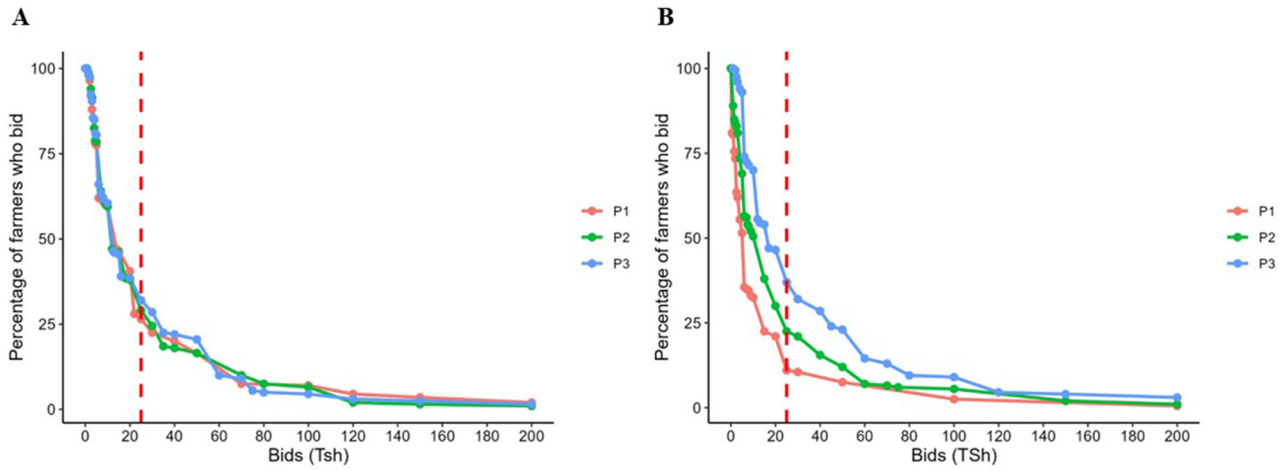


FIGURE 3
Demand curve for products P1, P2, and P3 in **(A)** first round and **(B)** second round auctions [note that in **(B)** the x-axis was adjusted to exclude one farmer who bid TSh 300 for P2 and one former who bid TSh 500 for P3].

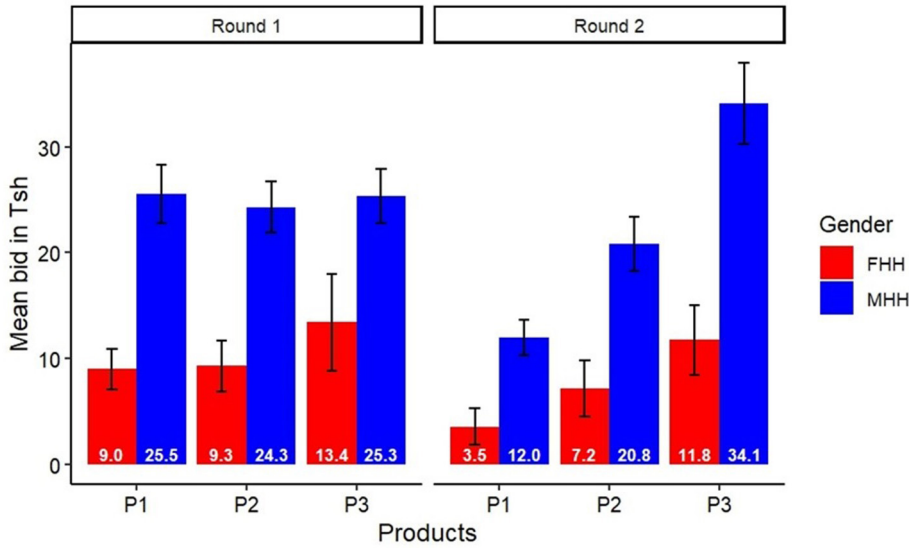


FIGURE 4
Mean bids by the gender of household head (HH) before information provision (Round 1) and after information provision (Round 2).

Post-auction phone interviews

Post-auction interviews with 39 farmers who had not made bids for at least one of the products in either auction round showed that for P1, the main factor was that this product could be obtained elsewhere for free (Table 5). One of the two next reasons for non-bidding was the lack of money to spend on cuttings, and this was the most important non-bidding factor overall for all three product types. For P2, a lack of familiarity with the improved variety was the most common reason for failure to offer a bid, although the next most common explanation was an expressed need to save money for higher quality material. The only response farmers provided for failure to bid for P3 was that they did not have any more money.

Discussion

Are farmers willing to pay for cassava seed?

Seeds are a crucial agricultural input that determines crop productivity and resilience to environmental stresses such as diseases and pests. The use of high-quality seeds of improved varieties is highly emphasized for enhancing resilient agrifood systems under the current conditions of changing climates and threats from biotic and abiotic stresses (Atlin et al., 2017). The benefits of using quality seeds of resilient crop varieties by smallholder farmers in Tanzania and Malawi are estimated to rise from 984 million USD in 2020 to 2.1 billion USD in

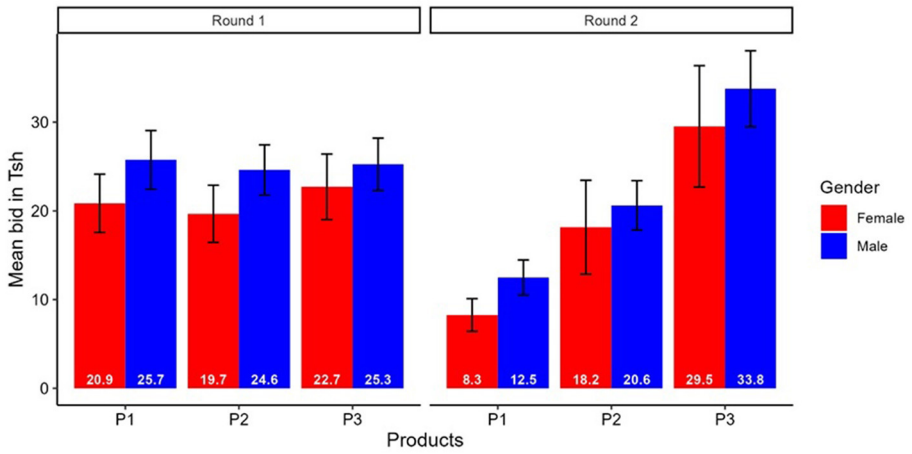


FIGURE 5
Mean bids of female vs. male bidders before information provision (Round 1) and after information provision (Round 2).

TABLE 5 Post-auction phone interview.

Why did you not bid for any of the products?	*n*	P1	*n*	P2	*n*	P3
I had no more money to spend on cassava planting materials	8	21.1%	4	18.2%	1	100%
I cannot pay for the product because I can obtain it for free from other sources	15	39.5%	0	0.0%	0	0%
I am not familiar with the variety traits such as yield, disease resistance, etc.	4	10.5%	9	40.9%	0	0%
I have already satisfied my demand for planting materials this season	4	10.5%	2	9.1%	0	0%
I am saving money to pay for higher quality cuttings	8	21.1%	7	31.8%	0	0%

2050 (Cacho et al., 2020). In Ghana, using certified seeds of rice provided an additional income of GH¢2.65 (USD 0.83) for every GH¢1.00 (USD 0.31) invested, whereas investing GH¢1.00 (USD 0.31) in farmer-saved seed yielded a comparatively lower additional income of GH¢1.98 (USD 0.61) (Dogbe et al., 2014). For cassava in Tanzania, Yabeja et al. (2025) noted an 81% increase in fresh yield when high quality seeds of improved cassava varieties were planted instead of farmer-saved seeds of the same varieties.

Despite the noted benefits of using certified seeds, many believe that farmers in Sub-Saharan Africa are not willing to pay for certified planting materials of vegetatively propagated crops, as they can recycle their own planting stock instead. In the study described here, we set out to examine this topic with farmers in Tanzania, with key questions being: (i) are farmers willing to pay for cassava seed? and (ii) do they place a premium on improved varieties, with or without quality certification? Results indicate that farmers are willing to pay for cassava seed, particularly the cassava seed of improved varieties that offer better yields and resistance to diseases. They are also ready to pay a premium for the seeds of improved varieties if they come with a quality assurance label. As well as obtaining qualitative (yes/no) answers to these questions, we also aimed to quantify any added value expressed by farmers for improved varieties and quality certification. The specific auction approach taken proved to be an appropriate mechanism for assessing farmers' willingness to pay for cassava seed in Tanzania, generating important insights.

Role of information asymmetry

Information asymmetry—where one side has lots of information and the other side has little or none—is a critical challenge that affects farmers' willingness to pay for and adopt new agricultural technologies, including improved cassava varieties (Bai, 2021; Michelson et al., 2023; Wossen et al., 2024). When the quality of planting materials is not explicitly specified, there exists a significant likelihood of information asymmetry between the buyer and the seller of such materials. The first round of auctions was designed to mimic this situation. Results in this round showed no significant variation in the mean bids for P1, P2, and P3.

Furthermore, the unusually high willingness to pay for P1, a local landrace, was most likely an outcome of quality misperception resulting from information asymmetry between bidders and auctioneers of the cassava seed. It could also mean farmers assigned the same level of quality to all three products because they thought cassava cuttings brought by auctioneers (researchers from a government agency and IITA) would be of a similar higher quality compared to what is available in their local market. This has important implications for the cassava seed system in the real market situation.

Suppose CSEs fail to effectively communicate the quality of the improved planting materials they offer, and do not strengthen their value proposition strategies, then farmers are likely to assign the same price as low quality local landrace cuttings available in the market to the high quality cuttings of improved varieties produced by CSEs. If that happens, the CSEs' business

model will ultimately collapse because the cost of production of quality assured planting materials of improved cassava varieties is higher than that of the unregulated planting materials of local landraces. Akerlof's theory of asymmetric information describes how information asymmetry between buyers and sellers can lead to products of poor quality ultimately flooding the market in a phenomenon termed as a *"market for lemons"* (Akerlof, 1978). In such a market, lower prices are applied to both poor-quality products (lemons) and higher-quality products, ultimately leading to the exit of higher-quality product sellers due to reduced returns (Giannakas and Fulton, 2020).

In contrast, when bidders received adequate information about seed quality in the second round of auctions, the bids for P1 and P2 decreased by 53.3% and 14.5%, respectively, while bids for P3 increased by 32.9%. The bids for P2 and P3 were significantly higher than those for P1 (local landrace), suggesting that bidders are willing to pay a premium for the improved variety products (TARICASS4). These results align with Delaquis et al. (2024) study, which found that farmers in Laos and Cambodia were willing to pay a higher price for clean stem cuttings of the improved cassava variety (KU50) from sources that are subject to routine PCR-based testing and visual inspection. Wossen et al. (2024) similarly found that smallholder farmers in Nigeria demonstrated a higher willingness to pay for certified cassava stems of the officially registered variety TME 419.

Effect of improved quality signaling

Quality signaling through seed certification and labeling has been noted to effectively change the "*credence attributes*" of marketed certified seeds into "*search attributes*" (Auriol and Schilizzi, 2015). This process is facilitated by labeling systems, in which certified seeds are accompanied by quality assurance labels that provide essential information regarding quality attributes. Quality assurance labels in Tanzania are provided by TOSCI and have only recently been piloted for cassava seed and are yet to be fully adopted by CSEs.

The application of the TOSCI label on P3 in the second round of auctions led to a significantly higher mean bid for P3 compared to P2, indicating that farmers are willing to pay a premium for TARICASS4 cuttings with quality assurance labels. This finding demonstrates that the issue of information asymmetry in the VPCs' seed markets can be addressed by enhancing quality signaling through a labeling system by regulators such as TOSCI in Tanzania. The willingness of bidders to pay 63.5% more for the premium product P3 (TARICASS4 with the added TOSCI quality assurance label) compared to the price of P2 (TARICASS4) makes a strong case to mandate the inclusion of such labels on certified cassava planting materials within the formal seed system.

It is crucial to note that a corollary of the increase in bids for quality assured seed of the improved variety (P3) following the information "reveal" was a significant reduction in bids for farmer saved seeds of the local landrace (P1). This observation suggests that as quality signaling for VPCs' planting materials becomes more common, the demand for low-quality, cheap planting materials from unregulated sources is likely to decline, leading to an overall improvement in the quality of planting materials being made available to farmers. The results of this study provide a strong indication that if TOSCI implements a labeling system for certified cassava seed in Tanzania, it is likely to boost sales of improved varieties by CSEs and increase adoption of improved varieties.

Gender implications in the WTP of bidders

Although there were no significant differences in mean bids between male and female bidders overall, a statistically significant difference was found when comparing the mean bids of participants from male-headed households (MHH) and female-headed households (FHH). Bids were significantly higher among bidders from MHH compared to those from FHH across all products in rounds 1 and 2, indicating that the gender of the head of the household of the bidders influenced their bidding behavior. Bidders from FHH bid lower than bidders from MHH, probably because households with female heads have comparatively lower disposable income. Women generally have less access to and control over resources than men in rural Tanzania (Liani et al., 2023); nonetheless, they are equally or even more engaged in agriculture than men. However, there is evidence that women's engagement in agriculture in central and eastern Africa increases income inequality, favoring men over women (Akpa et al., 2024). This might also be true in the Lake Zone of Tanzania. To remedy the situation, stakeholders should implement policies that strengthen women's rights in agriculture by enhancing their access to credit, land, and education. This will help narrow the income gap and boost their willingness to pay for quality assured cassava cuttings of improved cassava varieties as well as other agricultural technologies.

While bidders from FHH preferred P3 in the first round, the bid variations among products were not significant. This means they exhibited a level of quality misperception regarding the presented products due to information asymmetry. In the second round, their mean bid for P1 shifted downward by 61.1% and there was a significant difference in mean bids between P1 and P3, which shows that they valued the premium product (P3) more than the local landrace (P1). For the bidders from FHH, the provision of additional information did not lead to general increases in bid size, suggesting that their resources were restricted to a fixed amount, with no scope for increase, even though bids show they favored P3 over other products.

On the other hand, in the absence of any information about the auctioned cuttings in the first round, bidders from MHH favored P1 (local landrace), over P2 and P3 (both TARICASS4), presumably because they were familiar with P1 and were not willing to bet on the unfamiliar P2 and P3 in the absence of any information about quality attributes. Nevertheless, they changed their bids in the second round, in which we observed a large and significant decrease in the mean bid for P1 by 52.9% and an increase in the mean bid for P3 by 34.8%. Bids of participants from MHH for P3 (labeled, certified TARICASS4) were almost three times as great as those for the farmer-saved seed of a local landrace (P1).

Conclusion

This study investigated how the prevalent market conditions for cassava planting material in the Lake Zone of Tanzania affect

the willingness to pay and consequently the demand for certified cassava planting materials, a critical staple food in the region. We used two rounds of a second price sealed bid method to examine (i) how asymmetric information regarding product quality and (ii) how enhanced quality signaling using quality assurance labels issued by TOSCI influenced bids in the two rounds of the experimental auction. We demonstrated that most smallholder farmers in the surveyed areas are prone to quality misperceptions when information about products was withheld in round 1, as there was no significant variation in mean bids for auctioned products. This is unsurprising since the diseases that reduce the quality of cassava planting material are not readily recognized just from viewing stem cuttings. The overwhelming majority of farmers revised their bids upwards (P2 and P3) or downwards (P1) in response to information shared in round 2. Even though P2 and P3 were both the same variety and both produced by QDS farmers, bidders placed a premium price on P3 because it had the TOSCI quality assurance label. This implies that the provision of information about quality can improve the demand for quality cassava cuttings of improved varieties. Consequently, the enhanced quality signaling achieved by using TOSCI quality assurance labels has the potential to greatly improve farmers' willingness to pay for planting materials of improved cassava varieties and therefore increase the demand for the same. Participants from female-headed households demonstrated lower WTP compared to those from male-headed households, even lower than the reported average market price of TSh 25 (USD 0.0096) per cutting for improved cassava cuttings from CSEs. We speculate that participants from female-headed households in our study bid lower because they have marginal access to and control over resources such as land due to the prevalent gender norms and traditions in the region. Implementing policies that strengthen women's access to credit and land ownership would boost their willingness to pay for agricultural technologies including the willingness to pay for quality assured planting materials of improved cassava varieties. Overall, the results reveal that farmers are not only willing to invest in cassava seed but are also inclined to pay a higher price for improved varieties, which offer better yields and disease resistance. Furthermore, there is a notable willingness among farmers to pay a premium for improved variety seeds that come with a quality assurance label, indicating a commitment to superior standards and reliability in their farming practices. This reflects farmers' recognition of the value that enhanced seed quality brings to their agricultural productivity and overall success.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Internal Review Board of International Institute of Tropical Agriculture. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

JM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. JN: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. HK: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review & editing. JJN: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review & editing. JL: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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How agricultural technological innovation influences carbon emissions: insights from China

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Under the context of global warming, the continuous rise in greenhouse gas emissions has become a critical concern. As a significant source of greenhouse gas emissions, the carbon emissions from agriculture exert a considerable impact on climate change, which cannot be overlooked. Agricultural technological innovation is crucial for reducing carbon emissions. Examining how the scale and structure of agricultural technological innovation impact agricultural carbon emissions is important for achieving the Carbon Peaking and Carbon Neutrality Goals. This research is based on data from 30 provinces in China over the period of 2013–2022. It utilizes fixed-effects models, moderation models, and spatial econometric models to empirically investigate the impact mechanisms of the scale and diversity of agricultural technological innovation on agricultural carbon emissions. The research findings reveal that: (1) China's agricultural carbon emissions exhibit an overall declining trend, while the scale of agricultural technological innovation and the level of technological diversity demonstrate a general upward trend. However, regional disparities exist. The total agricultural carbon emissions in the central regions remain relatively high, whereas the scale of agricultural technological innovation and the level of diversity decrease progressively from the southeastern coastal areas toward the inland regions. (2) The scale of agricultural technological innovation and the diversity of technologies have a significant inhibitory effect on agricultural carbon emissions. (3) Mechanism analysis reveals that the scale of agricultural technological innovation positively moderates the impact of technological diversity on agricultural carbon emissions. Specifically, an increase in the scale of technological innovation enhances the inhibitory effect of diversity on carbon emissions. (4) Spatial effect analysis indicates that there is a significant spatial correlation between the scale and diversity of agricultural technological innovation. The scale of agricultural technological innovation has a negative spatial spillover effect on agricultural carbon emissions in adjacent areas. The increase in the scale of local technological innovation helps to spread agricultural technological resources to neighboring areas and reduce their agricultural carbon emissions. This study enriches the research on the impact of agricultural technology innovation on agricultural carbon emissions, providing theoretical references for promoting agricultural technology innovation and sustainable agricultural development.

KEYWORDS

agricultural carbon emissions, innovation scale, technological diversity, sustainable development, China

1 Introduction

In recent years, the issue of global warming has increasingly become a focal point of worldwide attention, with total greenhouse gas emissions continuing to rise. Governments around the world have prioritized addressing climate change and reducing greenhouse gas emissions on their agendas. The Chinese government has explicitly stated that

tackling global warming hinges on technological progress (Xiaochun et al., 2023), emphasizing that technological innovation is a decisive factor in achieving carbon reduction goals and developing a low-carbon economy (Yin and Li, 2019; Lamini et al., 2021). As the second-largest source of global greenhouse gas emissions, the agricultural sector plays a critical role in mitigating global warming by controlling its carbon emissions. In China, agricultural activities account for ~16% to 17% of total carbon emissions (Huang and Sun, 2022), making the reduction of agricultural carbon emissions of paramount importance. The academic community has increasingly focused on studying the mechanisms influencing agricultural carbon emissions. Among the various factors affecting agricultural carbon emissions, agricultural technological innovation has emerged as a significant and indispensable force in promoting energy conservation and emission reduction (Li and Xu, 2022).

Furthermore, the agricultural industrial structure is also recognized as a significant factor influencing agricultural carbon emissions (Cui et al., 2024). The primary challenge in China's agricultural sector has shifted from insufficient total supply to structural imbalances (Wei, 2017). Currently, China's agricultural industrial structure faces numerous challenges, including heavy reliance on resource consumption, outdated technologies, and extensive development practices. These issues have led to high levels of agricultural carbon emissions and increased difficulty in emission reduction, thereby hindering the transition to low-carbon agriculture and sustainable development. The technological structure serves as the foundational support for the industrial structure, and restructuring the technological system of an industry can drive the transformation of the industrial structure toward low-carbon practices (Liu et al., 2022). To achieve the low-carbon transition of the agricultural industrial structure, the key lies in overcoming the structural constraints of the agricultural technological system. The optimization and upgrading of the technological structure represent the core pathway to achieving this breakthrough (Liu, 2012).

From the theoretical perspective of evolutionary economic geography, diversity is considered a critical factor influencing regional development (Yan and An, 2013). A homogeneous technological structure carries the risk of "technological lock-in," which can hinder the innovation and development of local technological systems (Aantoalha, 2019). Technological diversity, on the other hand, can break path dependence and foster knowledge spillovers and cross-disciplinary integration across different technological fields. Interdisciplinary technological exchanges often lead to breakthrough innovations. Therefore, transitioning from a single-technology agglomeration model to a diversified technology cluster model is an inevitable pathway for regional sustainable development (Shanlang et al., 2023). To achieve sustainable agricultural development, it is essential to enhance regional agricultural technological diversity.

In summary, existing literature has made significant progress in exploring the mechanisms influencing agricultural carbon emissions. However, several gaps remain: first, current studies have not incorporated the structural changes in agricultural industries induced by technological diversity into their analytical frameworks, thereby overlooking the impact of agricultural technological diversity on agricultural carbon emissions. Second, there is insufficient research on whether the scale of agricultural innovation influences the structure of agricultural technology and, consequently, its impact on agricultural carbon emissions. Although some studies have indicated that agricultural technological innovation significantly reduces agricultural carbon emission intensity through mechanisms such as reducing non-clean energy use, lowering agricultural chemical inputs, and increasing agricultural output levels (Zhang et al., 2024), the relationship between the scale of agricultural innovation, the structure of agricultural technology, and agricultural carbon emissions requires further exploration. Therefore, this paper examines the mechanisms through which both the scale and structure of agricultural technological innovation influence agricultural carbon emissions.

2 Literature review and research hypotheses

2.1 Scale of agricultural technological innovation and agricultural carbon emissions

Current research on the impact of innovation on carbon emissions primarily focuses on the scale of innovation. Existing studies, based on an output perspective, often use the number of patents as a measure of technological innovation scale (Nyarko et al., 2018; Khattak et al., 2020) and suggest that the scale of innovation can inhibit carbon emissions (Zhu et al., 2024). In terms of research scope, most literature concentrates on the emission reduction effects of technological innovation in the industrial sector. For instance, Richmond and Kaufmann (2005) argue that technological progress and innovation contribute to environmental improvement. Gu (2022) using patent data and focusing on 275 prefecture-level cities in China, demonstrate that the scale of technological accumulation enhances emission reduction effects. However, research specifically addressing the relationship between agricultural technological innovation and agricultural carbon emissions is limited. Most scholars approach this issue from the perspective of technological progress. For example, Yang and Li (2017) indicate that agricultural technological progress can improve energy efficiency, thereby reducing agricultural carbon emission intensity. Li and Zhou (2020) notes that agricultural technological progress generally contributes to the reduction of agricultural carbon emissions, but a detailed analysis reveals significant differences in the impacts of different pathways of agricultural technological progress on carbon emissions.

This research posits that the increase in the scale of agricultural technological innovation can reduce carbon emissions. The impact of agricultural technological innovation scale on agricultural carbon emission intensity can be explained through two pathways. The first pathway is the direct effect: the application of advanced agricultural technologies in production processes can reduce the use of "non-clean" technologies in traditional agriculture, enhance energy efficiency, and improve high-energy-consumption production methods (Fan, 2022). When innovative technologies

are applied in clusters, the scale effect can further reduce energy consumption, thereby lowering agricultural carbon emissions. The second pathway is the indirect effect: when the scale of innovation reaches a certain threshold, it can trigger structural restructuring, promoting industrial upgrading and rationalization (Yang, 2013). The emergence of new technologies can influence changes in the input structure of agricultural production factors, guiding the flow of resources from low-efficiency sectors to high-efficiency sectors, leading to transformations in agricultural structure (Tang and Yi, 2024), and ultimately reducing agricultural carbon emissions. Based on this, the following hypothesis is proposed:

Hypothesis 1: The scale of agricultural technological innovation inhibits agricultural carbon emissions.

2.2 Agricultural technological diversity and agricultural carbon emissions

Technological diversity refers to the variety of technological combinations and structures within a specific field (Guo et al., 2024), reflecting the heterogeneity of knowledge within a region. Technological diversification can promote the sharing of industrial technologies through various means, such as collaborative exchanges, effectively bridging the technological gaps between different sectors. This fosters spillover effects of technological innovation and contributes to the reduction of carbon emissions (Liu, 2024).

In the research of technological diversity and carbon emissions, most scholars focus on the impact of technological diversity on carbon emissions and energy intensity in manufacturing enterprises. For instance, Shanlang et al. (2023) conducted an empirical analysis using patent data and urban energy data from 249 prefecture-level cities in China. Their results indicate that as the level of green technological diversity increases, the energy intensity of these cities initially rises and then declines, highlighting the importance of enhancing regional technological diversity. Zhou et al. (2024). point out that technological diversity facilitates the adoption of clean energy, reduces reliance on fossil fuels, and contributes to carbon emission reduction. Wu's (2024) related research identifies two mechanisms through which technological diversity reduces carbon emissions in manufacturing enterprises: first, by promoting shifts in production patterns to reduce emissions, and second, by fostering green technology-biased progress. Influenced by environmental regulations, manufacturing enterprises tend to adopt low-carbon and environmentally friendly technologies, achieving green technology-biased progress and thereby reducing carbon emissions.

This research posits that diversity in agricultural technological structures can reduce agricultural carbon emissions. The mechanisms through which agricultural technological diversity mitigates carbon emissions are primarily reflected in the following three aspects: first, by promoting the transformation of agricultural production models, improving energy efficiency, reducing dependence on fossil fuels, and driving the low-carbon transition of the agricultural industrial structure, thereby lowering agricultural carbon emissions. Second, through knowledge spillovers and synergistic effects, facilitating the exchange and integration of different technologies, promoting agricultural technological innovation and upgrading, and enabling low-carbon sustainable development in agriculture. Based on this, the following hypothesis is proposed:

Hypothesis 2: Agricultural technological diversity inhibits agricultural carbon emissions.

2.3 The moderating role of agricultural technological innovation scale

The literature on technological diversification indicates that a city's level of innovation is closely related to its technological diversity (Gao, 2021). Therefore, the inhibitory effect of technological diversification on agricultural carbon emissions requires a corresponding level of innovation to be effective. As the scale of agricultural technological innovation increases, it first generates a cost-decreasing effect in technology integration. Large-scale innovation investments lead to the accumulation of knowledge capital, reducing the coupling costs between different technological modules. This makes technological diversity more achievable, thereby contributing to the reduction of agricultural carbon emissions.

Hypothesis 3: The scale of agricultural technological innovation positively moderates the relationship between agricultural technological diversity and agricultural carbon emission.

2.4 The spatial spillover effects of agricultural technological innovation

Regarding the spatial spillover effects of innovation on carbon emissions, many scholars have employed spatial econometric methods to study the spillover effects of innovation on regional carbon emissions (Jing et al., 2023; Zhao et al., 2025). According to the First Law of Geography, all objects in space exhibit spatial correlation and influence each other. Regions in close geographic proximity often demonstrate a certain degree of spatial correlation in technological innovation, typically showing a positive relationship. That is, technological changes in one region can generate positive spillover and feedback effects on geographically adjacent areas. Similarly, agricultural technological innovation activities may also exhibit spillover effects akin to those of general technological innovation in the process of promoting agricultural carbon emission reduction. Based on this, the following hypothesis is proposed:

Hypothesis 4: Agricultural technological innovation exerts significant spatial spillover effects on agricultural carbon emissions.

3 Data sources and research methods

3.1 Data sources

This research analyzes panel data from 30 provinces, autonomous regions, and municipalities in mainland China from 2013 to 2022 (excluding the Tibet Autonomous Region). Agricultural patent data are sourced from the incopat patent

TABLE 1 Agricultural carbon emission accounting index system.

Carbon source category	Carbon source	Carbon emission coefficient	Reference source
Agricultural energy use	Diesel	0.5927 kgC/kg	IPCC2013
Agricultural material input	Fertilizer	0.8956 kgC/kg	Oak Ridge National Laboratory, USA
	Pesticide	4.9341 kgC/kg	Oak Ridge National Laboratory, USA
	Agricultural film	5.1800 kgC/kg	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
Crop cultivation	Sowing	312.60 kg/km^2	College of Agronomy and Biotechnology, China Agricultural University
	Irrigation	266.48 kg/hm^2	College of Agriculture, Nanjing Agricultural University

database (www.incopat.com). Data on agricultural carbon emissions and control variables are obtained from *China Statistical Yearbook*, *China Rural Statistical Yearbook*, and provincial statistical yearbooks.

3.2 Variable selection

(1) Agricultural carbon emissions

Current methods for measuring agricultural carbon emissions primarily include the carbon emission coefficient method (He et al., 2018), input-output analysis (Zhang et al., 2022), and the carbon footprint lifecycle method (Yao et al., 2017). Among these, the carbon emission coefficient method is widely recognized and utilized by scholars due to its simplicity and ease of calculation. Therefore, this research measures agricultural carbon emissions based on the IPCC Guidelines for National Greenhouse Gas Inventories, focusing on three aspects: agricultural energy consumption, agricultural material inputs, and methane emissions from crop cultivation. The specific calculation formula is as follows:

$$ACE = \sum ACE_i = \sum (T_i \cdot \xi_i) \tag{1}$$

In Equation 1, ACE represents the total agricultural carbon emission, ACE_i represents the carbon emission from various agricultural production activities, T_i represents the quantity of carbon sources, ξ_i represents the emission factor of the carbon source. The calculation of total carbon emissions is presented in Table 1.

(2) Scale of agricultural technological innovation

Currently, the academic community widely adopts the number of patents as a primary indicator to measure the scale of innovation activities (Liang et al., 2023), as patents, being a significant output of innovation, directly reflect the scale of innovation. This research selects patent authorization data as the basis for analysis. According to information released by the National Intellectual Property Administration, the International Patent Classification (IPC) code A01 encompasses technologies related to agriculture, forestry, animal husbandry, hunting, trapping, and fishing. Therefore, this paper screens invention patents with IPC classification numbers containing "A01" to ensure the agricultural attributes of the patent data. A total of 128,366 agricultural authorized patents are identified and used as the measurement data for agricultural technology innovation scale (APT).

(3) Agricultural technological diversity

The measurement of agricultural technological diversity draws on Frenken et al.'s (2007) entropy method, using the three-digit IPC classification to measure technological diversity (ADV), with the formula below:

$$ADV_{it} \sum_{s=1}^{g} P_{s,it} Ln\left(\frac{1}{P_{s,it}}\right) \tag{2}$$

In Equation 2, ADV_{it} represents t the technological diversity of non-related technologies in province i in year t, $P_{s,it}$ represents the proportion of three-digit patent s in province i in year t relative to all invention patents authorized in that province that year.

(4) Control variables

Drawing on previous research, relevant variables were selected to control for potential influences on agricultural carbon emissions. This paper selects the agricultural industrial structure (AIS), agricultural mechanization level (AM), and agricultural economic level (AGDP) as control variables. Specifically, the agricultural industrial structure (AIS) is measured by the proportion of the added value of the primary industry in GDP, the agricultural mechanization level (AM) is indicated by the total power of agricultural machinery, and the agricultural economic development level (AGDP) is represented by the total output value of agriculture, forestry, animal husbandry, and fishery in the region.

3.3 Model setting

To clarify the direct effects of agricultural technological diversity and innovation on agricultural carbon emissions, this research constructs a spatial-temporal double fixed-effect model as follows:

$$ACE_{i,t} = \beta_0 + \beta_1 APT_{i,t} + \beta_2 ADV_{i,t} + \beta_3 Controls_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \tag{3}$$

In Equation 3, $ACE_{i,t}$ represents the agricultural carbon emissions in province i in year t, $APT_{i,t}$ represents the scale of agricultural technological innovation in province i in year t, $ADV_{i,t}$ represents the agricultural technological diversity in province i in year t, λ_i and μ_t are time and provincial fixed effects, and Controls denote the control variables.

To examine whether the agricultural technological innovation scale is a moderating factor in the impact of technological diversity on agricultural carbon emissions, the following moderation model is constructed:

$$ACE_{i,t} = \beta_0 + \beta_1 APT_{i,t} + \beta_2 ADV_{i,t} + \beta_3 APT_{i,t} * ADV_{i,t} + \beta_4 Controls_{i,t} + \lambda_i + \mu_t + \varepsilon_{i,t} \tag{4}$$

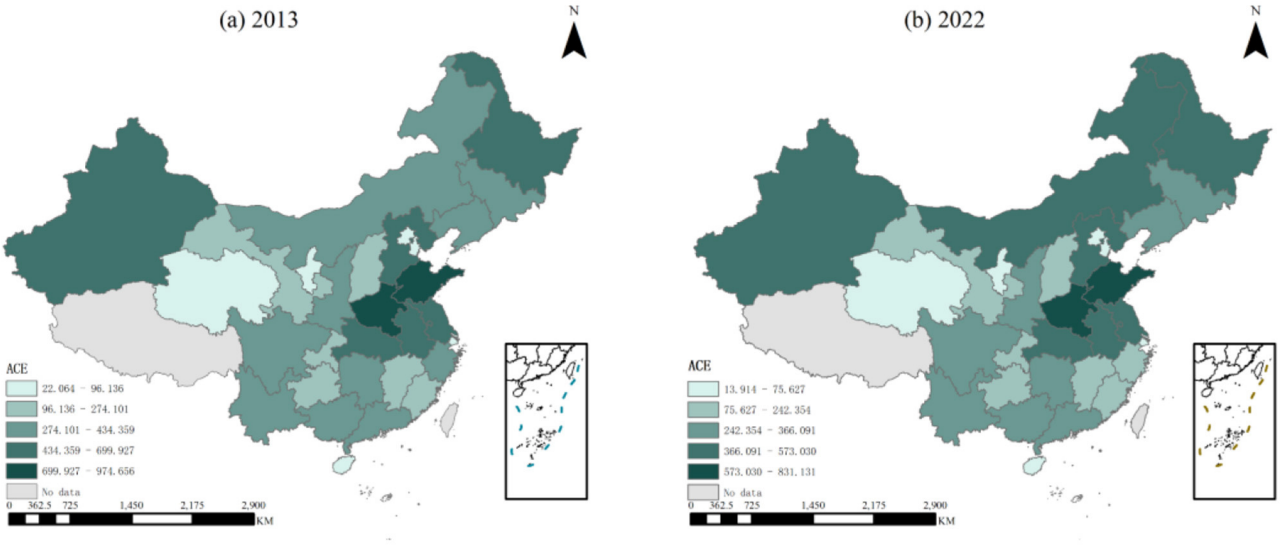


FIGURE 1
Spatial-temporal distribution of agricultural carbon emissions.

In Equation 4, $APT_{i,t} * ADV_{i,t}$ represents the interaction between agricultural technological innovation and diversity. If β1 and β3 have the same sign and the β3 term is significantly regression, it suggests that agricultural technological innovation positively moderates the inhibitory effect of technological diversity on agricultural carbon emissions.

To further explore the spatial effects of agricultural technology diversity and agricultural technology innovation on agricultural carbon emissions, the Spatial Autoregressive (SAR) model (Equation 5) and the Spatial Error Model (SEM) (Equations 6, 7) are constructed. The expressions are as follows:

$$Agrca_{i,t} = \rho W Agrca_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \quad (5)$$

$$Agrca_{i,t} = \beta X_{i,t} + \varepsilon_{i,t} \quad (6)$$

$$\varepsilon_{i,t} = \theta W_{i,t} + \mu_t \quad (7)$$

In Equations 5–7, ρ represents the spatial regression coefficient, capturing the spatial dependence in the regression relationship; W denotes the spatial weight matrix, which reflects the spatial interactions or connections between different units; $X_{i,t}$ is the vector of explanatory variable; $\varepsilon_{i,t}$ is the vector of random error terms; θ measures the spatial dependence in the spatial error model, indicating how the error terms are correlated across different units.

4 Results and analysis

4.1 Measurement results analysis

(1) Spatial-temporal distribution characteristics of agricultural carbon emissions

There are significant differences in agricultural carbon emissions across China's provinces. The (a) 2013 and (b) 2022 graphs in Figure 1 are visual representations of agricultural carbon emissions for 2013 and 2022, respectively. In 2013, the top five provinces for agricultural carbon emissions accounted for over one-third of the national total, while the bottom five made up <2%. Between 2013 and 2022, agricultural carbon emissions in Chinese provinces showed a downward trend, with the national average decreasing from 347.983 to 299.557 million tons (Figure 1).

From a spatial perspective, agricultural carbon emissions exhibit distinct spatial clustering characteristics. In 2013, provinces with higher agricultural carbon emissions included Henan, Shandong, Hebei, Anhui, and Jiangsu, most of which are located in or adjacent to the central region of China. This is primarily due to the relatively homogeneous industrial structure and less rational energy consumption patterns in the central region, where agricultural practices heavily rely on traditional high-carbon emission methods, such as extensive use of fertilizers and pesticides, and lower levels of agricultural mechanization, leading to increased agricultural carbon emissions. In contrast, regions with lower agricultural carbon emissions, such as Shanghai, Tianjin, and Beijing, are located in economically developed areas with higher levels of industrialization, where agriculture constitutes a relatively smaller share of the regional economy. Additionally, agricultural production in these areas focuses more on cash crops and vegetables, with less cultivation of methane-emitting crops like rice, resulting in lower overall agricultural carbon emissions.

(2) Spatial-temporal distribution characteristics of agricultural technological innovation scale.

The (a) 2013 and (b) 2022 graphs in Figure 2 are visual representations of agricultural technological innovation for 2013 and 2022, respectively. From 2013 to 2022, the scale of agricultural technological innovation in China has significantly increased. Spatially, agricultural technological innovation exhibits a pattern of higher levels in the southeast and lower levels in the northwest. High-value regions are concentrated in the eastern coastal provinces, while low-value regions are located in inland western provinces such as Inner Mongolia and Qinghai. This disparity arises because the eastern coastal regions possess stronger economic foundations and technological capabilities, enabling higher levels of agricultural technological innovation under policy support. In contrast, inland western provinces like Inner Mongolia and Qinghai, with relatively weaker economic bases and

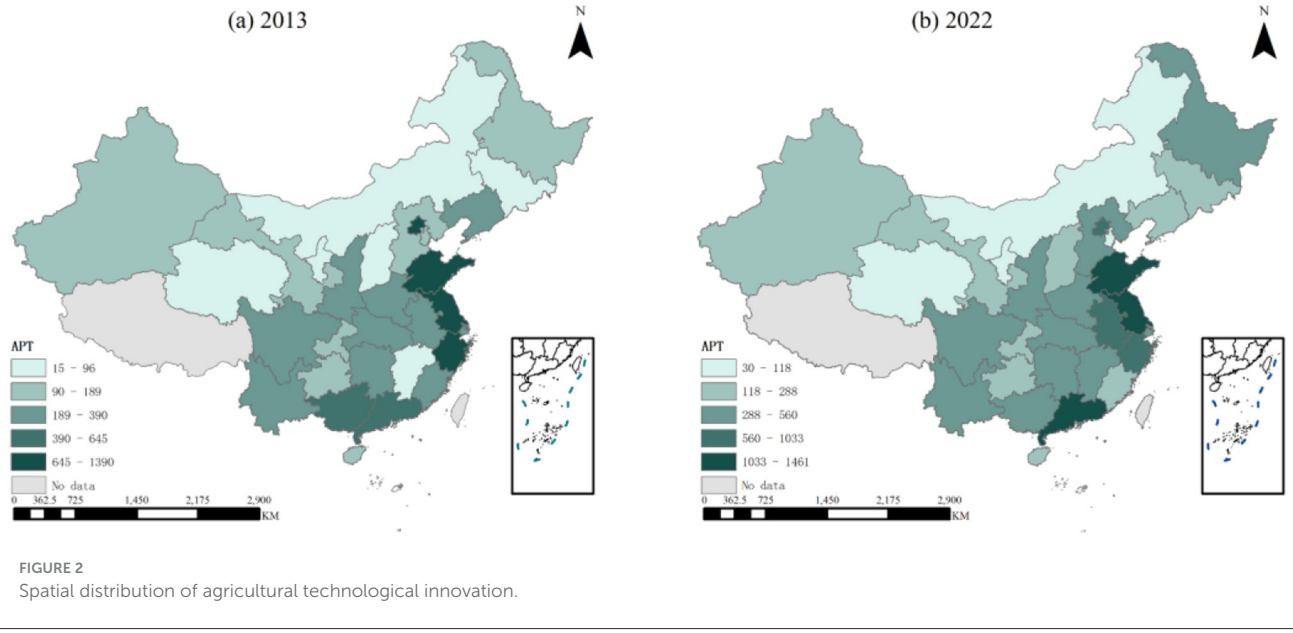


FIGURE 2
Spatial distribution of agricultural technological innovation.

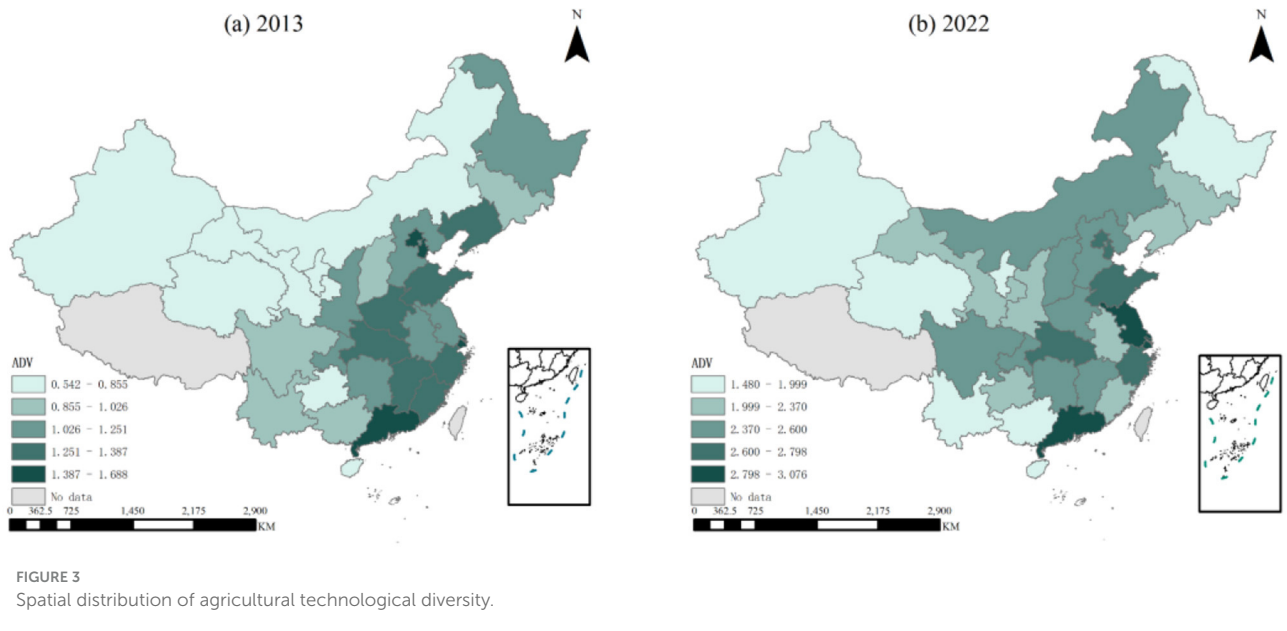


FIGURE 3
Spatial distribution of agricultural technological diversity.

limited technological resources, have become low-value regions for agricultural technological innovation (Figure 2).

(3) Spatial-temporal distribution characteristics of agricultural technological diversity.

To reveal the spatial evolution characteristics of agricultural technological diversity in China, a visual analysis of agricultural technological diversity was conducted. The (a) 2013 and (b) 2022 graphs in Figure 3 are visual representations of agricultural technological diversity for 2013 and 2022, respectively. From a time-series perspective, the agricultural technological diversity of Chinese provinces and cities has significantly improved, with the national average increasing from 1.1423 to 2.391.

Spatially, agricultural technological diversity in China exhibits notable regional disparities, generally characterized by a distribution pattern of "higher in the east and south, lower in the west and north," with a gradual decline from the southeastern coastal areas toward the inland regions. Specifically, significant spatial clustering is observed in the eastern and central regions. Areas with higher agricultural technological diversity are concentrated in the eastern and southern regions, showing a clustering trend. These include the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing, as well as provinces such as Jiangsu, Shandong, Henan, Hubei, Zhejiang, Fujian, and Guangdong. This is attributed to the relatively developed

economies of these regions, which possess strong economic foundations and attract substantial talent, capital, and technological investments, thereby promoting the research, development, and application of agricultural technologies and resulting in higher levels of agricultural technological diversity.

In contrast, the western and northern regions exhibit lower levels of agricultural technological diversity. This is due to the relatively lagging economic development in these areas, where government policies focus more on infrastructure construction and basic livelihood security, with comparatively less investment in agricultural technology. Consequently, the level of agricultural technological diversity remains lower in these regions.

4.2 Mechanism analysis of agricultural technological innovation's impact on agricultural carbon emissions

4.2.1 Benchmark regression analysis

Model 1 selects agricultural technological innovation scale (APT) as the independent variable. Model 2 selects agricultural technological diversity (ADV) as the independent variable. Model 3 includes agricultural technological innovation (APT), agricultural technological diversity (ADV), and their interaction term (APT*ADV). As shown in Table 2.

TABLE 2 Benchmark regression model test.

Variables	(1)	(2)	(3)
APT	−0.052***		−0.007
	(−4.46)		(−0.38)
ADV		−12.443*	−2.983
		(−1.82)	(−0.42)
APT*ADV			−0.016***
			(−2.77)
AIS	1.713	2.182	1.243
	(0.93)	(1.15)	(0.68)
AGDP	1.028	1.818	0.447
	(0.31)	(0.53)	(0.14)
AM	30.878***	30.353***	28.053***
	(2.86)	(2.72)	(2.62)
_cons	102.215	93.150	128.549
	(1.20)	(1.06)	(1.53)
N	300	300	300
adj. R^2	0.447	0.411	0.464

*$p < 0.1$, ***$p < 0.01$.

The results of Model 1 indicate that the scale of agricultural technological innovation is significantly negatively correlated with agricultural carbon emissions at the 1% level, suggesting that an increase in the scale of agricultural technological innovation inhibits agricultural carbon emissions. This validates Hypothesis 1. Agricultural technological innovation promotes the development and application of clean technologies, enhances energy efficiency, and drives industrial structure upgrading, thereby reducing agricultural carbon emission intensity. The results of Model 2 show that agricultural technological diversity is significantly negatively correlated with agricultural carbon emissions. For every unit increase in agricultural technological diversity, agricultural carbon emissions are reduced by 11.742 units, indicating that an increase in agricultural technological diversity exerts an inhibitory effect on agricultural carbon emissions. This validates Hypothesis 2. When a region has a high level of agricultural technological diversity, a diversified agricultural technology structure can facilitate the transformation of production models, improve energy efficiency, promote the use of clean energy, and accelerate the development of green technologies, thereby reducing carbon emissions in agricultural production. Model 3 introduces the interaction term between agricultural technological diversity and the scale of agricultural innovation to analyze the moderating effect between technological diversity and innovation scale. The results demonstrate that an increase in the scale of agricultural technological innovation enhances the inhibitory effect of agricultural technological diversity on agricultural carbon emissions, validating Hypothesis 3. This is because regions with a higher scale of agricultural technological innovation can quickly learn and adapt when faced with unfamiliar fields or complex technological challenges, reducing the costs and risks of technology integration. The increase in the scale of agricultural technological innovation not only expands the range of technological options but also improves the specificity and efficiency of technology application, thereby more effectively utilizing these diversified technological means to reduce carbon emissions in agricultural production and achieve green and sustainable agricultural development.

Regarding the control variables, the level of agricultural mechanization is also significantly positively correlated with agricultural carbon emissions. The reason lies in the fact that increased agricultural mechanization heightens the dependence of agricultural production on fossil fuels, particularly the sharp rise in the consumption of fuels such as diesel for agricultural machinery. This, in turn, leads to a significant increase in greenhouse gas emissions.

4.2.2 Endogeneity test

To address potential endogeneity issues in the model, all variables were lagged by one period. The regression results in Table 3 show that, after accounting for potential endogeneity, the main conclusions of this research remain valid.

4.2.3 Robustness test

To further enhance the reliability of the conclusions, this research conducted robustness tests by altering the time window. The research period was adjusted from 2013–2022 to 2013–2021, and the regression results remained consistent with the previous findings. As shown in Table 4.

4.2.4 Heterogeneity analysis

To further explore the regional heterogeneity in the impact of agricultural technological innovation scale and diversity on

TABLE 3 Results of endogeneity test.

Variables	(1)	(2)	(3)
L.APT	−0.047***		−0.006
	(−4.10)		(−0.30)
L.ADV		−12.910*	−4.733
		(−1.89)	(−0.67)
L.APT*ADV			−0.014**
			(−2.34)
L.AIS	3.618*	4.325**	3.368*
	(1.91)	(2.24)	(1.80)
L.AGDP	1.180	2.280	0.886
	(0.30)	(0.55)	(0.22)
L.AM	17.608	18.969*	16.304
	(1.64)	(1.72)	(1.53)
_cons	188.466**	162.175*	201.130**
	(2.22)	(1.86)	(2.40)
N	270	270	270
adj. R^2	0.488	0.459	0.502

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 4 Results of robustness test.

Variables	(1) Car	(2) Car	(3) Car
APT	−0.044***		0.004
	(−3.62)		(0.22)
ADV		−12.606*	−3.098
		(−1.87)	(−0.44)
APT*ADV			−0.017***
			(−2.95)
AIS	0.507	0.596	−0.228
	(0.24)	(0.27)	(−0.11)
AGDP	0.027	0.626	−0.487
	(0.01)	(0.19)	(−0.15)
AM	24.243**	23.522*	20.241*
	(2.02)	(1.92)	(1.70)
_cons	177.531*	175.354*	212.842**
	(1.87)	(1.81)	(2.28)
N	270	270	270
R^2	0.469	0.446	0.490

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

agricultural carbon emissions, this research divides the sample data into three sub-samples representing the eastern, central, and western regions for separate regression analyses. As shown in Table 5.

In terms of agricultural technology innovation scale, the results show that the agricultural technology innovation scale in the eastern and central regions significantly curbs agricultural carbon emissions, while the inhibitory effect of agricultural technology innovation scale on agricultural carbon emissions in the western region is not significant. This is mainly due to differences in industrial structure, economic development level, and policy support among regions. The eastern region, with a diversified industrial structure and a strong economic foundation, can effectively utilize agricultural technology innovation to suppress carbon emissions. The central region, driven by policy support and the transformation of agriculture toward modernization, has also significantly reduced carbon emissions through the expansion of agricultural technology innovation scale. In contrast, the western region, characterized by a relatively single industrial structure, weak economic base, and limited capacity for technology promotion, shows no significant effect of agricultural technology innovation scale on curbing carbon emissions.

The impact of agricultural technology diversity on agricultural carbon emissions varies by region, mainly due to significant differences among regions in terms of economic development level, industrial structure, technological level, resource endowment, and policy support. The impact of agricultural technology diversity on agricultural carbon emissions is not significant overall. However, in the eastern and western regions, agricultural technology diversity can curb agricultural carbon emissions, while in the central region, it may promote agricultural carbon emissions. The eastern region, with its economic and technological advantages, can better utilize technology diversity to suppress carbon emissions. The western region, driven by ecological protection needs and policy support, leverages technology diversity to achieve low-carbon development. As for the central region, despite its efforts to promote agricultural technology innovation, the unique characteristics of its agricultural industrial structure, production methods, and resource utilization patterns mean that the increase in technology diversity has not effectively reduced carbon emissions. On the contrary, due to an over-reliance on high-energy-consuming and high-emission agricultural inputs such as chemical fertilizers and pesticides, there has been a certain degree of increase in carbon emissions.

4.2.5 Analysis of spatial spillover effects

Using the ArcGIS spatial statistics tool, provincial adjacency (shared borders and points) was employed as the spatial weight matrix, and Moran's I index was applied to test whether the variables exhibit spatial correlation. The test results, as shown in Table 6, indicate that Moran's I indices for agricultural carbon emissions and the scale of agricultural technology innovation are significantly positive, demonstrating a notable positive spatial correlation. Although the Moran's I index for agricultural technology diversity is not significant in a few years, it still exhibits a certain degree of positive spatial correlation overall. Therefore, it is necessary to further explore the spatial carbon emission reduction effects of agricultural technology innovation.

Firstly, this article uses LM test to determine the type of spatial effect. Secondly, through Hausman test and LR test, it is found that using a fixed effects model is more appropriate. Therefore, this article ultimately chooses a spatial lag model with double fixed effects to study the spatial spillover effects of agricultural technology

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TABLE 5 Heterogeneity test results.

Variables	(1) Eastern	(2) Central	(3) Western	(4) Eastern	(5) Central	(6) Western
APT	−0.032**	−0.122***	0.004			
	(−2.38)	(−3.50)	(0.08)			
ADV				−14.771	13.074	−4.326
				(−0.99)	(0.83)	(−0.65)
AIS	28.230***	−3.114	−7.312***	27.791***	−0.010	−7.031***
	(6.34)	(−1.13)	(−3.25)	(5.88)	(−0.00)	(−3.09)
AM	−12.886	18.655	81.832***	−15.430	10.196	82.416***
	(−0.61)	(1.20)	(4.26)	(−0.70)	(0.61)	(4.31)
AGDP	−0.388	−49.305	2.690	−0.338	−73.089*	2.731
	(−0.06)	(−1.32)	(0.91)	(−0.05)	(−1.74)	(0.95)
Cons	257.741*	707.724**	−291.934*	281.564*	964.732**	−295.448**
	(1.77)	(2.10)	(−1.97)	(1.89)	(2.64)	(−2.00)
N	120	90	90	120	90	90
R^2	0.602	0.551	0.424	0.582	0.476	0.428

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 6 Morans'I index.

Period	Carbon emissions			Scale			Diversity		
	Morans'I	*Z*	*P*	Morans'I	*Z*	*P*	Morans'I	*Z*	*P*
2013	0.300***	2.928	0.003	0.295***	3.020	0.003	0.381***	3.567	0.000
2014	0.300***	2.921	0.003	0.430***	4.155	0.000	0.160**	1.688	0.091
2015	0.271***	2.672	0.008	0.365***	3.156	0.000	0.063	0.839	0.401
2016	0.264***	2.610	0.009	0.442***	4.050	0.000	0.304***	2.938	0.003
2017	0.260***	2.573	0.010	0.389***	3.772	0.000	0.103	1.229	0.219
2018	0.258**	2.555	0.011	0.431***	4.233	0.000	0.085	1.040	0.298
2019	0.254**	2.524	0.012	0.353***	3.435	0.000	0.149	1.620	0.105
2020	0.256**	2.539	0.011	0.381***	3.682	0.000	0.192**	1.959	0.050
2021	0.248**	2.461	0.014	0.342***	3.338	0.000	0.295**	2.817	0.005
2022	0.238**	2.366	0.018	0.331***	3.240	0.002	0.175*	1.802	0.072

*p < 0.1, **p < 0.05, ***p < 0.01.

innovation scale, and chooses a spatial error model with double fixed effects to study the spatial spillover effects of agricultural technology diversity.

As shown in Table 7, the estimated coefficient of Spatial-rho is significantly positive, indicating that agricultural carbon emissions have a significant positive spatial spillover effect. That is, a reduction in local agricultural carbon emissions can affect the agricultural carbon emissions in neighboring regions. Technological innovation can optimize production methods, support local agricultural development, and reduce agricultural carbon emissions. At the same time, agricultural technology can spread and penetrate into surrounding areas, thereby reducing agricultural carbon emissions in those regions. Moreover, the successful experience of low-carbon transformation in a region can be transmitted through multiple channels. Neighboring regions, inspired and motivated by this, may imitate these practices, thereby reducing agricultural carbon emissions.

Since the spatial model includes a spatial lag term, the regression coefficients cannot accurately describe the impact of the independent variables on the dependent variable and need to be decomposed into effects. The results of the effect decomposition show that the direct effect, indirect effect, and total effect of agricultural technology innovation scale on agricultural carbon emissions are significantly negative. This indicates that the agricultural technology innovation scale in a province can reduce both local agricultural carbon emissions and those in surrounding areas. This suggests that an increase in the local agricultural technology innovation scale helps spread agricultural technology resources to neighboring regions, thereby reducing agricultural carbon emissions. This is mainly due to the following

two aspects: first, agricultural technological knowledge has a significant diffusion and spillover effect, which can accelerate the flow of agricultural technology between regions. On the other hand, high-level agricultural technology innovation in a region can serve as a leading example for neighboring areas. Through cross-regional exchanges of agricultural technology, surrounding regions can not only learn and adopt advanced agricultural technologies but also enhance the exchange and interaction of agricultural technologies, thereby promoting local agricultural development and reducing agricultural carbon emissions. Table 8 presents the estimation results of the spatial error model, with a spatial lag coefficient of 0.231, which is significant at the 1% level. This indicates that agricultural carbon emissions in a province are influenced not only by observable factors such as the level of agricultural technology diversity, agricultural industrial structure, and agricultural mechanization level, but also by unobservable factors in neighboring regions.

TABLE 7 Estimation results of spatial lag model.

Variables	Direct effect	Indirect effect	Total effect
APT	−0.049***	−0.012**	−0.061***
	(−4.44)	(−2.15)	(−4.35)
Spatial–rho	0.207***		
	(2.69)		
Controls	YES		
N	300		
R^2	0.291		

**$p < 0.05$, ***$p < 0.01$.

TABLE 8 Estimation results of spatial error model.

Variables	SEM
ADV	−10.614*
	(−1.72)
Lambda	0.231***
	(2.88)
sigma^2_e	371.682***
	(12.17)
Controls	YES
N	300
adj. R^2	0.678

*$p < 0.1$, ***$p < 0.01$.

5 Conclusions and policy implications

5.1 Conclusions

This research is based on panel data from 30 provinces, municipalities, and autonomous regions in China from 2013 to 2022. Using fixed-effects models, moderating effects models, and spatial econometric models, it explores the impact mechanisms of agricultural technology innovation on agricultural carbon emissions from the perspectives of technological innovation scale and technological structure. The research empirically examines the impact mechanisms of agricultural technology innovation scale and agricultural technology diversity on agricultural carbon emissions. The main conclusions are as follows:

First, agricultural carbon emissions generally show a downward trend. During the period from 2013 to 2022, agricultural carbon emissions in various provinces and cities across China exhibited an overall declining trend. Both the scale of agricultural technology innovation and the level of agricultural technology diversity showed an upward trend, but with significant regional disparities. The total agricultural carbon emissions in the central region were higher than those in the eastern and western regions, while the scale of agricultural technology innovation and the level of agricultural technology diversity displayed a spatial distribution pattern that decreased from the southeastern coastal areas inland.

Second, the inhibitory effect of agricultural technology innovation and diversity on carbon emissions. The research results indicate that both the scale of agricultural technology innovation and agricultural technology diversity have a significant inhibitory effect on agricultural carbon emissions. Specifically, the increase in the scale of agricultural technology innovation can promote the development and application of clean technologies, enhance energy efficiency, drive industrial structure upgrading, and thereby reduce the intensity of agricultural carbon emissions. The improvement in agricultural technology diversity can facilitate the transformation of production modes, increase energy efficiency, promote the use of clean energy, and accelerate the development of green technologies, thus reducing carbon emissions in agricultural production.

Third, the moderating role of the scale of agricultural technology innovation. Mechanism analysis reveals that the scale of agricultural technology innovation has a positive moderating effect on the inhibitory impact of agricultural technology diversity on agricultural carbon emissions. That is, an increase in the scale of agricultural technology innovation can enhance the inhibitory effect of agricultural technology diversity on agricultural carbon emissions. This is mainly because regions with a larger scale of technological innovation can engage in more complex and advanced technological activities and find matching resources and opportunities in a broader range of technological fields, thereby exerting a more significant impact on agricultural carbon emissions.

Fourth, spatial effect analysis shows that agricultural technology innovation and agricultural technology diversity exhibit significant spatial correlation and have a negative spatial spillover effect on agricultural carbon emissions in neighboring regions. Specifically, the increase in local agricultural technology innovation scale and agricultural technology diversity not only reduces local agricultural carbon emissions but also promotes agricultural technology progress in adjacent regions through technology diffusion and demonstration effects, thereby reducing agricultural carbon emissions in neighboring areas.

5.2 Policy implications

First, Strengthen Investment in Agricultural Technology Innovation. The government should increase support for agricultural technology innovation, particularly in terms of

funding and technological investment in the central and western regions, to narrow the technological gap between regions. Through policy guidance and financial support, enterprises and research institutions should be encouraged to engage in agricultural technology innovation activities, develop and promote clean production technologies, energy-saving technologies, and other solutions to reduce agricultural carbon emission intensity.

Second, Promote Agricultural Technology Diversity. Encourage the diversified development of agricultural technologies and avoid over-reliance on single technologies. Through technology introduction, collaborative research and development, and talent cultivation, the variety and combination of agricultural technologies should be enriched to improve their diversity and adaptability. This will not only help reduce agricultural carbon emissions but also enhance the stability and sustainability of agricultural production.

Third, Enhance Policy Coordination and Demonstration Effects. Leverage the spatial spillover effects of agricultural technology diversity and innovation to encourage technological cooperation and exchange between advanced regions and neighboring areas. Eastern regions can provide technological exports and share experiences to help central and western regions improve agricultural production efficiency and emission reduction capabilities. Meanwhile, establish a collaborative mechanism for regional agricultural sustainable development, promoting healthy competition and cooperation among regions through policy guidance and financial support.

Fourth, policies should be tailored to the specific conditions of different regions. The eastern region should continue to increase investment in agricultural technology innovation, encouraging enterprises and research institutions to develop and apply more advanced agricultural technologies. This will not only drive local progress but also provide models and guidance for the central and western regions. Additionally, the eastern region should further optimize its agricultural industrial structure, reducing reliance on traditional high-carbon agricultural practices to achieve an upgrade in the agricultural industry structure. The central region should receive more policy support and financial subsidies to support agricultural technology innovation and the promotion of low-carbon technologies. This will help bridge the technology gap and enhance the region's capacity for sustainable agricultural development. The western region should focus on strengthening agricultural infrastructure construction to improve the hardware conditions for agricultural technology application. At the same time, through policy guidance and financial support, the region should actively introduce and apply advanced agricultural technologies from the eastern region. This will not only enhance the agricultural technology level in the western region but also reduce agricultural carbon emissions and promote sustainable agricultural development.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

FT: Writing – original draft. JT: Writing – original draft, Writing – review & editing. FQ: Writing – review & editing. SG: Writing – review & editing.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impacts of rural digitization on agricultural carbon emission efficiency: evidence from 30 provinces in China over 2011–2022

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Under the dual goals of the "dual carbon" and digital rural development strategies, giving full play to the role of rural digitalization to enhance the carbon emission efficiency of agriculture is of great significance to the green and sustainable development of agriculture. Based on the panel data of 30 provinces in China from 2011 to 2022, dynamic spatial Durbin and threshold effect models were used to demonstrate the impact of rural digitalization on agricultural carbon emission efficiency. The results show that: (1) Both of the agricultural carbon emission efficiency and the level of rural digitalization in all provinces in China show a steady upward trend. During the study period, the agricultural carbon emission efficiency in the central region improved the fastest, as well as the rural digitalization level in the western region; (2) Rural digitalization has a significant positive promoting effect on agricultural carbon emission efficiency, and this promoting effect has a spatial spillover effect. Digital development in neighboring rural areas will also improve the carbon efficiency of agriculture in the region. The direct effect is the strongest in the central region, and the spillover effect of the eastern region is the most prominent; (3) The impact of rural digitization on agricultural carbon emissions efficiency has a threshold characteristic. With the improvement of rural digitalization, the promoting effect on agricultural carbon emissions efficiency is more significant. Among the four regions, the threshold value of the rural digital level is the lowest in the eastern region, while in the western region has the highest threshold value. The results of this study provide useful insights for promoting rural digital development, improving agricultural carbon emission efficiency, and promoting agricultural green development.

KEYWORDS

rural digitization, agricultural carbon emission efficiency, spatial spillover effect, threshold effect, China, impact

1 Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations, the amount of greenhouse gases (GHGs) released from agricultural land exceeds 30% of the total global anthropogenic GHG emissions, which is equivalent to generating 15 billion tons of carbon dioxide per year (Huang et al., 2019). The agricultural carbon emission efficiency is not prominent compared with that of total industrial carbon emissions, but the source of agricultural carbon emissions is more complex, and agricultural carbon emission efficiency accompanied by the high growth of agricultural production has been increasing (Liu et al., 2024). It is predicted that global agricultural GHG emissions may increase by 58% in 2050,

making it the most difficult carbon emission source to control (Gao et al., 2024; Zhang et al., 2024). Extreme weather triggered by greenhouse gas emissions has profoundly affected the survival and development of human beings and has become a major challenge common worldwide. Among them, the intensity of agricultural carbon emission efficiency has also gradually increased with the rapid development of agricultural production, becoming the second largest source of greenhouse gas emissions. On the other hand, the complexity of agricultural carbon emission sources, involving the use of agricultural machinery, fertilizer application, animal husbandry development, and other aspects, increases the difficulty of controlling carbon emission sources (Zheng et al., 2024). Therefore, a global consensus has been reached to mitigate climate change by reducing agricultural carbon emissions.

Since the reform and opening up, China has made remarkable achievements in agricultural development. According to statistics, China's total grain output increased from 430.7 million tons in 2003 to 706.5 million tons in 2024, achieving 21 consecutive years of growth. In spite of this, the green development of China's agriculture still faces serious challenges. In the process of the rapid development of agricultural modernization, the large consumption of fossil energy, the excessive use of pesticides, and the irrational use of agricultural waste have led to serious agricultural non-point source pollution and carbon emission (Zhang and Liu, 2024). As a traditional agricultural country, agriculture has now become the second largest source of greenhouse gas emission in China. Therefore, how to explore the low-carbon transformation and green development of agriculture under the background of "dual carbon" strategy has become an important issue facing the current society (Li et al., 2024).

Agricultural carbon emission efficiency (ACEE) refers to the ratio of the minimum carbon emission that can be realized by agricultural production activities to the actual carbon emission under the conditions of given expected output and input factors. The higher the actual carbon emission, the lower the agricultural carbon emission efficiency, which is closely related to agricultural production input factors and output. Under the framework of the "two-carbon" strategy, improving agricultural carbon emission efficiency is not only an inevitable requirement to achieve the goal of carbon peak carbon neutrality but also the core path to break the constraints of agricultural resources and environment and build a modern ecological agriculture system.

Research studies showed that although China's total agricultural carbon emission efficiency has raised in a fluctuating trend, their growth rate has slowed down significantly. In recent years, it has even been on a downward trend, and agricultural carbon emission efficiency has been significantly improved in most provinces (Yao et al., 2024). However, FAO data show that China's total agricultural carbon emission efficiency in 2019 was 782,839,100 tons, still the world's largest agricultural carbon emission efficiency country. In this context, it is necessary to further improve the agricultural carbon emission efficiency to facilitate the low-carbon transformation of agricultural production.

At the same time, the Chinese government attaches great importance to the construction of digital countryside, has issued the "Digital rural Development Strategy Outline," "Digital rural Development Action Plan (2022–2025)" and other policies, document No. 1 of the CPC Central Committee in 2023 also proposed to in-depth implementation of digital rural development actions, to promote the development of digital application scenarios. Rural digitalization refers to the process of systematically reconstructing agricultural production mode, rural governance mode, and farmers' lifestyle through the deep integration of new generation information technology (such as big data, Internet of Things, artificial intelligence, and 5G) with agricultural and rural economy and society. Its core is to use data as a key production factor to promote the comprehensive digital transformation of rural infrastructure, industrial system, public services, and ecological protection and ultimately achieve the strategic goals of bridging the urban–rural digital divide, accelerating agricultural modernization and sustainable rural development. Through the deep integration of digital technology and agricultural and rural systems, rural digital development is reshaping the improvement path of agricultural carbon emission efficiency. As the core carrier of rural digitalization, the wide application of intelligent monitoring equipment and agricultural big data platform not only realizes the accurate control of farmland water and fertilizer, the optimization of agricultural machinery operation path, and the whole process management of waste resource utilization but also significantly reduces the energy consumption and greenhouse gas emission intensity per unit output through dynamic carbon emission monitoring and traceability analysis (Guo et al., 2022).

In view of improving the agricultural carbon emission efficiency, scholars have proposed that agricultural carbon trading markets can be established land-use change (Ryan and Tiffany, 1998) and reasonable setting of standard price of agricultural tax (Murray, 2004), so as to reduce agricultural non-point source pollution and improve agricultural carbon emission efficiency. In recent years, scholars have also begun to conduct in-depth studies on the impact of agricultural economic development (Khan et al., 2021; Huang et al., 2019), agricultural technology progress (Sun, 2022), and agricultural comprehensive development investment (Chu et al., 2024) on agricultural carbon emission efficiency and put forward targeted strategies to promote the improvement of agricultural carbon emission efficiency.

In view of the environmental effects of the application of digital technology, some scholars believe that the rapid development of digital economy will promote the increase in energy consumption such as electricity, thus leading to the growth of carbon emissions (Hamdi et al., 2014). Some other scholars hold the opposite view, believing that the application of digital technology can improve production efficiency and technological innovation level, enhance the public's concern for the environment, and thus inhibit carbon emissions (Zhang et al., 2024). In addition, some scholars believe that the impact of digital technology on carbon emissions is non-linear, and the two show an inverted U-shaped relationship of "first increase and then decrease" (Li et al., 2024). Liu (2019) took the lead in introducing digitalization into the field of agricultural production, believing that digital development may reduce agricultural carbon emission efficiency. Tian et al. (2024) found through their research that digital development in agriculture and rural areas can significantly reduce the carbon emission level of grain cultivation, but at the same time, there are obvious spatial differences.

At present, research studies on rural digitalization and agricultural carbon emission efficiency mainly focus on the following three aspects: (1) Research on the development of rural digitalization and agricultural green transformation. One view holds that rural digitalization can promote the improvement of rural human capital by

optimizing rural communication infrastructure and improving rural residents' awareness of modern information technology, so as to further promote the wide application of green agricultural technology in agricultural production process (Lu et al., 2024a). Another view is that smart agriculture, precision agriculture, and other new agricultural development models based on digital technology have accelerated the flow of production factors such as labor, capital, and information technology and reconstructed the structure and spatial organization of rural production factors (Han et al., 2018; Qaim, 2020; Sun, 2022). It will help accelerate the transformation of agricultural production mode and promote the green transformation of agricultural development (Zhang et al., 2024). (2) Research on rural digitalization and agricultural green total factor productivity. Some scholars believe that rural digitalization can improve agricultural green total factor productivity and reduce agricultural input–output ratio by promoting agricultural scale management, alleviating resource factor mismatch, and promoting green technology progress (Liu et al., 2021; Lu et al., 2024a). At the same time, rural digitalization can also have a positive impact on the agricultural green total factor productivity in the surrounding areas through the spatial spillover effect. (3) Research on the development of modern agriculture and efficiency. Existing literature has analyzed the impact of modern agricultural development on agricultural carbon emission efficiency from the perspectives of agricultural mechanization degree, agricultural industry agglomeration, agricultural land management scale, and agricultural insurance (Guan et al., 2023; Sun, 2022). A basic consensus has been reached that technological progress has an important positive impact on agricultural carbon reduction. It can be seen from the existing studies that there are abundant studies on the impact of rural digitalization on the green development of agriculture and the impact of modern agriculture on agricultural carbon emission efficiency.

However, existing research studies on the relationship between rural digitalization (RUD) and agricultural carbon emission efficiency (ACEE) are still in the initial stage, and the spatial effect of rural digitalization on agricultural carbon emission efficiency has not been considered. In addition, most of the existing studies are based on a static perspective, ignoring the dynamic change of carbon emissions. Based on the panel data from 2011 to 2022, this study first calculated the rural digitization level and agricultural carbon emission efficiency and analyzed the change trend of the two during the study period. Then, based on the dynamic spatial econometric model, the impact of rural digitalization on agricultural carbon emission efficiency was analyzed. Then, a dynamic threshold effect regression model was constructed to analyze the non-linear impact of rural digitalization on agricultural carbon emission efficiency, aiming to provide scientific basis and theoretical reference for low-carbon agricultural development.

Therefore, the marginal contribution of this study is shown in the following aspects: First, the impact of rural digitalization on agricultural carbon emission efficiency is demonstrated through empirical analysis, which provides a new perspective for exploring the factors that may affect the green development of agriculture. Second, most studies focus on the impact of rural digital development on regional industrial economic development, while this study focuses on the environmental impact of rural digital development, which is conducive to expanding the scope of research on the impact of rural digital development. Third, the spatial Durbin model and threshold effect model were used to verify the spatial spillover and non-linear effects of rural digitalization on agricultural carbon emission efficiency, which is conducive to scientifically explaining the influence and characteristics of rural digitalization on agricultural carbon emission efficiency.

2 Theoretical analysis and research hypotheses

Digital technologies have successfully changed the agricultural carbon emissions landscape through infrastructure, structural optimization, technological innovation efficiency, and resource allocation effects. Agricultural carbon emission efficiency refers to the ratio between the minimum carbon emission that can be realized by agricultural production activities and the actual carbon emission under the given conditions of expected output and input factors. The greater the actual carbon emission, the lower the agricultural carbon emission efficiency, which is closely related to agricultural input and output factors (Chen et al., 2024). Under the framework of Cobb–Douglas production function, traditional agricultural production relies on the linear combination of labor, capital, and technology, while the intervention of digital technology breaks through this static paradigm and reshapes production logic through factor virtualization and network synergy (Oenema, 2020). As a new production factor, digital technology not only expands the production boundary in the form of independent multiplier but also reconstructs the function mechanism of traditional factors through data flow (Jin et al., 2024). They will affect the expected output and unexpected output of agriculture at the same time and then affect the efficiency of agricultural carbon emission. In addition, the digital economy is more likely to break through geographical space boundaries, and its impact on agricultural carbon emission efficiency will also spill over to other regions, forming a spatial spillover effect. Therefore, this study starts with the development of rural digitalization and builds a theoretical analysis framework on how rural digitalization affects agricultural carbon emission efficiency on the basis of the application status of digital technology.

2.1 Influence mechanism of rural digitalization on agricultural carbon emission efficiency

With the improvement of rural digitization level, digital elements have gradually become the key elements of rural production activities. They can optimize the original factor allocation structure on the basis of big data, promote the digital transformation of traditional agricultural production, improve the efficiency of agricultural resource utilization, change the extensive production mode, and improve the efficiency of agricultural carbon emissions. First of all, according to the Environmental Kuznets Curve (EKC), the extensive development of traditional agriculture leads to rising carbon emissions, whereas digital technologies such as smart agricultural machinery and agricultural IoT enable agricultural production to surpass the EKC turning point through precision fertilization, real-time monitoring, and resource optimization (Zhang et al., 2022; Wang et al., 2024b). This drives a "win–win" scenario where crop yields increase while

carbon intensity decreases. Digital technology uses big data, Internet of things, and other technologies to carry out accurate research and judgment on other input factors in agricultural production activities, update agricultural data in real time through sensors, drones, climate monitoring, and other equipment, and help farmers make more scientific production decisions through intelligent algorithms (Zheng et al., 2024). Second, digital technology is conducive to the realization of modern agricultural management through intelligent agricultural machinery, the realization of automated farming, precision irrigation, scientific fertilization, and other agricultural production work and effectively avoid the risk of excessive land reclamation, land degradation, and waste of natural resources caused by excessive fertilizer (Yang et al., 2022). Therefore, the degree of rural digital development will drive the level of agricultural technology, along with the continuous improvement of agricultural production efficiency and the growth of agricultural economy. Through the interaction of various elements, agricultural production is moving toward green and sustainable development, gradually forming a green and low-carbon agricultural industry, creating new types of employment, increasing employment opportunities for rural labor, improving agricultural carbon emission efficiency, and forming a virtuous cycle.

Thus, Hypothesis 1 is proposed: Rural digital development can promote agricultural carbon emission efficiency.

2.2 Spatial spillover effects of rural digital on agricultural carbon emission efficiency

Digital technology is non-competitive and replicable, and digital innovation in core regions can radiate to neighboring regions through technology imitation, knowledge sharing, or industrial chain coordination. For example, after digital planting patterns are replicated across regions, the redundancy of agricultural inputs in multiple places can be reduced simultaneously (Lu et al., 2024a). At the same time, digital platforms break geographical barriers and promote the cross-domain flow of labor, capital, and other factors, such as developed regions through e-commerce networks to transmit low-carbon agricultural standards to less developed regions, forcing the latter to optimize production processes. In addition, carbon emissions are spatially related, and the transformation of energy structure caused by digitization in one place (such as the popularization of photovoltaic agriculture) can affect the carbon balance of surrounding areas through regional power networks or ecological compensation mechanisms (Guo et al., 2022). The research also shows that the strengthening effect of environmental regulation generated by the application of digital technology will form regional linkage governance through inter-governmental policy learning (Zhou et al., 2023).

In short, the impact of rural digitalization on agricultural carbon emission efficiency forms a spatial spillover through three dimensions of peer effect, learning effect, and diffusion effect: The peer effect is manifested as the "demonstration-imitation" cycle in the geographic neighboring regions. The digital technology leading regions form a visual emission reduction paradigm through shared platforms (such as the intelligent agricultural machinery cross-regional cooperation system), which promotes the technological replication and institutional benchmarking in the neighboring regions, and reduces the trial-and-error cost of low-carbon transition (Xiong and Zhou, 2024). The learning effect relies on the cross-regional knowledge network, and the implicit experience (such as the practice of digital soil testing formula) is coded and spread through the agricultural technology extension system, enterprise alliance, and other channels, while the explicit knowledge (such as AI bug warning algorithm) is cross-domain integration through the open data interface to improve the absorption capacity of global emission reduction technology (Lu et al., 2024b). The diffusion effect follows the "core-edge" level penetration logic, and digital infrastructure hub areas (such as national agricultural science and technology parks) radiate technical standards to the edge areas through industrial chain digitization (such as blockchain traceability system), while policy dividends are transmitted top-down through administrative levels (provincial-city-county), forming synergy on emission reduction scale.

On this basis, the Hypothesis 2 is proposed: Rural digitization has a spatial spillover effect on agricultural carbon emission efficiency.

2.3 Non-linear threshold characteristics of rural digitization on agricultural carbon emission efficiency

In the early stage of digitalization, due to weak infrastructure, lack of digital skills of farmers, and high cost of technology application, digital technology is difficult to deeply embed in the agricultural production system, resulting in its function of optimizing resource allocation and replacing high-carbon elements cannot be effectively released (Zhang et al., 2018). For example, due to the lack of equipment operation capacity or financial support, small-scale farmers are difficult to digest the fixed investment of intelligent agricultural machinery, remote sensing monitoring, and other technologies, and digitalization only stays in shallow applications such as information transmission, which cannot trigger substantial carbon reduction behavior (Zhou et al., 2023). With the increase in digitization level, the marginal cost of technology application decreases, and agricultural production entities can rely on digital platforms to integrate land, labor, and other factors, accurately match water and fertilizer needs, and optimize agricultural machinery scheduling, thus significantly reducing energy and chemical consumption per unit output (Song et al., 2022). In addition, after the digitalization level is improved, the data interoperability of the upstream and downstream of the agricultural industry chain is enhanced, which promotes the formation of a "technology-organization-market" collaborative carbon reduction mechanism, and further amplifies the emission reduction effect, which is shown in Figure 1. Therefore, Hypothesis 3 is proposed: There is a non-linear characteristic of the impact of rural digitization on the carbon emission efficiency of agriculture.

3 Variable selection, model construction, and data sources

3.1 Variable selection

3.1.1 The explained variable

Agricultural carbon emission efficiency (ACEE) is the explained variable in the empirical study. Agricultural carbon emission efficiency is commonly calculated by the Data Envelopment Analysis

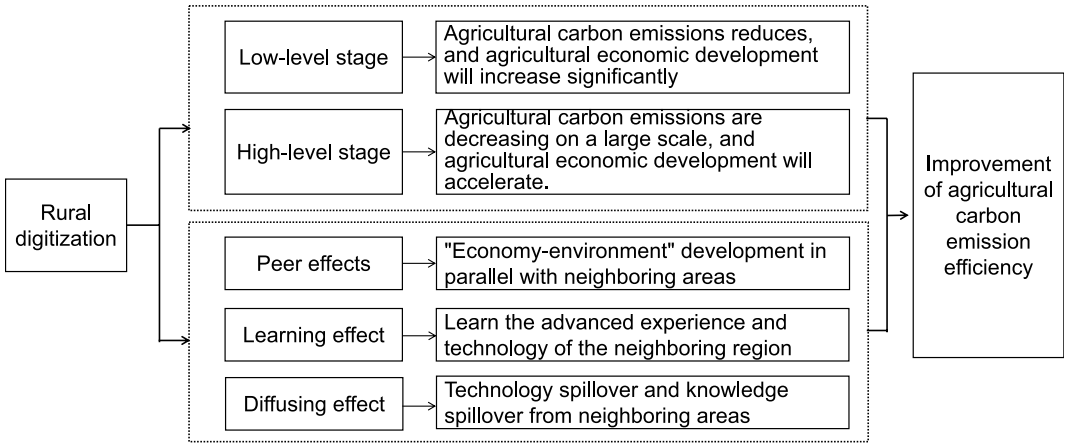


FIGURE 1
Influence mechanism of rural digitalization on agricultural carbon emission efficiency.

TABLE 1 Measuring indicators of CAEE.

Primary index	Secondary index	Unit
Input indicators	Agricultural fixed capital stock	10 thousand yuan
	Crop sown area	1 thousand hectares
	Number of people employed in agriculture, forestry, husbandry and fishery	10 thousand of people
	Application amount of converted agricultural chemical fertilizer	10 thousand tons
	Pesticide usage	10 thousand tons
	Agricultural film usage	ton
	Total power of agricultural machinery	1 million kw
Desirable output indicator	Total output value of agriculture, forestry, animal husbandry and fishery	100 million yuan
Undesirable output indicator	Agricultural carbon emission	10 thousand tons

(DEA), to overcome the deficiency of neglecting the relaxation of input and output variables in the traditional DEA method. Based on research of Liu et al. (2021), the super-efficiency SBM model is used to effectively measure ACEE. Input and output indicators were selected based on the study of Chen et al. (2024), and an evaluation indicator system for agricultural carbon emission efficiency was established as shown in Table 1. Among them, the input indicators include agricultural fixed capital stock, crop sown area, primary industry employees, fertilizer application amount, pesticide use amount, agricultural film use amount, and agricultural machinery input. The agricultural fixed capital stock is calculated based on the research of Lu et al. (2024b). The desirable output indicator is the total output value of agriculture, forestry, animal husbandry, and fishery, and the undesirable output indicator is the agricultural carbon emission.

The total amount of agricultural carbon emissions (CAE) was measured from three aspects, namely, agricultural land use, rice cultivation, and livestock and poultry farming, with reference to the study of Guan et al. (2023). Among them, the carbon emission measurement of agricultural land refers to the research results of Tian et al. (2024), including six carbon sources: chemical fertilizer, pesticides, agricultural film, agricultural diesel oil, tillage, and irrigation. The CH_4 emissions generated by rice planting were considered, and the emission coefficient referred to Han et al. (2018) and was calculated for early, medium, and late rice. Carbon emissions from livestock and poultry breeding mainly include CH_4 from animal intestinal fermentation and CH_4 from fecal management and N_2O gas. Due to the differences in the livestock and poultry feeding cycles, the average annual feeding amount must be corrected. According to the global warming potential results and coefficients reported by IPPC, two types of greenhouse gases, namely, CH_4 and N_2O, are converted to equal amounts of CO_2 for subsequent analytical calculations.

$$CA = \sum_{i=1}^{m} CA_i = \sum_{i=1}^{m} e_i \times \sigma_i \quad (1)$$

In Equation 1, CA is the total agricultural carbon emissions. In Equation 1, CA is the total agricultural carbon emissions, CA_i represents the carbon emissions of carbon source i, and $e_{a.}$ represents the activity level of carbon source if, σ_i represents the carbon emission coefficient of carbon source i.

3.1.2 The core explanatory variable

As explained in the introduction, rural digitalization refers to the process of systematic reconstruction of agricultural production mode, rural governance mode, and farmers' lifestyle through the deep integration of a new generation of information technology with agricultural and rural economy and society. According to studies of Lu et al. (2024b), AUD is measured from the three dimensions of digital infrastructure, digital innovation level, and digital industry development, according to the logic of "development foundation–development power–development achievement." The development of digital infrastructure is reflected the Internet penetration rate in rural areas, rural information technology equipment, and rural meteorological observation services. The digital innovation level is reflected by the information technology application in rural areas, the rural consumption of digital products and services, the rural digital finance, and the rural production investment. The digital industry development is reflected by the digitizing of rural production, the digitizing of rural circulation, the digitizing of rural operations, and the rural digital industry base. All the measuring indicators are shown in Table 2. On this basis, the entropy weight method is used to determine the weight of each index.

3.1.3 Control variables

Other variables affecting the ACEE were further controlled to alleviate the missing variable bias as much as possible. Control variables were selected as follows: ① The agricultural economic development level (pgdp) is expressed as the ratio of the added value of the primary industry to that of employees in the primary industry. ② Agricultural industrial structure (str), expressed as the ratio of the added value of the planting industry and animal husbandry to the added value of agriculture, forestry, animal husbandry and fishery, the planting industry, and animal husbandry, are the main sources of agricultural carbon emissions (Xu et al., 2022). ③ Agricultural financial support (afs) is expressed as the ratio of expenditure on agriculture, forestry, and water affairs to financial expenditure. External policy intervention by the government can affect carbon emissions (Wang et al., 2022). ④ Environmental regulation intensity (enr) is measured by the ratio of pollution control investment to GDP to reflect the local environmental regulation intensity as much as possible (Sun, 2022). ⑤ Rural human capital (edu) is measured by the average length of education in rural areas. In general, improving education can affect the marginal cost of emission reduction.

3.2 Global Moran's I index

To better analyze the spatial spillover effect of rural digitization on agricultural carbon emissions, this study first uses the global Moran's I index to measure the spatial autocorrelation of the rural digitization level and agricultural carbon emission efficiency. The calculation formula is as follows:

$$I = \frac{n\sum_{n=1}^{n}\sum_{j=1}^{n}W_{ij}\left(X_i-\overline{X}\right)\left(X_j-\overline{X}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}\sum_{i=1}^{n}\left(X_i-\overline{X}\right)^2} \quad (2)$$

In the above (Equation 2) formula, I is the global Moran's I index, W_{ij} is the spatial weight matrix, X is the variable, which refers to RUD or ACEE, X_i and X_j refer to the values of the variables in the corresponding spatial units *i* and *j*, respectively, $\overline{X}$ is the average of the variables, *n* is the total number of provinces, and *i* and *j* represent different provinces. The value range of the global Moran's I index is [−1, 1]. When its value is greater than 0, it indicates that the variable has a positive spatial correlation. The closer the value is to 1, the more significant the spatial correlation. When the value of the Moran's I index is less than 0, the variable has a negative spatial correlation, and the closer it is to −1, the more significant the spatial dispersion. When the value of the Moran's I index is equal to 0, it indicates that the variable has spatial randomness.

3.3 Empirical models

3.3.1 Dynamic spatial Durbin model

The spatial Durbin model was constructed because there may be spatial dependence of both the explained variable ACEE and the explanatory variable RUD. Considering the time lag of the impact of rural digitization on agricultural carbon emissions, this study further constructed a Durbin model of dynamic space, for which the ACEE of lag one phase term is introduced in the model ($ACEE_{i,t-1}$). To alleviate the possible endogeneity problems of the model, the model is constructed as follows:

$$ACEE_{it} = \alpha_0 + \tau ACEE_{i,t-1} + \rho\sum_{j=1}^{n}W_{ij}ACEE_{jt} + \beta X_{it} + \theta\sum_{j=1}^{n}W_{ij}X_{jt} + \mu_i + \upsilon_t + \varepsilon_{it} \quad (3)$$

In Equation 3, $ACEE_{it}$ and X_{it} represent the explained and explanatory variables (including control variables), respectively, and the subscripts *i* and *t* represent the province and year, respectively. ρ is the spatial correlation coefficient, W_{ij} is the spatial weight matrix, β, τ, ρ, and θ, the underestimated parameters, u_i and v_t represent the spatial and temporal effects, and ε_{it} represents the spatial error terms following an independent distribution. Two types of spatial weight matrices, namely, the geographic distance spatial matrix (W1) and the economic geographic nested spatial weight matrix (W2), are used for model estimation, while the economic geographic nested spatial weight matrix is used for robustness analysis.

3.3.2 Dynamic threshold effect model

According to the previous analysis, there may be a non-linear relationship between the impact of rural digitization (RUD) on agricultural carbon emissions (ACEE). At the same time, the rural digitization level should be considered the threshold variable. In view of the continuous characteristics of ACEE, $ACEE_{i,t-1}$ is also added as an explanatory variable. Owing to the lack of a mature method of combining the spatial measurement model with the threshold regression model, the ordinary dynamic panel threshold regression model is finally established as follows:

TABLE 2 Comprehensive evaluation index system of rural digitalization.

Objective	Dimension index	Secondary indicators	Measurement methods	Attribute
Digitization in rural areas	Digital infrastructure	The Internet penetration rate in rural areas	The proportion of administrative villages with Internet broadband services is /%	+
			Number of rural broadband access users / rural households	+
		Rural information technology equipment	Rural residents per 100 households / computer ownership	+
			The number of mobile phones per 100 rural households	+
			The number of color TV sets per 100 rural households	+
		Rural meteorological observation services	Agricultural meteorological observation station/ station	+
	Level of digital innovation	Information technology application in rural areas	Rural business outlets service population / 10,000 people	–
		Rural consumption of digital products and services	Consumer expenditure on digital products and services for rural residents /%	+
		Rural digital finance	Digital financial inclusion level (Index)	+
		Rural production investment	Investment in fixed assets in primary industry (excluding rural households) /10 thousand yuan	+
	Digital industry development	Digitizing of rural production	The added value of digital economy in the primary industry / 100 million yuan	+
		Digitizing of rural circulation	Rural logistics business / 100 million yuan	+
		Digitizing of rural operations	Rural e-commerce sales purchase volume / 100 million yuan	+
		Rural digital industry base	Number of Taobao villages / one	+

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$$ACEE_{it} = \alpha_0 + \rho ACEE_{i,t-1} + \beta_{11} RUD_{it} I(RUD_{it} \le \theta_1) + \beta_{12} RUD_{it} I(\theta_1 < RUD_{it} \le \theta_2) + \cdots + \beta_{11} RUD_{it} I(\theta_{n-1} < RUD_{it} \le \theta_n) + \beta_{1,n+1} RUD_{it} I(RUD_{it} > \theta_n) + \sum_{k=1}^{n} \lambda_k C_{it,k} + \mu_i + \upsilon_t + \xi_{it} \quad (4)$$

In Equation 4, θ_1, θ_2, and θ_n are the threshold values, and β_{11}, β_{12}, and $\beta_{1,n}$ are the regression coefficients of different threshold intervals. I (·) is a schematic function, and the other variables explain the same function as Equation 3.

3.4 Data sources

Considering the availability of data, panel data for 30 provinces in China from 2011 to 2022 were used in this study (not involving Tibet, Hong Kong, Macao, and Taiwan). The data mainly come from the China Rural Statistical Yearbook, China Statistical Yearbook, China Monthly Statistical Bulletin of Agricultural Products Import and Export, China Statistical Yearbook of Population and Employment, and the provincial yearbooks of the corresponding years. The number of Taobao villages in each province comes from the report of Ali Research Institute. Some missing data were supplemented by interpolation method. The descriptive statistics for all the variables are shown in Table 3.

3.5 Characteristics of ACEE and RUD in China

According to the results of the Super-SBM method to calculate the ACEE, the change trend of annual means ACEE in 30 provinces and four regions from 2011 to 2022 is shown in Figure 2. The annual mean of ACEE in the whole region fluctuated roughly between 0.968 and 1.192 from 2011 to 2022 and reached its maximum in 2022. In recent years, the central government has

TABLE 3 Descriptive statistics of the variables.

Variable name	Sample	Mean	Standard deviation	Minimum value	Maximum value
Agricultural carbon emission efficiency (ACEE)	360	1.063	0.252	0.205	1.323
Rural digitalization (RUD)	360	0.267	0.114	0.096	0.756
Agricultural economic development level (pgdp)	360	2.911	1.256	0.642	10.348
Agricultural industrial structure (str)	360	81.714	10.901	56.833	96.606
Agricultural financial support (afs)	360	11.455	3.284	4.11	20.384
Environmental regulation intensity (enr)	360	0.114	0.104	0.001	0.993
Rural human capital (edu)	360	7.879	0.576	6.125	9.878

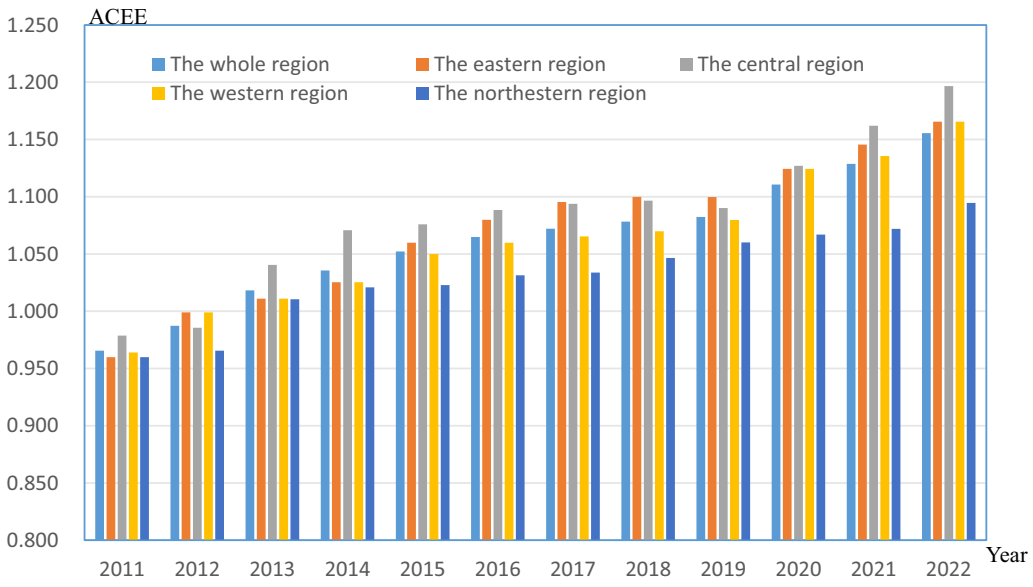


FIGURE 2
Development trend of ACEE in China from 2011 to 2022.

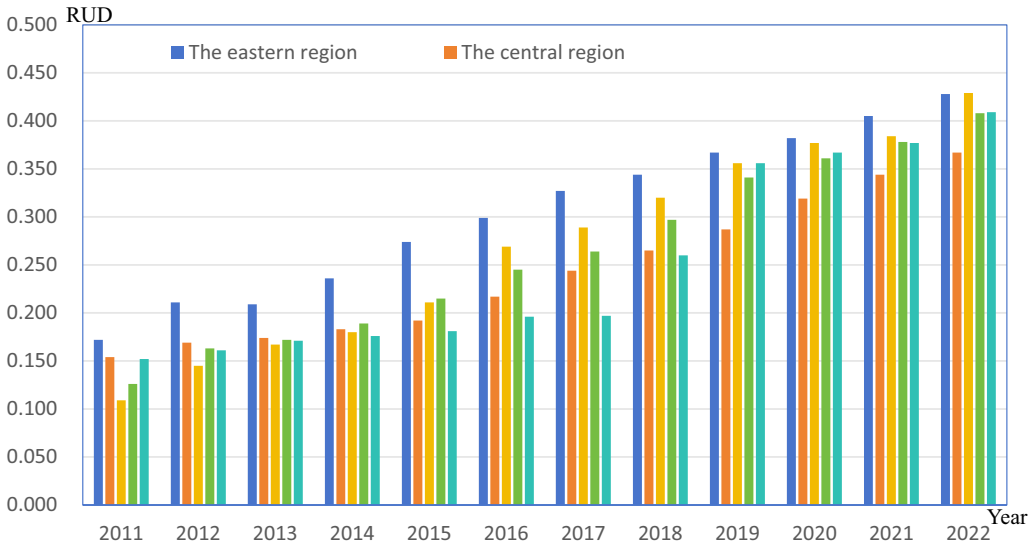


FIGURE 3
Development trend of RUD in China from 2011 to 2022.

attached great importance to environmental protection, aiming at agricultural pollution, governments at all levels have formulated a series of control measures, so agricultural clean production technology has been effectively promoted. Overall, China's ACEE showed an upward trend from 2011 to 2022, with an average annual growth rate of 1.650%. For four different regions, ACEE is greater than 1 in most years. The average annual growth rates of ACEE in eastern, central, western, and northeastern regions during the study period were 1.786, 1.859, 1.748, and 1.208%, respectively. As the core grain-producing region in China, the central area has become a key focus of national agricultural policies in recent years. For instance, high-standard farmland construction policies have significantly enhanced resource utilization efficiency and green technology efficiency by improving agricultural infrastructure, such as irrigation systems and soil quality, thereby making it the fastest-improving region in ACEE.

Meanwhile, RUD was measured with panel data based on entropy evaluation method. The results show that the mean value of RUD in eastern China is the highest, while the mean value of RUD in western China and Northeast China is relatively lower among the four regions. From Figure 3, it can be seen that the average of RUD in the eastern region is the highest among all regions over the study period. The annual average of RUD of the whole research region continuously improved over time, with average annual growth rates of 2.56%. The average annual growth rates of RUD in eastern, central, western, and northeastern region during the study period were 2.32, 2.43, 3.03, and 2.33%, respectively. The growth rate of RUD in western region is higher than that of other regions. The digitalization level of rural areas in the western region has improved the fastest, mainly benefiting from the dual drive of policy inclination and latecomer advantage: The national "rural revitalization" and "digital China" strategies give priority to the layout of the western region, through special funds to support new infrastructure (such as 5G base stations and optical fiber networks) and e-commerce logistics sinking; at the same time, its original digital foundation is weak, and the eastern and western cooperation mechanisms are superimposed to introduce eastern technical resources, promoting the rapid popularization of smart agriculture, distance education, and other applications and realizing leapfrog shortcomings.

4 Model estimation results and analysis

4.1 Spatial panel model estimation results and analysis

4.1.1 Global spatial auto-correlation test

According to the calculation, the global Moran's I index values of rural digitization (RUD) and agricultural carbon emission efficiency (ACEE) over the years were significantly positive (Table 4), indicating a significant spatial correlation of RUD and ACEE. In terms of time, the mean values of the global Moran's I index values of RUD and ACEE were increasing annually. Thus, the trend of spatial agglomeration of RUD and ACEE was constantly increasing.

4.1.2 Identification of spatial econometric models

The above spatial auto-correlation test reveals that both the ACEE and RUD have strong spatially correlated characteristics; thus, spatial factors should be considered when studying their relationship. The appropriate space measurement model was then chosen according to Elhorst (2003): First, it has to judge whether the spatial econometric model is applicable. The test statistics for LM lag, robust LM lag, LM error, and robust LM error all passed the significance test, indicating that the null hypothesis that the SPM or SEM is not present can be rejected, where the spatial panel model is applicable. The Wald and LR statistics were then combined to determine which spatial model was more appropriate. The estimation with the SDM as the parent

TABLE 4 Global Moran's I values of RUD and ACEE from 2011 to 2012.

Rural digitization (RUD)						Agricultural carbon emission efficiency (ACEE)					
Year	Moran's I value	*p*-value	Year	Moran's I value	*p*-value	Year	Moran's I value	*p*-value	Year	Moran's I value	*p*-value
2011	0.334**	0.041	2017	0.369**	0.022	2011	0.328*	0.078	2017	0.387*	0.071
2012	0.339***	0.006	2018	0.373**	0.034	2012	0.335*	0.019	2018	0.39^{0}**	0.043
2013	0.343*	0.085	2019	0.376***	0.008	2013	0.339*	0.096	2019	0.402*	0.054
2014	0.347*	0.097	2020	0.369***	0.003	2014	0.367**	0.045	2020	0.404**	0.019
2015	0.356**	0.039	2021	0.384***	0.004	2015	0.374**	0.021	2021	0.412***	0.006
2016	0.357***	0.002	2022	0.389***	0.008	2016	0.369**	0.044	2022	0.417***	0.003

***, **, and * represent $p < 0.01$, $p < 0.05$, and $P < 0.1$, respectively, and the T value is in parentheses.

TABLE 5 Tests of spatial regression models.

Tests	Static Durbin model	Dynamic Durbin model
LM-lag test	48.464***	45.545***
Robust LM-lag test	41.323***	35.438***
LM-error test	55.322***	76.523***
Robust LM-error test	36.448***	54.654***
Wald-spatial lag test	108.732***	232.161***
LR-spatial lag test	151.154***	76.863***
Wald-spatial error test	124.091***	231.821***
LR-spatial error test	51.676***	48.676***
Hausman test	45.766***	70.644***

***Represents $p < 0.01$, and the T value is in parentheses.

TABLE 6 Estimation results of spatial Durbin model.

Variables	The static SDM model		The dynamic SDM model	
	Model 1 (W1)	Model 2 (W2)	Model 3 (W1)	Model 4 (W2)
$ACEE_{it-1}$			0.311*** (3.379)	0.265*** (2.760)
RUD_{it}	0.075** (2.997)	0.112*** (4.315)	0.137*** (3.752)	0.153*** (4.432)
pgdp	0.045*** (3.186)	0.028*** (1.191)	0.170*** (4.966)	0.121** (3.221)
str	−0.196*** (−1.969)	−0.075*** (−4.139)	−0.143* (−2.118)	−0.113** (−3.127)
afs	−0.135*** (−3.326)	−0.123*** (−3.176)	−0.129** (−2.765)	−0.186*** (−6.176)
enr	0.031 (1.180)	0.074 (1.143)	0.065 (0.995)	0.074 (1.121)
edu	0.143** (2.496)	0.085** (2.989)	0.101** (2.383)	0.122** (2.965)
W* RUD_{it}	0.035** (3.197)	0.081** (2.135)	0.035** (2.946)	0.050** (3.031)
Adj R^2	0.820	0.763	0.841	0.764
Log L	187.325	145.866	109.875	186.521

***, **, and *represent $P < 0.01$, $P < 0.05$, and $P < 0.1$, respectively, and the T value is in parentheses. Limited by space, this table does not give the spatial interaction coefficients of each control variable in the estimated results.

showed that both the Wald and the LR statistics passed the significance test, indicating that fitting the data via the SDM is more appropriate. A geographic distance spatial weight matrix was used for each test, and the results are shown in Table 5. For both types of spatial Durbin models, the Hausman test rejected the null hypothesis ($p < 0.01$); thus, the fixed effects model was more appropriate. Moreover, the two-way fixed Durbin model was selected for empirical analysis to avoid the influence of unobserved time changes on the estimated results.

4.1.3 Estimation results of the spatial Durbin model

4.1.3.1 Estimation results of the spatial Durbin model

Model estimation was performed on two types of spatial weight matrices, and the estimation results are shown in Table 6. The coefficients of RUD on ACEE in all the models were positive and passed the significance tests, indicating that the rural digitization had

TABLE 7 Results of spatial effect decomposition.

Variable	RUD	pgdp	str	afs	enr	edu
Direct effect	0.161** (3.153)	0.165** (2.316)	−0.123** (−3.026)	−0.141*** (−2.638)	0.095 (1.221)	0.193** (2.814)
Indirect effect	0.075* (3.785)	0.095** (2.711)	−0.048* (−1.995)	−0.075** (−2.237)	0.091 (1.095)	0.015 (0.021)
Total effect	0.236** (3.051)	0.260** (2.982)	−0.171* (−2.328)	−0.216** (−1.993)	0.186 (1.135)	0.208* (2.126)

***, **, and *represent $P < 0.01$, $P < 0.05$, and $P < 0.1$, respectively, and the T value is in parentheses.

a significant positive effect on ACEE. The improvement of rural digital boosts the transformation of traditional agricultural production to digital production, improves the efficiency of the use of agricultural resources, changes the extensive production mode, and improves ACEE. Thus, the research hypothesis H1 was confirmed. The R^2 value of model fitting indicates that the dynamic Durbin model has a greater degree of fit than the static Durbin model does, indicating that the dynamic Durbin model is better. Therefore, the fit degree of the dynamic Durbin model is greater than that of the static Durbin model, indicating that the dynamic Durbin model is better fit for estimation. This is mainly because the static Durbin model does not consider the dynamic influence of ACEE in the regression process, resulting in estimation errors. According to the regression results of the dynamic panel model, the coefficient of $ACEE_{i,t-1}$ is positive ($p < 0.01$), fully indicating that the ACEE has a significant dynamic persistence characteristic. In addition, a comparison of the estimation results of different models reveals that the dynamic Durbin model, which is based on the geographic distance weight matrix, has the highest fit degree. Therefore, the results in Column 3 (Model 3) in Table 6 were analyzed here. The RUD coefficient of Model 3 was 0.137 ($p < 0.01$), which was lower than the estimated coefficient of the static Durbin model, indicating that the static model overestimated the promoting effect of RUD on ACEE. The spatial lag term coefficient (W*RUD) of RUD was significantly positive at the 5% confidence level, indicating the interaction of RUD between provinces and that local RUD affects the ACEE in its neighboring provinces. In conclusion, it can be seen that the promoting effect of RUD has a spatial spillover effect on ACEE, verifying Hypothesis H2.

In terms of control variables, the agricultural economic development level (pgdp), the environmental regulation (enr), and the agricultural technology investment (tech) all have significant positive effects on ACEE. The improvement of agricultural economic development will promote the allocation of agricultural resources, optimize the structure of agricultural production, and contribute to the upgrading of agricultural production technology, the improvement of resource utilization efficiency, and the promotion and application of energy saving and emission reduction technologies, thus promoting the improvement of ACEE. In addition, the higher the level of environmental regulation, the more local governments attach importance to farmers' low-carbon production by introducing relevant emission reduction policies, providing green subsidies to farmers and other measures. Local governments guide farmers to cultivate the awareness of emission reduction and promote their green production from passive to active; this will improve agricultural green production efficiency and reduce agricultural carbon emissions. Meanwhile, the improvement in the level of human capital usually tend to lead to the adoption of a lower-carbon agricultural production mode, thus reducing carbon emissions.

The agricultural industrial structure (str) and the agricultural financial support (afs) have a significantly positive impact on ACEE. That may because the planting and breeding industries are the two main sources of agricultural carbon emissions. The increasing proportion of these two industries often results in greater agricultural carbon emissions, which is not conducive to the improvement of ACEE. The improvement of agricultural financial investment does not mean the improvement of agricultural financial investment efficiency. Specifically, when investing in agricultural production technology reform, the government will consider the cost first of all. When the technology is fully mature, it is usually cost-effective to put it into the market, so it is generally chosen to put it into application when the technology is relatively mature. However, in this process, some technologies with insufficient verification not only cannot achieve emission reduction after being put into use but also may lead to an increase in carbon emissions, or the government pays more attention to the development of agricultural economy and fails to strike a good balance between them and green development. As a result, more carbon emissions are generated, which is obviously not conducive to the improvement of ACEE.

4.1.3.2 Spatial effect decomposition

To accurately reflect the influence of each factor on ACEE, the total effects of the SDM model were decomposed into direct and indirect effects (Table 7). The direct effect is the influence of RUD on ACEE in the local region. Indirect effect, that is, spatial spillover effect, refers to the impact of RUD of neighboring areas on the ACEE of the local area.

The direct effect coefficient of RUD in Table 7 is 0.161 ($p < 0.05$), which is 0.008 lower than the value of 0.153 before the unbiased treatment in Table 6, indicating that the local rural digitization affects the surrounding provinces, reversing the province and decreasing agricultural carbon emission efficiency. The indirect effect of RUD was 0.075 ($p < 0.1$), which passed the significance test at the 10% level, indicating that RUD has a significant spatial spillover effect on ACEE. The possible reason is that with the improvement of the digitalization level in rural areas, digital agriculture and low-carbon ecological agriculture are gradually promoted, so farmers will steadily promote agricultural carbon reduction. At the same time, the low-carbon economic effect of external agriculture effectively drives the surrounding areas to learn from and follow suit. This has improved the digitalization level of the surrounding rural areas and improved the efficiency of agricultural carbon emissions in the surrounding areas.

4.1.4 Analysis of regional heterogeneity

Given the large differences between rural digitization and agricultural carbon emissions in different regions of China, the approach of Xu et al. (2022) is applied to divide the whole study area into eastern, central, western, and northeast regions for model estimation to test regional heterogeneity. The model estimation results are shown in Table 8. As shown in Table 8, the estimated results for each region are consistent with the results for

TABLE 8 Estimation results by regions.

Variable	Eastern region	Central region	Western region	Northeast region
$ACEE_{i,t-1}$	0.205*** (3.379)	0.235*** (2.760)	0.332*** (3.379)	0.276*** (2.760)
RUD_{it}	0.166*** (2.738)	0.224*** (3.153)	0.089** (3.074)	0.118*** (3.765)
pgdp	0.122* (2.003)	0.101* (1.999)	0.109* (2.441)	0.131* (1.997)
str	−0.084* (−1.984)	−0.114* (−2.068)	−0.144* (−2.241)	−0.095* (−2.168)
afs	−0.181** (−3.054)	−0.236*** (−3.986)	−0.254** (−2.663)	−0.179*** (−4.086)
enr	0.092 (1.132)	0.085 (1.265)	0.059* (2.042)	0.651 (1.221)
edu	0.172* (2.615)	0.125** (3.164)	0.109 (1.155)	0.125** (2.965)
W* RUD_{it}	0.034* (2.132)	0.016** (−2.875)	0.021** (2.635)	0.013 (1.832)
Adj R^2	0.8765	0.8165	0.8907	0.7146
Log L	161.631	182.732	139.543	59.4328

***, **, and *represent $P < 0.01$, $P < 0.05$, and $P < 0.1$, respectively, and the T value is in parentheses.

TABLE 9 Analysis of the spatial effects of the different regions.

Variable	Eastern region	Central region	Western region	Northeast region
Direct effect	0.171** (2.975)	0.253** (2.997)	0.135** (3.096)	0.121** (3.132)
Indirect effect	0.105** (3.031)	0.099** (3.115)	0.086** (2.616)	0.051 (1.065)
Total effect	0.276** (2.786)	0.342** (3.113)	0.221** (2.867)	0.172** (1.987)

**Represents $p < 0.05$, and the T value is in parentheses.

the whole study area sample: The direct and spatial spillover effects of RUD on ACEE are significant, indicating that the above study results are relatively robust. For all four regions, the coefficients of $ACEE_{i,t-1}$ are significantly positive, indicating that ACEEs of all regional are affected by the state of the previous stage. In addition, the coefficients of W*RUD in the eastern, central, and western regions are all significantly positive, indicating that local RUD has a spatial spillover effect on ACEE in its surrounding regions, whereas this effect is not significant in the northeast region.

The spatial effects of different regions were then decomposed, and the results are shown in Table 9. The direct (local) effect of the central region is the strongest, with a coefficient of 0.253 ($p < 0.05$). This may be because the resource base of rural digital development in central China is relatively well, whereas the ACEE is not so high; thus, the marginal effect of rural digital development on the ACEE is more prominent. Regarding spatial spillover effect, the spillover effect of RUD on ACEE in the eastern region had a regression coefficient of 0.105 ($p < 0.05$), which was greater than the coefficients in other regions. That may because the eastern region has a quite good economic foundation and good infrastructure, and the information and factor flows operate conveniently and efficiently. Therefore, the spillover effect in the eastern region is more prominent. However, the spillover effect in northeast China is not significant, possibly because the local natural geography and climate conditions cause weak resource factor liquidity, which is not conducive to the spillover effect of digital carbon reduction in rural areas.

4.1.5 Endogeneity test

To alleviate the possible endogenous problems of the model, the two-stage least square method of instrumental variables (IV-2SLS) was used for processing. Proximity to digital infrastructure hubs is selected as the instrumental variable, and the selection of the instrumental variable must meet the two conditions of correlation and exogeneity: First, rural digitalization is related to proximity to digital infrastructure hubs. Therefore, proximity to digital infrastructure hubs can represent the level of rural digitalization to a certain extent. The correlation conditions between instrumental variables and independent variables are satisfied. Second, proximity to digital infrastructure hubs does not directly affect the efficiency of agricultural carbon emissions, thus satisfying the exogenous conditions of instrumental variables. The results show that: in the first stage, instrumental variables are positively correlated with RUD, and the closer the distance to the digital infrastructure hub, the more conducive the subsequent RUD improvement; and in the second stage, the impact of rural digitization on ACEE was still significantly positive at 1% level, and all passed the validity test of instrumental variables.

4.2 Threshold effect test results and analysis

In this study, the threshold effect model was used to verify the non-linear effects of RUD on (ACEE). Based on Hansen (1999) framework, the threshold test adopts grid search method to iterate through all potential threshold values, preliminarily identifies threshold values based on the minimization of residual sum of squares (RSS), and calculates the significance level of threshold effect through 200 Bootstrap self-sampling. The results show (Table 10) that the F statistic of the single threshold model is 18.987, which is significant at 1% level ($p = 0.003$), and the corresponding threshold is 0.289, indicating that when the rural digitization index crosses this critical value, its mechanism of

TABLE 10 Threshold characteristic test.

The threshold variable	Model testing	Threshold value	*F* statistics	*p*-value	Critical value		
					1%	5%	10%
RUD	A single threshold	0.289	18.987***	0.003	24.097	12.865	9.432
	Double thresholds	Threshold 1:0.265 Threshold 2:0.383	3.210	0.214	11.977	4.843	3.664
	Three thresholds	—	1.891	0.142	7.909	5.558	4.029

*** represents $P < 0.01$, and the T value is in parentheses.

TABLE 11 Estimation results of dynamic threshold effect.

Region	The threshold variable	Threshold and interval	Regression coefficient	*T* value	Standard error
The whole region	RUD	RUD ≤ 0.289	0.104**	3.024	0.001
		RUD > 0.289	0.171**	2.822	0.015
Eastern region	RUD	RUD ≤ 0.206	0.121***	5.951	0.101
		RUD > 0.206	0.217***	4.822	0.081
Central region	RUD	RUD ≤ 0.238	0.198***	5.931	0.001
		RUD > 0.238	0.311***	4.328	0.015
Western region	RUD	RUD ≤ 0.307	0.074	0.985	0.174
		RUD > 0.307	0.097***	4.373	0.157
Northeast region	RUD	RUD ≤ 0.303	0.104**	2.687	0.071
		RUD > 0.303	0.147**	2.761	0.038

*** and ** represent $P < 0.01$ and $P < 0.05$, respectively, and the T value is in parentheses.

action on ACEE will undergo structural changes. However, both the double threshold ($F = 3.210$, $p = 0.214$) and the triple threshold failed the 10% significance test, which proved that there was only a single inflection point. Further combined with the explanation of economic significance, the threshold value of 0.289 corresponds to the critical level of 28.9% coverage of digital infrastructure in counties; at this time, the penetration rate of the synergy degree of agricultural data platform reaches the scale effect threshold, digital technology changes from "local pilot" to "global empowerment," and the marginal emission reduction cost is significantly reduced.

Since the threshold regression model contains the lag term of the explained variable, biased results will be obtained if the OLS method is used to estimate the threshold value regression model with the explained variable lag term. Therefore, the systematic generalized moment estimation method is used here, and the estimation results are shown in Table 11. When the RUD of the whole study area was less than or equal to the threshold value of 0.289, the regression coefficient of RUD was 0.104 ($p < 0.05$). When RUD exceeded 0.289, the regression coefficient of RUD was 0.171 ($p < 0.05$). This finding indicates that as the rural digitalization level (RUD) increases, its promoting effect on ACEE increases. This is mainly due to the continuous accumulation of digital production factors, the rapid increase in the use of internet users, the continual decrease in the marginal cost of farmers' access to information, knowledge, and technology, and the decrease in the cost of farmers adopting green production technology; thus, carbon emissions in the agricultural production process are also reduced. Thus, carbon emission efficiency in the agricultural production process is promoted.

Moreover, the influence of different regions is estimated with the help of the dynamic threshold panel model, and the number and threshold values of different regions are determined. Each of the four regions had only one threshold value, as shown in Table 11. Among the four regions, the eastern region had the lowest threshold value (RUD = 0.206). When the RUD was less than the threshold, the coefficient of RUD was 0.121 ($p < 0.01$), and when the RUD exceeded the threshold, it climbed to 0.217 ($p < 0.01$). The eastern region has a high level of urbanization and economic development, the perfect digital infrastructure in rural areas, and the improvement of the rural digital level further highlights the agricultural ecological value and strengthens ecological awareness of agricultural producers. Therefore, they will earnestly practice agricultural, ecological, and environmental behavior and reduce the input of harmful substances. At this time, the positive effect of rural digitalization on the ACEE is enhanced. The threshold value of RUD in the western region was the highest (RUD = 0.307), but when the RUD was less than the threshold value, its influence coefficient was not significant. When the RUD exceeds the threshold value, its coefficient reaches 0.097 ($p < 0.015$). This finding indicates that if rural digital development in western China is at a low level, it cannot significantly improve ACEE; only when the RUD crosses the threshold and increases to a high level, it will have a significant promoting effect on the ACEE. This may be because the economies of most western regions are underdeveloped, the level of rural digital development is not high, and advanced agricultural technology is difficult to popularize. Thus, RUD did not significantly affect the ACEE at the beginning of the fusion. When RUD exceeds the threshold value of 0.621, agricultural producers realize that agricultural ecological capital creates more value, at which point

agricultural carbon emissions become important and using harmful environmental factors in production is consciously reduced, ultimately improving the ACEE. Compared with that in the western region, the rural digitalization level in the central region has a stronger promoting effect on ACEE, perhaps because of the relatively high economic development level in the central region and good rural digital construction, which can support the low-carbon and green development of agriculture. Therefore, improving RUD is highly important for increasing ACEE.

5 Conclusion and implications

Based on data from 30 provinces and regions in China (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2011 to 2022, this study examines the impact of rural digital development on agricultural carbon emissions with the help of a dynamic spatial Durbin model and threshold effect model and obtains the following conclusions: First, both agricultural carbon emissions (ACEE) and the level of rural digitization (RUD) have a significant spatial clustering feature. Therefore, the spatial Durbin model can better reveal the relationship between the two. Moreover, the dynamic sustainability of ACEE and the accumulation of ACEE in the early stage directly affect ACEE in the current and later periods. Therefore, the dynamic panel model can objectively reflect the actual development of ACEE and is beneficial for solving the endogeneity problem. Second, RUD has a spatial spillover effect on ACEE. As far as the whole study area is concerned, an increase in the degree of RUD can increase ACEE in the local area and has a certain promoting effect on ACEE in its surrounding regions, which is consistent with that of Wang et al. (2024a). By region, RUD of the central region has the strongest direct (local) effect on ACEE, whereas the eastern region has the greatest spillover effect. Third, there are threshold characteristics for the influence of RUD on ACEE, and there is only one threshold value in the whole region as well as in four different regions. This conclusion is different from the study of Wang et al. (2024a), whose study showed a double threshold effect of agriculture and tourism integration on agricultural eco-efficiency, and this difference may be due to the different scale of the study area. The promoting effect of RUD on ACEE increases significantly when RUD exceeds the threshold across the study area. This indicates that as RUD increases, its promoting effect on ACEE enhances. Among the four regions, the eastern region has the lowest threshold value, and the western region has the highest threshold value. Moreover, when the RUD in western China was lower than the threshold value, its impact on the ACEE failed the significance test. Only when it crosses the threshold value, does RUD have a significant effect on the improvement of ACEE. Therefore, improving RUD is the key way to fully realizing its role in improving ACEE.

The above research conclusions have the following implications for the role of RUD in reducing ACEE.

First, given the positive role of rural digitization in improving ACEE, the application and promotion of new technologies, new products, and new models in the field of digital agriculture should be increased in the future, and agricultural sensors and intelligent equipment should be included in the purchase subsidies of agricultural machinery as soon as possible. It is important to continue to promote the strategies of "broadband to the countryside" and "digital countryside," achieve 4G or 5G network coverage in rural areas, and ensure basic information services for rural residents. It is necessary to establish digital economy demonstration villages and agricultural big data pilot counties to promote the transformation of digital achievements into real productivity as soon as possible.

Second, given the significant regional heterogeneity of the impact of rural digitalization on agricultural carbon productivity, dynamic and differentiated digital rural development strategies should be implemented in the future. For areas that have achieved good results in green and low-carbon agricultural development, we will further consolidate the dividend of digital carbon reduction and yield increase in rural areas, pay attention to technology diffusion, and help areas with low digitalization levels. The eastern region should continue to play a leading role in the demonstration of low-carbon agriculture, and the central and western regions should speed up the strengthening of weak spots, continuously develop ecological low-carbon agriculture, promote a comprehensive green transformation of agricultural development, narrow regional differences, and break the regional imbalance in the development of low-carbon agriculture.

Third, in view of the significant spatial spillover effect of rural digitalization on ACEE, efforts should be made to improve the inter-regional cooperation mechanism in the future, take advantage of digitalization to overcome the limitation of economic distance, build an integrated digital economy smart service platform, establish a large digital economy service database, and realize the sharing of data resources and platforms. Information disclosure and technology popularization of agricultural production environment will be strengthened.

The research limitations of this study mainly include the following two aspects: First, although this study has carried out a theoretical analysis of the influence mechanism, it has not been empirically tested due to the limited version of the study. The influence mechanism can be further tested through empirical analysis in the future; second, due to the limitation of data availability, this study adopts provincial panel data for research. The spatial scale of sample measurement is large, which may affect the accuracy of results. In the future, it can be quantitatively analyzed by using smaller scale sample data such as municipal panel data.

Note: The eastern region comprises 10 provinces: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; the central region consists of 6 provinces: Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan; the western region comprises 11 provinces: Chongqing, Sichuan, Guizhou, Guangxi, Yunnan, Shaanxi, Inner Mongolia, Gansu, Ningxia, Qinghai, and Xinjiang; and the northeastern region consists of 3 provinces: Heilongjiang, Jilin, and Liaoning.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

WJ: Writing – original draft. CC: Writing – review & editing.

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Conflict of interest

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Dynamic influence of international price fluctuation on soybean market price in China: based on Bayesian-VAR model

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Context: Under the suppression of Trump 2.0 tariffs in the United States, fluctuations in agricultural product prices have become one of the significant risks to the security of China's supply chain, especially for soybeans which are greatly affected by the US market.

Methodology: Based on the monthly data of international and Chinese soybean futures prices and spot prices from May 2008 to October 2024, this paper constructs a Bayesian VAR model to explore the transmission path of international price fluctuations to Chinese soybean futures and spot prices.

Innovation: Different from many previous studies, this paper adopts the Bayesian VAR model, which can alleviate overfitting more effectively than the VAR model, improve the prediction accuracy, and reflect the dynamic impact of price fluctuations more accurately.

Conclusion: The results show that fluctuations in international market prices have a significant price discovery effect on the Chinese soybean market, which can help participants in the upstream and downstream of the supply chain reduce the risk of price fluctuations in the short term. However, the hedging function of the futures market still needs to be improved in the long term.

KEYWORDS

Bayesian-VAR model, soybean, price discovery, international price fluctuation, hedging function

1 Introduction

Both price fluctuations and environmental pollution pose significant risks to the security of the agricultural product supply chain (Huang et al., 2023; Lin et al., 2022; Xu et al., 2024; Xu et al., 2025). Since the advent of the Trump 2.0 era in 2025, the tariff-centered international trade environment has grown increasingly complex, intensifying the uncertainty and price volatility of agricultural markets and posing substantial risks to the security of China's soybean supply chain. As the world's largest soybean importer, China is heavily dependent on international markets, sourcing approximately 80 percent of its soybean imports from major producers such as the United States and Brazil. However, the trade conflict between USA and China since 2018 has not only driven up import costs, but also increased price volatility in China's soybean market, affecting all sides of the soybean supply chain. Meanwhile, as an important tool for risk management, the role of the futures market in the soybean supply chain is becoming increasingly prominent. However, the development of China's futures market is relatively late and there is insufficient price risk management. Therefore, how to effectively avoid the risks brought to the soybean supply chain by international price fluctuations through

the price discovery and hedging functions of the futures market is a practical problem.

The unique seasonality, supply peaks and perishability of agricultural products make the management of agricultural supply chain more complex and challenging than that of manufacturing supply chain (Imbiri et al., 2021). The prices of agricultural products are highly susceptible to factors such as weather and natural disasters (Zia et al., 2022). Furthermore, changes in supply and demand, exchange rate fluctuations, policy adjustments, etc. will also have a significant impact on prices, making price fluctuations an inevitable source of risk in the supply chain. Especially under the high trade interdependence among countries and the impact of the novel coronavirus epidemic and other factors, the risks associated with agricultural product prices have also increased, attracting growing global attention to food security (Pu and Zhong, 2020; Laborde et al., 2020). Soybeans are one of the most important agricultural products. China is the world's largest consumer and importer of beans. Consequently, fluctuations in international soybean prices directly influence soybean prices in China (Montanía et al., 2021; Zhang et al., 2021). In addition, fluctuations in energy prices also impact China's soybean market. During periods of crisis, market efficiency tends to decline due to greater susceptibility to extreme events (Hu et al., 2024). For instance, the U.S.-China trade war, as a political and economic event, undermined the information dominance of the U.S. soybean futures market (Bandyopadhyay and Rajib, 2023; Adjemian et al., 2021), increased price volatility in China's soybean market, and prompted China to accelerate the diversification of its soybean import sources (Wen et al., 2023). Additionally, it strengthened the co-movement between soybean prices and energy prices such as crude oil (Cheng et al., 2023). In this context, Han et al. (2013) examined the role of the Dalian Commodity Exchange (DCE) in the global price discovery process of soybean futures and found that the DCE's soybean futures prices exert a significant influence on price discovery relative to the Chicago Board of Trade (CBOT).

The agricultural futures market plays the role of an "information center" in shaping price expectations in the spot market (Garcia and Leuthold, 2004). As early as 1983, Garbade and Silber (1983) pointed out that in markets characterized by rapid information dissemination and high liquidity, futures markets typically lead spot markets. In the international soybean market, Brazil has become the world's largest soybean exporter, accounting for more than 40% of global soybean exports. However, the United States still plays an important role in the global soybean market. Changes in the futures price of soybeans in the United States will affect other markets and even drive up the price of soybeans in Brazil (Li and Hayes, 2017). Studies have found that the volatility of the U.S. soybean futures market significantly affects the Chinese market, which confirms the United States' status as a global financial market leader (Fung et al., 2003). Such volatility transmission has been observed across all commodities studied (including soybeans, corn, wheat and sugar), especially in the soybean market (Jiang et al., 2017). The relationship between spot and futures prices of soybeans exhibits distinct characteristics across different market phases. Futures market typically plays a leading role in price discovery. In the price transmission process, the soybean futures market plays a leading role, particularly under conditions of high market liquidity, where futures prices often precede spot prices. The international soybean futures market exerts a significant price discovery effect on the spot price of Chinese soybean (Xu et al., 2019; Wu et al., 2024). The research finds that the role of the futures market in price discovery is enhanced during periods of market bubbles, while it weakens during periods of non-bubbles, indicating that market conditions have a significant impact on the effectiveness of the price discovery function (Li and Xiong, 2019). Gao et al. (2024) noted that China's recent retaliatory tariffs on U.S. soybeans have strengthened China's position in the discovery of soybean futures prices.

In recent years, fluctuations in commodity prices have led to an increasing income risk for farmers, and hedging in the futures market has been an effective coping strategy (Penone et al., 2021). Rutledge (1972) mentioned that hedgers use the futures market to mitigate risks associated with spot market price fluctuations. In order to attract speculative capital to match the trades of hedgers, a discrepancy between the futures price and the expected expiration price will arise (Li and Hayes, 2022). This means that soybean price risk can be reduced by hedging. Due to the multifractal characteristics of the soybean futures market, investors need to design effective hedging strategies to manage price risks and help them maintain stable returns during market fluctuations (Yin and Wang, 2021; Erasmus and Geyser, 2024). Tejeda and Goodwin (2014) compared the effectiveness of multi-product hedging strategies with single-commodity hedging and found that dynamic multi-product hedging can significantly lower risk, providing more effective risk management tools. Notably, some scholars have studied the risk transmission mechanisms between the most mature (U.S.) and the fastest-growing (China) commodity futures markets. Their research confirmed the dominant role of the U.S. agricultural futures market in price leadership, while also acknowledging the increasingly significant role of China's futures market in price discovery (Ke et al., 2019).

Building upon the aforementioned research, this study discusses the dynamic influence of international price fluctuations on the soybean market in China by combining the price discovery and hedging function of futures market. The innovations of this study are as follows: First, a Bayesian VAR model is innovatively constructed. This approach is rarely applied in prior studies, which predominantly use traditional VAR models. The Bayesian VAR model incorporates prior distributions to constrain parameter estimation, effectively mitigating overfitting, enhancing forecasting accuracy, and improving the modeling of parameter uncertainty. Second, the longitudinal scope and novelty of the data. Using international soybean futures prices and Chinese soybean spot prices from May 2008 to October 2024, this study provides a more dynamic reflection of the impact of international price fluctuations. For instance, this study finds that although hedging operations in the Chinese futures market can reduce the risk of fluctuations in spot prices in the short term. However, due to the liquidity of the Chinese futures market and the limitations of basis fluctuations, there is still room for improvement in the hedging effect in the long term.

2 Materials and methods

2.1 Theoretical analysis

Price fluctuations are the main source of risk faced by participants in the upstream and downstream of the soybean supply chain. By

taking advantage of the price discovery and hedging functions of the futures market, farmers and other suppliers can analyze price signals, hedge against price fluctuations in the spot market, stabilize profits and control costs.

2.1.1 Risk avoidance mechanism of upstream suppliers

As the production and supply link of the soybean supply chain, the main risk for upstream suppliers comes from the impact of falling soybean prices on planting income and inventory value.

Firstly, the price discovery function. The price discovery function of the futures market provides upstream suppliers with price expectations for the soybean market, enabling them to plan production and inventory reasonably. When futures prices indicate that they may rise in the future due to insufficient supply, growers can expand their planting area and soybean suppliers can increase their purchasing scale to seize the market opportunity first. On the contrary, price signals indicating a decline in prices can optimize resource allocation and avoid market risks.

Secondly, the hedging function. In the futures market, by establishing futures positions, suppliers can convert the risk of price fluctuations into a relatively controllable level of returns. When suppliers hold soybean inventories and predict a future decline in market prices, they can sell futures contracts in the futures market to hedge against the risk of a possible drop in spot prices in the future. If inventory prices fall, the profits in the futures market will make up for the losses in the spot market and ensure that inventory values are not affected by price fluctuations.

2.1.2 Risk avoidance mechanism of downstream demand side

The downstream demand side, as the final consumption link of the soybean supply chain, its main risk comes from the impact of market price fluctuations on raw material costs.

Firstly, the price discovery function. The price discovery function of the futures market provides the demand side with a clear global cost warning, helping them optimize their purchasing decisions and reduce price risks. When the futures price signal indicates that the future market supply and demand are tight and prices may rise, the demand side can purchase raw materials in advance to lock in low-cost supplies. When the signal indicates that the price may fall, the demand side can postpone the purchase to reduce the risk of high inventory squeezing the price.

Secondly, the hedging function. The actual risk management operations on the demand side of soybeans rely on the Chinese futures market, further locking in procurement costs and production profits through futures tools. By purchasing futures contracts, the future purchase price can be locked in advance, enabling the demand side of soybeans to stabilize profits amid the sharp fluctuations in raw material prices.

2.1.3 The coordination mechanism under the linkage of Chinese and international futures markets

The international soybean futures price reflects the global soybean market and the international supply and demand relationship. International futures prices influence the trend of Chinese futures prices through price transmission and guide the Chinese soybean market price. The Chinese futures market not only provides a reference for supply and demand through the price discovery function, but also uses hedging tools to help the upstream and downstream of the soybean supply chain lock in profits or costs. Through the coordinated operation of Chinese and international futures markets, the upstream and downstream of the soybean supply chain have effectively reduced the uncertainty risks of the supply chain and enhanced the overall stability and resilience. As shown in Figure 1.

2.2 Model construction-Bayesian-VAR model

This paper adopts the BVAR empirical method. The Bayesian Vector Autoregression (BVAR) model incorporates prior distributions to constrain parameter estimation, effectively mitigating overfitting, enhancing forecasting accuracy, and improving the modeling of parameter uncertainty. While the Vector Autoregression (VAR) model is widely used for forecasting macroeconomic variables, it tends to suffer from overfitting in high-dimensional settings. The introduction

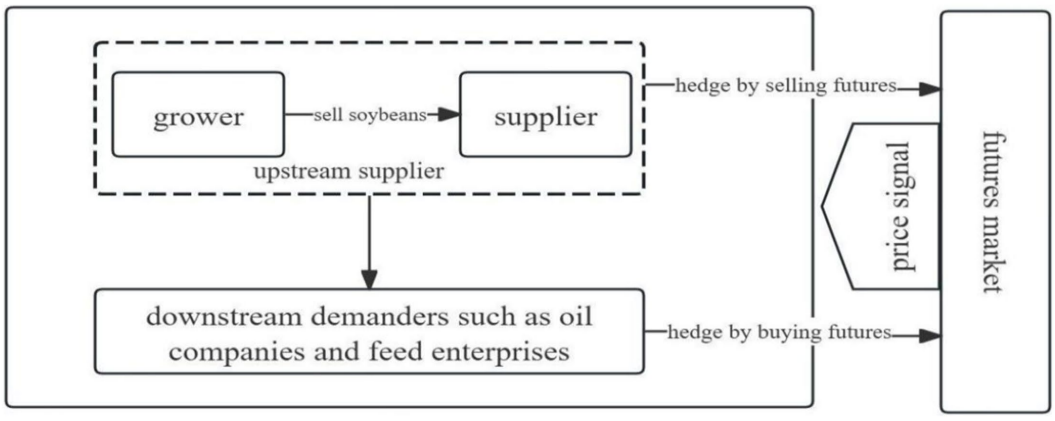


FIGURE 1
Supply chain upstream and downstream coordination mechanism.

of Bayesian methods-particularly shrinkage priors-has demonstrated strong performance in improving predictive accuracy (Van der Drift et al., 2024). Moreover, BVAR models are more data-driven and offer greater flexibility, whereas DSGE models face limitations in handling high-dimensional data and lack model flexibility.

For a time series vector $Y_t = (y_{1t}, y_{2t}, \ldots, y_{kt})'$ with k variables, The VAR (P) model can be expressed as Equation 1:

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + \in_t \quad (1)$$

Where Y_t is a k × 1 vector representing the value of all variables at time t; A_i is a k × k coefficient matrix for lag i; p denotes the lag order; c represents the intercept term; and $\in_t$ is the error term assumed to be white noise.

In the Bayesian framework, the sum of A_i and $\sum$ parameters are assigned prior distributions. Normal distribution or independent and identically distributed Gaussian distribution is typically selected as the prior. Common prior distribution forms include a Gaussian distribution (assuming parameters A_i follow a zero-mean normal distribution) and a Wishart distribution for the prior of the covariance matrix $\sum$.

In the posterior distribution, observed data are used to update the prior distribution to obtain the posterior distribution of the parameters. The posterior distribution represents the probability distribution of parameter values given the observed data (Equation 2).

$$P(\theta|Y) \propto P(Y|\theta)P(\theta) \quad (2)$$

Where $P(\theta|Y)$ is the posterior distribution of parameter θ, $P(Y|\theta)$ is the likelihood function, and $P(\theta)$ is the prior distribution.

Common sampling methods include Markov chain Monte Carlo (MCMC) method, which is used to extract samples in the posterior distribution, so as to obtain the estimated value of model parameters and their uncertainty.

2.3 Data sources and sample description

This study selects the closing price of yellow soybean No.1 futures from May 2008 to October 2024 as the sample of Chinese soybean futures price, the CBOT soybean futures closing price as the international soybean futures price, and Chinese soybean spot price as the soybean market price. All data are sourced from the WIND database. Among them, the CBOT soybean futures closing prices, originally quoted in cents per bushel, have been converted into yuan per ton based on prevailing exchange rates. The basic descriptive statistics of the core variables are presented in Table 1.

3 Results

3.1 Unit root test and granger causality test

3.1.1 Unit root test

ADF test is used to test the stability of each price series. The results indicate that all original sequences of China's soybean spot price (SP), China's soybean futures price (FP) and international soybean futures price (CBOT) are non-stationary, while their first-order differenced series reject the null hypothesis at the 1% significance level, thereby demonstrating stationarity. Therefore, the subsequent analysis utilizes the first-order differenced series of these three variables, denoting them with a 'd' prefix to indicate differencing.

3.1.2 Granger causality test

The Granger causality test requires stationarity of time series data and is used to determine whether a time series can effectively predict another. In the Granger causality test, the selection of the lag length has an important impact on the results. When selecting the lag length, the minimum values of AIC and SC are primarily referenced, supplemented by subsequent test results to determine the most appropriate lag structure. Consequently, a lag length of two is selected, and the relevant test results are presented in Table 2.

According to Table 2, both dCBOT and dFP are found to Granger-cause dSP at the 5% significance level, indicating a unidirectional relationship. Fluctuations in the futures market (including international and Chinese futures prices) significantly influence spot market prices, suggesting that price changes in the international and Chinese futures markets are transmitted to the soybean spot market through the futures market's price discovery function.

3.2 Lag order selection and MCMC stability test

During the construction of the BVAR model, it is necessary to specify prior distributions for the coefficients. This study adopts the conjugate Minnesota prior. The default prior assumes that only the first own-lag coefficient has a mean of 1, while all other coefficients have a mean of 0. Selecting the lag length is a critical consideration when establishing the model. Traditional methods, such as using the AIC standard method, may overestimate the number of lags. Therefore, this study employs the Bayestest model to compute the posterior probability of the model. It is assumed that each candidate model has an equal prior probability. According to Table 3, the model with three lags exhibits the highest posterior probability among the three considered models, thus, a third-order lag is selected for subsequent impulse response and variance decomposition analyses.

Prior to further analysis in the BVAR model, it is essential to verify the convergence of the MCMC sampling. According to Figure 2, the trace plot exhibit no apparent trends, and autocorrelation levels are low, indicating successful convergence of the MCMC sampling.

As shown in Table 4, the 95% confidence intervals for all eigenvalue moduli do not encompass values greater than or equal to one, confirming that all eigenvalues lie within the unit circle and that the system is stable.

TABLE 1 Core variables descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
SP	198	4169.156	666.5048	3363.76	5888.17
FP	198	4410.201	762.9892	3131.83	6312.68
CBOT	198	2810.077	543.9256	2027.31	4087.96

TABLE 2 Granger causality test results.

Lag phase	Null hypothesis	*F*-statistic	p v.	Causality
2	dCBOT is not the Granger cause of dSP	7.4129	0.025	yes
	dFP is not the Granger cause of dSP	9.5583	0.008	yes
	dCBOT is not the Granger cause of dFP	4.8968	0.086	no
	dSP is not the Granger cause of dCBOT	2.4319	0.296	no
	dSP is not the Granger cause of dFP	2.205	0.332	no

TABLE 3 The selection of lag order.

Order	Log(ML)	P(M)	P(M|y)
Lag1	−3.78e+03	0.3333	0.0000
Lag2	−3.76e+03	0.3333	0.0000
Lag3	-3.73e+03	0.3333	1.0000

3.3 Impulse response analysis

It can be seen from Figure 3a that in the early stage of the international soybean futures prices shocks, China's soybean futures prices (dFP) exhibit a significant negative response. In the initial phase of price decline, the magnitude of the negative response is large, indicating that international soybean futures fluctuations exert a short-term disturbance effect on China's soybean futures market. Over time, this negative impact gradually weakened, and the response curve returned to near zero, indicating that China's futures market absorbs and adjusts to international market shocks. The negative impact may reflect the excessive short-term sensitivity of China's soybean futures market to international shocks, implying potential market instability or speculative behavior. These findings further confirm that the international soybean futures price (CBOT) has a significant influence on the Chinese futures price, highlighting the international market as a key external factor for China's soybean futures market.

In the initial stage, the spot price (dSP) of Chinese soybeans showed a significant positive response to the international futures price, which indicates that the spot market of Chinese soybeans is highly sensitive to the price fluctuations of the international soybean futures market. However, as time goes by, the positive response gradually weakens but still remains above zero. This reflects that the Chinese soybean market is highly dependent on the international market. Especially against the backdrop of a relatively high proportion of soybean imports, changes in international market prices have a significant external impact on China's spot prices.

Meanwhile, it can be seen from Figure 3b that in the initial stage of the impact of China's soybean futures price on China's soybean spot price, China's soybean spot price (dSP) showed a positive response, that is, the spot price increased with the rise of futures price, and the positive response amplitude reached the maximum at the initial stage, indicating that the futures market price fluctuation had a significant guiding effect on the spot market. With the passage of time, the positive impact gradually weakened, the response curve showed a trend of gradual decline, and finally approached zero. This shows that there is a significant price transmission mechanism between China's soybean futures market and spot market. Fluctuations in futures prices will directly affect spot prices, reflecting the price discovery function of the futures market. This positive impact also shows that the futures market can guide the spot market to make pricing adjustments by reflecting future price expectations.

From the above impulse response diagram, it can be seen that the international soybean futures price (dCBOT) has a significant price transmission effect on the Chinese market, which is manifested in two direct and indirect paths: on the one hand, the international futures price (dCBOT) will directly affect the Chinese spot price (dSP); on the other hand, international futures prices are indirectly transmitted to Chinese spot prices (dSP) through Chinese futures prices (dFP). Among them, the impact of dCBOT on dFP is significant in the short term, and the positive impact of dFP on dSP is also obvious, indicating that the Chinese futures market plays an intermediary role in price transmission, which further verifies the price guidance and transmission mechanism of the international market to the Chinese market.

3.4 Variance decomposition analysis

Table 5 indicates that the fluctuations of the International Soybean Futures Price (dbot) are less affected by external factors (dSP and dFP), which suggests that the prices in the international market (such as CBOT) are less influenced by the feedback from the Chinese market.

Firstly, the fluctuations of China's spot price (dSP) were mainly explained by itself in the short term (the contribution rate in the first period was 83.66%), but as time went by, the contribution rate of its own shock gradually decreased (72.78% in the eighth period), indicating that the influence of external factors (dCBOT, dFP) on it gradually increased.

Secondly, the contribution of international futures prices to China's spot prices gradually increased from 9.79% in the first period to 17.17% in the eighth period, indicating that the price transmission effect of the international market on China's spot market has become more significant and gradually strengthened.

Thirdly, the contribution rate of futures prices to spot prices rose from 6.55% in the first quarter to 10.04% in the eighth quarter. This indicates that China's futures market has a certain influence on the price guidance of the spot market, but it is lower than the direct influence of the international market.

3.5 Further analysis: verification of hedging function

In order to quantify the actual role of the futures market in reducing the risk of soybean price fluctuations, this paper estimates

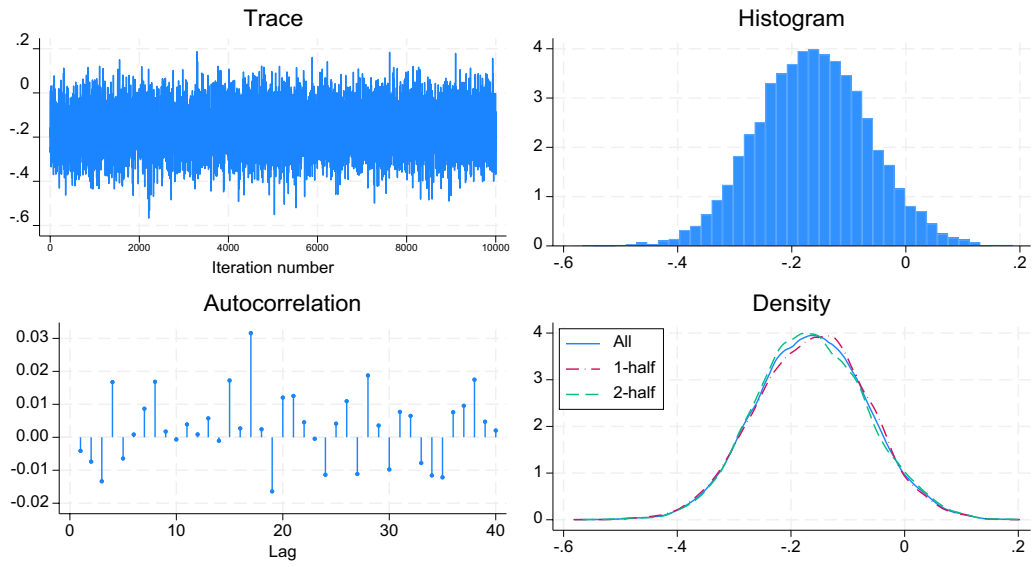


FIGURE 2
MCMC test diagram.

TABLE 4 Parameter stability test.

Eigenvalue modulus	Mean	Std.dev.	MCSE	Median	Equal-tailed [95%cred. interval]	
1	0.5960851	0.0671138	0.000336	0.5946916	0.4645424	0.7304319
2	0.5229635	0.762327	0.000381	0.528827	0.3644732	0.6578511
3	0.4131889	0.0960316	0.00048	0.4141151	0.2431756	0.5843047
4	0.2152237	0.0888426	0.000444	0.20005	0.077098	0.3856478
5	0.1243613	0.0580975	0.00029	0.11168123	0.0331408	0.2606396
6	0.0651273	0.0443594	0.000222	0.0587793	0.0030418	0.1661547

Pr(eigenvaluse lie inside the unit circle) = 1.0000.

the hedging performance degree measured by the optimal hedging ratio (Equations 3, 4).

$$\Delta HF_c = c + b\Delta HF_t + \varepsilon_t \tag{3}$$

$$b = \frac{\mathrm{cov}\left(\Delta HF_c, \Delta HF_t\right)}{\Delta HF_t} \tag{4}$$

Among them, $\triangle HF_c$ is the difference sequence of soybean spot at time t, which can be understood as the price yield of soybean spot, and $\triangle HF_t$ is the difference sequence of soybean futures at time t, which can be understood as the price yield of soybean futures. c is a constant term, $\mathring{a}_t$ is the residual of the regression equation, b is the hedging rate.

This paper uses the HE index proposed by Ederington to evaluate the hedging performance under the optimal hedging ratio. The HE index, also known as the Edlington index, is based on the principle of minimizing risk to measure the hedging effect. Specifically, the HE value reflects the degree to which the variance of the yield of the hedging portfolio is reduced compared to the variance of the spot yield without hedging when hedging through the use of futures contracts (Equations 5–7):

$$HE = \frac{\mathrm{Var}\left(U_t\right) - \mathrm{Var}\left(H_t\right)}{\mathrm{Var}\left(U_t\right)} \tag{5}$$

$$\mathrm{Var}\left(H_t\right) = \mathrm{Var}\left(\Delta \mathrm{lnHC}\right) + \beta^2 \mathrm{Var}\left(\Delta \mathrm{lnHF}\right) - 2\beta \mathrm{Cov}\left(\Delta HF_c, \Delta HF_t\right) \tag{6}$$

$$\mathrm{Var}\left(U_t\right) = \mathrm{VAR}\left(\Delta \mathrm{lnHC}\right) \tag{7}$$

$\mathrm{Var}\left(H_t\right)$ represents the variance of the return rate of the portfolio after hedging, â is the calculated optimal hedging ratio, and $\mathrm{Var}\left(U_t\right)$ is the variance of the spot return rate without hedging. The larger the value of the HE index, the more the variance of the combination after hedging is reduced, that is to say, the more the risk is reduced, the

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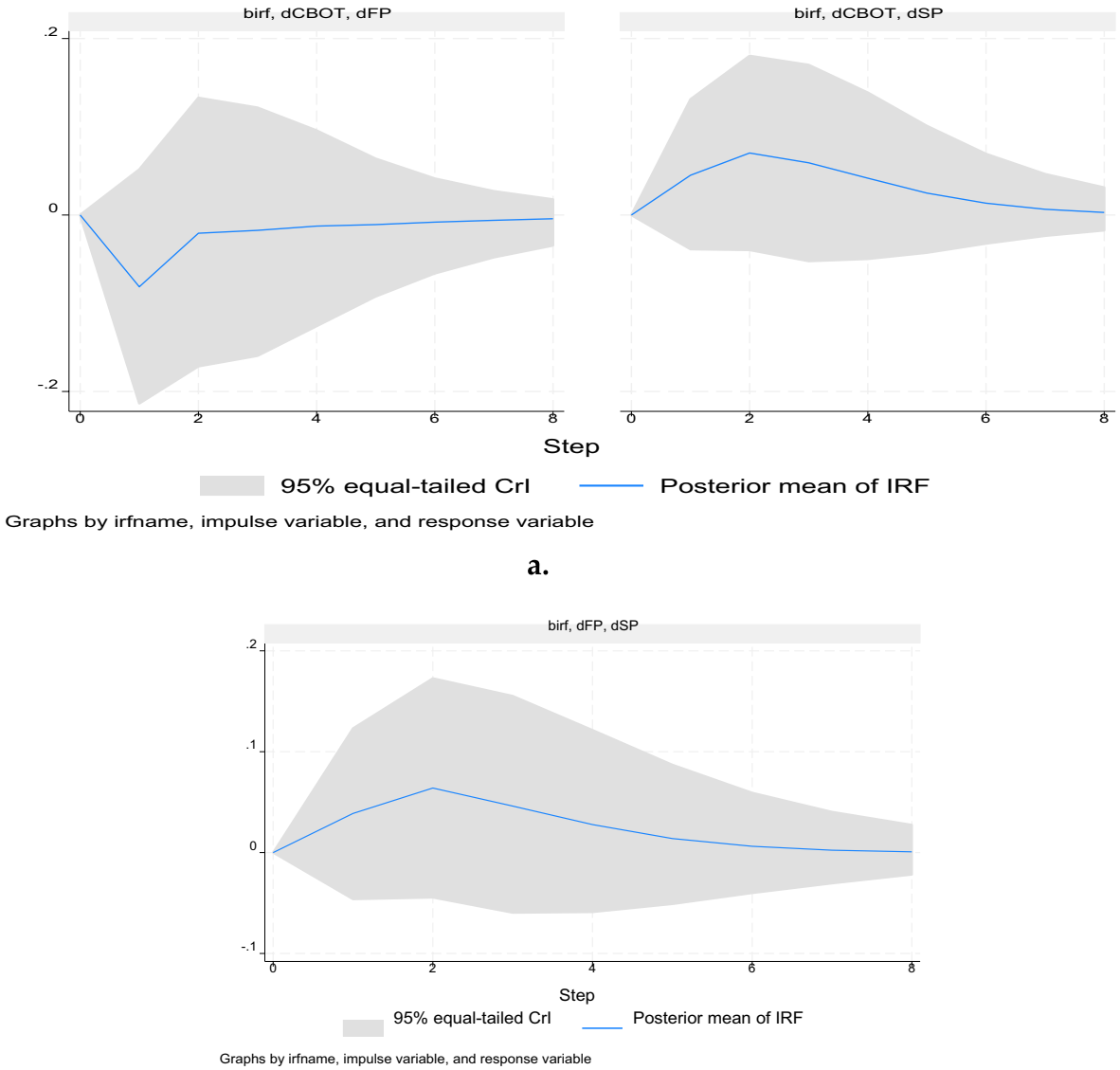


FIGURE 3
(a) Impulse response of dCBOT to dFP and dSP. **(b)** Impulse response of dFP to dSP.

TABLE 5 **Variance decomposition diagram.**

Period	Variance Decomposition of dCBOT			Variance Decomposition of dSP			Variance Decomposition of dFP		
	dCBOT	dSP	dFP	dCBOT	dSP	dFP	dCBOT	dSP	dFP
1	1	0	0	0.09787	0.83657	0.06554	0.17470	0	0.82529
2	0.97816	0.00863	0.01320	0.12536	0.79646	0.07816	0.15678	0.01025	0.83296
3	0.96542	0.01339	0.02118	0.15174	0.75765	0.09060	0.15622	0.01507	0.82869
4	0.95455	0.01817	0.02727	0.16421	0.73965	0.09614	0.15693	0.01925	0.82380
5	0.94866	0.02087	0.03046	0.16928	0.73212	0.09859	0.15761	0.02141	0.82097
6	0.94584	0.02214	0.03201	0.17099	0.72932	0.09968	0.15804	0.02238	0.81956
7	0.94467	0.02263	0.03269	0.17155	0.72825	0.10019	0.15826	0.02277	0.81896
8	0.94418	0.02282	0.03299	0.17174	0.72780	0.10044	0.15837	0.02292	0.81870

TABLE 6 OSL regression results of dSP and dFP.

Variable	Coefficient	Std. Error	*T*-Statistic	Prob.
C	−3.524743	7.470146	−0.471844	0.6376
dFP	0.35333	0.045099	7.834605	0.0000

better the hedging effect is; on the contrary, the smaller the HE index value is, the smaller the degree of risk reduction is, and the hedging effect is poor.

Among them, the first-order difference sequences of soybean futures price (FP) and soybean spot price (SP) are stationary sequences, so the OSL model is established directly. The regression results are as follows.

The expressions of dSP and dFP can be obtained from Table 6:

$$dSP_t = 0.35333dFP_t - 3.524743 + \varepsilon_t \quad (8)$$

The results calculated based on Equation 8 show that after hedging through the futures market, the risk of spot price fluctuations is reduced by 23.94%. That is, although the futures market has played a risk-aversion function to a certain extent, its hedging effect is still not significant enough. Possible reasons include relatively low liquidity in China's futures market, large basis fluctuations, and incomplete transmission of international market price fluctuations.

4 Conclusion

4.1 Main conclusion

Based on the role of futures market in China's soybean supply chain, this paper discussed the mechanism and conduction effect of the price discovery and hedging function. The main conclusions are as follows:

First, the international soybean futures market reflects the changes in supply and demand in the global market and provides a price benchmark for the soybean supply chain. The research results reveal that international futures prices have a price transmission effect on China's futures and spot prices. Furthermore, the impact on the spot price of soybeans has a strong external effect, which is manifested as direct transmission and long-term continuous influence. This conclusion reflects the high sensitivity of China's soybean prices to the international market.

Second, the soybean futures market has a certain transmission effect on the spot price. Soybean suppliers can reduce the risk of soybean prices to a certain extent through the futures market, lock in the selling price and avoid the risk of price decline. However, the calculation results of Edlington show that although hedging operations in China's futures market can reduce the risk of spot price fluctuations by 23.94%, due to the limitations of liquidity and basis fluctuations in the futures market, there is still room for improvement in the hedging effect.

4.2 Policy suggestion

The research conclusion reveals that the price discovery function of the soybean futures market has played a good role, but the hedging function needs to be further enhanced. Based on this, this paper puts forward the following suggestions.

Firstly, the government should actively promote the application of the "futures + insurance" model in the soybean supply chain. By promoting insurance companies and futures exchanges to design "futures + insurance" products for soybean growers, it is ensured that soybean growers can obtain stable income regardless of whether the price rises or falls. Meanwhile, as the government increases subsidies to growers, purchasing enterprises can also safeguard their own interests by lowering the purchase price and stabilize the soybean supply chain from the production end.

Secondly, the government should further improve the system of the soybean futures market. The research results show that there is a strong correlation between the international market and the Chinese soybean market, and the international futures price has a significant transmission effect on the price of Chinese soybeans. Therefore, by improving the futures market system, the role of risk management and price stability of the futures market can be strengthened.

Thirdly, the government should further strengthen the construction of the linkage mechanism with the international futures market. By establishing a data docking mechanism between the international futures market (such as CBOT) and the Chinese futures market (such as DCE), we can promote the real-time transmission of global supply and demand information in the Chinese market and help Chinese participants respond to international price fluctuations faster.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XX: Writing – original draft. SC: Data curation, Writing – original draft, Methodology. LZ: Writing – review & editing, Project administration.

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Conflict of interest

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Does institutional openness improve the trade efficiency of China's agricultural products imported from Central Asian countries? A time-varying stochastic frontier gravity model

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Introduction: Institutional openness is becoming increasingly important for agricultural trade between China and Central Asian countries.

Methods: This study employs a time-varying stochastic frontier gravity model to investigate the influence of institutional openness on the trade efficiency of China imported agricultural products from Central Asian countries under uncertainty, and further computes the import potential from 2000 to 2022.

Results: The research reveals that the impacts of different aspects of institutional openness on trade efficiency vary. Firstly, in terms of border opening measures, the joint accession to the WTO and the signing and implementation of the "Belt and Road Initiative" have effectively enhanced China's import trade of agricultural products from Central Asian countries. Secondly, regarding the impact of infrastructure, a higher efficiency of trade logistics clearance and a lower tariff are more beneficial for improving the trade efficiency. Thirdly, as for the degree of openness of the socio-economic system, a higher level of economic freedom in Central Asian countries societies are more conducive to promoting the export of agricultural products to China. Additionally, a higher uncertainty of China's economic policies may enhance the trade efficiency. However, the outbreak of the COVID19 and the Russia-Ukraine war have significantly diminished the trade efficiency. Fourthly, from 2015 to 2022, China's average export trade efficiency to Central Asian countries range from 0.3 to 0.6, with an import potential value of approximately 2.1 to 2.2 billion US dollars, indicating substantial import potential, especially for Kazakhstan and Uzbekistan.

Discussion: It is recommended to implement the "Belt and Road Initiative", enhance the logistics infrastructure, improve the efficiency of trade clearance, reduce the tariff burden on agricultural products, and stabilize the trade expectations of Central Asian countries under the unstable external economic environment, thereby enhancing the efficiency of agricultural trade between China and Central Asia countries.

KEYWORDS

Central Asian countries, uncertainty, institutional openness, agricultural trade, trade efficiency

1 Introduction

China first put forward the "Belt and Road Initiative" (BRI) in Central Asian countries. With the implementation and promotion of the BRI, the scale of agricultural trade from Central Asian countries to China has been growing continuously, from 9.9 million U.S. dollars in 2000 to 691 million U.S. dollars in 2022, with an average annual growth rate of 21.3% (Table 1). The economies of the Central Asian countries are in the process of transition, and the agricultural sector is one of the most important sectors in the five Central Asian countries, accounting for 10% ~ 45% of their GDP and employing 20% ~ 50% of total employment (Hamidov et al., 2016; Yu et al., 2020). This means that agricultural production and trade occupy a major position in its economic structure, which is related to the local livelihood. To cope the current international environment with steeply increasing in uncertainty and instability, the export trade of agricultural products between China and Central Asian countries, can effectively improve the farmers' employment and incomes in Central Asian countries, which will enhance the degree of openness in the agricultural sector and the resilience of the food system in Central Asian countries.

However, agricultural trade in Central Asian countries still faces high costs, both for geographical reasons and institutional barriers. And institutional openness is becoming increasingly important for agricultural trade (Pomfret, 2017; Sun and Zhang, 2021). In 2023, China and Central Asia countries signed the China-Central Asian countries Summit Outcome List, which proposed the need to promote the level of agricultural trade between China and Central Asian countries in terms of mechanisms and institutions. Therefore, it is of great significance to evaluates the impact of institutional openness on the efficiency of agricultural trade between China and Central Asian countries.

The research on institutional openness mainly focused on the exploration of its definition (Research Group of Institute of International Economics, National Development and Reform Commission, 2021; Zhang, 2021; Dai, 2021). Relevant studies believed that the essence of systematic opening up is the expansion, extension and deepening of "border opening up" to "internal opening up" in the past, and the formation of basic rules and systems in line with the prevailing rules of international economic and trade activities in the process of promoting rule changes and optimizing system design. In promoting rule and optimizing institution design, it forms basic rules and systems that are in line with the prevailing rules in international economic and trade activities, which is an advanced institutional arrangement that plays a leading role in the adjustment and improvement of the new round of highly standardized international economic and trade rules (Chang and Qian, 2022; Zhao and Zhang, 2022). With the deepening of the understanding of institutional openness, some researchers have also tried to sort out the characteristics of institutional openness, the mechanism and industrial chain risk, as well as the practical foundation and realization path with the Free Trade Zone (FTZ) as the core (Guo, 2022; Liu et al., 2023; Zhao and Zhang, 2022). At the same time, some studies have begun to use three dimensions of business environment, trade and investment liberalization and facilitation, and institutional innovation to measure institutional openness (Nie and Xue, 2022), as well as to quantitatively assess the impact of institutional openness on enterprise innovation (Wang and Chang, 2023). Related studies have paid less attention to institutional openness and its influence on agricultural trade (Wang and Chang, 2023).

TABLE 1 China's total imports of agricultural products from Central Asian countries (millions of dollars).

Year	Imports	Year	Imports
2000	98.74	2012	610.81
2001	20.24	2013	720.65
2002	36.96	2014	1255.76
2003	71.86	2015	1107.34
2004	73.97	2016	1440.11
2005	47.20	2017	2408.31
2006	47.74	2018	3234.62
2007	69.05	2019	4711.40
2008	38.64	2020	4994.37
2009	61.07	2021	3731.02
2010	159.08	2022	6914.32
2011	106.03	Annual rate of growth	21.3%

Calculated by the authors based on HS01-24 coded data collated from the UN Comtrade database.

With the deepening of China's economic and trade cooperation relations with Central Asian countries, the research on China's trade in agricultural products with Central Asian countries have gradually increased. Relevant studies are mainly focused on the following aspects: first, the competitiveness and complementarity of China's agricultural products trade with Central Asian countries (He et al., 2016; Jia, 2021; Liu, 2020; Li and Li, 2011; Yi and Abula, 2008). Relevant studies have shown that Central Asian countries has strong international competitiveness in the export of land-intensive products such as cotton and silk, and China has relatively strong competitiveness in technology-intensive agricultural products such as vegetables and fruits, meat, fish, and eggs, while the complementarity of bilateral trade in agricultural products has increased significantly, and the categories of agricultural products that have strong complementarities are mainly concentrated in vegetables, sugar, flour products, and textile fibers of the cotton category (Meng, 2018). Secondly, China's trade with Central Asian countries in agricultural products is growing. The study on the growth drivers of agricultural trade between China and Central Asian countries (Gong and Zhang, 2014; Hong, 2019; Zhu et al., 2018; Guo et al., 2021). These studies point out that the growth of market demand is the primary reason for the growth of agricultural trade. Third, the potential and efficiency of agricultural trade between China and Central Asian countries (Lv et al., 2020; Qi, 2019; Tan et al., 2016; Wumuer, 2016) and trade structure studies (Yan et al., 2021). Relevant studies have shown that the trade in agricultural products between Central Asian countries and China has a high potential. Fourth, there are studies are about China and Central Asian countries' agricultural trade patterns (Chen, 2014; Li, 2018), trade costs (Hou and Abula, 2015), trade facilitation (Felipe and Kumar, 2014; Hu, 2014; Kai et al., 2021; Yu, 2022; Yu, 2020), FTA construction (Wang et al., 2019), trade margins (Fang and Li, 2023), and supply chain performance evaluation (Abula, 2022). Fifthly, rising studies focused on agricultural value chains and infrastructure in Central Asian countries (Pomfret, 2014; Pomfret, 2017), soil and water resource use

efficiency (Liu et al., 2021), virtual soil and water trade (Zhou et al., 2022), water resource use and food system relationships (Ma et al., 2022), trade openness and food security, and trade openness and food security (Sun and Zhang, 2021).

Compared with existing studies, this study has three notable contributions. First, previous research on institutional openness mainly focused on its connotation, however, how to measure institutional openness has not formed a unified standard. Our study contributes by measuring institutional openness with multiple indicators as comprehensively as possible. Secondly, there are many existing studies on the potential and efficiency of agricultural trade in Central Asian countries, but more on the impact of trade facilitation and less on the efficiency of agricultural trade from the perspective of institutional openness. This study focuses on the impact of institutional openness on the efficiency of agricultural trade in Central Asian countries, which can fill the lack of research in this area. Third, fewer studies have considered the impact of uncertainty risks such as the Russia-Ukraine war and the Covid-19 on agricultural trade between China and Central Asian countries. Instead, this study considers it. Therefore, this study tries to adopt suitable indicators to quantitatively measure the institutional openness, and assesses its impact on the efficiency of China's agricultural trade with Central Asian countries under the background of uncertainty based on UN Comtrade database from 2000 to 2022. This study will provide policy references for improving the efficiency of agricultural trade between China and Central Asian countries.

The rest of this research is constructed as follows. Section 2 describes the material and methods, we provide detailed information about the data sources and data structure; the time-varying stochastic frontier gravity model of trade and the estimation techniques involved in the analysis. Section 3 presents and discusses the estimated results under study. All the findings of the study are concluded in Section 4 of this study.

2 Materials and methods

In this section, we present how we conducted this study and the tools we used. First, we explain the basic idea of the Stochastic Frontier Gravity Theory equation. Second, we describe our derived model for the agriculture exports from Central Asian countries, and give information about the data source and summarize the main characteristics of the data. Finally, we provide the detailed protocol involved in the estimation of our model.

2.1 Time-varying stochastic frontier gravity model

This paper intends to use a stochastic frontier gravity model to investigate the impact of institutional openness on the trade efficiency of China's imports of agricultural products from Central Asian countries. The traditional gravity model does not take into account the influence of policy factors, such as institutional factors and other subjective factors, which means the trade potential it calculates does not truly reflect the trade potential between countries. To solve this problem, the stochastic frontier gravity model was introduced into the field of trade research. The stochastic frontier production function first originated from the concept of technical efficiency proposed by Farrell (1957) and Lebenstein (1966), Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) subsequently used the stochastic frontier model to analyse the technical efficiency of the production function. Since the traditional trade model is essentially similar to the production function, Armstrong (2007) argues that it is equally feasible to use the stochastic production function to analyse trade efficiency, providing a theoretical basis for the stochastic frontier gravity model to study trade efficiency. As the stochastic frontier gravity model takes into account the technical inefficiency term, it is more scientific than the traditional gravity model, and has been widely used in the field of trade. According to the theoretical setting of Aigner et al. (1977), Meeusen and Van Den Broeck (1977) and Armstrong (2007), the general form of the stochastic frontier gravity model is as follows (Equations 1–3):

$$T_{ijt} = f\left(x_{ijt}\beta\right)e^{\left(v_{it}-u_{it}\right)} \tag{1}$$

$$T_{ijt}{}^{*} = f\left(x_{ijt}\beta\right)e^{\left(v_{it}\right)} \tag{2}$$

$$TE_{ijt} = \frac{T_{ijt}}{T_{ijt}{}^{*}} = e^{\left(-u_{it}\right)} \tag{3}$$

In Equation 1 where T_{ijt} represents the actual trade value between country i and country j, and $T_{ijt}{}^{*}$ in Equation 2 represents the trade potential value between country i and country j under the ideal condition, i.e., the maximum trade value under the frontier condition, where all the trade inefficiencies are overcome. x_{ijt} is a vector of order 1*k, which represents the natural factors affecting the trade value, such as gross domestic product (GDP), population, and geographic distance, etc., and β is the parameter to be evaluated parameters. v_{it} is the random error term and u_{it} is the trade inefficiency term, where TE_{ijt} in Equation 3 is the trade efficiency value, which is the ratio of the actual trade value and the trade potential value. The size of this value can be used to judge whether the trade is efficient or not, when the value is 1, it indicates that there is no trade inefficiency, the two sides of the trade has reached the maximum frontier value, the trade potential is fully tapped; when the value is 0, it indicates that the trade friction between the two sides of the trade reaches the maximum value so that the two sides cannot trade, and the trade potential that can be tapped in the future reaches the maximum; when the TE $\in$ (0,1), it indicates that there are trade inefficiencies. In specific empirical evidence, generally take the logarithm of both sides of Equation 1 to get the following Equation 4:

$$lnT_{ijt} = lnf\left(x_{ijt}\beta\right) + v_{it} - u_{it} \tag{4}$$

In order to explore the influencing factors of trade inefficiency, this paper draws on the one-step method proposed by Battese and Coelli (1995) to estimate trade inefficiency by regressing the stochastic frontier model and the trade inefficiency model simultaneously. The

theoretical equations for the stochastic frontier gravity model and the trade inefficiency model are given in the following Equations 5 and 6:

$$u_{it} = \left(\alpha z_{it} + \varepsilon_{it}\right) \tag{5}$$

$$lnT_{ijt} = lnf\left(x_{ijt}\beta\right) + v_{it} - \left(\alpha z_{it} + \varepsilon_{it}\right) \tag{6}$$

where z_{it} represents the factors affecting trade inefficiency and α is the parameter to be estimated for the factors affecting trade inefficiency. v_{it} and u_{it} are independent of each other, and u_{it} obeys a truncated normal distribution.

Since the data in this paper belongs to inter-period panel data, in order to accurately measure whether the trade efficiency of China's imported agricultural countries changes over time, this paper draws on the research of Cornwell et al. (1990) and introduces time-varying factors into the stochastic frontier gravity model, whose expression is:

$$u_{ijt} = \left\{\exp\left[-\eta\left(t - T\right)\right]\right\} u_{ij} \tag{7}$$

In Equation 7 where u_{ijt} represents the trade inefficiency term, T denotes the number of observation periods, and η is the time effect parameter to be estimated, which is the eigenvalue that characterizes whether trade efficiency changes. When η>0, it means that the technical inefficiency increases over time, the trade potential is suppressed, and the trade efficiency decreases; η<0 means that the trade inefficiency decreases over time, i.e., the trade potential is gradually released, and the trade efficiency increases; η=0 means that the technical inefficiency term does not change over time, and a time-invariant model should be used at this time.

2.2 The model and data

We constructed a time-varying stochastic frontier gravity model based on Equation 5 as follows:

$$\begin{aligned} lnT_{ijt} &= \beta_0 + \beta_1 \ln \mathrm{GDP}_{it} + \beta_2 \ln \mathrm{GDP}_{jt} + \beta_3 \ln \mathrm{POP}_{it} \\ &+ \beta_4 \ln \mathrm{POP}_{jt} + \beta_5 \ln \mathrm{DIS}_{ijt} + \beta_6 CONTIG_{ijt} + \beta_7 land_{it} \\ &+ \beta_8 AGR_{it} + v_{it} \end{aligned} \tag{8}$$

In Equation 8, T_{ijt} is explanatory variable, representing the amount of agricultural exports from China j to Central Asian country i in period t. The right side of the equation is the explanatory variable. Among them, GDP_{it} and GDP_{jt} are the real GDP (2015 constant dollar statistical caliber) of China and the import source country, which measures the level of economic development and the living standard of the residents, and the data are soured from the World Bank's World Development Indicators (WDI) database. POP_{it} and POP_{jt} represent the population sizes of the import source country and China, which measures the domestic market demand, and it is usually considered that the larger the population out of the importing source country, the larger the domestic market demand and the larger the imports are likely to be, whereas the larger the population in the exporting country, the larger the domestic demand and the smaller the exports, data from WDI. $\ln \mathrm{DIS}_{ijt}$ represents the logarithm of the distance between the two countries utilizing their capitals, and it is generally considered that the greater the distance, the greater the transportation costs, which will reduce trade between the two countries, data from the database of the CEPII. $CONTIG_{ijt}$ represents whether Central Asian countries border with China, if yes, it is 1, otherwise it is 0, this data is also from CEPII. $land_{it}$ measures the per capita arable land area of the exporting country, which measures the agricultural arable land resources of the exporting country, in general, the more abundant the arable land resources are, the higher the possibility of exporting agricultural products (Edison, 2021), this data is from WDI. AGR_{it} is the share of value added of agricultural industry in the total GDP of the exporting country, which measures the degree of abundance of agricultural resource endowment of the exporting country, and it is generally believed that the more abundant the agricultural resources, the higher the possibility of agricultural products export, and the data is sourced from WDI.

In order to further explore the impact of institutional openness on trade inefficiency, this paper constructed a trade inefficiency model that includes institutional openness measurement index system as follows:

$$\begin{aligned} u_{it} &= (\alpha_0 + \alpha_1 WTO + \alpha_2 BRI + \alpha_4 logis_{it} + \alpha_5 MFN_{it} \\ &+ \alpha_6 freedom_{it} + \alpha_7 freedom_{jt} + \alpha_8 uncertainty_{jt} \\ &+ \alpha_9 conflict_{jt} + COVID19 + \varepsilon_{it}) \end{aligned} \tag{9}$$

According to existing studies, institutional openness has rich connotations, including not only the traditional "border opening" based on the signing of relevant trade agreements, but also the deepening of "domestic opening" based on the optimization of institutional rules. Therefore, in order to comprehensively measure the institutional openness, we constructed the relevant indicator system from the following four aspects in Equation 9:

First, trade "border openness" indicators included two main indicators: WTO represents whether the trading country joins the WTO or not, with a value of 1 for yes and 0 for no. Studies have shown that joining the WTO is effective in stabilizing trade relations (Guo et al., 2015). BRI represents whether countries join the Belt and Road Initiative (BRI), which takes the value of 1, otherwise it takes the value of 0. Existing studies show that BRI can effectively promote agricultural trade (Zhao et al., 2024). So the signing of the BRI may improve the efficiency of China's agricultural import trade with Central Asian countries. This paper utilizes WTO and BRI to measure the degree of openness of the trade regimes of the two countries.

Secondly, the agricultural trade environment mainly contains: $logis_{it}$ and $logis_{jt}$ are the trade clearance efficiency indexes of country i and China (j) respectively, which are derived from the efficiency of customs clearance procedures in the World Bank's Digital Logistics Performance Index (DLPI). And the values are from 1–5, with 1 representing very low and 5 representing very high. Because agricultural products are not easy to be preserved, the clearance time of international agricultural trade has a great influence on the trade efficiency of agricultural products, and this index can effectively

TABLE 2 Descriptive statistics.

Variable	Definition	Mean	Std. dev.	Min	Max
$\ln GDP_i$	Ln GDP of exporting country *i*	23.888	1.482	21.716	26.124
$\ln GDP_j$	In GDP of China	29.648	0.564	28.650	30.424
$\ln POP_i$	Ln population size of exporting country *i*	16.310	0.655	15.404	17.389
$\ln POP_j$	Ln China's population	21.020	0.036	20.956	21.069
$\ln DIS_{ij}$	Ln the distance between the two capitals	8.236	0.062	8.152	8.307
$CONTIG_{ijt}$	Adjacency of the border between the two countries	0.750	0.435	0	1
$land_{it}$	Cultivated land per capita (ha/person)	0.560	0.703	0.088	2.026
AGR_{it}	Share of agricultural GDP of exporting countries (%)	18.630	9.132	4.288	34.541
WTO	Accession to WTO (yes = 1, no = 0)	0.446	0.500	0	1
BRI	Whether or not signed the Belt and Road Initiative (Yes = 1, No = 0)	0.304	0.463	0	1
$logis_{it}$	Efficiency of trade clearance procedures in exporting countries i	2.174	0.28	1.800	2.750
MFN_{it}	Weighted average most-favored-nation (MFN) tax rate for country *i* (%)	6.456	2.777	1.910	17.500
$freedom_{it}$	Economic freedom in country *i*	55.023	7.381	38.100	71.100
$freedom_{jt}$	China's economic freedom	53.709	2.823	48.000	59.500
$uncertainty_{it}$	Ln of the Chinese Economic Policy Uncertainty Index	141.258	106.706	35.566	390.388
$conflict_{it}$	Whether or not a Russo-Ukrainian war broke out (Yes = 1, No = 0)	0.043	0.205	0	1
Covid-19	Whether or not there is an outbreak of Covid-19(Yes = 1, No = 0)	0.130	0.339	0	1

"std.dev." means standard deviation.

measure the trade facilitation degree of agricultural trade, which is an important part of system-oriented opening. These trade facilitation measures related to procedures can profoundly affect agricultural trade (Fu et al., 2023). MFN_{it} is the most favored nation (MFN)-weighted average tax rate of country *i*. This index can effectively measure the trade tax burden of agricultural trade, which sourced from WDI.

Thirdly, we used economic freedom to measure the degree of openness of socio-economic system. $freedom_{it}$ and $freedom_{jt}$ represent the degree of economic freedom of country i and China (j) respectively, which is obtained from the Heritage Foundation Database, with a value range of 0–100. The higher the score indicates a better evaluation of the indicator, which exogenously measures the socio-economic system and the degree of openness of the importing source country from different dimensions (Pan and Fu, 2018), including the degree of protection of property rights, the degree of governmental economic intervention, judicial efficiency, governmental fiscal expenditure, commercial freedom, labour freedom, monetary freedom, trade freedom, investment freedom, and financial freedom, etc. The degree of openness in all aspects of the social system.

Fourth, regarding the stability of the external environment, supply chain disruption caused by external policy environment will have a negative impact on agricultural trade (Cao et al., 2020), the external policy environment's changes may have a greater impact on the efficiency of agricultural trade. So this study cheese three variables to capture the stability of the external environment. $uncertainty_{jt}$ represents China's economic policy uncertainty index, data from http://www.policyuncertainty.com/. The Economic Policy Uncertainty Index (EPU), developed by Baker et al. (2015), is a standardized index of the number of articles related to economic policy uncertainty in China's mainstream newspapers, which is used to reflect China's economic and policy uncertainty. And we also investigated the impact of the Russian-Ukrainian war ($conflict_{jt}$) and Covid19 ($COVID19$).

The descriptive statistics and expected direction of action of all the above variables are shown in Table 2.

2.3 Estimation protocol

It is necessary to choose an appropriate functional form before utilizing the stochastic frontier gravity model. The test consists of two steps: the first one is to test the existence of trade inefficiency; the other is to test whether trade inefficiency changes over time. As shown in Table 3, the LR statistic is 74.353, which rejects the original hypothesis of "there is no trade inefficiency" at 1% significance level, indicating that there existed trade inefficiency in the model and it's suitable for adopting the stochastic frontier gravity model. The time-varying test result shows that the LR statistic is 56.521, which rejects the original hypothesis of "trade inefficiency does not change over time" at 1% significance level, i.e., $\eta = 0$ is not valid, indicating that trade inefficiency changes over time, and it is more

TABLE 3 Stochastic frontier gravity model hypothesis testing.

Original hypothesis	Unconstrained model	Constrained model	LR statistic	1% Critical value	Test conclusion
No trade inefficiency: $\gamma = \mu = \eta = 0$	−244.87	−207.67	74.353	10.501	Rejected
No change in trade inefficiency: $\eta = 0$	−238.41	−210.15	56.521	8.273	Rejected

Compiled from Frontier 4.1 regressions.

TABLE 4 Regression results of the non-efficiency model.

Variable	Coefficient	Std. dev.	T-value	Variable	Coefficient	Std. dev.	T-value
Constant	−7545.156***	1.004	−7515.509	Constant	3.894	1.558	2.500
$\ln GDP_{it}$	12.717***	0.667	19.076	WTO	−2.939***	1.150	−2.556
$\ln GDP_{jt}$	−43.999***	1.866	−23.577	BRI	−8.852***	1.525	−5.806
$\ln POP_{it}$	−91.132***	1.080	−84.359	$logis_{it}$	−9.457***	2.066	−4.577
$\ln POP_{jt}$	418.012***	2.133	196.015	MFN_{it}	2.317***	0.358	6.464
$\ln DIS_{ijt}$	153.665***	1.211	126.936	$freedom_{it}$	−0.799***	0.176	−4.538
$CONTIG_{ijt}$	−95.180***	1.480	−64.290	$freedom_{jt}$	0.077	0.180	0.426
$land_{ijt}$	36.762***	1.225	30.008	*uncertainty -jt*	−0.095***	0.022	−4.316
AGR_{it}	0.314***	0.074	4.255	$conflict_{it}$	13.020***	2.684	4.850
t	3.118***	0.140	22.277	*COVID-19*	11.121***	2.118	5.252
				δ2	16.552***	1.878	8.813
–	–	–	–	γ	0.788***	0.058	13.548
Log Likelihood	−209.232						
LR test	58.352						

Obtained by collating results from Frontier 4.1, *, **, and *** indicate significance levels at 10, 5, and 1%, respectively.

appropriate to use time-varying stochastic frontier gravity model.

3 Results and discussion

3.1 Results

Table 4 shows the estimation results of the time-varying stochastic frontier gravity model and the trade inefficiency model using the "one-step" regression. The value of γ is 0.768, which indicates that the trade inefficiency model captures the trade inefficiency information comprehensively. According to the regression results, it can be found:

In the stochastic frontier gravity model, the coefficient of $\ln GDP_{it}$ was positive and significant indicating that the higher the GDP of the export source country could improve the agricultural trade with China. It may be due to the fact that the higher the economic development level of the exporting country has abilities to increase the export of agricultural products accordingly. The significant negative coefficient of $\ln GDP_{jt}$ indicated that the higher the GDP of China have the higher the demand for agricultural products, and the less reliance on Central Asian countries were. The impact of $\ln POP_{it}$ was significantly negative, indicating that the higher the population of the export source country, the higher its domestic consumption of agricultural products, the more unfavourable for exporting agricultural products. The coefficient of $\ln POP_{jt}$ was significantly positive, indicating that the higher the population of China, which promotes imports. The coefficient of $\ln DIS_{ijt}$ was significantly negative, which indicated that the higher the trade and transportation cost was, and the more unfavourable it was for China to import agricultural products from Central Asian countries. And the result was consistent with the existing studies (Fu et al., 2023). The impact of $CONTIG_{ijt}$ was significant negative, it's because that the transportation cost was higher when China imported agricultural products from Central Asian countries mainly through land transportation compared to sea transportation. The coefficients of $land_{ijt}$ and AGR_{it} were significantly positive, which implied that the land resources and agricultural endowment of Central Asian countries are more abundant, the they are more favourable for exporting agricultural products to China.

In the trade inefficiency model, considering the trade "border opening": First, the coefficient of WTO was-2.942, which was significantly negative at the 1% significance level. It indicated that the exporters to join the WTO can significantly promote China's imports of agricultural products from Central Asian countries. China's accession to the WTO in 2001, if exporters is also a member of the

WTO, which meant that both sides need to comply with the WTO's rules of free trade. And the trading countries on both sides of the automatic access to MFN, which eliminates the trade inefficiency in favour of China's imports of agricultural products. This is consistent with the research conclusions of previous research, which shows the joint accession of countries to the WTO is an institutional arrangement that effectively enhances the trade efficiency of both sides (Guo et al., 2015). Second, the impact of BRI on trade inefficiency was negative and significant, which indicated that the signing of the BRI agreement between China and Central Asian countries had reduced trade inefficiency and promote China's imports of agricultural products from Central Asia countries (Zhao et al., 2024). It is mainly due to the fact that BRI can enhance facility connectivity, trade flows, financial integration, policy communication and people-to-people ties, which highlighted the mutually beneficial nature of BRI in agricultural trade (Liu and Xu, 2025).

Secondly, regarding the impact of agricultural trade environment, the coefficient of $logis_{it}$ was significantly negative, which expressed that the higher the efficiency of China's trade clearance with Central Asian countries, the more it could reduce the inefficiency of agricultural trade. And the coefficient of MFN_{it} was also significantly positive, which indicated that the lighter the tax burden of agricultural trade between the two sides of the trade, the more trade inefficiency can be reduced.

Third, regarding the degree of openness of socio-economic system, the coefficient of $freedom_{it}$ was significantly negative for Central Asian countries, which implied that the higher economic freedom of Central Asian countries may reduce trade inefficiency, i.e., increase trade efficiency (Siddika and Ahmad, 2022). Whereas, the coefficient of $freedom_{jt}$ for China was positive and insignificant, which meant that the higher the economic freedom of China, the more likely it was to import agricultural products from the rest of the world, and thus may reduce its dependence on Central Asia countries market.

Fourth, regarding the stability of the external environment, China's economic policy uncertainty index $uncertainty_{jt}$ was significantly positive, which implied that when China's economic faced higher policy uncertainty, it could reduce the inefficiency of agricultural trade. The reason is that when there was a big change in the external policy environment, in order to ensure the stability of China's domestic supply of agricultural products, China would increase the import of agricultural products from Central Asian countries. And the impact of Russia-Ukraine war $conflic_{it}$ was significantly positive, which indicated that the outbreak of Russia-Ukraine war has lowered the efficiency of Central Asian countries in exporting agricultural products to China. The Russian-Ukrainian war and the outbreak of *COVID19* significantly reduced the efficiency of Central Asian countries in exporting agricultural products to China, which is in line with the judgment of existing studies that *COVID19* would have a negative impact on agricultural trade (Miao et al., 2024).

3.2 Trade efficiency and trade potential

Based on the previous results, we further analysed the trade efficiency and trade potential of China's agricultural products imported from Central Asian countries. Figure 1 shows the average trade efficiency of China's agricultural products imported from Central Asian countries from 2000 to 2022. The overall trade efficiency fluctuates greatly, and the overall change trend of Kazakhstan, Kyrgyzstan and Tajikistan tends to be consistent. Among them, there were several important points in time that are worth paying attention to: first, during the period of 2002–2005, China's trade efficiency towards Central Asian countries showed a downward trend. It is mainly because China's accession to the WTO in November 2001 has led to an increase in trade potential value, while the actual trade value has increased slowly in the short term, resulting in a sudden decrease in trade efficiency. And it also meant that the value of the trade potential has become larger. From 2005 to 2012, the stable trade

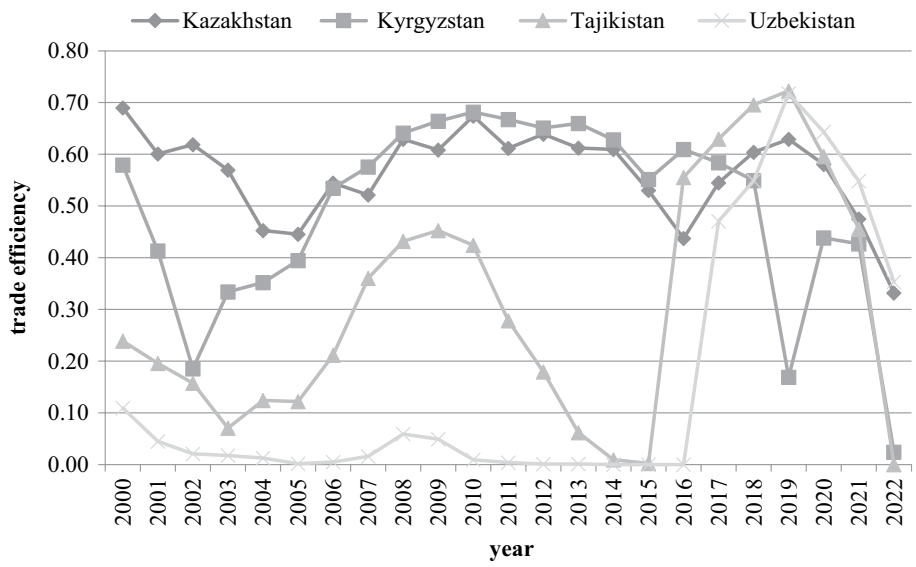


FIGURE 1
Trade efficiency of China's agricultural products imported from Central Asian countries from 2000 to 2022.

environment made the import trade efficiency rise. After the "Belt and Road" initiative was put forward in 2013, the open trade environment also improved trade potential value, and reduced the trade efficiency, which meant the trade potential value went up to a new level. From 2020 to 2022, with the outbreak of the COVID19 and the Russia-Ukraine war, the trade efficiency value was low, which also meant that the trade potential value became larger. During the period, the trade efficiency of both sides fluctuated greatly, from the current 0.6 ~ 0.7 to about 0.3 ~ 0.4. The changes in Uzbekistan and Tajikistan were more pronounced, because the two countries with a lower degree of economic development have been more affected by the frequent occurrence of international uncertainty risk events. In particular, it should be noted that in Figure 1, the zero value of Uzbekistan's trade potential for the period 2010–2015 is due to the fact that Uzbekistan's trade with China was zero during the same period.

In terms of trade potential, there is still more room for China to import agricultural products from Central Asian countries. According to Table 5, China imported a total of $591 million from Central Asian countries in 2022, with an overall trade efficiency of 0.325 and a trade potential value of $2.126 billion, which means that nearly 70% of the trade potential remains to be realized. As for countries, the trade efficiency of Kazakhstan and Uzbekistan were 0.332 and 0.353 respectively, Tajikistan was 0.024, while Kyrgyzstan was zero in 2022. To avoid the bias of a single year on the measurement of trade efficiency, this paper progressed to measure the average trade efficiency of each country in 2015–2022. The results shown that Kazakhstan, Tajikistan, Kazakhstan, Tajikistan, Kyrgyzstan and Uzbekistan were 0.474, 0.294, 0.591 and 0.504, respectively. And the average value of trade potential calculated accordingly was 762 million dollars and the highest value of trade potential is 2.21 billion dollars. In summary, the highest trade potential of China's trade with Central Asian countries is less than 60%, and the lowest is only 30%, with a trade potential value of between 2.1 ~ 2.2 billion USD. Assuming that the trade potential is fully realized, China's trade potential for agricultural products imported from Central Asian countries could increase by 2.1 ~ 2.2 times on the current basis. It indicated that the trade prospects will be very broad between China and Central Asian countries. Among them, Kazakhstan and Uzbekistan are the key countries, and Tajikistan, Kyrgyzstan and Turkmenistan need larger agricultural investment and cooperation in order to fully realize the trade potential.

4 Conclusion and policy implications

Based on the data of UN Comtrade database from 2000 to 2022, this study employed a time-varying stochastic frontier gravity model to investigate the impact of institutional openness on China's trade efficiency of agricultural products imported from Central Asian countries in the context of uncertainty, and finally measured the trade efficiency and trade potential of China's imports of agricultural products from Central Asian countries. The following conclusions can be drawn from the above analysis.

Firstly, China's agricultural imports from Central Asian countries will have a lot of room for growth. As mentioned above, during the period 2001 ~ 2022, the scale of China's agricultural imports from Central Asia countries grew from less than US$10 million to US$690 million, maintaining a superb average annual growth rate of 21.3%. And China's average export trade efficiency to Central Asian countries for 2015 ~ 2022 is between 0.3 and 0.6, and the import potential is about $2.1–2.2 billion, indicating that 60% ~ 70% of the trade potential can still be tapped, and there is a large import potential.

Secondly, institutional openness could improve the trade efficiency in generally of China's imports of agricultural products from Central Asian countries. As for border opening, the signing and implementation of the WTO and the BRI have effectively promoted China's trade in agricultural products imported from Central Asia countries, which suggests that border opening such as the signing of preferential trade agreements contributes to improved trade efficiency. As for trade environment, the higher the efficiency of the trade logistics and customs clearance, and the lower the most favoured MFN, the more conducive to improving the trade efficiency of China's imports of Central Asia agricultural products. Considering the socio-economic system, the higher the trade freedom of the Central Asia countries societies, the more conducive to promoting the export of agricultural products to China.

Thirdly, uncertainties such as the COVID19 and Russo-Ukrainian war have reduced the scale of imports. However, when China's economic policies face higher uncertainty risk, China would increase in importing agricultural products from Central Asian countries, which would promote the trade efficiency.

Based on these conclusions, several suggestions can be made. In order to promote the efficiency of China's agricultural imports

TABLE 5 China's trade potential in agricultural products imported from Central Asian countries.

Year	Kazakhstan	Tajikistan	Kyrgyzstan	Uzbekistan	Total
Trade efficiency					
2022	0.332	0.024	0.000	0.353	–
Average 2015–2022	0.474	0.294	0.591	0.504	–
Imports (millions of dollars)					
2022	545.3	1.8	0.0	144.3	691.4
Average 2015–2022	265.89	14.86	1.11	74.91	356.8
Import potential (millions of dollars)					
2022	1642.5	75.0	0.0	408.5	2126.0
Average 2015–2022	561.2	50.5	1.9	148.7	762.3
Maximum 2015–2022	1642.5	152.6	6.7	408.5	2210.4

Author's measurements based on regression results.

to Central Asian countries, both countries should focus on the following aspects of institutional openness: firstly, from the viewpoint of liberalization measures of the trade system, joining international organizations (such as the WTO) to jointly promote free trade, actively and steadily extending the duration of the free trade agreement, and accelerating the implementation of the BRI and other agreements on agricultural products, can effectively promote the efficiency of China's agricultural import. Secondly, as for the infrastructure of agricultural trade, our government should take relevant measures to cooperate with partner countries in many fields such as seeds, fertilizers, agricultural machinery, port transportation, etc. Specifically, to improve the logistics infrastructure, to increase the clearance efficiency of the trade, to lower the burden of taxes on agricultural products, and to improve their agricultural production capacity and export capacity are very feasible measures. Thirdly, in the case of unstable external economic environment risks, China should establish medium- to long-term procurement agreements or develop regional agricultural early-warning and coordination mechanisms with Central Asian countries in advance to stabilize the trade expectations, so as to enhance the trade efficiency in a targeted manner, which will further strengthen the cooperation and opening up of the agricultural field through the trade of agricultural products.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found at: UN Comtrade.

Author contributions

FC: Writing – original draft, Writing – review & editing, Validation, Data curation. XL: Resources, Conceptualization, Writing – review & editing, Funding acquisition, Supervision. ZZ: Validation, Writing – review & editing, Resources.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

Correction note

A correction has been made to this article. Details can be found at: 10.3389/fsufs.2025.1645833.

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The impact of the China-Australia free trade agreement on China's agricultural imports

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China and Australia signed the Free Trade Agreement (ChAFTA) in 2015, which aims to eliminate or reduce trade barriers between countries through tariffs or quotas. Eliminating trade barriers has expanded China's agricultural imports from Australia. ChAFTA will strengthen the trade relationship between the two countries, enabling agricultural product imports to have a trade creation effect. This article systematically evaluates the trade effects of ChAFTA on the scale of China's agricultural product imports based on data from 2000 to 2020. Two statistical methods, Ordinary Least Squares (OLS) and Poisson Pseudo Maximum Likelihood (PPML) are applied to estimate the trade effects of agreements. Empirical studies have shown that ChAFTA has a significant trade creation effect on China's agricultural product imports, while the trade diversion effect is insignificant. When time fixed effects and export country fixed effects are controlled, the PPML method exhibits stronger explanatory power compared to OLS and the estimated trade creation effect is more significant. The empirical research results remain robust even after considering the impact of WTO. There are no endogeneity issues in the results after adding lead variables. By incorporating lagged terms, we find there is no phase-in effect. Empirical research on heterogeneity analysis of agricultural product classification found that ChAFTA had the most significant impact on the import of forest products and aquatic products, followed by textiles and agricultural products.

KEYWORDS

free trade agreements, agricultural products trade, import trade, Poisson pseudo-maximum likelihood, trade creation

1 Introduction

Free Trade Agreements (FTAs) are important tools for international economic cooperation, designed to lower trade barriers and strengthen commercial relationships among member countries. Their importance is especially clear in agriculture, which is an sector that often faces high tariffs. The World Trade Organization's (WTO, 2023) Regional Trade Agreements database shows that by the end of May 2024, 369 RTAs (including FTAs, customs unions, and preferential trade areas) were established worldwide. Both China and Australia have actively participated and signed 20 and 18 FTAs, respectively. The China-Australia Free Trade Agreement (ChAFTA), which started on December 20, 2015, began an 11-year process to cut tariffs with the goal of removing tariffs on many goods. China promised to remove tariffs on 1,375 types of Australian agricultural products over 12 years, covering about 93.7% of all agricultural categories. In contrast, Australia will eliminate tariffs on all 1,061 types of Chinese agricultural products within 3 years. When fully implemented, this agreement will reduce China's average tariff on agricultural imports from 15.6 to 13.8%. With its large population, China has a big need for agricultural products, making it a major importer in global agricultural trade. Since 2020, China has been the world's top importer of agricultural

products. Countries like Brazil, the US, Australia, New Zealand, and Thailand are key suppliers to China. Known for advanced and efficient farming, Australia plays a big role in global agriculture. It is a leading exporter of wool and lamb, and also exports significant amounts of barley, beef, cotton, sugar, and wheat.

The analysis of trade creation and trade diversion is commonly used to measure the impact of FTAs on trade. Viner (1950) first looked at the economic effects of customs unions, introducing the ideas of trade creation and trade diversion. Trade creation means reducing internal trade barriers so countries can benefit from comparative advantages. Trade diversion happens when consumers buy more expensive goods from member countries instead of cheaper options from non-member countries, leading to inefficient resource use. These concepts laid the foundation for analyzing regional trade agreements. For example, Sun and Reed (2010) found that FTAs significantly boost agricultural trade, though the growth varies by product and time. Wang (2017) studied CAFTA's impact on China's agricultural exports, finding strong creation effects but weak diversion effects. Fu and Cao (2023) examined how environmental rules in RTAs affect trade, showing that strict policies can hurt trade between members while causing diversion toward non-members.

Despite extensive studies on FTAs, the Research on the trade creation and trade diversion effects of trade agreements on China's agricultural trade remain underexposed. Specifically, two gaps emerge, the first one is that existing models (e.g., Grant and Lambert, 2008) may inadequately capture phasing-in effects. The second one is that aggregated analyses (Wang, 2017; Fu and Cao, 2023) obscure sector-specific responses to preferential market access. To address this, we examines how ChAFTA affects China's agricultural imports, focusing on creation and diversion effects. It compares Ordinary Least Squares (OLS) and Poisson Pseudo Maximum Likelihood (PPML) methods. Additionally, the study observes the phasing-in effect and the heterogeneity in import volume changes across different categories of agricultural products in China.

The rest of this study is organized as follows: Section 2 reviews related literature, Section 3 provides background on China-Australia trade, Section 4 describes data sources and model construction, Section 5 presents empirical results, and Section 6 includes the discussion and conclusions.

2 Literature review

Since the 1990s, FTAs have become a primary form of trade liberalization. By reducing trade costs and facilitating cross-border transactions, FTAs can increase the volume of trade between participating countries (Froning, 2000) and enhance the aggregate economic welfare of member nations (Meade, 1955; Ohyama, 1972). The mechanism by which FTAs affect income disparities between countries is complex and can be either positive (Ben-David, 1993) or negative (Quah, 1994).

Many empirical research has revealed the effect of FTAs on bilateral trade between member countries. Several studies have assessed the impact of FTAs by comparing data before and after policy implementation. For instance, Ghazalian (2016) examined the influence of the North American Free Trade Agreement (NAFTA) and the Canada-U.S. Free Trade Agreement (CUSFTA) on various categories of agricultural products, revealing changes in trade flows following the agreements' entry into force. The study indicated that NAFTA and CUSFTA significantly boosted trade growth for certain agricultural categories. It was worth noting that the growth was not evenly distributed across all products or periods.This research highlighted the need for in-depth investigations into specific agricultural categories, thereby addressing gaps in macro-level studies.

Other literature focused on particular commodities or industries. Harada and Nishitaten (2022), for example, concentrated on the sector-specific impacts, specifically analyzing the trade creation effects resulting from reduced wine import tariffs in East Asia. The study focused on the different impacts of FTA preferential tariff rates and Most Favored Nation (MFN) tariff rates. The research results showed that every one percentage reduction in tariffs would lead to a 0.042% increase in wine imports among FTA member countries, which was seven times the effect of the same tariff reduction based on MFN. Lambert and McKoy (2009) explored the effects of multiple Preferential Trade Agreements (PTAs) on food trade. The study focused on how these agreements altered trade patterns within and outside member countries. They found that PTAs notably increased intro-regional trade, especially in agriculture, with significant trade creation effects for agricultural products. However, there was evidence of trade diversion in the food sector for some PTAs primarily involving developing countries. Their research provided more precise guidance for policy formulation by distinguishing between PTAs formed by countries at varying stages of development.

Some studies also considered the role of FTAs within a broader multilateral framework. Grant and Boys (2012) investigated whether WTO/GATT membership truly enhanced agricultural trade among member countries. Although the sensitivity and slow reform progress happened in agriculture, overall positive impacts were observed. The study emphasized the role of FTAs within a multilateral context, offering new perspectives on global trade governance structures. Berlingieri et al. (2021) approached the assessment of new-generation EUFTAs from the angle of consumer welfare, focusing on improvements in product quality rather than price or variety. They discovered that FTAs had improved average product quality by 7%, which corresponded to a cumulative decrease of 0.24% in the Consumer Price Index over the sample period. High-income EU countries experienced stronger quality improvements and greater overall consumer benefits. This study introduced a novel method for evaluating the impact of FTAs through the consumer welfare. Moreover, there is a fact that the implementation of FTAs is carried out in phases. Grant and Lambert (2008) found that free trade agreements such as NAFTA have significant phase-in effects. Therefore the entire treatment effect cannot be fully captured in the current year (Baier and Bergstrand, 2007a). Additionally, there is very different impact on disaggregated data. Timsina and Culas (2020) found that the ChAFTA significantly increased Australia's exports of beef, wine, and edible nuts, but had no significant impact on sugar exports.

The gravity equation is the primary method for quantifying the impact of FTAs on trade volumes[1]. This approach involves incorporating FTAs as dummy variables into the gravity model to assess their impact

1 Anderson and van Wincoop (2003) introduced a multi-variable resistance term into the gravity equation to study the border puzzle in trade. Caliendo and Parro (2015) incorporated a multi-sector Ricardian model into the gravity equation to derive a structured form, examining trade issues within the North American Free Trade Agreement (NAFTA).

on trade flows. Early studies confirmed significant trade creation effects of FTAs (Bergstrand, 1985; Frankel and Wei, 1994; Frankel and Rose, 2002; Bergstrand et al., 2015), but the stability of average treatment effects (ATE) has been questioned (Ghosh and Yamarik, 2004). Magee (2003) attempted to address the endogeneity issue of FTAs variables in cross sectional data using instrumental variable methods but found high error rates. Magee (2008, 2016) further incorporated fixed effects into his research. Given the difficulty in obtaining ideal instrumental variables, Baier and Bergstrand (2007b) suggested that fixed effect models are an effective way to mitigate endogeneity issues. Baier and Bergstrand (2007a) used two-way fixed-effects OLS estimation to examine bilateral trade among 96 countries from 1960 to 2000, finding that considering time fixed effects and bilateral fixed effects significantly enhances the positive impact of FTAs on trade volume among member countries. Pfaffermayr (2019, 2020) explored the tendency of robust standard errors in PPML estimations in cross sectional and panel data gravity models to be significantly downward biased.

Due to its sensitivity and high level of protection, the agricultural sector typically faces much higher tariff rates than non-agricultural sectors before the implementation of FTAs. Therefore, FTAs tend to have a greater trade-stimulating effect on agricultural sectors (Grant and Lambert, 2008). In response to the common issue of zero bilateral trade values in international trade research, some scholars have adopted the PPML method for parameter estimation. Sun and Reed (2010) utilized fixed-effect PPML to investigate the trade creation and diversion effects of FTAs on agriculture across 81 countries at different stages of development, confirming that FTAs significantly boost agricultural trade. Similar studies also found that FTAs effectively increase trade volumes between signatory countries (Bureau and Jean, 2013; Yang and Martinez-Zarzoso, 2014; Hndi et al., 2016; Timsina and Culas, 2020). Recently, more attention has been given to specific terms and depths of trade agreements in FTA research (Mattoo et al., 2022; Howard et al., 2023; Guillin et al., 2023), which is also a direction for my future research.

In the context of deepening global economic integration, as important mechanisms promoting trade liberalization between countries, FTAs have received widespread attention. However, there remains considerable scope for exploring how FTAs specifically affect bilateral agricultural trade, particularly the specific impacts of the ChAFTA on China's agricultural imports. By thoroughly analyzing bilateral agricultural trade data between China and trading partners worldwide from 2000 to 2020, this study fills a gap in the existing literature.

This paper makes three contributions to FTA research: First, while prior studies more focus on aggregate FTA effects (e.g., Baier and Bergstrand, 2007a, 2007b; Frankel and Wei, 1994), industrial goods (Fu and Cao, 2023), or agricultural exports (Wang, 2017), we provide the first quantitative analysis of ChAFTA's impact on China's agricultural imports because agricultural trade is important in China-Australia trade. Second, we have conducted research on the phase-in effects of FTAs, similar to the work of Baier and Bergstrand (2007a) and Grant and Lambert (2008). Third, departing from macro-level analyses (Grant and Boys, 2012; Grant and Lambert, 2008), we conduct heterogeneity analysis by categorizing agricultural products into seven major types from a micro perspective. This approach aligns with Ghazalian (2016), which covers sector-specific responses to preferential market access.

Based on this framework, we propose three hypotheses:

Hypothesis 1: The implementation of the ChAFTA can significantly increase China's agricultural imports.

Hypothesis 2: The effect of ChAFTA on China's agricultural imports exhibits phase-in dynamics.

Hypothesis 3: There are heterogeneous effects of ChAFTA on China's imports of different agricultural product types.

3 Background

The trend lines of Figure 1 show that China's agricultural import market has expanded rapidly. From 2000 to 2020, the import value surged from 12.2 billion to 176.0 billion, demonstrating a remarkable annual growth rate of 15.13%. Meanwhile, Australia's agricultural exports also showed steady growth, though at a slightly slower pace. The total export value increased from 18.7 billion in 2000 to 35.0 billion in 2020, corresponding to an annual growth rate of 3.95%. Notably, the value of agricultural products imported by China from Australia grew at an annual rate of 11.76%. China has absorbed 32.41% of Australia's total agricultural product exports by 2019, highlighting its core position in the Australian agricultural product export market.

China has become Australia's largest trading partner for agricultural products since 2008. The stability of this role became increasingly prominent in the following years. Although the import volume of agricultural products in China has slowed down to an average annual growth rate of 6.09%, it still maintains a strong upward trend after 2015. In contrast, Australia's total agricultural exports have shown an average annual negative growth rate of −3.68%, indicating a contraction in the overall export scale. However, Australia's agricultural exports to China still maintain an average annual growth rate of 2.05% This growth rate further highlights the strategic importance of China as an export market for Australian agricultural products, as well as the resilience and vitality of bilateral trade relations. The agricultural trade between China and Australia is expected to promote sustainable development and prosperity of agriculture in both countries through mutually beneficial cooperation (Zhou et al., 2007).

China is also actively engaging in the negotiation and implementation of FTAs with other countries, aiming to enhance bilateral trade through this approach. The lists of FTAs signed and implemented by China and Australia between 2000 and 2020 is shown in Table 1. China had concluded and put into effect FTAs with a total of 15 countries or regions by 2020. Meanwhile, Australia had signed and enforced FTAs with 12 countries or regions. These trends and agreements highlight the growing importance of bilateral and multilateral trade relationships in shaping the agricultural trade dynamics between China and Australia. The ChAFTA, in particular, has played a pivotal role in enhancing the depth and breadth of trade between the two countries, contributing to the significant growth in agricultural imports and exports.

The signing and implementation of these FTAs are significant measures taken by China to actively participate in global economic governance, promote trade liberalization, and advance economic globalization. Looking at the partner countries involved in these agreements, China has signed FTAs with nations and regions at various

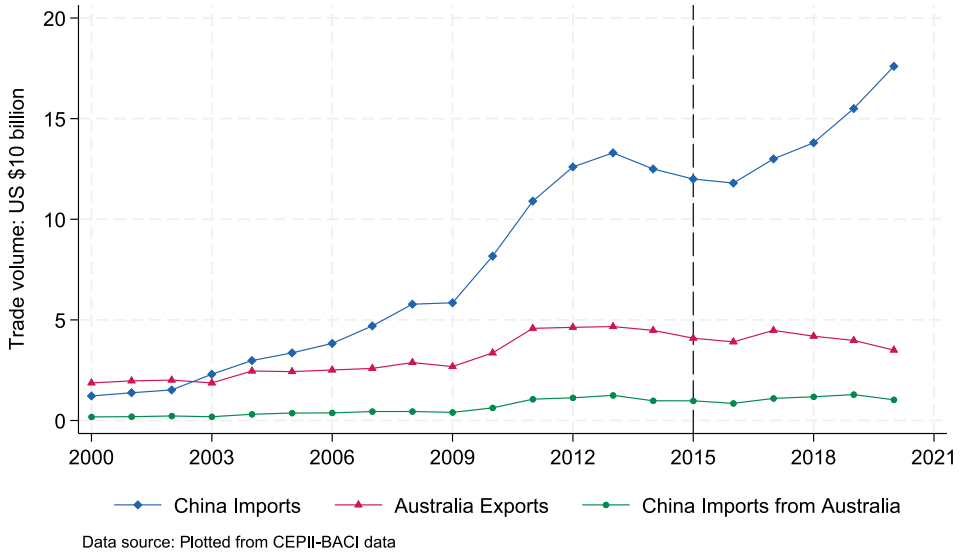


FIGURE 1
Sino-Australian agricultural trade 2000–2020.

TABLE 1 Free trade agreements signed by China and Australia.

China's FTA		Australia's FTA	
Partner country	Time	Partner country	Time
Macau and Hong Kong	2003	Singapore	2003
ASEAN	2004	United States	2005
Chile	2006	Thailand	2005
Pakistan	2007	Chile	2009
New Zealand	2008	ASEAN-New Zealand	2010
Singapore	2009	Malaysia	2013
Peru	2010	Korea	2014
Costa Rica	2011	Japan	2015
Taiwan	2011	China	2015
Switzerland	2014	Hong Kong	2020
Iceland	2014	Peru	2020
Australia	2015	Indonesia	2020
Korea	2015	–	–
Maldives	2018	–	–
Georgia	2018	–	–

Data Source: Compiled from the WTO RTA database.

stages of economic development and geographic locations. For instance, China has entered into FTAs with ASEAN, South Korea, Australia, Chile, and other countries and regions, demonstrating its diversified cooperation within the global trade landscape. In terms of the content covered by these agreements, they not only encompass traditional goods trade but also extend to multiple areas such as services trade, investment, intellectual property protection, e-commerce, and competition policy, reflecting their globality and integration. Some FTAs have set high standards at the regulatory level, introducing advanced international rules in areas like intellectual property protection, environmental protection, and labor standards. These provisions have driven reforms and development in relevant sectors within China.

According to the provisions of the ChAFTA, major agricultural products exported from Australia to China, such as beef, dairy products, wool, seafood, grains, and wine, will gradually enjoy lower or even zero tariffs. Specifically, tariffs on beef will be progressively reduced to zero over 9 years. Various dairy products, including powdered milk, will achieve zero tariffs within 4 to 11 years. Import quotas for wool will be increased, and tariffs on quantities exceeding these quotas will gradually decrease. Most seafood products, such as

TABLE 2 Explanatory variables and expected symbols.

Variable	Description	Explanation	Expected signs
$\ln GDP_{it}$	Log of GDP of import country *i* in period *t*	Reflects the economic size of the import country	+
$\ln GDP_{jt}$	Log of GDP of export country j in period *t*	Reflects the economic size of the export country	+
$\ln Dist_{ij}$	Log of the distance between import country *i* and the exporting country *j*	Reflects transportation and communication costs	–
Adj_{ij}	Dummy variable indicating whether country i and country *j* share a border (1 if true, 0 otherwise)	Reflects trade costs between the two countries; a closer border distance facilitates trade	+
$Lang_{ij}$	Dummy variable indicating whether country i and export country *j* share a common language (1 if true, 0 otherwise)	Reflects the cultural relationship between the two countries;	+
FTA_t	Dummy variable,=1 if import country *i* and export country *j* are part of the ChAFTA in period *t*, 0 otherwise	Reflects the changes in trade volume brought about by the establishment of an FTA between the two countries.	+
$NFTA_{jt}$	Dummy variable, =1 if China has trade with any country j (other than Australia) after 2015	Reflects China's import from countries other than Australia during period t, influenced by the ChAFTA.	–

lobster and abalone, quickly achieved zero-tariff entry into the Chinese market. Tariffs on wine will be completely eliminated within 5 years.

Additionally, the agreement addresses technical barriers to trade (TBT) and sanitary and phytosanitary measures (SPS) in the agricultural sector, ensuring that both parties adhere to international standards while minimizing unnecessary trade restrictions. The aim of these provisions is to facilitate smoother bilateral agricultural trade and provide consumers with a wider variety of product choices.

4 Model and data

4.1 Benchmark model

The gravity equation is the most commonly used model in trade policy research. In order to solve the endogenous problem of free trade agreements, a gravity equation with two-way fixed effects is established according to the method of Baier and Bergstrand (2007a). As shown in Equation 1:

$$\ln X_{ijt} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln GDP_{jt} + \beta_3 \ln Dist_{ij} + \beta_4 Adj_{ij} + \beta_5 Lang_{ij} + \beta_6 FTA_t + \beta_7 NFTA_{jt} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (1)$$

Where: $\ln x_{ijt}$ is the log of the bilateral trade volume between import country *i* and export country *j* in year *t*.

$\ln GDP_{it}$ and $\ln GDP_{jt}$ are the log of gross domestic products of import country i and the export country j.

$\ln Dist_{ij}$ is he log of the distance between import country *i* and export country *j*.

Adj_{ij} is a dummy variable indicating whether import country *i* and export country *j* share a border.

$Lang_{ij}$ is a dummy variable indicating whether import country *i* and export country *j* share a common language.

FTA_t and $NFTA_{jt}$ are dummy variables indicating the trade creation and trade diversion between import country *i* and export country *j* in year *t*.

This α_t represents a time fixed effect. The time fixed effect reflects the time trend of trade and any shocks that affect the flow of China's agricultural import trade in a specific year. This α_j represents a export-country fixed effect. Export-country fixed effects measure the impact of unobserved country-specific shocks, such as infrastructure, factor endowments, and so on. ϵ_{ijt} is the error term.

This model allows us to estimate the impact of various factors on bilateral trade volume, particularly the effect of the ChAFTA on China's agricultural imports.

The content of each variable is summarized in Table 2.

In this analytical framework, the import country *i* and the export country *j* encompasses 128 countries that traded agricultural products from 2000 to 2020. $\ln GDP_i$ represent the demand potential for agricultural products and $\ln GDP_j$ represent the supply potential of agricultural products from the exporting country.

Trade costs include two main components. One component is represented by the logarithm of distance $\ln Dist_{ij}$ measures the physical distance between the two countries and its impact on trade costs. Two binary dummy variables, Adj_{ij} and $Lang_{ij}$, indicate whether the import country *i* and the exporti country *j* share a border and a common language, respectively. If the condition is met, the value is 1; otherwise, it is 0.

FTA_t is a binary dummy variable representing the ChAFTA, taking a value of 1 if the importing country *i* and the exporting country *j* are part of the ChAFTA in period *t*, and 0 otherwise. $NFTA_{jt}$ is a binary dummy variable measuring trade diversion, taking a value of 1 if only China has trade with any country j (other than Australia) after 2015, and 0 otherwise.

The core focus of this study is on two key variables:

The first one is FTA_t, the coefficient β_6 aims to evaluate whether the bilateral trade volume between countries within the same free trade agreement is significantly higher than that between non-agreement countries, known as the trade creation effect. The coefficient is in semi-elastic form, so its economic interpretation requires exponentiation using $(\exp(\beta_6)-1) \times 100\%$ to accurately reflect the strength of the trade creation effect.

The second one is $NFTA_{jt}$, The coefficient β_7 is used to explore the existence of trade diversion effects. If the coefficient is significant and $\beta_6 > 0$ $\beta_7 > 0$, it indicates the presence of trade creation effects but no trade diversion effects. If the coefficient is significant and $\beta_6 > 0$ $\beta_7 < 0$, it indicates the presence of both trade creation and trade diversion effects. If the coefficient is not significant or $\beta_6 < 0$ $\beta_7 > 0$, it suggests the absence of both trade creation and trade diversion effects.

TABLE 3 Statistical description.

Variables	Number	Mean	Variance	Minimum	Maximum
$\ln x_{ijt}$	341,376	5.550	4.530	−6.910	17.28
$\ln GDP_{it}$	341,376	18.05	2	12.46	23.79
$\ln GDP_{jt}$	341,376	18.05	2	12.46	23.79
$\ln Dist_{ij}$	341,376	8.740	0.800	4.010	9.900
Adj_{ij}	341,376	0.020	0.150	0	1
$Lang_{ij}$	341,376	0.100	0.300	0	1
FTA_t	341,376	0.000	0.000	0	1
$NFTA_{jt}$	341,376	0.000	0.050	0	1

4.2 Variable selection and data sources

4.2.1 Variable selection

To investigate the impact of the ChAFTA on China's agricultural imports, this study selects the following variables for empirical analysis:

Dependent variable: We choose $\ln x_{ijt}$ as the explained variable to analyze the creation effect and diversion effect.To analyze the creation and diversion effects, 128 countries with bilateral trade are selected[2], because there are 127 countries that maintained continuous agricultural trade relations with China from 2001 to 2021. The 127 countries include Australia and the other 126 non-member countries. This design aims to identify the trade diversion effect by conducting a comparative analysis of the changes in China's imports from Australia (member country) and other countries (non-member countries) before and after the implementation of the ChAFTA.

The datasets initially includes 128 countries (including China) to capture all potential bilateral trade pairs. Since trade occurs between two distinct countries, the total number of country pairs is 128 × 127 = 16,256 (excluding domestic trade). However, our analysis focuses specifically on China's imports from its trading partners.

Key explanatory variables: We choose the dummy variables FTA_t and $NFTA_{jt}$ as explanatory variables to find the FTA how to influence the bilateral trade volume.

Control variables: These include the gross domestic product (GDP) of the import country *i* and the export country *j*, the distance between the bilateral countries, and two dummy variables indicating whether the bilateral countries share a border and have a common language. These control variables account for other costs that influence bilateral trade volume.

4.2.2 Data sources

This study focuses on bilateral trade activities in the agricultural sector 128 global trading partners from 2000 to 2020. This period covers multiple stages before and after the implementation of ChAFTA, which allows for a good reflection of the effects before and after the policy implementation. The data over this extended period also helps to capture long-term trends and reduces the disturbance caused by short-term fluctuations. The countries involved are widely distributed across continents, including 25 countries in Africa, 42 in Asia, 32 in Europe, 12 in North America, 10 in South America, and 7 in Oceania. This sample set comprises 341,376 independent observations (128 × 127 × 21),[3] ensuring the breadth and depth of the research.

The agricultural trade data are sourced from the authoritative CEPPII BACI database. The commodity scope includes agricultural products defined under the Uruguay Round Agriculture Agreement, extended to cover aquatic products, specifically the first 24 chapters of the Harmonized System (HS) coding system, as well as chemical products and textiles based on animal and plant materials. This detailed classification ensures the precision and comprehensiveness of the study.

Geographic distance, shared boundaries, and language similarity have fixed and invariant bilateral relationship characteristics. These data are taken from the CEPPII gravity database, providing a stable structural foundation for the model. Meanwhile, the gross domestic product (GDP) and free trade agreements of each country are dynamic trade policy variables. These data are sourced from the World Bank WDI database and the RTAs database of the WTO. The GDP data of Taiwan of China is from CEIC database. These multidimensional data sources collectively construct a analysis framework aimed at delving into the key factors influencing China's agricultural trade pattern. The following Table 3 provides a statistical summary of the data.

In Table 3, since the bilateral trade volume of some countries is less than 1,000 USD, their logarithmic values are negative. As the data represents bilateral trade, the number of importing and exporting countries is the same, hence the data description is consistent. The binary dummy variable representing the ChAFTA has relatively few numbers with a value of 1, therefore its mean and variance are close to 0.

5 Empirical results

5.1 Benchmark results

The parameters of the gravity equation were estimated using both OLS and PPML. The results are detailed in Table 4. Columns (1) to (6) are divided into three groups, presenting estimates without fixed effects, with time fixed effects, and with both time and exporter fixed effects, respectively.

2 A detailed list of countries is provided in the Appendix.

3 Since trade occurs between two distinct countries, the total number of country pairs is 128 × 127 (excluding domestic trade), so the data numbers is 128 × 127 × 21 = 341,376.

TABLE 4 Impact of the ChAFTA on Chinese agricultural imports.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	ppml	ols	ppml	ols	ppml
$\ln GDP_{jt}$	0.516***	0.195***	0.199***	0.200***		
	(45.23)	(372.92)	(22.95)	(376.74)		
$\ln GDP_{it}$	0.683***	0.176***	0.582***	0.181***		
	(61.91)	(337.06)	(66.96)	(339.23)		
$\ln Dist_{ij}$	−1.341***	−0.203***				
	(−45.44)	(−178.92)				
Adj_{ij}	1.670***	0.010				
	(11.64)	(1.61)				
$Lang_{ij}$	1.289***	0.237***				
	(18.08)	(78.67)				
FTA_t	−0.102***	−0.194***	−0.280	−0.216***	0.152***	0.498***
	(−7.32)	(−22.69)	(−0.38)	(−44.03)	(2.92)	(77.90)
FTA_t	0.277***	−0.156***	0.230***	−0.153***	0.669***	0.624***
	(2.72)	(−11.43)	(3.44)	(−11.51)	(7.41)	(20.83)
Constant	−4.496***	−3.389***	−11.616***	−3.516***	4.596***	1.278***
	(−12.57)	(−192.57)	(−6.40)	(−189.33)	(77.60)	(150.53)
Observations	341,376	341,376	341,376	341,376	341,376	341,376
R-squared	0.112	0.480	0.118	0.479	0.104	0.393
Year FE	No	No	Yes	Yes	Yes	Yes
exporter FE	No	No	No	No	Yes	Yes

Robust z-statistics in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The coefficients for the logarithm of GDP of the exporting and importing countries are significantly positive from columns (1) and (2), which are consistent with theoretical predictions. This indicates that an increase in the GDP of bilateral countries enhances the demand for importing agricultural products. The coefficient of the variable representing bilateral distance is significantly negative and consistent with expectations, indicating that trade costs increase with distance, leading to a reduction in bilateral trade. Additionally, the significantly positive coefficients of the dummy variables for shared borders and language are also in line with expectations, suggesting that countries sharing a border and a language experience increased bilateral trade due to reduced communication costs. However, the core parameter—the coefficient of the FTA_t—is significant negative, contrary to expectations. In the case of OLS estimation, the coefficient of the $NFTA_{jt}$, which measures the trade diversion effect, is significantly positive, inconsistent with expectations. Nevertheless, the sum of the two coefficients is positive, this indicate that the total volume of China's agricultural imports is still increasing, the result aligns with reality. In contrast, under PPML estimation, the $NFTA_{jt}$ coefficient is significantly negative, consistent with expectations, but the sum of the two coefficients is negative, suggesting that the total volume of China's agricultural imports is decreasing, which does not align with reality. The underlying reasons may involve endogeneity issues or the impact of zero trade volume data. This combination suggests that the ChAFTA has not produced a significant trade creation or trade diversion effect. Notably, the PPML estimation results exhibit greater robustness compared to OLS, particularly in terms of goodness of fit.

In columns (3) and (4), we estimate the parameters including time fixed effects, so variables that do not change over time were eliminated. At this point, the coefficient of the variable FTA_t in OLS estimation remains negative but does not statistical significance. The coefficient of the variable $NFTA_{jt}$ is significantly positive. Meanwhile, under PPML estimation, the coefficients of both FTA_t and $NFTA_{jt}$ remain significantly negative, with their absolute values changing little compared to the case without fixed effects. However, the inclusion of time fixed effects improves the goodness of fit.

Columns (5) and (6) simultaneously incorporate time fixed effects and exporting country fixed effects. Following Baier and Bergstrand (2007a), the country fixed effects help to account for the endogeneity bias created by prices and the influence of FTAs among other countries. Here, due to perfect collinearity, control variables were removed. When we introduce both time fixed effects and country fixed effects, we assign a unique fixed effect for each pair of countries. This means each country has a specific influencing factor to capture those unobserved but fixed characteristics, such as cultural differences and long-term political relationships. However, due to the issue of perfect collinearity, we cannot include these fixed effects and standard gravity variables that do not change over time in the model at the same time.

This adjustment brings significant changes. Under both estimation scenarios, the coefficients of the variables FTA_t and $NFTA_{jt}$ are positive and statistically significant, but the goodness of fit is higher under

PPML estimation. Specifically, under PPML estimation, the coefficient of FTA_t is 0.498, which means that a one-unit increase in FTA_t can promote China's agricultural imports from Australia by approximately 64.5%.[4] This is four times the effect estimated using OLS(16.4%).[5] The coefficient of $NFTA_{jt}$ is 0.624, which means that a one-unit change in the ChAFTA can promote China's agricultural imports from other countries by approximately 86.6%.[6] Both coefficients being positive strongly support the positive impact of the ChAFTA on trade creation effects, but there is no trade diversion effects. This aligns with the reality of China's agricultural imports.

Overall, the results suggest that while the initial estimates without fixed effects did not show a significant positive impact of ChAFTA, incorporating time and exporter fixed effects reveals a significant positive effect on Chinese agricultural imports. The trade diversion effect, however, is insignificant in these more comprehensive models.

5.2 Robustness checks

5.2.1 Considering the WTO

Before the signing of the ChAFTA, China's accession to the WTO had a significant impact on its import and export trade. Since China joined the WTO in 2001, its import and export trade has grown rapidly, as illustrated in Figure 1, which shows a rapid increase in the import of Chinese agricultural products. This section incorporates a binary dummy variable indicating China's accession to the WTO or China and Australia being simultaneous members of the WTO.

The robustness checks confirm the stability of the estimation results by controlling for the impact of China's WTO accession. A binary dummy control variable is included to represent China's accession to the WTO, resulting in the following equation (Equation 2):

$$\ln x_{ijt} = \beta_0 + \beta_1 FTA_t + \beta_2 NFTA_{jt} + \beta_3 WTO_t + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (2)$$

Among them, WTO_t represents a binary dummy variable indicating China's accession to the WTO. If China joined the WTO in period t, the value is 1; otherwise, it is 0.

The results are shown in column (1) of Table 5. We find that the differences are minimal, indicating that the estimation results are robust.

The results are significantly positive, indicating that China's accession to the WTO has a significant positive impact on agricultural imports. The coefficient of the variable FTA_t remains significantly positive, with its magnitude similar to that in the baseline model, suggesting robust results for the baseline model. The coefficient of the variable $NFTA_{jt}$ is positive but not significant. The coefficient of the variable WTO_t is significant and much larger than the coefficient of the variable representing the free trade agreement.

From these results, we can draw two conclusions: first, the impact of China's accession to the WTO on agricultural imports is significantly greater than the implementation of the ChAFTA. Second, the increase in imports from countries other than Australia is mainly due to the impact of the WTO. These findings indicate that the ChAFTA has a significant trade creation effect on China's agricultural imports but no trade diversion effect.

5.2.2 Considering the lead effect

In the study of trade agreements, a common issue is reverse causality, where countries that sign trade agreements may already have close trade relationships. While the inclusion of two-way fixed effects is a reasonable method to address this issue, to further test for potential reverse causality, this section introduces a lead FTA variable (Baier and Bergstrand, 2007a) in the regression equation. This approach helps to identify whether there is an endogeneity problem.

The modified equation (Equation 3) is as follows:

$$\ln x_{ijt} = \beta_0 + \beta_1 FTA_t + \sum_{s=1}^{3} \beta_s FTA_{t+s} + \alpha_t + \alpha_j + \varepsilon_{ijt} \quad (3)$$

Among them, FTA_{t+s} represents a binary dummy variable for FTA_t with leads of s = 1,2,3 periods. If the free trade agreement is an exogenous variable relative to trade volume, then the coefficient should not be statistically significant, reflecting changes in trade volume before the implementation of the free trade agreement.

Column (2) of Table 5 shows the results of the lead effects. It is found that when there are time fixed effects and exporting country fixed effects, the coefficient of FTA_{t+s} is significantly positive in the third lead period but significantly negative in the second and first lead periods. This indicates that before the signing and implementation of the ChAFTA, there was no significant increase in agricultural trade between China and Australia. The signing of the ChAFTA was not a consequence of increased trade volume between China and Australia. There is no reverse causality issue.

The results provide robust evidence that the ChAFTA is exogenous relative to trade volumes. The significant negative coefficient of the lead FTA variable supports the conclusion that the trade agreement was not driven by preexisting trade trends. This finding strengthens the validity of the earlier results, which indicated a significant positive impact of ChAFTA on Chinese agricultural imports. The inclusion of the lead FTA variable and the use of fixed effects help to mitigate potential endogeneity concerns, ensuring that the estimated effects are reliable and not biased by reverse causality.

5.2.3 Considering the phasing-in effect

In order to capture the effects of ChAFTA change over time, we incorporate the lagged terms of the FTA into the model. As highlighted in column (3) of Table 5, the estimated coefficients of the lagged FTA variables point to no phasing-in effects of FTA, which is consistent with findings from related studies (Bureau and Jean, 2013). The first-order lagged FTA is significantly negative, indicating a reduction in trade volume 1 year after the implementation of the trade agreement. But the reduction is small (1.7%). This result may be due to companies having to adapt to the rule changes. The trade creation effect still remain significant.

4 According to the definition of semi-elasticity, it refers to the rate of change in the dependent variable when the independent variable increases by one unit.so 64.5% = (exp(0.498)-1) × 100%.

5 16.4% = (exp(0.152)-1) × 100%.

6 86.6% = (exp(0.624) 1) × 100%.

TABLE 5 Robustness check results (PPML).

Variable	(1)	(2)	(3)
	WTO dummy	The lead effect	Phasing-in effect
FTA_t	0.494***	0.319***	0.507***
	(76.42)	(54.52)	(92.92)
$NFTA_{jt}$	0.009	0.009	0.009
	(0.92)	(0.92)	(0.92)
WTO_{it}	2.472***	0.615***	0.615***
	(289.37)	(19.32)	(19.32)
FTA_{t+3}		0.347***	
		(126.47)	
FTA_{t+2}		−0.008***	
		(−3.46)	
FTA_{t+1}		−0.006***	
		(−3.07)	
FTA_{t-3}			0.001
			(0.23)
FTA_{t-2}			0.001
			(0.54)
FTA_{t-1}			−0.017***
			(−5.88)
Constant	0.494***	2.472***	2.472***
	(76.42)	(289.59)	(289.37)
Observations	341,376	341,376	341,376
R-squared	0.396	0.396	0.396
Year FE	Yes	Yes	Yes
exporter FE	Yes	Yes	Yes

Robust z-statistics in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5.3 Heterogeneity analysis

This study utilizes the classification principles of the Central Product Classification (CPC) version 1.1 to categorize agricultural products into seven major categories: agricultural products, forestry products, fishery products, food, beverages and tobacco, textiles, and other agricultural products. Table 6 below presents the estimation results.

From Table 6, we observe that the coefficients of the FTA_t and $NFTA_{jt}$ variables are significantly positive across all seven categories of agricultural products. This indicates that the signing of the ChAFTA had a notably positive impact on the import of these products, demonstrating a trade creation effect without evidence of a trade diversion effect.

The most significant impacts were on forest products and aquatic products, with estimated increases of approximately 473 and 376%, respectively. Following these, textiles and livestock products showed increases of around 361 and 144%, respectively. Observations indicate that food and livestock product categories are those from which Australia imports the most varieties to China.

These results suggest that ChAFTA not only boosted overall imports from Australia to China but also had positive effects on specific sectors. The significantly positive coefficients across multiple categories highlight the broad benefits of the trade agreement, particularly in sectors such as forest products, aquatic products, textiles, and livestock products. The absence of significant trade diversion effects further supports the notion that ChAFTA mainly facilitated the creation of new trading opportunities rather than altering existing trade patterns.

6 Discussion and conclusion

6.1 Discussion

6.1.1 Summarize the main findings

In this study, we examined the impact of the ChAFTA on China's agricultural imports. Our key findings indicate that the implementation of ChAFTA has significantly enhanced trade creation effects in China's agricultural sector, promoting a 64.5% increase in agricultural product import trade volume. The OLS and PPML estimation methods were compared in empirical research, and the results showed that PPML estimation has more advantages in analyzing data with zero transactions. This finding aligns with the first hypotheses and addresses the literature gap by providing causal evidence on agricultural imports.

TABLE 6 Heterogeneity analysis.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Agricultural Products	Forestry Products	Fishery Products	Food	Beverages and Tobacco	Textiles	Other Agricultural Products
FTA_t	0.893***	1.560***	1.745***	0.767***	0.832***	1.528***	1.170***
	(107.87)	(100.73)	(113.12)	(84.37)	(54.15)	(63.33)	(90.62)
$NFTA_{jt}$	0.897***	1.350***	1.322***	0.736***	0.820***	1.979***	1.197***
	(22.37)	(17.56)	(18.67)	(20.00)	(15.23)	(20.95)	(22.69)
Constant	0.717***	−2.988***	−1.423***	−0.388***	−1.567***	−2.630***	−1.490***
	(64.62)	(−133.73)	(−63.96)	(−32.83)	(−78.28)	(−70.34)	(−86.19)
Observations	682,752	338,709	341,376	1,024,128	682,752	333,375	1,365,504
R-squared	0.233	0.247	0.204	0.356	0.304	0.177	0.190
exporter FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES

Robust z-statistics in parentheses: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The empirical research, taking into account the impact of China's accession to the WTO in 2001, remains robust. The result indicate that joining the WTO has had a significant positive impact on China's agricultural product imports. Although, the trade creation effect still significant, but there is no trade diversion effect. This study further investigates whether there is an endogeneity issue in the empirical results by considering the impact of the lead FTA variables. The results showed that there was no endogeneity issue.

We also considered the phasing-in effects by considering lagged FTA variables and found the phasing-in effects is insignificant. This result is inconsistent with the second hypothesis. This phenomenon may be due to the fact that China has immediately reduced tariffs on most agricultural products imported from Australia, enabling Australian agricultural products to quickly enter the Chinese market and reducing the possibility of a phase-in effect.

In heterogeneity analysis, experiments were conducted to test the import of various agricultural products, and the results showed that ChAFTA has a significant positive impact on the types of agricultural products imported to China. This result confirms the third hypothesis. The most significant impact of ChAFTA on the types of agricultural products imported into China is in the forest products and aquatic products, with estimated increases of approximately 473 and 376%. The growth of textiles and livestock products was approximately 361 and 144%, respectively. The trade diversion effect is not significant in all categories. This study supports the research hypothesis that ChAFTA has a trade creation effect on China's agricultural product imports and heterogeneity in agricultural product imports.

From an economic principles perspective, these findings can be explained as follows: Firstly, economies of scale enable countries within an FTA framework to trade at lower costs, thereby promoting bilateral trade growth. Secondly, the tariff reductions and lowering of other trade barriers brought about by the FTA directly decrease transaction costs, further boosting the growth of trade flows.

6.1.2 Compare with existing literature

From the empirical results, the implementation of the ChAFTA has significantly promoted agricultural imports from China to Australia, and this effect is quite stable. This conclusion differs from that of Baier and Bergstrand (2007a), who found in their study of cross-sectional data from 96 partner countries that the trade effects of trade agreements can sometimes be positive and sometimes negative. The coefficient value of 0.498 is higher than the result of 0.33 obtained by Grant and Boys (2012) in their study on the WTO, but it is lower than the findings of Ghosh and Yamarik (2004) on ASEAN (0.7082) and APEC (1.293), as well as lower than Wang (2017) on China's agricultural exports to ASEAN, which had a result of 0.591.

Our results align with previous studies such as Sun and Reed (2010), who found that FTAs have significant creation effects on agricultural trade. However, our research also highlights distinctions, particularly in the observed heterogeneity of impacts across various agricultural product categories. Unlike earlier work by Wang (2017) which focused on the trade effects of CAFTA on China's agricultural exports, our study provides insights into the import side, showing that not all agricultural imports experience equal benefits under ChAFTA. This suggests that while trade creation is evident, its extent varies based on the type of agricultural product involved, indicating a need for more nuanced policy considerations tailored to specific agricultural sectors.

7 Limitations and propose

Despite these contributions, our study faces several limitations. Firstly, our study focuses on the impact of FTAs themselves and does not capture the significant differences that may exist in the content, depth, and scope of trade agreements, such as non-tariff barriers, service trade, and investment rules. Secondly, the use of a binary dummy variable to represent FTAs fails to separate the independent effects of other economic policies implemented alongside the trade agreements, like exchange rate policies or the RCEP.

These limitations suggest that future research should consider a more comprehensive approach to analyzing the impacts of FTAs. Specifically, it is important to account for the diverse elements within trade agreements, including non-tariff barriers, service trade, and

investment rules, which can significantly influence trade outcomes. By addressing these gaps, future studies can provide a more nuanced understanding of how different components of FTAs and concurrent policies affect international trade.

By continuing to investigate these aspects, scholars can contribute to a more nuanced view of how FTAs shape global agricultural markets, ultimately benefiting both producers and consumers.

8 Conclusion

This study provides the first systematic evidence of how the ChAFTA reshaped China's agricultural imports through trade creation and diversion. Using a modified gravity model, we find Strong trade creation effects, ChAFTA can increased China's agricultural imports from Australia, with peak effects in sectors like forest products and aquatic products. The limited diversion effects suggest that multilateral trade relationships remain resilient to bilateral FTAs. While this analysis focuses on FTA, future studies should integrate non-tariff measures and environmental clauses to fully capture modern FTA impacts.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YC: Methodology, Writing – original draft. WC: Data curation, Writing – review & editing. XZ: Writing – original draft, Data curation.

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Supplementary material

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Exploring the driving mechanisms behind the formation of agricultural science and technology innovation clusters: a case study of Lanling County, China

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This study examines the mechanisms underlying the formation and development of agricultural science and technology innovation clusters, using Lanling County in China as a representative case. It addresses how localized innovation strategies contribute to rural industrial transformation within the broader context of national agricultural modernization. Employing a qualitative case study approach, the research integrates field observations, semi-structured interviews, and document analysis. The analytical framework is informed by industrial cluster theory and the regional innovation systems perspective. The study identifies and examines the interactive dynamics among four major drivers: natural and socioeconomic resource endowments, market demand, policy support, and technological innovation. The findings reveal that the emergence and consolidation of the Lanling vegetable innovation cluster is the outcome of synergetic interactions between endogenous innovation capabilities and exogenous enabling conditions. Strategic interventions—such as the construction of intelligent greenhouses, the expansion of specialized production bases, cooperative organization development, and the implementation of quality control systems—have collectively advanced the region's agricultural upgrading. The study contributes to theoretical discourse by extending cluster theory to the agricultural sector and illustrating the applicability of regional innovation systems in rural contexts. Practically, it offers policy-relevant pathways including the enhancement of technological service networks, market responsiveness, environmental governance, and enterprise collaboration. The research provides replicable insights for other regions seeking to promote sustainable agricultural transformation through innovation-driven development.

KEYWORDS

agricultural innovation cluster, technological upgrading, regional development, innovation systems, Lanling county, policy-driven modernization, rural transformation

1 Introduction

The theory of industrial clusters, as advanced by Michael Porter, represents a significant extension of Alfred Marshall's notion of localized industrial specialization (Lepori, 2022). In Warr (1994), Porter formally introduced the concept of industrial clusters, arguing that the spatial concentration of interconnected firms and institutions enhances regional competitiveness through innovation and productivity (Yellice and Türko, 2023). Building on this foundation, the Organization for Economic Cooperation and Development (OECD) released its landmark report Boosting Innovation: The Cluster Approach in 1999, which formally conceptualized the idea of "innovation clusters," emphasizing their pivotal role in driving technological progress and economic development (Kowalski and Mackiewicz, 2021).

In recent years, with increasing attention on the transformative role of science and technology in agricultural modernization (Yadav et al., 2023), a key challenge has emerged: how to integrate the fragmented innovation elements in agriculture (Annosi et al., 2022)—such as R&D, technological diffusion, production systems, and enterprise participation—into a cohesive and dynamic innovation ecosystem. Addressing this challenge is critical not only for enhancing the overall functionality of agricultural systems but also for advancing regional economic development and sustainable agricultural practices (Adisa et al., 2024). As the awareness of the agglomeration effect of innovation in agriculture deepens, the formation and evolution of science and technology-based agricultural clusters has become a prominent topic in both theoretical and empirical research.

Existing research on regional innovation systems has largely focused on industrial and urban contexts, often neglecting the agricultural sector and its particular dynamics in rural regions. This study addresses this gap by investigating how agricultural innovation clusters develop under conditions shaped by local resources, social networks, market dynamics, and institutional arrangements. Using Lanling County as a case study, the research extends the theoretical scope of regional innovation models by showing how rural innovation systems integrate both endogenous capacities and exogenous supports. This provides a more comprehensive understanding of innovation processes in agri-based economies and highlights the adaptive mechanisms through which rural areas foster sustainable development.

This study, therefore, seeks to systematically examine the driving mechanisms behind the formation of agricultural science and technology innovation clusters, with a particular focus on Lanling County, China—a region that has developed a strong specialization in vegetable production. Based on extensive field research, it is observed that Lanling County has entered a new stage of cluster-based development. In response to both domestic and international market demands, the county has proactively leveraged advanced agricultural technologies to enhance the technological content of its vegetable industry. These efforts have culminated in a comprehensive industrial upgrade and the emergence of a well-defined innovation cluster in the vegetable sector, characterized by synergistic integration of enterprises, research institutions, and service organizations.

This study centers on the following scientific question: What are the principal internal and external forces driving the emergence, evolution, and consolidation of agricultural science and technology innovation clusters in Lanling County? By addressing this question, the research seeks to uncover the underlying structural and functional mechanisms that shape innovation-led agricultural clustering. The findings are intended to generate both theoretical contributions to the understanding of rural innovation systems and practical guidance for regional agricultural policy, ultimately aiming to improve productivity, promote sustainability, and strengthen the competitiveness of China's rural economy.

2 The concept and connotation of agricultural industry clusters driven by technological innovation

Agricultural industry clusters, as defined by the Organization for Economic Co-operation and Development (OECD), refer to geographically proximate groups of enterprises and complementary institutions engaged in the production and processing of agricultural products (Medeiros, 2021). These entities form an organic system centered around agricultural production bases through interlinked relationships based on shared or complementary functions. This framework highlights the spatial agglomeration and network-based cooperation among agricultural actors (Wei and Chen, 2024). Agricultural industry clusters into three core sub-clusters: agricultural production, food processing, and agricultural input manufacturing (Foutakis, 2025). This classification has provided a foundational structure for empirical research in North American and European contexts.

From the perspective of innovation dynamics, innovation clusters as networks of collaboration between research institutions and industry actors, jointly engaged in technological development and knowledge exchange (Fioravanti et al., 2023). According to the OECD's innovation systems approach, such clusters emerge from complex and continuous interactions among firms, research institutions, educational bodies, and public administration (Klarin et al., 2021). These are referred to as technologically linked innovation clusters, embedded within broader regional innovation ecosystems (Sandoval Hamón et al., 2024). A key feature distinguishing innovation clusters from conventional industrial clusters lies in their intrinsic capacity for generating new knowledge and products (Pinto et al., 2023). Innovation clusters are characterized not only by spatial proximity and industrial specialization but also by knowledge flows, institutional infrastructure, and multi-actor collaboration (Bravaglieri et al., 2025). Within this context, the concept of science and technology innovation clusters denote territorially concentrated networks of scientific and technological resources—including research outputs, projects, and talent—that interact synergistically through shared innovation goals (Rodríguez Ochoa et al., 2025). These clusters facilitate the mobility of knowledge, the co-creation of technologies, and the institutionalization of feedback mechanisms among scientific, technological, and socio-economic agents (Bianchi and Grippi, 2025).

In the agricultural sector, the growing integration of technological innovation has fundamentally transformed traditional industrial cluster structures, giving rise to what is now termed agricultural science and technology innovation clusters (Chen and Li, 2022). These clusters represent a higher stage in the evolution of agricultural industrial clusters, marked by the spatial agglomeration of innovative agricultural entities and the establishment of dynamic linkages with external systems of knowledge, finance, and governance (Bittencourt et al., 2023). An agricultural science and technology innovation cluster can be understood as a spatially organized, innovation-oriented agri-technological network system, where scientific and technological inputs are concentrated, and collaborative interactions are institutionalized. These clusters apply cutting-edge agricultural science and technology to develop new products, adopt modern production methods, and optimize management models, thereby improving the quality and competitiveness of agricultural outputs. In addition to upgrading traditional agricultural industrial clusters, these innovation clusters encompass agricultural science parks, functional agricultural zones, and science-driven agri-innovation ecosystems. The coordinated integration of agricultural innovation with regional planning enhances the formation and growth of such clusters. Ultimately, this convergence facilitates the emergence of comprehensive agricultural innovation complexes, serving as hubs for sustainable rural development and global agri-tech competitiveness.

3 Data collection and analytical procedures

Lanling County, located in Shandong Province, is widely recognized as one of China's leading agricultural production bases, particularly known for its vegetable industry. The county benefits from abundant natural resources, a favorable climate, well-developed agricultural infrastructure, and a long-standing tradition of market-oriented farming. In recent years, Lanling has emerged as a prominent example of an agricultural innovation cluster, characterized by the integration of advanced technologies, cooperative networks, and supportive policy frameworks.

The selection of Lanling County as a case study inevitably raises questions about representativeness and the potential for selection bias. While Lanling represents a highly successful and mature cluster that may not fully reflect conditions in less developed regions, it was intentionally chosen as a critical case to illuminate the mechanisms and enabling conditions behind the formation and consolidation of agricultural science and technology innovation clusters. Rather than constituting a singular outlier, Lanling can be understood as a frontrunner within broader national trends of rural innovation and agricultural modernization, especially under China's rural revitalization strategy. Although the study does not claim universal applicability, it aims to generate transferable insights and hypotheses that can inform comparative research and offer practical lessons for cluster development in diverse regional contexts, both within China and internationally.

The study employed a qualitative case study approach, combining field observations, semi-structured interviews, and document analysis to investigate the formation and dynamics of agricultural science and technology innovation clusters in Lanling County. The interview sample was purposefully designed to capture a broad range of stakeholder experiences. By including farmers, cooperative leaders, enterprise managers, and local government officials, the study ensured that multiple voices were heard, allowing for a more comprehensive understanding of the innovation cluster's development from the ground up. A total of 28 interviews were conducted between November and December 2024 with key stakeholders, including farmers, cooperative leaders, enterprise managers, local government officials, and technical extension agents. The interviews, which ranged from 45 to 90 min, were audio-recorded with the participants' consent and subsequently transcribed in full. The collected data were analyzed thematically using a combination of inductive and deductive approaches. Themes were identified through multiple coding rounds, with the aid of NVivo qualitative analysis software, to ensure consistency and rigor in data interpretation. To enhance validity, triangulation was achieved by integrating interview data with secondary sources, including local government reports, statistical yearbooks, and relevant policy documents. This methodological design provides a robust basis for understanding the mechanisms driving agricultural innovation clustering in the local context.

The data analysis process followed a rigorous thematic analysis framework. After completing the transcription of interview recordings, the research team conducted an initial open coding phase to identify emergent categories and patterns within the data. This was followed by axial coding, which allowed for the clustering of related codes into broader thematic categories aligned with the study's research questions. Throughout this process, NVivo software was employed to organize, code, and manage the qualitative data, enhancing analytical transparency and traceability. To ensure the credibility and consistency of coding, two researchers independently coded a subset of transcripts and resolved discrepancies through discussion and consensus. The analysis also incorporated constant comparison techniques, whereby insights from interview data were systematically cross-checked against field notes, policy documents, and statistical reports to refine interpretations. This multi-layered analytical approach enabled the study to capture the complexity of interactions among actors, institutions, and technologies in the development of agricultural innovation clusters.

To ensure the reliability and validity of the study, several methodological strategies were employed. First, data triangulation was used by integrating multiple sources of evidence, including interview data, field observations, government reports, and statistical records, which allowed for cross-verification of key findings. Second, investigator triangulation was applied during the coding process, with two researchers independently coding a subset of transcripts and subsequently discussing any discrepancies until consensus was reached, thus enhancing coding reliability. Third, member checking was conducted by sharing preliminary findings with selected interview participants to confirm the accuracy and credibility of the interpretations. Finally, detailed documentation of the research procedures and analytic decisions

was maintained throughout the study, ensuring transparency and enabling future replication. These combined strategies contributed to strengthening the study's methodological rigor and ensuring the trustworthiness of its conclusions.

4 Typologies of agricultural science and technology innovation clusters in Lanling County, China

The classification of agricultural industry clusters varies depending on the criteria adopted. A review of existing literature reveals multiple typologies based on spatial distribution, industrial organization, and technological attributes. While the emergence of high-tech agricultural clusters built on technological and professional advantages (Li et al., 2022). Currently, three mainstream forms of agricultural clusters have gained significant attention in China: agricultural high-tech parks, leading-enterprise-driven clusters, and market-oriented clusters (Wan, 2022).

Some scholars' application of cluster life cycle theory to the agricultural sector offers an additional perspective, dividing the development of agricultural clusters into four stages: emergence, growth, maturity, and decline (Ostapenko et al., 2024). As agricultural clusters enter the mature stage, technological innovation becomes essential to extend the cluster's life cycle and avoid stagnation. In this context, agricultural science and technology innovation clusters serve as strategic vehicles for upgrading traditional agglomerations.

Spatial-temporal categorization of innovation clusters provides further nuance (Wang et al., 2025), while contemporary Chinese scholars have expanded these frameworks by incorporating spatial distribution and techno-economic dimensions. Drawing from both domestic and international studies, this section classifies the vegetable industry cluster in Lanling County into the following five types. To facilitate a clearer understanding of the diversity and organizational dynamics of agricultural innovation clusters in Lanling County, Table 1 provides a comparative summary of the five identified cluster types. The table outlines their main organizational forms, core activities, governance arrangements, and innovation strategies.

4.1 Market-driven clusters

These clusters are characterized by the formation of specialized agricultural markets linked with households and supply/distribution networks. Lanling County currently hosts over 30 specialized vegetable markets, including the prominent Lunan Wholesale Market, with an annual transaction volume exceeding 800 million kilograms. These markets have established stable trade relationships with major urban centers such as Shanghai, Suzhou, and Wuxi. Notable examples include the Changcheng Chili Market, Tianma Winter Melon Market, and Zhuangwu Export Vegetable Market. These trading hubs have accelerated the development of specialized vegetable production zones.

4.2 Leading enterprise-driven clusters

These clusters are formed through the coordination between leading enterprises and farmers, creating loosely or tightly integrated production communities. Companies such as Huangpu Group, Yixing, and Shenda have established vertically integrated value chains encompassing storage, preservation, processing, and logistics. By linking domestic and international markets, these enterprises drive industrial upgrading and foster technology adoption in the vegetable sector.

4.3 Cooperative organization-driven clusters

These clusters rely on cooperative societies or associations that connect farmers with enterprises and markets. Guided by the Farmers' Specialized Cooperatives Law, Lanling County has actively promoted the development of economic cooperation organizations in key vegetable-producing towns. These cooperatives have enhanced farmer organization levels and facilitated contract farming and export-oriented production. One example is the Huibao Cooperative in Shangyan Town, which has successfully linked farmers to stable distribution channels.

4.4 Intermediary- and contract-based clusters

These clusters involve intermediary agencies or agents that serve as coordinators between enterprises and farmers through contract farming arrangements. Since 1999, companies like Nanyuan and Xincheng in Nanqiao Town have signed annual contracts with large buyers such as Shanghai's Baishi Corporation. These agreements involve capital investment, seed provision, and guaranteed purchase prices, promoting the scale-up of contract-based production. By 2023, Lanling County had developed 7,000 hectares of contract-grown vegetables.

4.5 Export-oriented specialization clusters

These clusters are built on aligning foreign market demands with the county's comparative advantages—such as favorable natural conditions, labor intensity, and green certification. For example, Zhuangwu Town has established export-oriented production bases through partnerships with companies like Haidu and Yuanye. These firms import high-quality seed varieties, organize local production, and process the vegetables for export, thus forming an "externally driven" value chain. Zhuangwu has since emerged as a major hub for vegetable export in the region.

This diversified cluster typology not only reflects the multi-scalar and multi-actor nature of agricultural innovation in Lanling County but also illustrates how technology, organization, and market forces interact to shape regionally embedded innovation ecosystems. Understanding these forms provides critical insight into the structural composition and functional mechanisms of

TABLE 1 Summary of the five cluster types in Lanling County.

Cluster type	Organizational form	Core activities	Governance structure	Innovation strategies
1. Farmer-based cluster	Individual farmers, smallholder networks	Production of specialty vegetables	Informal networks, farmer cooperatives	Adoption of improved varieties, ecological farming
2. Cooperative-led cluster	Agricultural cooperatives, farmer groups	Coordinated production, marketing, input supply	Cooperative boards, member meetings	Joint purchasing, collective marketing, training
3. Enterprise-driven cluster	Agribusiness firms, contract farming	Large-scale production, processing, export	Corporate governance, contractual relations	Vertical integration, investment in processing tech
4. Government-guided cluster	Government agencies, public-private partnerships	Infrastructure development, R&D support	Local government leadership, multistakeholder platforms	Subsidies, technical extension, demonstration projects
5. Innovation platform cluster	Research institutes, universities, tech parks	R&D, technology transfer, incubation services	Research consortia, innovation alliances	Joint research, patenting, pilot projects

agricultural science and technology innovation clusters in China's rural economy.

5 Driving mechanisms behind the formation of agricultural science and technology innovation clusters in Lanling County, China

The formation and evolution of agricultural innovation clusters are influenced by a complex interplay of natural endowments, market dynamics, policy interventions, and technological advancement (Annosi et al., 2022). Western scholarship has identified several core drivers—such as geographic and cultural contexts, consumer demand, competitive pressure, and institutional support—as fundamental to cluster development (Rocha and Audretsch, 2022). In particular, the knowledge spillover effect, cumulative learning processes, and paradigm shifts in technology are widely recognized as critical catalysts for innovation clustering (Song et al., 2022).

Drawing from these theoretical frameworks, this section analyzes the driving mechanisms that have underpinned the formation of the agricultural science and technology innovation cluster in Lanling County (Figure 1). Four key forces are identified: resource endowment, market demand, policy and planning, and technological innovation.

5.1 Resource endowment: the foundational basis for cluster formation

Agricultural production is inherently shaped by natural resource conditions, which guide spatial distribution and determine geographic advantages. In a market economy, firms facing competitive pressures and seeking profit maximization are compelled to optimize land use according to resource availability. Resource endowments can be categorized into two types: (1) natural resources—including soil quality, climate, topography, water availability, and geographical location; and (2) socioeconomic resources, such as capital, labor, and knowledge.

Lanling County is uniquely endowed in both respects. It features a diversified landscape of northern hills and southern lowlands, a warm temperate monsoon climate with sufficient sunlight, fertile soil, and clean, abundant water resources. The average annual temperature is 14.4°C, with ~2,473 h of sunshine and 202 frost-free days, making it highly suitable for vegetable cultivation. Moreover, with a population of over 1.16 million and a long-standing tradition in vegetable farming, the region benefits from a rich pool of skilled labor and adaptive knowledge systems. These conditions form the ecological and human capital foundation for innovation-driven cluster development.

Local stakeholders repeatedly emphasized the importance of these resource endowments in interviews. As one farmer noted, "Our soil is fertile and easy to work with, and the climate gives us a long growing season—this is what allows us to produce vegetables that are in high demand even outside the province." A cooperative leader commented, "The local farming community has accumulated generations of experience in vegetable cultivation, so when new technologies or practices are introduced, people here are quick to learn and adapt." A government official highlighted, "What makes Lanling competitive is not just the natural conditions, but also the people—hardworking farmers and innovative entrepreneurs who are willing to experiment and improve." These perspectives underscore that the region's innovation potential stems from the dynamic interplay between ecological advantages and a vibrant, knowledge-rich local workforce.

5.2 Market demand: the primary external driver

The vertical deepening of social division of labor and the expansion of market-oriented agriculture have fueled the rise of large-scale, specialized production zones. As economic growth and urbanization accelerate, stable consumer markets have emerged, both domestically and internationally, creating sustained demand for high-quality agricultural products. The development of specialized agricultural markets in Lanling County has triggered value chain integration, facilitating the alignment of production, logistics, and consumption.

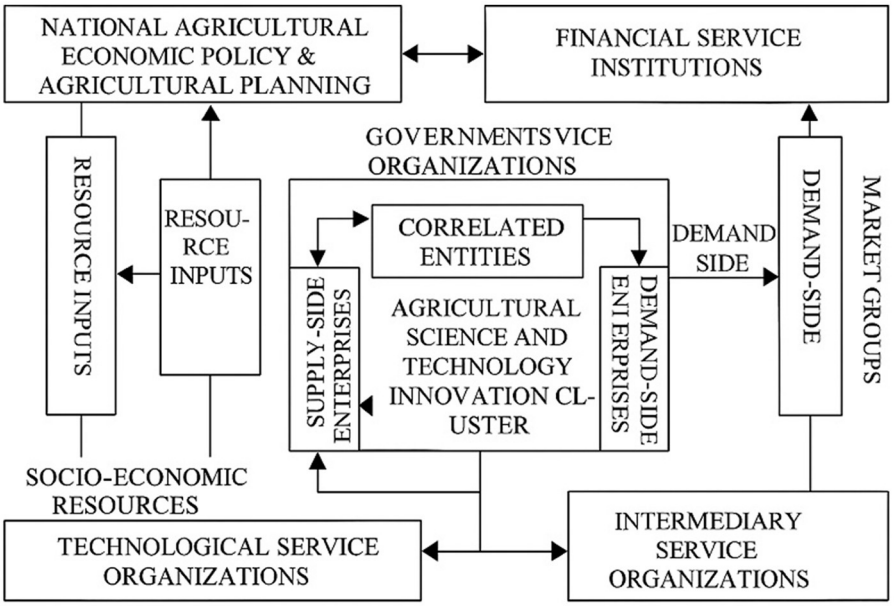


FIGURE 1
Driving mechanisms behind the formation of agricultural science and technology innovation clusters in Lanling County, China.

Local stakeholders highlighted how these market dynamics have transformed their operations. A vegetable farmer explained, "We used to sell mainly to local markets, but now, with buyers from big cities and even abroad, we have to upgrade our production methods to meet their standards." An enterprise manager remarked, "Customized supply chains and contract farming have become the norm here—clients want specific varieties, sizes, and packaging, and we need to coordinate tightly with farmers to deliver on time." A government official observed, "The development of specialized wholesale markets and cold-chain logistics has not only expanded sales channels but also pushed farmers and enterprises to adopt better technologies, from precision irrigation to improved seed varieties."

This market pull mechanism has not only promoted economies of scale and agglomeration but also reinforced the need for technological upgrades to meet increasingly differentiated consumer preferences. The proliferation of contract farming, customized supply chains, and export-oriented production has significantly shaped the cluster's industrial structure, embedding technological and organizational innovation deeply within the local agricultural system.

5.3 Government policy and planning: the institutional driver

State policies and strategic planning play a guiding and enabling role in cluster formation, particularly in developing economies. The Chinese government has actively supported regional specialization and modernization through targeted subsidies, infrastructure investment, and agricultural science promotion. In Lanling County, local authorities have leveraged national agricultural industrialization policies to channel resources—land, labor, and capital—toward high-potential sectors.

Local stakeholders consistently underscored the significance of government action. A vegetable farmer noted, "Without government subsidies, we couldn't afford the drip irrigation systems or greenhouses that have boosted our yields so much in recent years." A cooperative leader observed, "The government's support in setting up cooperatives has been critical—it's allowed small farmers like us to pool resources, access markets, and share new techniques." An enterprise manager remarked, "Public investment in logistics and cold-chain infrastructure has transformed how we do business, making it possible to ship fresh vegetables across the country and even export them." A government official reflected, "Our goal is to create the right environment for innovation—by improving roads, supporting agricultural R&D, and offering training programs, we help farmers and companies build competitive capacity."

Through financial incentives, land-use planning, and institutional support (e.g., cooperatives and technology extension services), the government has helped to reduce coordination costs, mitigate market failures, and strengthen regional comparative advantages. While public intervention cannot substitute for market mechanisms, it plays a vital role in overcoming structural bottlenecks, facilitating public-private partnerships, and promoting collective learning among actors in the cluster.

5.4 Technological innovation: the core internal engine

Technological innovation functions as the core endogenous driver of agricultural innovation clusters, particularly in the

polarization stage of development. Advances in biotechnology, precision agriculture, cold chain logistics, and intelligent monitoring systems have reshaped the spatial logic of agricultural production and expanded the scope of high-value cultivation zones.

Stakeholders in Lanling County vividly described the transformative role of technology in interviews. A farmer shared, "The improved seed varieties we use now are much more resilient to pests and weather changes, which means we can plant on land that wasn't suitable before." A cooperative leader added, "Precision irrigation and greenhouse monitoring systems have allowed us to reduce input costs while improving product quality—this has been a game changer for smallholders." An enterprise manager explained, "With new cold chain logistics, we can reach markets in big cities and even export fresh produce without worrying about spoilage, which has opened up entirely new opportunities for growth." A local researcher emphasized, "Our breeding programs are not just about yield but about tailoring crops to local conditions, ensuring that innovation is relevant and applicable on the ground."

On one hand, scientific breakthroughs in seed quality and crop traits have redefined the ecological adaptability of farming practices, enabling expansion into new geographies. On the other hand, technological progress in storage, processing, and distribution has enhanced the functional integration of the agricultural supply chain, making region-specific specialization more viable.

Furthermore, innovation generates competitive differentiation, creating first-mover advantages for pioneering firms. As new technologies diffuse through demonstration effects and imitation, they promote the cumulative upgrading of the cluster. Due to the spatial stickiness of knowledge spillovers, proximity to innovation sources becomes increasingly important, thereby reinforcing the cluster's spatial concentration and institutional cohesion.

This cumulative feedback loop—where innovation leads to agglomeration, which in turn facilitates more innovation—is consistent with the dynamics described in regional innovation systems (RIS) and technological trajectory theories. In the case of Lanling County, this cycle has supported the emergence of a tightly integrated, innovation-led vegetable industry cluster.

6 Strategic pathways for advancing agricultural science and technology innovation clusters in Lanling County

The development of agricultural science and technology innovation clusters in Lanling County is shaped by a dynamic interaction of inflow, outflow, and multiplier effects. These forces jointly influence the spatial concentration of innovation factors, the dissemination of knowledge, and the amplification of economic and social value across the region. In order to further strengthen and expand the cluster, it is necessary to optimize its internal structure by improving the key elements linked to the main driving mechanisms. Enhancing cluster cohesion, reinforcing innovation linkages, and upgrading technological infrastructure are fundamental to achieving sustainable growth and competitiveness in agriculture.

To improve the accessibility and policy relevance of the strategic pathways, a conceptual framework has been developed to visually summarize the main findings. As shown in Figure 2, the framework integrates four interrelated domains—technological upgrading, market development, institutional support, and governance innovation—that together drive the emergence and consolidation of agricultural innovation clusters. By mapping the interactions and feedback loops among these dimensions, the framework provides a practical roadmap for policymakers and development practitioners seeking to promote agricultural modernization and rural transformation in China and beyond.

6.1 Strengthening production bases to enhance the scale and quality of vegetable cultivation

To build a more robust foundation for agricultural clustering, it is imperative to strengthen the construction of high-quality vegetable production bases. This involves formulating long-term development plans, optimizing regional planting structures, and promoting specialized cultivation at the township and village levels. Emphasis should be placed on leveraging the county's natural advantages to expand base areas, introduce superior vegetable varieties, and develop intelligent greenhouse systems. At the same time, demonstration zones focusing on early-, peak-, and off-season vegetable cultivation should be established to support experimental application of novel breeding techniques and advanced agronomic practices. Ecological approaches such as biogas utilization and organic cultivation methods also play a critical role in promoting green production. With the support of leading enterprises and coordinated government planning, these bases have become platforms for regional innovation diffusion, enabling large-scale, standardized, and modernized vegetable production.

6.2 Enhancing market responsiveness and improving product quality

Improving the responsiveness of agricultural production to evolving market demands is essential for sustaining the competitiveness of the cluster. This requires the construction of a multi-tiered technical service system, integrating county-level coordination, township-level implementation, and village-level outreach. By strengthening the linkage between market information, production guidance, and technology extension, farmers can be equipped with the necessary tools to adjust their practices to shifting consumer preferences. The integration of modern technologies—such as precision fertilization, micro-irrigation, biological pest control, seedling automation, and soilless cultivation—can significantly enhance production efficiency and product quality. In parallel, quality assurance mechanisms must be improved through the establishment of regular testing, rapid quality inspection stations, and environmental monitoring networks. These efforts not only ensure food safety but also protect

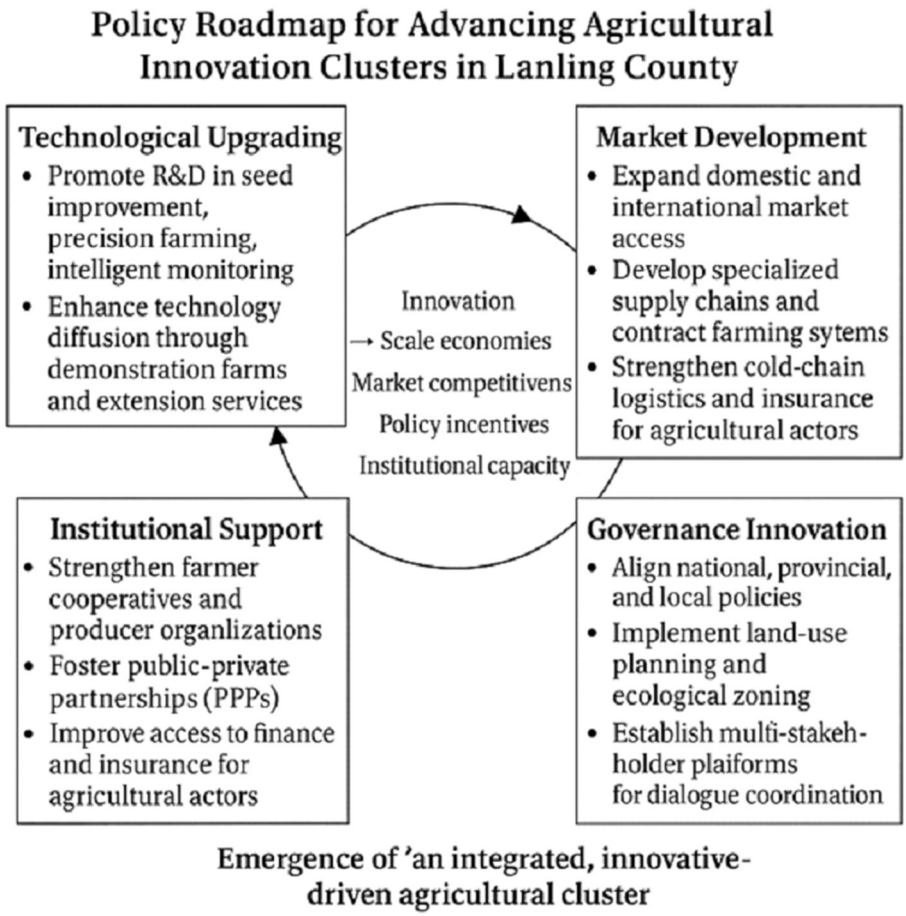


FIGURE 2
Policy roadmap for advancing agricultural innovation clusters in Lanling County.

the ecological integrity of major production zones. By aligning production with quality standards and consumer expectations, Lanling County can further consolidate its reputation as a leading supplier of premium vegetables.

6.3 Advancing technological innovation to increase value and productivity

Accelerating the application of agricultural science and technology is vital for enhancing the innovation capacity of the cluster. A comprehensive technology service network should be developed, linking public institutions, agricultural enterprises, and grassroots organizations to form an integrated system that supports continuous learning and technology dissemination. The promotion of high-quality varieties, expansion of protected agriculture (particularly greenhouse systems), and integration of multiple advanced technologies into production processes can effectively drive the modernization of vegetable cultivation. Furthermore, collaboration with specialized institutions—such as the Shandong Agricultural Product Quality Supervision Center—will facilitate the establishment of a more robust monitoring and evaluation system. Technological upgrading not only enhances production efficiency but also lays the groundwork for a knowledge-based, innovation-driven rural economy.

6.4 Creating a supportive policy and institutional environment

Government intervention is essential in providing strategic direction and cultivating an enabling environment for innovation clusters. Policymakers must develop scientifically grounded plans for the growth of agricultural science and technology innovation clusters, identify leading sectors based on local strengths, and prioritize infrastructure investment to support logistics, storage, and irrigation systems. At the same time, regulatory frameworks and policy instruments should be refined to facilitate inter-firm trust, coordinated development, and positive competitive dynamics. An open, transparent, and innovation-friendly institutional environment encourages cooperation among cluster participants, reduces transaction costs, and supports long-term collaboration between public and private actors. By aligning policy incentives with development goals, the government can effectively stimulate endogenous innovation and ensure the sustainable evolution of the cluster.

6.5 Developing circulation channels to support industrialized operations

A well-functioning market system is a cornerstone of cluster industrialization. The rational planning and restructuring of local markets are crucial to ensure orderly trading and eliminate unregulated and low-standard outlets. Upgrading wholesale markets to include sorting, cleaning, environmentally friendly packaging, and value-added services will better align supply with the demands of urban consumers. Meanwhile, the introduction and integration of large-scale, high-tech processing enterprises will further promote the industrial chain extension and value enhancement. In addition, the development of farmer-led marketing cooperatives and rural distribution networks should be prioritized to improve logistics efficiency and expand market reach. These initiatives will enable Lanling's vegetable industry to strengthen its competitiveness in both domestic and international markets, laying the foundation for a resilient and innovation-oriented agricultural economy.

To complement these policy recommendations, it is worth considering possible risks and challenges that could emerge during implementation, particularly concerning the balance between public support and market-based mechanisms. While the paper highlights the important role of government in providing infrastructure, strategic planning, and institutional support, it is equally important to acknowledge potential challenges and risks associated with such interventions. One concern is the possibility of over-reliance on top-down support, which may undermine local initiative and entrepreneurial dynamics within the cluster. Excessive dependence on government subsidies or directives can also lead to inefficiencies or distortions in resource allocation. Moreover, questions of long-term sustainability arise, particularly regarding the cluster's ability to maintain competitiveness once initial public investments taper off. Ensuring the resilience of the cluster will require a balanced approach that fosters not only state-led coordination but also bottom-up innovation, private sector engagement, and adaptive capacity among local actors. Recognizing these challenges can enrich the analysis and provide more nuanced policy recommendations for achieving sustainable agricultural innovation clusters.

7 Conclusion and future directions

This study explored the driving mechanisms and development pathways of agricultural science and technology innovation clusters, using Lanling County in China as a representative case. Grounded in industrial cluster theory and the broader framework of regional innovation systems, the research addressed the central scientific question: What are the key internal and external forces that drive the emergence and consolidation of agricultural innovation clusters in a region with strong agricultural specialization? Through a comprehensive review of the theoretical foundations, cluster typologies, and empirical evidence from Lanling's vegetable industry, the study identified four major drivers: resource endowment, market demand, institutional support, and technological innovation. These factors interact dynamically to shape the spatial and organizational structure of innovation clusters and foster a cumulative cycle of agglomeration, learning, and value creation.

Beyond its practical and policy contributions, this study offers theoretical insights that enrich current debates in agri-food innovation research. The case of Lanling County illustrates how innovation in peripheral regions is shaped by a combination of path dependency, where historical resource configurations and institutional arrangements condition present trajectories, and adaptive responses that help avoid innovation lock-in. Furthermore, the findings highlight the capacity of rural areas to become sites of periphery-driven innovation, where localized experimentation, learning, and multi-actor collaboration can generate novel development pathways. By situating the empirical findings within these broader theoretical discussions, the study contributes to a more nuanced understanding of the complexities and adaptive dynamics underpinning agricultural innovation systems in developing country contexts.

The findings suggest that Lanling County's success in developing a science-driven agricultural cluster lies in its ability to integrate localized production systems with advanced technological services, responsive market mechanisms, and enabling policy environments. The county's strategic deployment of greenhouses, cooperative organizations, processing enterprises, and quality control infrastructure has transformed its vegetable industry from fragmented production into a coordinated innovation ecosystem. Moreover, the case of Lanling illustrates how endogenous innovation capacity—amplified by external policy support and global market linkages—can catalyze rural transformation and agricultural modernization.

From a theoretical perspective, this study contributes to the growing literature on innovation clusters in non-metropolitan contexts. While most existing research on innovation agglomerations focuses on manufacturing or urban-based high-tech sectors, this study underscores the relevance of cluster theory in agriculture and rural development. The results affirm the applicability of concepts such as knowledge spillover, institutional thickness, and innovation system integration within the agricultural domain. This study makes a theoretical contribution by refining the regional innovation systems framework to better capture the complexities of agricultural cluster development in rural regions. The Lanling County case shows that the evolution of agricultural innovation clusters is driven by the dynamic interaction between local assets, institutional flexibility, and market orientation, combined with the selective adoption of advanced technologies. These findings call for a rethinking of conventional innovation models to account for the specific governance patterns, resource dependencies, and innovation trajectories observed in agri-based systems. By bridging the gap between theory and rural practice, this study provides a robust foundation for future comparative research on innovation in diverse peripheral regions.

Looking forward, several avenues for future research remain open. First, longitudinal studies are needed to assess the evolutionary trajectory of agricultural innovation clusters and to evaluate the long-term impacts of government interventions. Second, quantitative models—such as spatial econometrics and

system dynamics—can be applied to further analyze the feedback loops and spillover effects across regions. Third, comparative case studies between counties with different agro-ecological conditions, governance capacities, and market structures would enrich our understanding of the contextual factors shaping cluster formation. Finally, as digital agriculture continues to evolve, future research should examine how smart technologies and data-driven innovation platforms can be embedded into existing agricultural clusters to enhance their resilience, efficiency, and sustainability.

In conclusion, the development of agricultural science and technology innovation clusters presents a viable pathway for revitalizing rural economies and achieving sustainable agricultural transformation in China and beyond. By systematically identifying and reinforcing the multidimensional drivers of cluster development, policymakers and practitioners can better design place-based innovation strategies tailored to the specific needs and potentials of local agricultural systems.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

AX: Software, Writing – original draft, Investigation, Conceptualization, Writing – review & editing. YY: Writing – original draft, Data curation, Methodology, Writing – review & editing, Supervision. FC: Formal analysis, Project administration, Validation, Writing – review & editing, Writing – original draft. NR: Writing – review & editing, Formal analysis, Validation, Project administration, Writing – original draft. YM: Writing – original draft, Visualization, Resources, Writing – review & editing, Funding acquisition.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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Trade war and grain import resilience: evidence from China's response to U.S. Tariffs

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Examing the impact of China-US trade friction on China's grain import resilience can provide valuable insights for China and other developing countries in achieving food security. On the basis of defining the theoretical connotation of China's grain import resilience, this study employs data from 2013 to 2023 and applies a difference-in-differences (DID) approach to quantitatively analyzes the impact of China US trade frictions on China's grain import resilience. The study shows that the trade friction between China and the United States has an obvious negative impact on the resilience of China's grain imports. During the U.S.-China trade friction period, China's grain import prices rose, price volatility increased, import volume declined, import tempo changed, and the degree of import diversification declined. This shows that China's grain import resilience, recovery capacity and transformation and upgrading capacity need to be improved. Developing countries can enhance their food supply capacity by adopting measures such as diversifying import sources, expanding domestic production, promoting regional cooperation, and establishing strategic reserve systems. Specific strategies may include actively cultivating new trade partnerships, strengthening irrigation and water conservancy infrastructure, and modernizing grain storage facilities.

KEYWORDS

trade friction between China and the United States, China's grain imports, DID, resilience, developing countries

1 Introduction

The current landscape of international economic cooperation and competition is undergoing profound transformations. The Sino-US trade friction since 2018 has significantly impacted the stability of the global food supply chain, with measures such as tariff impositions and export restrictions further exacerbating volatility in the global food market. As the world's largest food importer, China's food industry has been notably affected by this trade friction. In response, China is actively working to enhance the resilience and risk resistance of its food supply chain to effectively mitigate the potential long-term challenges posed by the trade friction.

The concept of resilience thinking originated in ecology (Holling, 1973) and has since been widely applied across multiple disciplines, including ecosystems, regional economies, and industrial development. Similarly, the resilience of the food supply chain has garnered significant policy attention and academic discussion. Against the backdrop of profound changes in both domestic and international landscapes, the Chinese government has shifted its strategic focus in agricultural supply chain construction from emphasizing "stability" to enhancing "resilience." The 2022 report of the 20th National Congress of the Communist Party of China explicitly called for "strengthening the resilience and security of industrial and supply chains." This was further reinforced in the 2023 No. 1 Central Document, which

emphasized "building a strong agricultural nation with robust supply security, advanced technological equipment, efficient management systems, strong industrial resilience, and competitive capabilities." These policy directives underscore that enhancing supply chain resilience has become a core objective in China's agricultural modernization efforts.

As for the concept of agricultural industry chain resilience, existing studies define it as the agricultural system's capacity to withstand external shocks and rapidly recover from them (Lyu et al., 2025). In the context of the grain industry, resilience specifically denotes: the capacity to recover and even exceed pre-shock performance levels following disruptions (Ma et al., 2023), the ability to maintain supply chain continuity when confronted with internal and external shocks (Ansah et al., 2019), and the adaptive capacity and recovery speed of internal systems (Tendall et al., 2015). For China as a major grain importer, imports constitute a critical component of its grain industrial chain. However, current research on China's grain import resilience remains limited, primarily focusing on influencing factors (Tian et al., 2024) and existing challenges (Zhang and Long, 2023). However, existing studies have rarely conducted quantitative analyses of grain trade resilience. Some research has proposed quantitative approaches to assess trade stability, which may inform resilience measurement. For instance: Export stability has been measured by the temporal persistence of trade flows (Hess and Persson, 2011); Trade stability has been evaluated through variations in trade values (Gnangnon, 2018).

Similarly, studies examining the relationship between trade frictions and grain import resilience are scarce. Chinese scholars have approached this topic through various lenses: food import security under current international circumstances (Wang and Wu, 2024), import risks induced by trade conflicts (Cheng and Zhu, 2020), and price/cost implications of imports (Adjemian et al., 2021). Against the backdrop of escalating U.S.-China decoupling risks and the normalization of great-power competition (Wang and Yang, 2025), the impacts of Sino-U.S. trade friction extend far beyond the two nations. These tensions have not only affected economic development in ASEAN and Brazil (Aslam, 2019; Rasador et al., 2024) but have also undermined the multilateral trade rule system (Bown, 2019). Compared to developed countries, developing nations often suffer disproportionately negative impacts from trade frictions. Analysis of global grain trade network resilience metrics reveals that developed economies demonstrate stronger pandemic shock absorption capacity, while smaller developing countries face persistent challenges (Zeng et al., 2025). Regional disparities in grain import costs emerge due to high production costs and trade conflicts, with Oceania, Central America, and landlocked African regions bearing the highest landed costs (Verschuur et al., 2025). Evidence from Bangladesh suggests governments must account for market instability and other factors affecting food system resilience (Ahmed et al., 2025). Recent research has also explored geopolitical conflicts' impacts on food resilience in developing economies. Studies by Pan (2023) and Chen and Zhang (2024) reveal that geopolitical tensions have compromised food resilience in Indonesia and Russia, suggesting that developing nations should adopt more proactive measures to enhance domestic food security. These empirical findings demonstrate that developing countries should prioritize enhancing the resilience of their grain industries to strengthen their capacity to withstand trade frictions and geopolitical conflicts.

In summary, existing research has provided limited exploration of grain import resilience, leaving significant knowledge gaps in this field. Notably, three critical lacunae persist: the absence of a clear conceptual framework for grain import resilience, insufficient development of quantitative measurement indicators, and particularly scarce investigation into how trade frictions affect import resilience in developing economies. As the world's largest developing country and top food importer, a systematic assessment of how trade frictions impact China's grain import resilience holds dual significance: advancing theoretical frameworks while providing empirical foundations for other developing nations to enhance their import resilience. Compared to previous studies, this paper makes three key marginal contributions: First, it constructs a conceptual framework and quantitative metrics for import resilience; second, it employs difference-in-differences (DID) estimation to assess the magnitude of Sino-US trade friction's impact on China's food import resilience; third, it advances actionable policy recommendations to strengthen food import resilience in developing economies.

Following the introduction, Section 2 elaborates on the theoretical framework and impact mechanisms. Section 3 details the research design, while Section 4 presents the empirical findings. Section 5 provides an in-depth discussion, and Section 6 concludes with multilateral governance recommendations.

2 Theoretical analysis

2.1 Conceptualizing resilience in grain import systems

The concept of "resilience" encompasses not only the capacity to withstand and adapt to systemic shocks but also the ability to transition to a more desirable state (Hodbod and Eakin, 2015; Tendall et al., 2015). Supply chain resilience typically manifests through three core capacities: resistance, recovery, and transformation (Béné, 2020). Building on this framework, grain import resilience is defined as "the capacity of a grain import system to recover and transform in response to external and internal shocks and stressors." Specifically, it reflects the system's ability to maintain stable operations, recover to pre-shock conditions (Beyene et al., 2023), and achieve long-term adaptive upgrading (Nichols et al., 2022) when confronted with domestic or global disruptions. This resilience manifests in three dimensions: resistance capacity, recovery capacity, and transformative upgrading capacity. A highly resilient grain import system can rapidly restore trade to its original state or transition to an improved state following sudden shocks.

Grain import resistance refers to a nation's capacity to maintain stable import operations amidst disruptions in international trade environments–such as geopolitical conflicts or natural disasters. For instance, during the Russia-Ukraine conflict when Ukrainian grain exports were severely disrupted, the European Union established a "Solidarity Lane" through Poland, Hungary, and Romania in May 2022. Approximately half of Ukraine's grain exports were redirected through this land corridor, ensuring continued grain supplies to EU markets (Xu, 2024). Similarly, when soybean import prices surged due to droughts in South America, China stabilized domestic prices through strategic import pacing and reserve releases (NFSRA, 2022). These cases demonstrate that grain import stress resistance can

be quantitatively measured through three key indicators: import volumes, import prices, and import price volatility.

Grain import recovery capacity denotes a nation's ability to restore its import trade system to steady-state levels through adaptive adjustments following environmental shocks. Specifically, when abrupt disruptions sever existing trade relationships, entities with robust recovery capacity can rapidly establish alternative trade partnerships, smooth volumetric volatility, and rebalance import flows. For instance, when the 2022 Russia-Ukraine conflict drastically reduced Ukrainian wheat exports, Egypt mitigated the supply gap by increasing imports from France and Romania (FAO, 2023). This demonstrates that import volume volatility can serve as a measurable indicator of grain import recovery capacity.

As the breakthrough dimension of resilience, transformative upgrading capacity reflects dynamic adaptation process wherein the import system achieves efficiency gains and risk mitigation through structural optimization amid external shocks. Distinct from stress resistance capacities focused on short-term stabilization, this transformation capacity emphasizes systemic import system restructuring under protracted trade environment changes—converting external pressures into modernization drivers, most tangibly manifested through import diversification strategies. Economies with strong upgrading capacity can proactively develop superior alternative channels, diversify sourcing origins, and reduce systemic import risks. For instance, during the 2018 global rice price surge when traditional Philippine import sources (Vietnam and Thailand) imposed export restrictions, the Philippines secured rice import quotas through the ASEAN Emergency Rice Reserve Agreement with Cambodia and Myanmar. This strategic diversification stabilized domestic rice prices without triggering panic buying. Therefore, import diversification can serve as a measurable proxy for grain import transformation and upgrading capacity. This study employs the Herfindahl–Hirschman Index (HHI) to quantify diversification, where higher HHI values indicate lower diversification levels. The primary rationale for adopting HHI lies in its squaring calculation, which amplifies the weight of large supply sources, thereby more sensitively capturing the risks of "critical channel dependency." Moreover, the HHI has been consistently employed by institutions such as the WTO and the EU to assess food market concentration, lending the metric greater universality and institutional validity.

2.2 The impact mechanism of trade frictions on food import resilience

Trade frictions undermine grain import resilience by distorting trade flows, exacerbating import dependency risks, and weakening supply diversification channels.

According to the theory of comparative advantage, grain trade should align with countries' comparative advantages. However, trade frictions—particularly tariff barriers—artificially alter relative prices. Import tariffs elevate global grain prices (Bowm and Crowley, 2016), directly increasing consumer costs and inducing abnormal fluctuations in both import volumes and prices.

The strategic trade theory posits that governments should intervene in international trade to maximize national welfare. When major grain-exporting countries simultaneously raise trade barriers, importing countries face deteriorating terms of trade, which exacerbates market volatility (Johnson, 1953), increases procurement costs (Martin and Anderson, 2012), and may trigger broader food security crises (Cheng and Zhu, 2020). This subjects import-dependent nations to abnormal fluctuations in both import prices and quantities.

The theory of economies of scale suggests that non-tariff barriers (NTBs) increase fixed costs (e.g., certification fees), thereby intensifying market concentration and making trade more reliant on a limited number of large firms (Krugman, 1980). Additionally, NTBs induce a "selection effect," favoring high-productivity firms while reducing the number of exporters—a process that heightens supply chain disruption risks (Melitz, 2003). Consequently, import-dependent countries face heightened import risk concentration and diminished diversification.

2.3 Impact mechanisms of U.S.-China trade frictions on China's grain import resilience

China is the world's largest importer of agricultural commodities, with soybeans constituting its most imported crop at an external dependency rate of approximately 90%. China's wheat and corn imports have consistently exceeded tariff-rate quotas (TRQs) during 2020–2024. Meanwhile, China's soybeans, corn, and wheat imports demonstrate high concentration on a few major producing nations, with the U.S. serving as a pivotal agricultural trade partner. Consequently, U.S.-China trade frictions have significantly undermined China's grain import resilience.

U.S.-China trade frictions significantly erode China's grain import resistance capacity, manifesting in reduced import volumes, elevated import prices, and amplified price volatility. According to the theory of comparative advantage, U.S. measures such as tariff impositions and export restrictions against China have increased China's food import costs. This exposes China to risks of rising import prices and insufficient import volumes, ultimately leading to decreased import quantities, higher import prices, and increased price volatility.

U.S.-China trade frictions disrupt China's grain import rhythm, undermining its recovery capacity. China's heavy reliance on the United States and other major producers for grain imports, coupled with U.S. export restrictions under strategic trade protection theory, has significantly deteriorated China's import conditions. Given China's limited capacity to identify suitable alternative sources in the short term, import volume volatility has become inevitable. Furthermore, seasonal production cycles exacerbate these disruptions. Even when alternative suppliers (e.g., Ukraine for corn) theoretically possess surplus capacity, asynchronous harvest periods between hemispheres prolong adjustment timelines. This structural misalignment transforms transient trade shocks into sustained import instability.

U.S.-China trade frictions have elevated China's grain import dependency risks. According to economies of scale theory, US measures like tariff impositions and export restrictions against China have increased exporters' costs, thereby concentrating grain trade among fewer multinational corporations. Furthermore, these frictions have reduced China's US grain imports while increasing reliance on alternative producers like Brazil. Collectively, this has intensified China's import dependency risks, diminished diversification, and manifested in rising HHI values in China's grain import markets during the trade conflict period.

3 Empirical methodology

3.1 Empirical strategy and contextual background

The U.S.-China trade conflict entered an escalatory phase on March 23, 2018, when the U.S. administration imposed 25% tariffs on $60 billion worth of Chinese imports under Section 301 of the Trade Act of 1974. This unilateral action marked the onset of sustained bilateral trade tensions, which persisted until December 2018 when both nations temporarily suspended tariff escalations through the Buenos Aires Consensus. Subsequently, China's soybean import prices and volumes exhibited significant fluctuations, with imports from the United States even plunging to zero—a development that substantially impacted China's domestic soybean industry. The impacts on China's soybean sector have exposed systemic vulnerabilities in developing countries' food supply chains and their limited bargaining power in international trade. Therefore, examining how U.S.-China trade frictions affect China's food import resilience essentially serves as a critical test of developing nations' food import security capacity under trade conflicts. This inquiry provides insights into potential pathways for China and other developing countries to build greater autonomy within asymmetric dependency relationships.

The escalation of U.S.-China trade frictions in 2018 represents a quintessential exogenous shock. Following U.S. tariff impositions on Chinese exports, China's retaliatory measures significantly distorted bilateral trade flows and price mechanisms between the two nations. The disruption of their historically stable commercial relationship provides a unique quasi-experimental setting. Soybean trade serves as an ideal natural experiment for three reasons:

Policy exogeneity: As a non-strategic commodity with no direct linkage to China's industrial policy disputes, soybean tariffs (implemented July 6, 2018) represent an exogenous shock.

Market concentration: The U.S. supplied 34.4% of China's soybean imports pre-conflict (Customs, 2017), creating measurable baseline dependence.

Substitution elasticity: Limited short-term substitutability (Brazilian soybean production cycles lag by 6 months) amplifies observable adjustment dynamics.

Thus, we employ a difference-in-differences (DID) design to isolate the conflict's impact on import resilience metrics.

3.2 Econometric model and variable description

3.2.1 DID baseline model

Currently, there is limited research on the resilience of grain imports, with most studies relying on qualitative analysis. This study draws on the methodologies of Wei et al. (2025) and Zhu et al. (2025). Wei et al. (2025) employed a difference-in-differences (DID) approach, treating the establishment of China's free trade zones as a natural experiment to analyze the resilience of China's grain industry chain. Similarly, Zhu et al. (2025) applied the DID method, using the National Modern Agricultural Demonstration Zones as a quasi-natural experiment to examine the resilience of China's grain production. Both studies utilized the DID framework to investigate the impact of policy shocks on the resilience of China's grain industry. Building on these works, this paper constructs the following econometric model to verify the impact of Sino-US trade friction on the resilience of grain imports.

$$\mathrm{Re}sl^{1}_{i,t} = a_1 did_{it} + a_2 fri_{i,t} + a_3 time_{i,t} + a_4 P^{us}_{i-1,t} + a_5 GDP_t + a_6 ex_{i,t} + a_7 pro_{i.t} + \varepsilon_{i,t} \quad (1)$$

$$\mathrm{Re}sl^{2}_{t} = b_1 time_t + b_4 P^{us}_{t-1} + b_5 GDP_t + b_6 ex_t + b_7 pro_t + b_8 \mathrm{Re}sl^{2}_{t-1} + \delta_t \quad (2)$$

$$\mathrm{Re}sl^{3}_{i,t} = c_1 did_{i,t} + c_2 fri_{i,t} + c_3 time_{i,t} + c_4 P^{us}_{i,t-1} + c_5 GDP_t + c_6 ex_{i,t} + c_7 P_{i.t} + \gamma_{i,t} \quad (3)$$

$$\mathrm{Re}sl^{4}_{i,t} = d_1 did_{i,t} + d_2 fri_{i,t} + d_3 time_{i,t} + d_4 P^{us}_{i,t-1} + d_5 GDP_t + d_6 ex_{i,t} + d_7 P_{i.t} + d_8 \mathrm{Re}sl^{4}_{i,t-1} + \eta_{i,t} \quad (4)$$

$$\mathrm{Re}sl^{5}_{i,t} = e_1 did_{k,t} + e_2 fri_{k,t} + e_3 time_{k,t} + e_4 P^{us}_{k,t-1} + e_5 GDP_t + e_6 ex_{k,t} + e_7 \Delta P_{k.t} + \lambda_{k,t} \quad (5)$$

In Equations 1–5, the subscripts t denote time, in Equations 1, 3, 4, the subscripts i denote region, in Equation 5 the subscripts k denote region varieties. Variable *Resl* serves as the proxy for grain import resilience. In alignment with the definition of grain import resilience proposed in this study, five indicators are utilized to capture the five dimensions of resilience: import price ($Resl^1$), import price volatility ($Resl^2$), import volume ($Resl^3$), import volume volatility ($Resl^4$), and import source diversification ($Resl^5$). Here, diversification is quantified using the Herfindahl Index of import markets. Drawing on the frameworks of Lin et al. (2023) and Li and Han (2020), control variables including China's Gross Domestic Product (*GDP*), market share of exporting countries in China's grain imports (*pro*), exchange rates (*ex*), and U.S. futures market prices (P^{US}) are incorporated. These variables collectively address the effects of China's grain import demand, competitive dynamics of China's import market, import costs, and global grain pricing mechanisms on resilience. Specifically: *GDP* reflects domestic demand for grain imports; market competition structure (*pro*) influences China's bargaining power and supply accessibility; exchange rates (*ex*), adjusted by exporting countries, directly affect import costs; U.S. futures prices (P^{US}) act as a global benchmark for grain pricing. Given their theoretical and empirical relevance to China's grain import resilience, these variables are integrated into the econometric model. Additionally, P denotes the soybean import price, ΔP represents the price difference between the top two importing countries, and *fri* is a policy dummy variable distinguishing the treatment group (*fri* = 1) from the control group (*fri* = 0). The time dummy variable captures the policy implementation period: the Sino-US trade friction began on March 23, 2018, and concluded in December 2018. Thus, *time* = 1 for April–December 2018, and *time* = 0 otherwise. The interaction term *did* (*fri* × *time*) quantifies the policy effect of the Sino-US trade friction. $\delta, \gamma, \eta, \lambda$ denote residual terms, while i and t represent individual and time variables, respectively.

Regarding the specification of the DID framework: In Equation 1, soybean imports from the U.S., Brazil, and Argentina are designated as the treatment group, while domestic soybeans serve as the control group. The China-US trade friction specifically imposed tariffs on

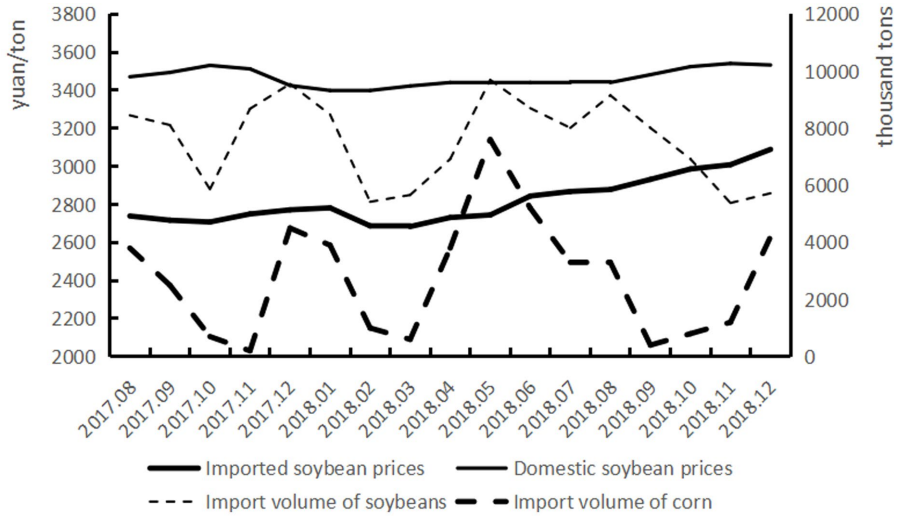


FIGURE 1
Price and import volume trends of treatment and control groups.

imported soybeans (treatment group), while domestic soybeans remained unaffected (control group). This natural experiment enables rigorous estimation of heterogeneous effects. Furthermore, as illustrated in Figure 1, their price trajectory closely mirrored that of imported soybeans prior to the Sino-US trade friction. Post-friction, imported soybean prices surged significantly, whereas domestic prices remained relatively stable, creating a divergence that satisfies the parallel trends assumption for DID analysis. For Equation 2, econometric testing reveals that imported and domestic soybean prices exhibited divergent trends prior to the policy intervention, violating the parallel trends prerequisite for control group selection.[1] Consequently, only a time dummy variable is employed to isolate the impact of the trade friction on imported soybean price volatility. In Equation 3, the treatment group comprises soybean imports from the U.S., Brazil, and Argentina, while imported corn is selected as the control group. Given that both corn and soybeans are China's primary agricultural imports, the selective imposition of tariffs solely on soybeans during the China-US trade friction creates a natural experiment. Using corn imports as the control group enables causal identification of tariff effects on import volume stability for soybeans. Furthermore, As shown in Figure 1, both soybean and corn import volumes followed similar trends pre-friction but diverged post-friction, fulfilling the DID parallel trends criterion. The experimental design in Equation 4 replicates Equation 3's treatment/control structure, as both equations analyze import volume determinants. In Equation 5, the imported soybean market is designated as the treatment group, with the imported corn market serving as the control group, to further assess differential policy effects across commodity markets.

3.2.2 Dynamic effect model

On the basis of Equations 1, 3–5, this chapter uses event analysis to construct a dynamic DID model, as follows:

$$Resl_{i,t}^{1} = \sum_{m=1}^{M} F_m\left(fri_i * time_{t+n}\right) + \sum_{n=0}^{N} L_n\left(fri_i * time_{t+n}\right) + \sum_{o=1}^{O} b_o control_{it} + \varepsilon_{it} \quad (6)$$

$$Resl_{i,t}^{3} = \sum_{m=1}^{M} F_m\left(fri_i * time_{t+n}\right) + \sum_{n=0}^{N} L_n\left(fri_i * time_{t+n}\right) + \sum_{o=1}^{O} b_o control_{it} + \varepsilon_{it} \quad (7)$$

$$Resl_{i,t}^{4} = \sum_{m=1}^{M} F_m\left(fri_i * time_{t+n}\right) + \sum_{n=0}^{N} L_n\left(fri_i * time_{t+n}\right) + \sum_{o=1}^{O} b_o control_{it} + \varepsilon_{it} \quad (8)$$

$$Resl_{i,t}^{5} = \sum_{m=1}^{M} F_m\left(fri_i * time_{t+n}\right) + \sum_{n=0}^{N} L_n\left(fri_i * time_{t+n}\right) + \sum_{o=1}^{O} b_o control_{it} + \varepsilon_{it} \quad (9)$$

In Equations 6–9, $fri * time_{t-m}$ represents the antecedent of the m ($m = 1,\ldots, M$) period of the China US economic and trade friction; $fri * time_{t+n}$ represents the lagged term of the n ($m = 1,\ldots, N$) period of the China US economic and trade friction, $control_{it}$ with being other control variables that are the same as Equations 1, 3–5.

1 This study also explored alternative controls, such as imported corn or wheat, but found inconsistent price dynamics due to China's early market liberalization and high external dependence on soybeans, which amplify its sensitivity to global market fluctuations.

3.3 Data sources

The trade data used in this study were obtained from the official website of the General Administration of Customs of China. U.S. futures price data were sourced from the Bric Agricultural Products Database, exchange rate data from the World Bank's official website, and China's GDP data from the National Bureau of Statistics of China. Monthly GDP values were calculated based on quarterly GDP data and monthly industrial value-added figures. To address endogeneity concerns, import prices were replaced with a three-month moving average of consecutive price data. Logarithmic transformations were applied to relevant variables in econometric tests to mitigate heteroscedasticity. This study employs monthly data spanning 2013–2018. For Equations 2, 4, the data selection period was narrowed to January 2016–December 2018 to isolate the direct impacts of China-U.S. economic and trade frictions by minimizing interference from multi-factor fluctuations over longer time spans. Equations 3, 5 utilize data from June 2014 to December 2018 due to publication timeline constraints on corn import price statistics. Missing values were imputed using interpolation methods.

To address potential multicollinearity concerns, we conducted diagnostic tests using variance inflation factors (VIFs). Following conventional diagnostic thresholds, VIF values below 10 are generally considered indicative of acceptable collinearity levels. As shown in Table 1, all explanatory variables demonstrated VIF values under 5, substantially below the critical threshold. These results confirm the absence of significant multicollinearity among the selected predictors in our empirical framework.

4 Analysis of empirical results

4.1 Baseline regression results and analysis

The econometric tests for Equations 1–5 were conducted in Stata 18.0 and the results are presented in Tables 2, 3. After controlling for region and year fixed effects, the coefficient on the core explanatory variable in Equation 1 equals 0.046 and is significant at the 1 percent level, indicating that Sino–US trade friction increases China's soybean import price by an average of 0.046 units; this effect likely reflects the need to source soybeans from alternative suppliers whose higher production or transportation costs, combined with China's lack of pricing power in the global market, drove up import prices. In Equation 3 the coefficient equals −1.282 and is significant at the 10 percent level, demonstrating that trade friction reduces China's soybean import volume by about 1.282 units, plausibly because higher tariffs and non-tariff barriers on US soybeans sharply increased import costs and led firms to curtail purchases from the United States and similarly affected regions. The coefficient in Equation 4 equals −0.096 but does not reach statistical significance, suggesting that trade friction has no discernible impact on the timing of soybean imports, a finding that may reflect the masking effects of firms' inventory strategies and seasonal demand fluctuations. Finally, the coefficient in Equation 5 equals −0.411 and is significant at the 1 percent level, implying a substantial decline in market diversification—as measured by the Herfindahl index—following the onset of Sino–US trade friction.

TABLE 1 Variance inflation factor.

DV	$Resl^1$		$Resl^3$		$Resl^4$		$Resl^5$	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
did	3.828	0.261	4.064	0.246	4.79	0.209	2.204	0.454
time	4.255	0.235	4.364	0.229	4.446	0.225	2.699	0.371
fri	1.289	0.776	2.105	0.475	1.73	0.578	1.209	0.827
LNGDP	2.516	0.397	1.729	0.578	1.089	0.918	2.672	0.374
LNex	1.148	0.871	1.077	0.929	1.108	0.903	1.886	0.53
LNP^{us}	1.816	0.551	1.175	0.851	1.127	0.887	1.206	0.829
LNpro	1.059	0.945	/	/	/	/	/	/
LNP	/	/	2.202	0.454	1.108	0.902	/	/
LNΔP	/	/	/	/	/	/	1.120	0.893
Mean VIF	2.273	.	2.388	.	2.200	.	1.857	.

Table 3 employs a stepwise regression approach, with the inclusion of pertinent control variables, to examine in detail the impact of Sino–US trade friction on the resilience of China's soybean imports. As shown in the table, the policy effect in Equation 1 is statistically significant at the 1% level with a positive coefficient, indicating that the China-U.S. economic and trade frictions significantly increased China's soybean import prices. Since Equation 2 incorporates a first-order lagged variable, both panel OLS and system GMM methods were applied for estimation. The GMM approach effectively mitigates endogeneity issues and demonstrates higher efficiency. Results from both panel OLS and system GMM models in Table 1 confirm that the policy effect remains significantly positive, suggesting that the trade frictions notably amplified volatility in China's soybean import prices. In Equation 3, the policy effect exhibits a statistically significant negative correlation at the 10% level, implying that the trade frictions substantially reduced China's soybean import volumes. Equation 4 shows an insignificant policy effect, indicating no statistically significant impact of the trade frictions on the import timing rhythm of Chinese soybeans. Finally, Equation 5 reveals a statistically significant negative coefficient for the policy effect at the 1% level, demonstrating that the trade frictions significantly lowered the Herfindahl index of China's soybean import market—thereby reducing the diversification level of China's soybean import sources.

The findings collectively demonstrate that the China-U.S. economic and trade frictions exerted significant adverse effects on the resilience of China's grain imports. Specifically, China's soybean import prices surged markedly, price volatility intensified, import volumes declined substantially, and import diversification diminished, reflecting insufficient price resilience and industrial upgrading capacity in China's grain import system. The vulnerabilities in price resilience and upgrading capacity primarily stem from China's high external dependency on grain imports, concentrated sourcing channels, and limited pricing power in international markets. Equation 4 suggests that the trade friction had no statistically significant effect on the temporal pattern of China's soybean imports. This resilience likely stems from import substitution: While China temporarily halted soybean imports from the U.S., the timing of the trade friction outbreak coincided with the harvest season of Brazilian soybeans (March annually). Consequently, increased imports from

TABLE 2 Results of econometric tests.

DV	Eq. 1 $Resl^1$	Eq. 3 $Resl^3$	Eq. 4 $Resl^4$	Eq. 5$Resl^5$
did	0.046***(0.010)	−1.282*(0.067)	−0.096(0.689)	−0.411***(0.010)
Constant	8.113***(0.000)	2.922***(0.000)	1.203***(0.000)	0.474***(0.000)
Observations	288	220	96	110
R^2	0.017	0.011	0.002	0.065
state	*Controlled*	*Controlled*	*Controlled*	*Controlled*
year	*Controlled*	*Controlled*	*Controlled*	*Controlled*

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 3 Results of econometric tests.

DV	Eq. 1 $Resl^1$	Eq. 2 $Resl^2$		Eq. 3 $Resl^3$	Eq. 4 $Resl^4$	Eq. 5 $Resl^5$
		OLS	GMM			
did	0.081***(0.031)	/	/	−1.480*(0.790)	−0.092(0.153)	−0.402***(0.142)
fri	0.012(0.029)	/	/	0.364(0.714)	0.027(0.098)	0.136(0.122)
time	−0.286***(0.012)	0.029*(0.075)	0.039**(0.020)	1.598***(0.421)	0.061(0.136)	−0.180***(0.058)
LNP^{us}	0.683***(0.037)	0.075(0.178)	0.122(0.209)	−0.442***(1.465)	0.070(0.424)	−0.383(0.308)
LNGDP	−0.043(0.042)	−0.213*(0.117)	−0.233*(0.130)	1.931*(1.096)	0.354(0.597)	−2.027***(0.398)
LNex	−0.026***(0.007)	−0.012(0.015)	−0.069(0.043)	0.435**(0.186)	−0.125(0.079)	−1.574*(0.896)
LNpro	0.117***(0.022)	−0.137**(0.054)	−0.160**(0.068)	/	/	/
$Resl^i_{t-1}$	/	0.429***(0.054)	0.029(0.725)	/	0.557***(0.050)	/
LNP	/	/	/	0.850(0.867)	−2.611***(0.595)	/
LNΔP	/	/	/	/	/	0.023(0.025)
Constant	3.976*** (0.658)	0.024(0.025)	0.043(0.032)	−22.947(18.459)	1.194***(0.082)	27.536***(5.019)
state	*Controlled*	*Controlled*	*Controlled*	*Controlled*	*Controlled*	*Controlled*
year	*Controlled*	*Controlled*	*Controlled*	*Controlled*	*Controlled*	*Controlled*
R^2	0.812	0.435	/	0.423	0.637	0.390
Observations	288	90	90	220	92	110

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Brazil offset the reduced U.S. imports during March–September 2018, aligning with China's typical seasonal procurement patterns. Although U.S. soybean imports remained suspended after September 2018, the December 2018 bilateral agreement to mutually reopen markets further mitigated disruptions to China's soybean import rhythm. Notably, while the 2018 trade frictions did not significantly disrupt China's soybean import patterns, potential future trade conflicts may still pose risks to the stability and diversification of China's grain import strategies.

4.2 Dynamic regression results and analysis

This section systematically examines the dynamic impact mechanisms of China-U.S. trade frictions on the resilience of China's soybean imports based on Equations 6–9, while controlling for key variables consistent with previous specifications. The regression results are presented in Table 4. The empirical analysis reveals that the policy effects of trade frictions exhibit significant time-varying characteristics and indicator heterogeneity, which can be decomposed into three dimensions:

First, regarding the immediate effects of trade friction shocks, the 5 months preceding the trade friction outbreak showed no statistically significant impact on import resilience indicators except for the soybean import diversification index. A significant negative shock emerged on both import volume and diversification index immediately upon the friction's initiation, demonstrating the direct structural reconfiguration effect of policy shocks on supply chains. Second, in terms of medium-term transmission effects, differentiated response patterns emerged across indicators: Import volumes exhibited progressively intensifying pressure, with impact magnitude significantly deepening several months post-friction; Import prices displayed significant positive fluctuations after an adjustment lag, showing persistent strengthening effects over time that confirm the existence of time-delay mechanisms in price transmission; The import diversification shock demonstrated convergent trends, reflecting market agents' dynamic adaptive capabilities. Third,

TABLE 4 Results of tests dynamic effect.

DV	Eq. 1 *Resl*[1]	Eq. 3 *Resl*[3]	Eq. 4 *Resl*[4]	Eq. 5 *Resl*[5]
Pre_5	−0.0173	0.4896	0.0360	0.0924
	(−0.38)	(0.43)	(0.17)	(0.30)
pre_4	−0.0202	0.4229	−0.1403	0.1601
	(−0.44)	(0.37)	(−1.00)	(0.51)
pre_3	−0.0255	0.7343	−0.2561	−0.2370
	(−0.57)	(0.67)	(−0.85)	(−0.74)
pre_2	−0.0307	0.3759	−0.3643	−0.2788
	(−0.69)	(0.34)	(−2.13)	(−0.86)
current	−0.0444	−0.3672	−0.1694	−0.5522*
	(−0.98)	(−0.30)	(−0.60)	(−1.69)
post_1	−0.0370	−2.4588**	−0.2305	−0.6749**
	(−0.82)	(−1.98)	(−0.70)	(−2.08)
post_2	−0.0263	−2.9829**	−0.2335	−0.6494**
	(−0.58)	(−2.40)	(−0.84)	(−2.03)
post_3	0.0469	−2.8583**	−0.2139	−0.5492*
	(1.04)	(−2.30)	(−0.91)	(−1.73)
post_4	0.1313***	−2.6051**	−0.1517	−0.6084*
	(2.90)	(−2.10)	(−0.64)	(−1.91)
post_5	0.1295***	−3.5357***	−0.3844	−0.5936*
	(2.86)	(−2.84)	(−1.23)	(−1.87)
post_6	0.1788***	−4.3990***	/	−0.4152
	(3.89)	(−3.53)	/	(−1.30)
post_7	0.1736***	−5.3653***	/	−0.4307
	(3.78)	(−4.29)	/	(−1.35)
Constant	3.2324***	21.5533	1.1624***	30.8896***
	(5.06)	(1.41)	(14.73)	(5.34)
Observations	288	220	96	110
R^2	0.743	0.361	0.132	0.295

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

regarding structural transmission mechanisms, the empirical results indicate: Import rhythm adjustments failed to achieve statistical significance, closely related to the buffering effect of China's strategic reserves and seasonal factors during the friction's onset; The asymmetry in price transmission highlights China's disadvantaged position in global soybean pricing power, with international futures market fluctuations demonstrating stronger explanatory power over domestic import prices than vice versa.

These findings yield crucial policy implications: First, the observed transmission lags provide critical time windows for establishing risk early-warning mechanisms; Second, the dynamic adjustment trajectory of import diversification underscores the necessity to strengthen market resilience through diversified supply alliances; Finally, the persistent intensification of price responses emphasizes the urgency to enhance pricing discourse power, warranting reforms in futures market mechanisms and innovations in reserve management systems. The conclusions provide theoretical foundations for improving agricultural trade risk prevention frameworks.

4.3 Robustness checks

4.3.1 Parallel trend test

Before applying the difference-in-differences method, it is essential to confirm the parallel-trend assumption to ensure that treatment and control groups followed similar paths before policy implementation. To this end, we employ an event-study design, creating a sequence of period-specific dummy variables interacted with the onset of Sino–US trade friction. Figure 2 presents the parallel-trend test results, using the "pre_1" period as the reference. All estimated coefficients for import price, volume, timing, and market diversification oscillate around zero before the intervention, and their confidence intervals include zero. This demonstrates that, prior to the trade-friction shock, the trajectories of China's soybean-import resilience indicators were statistically indistinguishable across treatment and control groups, thus satisfying the parallel-trend assumption and providing a valid foundation for subsequent difference-in-differences causal analysis.

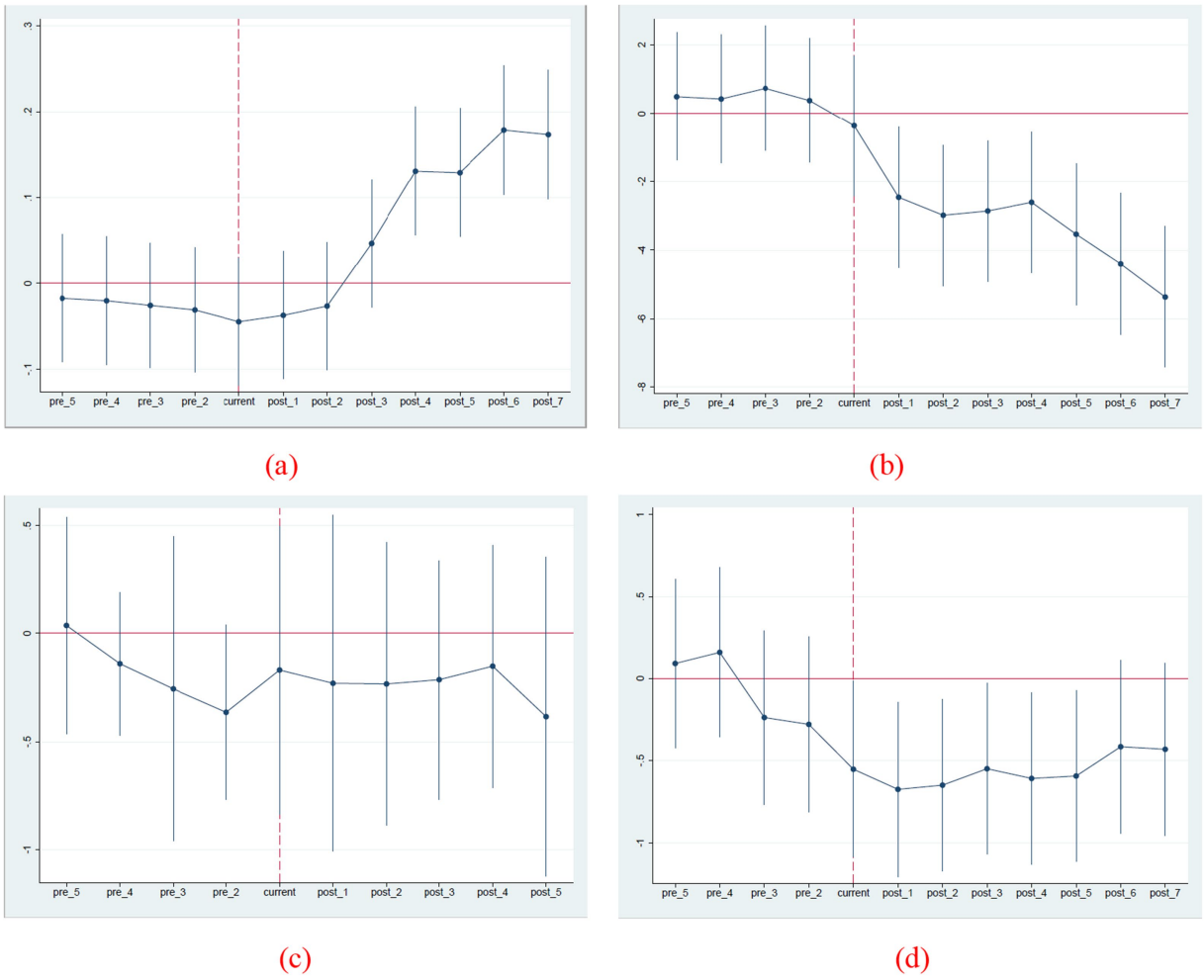


FIGURE 2
Parallel trend test of China's soybean import resilience. **(a)** Parallel trend test of import prices. **(b)** Parallel trend test of import volume. **(c)** Parallel trend test of Import rhythm. **(d)** Parallel trend test of import market diversification.

4.3.2 Placebo test

To ensure that the observed changes in China's soybean import resilience are attributable specifically to the Sino–US trade friction rather than to other unobserved factors, we conduct a placebo test inspired by Ferrara et al. (2012) and Li et al. (2016). We begin by randomly assigning trade regions to "treated" and "control" groups and independently generating fake intervention dates, thereby creating two layers of placebo experiments. For each random assignment, we re-estimate the baseline regressions from Table 2 and record the significance of the difference-in-differences coefficient. We repeat this procedure 500 times to enhance statistical power and then plot the resulting distribution of estimated coefficients in Figure 3. Had unobserved confounders driven our results, many placebo estimates would lie significantly away from zero. Instead, the distribution of the placebo coefficients is tightly clustered around zero, demonstrating that our specification does not omit any major influences and confirming that the impact of Sino–US trade friction on China's soybean import resilience is genuine and robust.

5 Impacts of the new wave of economic frictions on China's grain import resilience

The Russia-Ukraine conflict, which erupted in February 2022, triggered multiple rounds of Western sanctions against Russia, imposing severe restrictions on its participation in international trade. As both nations are critical global exporters of grain and energy, the conflict has escalated into a new wave of global economic and trade frictions, imposing significant shocks on global grain supply chains. This disruption is primarily manifested through three dimensions: heightened systemic fragility in global food networks, widespread supply chain blockages, and sharp price surges in key staple crops (Pan, 2023). Unlike the China-U.S. economic and trade frictions, China has not been directly involved in the Russia-Ukraine conflict. Nevertheless, its grain market has experienced significant volatility. It is therefore imperative to examine the shocks to China's grain import resilience, as the findings offer valuable insights for developing economies

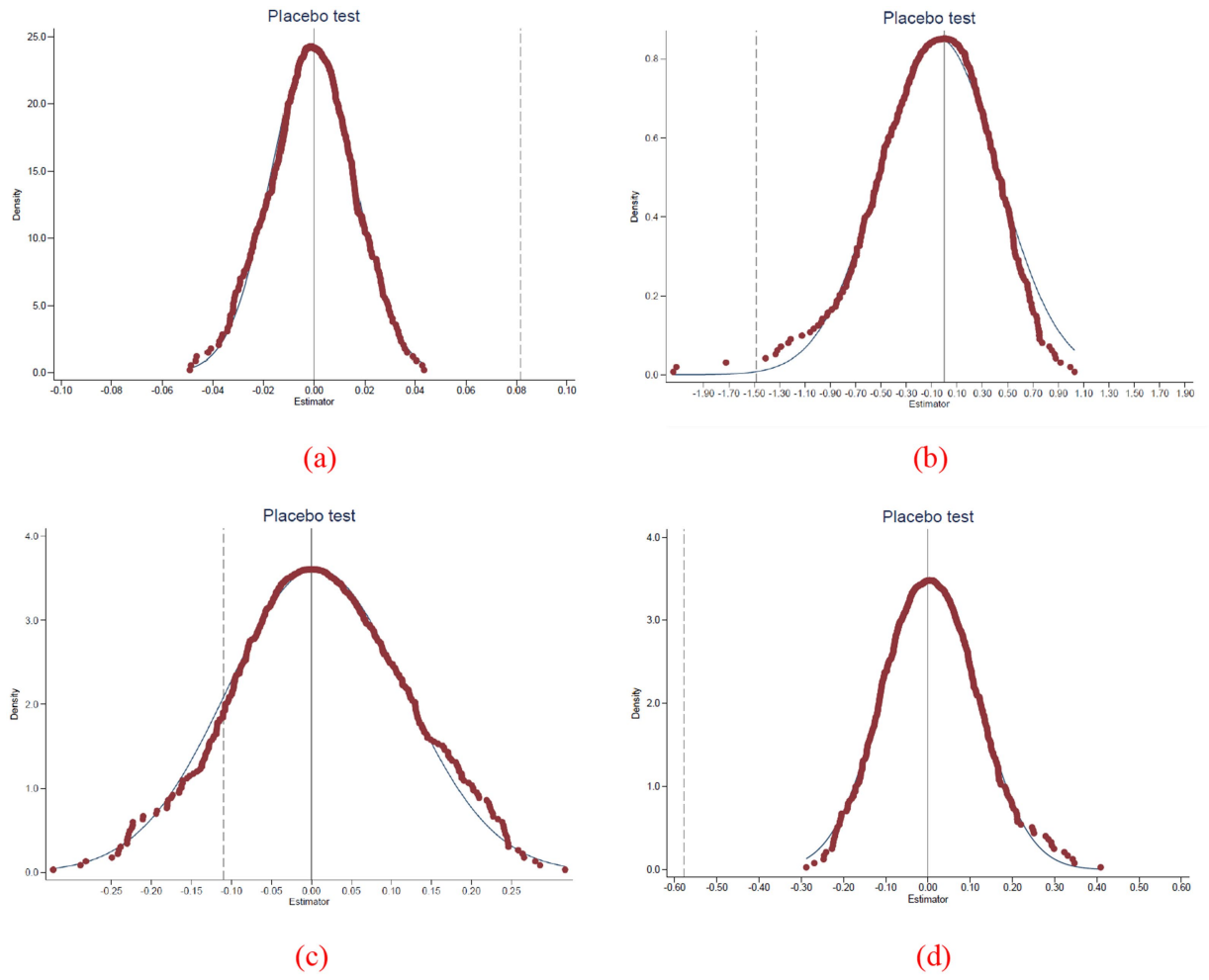


FIGURE 3
Placebo test of China's soybean import resilience. **(a)** Placebo test of import prices. **(b)** Placebo test of import volume. **(c)** Placebo test of Import rhythm. **(d)** Placebo test of import market diversification.

seeking to enhance resilience and mitigate systemic risks amid global turbulence. Given that Russia and Ukraine are major exporters of wheat and corn, with Ukraine being one of China's primary sources of corn imports and China having established wheat trade cooperation with Russia, this analysis focuses on wheat, and corn trade data to assess the impacts of the new economic frictions on China's grain import resilience.

During the Russia-Ukraine conflict, China demonstrated weak resilience in grain import pressure resistance. As illustrated in Figure 4, following the outbreak of the Russia-Ukraine conflict in February 2022, China experienced marked surges in import prices for corn and wheat. Figure 5 further reveals that price volatility for imported wheat and corn notably intensified after the conflict began. Furthermore, following the outbreak of the Russia-Ukraine conflict, China's wheat import growth rate narrowed significantly while corn imports declined substantially.[2] These observations demonstrate that China's grain import market experienced severe fluctuations during the conflict period, exhibiting inadequate pressure resistance capacity.

China demonstrated weak recovery capacity in grain imports during the Russia-Ukraine conflict. As illustrated in Figure 6, the volatility of China's corn and wheat import volumes underwent significant changes following the conflict's outbreak. With China's corn imports showing a sustained decline, the import volume volatility initially decreased gradually, before experiencing renewed fluctuations after June 2022. Concurrently, wheat import growth slowed markedly, with import volume volatility reaching a distinct peak in October 2022. These patterns reveal substantial fluctuations in China's grain import volumes during the conflict period, indicating limited import recovery capacity.

China exhibited weak industrial upgrading capacity in grain imports during the Russia-Ukraine conflict. As shown in Table 5, the HHI for China's corn and wheat import markets increased in 2022, with a particularly pronounced rise in the wheat import market concentration. Following the conflict's outbreak, China was compelled to expand corn imports from Brazil while increasing wheat imports from Australia and France, leading to greater concentration in its wheat and corn import markets. These

2 Calculated from official data of China's general administration of customs.

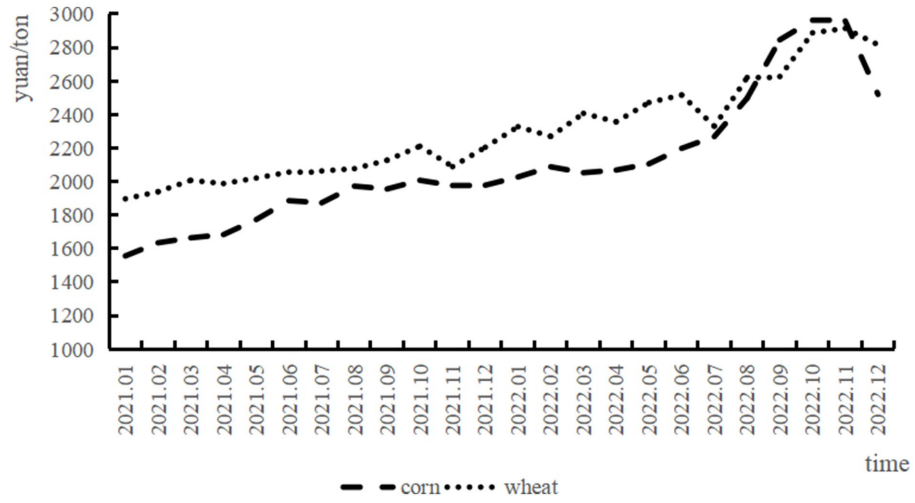


FIGURE 4
Import prices of China's corn and wheat. Data source: official website of the general administration of customs of the People's Republic of China.

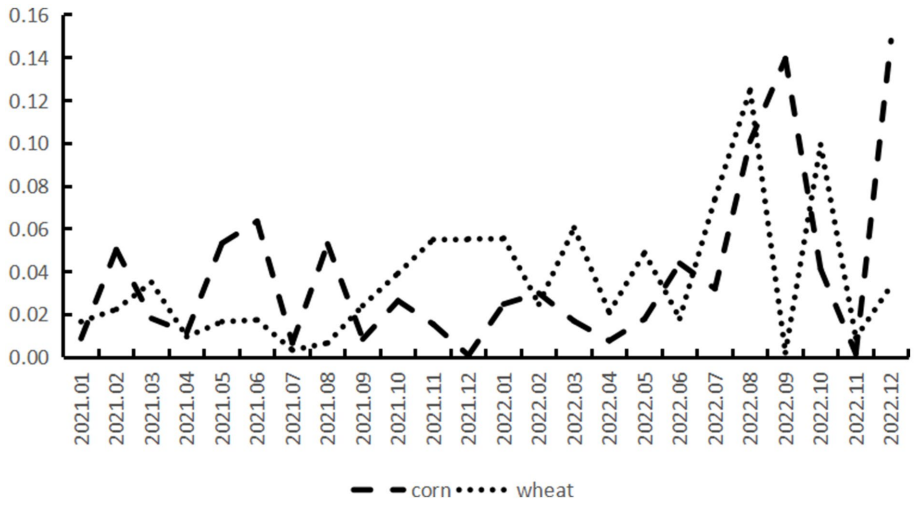


FIGURE 5
Import price volatility of china's corn and wheat. Data source: Official website of the general administration of customs of the People's Republic of China.

developments reveal the negative impact of the new wave of economic and trade frictions on the diversification of China's grain imports, thereby undermining its capacity for industrial upgrading in grain import markets.

In summary, the new wave of economic and trade frictions has indeed exerted significant impacts on China's grain import resilience, as evidenced by suboptimal performance across three critical dimensions: resistance capacity, recovery capacity, and transformative upgrading capacity. This reveals that such resilience is influenced not only by direct trade conflicts between China and other nations, but also indirectly through global economic confrontations between third-party countries. The global grain market currently exhibits a structural dichotomy: production and exports are highly concentrated in a limited number of countries, while consumption and imports are geographically dispersed. This configuration exacerbates market vulnerability to external shocks, including export policy adjustments, oligopolistic practices among suppliers, logistical disruptions, and regional conflicts (Wang and Wu, 2024). Therefore, economic and trade frictions between major grain-producing nations inevitably generate spillover effects on global markets, exposing grain-importing countries to persistent external risks. Concurrently, many developing countries occupy a structurally disadvantaged position within the global grain market, rendering them particularly vulnerable in securing stable food supplies. This phenomenon underscores the inadequate import resilience of developing economies, which exhibit greater sensitivity to price fluctuations and more vulnerable supply chains—often trapped in the dual dilemma of "high import dependence coupled with low adaptive capacity."

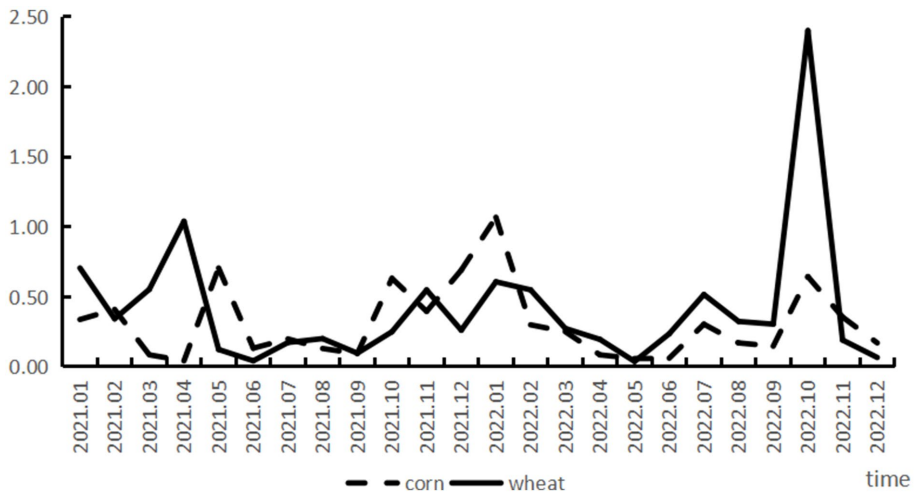


FIGURE 6
Fluctuation rates in China's rice and wheat import volumes. Data source: Official website of the General Administration of Customs of the People's Republic of China.

TABLE 5 HHI of China's rice and wheat import markets.

	2017	2018	2019	2020	2021	2022
Corn	0.489	0.701	0.751	0.459	0.574	0.585
Wheat	0.341	0.277	0.278	0.143	0.231	0.402

Data source: Compiled from official statistics published on the website of the general administration of customs of the People's Republic of China.

6 Research findings and policy implications

Against the backdrop of increasingly complex global dynamics, this study articulates the conceptual dimensions of grain import resilience, systematically examines the impact mechanisms of China-U.S. geo-economic tensions on grain import resilience, and quantifies these effects through a quasi-natural experiment design based on the 2018 bilateral economic confrontation. The principal findings are as follows:

First, grain import resilience constitutes a multi-dimensional construct encompassing shock absorption capacity, recovery capacity, and structural upgrading capabilities, which collectively safeguard national food security through their interdependent mechanisms. Second, the 2018 China-U.S. geo-economic tensions exerted significant negative impacts on grain import resilience. Empirical analysis reveals that during this period, soybean imports exhibited substantial price escalation, intensified price volatility, and notable declines in both import volume and source diversification, demonstrating deficiencies in price shock resistance and structural adaptation, though recovery capacity remained relatively resilient. Third, China's grain import resilience faces compound risks from indirect spillover effects of global economic confrontations. The 2022 geo-economic turbulence triggered synchronized pressures across staple grains: price surges, amplified volatility, import contraction, disrupted procurement patterns, and reduced source diversification, collectively indicating systemic vulnerabilities in risk buffering, market rebalancing, and supply chain transformation that necessitate continued vigilance against international market instabilities.

As the largest developing economy, China's experience with the U.S.-China geo-economic tensions provides critical insights into grain import resilience challenges confronting developing nations. Typically characterized by insufficient import resilience, developing economies face heightened risks of abnormal fluctuations in both import volumes and prices—along with increased import concentration—whether through direct bilateral trade conflicts or indirect global market disruptions. These findings underscore the imperative for China and peer developing countries to enhance grain supply chain resilience through the following strategic measures.

First, promote the diversification of import sources. Following the China-US trade friction, China has accelerated cooperation with emerging agricultural countries such as Brazil, Russia, and Southeast Asian nations to reduce its reliance on the United States. Following the outbreak of the Russia-Ukraine conflict, Egypt mitigated its supply gap by increasing grain imports from Romania and France (FAO, 2023). Therefore, developing countries should also actively explore new trade partners, strengthen agricultural collaboration with other developing nations, and formulate differentiated import strategies for various grain categories to avoid excessive concentration in a single product.

Second, promote the localization of production capacity enhancement initiatives. Developing countries should strengthen farmland water conservancy infrastructure by constructing irrigation systems and improving medium- and low-yield farmland. For instance, India has implemented the National Mission for Sustainable Agriculture (NMSA-RKVY), enhancing agricultural productivity and sustainability through the adoption of organic farming practices, precision agriculture technologies, and water-saving irrigation systems (Meng, 2025). Additionally, developing countries should promote agricultural technological innovation to enhance crop yields. The Indonesian government has forged public-private partnerships with agri-tech firms to deliver multimodal training programs for farmers. The adoption of novel technologies now constitutes the paramount

pathway for enhancing the nation's grain sector (Pan, 2023). Furthermore, developing countries shoul strengthen their enabling policy frameworks, exemplified by establishing agricultural insurance schemes and refining rural credit mechanisms. Illustratively, Brazil's provision of diversified agricultural credit instruments has accelerated the industrialization and commercialization of large-scale farms, thereby boosting agricultural output (Meng, 2025).

Third, establish new regional cooperation models. Developing countries should actively enhance cooperation by establishing regional food trade alliances, such as the China-ASEAN Food Security Partnership, to facilitate market information sharing and coordinated emergency reserves. Furthermore, within frameworks like RCEP and BRICS, they should reduce tariffs on food imports, streamline inspection and quarantine procedures, and promote trade facilitation.

Fourth, establishing reserve systems. China's quadripartite grain reserve system–integrating central government, local authorities, enterprises, and farm households–maintains coupled reserves of raw grains and processed grain products, effectively mitigating supply chain disruptions (Cheng and Zhu, 2020). Developing countries should establish robust grain reserve systems by defining reserve scales, rotation protocols, and emergency release procedures. Additionally, they should modernize storage infrastructure by enhancing ventilation and pest control functions in grain storage facilities. Promoting scientific grain storage equipment among smallholder farmers will further strengthen storage capacity to withstand sudden disruptions.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

Author contributions

DH: Writing – review & editing, Writing – original draft. YW: Writing – review & editing, Writing – original draft, Formal analysis, Software. S-SC: Writing – review & editing, Writing – original draft, Methodology, Software.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fsufs.2025.1593613/full#supplementary-material

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Roads, trade, and growth: PPML evidence on Pakistan's vegetable export performance

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The China-Pakistan Economic Corridor (CPEC) with the objective of enhanced infrastructural development, trade cooperation, and regional economic prosperity is a pivotal project. This study investigates the patterns and prospects of CPEC on vegetable exports in Pakistan. We analyze a panel dataset of Pakistan's vegetable export destinations countries from 2003 to 2021. We preferred the Poisson Pseudo Maximum-Likelihood (PPML) as the state-of-the-art technique in the trade gravity framework for estimation. The findings revealed that Pakistan's economic activities with the countries linked with CPEC have grown. The total length of the road as a proxy of road infrastructure is a key factor in determining Pakistan's vegetable export performance. The importer countries' GDP and the legacy of colonial links also enhance Pakistan's vegetable export performance. Distance, contiguity, and language negatively affect Pakistan's vegetable exports. Additionally, rising domestic vegetable consumption has reduced export capacity while increasing imports. Moreover, we also found an inverse relation of vegetable exports to the countries that were part of Pakistan in the past. Finally, based on the findings of our estimates we put forth suggestions to respond to the vegetable trade deficit of Pakistan.

KEYWORDS

agriculture, vegetables, trade, BRI, CPEC, infrastructure, gravity model

1 Introduction

The China-Pakistan Economic Corridor (CPEC), is known as the most ambitious project of the 21st century partnership between China and Pakistan (Hassan, 2020; Ahmad et al., 2024). CPEC links western parts of China to Pakistan's Gwadar Port. The geographical coverage of CPEC also includes Afghanistan and Iran (Escap, 2021). Launched in 2013, the project is divided into three phases with goals set for 2030. In the first phase spanning 2015–2022, CPEC priorities are the infrastructure, the port's development, and the energy sector. In the second phase spanning 2021–2025, CPEC brings efforts to revive the information and technology, industrial sector, and agricultural sectors, and develop Special Economic Zones in Pakistan. The road infrastructure spanning over 3,000 km is an integral part of the corridor by shortening the distance for trade. The economic corridor leads to alleviating poverty, expanded trade, and economic integration (Ullah et al., 2018; Rahman et al., 2021). The past decade has aroused tremendous debate, with a primary focus on the global economy, strategic relations, and geopolitics (Don McLain, 2019; Hussain and Jamali, 2019; Khan, 2020). However, one aspect that deserves a comprehensive investigation is its impact on agricultural trade performance (Irshad and Anwar, 2019; Asghar et al., 2021; Wen and Saleeem, 2021; Yar et al., 2021).

Globally agriculture significantly contributes to maintaining food stability and economic growth (Pawlak and Kołodziejczak, 2020). According to the Pakistan Economic Survey, 2022–2023 agriculture sector accounts for around 22.9 proportion of the GDP and contributes to the country's employment by creating 37 percent engagement (GoP, 2022-23). Pakistan's agriculture sector also contributes to food availability and supports the industrial sector by providing them with raw materials. This highlights the agriculture sector as the key area for growth, development, and economic reliance.

As of 2022, Pakistan has ranked as the 5th largest populated country with a population growth rate of 1.9 percent annually. The crops sector is of prime importance for feeding the 235.8 million population of the country. Among crops, vegetables with a diverse range of cultivation and being grown on small landholdings are of great importance in the agricultural sector of Pakistan (Khan and Chen, 2024). As of 2021, in Pakistan, vegetables are cultivated on 0.26 million hacter land with production of 4.3 million tons. Onions, tomatoes, and potatoes contribute 65 percent to the total annual production of vegetables (GoP, 2022). Despite the agriculture sector sustains Pakistan's economy, the vegetable sector faces a trade deficit in the international market (see Figure 1). Poor infrastructure for transportation, storage, and processing and the famine of knowledge about the markets are the key factors that undermine the performance of Pakistan's vegetables in the global market (Azam and Shafique, 2017).

International trade leads to a prosperous economy and serves as a source of foreign exchange earnings (Frankel and Romer, 1999; Makhmutova and Mustafin, 2017; Khan et al., 2020). When it comes to Pakistan-China, China is not only Pakistan's very close ally but also the largest trade partner (Khan et al., 2024). China stands as the second top export destination of Pakistan (TDAP, 2022). Table A1 (Appendix) presents Pakistan's agricultural and vegetable dynamic with China. Pakistan's agricultural exports to China experienced tremendous growth during the period from 2003 to 2021. Pakistan's agricultural exports surged from 193,558 thousand US dollars in 2003 to 1,794,739 thousand US dollars in 2021, marking an 826% increase. Agricultural imports from China at this period also show substantial growth. Although, the overall trade trend is increasing and positive. However, the share of vegetable exports to China is tiny. The vegetable exports have grown from 67 thousand US dollars in 2003 to 109 thousand US dollars in 2021. At the same time, Pakistan's vegetable imports from China have also grown rapidly resulting in the trade deficit. Although China shares a border with Pakistan most of the trade activities rely on sea routes, which are not only costly but also time-consuming. The CPEC infrastructure is likely to reduce both shipping time and carriage costs leading to an increase in bilateral

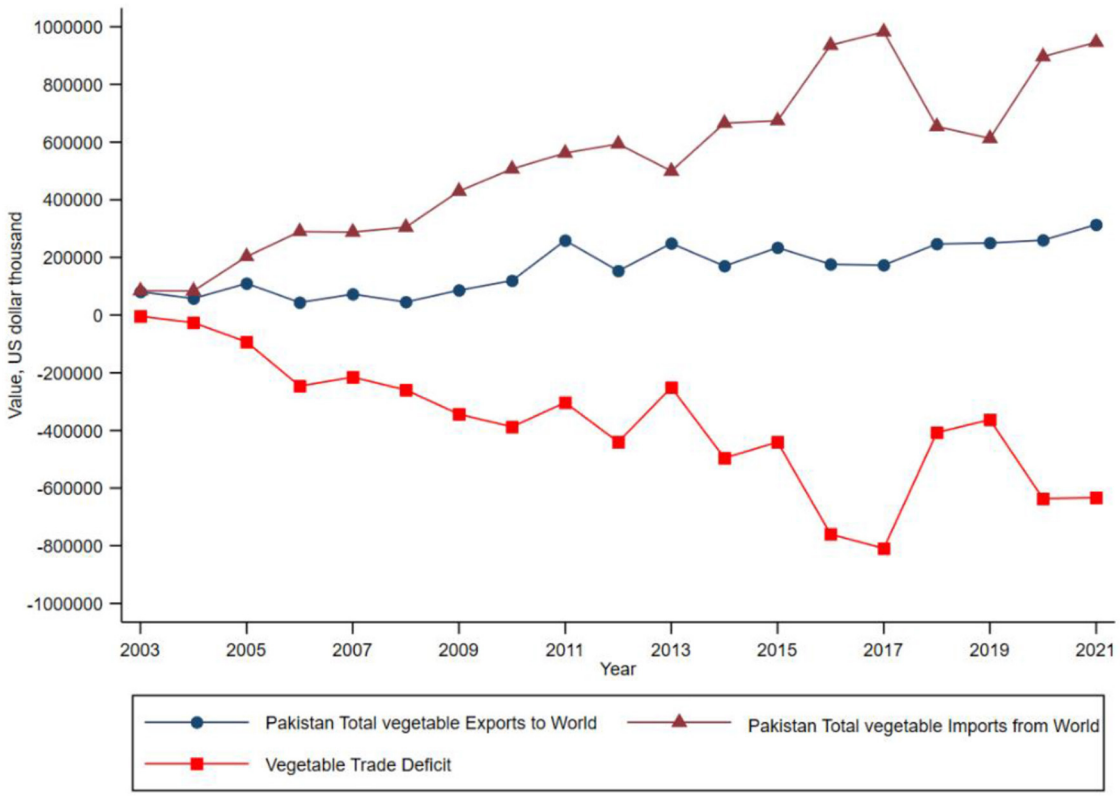


FIGURE 1
The line graph illustrates the annual trend of Pakistan's vegetable exports, imports, and trade deficit in USD thousand from the year 2003 to 2021, based on data from ITC, Pakistan Bureau of Statistics, and authors' estimations.

trade (Ali et al., 2022). The new route of CPEC from Kashghar, China to Gwadar will reduce the distance by about 80 percent (Shaikh et al., 2016; Lee et al., 2018). This will also enable Pakistan to export previously uncompetitive perishable agricultural harvests to the Chinese market. In the nexus of CPEC and trade, investigating the influence of CPEC on the agriculture industry in Pakistan is very important.

In the past decade, a vast literature about CPEC mainly focused on the global economy, strategic relationships, and geopolitical issues. For instance, Hali et al. (2015); Hussain (2017); Ahmed (2019); Don McLain (2019); Hussain and Jamali (2019); Khan and Liu (2019) addressed economic development in Pakistan, regional dynamics, geopolitical issues, and challenges of the CPEC. Ali (2018); Ali et al. (2018); Raza et al. (2018) studied the power and energy sector covered under the CPEC project. They determined that CPEC will help address Pakistan's energy shortfall. Boyce (2017); Garlick (2018) highlighted the economic, geographical, and security vulnerabilities confronted by CPEC in connecting China to the Indian Ocean. A major portion of the existing works places minimal focus on the CPEC and agricultural nexus, especially trade in perishable agricultural products.

We explore the contribution of the multi-billion-dollar CPEC on agricultural trade to fill this research gap. The enhanced road infrastructure under CPEC will reduce the trade cost and travel time to approach the Chinese market as well as other international markets. Thus, we will specifically investigate the transformative contribution of CPEC and road infrastructure to the vegetable exports of Pakistan. We will also examine the factors that determine the vegetable trade deficit.

This study has immense contribution in the following manners. First, to our knowledge, this is among the very first studies that evaluate the CPEC and agricultural trade nexus with a commodity-specific approach by addressing vegetable trade. Second, we utilize the total road length data of Pakistan as a proxy of the road infrastructure to find the effectiveness and implications of enhanced road infrastructure on the perishable agricultural produce of Pakistan (vegetables). Third, this study gives insight into the possible drivers that lead to Pakistan vegetable's trade deficit in the international market.

We structure this piece in the following manner. In section 2 of this article, we extend an overview of Pakistan's agricultural exports and discuss recent literature. Section 3 offers comprehensive pieces of information on the research approach and data utilized in the study. The results are given in Section 4. A comprehensive discussion of the findings is presented in Section 5 while Section 6 concludes the findings of the study.

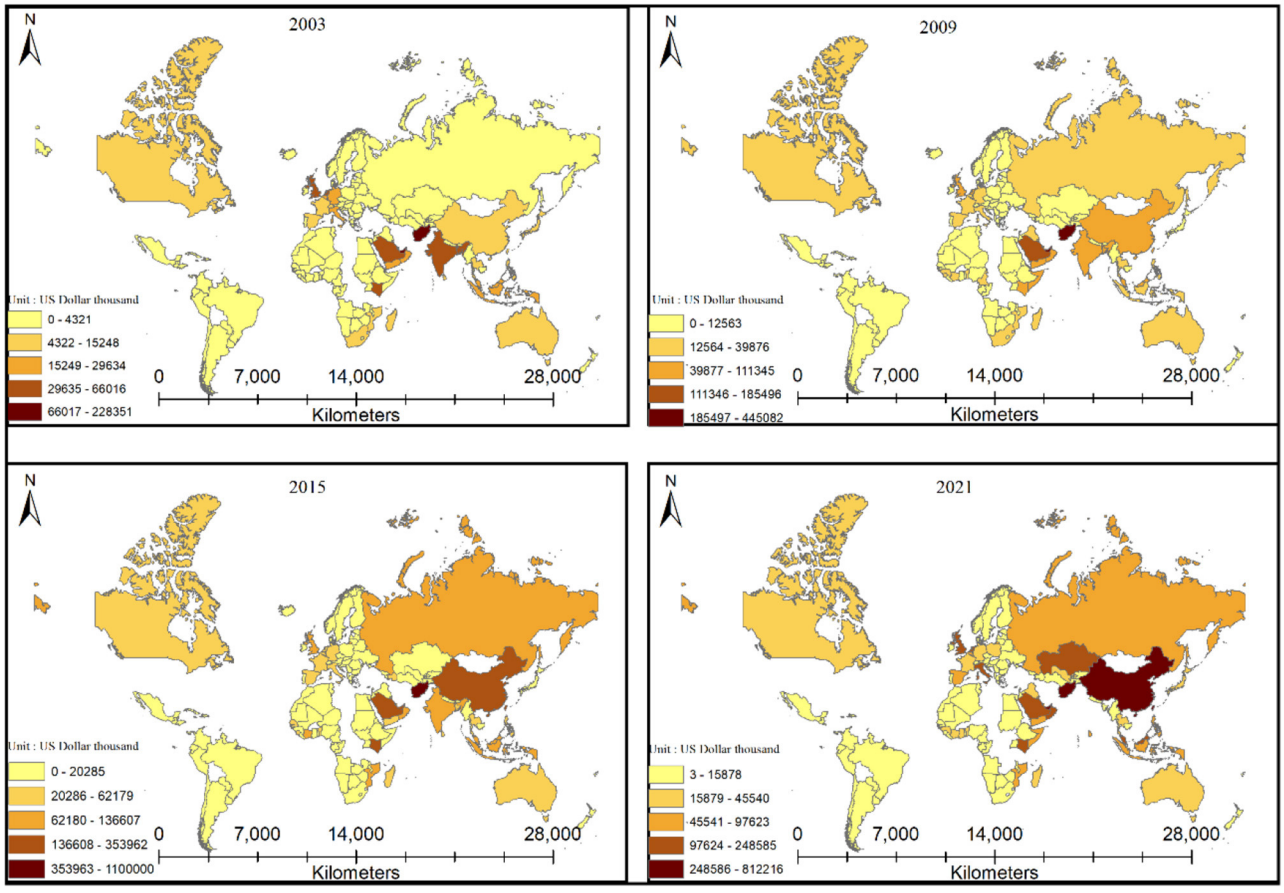


FIGURE 2
Map shows the distribution of Pakistan's agricultural exports to destination countries in 2003, 2009, 2015, and 2021. Data from ITC, based on the Pakistan Bureau of Statistics, is presented in USD thousands. Export values are indicated by color intensity, with darker shades representing higher export volumes (Basemap from Esri Garmin Map created in ArcMap 10.8).

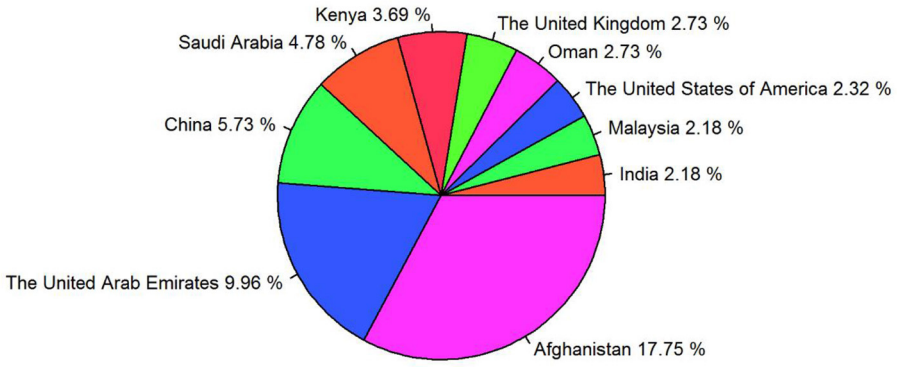


FIGURE 3
Pie chart presenting Pakistan's top 10 agricultural export markets by percentage from 2003 to 2021, based on ITC data from the Pakistan Bureau of Statistics, with estimations by the author.

2 Overview of Pakistan's agricultural exports

Pakistan exports agricultural commodities to a variety of countries, each contributing distinctively to its overall export volume. Pakistan agricultural exports in Figure 2, for the years 2003, 2009, 2015, and 2021 reveal an interesting trend in export destinations. One noticeable pattern is the increasing prominence of China as a destination market for the agricultural exports of Pakistan. The rising demand for Pakistan's agricultural harvests in the Chinese market, trade agreements between the two nations, and China's economic growth and development are all contributing causes to the rising export volumes to China. This pattern highlights how crucial China is as a market for Pakistan's agricultural produce and the necessity of ongoing cooperation and market presence in the rapidly expanding Chinese market. The statistics in Figure 2 clearly show a substantial growth in exports to China during the study period. The agricultural exports to China expanded from 8,923 (US dollars thousand) in 2003 to a staggering 812,216 (US dollars thousand) in 2021. This exponential growth highlights China's advent as a major destination for the agricultural produce of Pakistan and signifies the strengthening trade relationship between the two countries.

Apart from China, other noticeable changes in export destinations include significant increases in export volumes to countries like India, the United Arab Emirates, and the United States. The agricultural export for these countries also observes a notable rise over the years, indicating a diversification of export markets for Pakistan's agricultural products. There are also shifts in regional trade patterns, Southeast Asian countries and the countries in the Middle East are emergent key destinations for Pakistan's agricultural produce. The observation reflects a strategic focus on expanding trade in these regions, possibly driven by growing demand, favorable trade agreements, and economic development in these countries.

2.1 Composition of agricultural exports from Pakistan

Figure 3, presents the percent contribution of the 10 key export destinations of Pakistan's agricultural produce from 2003 to 2021. Malaysia and India each account for 2.18% of the exports, indicating a tiny, yet consistent share of the total export volume. The United States of America has a slightly higher share at 2.32%, reflecting a marginally larger demand for agricultural products from Pakistan within its extensive market. Oman and the United Kingdom both contribute 2.73%, which highlights equivalence in their import volumes and a moderate, stable demand. Kenya stands at 3.69%, showcasing a distinct footprint in the agricultural import market in East Africa. Saudi Arabia's contribution at 4.78% signifies a higher demand in the Middle Eastern region, underpinning its role as a significant trading partner for Pakistan's agricultural exports.

Further highlighting the regional demand distribution, China accounts for 5.73% of the agricultural exports from Pakistan. This substantial volume underlines China's considerable import capabilities and the two nation's solid bilateral ties. The United Arab Emirates (UAE) holds a significant portion of 9.96%, emphasizing its strategic position as a major hub for re-exports and consumption within the Middle Eastern market. Dominating the agricultural export destinations is Afghanistan, with a remarkable 17.75% share. This high percentage indicates an exceptionally strong bilateral trade relationship and a vital dependency on Pakistan for agricultural supplies. This diverse distribution of export percentages underscores the strategic significance of each market and reflects Pakistan's capacity to cater to the varying demands of different countries.

Figure 4, displays the diversity and scale of Pakistan's agricultural export portfolio. The top 10 agricultural exports of Pakistan in 2021 highlight the substantial contribution of HS 52 (Cotton), which dominates the chart with exports worth $3,413,592 thousand, making it the top export category. Trailing behind, HS 10 (Cereals) shows significant export numbers as well, totaling

$2,266,035 thousand. Although significantly smaller compared to the top two categories, HS 08 (Edible fruits, etc.,) holds the third place with an export of $492,855 thousand. It is closely followed by HS 22 (Alcoholic and non-alcoholic beverages, spirits, and vinegar) at $403,565 thousand and HS 03 (Fish, shellfish, and other aquatic invertebrates) at $399,389 thousand. Next in line are HS 02 (Meat and edible meat offal) and HS 07 (Vegetables, roots, and tubers) with export values of $340,935 thousand and $313,685 thousand, respectively. Moderate contributions come from HS 12 (Oilseeds, nuts, grains, and fruits used for industrial or medicinal purposes) at $295,764 thousand, while HS 17 (Sugar and confectionery—sugar based) and HS 09 (Coffee, tea, herbal teas, and spices) represent the minimal level, with export of $153,574 thousand and $127,058 thousand, respectively.

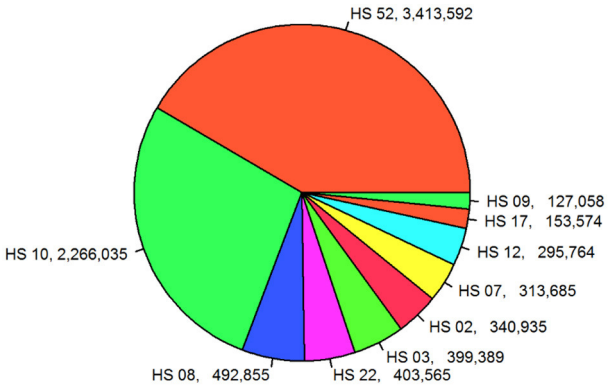


FIGURE 4
Pie chart illustrating exports of Pakistan's top 10 agricultural products for the year 2021, based on ITC data from the Pakistan Bureau of Statistics, with estimations by the author. Export values are in USD thousands.

The export of HS 07 "vegetables roots and tubers (edible)," from Pakistan to various international destinations in 2021, reveals significant variability in import values, reflecting the diverse demand across these regions (See Figure 5). Malaysia stands out as the largest importer, with an import value of $66,432 thousand, indicating a strong market for these commodities. Afghanistan also exhibits substantial demand with an import value of $57,947 thousand. The markets of Sri Lanka and the United Arab Emirates display notable import values of $49,985 thousand and $49,079 thousand, respectively, suggesting significant consumption patterns in these countries. Mid-range importers include Qatar, Oman, and the Russian Federation, with values of $24,460 thousand, $15,415 thousand, and $15,390 thousand, respectively, denoting moderate trade volumes. Smaller yet consistent import volumes are observed in Singapore ($6,794 thousand), Bahrain ($5,208 thousand), and France ($4,964 thousand). This detailed statistic underscores the global distribution and economic importance of "vegetable roots and tubers (edible)," exports from Pakistan, highlighting diverse market penetration and the varying scale of dependence on these agricultural commodities across multiple regions.

2.2 Literature review

We provide a brief literature review of our study in this section. The literature review section comprises two parts. The first part gives insight into previous studies conducted on CPEC and the second part discusses the role of infrastructure in trade. To provide a deeper analytical foundation for Pakistan agricultural

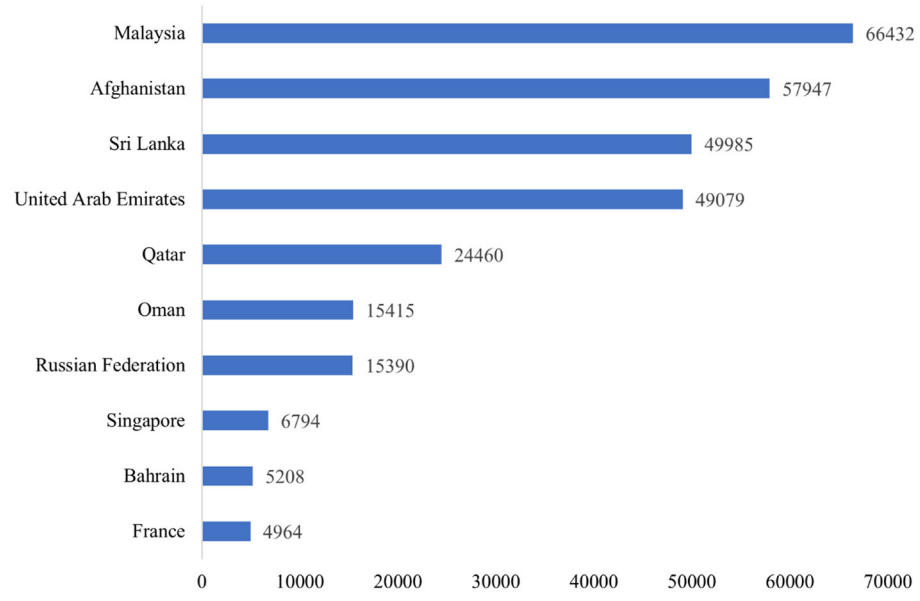


FIGURE 5
Bar chart demonstrating Pakistan's top 10 vegetable (HS 07) export destinations for the year 2021, based on ITC data from the Pakistan Bureau of Statistics, with estimations by the author. Export values are in USD thousands.

export performance, this literature review draws on core trade theories. The gravity model of trade posits that trade flows are determined by economic size and inversely influenced by trade costs, including infrastructure-related frictions (Anderson and Van Wincoop, 2003). In parallel, trade cost theory emphasizes the role of logistics, transportation, and institutional efficiency in shaping trade outcomes (Djankov et al., 2010). These theoretical lenses inform our assessment of how infrastructure development, including major initiatives under CPEC, has the potential to influence the spatial and temporal distribution of Pakistan's vegetable exports.

2.2.1 China-Pakistan economic corridor

CPEC's multifaceted and various trajectories have been the subject of interest for many researchers in the past decade (Sroosh and Sabir, 2013; Khalid, 2015; Ahmed, 2017; Sher et al., 2019; Kamran et al., 2021; Baig et al., 2023).

In this conjunction, Khan (2019) attempted to investigate the contribution of CPEC to regional connectivity and examine the challenges faced. Their results suggest transparency and the involvement of the stakeholders to obtain a positive effect on Pakistan and the South Asia region. Hadi et al. (2018) studied the potential role of CPEC in Pakistan. Their study concluded that CPEC will lead to prosperity, growth, and development in Pakistan. Spies (2021) explored the CPEC infrastructural development and investment. His study focused on the agricultural sector of Gilgit Baltistan, Pakistan. This study argues that, unlike the CPEC narrative, some agricultural exports are facing challenges like trade barriers and competition in Xinjiang, China. Ejaz et al. (2022) evaluated how CPEC's infrastructure could potentially influence Pakistan's trade volume. They employed the ARDL technique to estimate time series data spanning 1991–2020. Their results explain the positive connotation of the CPEC infrastructure with the trade volume of Pakistan. However, the results for some control variables were found insignificant. Likewise, Tabasam and Ismail (2019) examine the significance of transport infrastructure by employing the trade gravity model. Their study suggests that improving infrastructural connectivity enhances the agriculture trade by cutting transportation charges and time. Further, the study suggests that it is necessary to connect rural communities to highways if they are to benefit from CPEC. Some research examines how CPEC impacts the industrial sector of Pakistan. For instance, McCartney (2022) with theoretical and historical shreds of evidence to analyze the potential influence of CPEC on the industrial sector of Pakistan. Their findings revealed that CPEC has a supportive contribution to Pakistan's local employment. Their findings suggest that CPEC will shorten the trade routes to China, improve logistics, and make Pakistan's economy prosperous.

After thoroughly reviewing the literature we draw the following conclusions. Enhanced infrastructure is crucial for both domestic and international trade, more specifically for perishable agricultural commodities. Most of the previous studies are focused on regional connectivity, geopolitical issues, and other challenges faced by the economic corridor. Only a few of them attempted to find the contribution of CPEC to trade however they were limited to a specific area and varying outcomes. Hence we measure the contribution of CPEC to Pakistan's agricultural harvests with a focus on vegetable exports.

Concerning the estimation of trade analysis various techniques are followed in the recent literature (Nuno-Ledesma and Villoria, 2019; Yu et al., 2020; Saeed et al., 2021; Douch and Edwards, 2022). Some researchers favored the trade gravity to estimate the trade flow (Irshad and Anwar, 2019; Guan and Ip Ping Sheong, 2020; Subhan et al., 2021; Yotov, 2022). With its simple and intuitive framework, derived from Newton's law of gravity, the model became a rational choice for economists (Anderson, 1979; Anderson and Van Wincoop, 2003).

2.2.2 Infrastructure

Plenty of literature exists that uncovers the role of infrastructure in the context of trade cost, trade volume, and economic growth (Aschauer, 1989; Day and Zou, 1994; Ejiogu et al., 2000; Nordås and Piermartini, 2004; Sun and Heshmati, 2010; Ismail and Mahyideen, 2015; Wang et al., 2020). The impact of infrastructure on trade performance is supported in the trade economics literature. According to the gravity model, reductions in trade costs, stemming from improved roads, logistics, and transit systems, tend to increase bilateral trade volumes. This is particularly pertinent for perishable products such as vegetables, where delays or inadequate transport infrastructure can result in quality deterioration and financial loss. Limao and Venables (2001) and Djankov et al. (2010) have shown that inadequate infrastructure significantly raises trade costs, reducing a country competitiveness. In Pakistan, recent road infrastructure investments particularly those aligned with the CPEC) have been designed to reduce internal transport bottlenecks, improve access to seaports, and facilitate regional connectivity.

In this instance, Di Stefano et al. (2021) assessed the influence of improved infrastructure under the Belt and Road (BRI) on trade flow. Their study utilized the gravity model for the countries that are participating in the BRI. The findings suggest stronger bilateral trade among the countries linked to BRI. Baniya et al. (2020) uncovered the infrastructural development resulting in enhanced transportation and trade in the BRI countries. They used the gravity equation for estimation. They found that BRI has enhanced trade by up to 4.1 percent. They further argue that countries that are well connected and products that rely on quick delivery benefit more from enhanced infrastructure. In the same context, Alam et al. (2019) compared the trade route of CPEC with the existing route for a container with a size of 40 feet. The outcomes revealed that CPEC road infrastructure has not only shortened travel time but also reduced cost. In the context of the BRI, Reed and Trubetskoy (2019) by employing the gravity equation explore the impact of transportation investment. Their findings in the context of infrastructure are more interesting and broader. They argue that improved infrastructure is not just limited to one country or area but they have a positive impact on various regions. Edwards and Odendaal (2008) studied how infrastructure like seaports and road networks affect trade between countries. They employed the gravity equation and found that investing in better road infrastructure can lead to more trade with other countries. Bougheas et al. (1999) enhanced the model by incorporating transportation costs. Their

study results suggest that transportation costs and the quality of infrastructure are inversely related.

3 Research methodology and data statistics

This section outlines the primary methodology and model applied in this research, along with details regarding the dataset. Additionally, it includes a concise descriptive analysis of the dataset.

Drawing on literature we proceed with the trade gravity model. Characterized by Newton's law, the gravity model of trade explains that the trade turnover and the economic masses of countries have a direct relation. Countries with larger GDPs probably have more trade with each other. While the geographical remoteness between countries and trade volume has a negative relation. Geographically countries closer to each other are prospected to more trade with each other. In our case, we assume that the exports of the country are directly proportionate to their GDPs and inversely to their remoteness. The simplest gravity model of trade is illustrated as follows:

$$Exp_{ij} = A\left(GDP_i \times GDP_j\right)^{\beta} D^{\gamma} e_{ij} \quad (1)$$

Where *i and j* are the exporter and importer countries, respectively. *Exp* represents the export volume from exporting to destination countries. GDP_i and GDP_j indicated the gross domestic product values of both *i* and *j* countries. The stochastic term is e_{ij}. The coefficients β and γ are to be estimated. Equation 1 after log transformation is given as follows:

$$Ln(Exp_{ij}) = \beta Ln\left(GDP_i\, GDP_j\right) + \gamma LnD^{\gamma} + e_{ij} \quad (2)$$

Besides GDP and Distance, researchers commonly augmented the model with binary variables *comlang* (common language), *contig* (contiguity) *comcol* (common colonizer), *colony,* and *smctry* (same country before; Melitz, 2007; Trotignon, 2010; Jámbor et al., 2020). Likewise, some researchers augmented the model with the exchange rate, infrastructure, and population (Guan and Ip Ping Sheong, 2020; Hussain et al., 2020; Banik and Roy, 2021). Hence, we use the augmented model as shown in Equation 3, to find the association of CPEC with Pakistan's vegetable exports.

$$\begin{aligned} LnVegExp_{pjt} = {} & \beta_0 + \beta_1 LnGDP_p + \beta_2 LnGDP_j - \beta_3 LnD_{pj} \\ & + \beta_4 contig + \beta_5 comlang + \beta_6 comlang_ethno \\ & + \beta_7 colony + \beta_8 comcol + \beta_9 smctry \\ & + \beta_{10} cpec + \beta_{11} Lnroad + \beta_{12} LnCons + e_{pjt} \end{aligned} \quad (3)$$

Where, $LnVegExp_{pjt}$ represent Pakistan's vegetable exports to country *j* in year *t*. GDP_{pt} represents the GDP of Pakistan in year t. GDP_{jt} represent the importer's country GDP in year *t*. LnD_{pj} is the distance between Pakistan (origin) and the importer country (destination). *Comlang* and *Contig* are the paired variables if Pakistan and the importer countries share a common language or border. *Comlang_ethno* means if at least 9% population speaks the same language. The dummy *colony* means that both countries were in a colonial relationship. *Comcol* denotes the common colonizer power. *Smctry* designates if the countries were the same nation in the past. The dummy variable cpec takes the value of one if the country j is associated with CPEC otherwise is zero. The CPEC variable is specified as a post-treatment dummy (2013 onward). Pre-2013 data are used to control for baseline trade patterns and improve identification, rather than to infer any impact of CPEC during those years. As the infrastructure is the fundamental focus of the CPEC we include the variable *road* which is the total length of road in Pakistan (exporting country). In the traditional gravity equation GDP is used as a proxy of the country's overall economic strength to show how much they want to buy and how much they want to sell. However, when studying a single product, it is better to understand how much the country produces and consumes that commodity (Scheltema, 2014). In our case, studying the vegetable negative trade balance of Pakistan, we add the domestic consumption of vegetable *Cons* to our model. β_0 is a constant term, $\beta_1 \ldots \beta_{12}$ are the coefficients indicate how elastic the exports are concerning the independent variables. e_{pjt} represent the error term.

However, there are some common limitations in the specification of this model. The model becomes biased if there is zero trade (exports), of the undefined nature of the log of zero (Burger et al., 2009; Baldwin and Harrigan, 2011). Some studies noticed the problem of heteroskedasticity in the model (Stronge, 1978; Mnasri and Nechi, 2019). Linders and De Groot (2006) suggest that the zero trade problem can be effectively handled by either removing the zero flows or adjusting the observations with zero values by adding a small number. However, the exclusion of zero values from data results in the loss of key information, and censored data produces a biased coefficient (Eichengreen and Irwin, 1998; Martin and Pham, 2008; Philippidis and Resano-Ezcaray, 2013). Silva and Tenreyro (2006); Santos Silva and Tenreyro (2022) preferred PPML to address zero trade and heteroskedasticity. The recent literature mostly believes that instead of a log linearized model, PPML is more reliable (Lateef et al., 2018). Hence, we rely on the assessment from the PPML estimation technique.

3.1 Descriptive analysis

Reputable online databases serve as the main sources of data for this investigation. Based on data from the Pakistan Bureau of Statistics, the International Trade Center (ITC) published information on Pakistan's vegetable exports from 2003 to 2021. We use data from 2003 to 2021 to capture both the pre- and post-CPEC periods. The pre-2013 data serve as a baseline to control for existing trade trends and improve model precision, consistent with gravity model practice. CPEC is modeled as a post-2013 intervention, with no effects attributed to earlier years. Data from the World Development Indicators (WDI) was used to determine the GDP of Pakistan and its trading partners. Road length in kilometers was measured using data from the Pakistan Bureau of Statistics, while the Food and Agriculture Organization (FAO) provided the average annual vegetable consumption per capita. Furthermore,

TABLE 1 Descriptive statistics of variables, including key measures such as the number of observations ("Obs") and standard deviation ("Std. Dev."), which reflects the variability or dispersion of the data.

Variable	Obs	Mean	Std. Dev.	Min	Max
VegExp	843	3,670.696	1,3975.193	0	165,314
gdp o	855	2.256e+11	8.428e+10	9.176e+10	3.561e+11
gdp d	854	1.157e+12	2.883e+12	1.052e+09	2.332e+13
dist	855	5,092.159	3,422.593	374.652	15,622.2
contig	855	0.089	0.285	0	1
comlang off	855	0.267	0.442	0	1
comlang ethno	855	0.267	0.442	0	1
colony	855	0.022	0.147	0	1
comcol	855	0.356	0.479	0	1
smctry	855	0.067	0.25	0	1
cpec	855	0.067	0.25	0	1
road	854	29,9421.74	85,988.669	256,070	501,424
Cons	855	25.887	2.05	23.178	29.471

These statistics provide a summary of the dataset's central tendency and spread.

data on the distance between the origin country and the importer country, along with the dummy variables used in the model—such as Contig, Comlang, Comlang_ethno, Colony, Comcol, and Smctry were derived from the CEPII database. The list of all variables with their respective names, abbreviations, and anticipated signs is given in Table A2 (Appendix).

The basic statistical analysis is given in Table 1. The variable *VegExp* represents the vegetable exports of Pakistan with a mean value of 3,670.696. The standard deviation is 13,975.19. A zero value indicates that there are no exports in that specific period. The *gdp_o* indicates the GDP of Pakistan. The minimum value is 9.176e+10. The standard deviation is 8.428e+10. The highest GDP is in the year 2018. The *gdp_d* represents the destination country's GDP. We have 855 observations for the *gdp_d* with a mean value of 1.157e+12. The mutual distance between Pakistan and the importer country is indicated by *dist* which has a mean value of 5,092.159. All the dummy variables take the value of one and zero (1,0). *contig* (contiguity) is 1 if a county is sharing a border otherwise zero with its mean value of 0.089 which indicates that the countries in our dataset on average are not contiguous. The mean value of the *comlang_off* and *comlang ethno* suggests that 26 percent of countries in our dataset on average share a common official language. Likewise, the mean value of *colony* suggests that Pakistan exports a small proportion of vegetables to countries that were colonies. The mean value of *smctry* on average 6.7 percent of the export's destination countries was the same country in the past. The *cpec* variable represents the countries that are associated with CPEC. The *road* variable represents the road infrastructure of Pakistan in kilometers. The mean value of the road length is 299,421.74. The mean value and standard deviation of *Consm* variable are respectively 25.887 and 2.05.

To conclude, our dataset comprises a diverse array of economic, geographical, and historical factors to achieve comprehensive findings. The variability in the selection of variables highlights the diverse characteristics of exporter and export destination countries.

4 Results

4.1 Cross-sectional dependence

We tested our time variant variables for cross-sectional dependence in our panel dataset using (Pesaran, 2004) Cross-sectional Dependence (CD) test. The null hypothesis of no cross-sectional dependence was strongly rejected across all variables, with CD test statistics ranging from 16.91 to 135.21 and p-values <0.01 (Table A3 Appendix). These results indicate significant cross-sectional dependence among countries, suggesting that unobserved shocks or spillovers affect multiple countries simultaneously. Accordingly, we use estimation techniques robust to such dependence and cluster standard errors at the country level.

4.2 Gravity estimates

We report the estimated results of our gravity equation in this section. We interpret each variable included in the model.

We use a panel dataset of vegetable exports from Pakistan to its export destination countries. The study period runs from 2003 to 2021. To find robust evidence from the selected parameters, we used three techniques to estimate our gravity equation as presented in Table 2. The results from the fixed effect mode and OLS estimations are presented for comparison. Unlike the fundamental OLS and fixed effect estimations, the PPML is estimated on levels without log transformation (Silva and Tenreyro, 2006; Santos Silva and Tenreyro, 2022). The results obtained from different estimation techniques exhibit some degree of sign similarities except for the GDP of Pakistan. However, as reported earlier the PPML (Silva and Tenreyro, 2006) addresses most of the challenges in the model, we base our estimations on the PPML technique presented in the third column of the table.

The key variable of interest in this work is cpec (China-Pakistan Economic Corridor). The variable is statistically significant at 0.001 percent. According to the findings, a one percent increase in the cpec is leading to an increase of 3.07 percent in the vegetable exports of Pakistan. This observation suggests a surge in economic activity in the countries associated with CPEC. Chaudhry et al. (2017) in their study also found a positive association of CPEC with the Pakistan trade. However, as the CPEC is a combination of multiple projects in three phases and infrastructure is an essential part of the corridor we control for the length of road in Pakistan. We found that the total length of roads in Pakistan significantly supports and enhances the vegetable exports of Pakistan. As the shelf life of the perishable products (vegetables in our case) is short, requires faster transportation and storage. The enhanced road infrastructure of the CPEC reduces the distance and increases market access. As earlier discussed CPEC road infrastructure has reduced the distance from Kashghar, China to Gwadar port, not only benefiting China but also providing fast access to Pakistan's exporters into the Chinese

TABLE 2 Gravity estimations of Pakistan's vegetable exports.

Variables	OLS	S.E	FE	S.E	PPML	S.E
	lnVegExp		lnVegExp		VegExp	
lngdp_o	−0.187	(−0.60)	0	(.)	0.204	(0.61)
lngdp_d	0.724***	(12.42)	0.733***	(12.53)	0.400***	(8.80)
lndist	−2.452***	(−11.91)	−2.467***	(−12.00)	−1.839***	(−11.86)
contig	−2.403***	(−4.86)	−2.474***	(−5.01)	−1.721***	(−3.44)
comlang_off	0.594	(1.52)	0.566	(1.45)	−0.773*	(−2.41)
comlang_ethno	−1.205***	(−3.53)	−1.184***	(−3.46)	−1.602***	(−10.92)
colony	2.681***	(5.65)	2.669***	(5.63)	3.744***	(8.90)
comcol	2.550***	(11.69)	2.557***	(11.74)	2.412***	(13.89)
smctry	−3.815***	(−9.92)	−3.810***	(−9.90)	−2.762***	(−5.65)
cpec	2.331***	(3.55)	2.412***	(3.68)	3.076***	(5.47)
lnCons	−3.648**	(−2.64)	0	(.)	−2.962*	(−2.36)
lnroad	1.446***	(3.59)	0	(.)	0.814*	(2.34)
_cons	4.899	(0.49)	6.263**	(3.28)	5.139	(0.48)
N	619		619		841	
R^2	0.486		0.469		0.631	

The columns show results for three different models: OLS (Ordinary Least Squares), FE (Fixed Effects), and PPML (Poisson Pseudo Maximum Likelihood), along with their corresponding standard errors (S.E.). The variable "lnVegExp" represents the natural logarithm of vegetable exports, with "VegExp" denoting the exports in the PPML model. T-statistics are in parentheses with its significance level * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

market. Moreover, we found that the domestic consumption of vegetables in Pakistan demonstrates a negative and statistically significant coefficient. An increase of one percent in the domestic consumption of vegetables results in a 2.96 percent decrease in the vegetable exports of Pakistan. This finding suggests that most of the vegetable production is absorbed domestically in own country, leaving fewer vegetables to export. At the same time, the rise in consumption triggers the vegetable imports of Pakistan, which in turn creates a vegetable trade deficit.

In contrast to common gravity findings, our estimates show that Pakistan's GDP (origin country) is statistically insignificant which means that the GDP of Pakistan does not clearly explain the exports of vegetables from Pakistan. As the GDP comprehensively measures and aggregates all the economic activities of a country, might not provide clear evidence of the demand and supply of a sector or product (Hummels and Klenow, 2005; Almeida et al., 2012; Scheltema, 2014). Therefore, to understand the strength of the economy we also add vegetable per capita consumption to our model. Pakistan's vegetable exports have a positive and significant association with the GDP of the destination countries (importer). GDP_j is significant at 0.001 percent. One percent rise in the GDP of the importer countries accompanied a 0.40% increase in Pakistan's vegetable exports.

The distance variable (*dist*) represents the cost and time of transportation. Consistent with theory and literature, our estimates show a negative and statistically significant coefficient for distance at 0.001 percent. A one percent rise in the distance of the export destination countries results in a 2.45 percent decrease in Pakistan vegetable exports. Similarly, according to the gravity theory of trade proximity and contiguity are foretold to have a positive relation with the exports of one country. However, in contrast, to Pakistan vegetable exports we found a negative and significant association with the contiguity. This is probably because of the political disputes with India, and economic sanctions on Iran (Atif et al., 2017). Likewise, the variables representing the common official language are negative and significant at different levels. This means that Pakistan and its vegetable export destination countries mostly have different official languages. Historical colonial relations between the colony and the shared colonizer were predicted to positively impact Pakistan's vegetable exports. These variables have statistical significance. Pakistan is increasing exports to nations with colonial ties and those under colonization by the same power. Unlike the theory that countries engage in more trade with the economies that were formally the same country, we find a statistically significant and negative coefficient of *smctry* (same country in the past). This observation reveals that Pakistan has nominal exports to the countries that were previously part of Pakistan. As discussed earlier the controversies and strife with India might be making this variable statistically significant.

5 Discussion

This section provides a comprehensive discussion of the main findings derived from the study results. The discussion emphasizes the implications of CPEC, infrastructure, domestic consumption, and geopolitical factors on Pakistan's vegetable exports.

5.1 Role of infrastructure development in trade facilitation

Infrastructure development plays a central role in enhancing trade efficiency and competitiveness, as evidenced by the transformative impact of the China-Pakistan Economic Corridor (CPEC) on Pakistan's vegetable exports. CPEC's road infrastructure improvements have significantly reduced logistical barriers, particularly for perishable goods like vegetables that require rapid transportation and reliable storage facilities. The study shows a robust positive association between CPEC and export growth, highlighting the importance of connectivity in fostering trade. For instance, the Kashgar-Gwadar route has reduced transit times between Pakistan and key markets such as China, allowing exporters to capitalize on increased demand for fresh produce. This finding aligns with global evidence that better transportation infrastructure lowers trade costs, increases market access, and enhances competitiveness (Limao and Venables, 2001). The findings also align with previous studies. According to De Soyres et al. (2020) transport infrastructure development under the BRI has significantly reduced shipment time and trade costs, with estimated declines of 1.7–3.2% and 1.5–2.8%, respectively. (Tabasam and Ismail, 2019); Ali et al. (2022) suggests that improved transport infrastructure strengthens economic ties between Pakistan and China, with modest GDP growth, notable welfare gains, and significant trade increases, especially in agriculture, for Pakistan. For Pakistan, continued investments in transportation and logistics infrastructure are critical for consolidating these gains and ensuring the sustainability of export growth, particularly in the context of increasing competition in regional and global agricultural markets.

5.2 Balancing domestic consumption and export capacity

A critical challenge revealed in the study is the growing tension between rising domestic consumption and export capacity in Pakistan's vegetable sector. The significant negative relationship between domestic vegetable consumption and export volumes indicates a structural imbalance, where local demand limits the surplus available for international trade. This trend highlights the need for a more balanced production-consumption framework. With domestic consumption absorbing a substantial share of agricultural output, exports suffer, resulting in missed opportunities in lucrative foreign markets. As Ahmad et al. (2021b) documented, Pakistan has a comparative advantage in horticulture due to high domestic demand, favorable climate, and low-cost labor, but this is constrained as most produce is sold in local markets. Simultaneously, the increased reliance on vegetable imports to meet domestic demand exacerbates Pakistan's trade deficit, creating vulnerabilities in the country's agricultural trade balance. To address these challenges, Pakistan must prioritize measures to enhance agricultural productivity, such as adopting high-yield crop varieties, modern irrigation techniques, and post-harvest technologies. These interventions can increase the availability of surplus produce for export without compromising local food security. Additionally, fostering export-oriented production, supported by targeted subsidies and trade policies, can incentivize farmers to produce for international markets. Supply chain improvements, including better cold storage facilities and efficient distribution networks, are also essential to minimize post-harvest losses and ensure consistent export volumes. These strategies can help Pakistan strike a balance between meeting domestic needs and fulfilling export commitments, thereby achieving a more sustainable trade profile.

5.3 Geopolitical and historical dynamics in trade patterns

Geopolitical and historical factors significantly influence Pakistan's vegetable export dynamics, adding layers of complexity to the country's trade performance. Distance, as expected, negatively impacts exports by increasing transportation costs and transit times. However, the study's finding of a negative association with contiguity deviates from traditional expectations, revealing the role of political tensions in shaping trade outcomes. Pakistan's strained relations with neighboring countries such as India and Iran have constrained cross-border trade, reducing the benefits typically associated with geographical proximity. For example, long-standing disputes with India, coupled with economic sanctions on Iran, have limited market access and hindered trade opportunities in these neighboring countries (Kousar et al., 2023). Despite these challenges, CPEC's infrastructure investments offer a pathway to mitigate the impact of geopolitical constraints by facilitating access to alternative regional markets, particularly in Central Asia and China.

The influence of historical trade linkages further highlights the importance of leveraging institutional and cultural familiarity in export strategies. The positive relationship between colonial ties and vegetable exports underscores the enduring benefits of shared historical and trade networks. However, the negative association with former constituent regions, particularly India, underscores the detrimental effects of unresolved political conflicts on trade relationships. These findings emphasize the importance of adopting a multifaceted trade strategy that integrates infrastructural advancements with diplomatic efforts. Resolving political tensions with neighboring countries and fostering regional trade agreements can unlock significant export potential while leveraging historical ties can strengthen existing trade relationships. A holistic approach that addresses both logistical and geopolitical barriers is essential for Pakistan to optimize its vegetable trade and realize its full export potential.

5.4 Limitations and future research

With an emphasis on macro-level trade frictions such as distance, infrastructure, bilateral economic scale, governmental intervention, and infrastructure, this study draws on the gravity model to examine the factors influencing Pakistan vegetable

exports. Smallholder farmers, who produce the majority of Pakistan vegetables, are not included in our micro-level data, nevertheless. This is an acknowledged limitation, especially considering that more than two-thirds of Pakistani farmers, who form the foundation of the rural economy, work on smallholdings of less than five acres (Mazhar et al., 2019). Among the most marginalized members in the vegetable supply chain, smallholders are not only the main producers but also frequently lack direct market access, relying on middlemen or commission brokers to reach markets (Ahmad et al., 2021a; Hassan et al., 2021). Smallholders could not benefit equally from increased export opportunities due to these structural limitations. Data on production costs, supply chain margins, and involvement in export-oriented value chains at the farmer level could be incorporated into future studies to support this strategy.

6 Conclusions and policy implications

This section offers an overview of the objective of the study, data, and estimation techniques. Next, we conclude all the findings and offer suggestions based on our estimations.

This study looks into Pakistan's vegetable trade deficit in the international market. We have attempted to investigate the role of CPEC in shaping the vegetable exports of Pakistan. We also enlighten the road infrastructure and other important factors that impact Pakistan's vegetable exports either positively or negatively. The study covers the period from 2003 to 2021. A panel data set of the Pakistan vegetable export destination was selected for investigation. PPML as the state-of-the-art technique in the gravity model of trade was preferred to achieve robust results.

Among the 12 predictors included in the model, six variables were observed to have an inverse relationship with vegetable exports of Pakistan. CPEC as the main variable of interest of study found to have a positive association. CPEC was initiated in 2013 and is still going through its second phase which will complete in 2025. Despite this, the project demonstrates that Pakistan's economic activities are grown with the countries that are linked to the corridor in either way. The road infrastructure plays a crucial role in the transportation of the perishable product. CPEC will add 3,000 KM of road infrastructure to Pakistan's road network in the form of motorways, highways, and expressways. Our findings witnessed that the road infrastructure has increased Pakistan's vegetable exports by providing fast connectivity and access to markets.

Moreover, we found, that though Pakistan as an agricultural country produces an attractive volume of vegetables, most of the vegetables are absorbed in its own country. Pakistan by fulfilling the domestic demand for vegetables leaves fewer to export and also triggers imports. The inverse relation of domestic consumption with vegetable exports is contributing to Pakistan's vegetable trade deficit.

Furthermore, the GDP fails to explain Pakistan's vegetable exports. The importer country's GDP positively influences vegetable exports. Vegetable exports are negatively impacted by characteristics including distance, contiguity, and shared language. The colonial connections boost Pakistan's vegetable exports. Having a history of colonialism or being same country makes market collaboration simpler. Contrary to expectations we find that Pakistan's vegetable exports to countries that were formerly the same country are very tiny.

To solve the challenge of Pakistan's vegetable trade deficit, increasing productivity with enhanced and modern farming techniques is the possible solution. By increasing the production, the country will able to meet the domestic requirements and export the surplus products. Nearest markets should be of primary concern in the exports of perishable products. The exporter needs to introduce Pakistan's vegetables to the Chinese market in Xinjiang which is easily accessible on the CPEC route instead of the sea route which is time-consuming and costly. Resolving strife and making healthy trade cooperation with India can provide and huge and accessible market with no language barriers.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HK: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. ZY: Formal analysis, Methodology, Software, Visualization, Writing – review & editing. QC: Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

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APPENDIX

Table A1 Pakistan's agricultural and vegetable trade with China from 2003 to 2021, based on data from ITC, Pakistan Bureau of Statistics, and the authors' compilation, with values in USD thousands.

Year	Pakistan agricultural export to China	Pakistan agricultural imports from China	Agriculture trade balance	Pakistan vegetable exports to China	Pakistan vegetable imports from China	Vegetable trade deficit
2003	193,558	44,089	149,469	67	19,823	−19,756
2004	228,010	40,991	187,019	37	13,689	−13,652
2005	304,009	176,423	127,586	136	45,740	−45,604
2006	395,990	123,620	272,370	469	48,564	−48,095
2007	425,400	176,697	248,703	199	82,296	−82,097
2008	444,694	173,805	270,889	0	57,421	−57,421
2009	771,537	181,280	590,257	0	66,766	−66,766
2010	1,028,428	275,256	753,172	28	97,309	−97,281
2011	1,240,337	320,122	920,215	226	93,258	−93,032
2012	2,238,063	271,454	1,966,609	3952	35,048	−31,096
2013	2,220,515	309,322	1,911,193	598	30,043	−29,445
2014	1,872,269	324,991	1,547,278	889	67,822	−66,933
2015	1,612,291	287,068	1,325,223	923	63,130	−62,207
2016	1,294,441	357,770	936,671	852	107,378	−106,526
2017	1,114,640	345,146	769,494	11	87,191	−87,180
2018	1,335,388	316,322	1,019,066	36	43,989	−43,953
2019	1,403,510	325,403	1,078,107	41	58,339	−58,298
2020	1,122,721	391,191	731,530	302	112,518	−112,216
2021	1,794,739	437,309	1,357,430	109	71,260	−71,151

Table A2 Description of all variables included in the model, abbreviated forms, expected signs, and data sources.

Variable	Abbreviations	Expected sign	Source
Vegetable exports of Pakistan	VegExp	—	ITC
GDP of Pakistan	gdp_o	+	WDI
GDP of destination countries	gdp_d	+	WDI
Distance between Capital of Pakistan and destination countries	dist	-	CEPII
Contiguity	contig	+	CEPII
Official common language	comlang off	+	CEPII
Common language spoken by at least 9% population	comlang ethno	+	CEPII
colony	colony	+	CEPII
Countries share common colonizer	comcol	+	CEPII
Same country in the past	smctry	+	CEPII
China-Pakistan Economic Corridor	cpec	+	CPEC/BRI
Road length (KM) in Pakistan	road	+	PBS
Vegetable per person consumption in Pakistan	Cons	+/–	WFO

Table A3 Cross-sectional dependence test.

Variable	CD test statistics	p-value	Average correlation
VegExp	16.91	0.000	0.123
gdp_o	135.21	0.000	1.000
gdp_d	104.44	0.000	0.661
Cons	135.21	0.000	1.000
Road	135.21	0.000	1.000

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Labor-saving agricultural mechanization services and the technical efficiency in agricultural production: evidence from Chinese rural households

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Introduction: In the context of accelerating industrialization and urbanization, China's agricultural production faces challenges such as labor shortages and fragmented land supply. Labor-saving agricultural mechanization services (LAMS) have emerged as a scalable factor innovation to address such issues. However, the efficiency implications and moderating factors of LAMS adoption remain insufficiently understood.

Methods: Using 2019 cross-sectional survey data from 1,519 medium indica rice growers in China, this study investigates the impact of LAMS adoption on technical efficiency (TE) using a stochastic frontier analysis (SFA) approach. To address endogeneity concerns, a two-stage least squares (2SLS) instrumental variable strategy is employed. Moderating effect models further identify causal effects of market- and policy-based factors.

Results: The results show that LAMS adoption significantly improves technical efficiency. Market factors—measured by self-owned machinery—exhibit a substitution effect with LAMS, while policy factors—proxied by high-standard farmland construction (HSFC)—demonstrate complementary effects. Robustness checks confirm the validity of these effects across income groups.

Discussion: The findings suggest that service-based mechanization can alleviate structural constraints such as land fragmentation and labor scarcity. LAMS offer a viable pathway to enhance smallholder productivity. These insights provide valuable policy implications for agricultural transformation in land-constrained developing economies.

KEYWORDS

labor-saving agricultural mechanization services, technical efficiency, stochastic frontier analysis, rural households, household contract responsibility system

1 Introduction

Global agricultural output quadrupled between 1961 and 2020, accompanied by a 53% rise in per capita output. However, the post-2010 period witnessed decelerating productivity growth, escalating food price indices, and mounting pressure on natural resource utilization, coinciding with an increase in food-insecure populations since 2015 (Fuglie et al., 2024). Enhancing agricultural production efficiency thus emerges as a critical priority for ensuring food security.

Within China's high-quality development agenda, synchronizing smallholder development under the Household Contract Responsibility System (HCRS) remains a fundamental challenge. According to the Third National Agricultural Census (2016), smallholders account for 98.1% of agricultural entities, with 85.2% cultivating plots smaller than 0.67 hectares. It highlight the urgency of transforming production methods under resource constraints. This investigation aligns with Sustainable Development Goal Target 2.3, which emphasizes improving smallholder productivity (Ayalew et al., 2024).

The growing specialization of agricultural mechanization services (AMS) aligns with Alesina and Rosenthal's (1996) theoretical proposition that economic development entails functional disaggregation, where specialized entities assume responsibility for discrete production stages. Empirical evidence shows that mechanization service providers enhance both farm-level efficiency and sector-wide productivity through technology diffusion. China's agricultural modernization exemplifies this trajectory, where productivity growth are driven by ongoing technological advancement and its spatial dissemination across farming operations. Huang and Yang (2017) identify machinery investment as a critical channel for adopting productivity-enhancing technologies.

Unlike traditional ownership-based mechanization models that primarily benefits large-scale farms, AMS provides smallholders access to capital-intensive technologies through market-based outsourcing (Van Loon et al., 2020; Lu et al., 2022). By decoupling machinery use from ownership, AMS reduce fixed costs and facilitate the diffusion of advanced equipment among fragmented and resource-constrained rural producers (Yang et al., 2013). AMS improve production efficiency through two primary channels: direct technical improvements through mechanized operations and indirect market effects via demand-driven service linkages. The former boosts in-field operational efficiency, while the latter reduces transaction costs through specialized service provider networks.

Labor-saving Agricultural Mechanization Services (LAMS), a subset of AMS, refer to outsourced mechanized operations—such as plowing, sowing, and harvesting—provided by third-party service organizations or machinery-owning households. These services substitute machine labor for manual labor in physically intensive production stages, enabling smallholders to benefit from mechanization without owning equipment. The widespread adoption of LAMS in China over the past two decades has been driven by rapid industrialization and urbanization, which have triggered large-scale rural labor outmigration. As younger and more educated workers leave agriculture for better-paid nonfarm employment in cities, rural households face growing labor shortages and rising opportunity costs of on-farm work. Under such demographic and structural shifts, the demand for labor-saving technologies—particularly those that can be flexibly accessed through service outsourcing—has increased significantly.

Meanwhile, government investment in agricultural infrastructure, especially high-standard farmland construction (HSFC), has further facilitated the diffusion of LAMS by improving land conditions and machinery accessibility (Zhang et al., 2017). This dual transformation—labor outflow due to industrialization and institutional support for mechanization—offers a unique context to examine how service-based mechanization interacts with household heterogeneity and policy environment to influence agricultural productivity. While the literature has documented the rapid rise of AMS (Benin, 2015; Tufa et al., 2024), few studies have rigorously analyzed the mechanisms through which LAMS influence technical efficiency (TE) at the household level, especially under the land tenure constraints embedded in the HCRS.

Existing research often treats mechanization as a homogenous category, overlooking important distinctions between capital-deepening ownership and service-oriented outsourcing (Hamilton et al., 2022; Paul and Yasar, 2009). This masks key differences in access and outcomes. For instance, Lu et al.(2022) find that LAMS adoption for plowing and transplanting significantly increases rice yields in China, whereas less observable services, such as pesticide spraying, may generate negative productivity effects due to moral hazard. These findings underscore the dual nature of LAMS—as both a technological substitute for labor and an organizational innovation with principal-agent dynamics.

Theoretically, LAMS differ from conventional mechanization by introducing new transaction costs and coordination challenges, while simultaneously enabling scale economies through demand aggregation (Pingali, 2007; Van Loon et al., 2020). Under the framework of induced institutional innovation, LAMS can be viewed as an adaptive response to mismatches in land fragmentation, labor scarcity, and capital indivisibility. Despite their growing policy relevance, most empirical studies focus on adoption determinants rather than evaluating causal impacts on production efficiency (Lu et al., 2022; Zhang et al., 2017).

This study contributes to the literature in four ways. First, it develops a moderated effects framework to examine how LAMS and institutional policy jointly affect household-level TE. Second, it applies a two-stage econometric strategy using nationally representative survey data and instrumental variables to mitigate endogeneity in LAMS adoption. Third, by disaggregating machinery ownership from service usage, the study reveals heterogeneous efficiency outcomes based on household endowments and land characteristics. Fourth, from a global perspective, it offers insights into how service-based mechanization may improve productivity in smallholder systems characterized by fragmented land tenure, labor migration, and underdeveloped markets (Benin, 2015; Tufa et al., 2024). Overall, this paper provides empirical evidence on the micro-foundations of mechanization-driven productivity in fragmented land system, with practical implications for rural modernization strategies across the Global South.

2 Theoretical framework

LAMS represent a distinct form of mechanization that diverges from traditional capital-deepening pathways. It refer to outsourced machinery services—including plowing, sowing, harvesting, irrigation, pesticide application, equipment maintenance, and leasing—provided by service organizations or machinery-owning households to agricultural producers for a fee. A central advantage of LAMS lies in their ability to separate ownership from use, thereby reducing fixed investment burdens for smallholders and enabling access to mechanized technologies through market transactions. Unlike capital-intensive mechanization models that require large operational scales, LAMS allow small and fragmented producers to benefit from mechanization.

The functional differentiation of LAMS can be understood through the lens of production stage intensity. Agricultural production can be divided into labor-intensive and technology-intensive stages. Labor-intensive tasks include plowing, sowing, and harvesting, which heavily rely on manual labor, whereas technology-intensive tasks such as fertilization, irrigation, and pesticide application demand technical precision and expertise. Based on the classification of labor-saving versus resource-saving technologies in the theory of technical change, LAMS in this study correspond to labor-saving technologies: they substitute mechanical power for labor in physically demanding production stages, particularly within the 'plow-sow-harvest' cycle.

This functional design of LAMS plays a critical role in improving TE. TE is defined as the ratio of observed output to the maximum attainable output given a set of inputs, reflecting the extent to which producers minimize input waste. TE is conceptually distinct from total factor productivity (TFP): the former is a micro-level indicator of efficiency under a given technology, while the latter captures macro-level gains driven by innovation, economies of scale, and resource reallocation. As such, TE provides a more appropriate measure for assessing farm-level performance under real-world constraints.

LAMS influence TE through several channels. First, they alleviate labor bottlenecks during peak seasons by mechanizing time-sensitive tasks, thereby reducing yield losses caused by delays. Second, they improve input allocation by enabling scale-consistent machinery matching, especially under fragmented landholding conditions. Third, by lowering capital entry thresholds, LAMS allow farmers to reallocate scarce financial resources toward complementary inputs such as improved seeds, fertilizers, or technical services. These mechanisms collectively enhance a producer's ability to reach the production frontier—that is, to achieve output levels closer to the technically feasible maximum.

In sum, LAMS are not merely substitutes for labor, but also represent an institutional innovation that helps smallholders overcome structural inefficiencies in land, labor, and capital allocation. Their role in enhancing TE reflects the convergence of market-based service delivery with the diffusion of productivity-enhancing technologies in the modernization of smallholder agriculture. This paper empirically analyzes the indirect effects of LAMS on agricultural production efficiency from two perspectives: market factors and policy factors.

2.1 Market factor

We begin the analysis from the demand-side perspective of farmers. According to the theory of induced technical change, increases in the relative prices of labor and machinery stimulate farmers' demand for agricultural mechanization. Farmers typically adopt mechanized production either by purchasing agricultural machinery themselves or by procuring machinery services. From a cost-minimization and profit-maximization perspective, this decision reflects rational behavior, as farmers choose the production mode that best aligns with their resource endowments and the constraints of their operating environment.

Compared with manual labor, mechanized production can alleviate the burden of physically demanding and time-consuming tasks. However, adopting mechanized production entails certain costs, usually paid as a one-time fee to service providers or as capital investment in machinery. In practice, mechanized production requires both adequate financial capacity and alignment between machinery capacity and farm scale. On the one hand, farmers must be able to afford either machinery ownership or service fees. On the other hand, machinery use must be efficient—ideally, production scale should closely match machinery capacity. In cases of overcapacity, machinery-owning farmers can provide services to others, reducing idle costs and generating additional income.

When deciding on a production model, farmers must consider multiple factors. First, mechanized agriculture can improve household income through both output and substitution effects: increased yields compared to manual labor and the release of surplus labor for off-farm employment. Second, farmers must assess whether they can afford machinery and whether it can be fully utilized to enhance household returns. Under rational expectations, farmers will opt for the model that maximizes total income.

However, high purchase prices and significant transaction costs often prevent smallholders from affording agricultural machinery. Since the landholdings are highly fragmented, if all farmers were to purchase machinery individually, this would lead to significant overcapacity and idle assets, ultimately reducing resource allocation efficiency. Therefore, limited purchasing capacity and small-scale operations mean that not all farmers can achieve mechanization through ownership. For those lacking capital or scale, purchasing machinery services offers a viable alternative to realize mechanized production.

Based on the above analysis, this paper proposes the following hypothesis:

> *H1: When the farmers with less machine choose agricultural machinery service, their production efficiency will be improved more significantly.*

2.2 Policy factor

As a core component of China's agricultural development strategy, the HSFC Project aims to stabilize the quantity of arable land, improve land quality, and enhance the agricultural ecological environment. According to the General Rules for HSFC (GB/T 30600-2014), high-standard farmland is defined as permanently protected arable land designated as basic farmland, characterized by leveled terrain, spatial contiguity, comprehensive infrastructure, reliable agricultural power supply, fertile soil, resilient ecosystems, and strong disaster resistance. Such land is expected to support modern agricultural production systems capable of sustaining stable, high yields under both drought and flood conditions.

Since its nationwide rollout in 2011, land engineering has served as the cornerstone of HSFC policy. This initiative has employed field consolidation strategies—such as small-to-large field integration and fragmented-to-contiguous reconfiguration—to achieve land leveling and coordinated plot management. These measures have demonstrably reduced land fragmentation and expanded both individual plot size and the overall operational scale. In parallel, land exchange programs maintain total cultivated area while enlarging contiguous field dimensions at the household level.

The policy's land adaptation for mechanization approach promotes plot-level scale economies, thereby increasing the feasibility and efficiency of agricultural mechanization services. Plot consolidation enhances mechanization through two primary mechanisms. First, contiguous field layouts improve operational conditions for

labor-intensive tasks such as tillage, sowing, and harvesting. Second, reduced spatial discontinuities lower input transport costs and decrease the transaction costs associated with procuring machinery services, thus enabling providers to deliver services more efficiently.

Importantly, both self-owned machinery and outsourced mechanization services require terrain compatibility—specifically, leveled land, accessible field roads, and concentrated operating areas. Through infrastructure investments (e.g., field road construction) and land consolidation, the high-standard farmland policy systematically improves the physical environment for agro-mechanization. These terrain adaptation efforts have contributed to the development of local agricultural machinery service markets, especially for labor-intensive production stages, and have ultimately facilitated measurable gains in agricultural productivity. Therefore, this paper puts forward the following hypothesis:

> *H2: HSFC Project have a moderating effect on the impact of LAMS on agricultural production efficiency.*

3 Date and models

3.1 Data sources

The empirical analysis utilizes data from China's National Rural Fixed Observation Point Survey, a nationally representative longitudinal survey system established in 1984 by the Ministry of Agriculture and Rural Affairs. As the most authoritative socioeconomic monitoring system covering rural China, it encompasses 368 counties and 375 sample villages across 31 provincial-level administrative units, involving 23,000 registered farming households and over 1,600 new agricultural business entities through standardized bookkeeping procedures.

This study focuses on factor allocation and production efficiency among farmers, using rice—China's primary staple grain—as the focal crop. Given its moderate photosensitivity, stable growth duration, and broad regional adaptability, medium indica rice is selected as a representative type. All household production variables analyzed in this study are based on medium indica rice cultivation.

To ensure empirical rigor and regional relevance, the analysis draws on cross-sectional data from 2019, selecting 10 major indica rice-producing provinces (autonomous regions/municipalities) based on agricultural zoning maps and data accessibility criteria. After implementing rigorous data cleaning protocols—including removal of incomplete responses, outlier detection using interquartile range methods, and verification of internal consistency—the final analytical sample comprises 1,519 qualified observations. This geographical concentration ensures analytical validity given the study's emphasis on mechanization patterns in staple grain production systems.

3.2 Variable selection

3.2.1 Explained variable

The explained variable is agricultural production TE, which is calculated by the Stochastic Frontier Analysis (SFA) model proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). Whose general equation is specified in Equation (1):

$$\ln y_i = f\left(x_i;\beta\right) + v_i - u_i, \tag{1}$$

$$v_i \sim N\left(0,\sigma_v^2\right)$$

Where, y_i is the actual amount of output, $f(\cdot)$ is the value of potential output, x_i denotes the input factor vector, v_i is the random error term, u_i denotes the technical inefficiency term. Assuming y_i^* is the potential output, then the TE should be calculated as Equations (2–4):

$$\ln y_i^* = f\left(x_i;\beta\right) + v_i \tag{2}$$

$$\ln y_i = \ln y_i^* - u_i \tag{3}$$

$$\exp\left(-u_i\right) = \frac{y_i}{y_i^*} \tag{4}$$

In the SFA model, output is measured by the value of rice production. Input variables include (Table 1): (1) land area under rice cultivation, (2) labor input measured in person-days, (3) intermediate inputs covering seeds, fertilizers, pesticides, irrigation electricity, and livestock services, and (4) mechanized service expenditures. These variables capture the main factors of production and align with standard input–output modeling in agricultural efficiency analysis.

3.2.2 Core explanatory variables

This study focuses on identifying the mechanisms through which LAMS influence agricultural production efficiency. The core explanatory variable—LAMS adoption—is operationalized as a binary indicator that equals 1 if a medium-indica rice grower procured mechanized services during labor-intensive production stages, and 0

TABLE 1 Variable used in SFA model.

Variable Name	Unit	Definition
Output Value	Yuan	Value of main rice production output
Intermediate Inputs	Yuan	Total cost of seeds, fertilizer, mulch, pesticides, irrigation electricity, livestock services, etc. for rice cultivation
Machinery Operation Cost	Yuan	Total cost of mechanized operations for rice production
Labor Input	Day	Total number of labor days used in rice production
Land Input	Hectare (Ha)	Total land area cultivated for rice

TABLE 2 Variable description of indirect effect model of labor-intensive agricultural machinery service on agricultural production efficiency.

Variable category	Variable name	Variable unit	Variable definition
Explained variable	Agricultural production efficiency	-	TE of medium indica rice production
Core explanatory variables	Labor saving type Agricultural machinery services	-	Purchase of agricultural machinery operation services in the process of tillage, sowing and harvesting of land planted with medium indica rice = 1, otherwise = 0
Moderating variables	Own farm machinery	Tai	The number of farm machinery owned by the family
	High standard farmland	%	The proportion of high-standard basic farmland construction in the cultivated land area in the village group
Instrumental variable	Farm machinery service rate of village groups	%	The average purchase rate of agricultural machinery services in tillage, sowing and harvesting of land planted with medium indica rice by other farmers in the village group
Control variables	Age	-	The age of respondents was 1–17 years old = 1, 18–27 years old = 2, 28–37 years old = 3, 38–47 years old = 4, 48–57 years old = 5, 58–67 years old = 6, and >68 years old = 7
	Education level	-	Education level of interviewed farmers: primary school = 1, junior high school = 2, senior high school = 3, junior college or above = 4
	Health status	-	Healthy or good physical condition = 1, otherwise = 0
	Technical training	-	The surveyed farmers have participated in agricultural training by government departments = 1, otherwise = 0
	Number of labor force	person	Number of household labor
	Village cadre households	-	A member of the family serves as a village cadre
	Family farm	-	Family registered as family farm = 1, otherwise = 0
	Off-farm income	%	Proportion of household non-farm business income in total income

otherwise. This specification enables empirical estimation of the impact of LAMS adoption on household-level TE.

3.2.3 Moderating variables

Moderating variables are constructed in line with the proposed analytical framework. Farmer-owned agricultural machinery quantity serves as the proxy for market-related factors, while participation in HSFC programs captures policy-related influences. This dual approach reflects institutional economics theory and market access dynamics, allowing for the analysis of interaction effects between LAMS and external contextual factors.

3.2.4 Instrumental variable

To address potential endogeneity concerns typical of observational data, an instrumental variable strategy is employed. The village-level penetration rate of agricultural machinery services is used as an instrument. This variable exploits spatial variation in service diffusion while satisfying the exclusion restriction through the assumption that regional adoption patterns affect individual LAMS uptake but not household-level efficiency directly.

3.2.5 Control variable

The model includes a comprehensive set of household-level and village-level control variables. Household characteristics encompass demographic and socioeconomic indicators, including the age, education, and health status of the household head; participation in agricultural technical training; household labor force size; cadre status (political affiliation); share of non-agricultural income; and family farm registration. Village-level controls include the dominant type of agricultural operation and the availability of agricultural machinery services within the village. To control for unobserved regional heterogeneity, provincial fixed effects are included in the stochastic production frontier model. Detailed definitions and descriptive statistics of all variables are reported in Table 2.

3.3 Model setting

3.3.1 Benchmark regression

First, the OLS model was used for the analysis. The benchmark model is established as Equation (5) shows:

$$TE_i = \alpha_0 + \alpha_1 serv_i + \sum_{k=1}^{K} \alpha_{2k} ctrl_{ik} + \varepsilon_i \quad (5)$$

Where, TE_i represents the production efficiency of medium-indica rice by farmers, $serv_i$ represents the variable of purchasing agricultural machinery services, and $ctrl_{ik}$ represents the control variable. α_0 represents the constant term of the model, α_1 represents the coefficient to be estimated for the agricultural machinery service variable, α_{2k} represents the coefficient to be estimated for each control variable, and ε_i represents the random error term of the model.

3.3.2 The treatment of endogeneity problem

To address potential endogeneity concerns, this study employs an instrumental variable (IV) strategy. A valid instrument must satisfy two key conditions: relevance—i.e., a strong correlation with the endogenous regressor—and exogeneity, meaning independence from the error term in the structural equation. The latter condition, known as the exclusion restriction, requires that the instrument affects the dependent variable only through its relationship with the endogenous explanatory variable, with no alternative causal pathways.

The chosen instrument is the village-level adoption rate of LAMS, operationalized as the proportion of neighboring farmers within the administrative village who procure mechanization services. This measure captures spatial peer effects in technology adoption: farmers often observe and learn from their neighbors, leading to correlated adoption behaviors. The instrument satisfies the relevance condition because neighboring adoption significantly influences individual farmers' decisions through information diffusion and social learning. It satisfies the exogeneity condition because neighbors' adoption decisions are unlikely to correlate with unobserved determinants of the focal household's production efficiency, except through the endogenous adoption of LAMS.

This IV strategy is theoretically grounded on three considerations. First, village-level adoption rates reflect the development of localized service markets. Second, spatial autocorrelation in adoption behavior arises from shared institutional, infrastructural, and informational environments. Third, using the administrative village as the unit of analysis reduces the likelihood of cross-regional spillover effects, thereby enhancing the plausibility of the exclusion restriction. This strategy enables consistent estimation of the causal impact of LAMS adoption under the stated identification assumptions.

3.3.3 Moderating effect model of market factors

The theoretical framework posits that market forces may incentivize farmers' adoption of agricultural machinery services (LAMS), potentially moderating the relationship between service procurement and agricultural productivity. To empirically examine this hypothesized market-mediated effect, the analysis incorporates a moderating variable quantifying privately-owned agricultural machinery assets. Specifically, an interaction term between LAMS adoption and machinery ownership is introduced into the baseline regression specification, formalized as Equation (6):

$$TE_i = \alpha_0 + \alpha_1 serv_i + \sum_{k=1}^{K} \alpha_{2k} ctr_{ik} + \alpha_3 mec_own_i + \alpha_4 serv_i \times mec_own_i + \varepsilon_i \quad (6)$$

Where mec_own_i denotes the household's self-owned agricultural machinery stock. All other variables maintain their baseline model definitions and operationalizations. This multiplicative specification enables explicit testing of how market-driven machinery availability moderates LAMS' productivity effects.

3.3.4 Moderating effect model of policy factors

The theoretical framework further suggests that policy interventions may incentivize farmers' adoption of agricultural machinery services (LAMS), potentially moderating the service-productivity relationship. To empirically assess this policy-mediated mechanism, HSFC participation is incorporated as a moderating variable through interaction effects. The extended regression specification formalizes this analytical approach as Equations (7, 8) shows:

$$TE_i = \alpha_0 + \alpha_1 serv_i + \sum_{k=1}^{K} \alpha_{2k} ctrl_{ik} + \varepsilon_i \quad (7)$$

$$TE_i = \alpha_0 + \alpha_1 serv_i + \sum_{k=1}^{K} \alpha_{2k} ctr_{ik} + \alpha_3 highq_i + \alpha_4 serv_i \times highq_i + \varepsilon_i \quad (8)$$

Where $highq_i$ indicates household participation in HSFC programs. All other variables retain their baseline model definitions and measurement protocols. This interaction term specification enables precise estimation of how policy-driven infrastructure improvements condition LAMS' productivity effects.

4 Results

4.1 Benchmark regression

4.1.1 Model test

The empirical analysis employs ordinary least squares (OLS) and two-stage least squares (2SLS) estimation methods with regional fixed effects. Diagnostic tests confirmed heteroscedasticity (Breusch-Pagan test, $p < 0.01$), addressed using robust standard errors. Variance inflation factor (VIF) analysis ruled out multicollinearity (maximum VIF = 2.49). A summary of the main regression results is available in the Table A1.

The first-stage regression results confirm the relevance of the instrument, and its statistical insignificance in the second-stage regression with respect to TE supports the exclusion restriction. To further test for endogeneity, a Durbin–Wu–Hausman test was conducted by including the residuals from the first-stage regression in the structural model. The significance of the residual term ($p < 0.05$) leads to the rejection of the null hypothesis of exogeneity, thus validating the use of the IV approach (Table 3).

Specification (3) presents the 2SLS estimation results using village-level agricultural machinery service adoption as an instrument for LAMS. Diagnostic tests confirm the validity of identification assumptions, including instrument relevance, robustness against weak instruments, and exogeneity. The findings reveal a statistically significant positive effect of LAMS adoption on TE, suggesting that mechanization in labor-intensive indica rice cultivation improves productivity through more efficient factor allocation. These efficiency gains are particularly notable in the context of rising rural wages and the increasing opportunity cost of agricultural labor due to non-farm employment.

Control variable estimates yield several key insights. First, household labor availability, participation in technical training, and

access to local machinery services are all positively associated with TE. Second, village cadre status shows a negative correlation with efficiency. This counterintuitive finding aligns with dual mechanisms of social capital identified by Su and He (2013). On one hand, political connections may provide access to off-farm income opportunities, thereby reducing household agricultural labor input. On the other hand, social capital's productivity-enhancing effects are scale-dependent — beneficial for medium to large-scale farms, but less impactful for smallholders cultivating less than 3.33 hectares (Li et al., 2016). Given that this study focuses on small-scale farms (below 3.33 ha), the negative coefficient likely reflects reduced agricultural input intensity among politically connected households.

Comparable findings have been observed in other contexts where service outsourcing mitigates inefficiencies linked to suboptimal scale. For example, Picazo-Tadeo and Reig-Martínez (2006) find that outsourcing mechanical operations in Spanish citrus production enhances TE by lowering fixed capital costs and reducing input misallocation. Similarly, the results here suggest that LAMS substitute capital for labor and expand smallholder access to specialized services, thereby promoting efficiency in fragmented farming systems.

TABLE 3 Effect of labor-intensive agricultural machinery services on agricultural production efficiency (2SLS).

	TE		
	(1) OLS	(2) OLS	(3) 2SLS
Labor-saving farm machinery services	0.0190*** (0.0051)	0.0182*** (0.0051)	0.157* (0.095)
Family farm	0.2297 (0.1738)	0.2324 (0.1731)	0.236 (0.174)
Village cadre households	0.0137* (0.0070)	0.0140** (0.0069)	0.016** (0.0064)
Number of labor force	0.0043*** (0.0012)	0.0045*** (0.0012)	0.006** (0.003)
Non-farm income	0.0030 (0.0123)	0.0019 (0.0123)	0.013 (0.02)
Age	0.0001 (0.0023)	0.0002 (0.0022)	0.002 (0.004)
Education level	0.0024 (0.0032)	0.0027 (0.0032)	0.0004 (0.005)
Health status	0.0009 (0.0048)	0.0006 (0.0048)	0.004 (0.011)
Technical training	0.0105* (0.0060)	0.0114* (0.0061)	0.016* (0.0083)
Agricultural operating environment	0.0305* (0.0159)	0.0329** (0.0161)	0.14 (0.093)
Supply of Agricultural Machinery Services	0.0193** (0.0090)	0.0195** (0.0092)	0.0340** (0.015)
Service rate of farm machinery in the village group		0.0035 (0.0032)	
Area control variable	YES	YES	YES
Intercept term	0.7878*** (0.0215)	0.7810*** (0.0242)	0.678*** (0.081)
Sample size	1,519	1,519	1,519

① Values in brackets are robust standard errors; ②*,** and*** indicate significance at the level of 10, 5 and 1%, respectively.

4.1.2 Effect of LAMS on agricultural production efficiency under the effect of market factors

Table 4 presents the moderating effects of market factors on the relationship between LAMS and TE. Specification (4) reports baseline ordinary least squares (OLS) estimates, while Specification (5) incorporates the instrumental variable—village-level agricultural machinery service adoption rates—while maintaining instrument exogeneity, as confirmed by the statistical insignificance of the instrument in the second-stage regression.

Specification (6) reports the two-stage least squares (2SLS) estimates, yielding two key findings. First, self-owned agricultural machinery exhibits a statistically significant positive effect on TE, suggesting that capital-deepening through machinery ownership contributes to productivity gains. Second, the negative coefficient on the interaction term between LAMS adoption and machinery ownership confirms a substitution effect—households tend to substitute between owning machinery and purchasing mechanization services, rather than combining them complementarily.

These results are consistent with prior findings that highlight the positive effects of household labor availability, participation in technical training, and access to local service markets on productivity. Overall, the evidence supports research hypothesis H1, demonstrating that market-driven factors moderate the effectiveness of LAMS through substitution mechanisms between ownership and outsourcing.

4.1.3 Effect of LAMS on agricultural production efficiency under agricultural development policy

Table 5 presents the moderating effects of policy-related factors on TE. Specification (7) reports baseline ordinary least squares (OLS) estimates, while Specification (8) incorporates the instrumental variable—village-level agricultural machinery service adoption rates—with the instrument's statistical insignificance in the second stage satisfying the exclusion restriction.

Specification (9) displays the two-stage least squares (2SLS) results and reveals two principal findings. First, HSFC has a statistically significant positive effect on TE, confirming that land consolidation policies improve input allocation and production conditions. Second, the positive and significant interaction between LAMS adoption and farmland modernization indicates a complementary effect—policy infrastructure enhances the effectiveness of mechanization services.

These findings are consistent with prior evidence that household labor endowment, participation in technical training, and access to local services positively influence productivity. In addition, the operational environment variable—measured by enterprise participation in agricultural collectives—shows a positive and significant association with efficiency.

Overall, the results support research hypothesis H2, demonstrating that policy interventions such as HSFC enhance the productivity impact of LAMS. The interaction between LAMS and HSFC illustrates how infrastructural policies can mitigate constraints arising from land fragmentation and capital indivisibility. This finding aligns with recent evidence from Chari et al.(2021), which shows that land tenure reform and infrastructure investment significantly reduce land misallocation and improve agricultural productivity in China.

TABLE 4 The moderating effect of owned farm machinery on labor-intensive farm machinery service on agricultural production efficiency.

	TE		
	(4) OLS	(5) OLS	(6) 2SLS
Labor-saving farm machinery services	0.0188*** (0.0050)	0.0181*** (0.0051)	0.1954* (0.1129)
Owned farm machinery	0.0077*** (0.0027)	0.0071*** (0.0027)	0.0061* (0.0036)
Labor-saving farm machinery service × owned farm machinery	0.0026** (0.0012)	0.0028** (0.0012)	0.0033* (0.0019)
Family farm	0.2307 (0.1728)	0.2330 (0.1723)	0.2776 (0.1720)
Village cadre households	0.0152** (0.0070)	0.0154** (0.0069)	0.0194** (0.0115)
Number of labor force	0.0042*** (0.0012)	0.0043*** (0.0012)	0.0053** (0.0021)
Non-farm income	0.0016 (0.0122)	0.0008 (0.0122)	0.0093 (0.0197)
Age	0.0003 (0.0023)	0.0005 (0.0023)	0.0044 (0.0045)
Education level	0.0023 (0.0032)	0.0026 (0.0032)	0.0005 (0.0052)
Health status	0.0004 (0.0048)	0.0002 (0.0048)	0.0096 (0.0106)
Technical training	0.0117* (0.0061)	0.0124** (0.0061)	0.0161** (0.0092)
Agricultural operating environment	0.0358** (0.0164)	0.0375** (0.0166)	0.1501 (0.0954)
Farm Machinery Service Supply	0.0211** (0.0092)	0.0211** (0.0093)	0.0375** (0.0191)
Service rate of farm machinery in the village group		0.0031 (0.0031)	
Area control variable	YES	YES	YES
Intercept term	0.7822*** (0.0218)	0.7778*** (0.0241)	0.6468*** (0.1112)
Sample size	1,519	1,519	1,519

① Values in brackets are robust standard errors; ②*,** and*** indicate significance at the level of 10, 5 and 1%, respectively.

TABLE 5 The moderating effect of high standard farmland on labor-intensive agricultural machinery service on agricultural production efficiency.

	TE		
	(7) OLS	(8) OLS	(9) 2SLS
Labor-saving farm machinery services	0.0182*** (0.0051)	0.0184*** (0.0052)	0.3157* (0.1879)
High standard farmland	0.0049* (0.0018)	0.0058* (0.0021)	0.0598* (0.0358)
Labor-saving farm machinery service × high-standard farmland	0.0042* (0.0015)	0.0041* (0.0015)	0.0102* (0.0060)
The family farm	0.2145 (0.1584)	0.2164 (0.1567)	0.1988 (0.1180)
Village cadre households	0.0108 (0.0069)	0.0109 (0.0069)	0.0042 (0.0231)
Number of labor force	0.0044*** (0.0012)	0.0045*** (0.0012)	0.0013*** (0.0007)
Non-farm income	0.0017 (0.0123)	0.0013 (0.0124)	0.0206 (0.0372)
Age	0.0001 (0.0023)	0.0004 (0.0023)	0.0033 (0.0066)
Education level	0.0029 (0.0032)	0.0037 (0.0032)	0.0072 (0.0092)
Health status	0.0006 (0.0047)	0.0009 (0.0048)	0.0002 (0.0142)
Technical training	0.0093* (0.0050)	0.0102* (0.0062)	0.0049* (0.0029)
Agricultural operating environment	0.0285* (0.0154)	0.0305* (0.0158)	0.2655* (0.1590)
Supply of Agricultural Machinery Services	0.0191** (0.0090)	0.0177* (0.0091)	0.0413* (0.0223)
Service rate of farm machinery in the village group		0.0037 (0.0032)	
Area control variable	YES	YES	YES
Intercept term	0.7861*** (0.0213)	0.7915*** (0.0219)	1.0783*** (0.3199)
Sample size	1,519	1,519	1,519

① Values in brackets are robust standard errors; ②*,** and*** indicate significance at the level of 10, 5 and 1%, respectively.

4.2 Robustness test

To verify the consistency of the main findings and assess the indirect effects of LAMS on TE, robustness tests are conducted through heterogeneous analysis based on household income levels. The sample is stratified into income terciles to examine whether the impact of LAMS varies across different economic contexts.

4.2.1 The effect of LAMS on agricultural production efficiency under the effect of market factors

Table 6 presents instrumental variable estimates evaluating the effects of both self-owned machinery and LAMS adoption across different income groups. Three key findings emerge: (1) Both LAMS procurement and machinery ownership contribute positively to TE across all income strata, though the magnitude and significance vary; (2) Among low-income households, the interaction between LAMS and machinery ownership shows a complementary relationship—suggesting that these producers rely on both ownership and service procurement to overcome capital and labor constraints; (3) In contrast, middle- and high-income groups exhibit substitution effects, with high-income households' interaction terms remaining statistically insignificant. These findings suggest divergent mechanization strategies, where lower-income farmers utilize mixed approaches to mechanization, while higher-income households increasingly rely on service outsourcing.

4.2.2 Effect of LAMS on agricultural production efficiency under the influence of policy factors

Table 7 explores the interaction between LAMS and HSFC across income groups. The analysis yields three main results: (1) LAMS adoption significantly enhances TE in all income terciles; (2) HSFC exerts stronger positive effects among low- and middle-income households, likely due to their greater dependence on land as a primary production factor; (3) The interaction term between LAMS and HSFC is consistently positive and significant across income strata, confirming the presence of infrastructure-service complementarity. The magnitude of this moderating effect varies systematically, with the strongest synergy observed among middle- and low-income households.

These robustness checks reinforce the study's main conclusions and suggest that both market and policy environments condition the effectiveness of LAMS in improving production efficiency—especially among smallholders facing capital and land constraints.

5 Limitations

This study has several limitations. First, while the HSFC variable is measured at the village-group level and TE is assessed at the household level—raising the potential for ecological fallacy—we interpret HSFC as a contextual proxy representing shared infrastructure conditions rather than a direct household-level treatment. Second, some unobserved household characteristics may remain uncontrolled due to data limitations, introducing possible residual selection bias. These limitations do not undermine the study's core findings but highlight opportunities for future research using panel data and multi-level modeling.

6 Conclusion

This study systematically investigates mechanisms for enhancing smallholder agricultural productivity. Specifically, it examines (1) modern production factor integration pathways for smallholders, (2) the productivity effects of LAMS through technological diffusion and functional specialization, and (3) contextual factors influencing the effectiveness of LAMS adoption. These inquiries aim to understand how resource-constrained producers can utilize institutional innovations to achieve productivity gains.

The empirical analysis develops a moderated effects framework to evaluate the impact of LAMS on TE, incorporating both market and policy factors. Results show that LAMS adoption significantly improves TE. Market factors—such as self-owned machinery—exhibit a substitution effect, reducing LAMS' marginal returns, while policy infrastructure—measured by HSFC—positively moderates LAMS effects. These findings validate hypotheses H1 and H2. Income-stratified robustness checks further reveal heterogeneity in LAMS effectiveness and infrastructure-service complementarity, underscoring differential adoption pathways across income groups.

This study extends the existing literature on agricultural mechanization. While previous research emphasizes yield enhancement and adoption determinants, our findings identify TE improvement as a key outcome and highlight LAMS' capacity to mitigate inefficiencies stemming from land fragmentation and labor scarcity. Additionally,

TABLE 6 The moderating effects of market factors grouped by household income level.

	TE			
	(10) Q1	(11) Q2	(12) Q3	(13) Q4
Labor-saving farm machinery services	0.2273* (0.1367)	0.0981*** (0.0342)	0.4826* (0.2627)	3.3954** (1.6014)
Own farm machinery	0.0171* (0.0089)	0.0032* (0.0016)	0.0256* (0.0148)	0.0962** (0.0455)
Labor saving agricultural machinery service by its farm machinery	0.0064* (0.0035)	0.0035* (0.0016)	0.0088 (0.0060)	0.3526** (0.1660)
Control variables	YES	YES	YES	YES
Region dummy variable	YES	YES	YES	YES
Intercept term	0.8547*** (0.1391)	0.7109*** (0.0532)	0.4477 (0.6012)	4.7562 (3.4436)
Sample size	346	362	369	442

① Values in brackets are robust standard errors; ② *,** and*** indicate significance at the level of 10, 5 and 1%, respectively.

TABLE 7 The moderating effects of policy factors grouped by household income level.

	TE			
	(14) Q1	(15) Q2	(16) Q3	(17) Q4
Labor-saving farm machinery services	0.3613** (0.1680)	0.1782* (0.1041)	0.5879* (0.3439)	0.1066* (0.0631)
High standard farmland	0.0091** (0.0044)	0.0752* (0.0405)	0.0573 (0.0399)	0.0379 (0.0257)
Labor-saving farm machinery services × high-standard farmland	0.010 (0.0093)	0.077* (0.0458)	0.032 (0.0252)	0.021* (0.0116)
Control variables	YES	YES	YES	YES
Region dummy variable	YES	YES	YES	YES
Intercept term	0.891 (0.662)	0.654*** (0.186)	1.100 (0.693)	1.008*** (0.186)
Sample size	346	362	369	442

① Values in brackets are robust standard errors; ② *,** and*** indicate significance at the level of 10, 5 and 1%, respectively.

we demonstrate the complementary role of infrastructure by showing how HSFC amplifies the effectiveness of LAMS.

From an international perspective, the results offer insights into how service-based mechanization—when supported by land-use reforms—can enhance productivity in smallholder systems. Theoretically, this study contributes to understanding service-based mechanization as a form of induced institutional innovation suited to land-constrained, labor-scarce economies. Practically, the findings provide policy guidance for developing countries seeking to scale mechanization through decentralized service systems aligned with land-use infrastructure improvements.

Importantly, the study underscores the role of institutional context. Unlike much of the literature that focuses solely on LAMS adoption behavior, this analysis incorporates the moderating effect of HSFC, revealing how policy-led land consolidation enhances the impact of service-based mechanization. These results deepen our understanding of the interactions between labor-saving services, land-use policy, and household heterogeneity, and support the case for integrated agricultural modernization strategies in China and other developing countries.

Beyond this, several extensions merit exploration for future research. An illustrative case is employing panel datasets or longitudinal tracking surveys to assess the dynamic impacts of LAMS adoption over time, capturing persistence, spillover, and potential learning effects. In addition, more detailed investigation into the organizational structure and governance of service providers—such as cooperatives, enterprises, or informal networks—could offer insights into how service delivery mechanisms mediate mechanization outcomes.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The dataset used in this paper comes from the micro-study data of farmers in the national fixed observation point of the Ministry of Agriculture and Rural Affairs of China. The Ministry of Agriculture and Rural Affairs has strict restrictions on the use of this data. It can only be used in a specific computer room at the agreed time. The data cannot be disclosed. Data users can only copy the analysis results for academic research. Requests to access these datasets should be directed to http://www.rcre.agri.cn/jigou/csjs/gdgcdglc/. This is the official introduction of the administration of national fixed observation system.

Author contributions

DY: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. QY: Methodology, Software, Visualization, Writing – review & editing. MH: Funding acquisition, Resources, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Appendix

TABLE A1 Multicollinearity test of the model

Variables	VIF	1/VIF
Supply of agricultural machinery services	2.49	0.400923
Agricultural Business environment	2.34	0.426628
High standard farmland	1.83	0.546306
Farm machinery service rate of village groups	1.50	0.665079
LAMS	1.37	0.727587
Age	1.33	0.750022
Health status	1.24	0.806774
Level of education	1.20	0.832994
Technical training	1.18	0.844327
Number of labor force	1.18	0.849409
Village cadre households	1.15	0.867013
Family Farm	1.09	0.916606
Non-farm income	1.06	0.945421
Mean VIF	1.44	

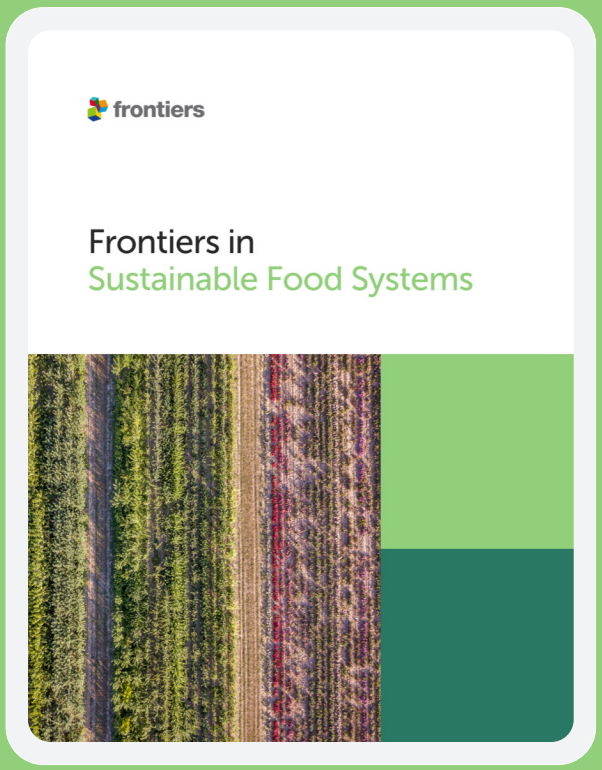
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