TYPE Original Research
PUBLISHED 22 July 2024
DOI 10.3389/fsufs.2024.1325915

OPEN ACCESS

EDITED BY
Mary Beth Arensberg,
Abbott, United States

REVIEWED BY
Siyu Wang,
Tianjin University of Finance and Economics, China
Gui Jin,
China University of Geosciences Wuhan, China

*CORRESPONDENCE
JunFu Cui
✉ 30087@sdwu.edu.cn

RECEIVED 14 November 2023
ACCEPTED 10 July 2024
PUBLISHED 22 July 2024

CITATION
Liu Y, Jiang H and Cui J (2024) County-level total factor productivity of food in China and its spatio-temporal evolution and drivers. *Front. Sustain. Food Syst.* 8:1325915.
doi: 10.3389/fsufs.2024.1325915

County-level total factor productivity of food in China and its spatio-temporal evolution and drivers

Yang Liu[1], Hui Jiang[2] and JunFu Cui[1]*

[1]School of Economics, Shandong Women's University, Jinan, China, [2]School of Economics and Trade, Shandong Management University, Jinan, China

In the context of the ongoing process of high-quality development in the new era, which is focused on improving total factor productivity, it is of great importance to explore the spatial and temporal variations of total factor productivity growth and its driving factors in China's county regions' grain cultivation industry. This paper employs a three-stage DEA-Malmquist productivity method, the Gini coefficient method, and a panel fixed-effects model to analyze data from Chinese counties between 2009 and 2019. The analysis indicates that the growth of county food total factor productivity (FTFP) exhibits a fluctuating upward trend during the examination period, with an average annual growth rate of 2.43%. This is primarily driven by technological progress, yet the core driving role of technological efficiency is not effectively played. The average annual growth rate of county FTFP varies across different regions. The highest average annual growth rate of county FTFP in the eastern region and the primary grain-producing area is 2.75 and 3.04%, respectively. The lowest growth rates were observed in the western region and the main grain marketing area, at 1.44 and 1.23%, respectively. Secondly, the Gini coefficient of county FTFP continues to demonstrate a persistent upward trend during the examination period, with an average annual growth rate of 14.729%. The primary factor contributing to the observed variation in total factor productivity growth of the food sector at the regional level is the existence of disparate technological progress. Thirdly, there is a notable positive correlation between county financial deepening and financial self-sufficiency rates and county FTFP growth, with impact coefficients of 0.0503 and 0.0924, respectively. Conversely, county population density, degree of economic development, farmers' income level, and industrial structure exert a significant negative influence on county FTFP growth and technological progress.

KEYWORDS

food security, food economics, county-level data, technological progress, spatio-temporal divergence, drivers, three-stage DEA-Malmquist, food total factor productivity

1 Introduction

The simultaneous occurrence of multiple crises, including the global spread of the novel coronavirus, climate-related shocks, and geopolitical conflicts, has led to a significant increase in the number of individuals experiencing hunger globally. The most recent edition of the State of Food Security and Nutrition in the World 2023 report indicates that there are currently approximately 735 million individuals experiencing hunger globally, representing a 122 million increase in the number of hungry people since the pre-New Crown outbreak in 2019. As the world's most populous country, China's food production is not only critical for domestic food security, but also has a significant impact on achieving Sustainable Development Goal 2, which is to eradicate hunger by 2030.

In order to cope with the ongoing food crisis, there is an urgent need to increase factor resource inputs for food production and improve total factor productivity for food (FTFP). Nevertheless, resource and environmental constraints have tightened in recent times, and the factor-driven approach to food production growth has been increasingly constrained (Gao and Wang, 2020). Consequently, the sustainable development of grain farming in the contemporary era is contingent upon the growth of FTFP. Despite the consistent expansion of China's grain production, there remains considerable scope for enhancement in grain yields relative to global benchmarks. This presents a promising avenue for the advancement of total factor productivity. China's grain production is concentrated in counties. It is of great importance to study the evolutionary trends and spatial and temporal differentiation characteristics of FTFP growth in these county areas in order to accurately assess the sustainable development of China's grain farming industry. Moreover, an investigation into the driving forces and influencing factors behind the growth of FTFP in the counties can provide a realistic basis for ensuring food security and achieving the global sustainable development goal of "zero hunger".

The literature on FTFP growth rate has been subjected to extensive study by scholars at both the national and international levels. These studies have employed a variety of perspectives and methodologies to measure the growth rate of FTFP and to explore the factors that influence it. Initially, scholars concentrated on measuring broad agricultural TFP, including Gong (2018), Wang et al. (2020), and Hu et al. (2021). Nevertheless, subsequent research has broadened the scope to encompass grain-specific TFP. Some studies have concentrated on the TFP growth of individual grain crops, such as rice, wheat, corn, soybean, and so forth, within the plantation industry. For example, Muftiadi (2018), Wang and Gao (2020), and Wu et al. (2022) have examined the TFP growth of specific grain crops. Although studies on food crop varietal productivity offer insights into the sustainable development of individual crops, they may not fully represent overall changes in food productivity.

A further category of literature concerns the overall technical progress of the food planting industry. For example, Gao and Song (2014) identified spatial autocorrelation in China's grain production technical efficiency, emphasizing notable disparities in technical efficiency across diverse grain production functional zones. Zheng and Cheng (2021) measured China's FTFP growth during the period between 1980 and 2018 and identified an accelerated growth pattern, which was primarily driven by technological progress. Some studies have also considered environmental issues and measured the green TFP of food production. The majority of scholars, including Min and Li (2012), Tian and Wang (2016), and Li (2021), posit that China's eco-efficiency in grain production evinces a fluctuating trend after accounting for environmental factors. Furthermore, scholars have investigated a range of factors influencing FTFP growth. These include production factors, such as an aging labor force (Peng and Wen, 2016), land transfer (Zeng et al., 2018), and agricultural mechanization (Peng and Zhang, 2020), as well as socioeconomic factors, including financial support for agricultural subsidies (Li et al., 2021) urbanization (He and Qiang, 2019), and natural factors, such as climate change (Yin et al., 2016).

Two principal methodologies exist for measuring total factor productivity in the food industry. One category is the parametric approach, represented by stochastic frontier analysis (SFA). Aigner et al. (1977) initially proposed the SFA framework using cross-sectional data. The SFA permits the existence of technical inefficiencies and divides the error term into two components: stochastic errors that are beyond the producer's control (stochastic perturbation term) and technological errors that are within the producer's control (technological inefficiencies).

Subsequently, two broad directions for improving technical inefficiency have been explored. The first direction is to model the technological frontier in a more flexible way. For instance, Sun and Kumbhakar (2013) and Yao et al. (2018) proposed the semiparametric smooth coefficient (SPSC) stochastic production frontier model. In this model, the input elasticities are unknown smooth functions of some non-traditional inputs. These inputs can be viewed as firm characteristics, policy variables, or any variables that describe the production environment. Guo et al. (2024) proposed the generalized Luenberger productivity indicator (GLPI) to analyze urban GTFP in China. This indicator uses distance elasticity shares as input weights in the production function and employs SFA for parameter decomposition to obtain technological change (TC), technical efficiency change (TEC), and scale efficiency change (SEC). The second direction of inquiry is to examine the manner in which error components of an SF model can be modeled in different ways. Badunenko and Kumbhakar (2017) proposed a four-component cost frontier model, and Lai and Kumbhakar (2018) suggested the use of maximum simulated likelihood to estimate a four-component production frontier model. Baležentis and Sun (2020) proposed a four-component stochastic frontier model in which the frontier function is represented by an unknown smooth input distance function, and inefficiency is decomposed into persistent and transient inefficiencies.

The second method is the non-parametric approach, which is represented by the Data Envelopment Analysis (DEA) method. The DEA method considers multiple inputs to produce multiple outputs without setting a specific function, thereby becoming the mainstream method of measuring TFP and being widely used in many fields, including industry (Liu F. et al., 2023), banking (Zha et al., 2016), the environment (Baležentis et al., 2024), and so on. Nevertheless, the non-parametric method does not fully consider the influence of external environmental factors and random factors, which results in certain limitations in the obtained results. To address these limitations, Fried et al. (2002) proposed a three-stage DEA model that combines the advantages of SFA and DEA. This model incorporates the SFA method into the DEA framework, enabling the consideration of random errors and the removal of heterogeneous effects caused by external environmental factors and managerial inefficiencies. Furthermore, the three-stage DEA model incorporates the Malmquist index, allowing the analysis of changes in technical progress and efficiency over different time periods. Parichatnon et al. (2018) applied a three-stage DEA- Malmquist model to measure the efficiency of rubber production in four regions of Thailand from 2005 to 2014. Liu et al. (2022) employs a nonseparable undesirable output modified three-stage DEA- Malmquist to evaluate the AGTFP of China's 30 provinces from 2000–2018.

In this study, we acknowledge and build upon the valuable contributions of existing research in exploring the spatial and temporal evolution of FTFP growth and its driving factors in China's county areas. Nevertheless, there are some limitations in the existing literature. Firstly, the existing studies primarily focus on measuring FTFP growth at the inter-provincial level or from the perspective of farmers, with a notable absence of analysis specifically at the county scale. As China's grain production is predominantly concentrated in county areas, this gap in the literature impedes a comprehensive understanding of the changes in FTFP growth in these regions. To address this, the present study conducted empirical research based on panel data from 729 counties in China spanning the period from 2009 to 2019. Secondly, a significant number of studies fail to adequately account for external environmental factors and random errors, resulting in biased assessments of China's FTFP growth and its dynamic evolution. To provide a more accurate analysis, we employ a three-stage DEA combined with the Malmquist productivity index. This approach is designed to effectively eliminate factors such as managerial inefficiency, external environment variations, and random errors from the analytical framework, thereby enabling more precise measurement and analysis of FTFP growth in Chinese counties. Thirdly, the existing literature lacks an in-depth analysis of the spatial and temporal variations in FTFP growth, particularly in the county areas. To address this gap, we propose utilizing the Gini coefficient method to reveal and analyze regional differences in county FTFP growth across the three major geographic regions and grain functional areas. Furthermore, there is a paucity of attention devoted to identifying the key drivers behind the growth of FTFP in these regions. To this end, a panel fixed-effects model will be constructed with the objective of identifying and exploring the driving factors of county FTFP growth.

2 Methods and data

2.1 Methods

2.1.1 Three-stage DEA dynamic analysis mode

The traditional DEA methods are unable to distinguish between non-input technical inefficiencies caused by environmental changes or stochastic shocks, which leads to biased measurement results. The three-stage DEA model effectively removes the heterogeneous effects of external environmental factors, random errors, and managerial inefficiency by introducing the SFA method. This allows for the accurate reflection of the real productivity of decision-making units under multiple-input and multiple-output situations. This is achieved by placing them in the same environment and under the same conditions for comparison (Fried et al., 2002). For this reason, this paper constructs a three-stage DEA-Malmquist productivity index to measure the total factor productivity of grain in Chinese counties. First, the DEA-Malmquist index model is utilized to measure the initial data to obtain the efficiency values and slack variables. Then, the environmental variables are selected to utilize the SFA-like regression to eliminate the effects of external environmental factors and random errors in the input variables. Finally, based on the input variables and output variables that have eliminated the influence of external environmental factors, the actual production efficiency is measured using the DEA-Malmquist index model. The specific model is constructed as follows:

Stage 1: construction of the DEA-Malmquist index model. The Malmquist productivity index is defined in accordance with the distance function, which quantifies the total factor productivity change between two data points by calculating the ratio of the distance of each data point with respect to the generalized technology distance. The TFP index is calculated by employing the geometrical mean of the Malmquist productivity index between the specified periods of t to $(t+1)$. The geometric mean of the Malmquist productivity index is employed to calculate the output-oriented TFP index in the following form:

$$M_i\left(x^{t+1},y^{t+1},x^t,y^t\right)=\left[\frac{D_i^t\left(x^{t+1},y^{t+1}\right)}{D_i^t\left(x^t,y^t\right)}\times\frac{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_i^{t+1}\left(x^t,y^t\right)}\right]^{1/2} \quad (1)$$

Where, $D_i^t\left(x^{t+1},y^{t+1}\right)$ denotes the technical distance between periods from t to $(t+1)$, when $M_i>1$ represents the growth of TFP from t to $(t+1)$, $M_i=1$ represents the stabilization of TFP from t to $(t+1)$, and $M_i<1$ represents the decline of TFP from t to $(t+1)$. Since Eq. (1) is the geometric mean of the TFP index for the two periods, it is collapsed at the base:

$$M_i\left(x^{t+1},y^{t+1},x^t,y^t\right)= \frac{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_i^t\left(x^t,y^t\right)}\times\left[\frac{D_i^t\left(x^{t+1},y^{t+1}\right)}{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}\times\frac{D_i^t\left(x^t,y^t\right)}{D_i^{t+1}\left(x^t,y^t\right)}\right]^{1/2} \quad (2)$$

The Malmquist productivity index is the result of the joint action of technical efficiency changes and technological progress. Technical efficiency is defined as the ability of producers to obtain the maximum output under the given factor inputs. This is achieved through the implementation of scientific management decision-making methods and organization, which reflect the effective degree of utilization of the existing technology by economic agents in the production process. Technological progress is reflected in productivity changes through the introduction of the time trend factor, which reflects productivity changes. The progress of production technology is manifested in the upward shift of the production frontier. In accordance with Eq. (2), the Malmquist productivity index can be further decomposed into two constituent parts: technical efficiency change (TE) and technical progress change (TC). This is expressed as follows:

$$TE=\frac{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}{D_i^t\left(x^t,y^t\right)} \quad (3)$$

$$TC=\left[\frac{D_i^t\left(x^{t+1},y^{t+1}\right)}{D_i^{t+1}\left(x^{t+1},y^{t+1}\right)}\times\frac{D_i^t\left(x^t,y^t\right)}{D_i^{t+1}\left(x^t,y^t\right)}\right]^{1/2} \quad (4)$$

The distance function required for the Malmquist productivity index is calculated using the linear programming method in DEA on the basis of the basic form of the Malmquist productivity index and its decomposition. Subsequently, TFP and its decomposition components are obtained. In light of the fact that variable returns to scale align with the empirical reality of county FTFP growth, this paper employs the variable returns to scale (VRS) DEA model to calculate the distance function requisite for the Malmquist productivity index. The model is specified as follows:

$$\min \varepsilon = 1$$
$$s.t.\begin{cases} \sum_{i=1}^{n} \lambda_i X_i + s^- = \varepsilon X_i \\ \sum_{i=1}^{n} \lambda_i Y_i - s^+ = Y_i \\ \lambda_i \geq 0, s^- \geq 0, s^+ \geq 0 \\ \sum_{i=1}^{n} \lambda_i = 1 \end{cases} \tag{5}$$

In Eq. (5), X_i denotes the inputs of the ith decision unit, Y_i denotes the outputs of the ith decision unit, n is the number of decision units, λ is the combination coefficient of input indexes of the decision unit, s^- is the slack variable reflecting the lack of outputs, s^+ is the residual variable reflecting the redundancy of inputs, and ε is the efficiency of the decision unit, and when $\varepsilon = 1$ indicates that the DEA is effective, and the other way around, it indicates that the DEA is ineffective. The above model can be measured to obtain the traditional TFP, TC and TE indices, as well as the target values and slack variables of the input indicators for each sample.

Stage 2: Construction of a panel SFA model. In light of the fact that a multitude of intricate elements, including external environmental factors, random errors, and managerial inefficiency, will inevitably exert an influence on the decision-making units in question, a parallel panel SFA is devised with the objective of adjusting the slack variables derived in the initial phase. This is done with the intention of eliminating environmental factors and statistical noise, and subsequently placing each decision-making unit under identical conditions for the purpose of measuring efficiency. The particular SFA model is as follows:

$$S_{ni}^t = f\left(Z_{ni}^t, \beta_n\right) + v_{ni}^t + u_{ni}^t t = 1,2,\cdots,T i = 1,2,\cdots,I n = 1,2,\cdots,N \tag{6}$$

S_{ni}^t is the input slack variable of the nth type of input factor for the ith decision unit in period t, $f(\cdot)$ represents the stochastic frontier production function, Z_{ni}^t and β_n are the environmental variables and parameter estimates, respectively, $\varepsilon_{ni}^t = v_{ni}^t + u_{ni}^t$ is the composite error term, v_{ni}^t is the stochastic error term, and $v_{ni}^t \sim \mathrm{N}\left(0, \sigma_{vn}^2\right)$, u_{ni}^t are the managerial inefficiency terms, and $u_{ni}^t \sim N^+\left(0, \sigma_{un}^2\right)$, u_{ni}^t and v_{ni}^t are independently un-correlated.

In order to distinguish between managerial inefficiency and random error terms and to place the input indicators of each decision unit under comparable conditions, this paper draws upon the study of Luo (2012) and employs the managerial inefficiency formula proposed by Sun and Kumbhakar (2013), which is as follows:

$$\bar{E}\left(u_{ni}^t / \varepsilon_{ni}^t\right) = \frac{\lambda\sigma}{1+\lambda^2}\left(\frac{\phi\left(\varepsilon_{ni}^t \lambda / \sigma\right)}{\Phi\left(\varepsilon_{ni}^t \lambda / \sigma\right)} + \frac{\varepsilon_{ni}^t \lambda}{\sigma}\right) \tag{7}$$

Eq. (7), $\lambda = \sigma_{un} / \sigma_{vn}$, $\sigma = \left(\sigma_{vn}^2 + \sigma_{vn}^2\right)^{1/2}$, $\phi(\cdot)$ and $\Phi(\cdot)$ are the density function and distribution function of the standard normal distribution, respectively. Meanwhile the estimation formula of the random error term is as follows:

$$\bar{E}\left(v_{ni}^t / \varepsilon_{ni}^t\right) = S_{ni}^t - f\left(Z_{ni}^t, \bar{\beta}_n\right) - \bar{E}\left(u_{ni}^t / \varepsilon_{ni}^t\right) \tag{8}$$

In order to eliminate the effects of external environmental factors, managerial inefficiency and random error terms of slack variables, according to Fried et al. (2002), it is necessary to place each decision unit in the same external environment for efficiency assessment, with the following adjustment formula:

$$\begin{aligned} x_{ni}^* = x_{ni} &+ \left[\max\left(f\left(Z_{ni}^t, \bar{\beta}_n\right)\right) - f\left(Z_{ni}^t, \bar{\beta}_n\right)\right] \\ &+ \left[\max\left(v_{ni}^t\right) - v_{ni}^t\right] \end{aligned} \tag{9}$$

where x_{ni}^* and x_{ni} are the adjusted and pre-adjusted input variables, respectively, and the two parentheses on the right-hand side of the equation indicate that all decision-making units are placed under the same conditions after removing environmental factors and random errors, respectively, independent of other factors.

Stage 3: Construction of an adjusted DEA-Malmquist index model. The DEA-Malmquist index model is employed to recalculate the adjusted data, thereby eliminating the influence of external environmental factors, management inefficiency, and random errors on the production efficiency value of each decision-making unit. Given that each decision-making unit is situated within the same environment, the adjusted efficiency values are more realistic and objective.

2.1.2 Panel fixed effects model

In order to analyze the driving factors of county FTFP growth, this paper constructs a panel fixed effects model, the model is as follows

$$gtfp_{i,t} = \beta_0 + \beta_1 X_{i,t} + u_i + e_t + \varepsilon_{i,t} \tag{10}$$

In Eq. (10), $gtfp_{i,t}$ is the FTFP of the ith county (county-level city) in year t, $X_{i,t}$ denotes the driver variable of FTFP, u_i denotes the area fixed effect, e_t denotes the time fixed effect, $\varepsilon_{i,t}$ is the random disturbance term, and β_0 and β_1 are the coefficients to be estimated. The corresponding variables are natural logarithmized in model parameter estimation to mitigate heteroskedasticity and multicollinearity among variables. In order to further explore the ways through which each driver affects FTFP, referring to the existing studies, the index of change in technological progress and the index of change in technological efficiency are taken as the dependent variables for regression estimation, and the model is as follows:

$$gtc_{i,t} = \beta_0 + \beta_1 X_{i,t} + u_i + e_t + \varepsilon_{i,t} \tag{11}$$

$$gec_{i,t} = \beta_0 + \beta_1 X_{i,t} + u_i + e_t + \varepsilon_{i,t} \tag{12}$$

In Eqs. (11, 12), $gtc_{i,t}$ is the index of change in food technology progress in year t of the ith county (county-level city), and $gec_{i,t}$ is the index of change in food technology efficiency in year t of the ith county (county-level city). The rest of the variables are explained as in Eq. (10).

2.2 Data description

To guarantee the reliability of the empirical data presented in the paper, specific criteria were employed in the selection of county samples. In view of the unavailability or significant absence of data pertaining to rural economic development indicators in a number of counties, a selection criterion was introduced. Consecutive years of missing data were identified in counties, resulting in their exclusion from the sample. Consequently, the paper ultimately selected 729 county samples for analysis. The paper focuses on calculating the Malmquist index, which requires a two-year efficiency change calculation. To assess the growth of FTFP over the 2010–2019 period, input–output variables from the 2009–2019 data of the selected 729 county samples were utilized. It is important to note that the statistical data does not include municipal districts, special districts, forest districts, and certain regions such as Beijing Municipality, Shanghai Municipality, Tianjin Municipality, Tibet Autonomous Region, and the Hong Kong, Macao, and Taiwan regions. This exclusion is due to the differences in economic and financial characteristics between municipal districts and counties (county-level cities) and the division of financial power and authority. Furthermore, China's county-level administrative divisions have undergone adjustments and changes in recent years, which have resulted in the exclusion of a small number of county samples due to county withdrawals or the division of counties into districts.

The county sample data presented in this paper is representative in two key respects. Primarily, the selection of samples is focused on China's principal grain-producing areas and the regions exhibiting a balance between production and marketing. In accordance with the standard delineation set forth in the Medium- and Long-Term Plan for National Food Security (2008–2020), the 729 county samples selected for analysis in this study are distributed across 381 counties in the primary grain production region, 277 counties in the production and marketing balance area, and 71 counties in the primary marketing region. This selection ensures that the samples are representative of the areas with significant grain production and marketing activities. Secondly, the samples were selected from different geographic regions, with consideration given to the variations in resource endowment, economic development level, and food production across these regions. In accordance with the regional divisions delineated by the National Bureau of Statistics (NBS) in 2017, the 729 county samples presented in this paper encompass 233 counties in the eastern region, 315 counties in the central region, and 181 counties in the western region. The inclusion of samples from these disparate regions ensures a certain level of representativeness across the entire country. In conclusion, the selection of county samples in this paper considers both the concentration of grain production areas and the representation of different geographic regions in China. This approach guarantees the representativeness of the data and, to a certain extent, enhances the generalizability of the findings.

2.3 Selection of variables

The FTFP is a measure of the comprehensive use efficiency of all input factors in the grain production process. In accordance with the calculation requirements of the three-stage DEA method, the relevant variables primarily encompass grain output variables, production input variables, and environmental variables. The grain output variable is derived from the study of Liu and Yan (2022), and the total grain output for each county area is selected for measurement.

The food production input factors include land, labor, and capital factors such as machinery and fertilizer. In this paper, we refer to the study of Zhao and Zhou (2020) and select the sown area of grain the labor input for grain cultivation, the total power of machinery for grain cultivation, and the amount of fertilizer applied for grain cultivation as input factor variables. The measurement of each input factor must be based on the production input data of food crops. As the China County Statistical Yearbook does not distinguish between factor input data for grain crops and cash crops, this paper draws on the studies of Wang et al. (2013) and employs the weight coefficient method to isolate the production input factor data for grain crops from generalized agriculture. The following formulae may be employed to calculate the input factors for grain cultivation:

- Grain cultivation labour input = number of employees in agriculture, forestry, animal husbandry and fishery × (agricultural output value/total output value of agriculture, forestry, animal husbandry and fishery) × (grain sown area/crop sown area)
- Grain cultivation total mechanical power = total power of agricultural machinery × (grain sown area/crop sown area)
- Grain cultivation fertilizer application (discounted pure quantity) = agricultural fertilizer application (discounted pure quantity) × (grain sown area)/(sown area of crops).

In order to eliminate the influence of external environmental factors on the efficiency evaluation of decision-making units, this paper selects the population conditions, industrial structure, and human capital of each county area as uncontrollable external social conditions. Among these factors, the demographic conditions are quantified by the ratio of the population size to the administrative area of each county. The industrial structure is quantified by the ratio of the sum of the value added of the secondary and tertiary industries to the gross regional product. The quality of human resources is measured according to the study of Liu and Xie (2016), which defines it as the ratio of the number of students enrolled in secondary schools in each county region to the regional population (Liu et al., 2024).

The data for the aforementioned variables were primarily sourced from the China County Statistical Yearbook, the China County (City) Social and Economic Statistical Yearbook, the Wind database, and the EPS database. In order to address the issue of missing values, the paper employs a number of different strategies. Firstly, some missing data are supplemented based on the statistical bulletins of counties

TABLE 1 Descriptive statistics of variables.

Variable name and symbol	Meaning of variables and units	Average value	Standard deviation
Food output (grain)	Total grain production (tons)	29255.660	36767.303
Land inputs (land)	Area sown with grain (ha)	5382.193	5307.790
Agricultural machinery inputs (machinery)	Total power of machinery for food cultivation (kWh)	34309.371	33331.171
Agricultural fertilizer inputs (fert)	Fertilizer application for food cultivation (net amount) (tons)	2211.393	3068.022
Agricultural labor inputs (labor)	Number of labor inputs for food cultivation (persons)	4555.762	4167.424
Rural human capital (hum)	Ratio of secondary school enrolment to total regional population	0.051	0.023
Industrial structure (industries)	Ratio of value added of secondary and tertiary industries to GDP	0.798	0.123
Population density (popu)	Ratio of district population to administrative area	0.032	0.031
County financial deepening (finas)	Loans to GDP ratio of financial institutions	0.668	0.410
Financial self-sufficiency (govz)	Ratio of fiscal expenditures to fiscal revenues	0.298	0.226
Level of farmers' income (income)	Disposable income of rural residents (ten thousand yuan)	1.049	0.578

TABLE 2 Pearson test for variables.

variable name	Land input	Mechanical inputs	Fertilizer inputs	Labor input
total grain production	0.9087*** (0.0000)	0.7293*** (0.0000)	0.8527*** (0.0000)	0.5633*** (0.0000)

[1] *** indicates significant at the 1% significance level; numbers in parentheses are *p*-values.

(county-level cities and flags). Secondly, missing data are supplemented and improved using the statistical yearbooks of the provinces, cities, where the sample counties (county-level cities and banners) are located. This process helps to fill in any gaps in the data. Finally, linear interpolation and linear extrapolation methods are employed to mitigate the impact of missing data on individual indicators. Furthermore, in order to accurately reflect economic growth, the relevant nominal economic variables are adjusted using the provincial GDP price deflators of the sample counties. This process ensures that the data is deflated to account for changes in prices over time, thereby providing a more accurate representation of economic growth.

2.4 Descriptive statistical analysis

The results of the definition and descriptive statistical analysis of the sample data are presented in Table 1. The principle of "homogeneous correlation" represents a fundamental assumption in the field of DEA. In order to test the correlation between input and output variables, the Pearson correlation test method was employed. The results of this test are presented in Table 2 of the paper. As evidenced by the data presented in the table, the correlation coefficients between the input variables and the output variables are positive and statistically significant at the 5% level. The positive correlation coefficient indicates that as the values of the input variables increase, so too do the values of the output variables. This confirms that the selected input and output variables in this study comply with the principle of isotropy or homogeneous correlation, thereby corroborating the accuracy and validity of the DEA analysis presented in the paper.

3 Measurement of county FTFP and spatio-temporal divergence

3.1 Measurement and decomposition of county FTFP growth rates

In order to ascertain the genuine county FTFP growth rate, this paper considers the input slack variables of agricultural fertilizer, agricultural machinery, labor, and grain sown area, which are measured by traditional DEA, as dependent variables. Furthermore, the paper considers external environmental variables, including industrial structure, population density, and the level of human capital, as independent variables. The parameters are estimated using SFA-like regression to exclude the effects of managerial inefficiencies, external environment factors, and random errors on the effects of input slack variables. The resulting estimation results are presented in Table 3.

As evidenced in Table 3, the γ value and LR one-sided test in the SFA regression of all slack variables surpassed the 1% significance test, with the γ value approaching 1. This indicates that managerial inefficiency exerts a dominant influence on the composite error term, or the deviation error between the actual input value and the target input value, which is predominantly affected by the external environment. Consequently, employing the SFA model to account for the stochastic factor and managerial inefficiency factor for each input variable is a suitable approach. If the coefficients are positive, an increase in the environmental variables will lead to an increase in the input slack variables or output. If the coefficients are negative, an increase in the environmental variables will lead to a decrease in the input slack variables or output. This is analyzed as follows:

The regression coefficients of the slack variables of industrial structure on agricultural machinery inputs are significantly positive, indicating that the optimization and upgrading of industrial structure promote agricultural mechanization inputs. This indicates that as industrial structure undergoes transformation and upgrading, there is an increase in the input of agricultural machinery, which consequently enhances the efficiency of agricultural production. It is, however, important to note that the transformation and upgrading of

TABLE 3 SFA-like regression results.

Parameter estimate	Fert	Machine	Labor	Land
β_0	3467.431***	3.570E+04***	6982.249***	6211.491***
β_1 (industs)	−997.078***	7781.338***	−3726.739***	−1755.694***
β_2 (popu)	−0.051***	0.440***	−0.056***	−0.046
β_3 (hum)	5371.760***	1.189E+05***	6.317E+04***	7120.024***
σ^2	5.582E+06***	1.294E+10***	2.512E+07***	1.245E+07***
γ	0.932***	0.938***	0.929***	0.950***
LR test	8906.947***	1.012E+04***	1.006E+04***	1.300E+04***

[1] ***, ** and * indicate 1, 5, and 10% significance levels, respectively.

TABLE 4 Changes in county FTFP, EC & TC indices.

Particular year	EC index	TC index	TFP index
2009–2010	0.9400	1.1000	1.0340
2010–2011	0.9600	1.0640	1.0214
2011–2012	0.9980	1.0130	1.0110
2012–2013	0.9940	1.0370	1.0308
2013–2014	1.0240	0.9610	0.9841
2014–2015	0.9670	1.0740	1.0386
2015–2016	1.0900	0.9300	1.0137
2016–2017	0.9450	1.0550	0.9970
2017–2018	1.0800	0.9310	1.0055
2018–2019	0.9580	1.1700	1.1209
average	0.9956	1.0335	1.0257

TABLE 5 Changes in county FTFP, EC & TC indices in different regions.

Area	EC index	TC index	TFP index
Eastern counties	0.9991	1.0405	1.0312
Central counties	1.0146	1.0350	1.0431
Western counties	1.0040	1.0311	1.0301
Major food producing area	1.0100	1.0391	1.0426
Food production and marketing balance area	1.0073	1.0293	1.0308
Major food marketing area	0.9901	1.0437	1.0217

regional industrial structure may also result in a loss of food production efficiency. This is due to the marginalization of the food cultivation industry as other industries become dominant. This suggests that while industrial restructuring may promote agricultural mechanization, it may also result in a decline in food production efficiency as the focus shifts away from agriculture. Conversely, the regression coefficients of the slack variables of industrial structure on fertilizer, arable land, and labor inputs are significantly negative. This suggests that the optimization and upgrading of the county's industrial structure result in a reduction in the production and input of agricultural fertilizers. This reduction is achieved through the gradual elimination of high-pollution chemical industries, which improves the efficiency of food production, particularly in the stage of diminishing marginal effect of fertilizer input. Furthermore, the growth of non-agricultural industries facilitates the transfer of residual factors of production from the agricultural sector to the industrial and commercial sectors. This process optimizes the efficiency of agricultural factors and contributes to the growth of FTFP. The growth of non-agricultural industries results in the reallocation of surplus production factors from agriculture to other sectors, thereby enhancing the overall allocation of agricultural resources.

Moreover, the regression coefficients of population density on the slack variables of fertilizer, labor, and arable land inputs are negative. The significance test indicates that the fertilizer and labor inputs are particularly affected. In regions with elevated population density and constrained arable land, the labor force is compelled to transition to the non-agricultural sector. This rational allocation of labor resources helps to protect regional grain cultivation through the use of intensive cultivation methods. This ultimately enhances grain production efficiency by reducing excessive fertilizer inputs. Finally, the regression coefficients of human capital on the slack variables of fertilizer, machinery, labor, and cropland inputs are all significantly positive. This suggests that regions with higher levels of human capital tend to have higher employment thresholds in the industrial and commercial sectors. Consequently, there is an increase in the agricultural labor force and land inputs due to the structural adjustment of human capital. Furthermore, individuals with higher levels of human capital are more likely to engage in non-agricultural employment, which in turn leads to higher disposable incomes. This leads family farmers to increase the inputs they make, such as those related to the use of fertilizers and machinery for food cultivation. However, an excessive input of production factors can result in an imbalance in factor allocation, which in turn hinders the growth of FTFP.

The input variables, with the exception of the influence of external environmental factors, were derived through the use of SFA-like regression. Subsequently, these variables were employed, in conjunction with the initial output data, to calculate the county's FTFP index, EC (Efficiency Change) index, and TC (Technological Change) index. Tables 4, 5 illustrate the dynamic evolution of these indices. A review of the tables reveals that the annual average growth rates of the TFP index, EC index, and TC index for the county as a whole are 1.0257, 0.9956, and 1.0335, respectively. These values indicate that the

FTFP and EC indices for the county have exhibited an overall upward trend during the examination period. However, the EC index has demonstrated a downward trend, suggesting the potential for improvements in management practices. Upon examination of the subregions, it becomes evident that the EC indexes of the central region, western region, main grain-producing region, and production and marketing balance region have exhibited an upward trend. This indicates that these regions have experienced improvements in agricultural management efficiency. Moreover, all regions have exhibited an increasing trend in both the TFP and EC indexes. This indicates that there have been advancements in overall food production efficiency and technological progress across all subregions. In conclusion, after accounting for external environmental factors, management inefficiencies, and random error factors, the county's FTFP index, TC index, and EC index have exhibited notable growth characteristics during the examination period. The growth of the county's FTFP has been influenced by the combined effect of technological progress and changes in technical efficiency.

3.2 Trend analysis of the dynamic evolution of county FTFP growth

The Malmquist productivity index was employed to ascertain the cumulative multiplication characteristics. In accordance with the study conducted by Zhang and Guo (2021), the county FTFP and its decomposition term for the period between 2010 and 2019 were calculated with 2009 as the base period. In addition, county FTFP and its decomposition terms were calculated for the three major geographic regions (East, Central, and West) and the three major grain functional areas (main grain producing areas, production and marketing balance areas, and main marketing areas), respectively. The results of the calculations are presented in Tables 6–8.

As illustrated in Table 6, the county FTFP exhibited a fluctuating upward trajectory during the 2010–2019 period, with an average annual growth rate of 2.43%. With regard to regional heterogeneity, the average annual growth rate of county FTFP in the three major geographic regions is highest in the east region at 2.75%, while the western region exhibits the lowest growth rate at 1.44%. In general, the eastern region is characterized by a high concentration of talent and a robust technological innovation capacity, which collectively contribute to enhanced food production efficiency. The western region is not only less technologically innovative than the eastern region, but also has a lower population density, which hinders the dissemination and adoption of new technologies and methods of food cultivation. Consequently, the growth of county FTFP is lower than that of the developed regions in the east and center.

Among the food production functional areas, the annual average growth rate of FTFP in the main production areas is the highest at 3.04%, while that in the main marketing areas is the lowest at 1.23%. Although the economy of the main marketing areas is more developed, with a high degree of technological innovation agglomeration, which contributes to the overflow of new technologies into the agricultural sector to bring about the growth of FTFP. This is also reflected in the economic and industrial structure of the main marketing areas, which is more inclined towards the secondary and tertiary industries. The level of urbanization is relatively high, which has led to a significant number of farmers moving out of the agricultural sector to enter the non-agricultural sector in search of employment and a better quality of life. This has resulted in a decline in the number of rural laborers and the level of human capital. Consequently, the number of rural laborers and the level of human capital have declined at a more rapid pace, and the phenomenon of "de-farming" and "de-fooding" in the countryside has become pronounced, with the food plantation industry becoming increasingly marginalized. In comparison, in the context of the strategy of guaranteeing national food security, the main grain-producing areas and areas with balanced production and marketing attach a high degree of importance to grain cultivation. Furthermore, the allocation efficiency of agricultural capital and labor factor inputs is relatively high, resulting in a higher growth of FTFP in the main grain-producing areas and areas with balanced production and marketing than in the main marketing areas.

Table 7 illustrates that the level of technological advancement in food production exhibited an upward trajectory with fluctuations, both at the county level and within each notable region, from 2010 to 2019. This trend aligns with the changes in county FTFP and suggests

TABLE 6 Evolution of county FTFP trends.

Timing	County overall	Eastern counties	Central counties	Western counties	Major food producing area	Food production and marketing balance area	Major food marketing area
2010	1.0584	1.0690	1.0484	1.0620	1.0759	1.0513	0.9918
2011	1.0917	1.1504	1.0905	1.0181	1.1513	1.0274	1.0223
2012	1.1076	1.1478	1.1213	1.0321	1.1673	1.0443	1.0342
2013	1.1656	1.1651	1.1999	1.1066	1.2393	1.1057	1.0039
2014	1.1441	1.1493	1.1568	1.1153	1.1873	1.1114	1.0401
2015	1.1942	1.2052	1.2002	1.1696	1.2380	1.1670	1.0651
2016	1.2214	1.2562	1.2137	1.1903	1.2617	1.1968	1.1013
2017	1.2548	1.2972	1.2455	1.2164	1.2929	1.2622	1.0216
2018	1.2407	1.2882	1.2373	1.1855	1.2884	1.2206	1.0632
2019	1.3917	1.4355	1.4177	1.2900	1.4938	1.3043	1.1842
average	1.1870	1.2164	1.1931	1.1386	1.2396	1.1491	1.0528

TABLE 7 Evolution of county food TC trends.

Timing	County overall	Eastern counties	Central counties	Western counties	Major food producing area	Food production and marketing balance area	Major food marketing area
2010	1.1018	1.1198	1.1054	1.0725	1.1126	1.0837	1.1150
2011	1.1729	1.1946	1.1764	1.1388	1.1856	1.1529	1.1831
2012	1.1899	1.2100	1.1974	1.1509	1.2059	1.1656	1.1986
2013	1.2327	1.2404	1.2403	1.2095	1.2487	1.2138	1.2203
2014	1.1851	1.1972	1.1941	1.1539	1.2053	1.1601	1.1744
2015	1.2772	1.2595	1.2759	1.3023	1.2751	1.2944	1.2215
2016	1.1942	1.1601	1.1859	1.2526	1.1777	1.2358	1.1203
2017	1.2532	1.2575	1.2451	1.2618	1.2589	1.2491	1.2389
2018	1.1582	1.1371	1.1634	1.1764	1.1611	1.1617	1.1291
2019	1.3638	1.4151	1.3564	1.3105	1.4003	1.2912	1.4508
average	1.2129	1.2191	1.2140	1.2029	1.2231	1.2008	1.2052

TABLE 8 Evolution of county food EC trends.

Timing	County overall	Eastern counties	Central counties	Western counties	Major food producing area	Food production and marketing balance area	Major food marketing area
2010	0.9623	0.9567	0.9507	0.9897	0.9695	0.9709	0.8897
2011	0.9333	0.9686	0.9305	0.8929	0.9764	0.8913	0.8663
2012	0.9363	0.9572	0.9433	0.8972	0.9771	0.8974	0.8693
2013	0.9410	0.9419	0.9594	0.9078	0.9876	0.9065	0.8251
2014	0.9608	0.9638	0.9610	0.9566	0.9810	0.9518	0.8875
2015	0.9266	0.9342	0.9430	0.8881	0.9575	0.8973	0.8749
2016	1.0124	1.0434	1.0279	0.9455	1.0476	0.9718	0.9819
2017	0.9821	0.9883	0.9947	0.9521	0.9996	0.9980	0.8261
2018	1.0485	1.0822	1.0598	0.9855	1.0806	1.0318	0.9415
2019	1.0182	1.0100	1.0506	0.9723	1.0660	0.9982	0.8394
average	0.9721	0.9846	0.9821	0.9388	1.0043	0.9515	0.8802

that technological progress is the primary driver of growth in county FTFP. When considering geographic regions, the eastern counties exhibit the highest average value of food TC, followed by the central counties, and the western counties have the lowest average value. This pattern is consistent with the varying levels of economic development observed across these regions. Regions with higher economic development tend to allocate a greater proportion of resources towards technological research and development, thereby enhancing their innovation capabilities. This, in turn, facilitates advancements in food cultivation technology. Conversely, the western regions encounter greater obstacles in agricultural technological innovation and adoption due to geographical and economic factors. Consequently, their levels of technological progress are comparatively lower. In terms of grain functional areas, the main grain-producing areas have the highest average value of grain TC, followed by the main marketing areas and the balance of production and marketing areas. The primary food-producing regions typically exhibit a higher ratio of food cultivation output to gross domestic product (GDP) compared to other regions. As income from food cultivation represents a significant source of revenue for farmers in these regions, there is a greater focus on activities related to food cultivation, including agricultural technology research and development, as well as the promotion and adoption of new agricultural machinery and equipment. Consequently, the main food-producing and marketing regions, as well as the balance-of-production and marketing regions, exhibit a higher level of technological progress.

Table 8 illustrates that the overall grain EC growth in counties and that of each significant region exhibit a cyclical pattern, characterised by an upward-declining fluctuation. This pattern reflects the relatively low level of technological efficiency in grain production within China's counties, which has hindered the improvement of FTFP. However, beginning in 2016, the grain EC growth in counties exhibited an upward trend with fluctuations, indicating that in recent years, advancements in management knowledge and planting experience, facilitated by the application of agricultural socialization services and agricultural production trusteeship, have been contributing continuously to the grain cultivation industry in counties. Consequently, the supportive role of FTFP growth in counties has gradually emerged. In contrast, the technical efficiency value of the principal grain marketing areas is the lowest. There are several potential explanations for this phenomenon. Firstly, the main grain marketing areas are predominantly comprised of economically developed regions along the eastern coast, such as Zhejiang. These regions have a dominant industrial structure in the secondary and tertiary sectors, with a relatively low percentage of agricultural output value in GDP. Consequently, the grain cultivation industry is undervalued in these areas. Furthermore, the main marketing areas have a high level of urbanization and industrialization, which has resulted in a significant transfer of the rural labor force from agricultural employment to non-agricultural sectors. This shift results in a decline in the levels of human capital in rural areas and an aging of the labor force, which in turn leads to a continuous decline in the technical efficiency of food production.

Secondly, there is a notable shift towards a "non-food" agricultural cultivation structure in the primary grain marketing regions. The high levels of urbanization and population concentration in these areas result in an increased demand for cash crops such as green fruits and vegetables. The high levels of urbanization and population concentration in these areas result in increased demand for cash crops such as green fruits and vegetables, thereby driving structural adjustments in the agricultural industry. As the income generated from cash crops is significantly higher than that from grain crops, farmers who are rational in their decision-making, when faced with a decline in agricultural labor and land resources and an increase in prices, adjust the internal planting structure by increasing the planting area of cash crops and reducing the area of grain crops. This reduction in the area dedicated to food crops is intended to generate higher agricultural operating income while simultaneously reducing factor inputs in the food cultivation industry. Consequently, the food cultivation industry becomes increasingly marginalized, impeding the improvement of technical efficiency in food production.

TABLE 9 Overall Gini coefficient for county FTFP.

Timing	FTFP	Technological progress	Technical efficiency
2010	0.0981	0.1025	0.0183
2011	0.1331	0.1325	0.0042
2012	0.1481	0.1470	0.0077
2013	0.1830	0.1843	0.0126
2014	0.1984	0.1986	0.0077
2015	0.2192	0.2187	0.0071
2016	0.2285	0.2288	0.0076
2017	0.2307	0.2308	0.0074
2018	0.2358	0.2315	0.0200
2019	0.2426	0.2389	0.0175
average	0.1918	0.1914	0.0110

3.3 Analysis of regional differences in county FTFP growth based on the Gini coefficient

Table 9 presents the Gini coefficients for county FTFP and its decomposition terms from 2010 to 2019. The analysis demonstrates that both the overall Gini coefficients for county FTFP and technical progress demonstrate a consistent upward trend over the examination period. Conversely, technical efficiency evinces a cyclical pattern, typified by a "downward-rising" cycle. It is noteworthy that there are considerable structural discrepancies between the overall Gini coefficients for county FTFP and its decomposition terms. Furthermore, the overall discrepancy in county food technical progress is markedly greater than that observed in technical efficiency. This finding indicates that regional disparities in county FTFP growth are predominantly influenced by variations in regional technical progress.

Table 10 presents the intra-group Gini coefficients for county FTFP and its decomposition terms within the three major geographic

TABLE 10 Intra-group Gini coefficients by geographic region.

Timing	FTFP			Technological progress			Technical efficiency		
	Eastern county	Central county	Western county	Eastern county	Central county	Western county	Eastern county	Central county	Western county
2010	0.0740	0.1119	0.1027	0.0787	0.1175	0.1043	0.0144	0.0208	0.0182
2011	0.1210	0.1450	0.1241	0.1189	0.1454	0.1235	0.0027	0.0055	0.0040
2012	0.1240	0.1495	0.1711	0.1214	0.1489	0.1702	0.0077	0.0077	0.0072
2013	0.1442	0.1877	0.2093	0.1450	0.1897	0.2098	0.0089	0.0152	0.0118
2014	0.1669	0.1861	0.2343	0.1656	0.1870	0.2340	0.0049	0.0097	0.0075
2015	0.1741	0.1808	0.2920	0.1713	0.1806	0.2917	0.0048	0.0091	0.0065
2016	0.1916	0.1863	0.3042	0.2204	0.1872	0.3043	0.0049	0.0097	0.0075
2017	0.2579	0.1793	0.2608	0.2562	0.1800	0.2613	0.0052	0.0094	0.0068
2018	0.2616	0.1716	0.2891	0.2487	0.1687	0.2895	0.0189	0.0236	0.0145
2019	0.2666	0.2000	0.2648	0.2555	0.1977	0.2642	0.0164	0.0211	0.0119
average	0.1782	0.1698	0.2252	0.1782	0.1703	0.2253	0.0089	0.0132	0.0096

TABLE 11 Intra-group Gini coefficient for food functional areas.

Timing	FTFP			Technological progress			Technical efficiency		
	Major food producing area	Food production and marketing balance area	Major food marketing area	Major food producing area	Food production and marketing balance area	Major food marketing area	Major food producing area	Food production and marketing balance area	Major food marketing area
2010	0.1003	0.1032	0.0398	0.1044	0.1062	0.0411	0.0200	0.0163	0.0087
2011	0.1507	0.1215	0.0488	0.1498	0.1212	0.0477	0.0054	0.0031	0.0024
2012	0.1520	0.1558	0.0571	0.1508	0.1554	0.0576	0.0091	0.0063	0.0032
2013	0.1917	0.1844	0.0659	0.1922	0.1856	0.0645	0.0142	0.0105	0.0098
2014	0.1894	0.2052	0.1140	0.1892	0.2054	0.1099	0.0090	0.0060	0.0066
2015	0.1863	0.2530	0.1212	0.1851	0.2528	0.1184	0.0091	0.0048	0.0042
2016	0.2003	0.2608	0.1114	0.2002	0.2612	0.1083	0.0095	0.0055	0.0052
2017	0.2078	0.2341	0.1474	0.2075	0.2347	0.1446	0.0097	0.0051	0.0035
2018	0.2065	0.2512	0.1284	0.2013	0.2512	0.1289	0.0241	0.0138	0.0065
2019	0.2271	0.2358	0.1436	0.2236	0.2350	0.1441	0.0218	0.0113	0.0053
average	0.1812	0.2005	0.0978	0.1804	0.2009	0.0965	0.0132	0.0083	0.0055

regions. Upon examination of the longitudinal dynamics, it becomes evident that the Gini coefficients for FTFP and technological progress in the eastern counties exhibit an increasing trend. Conversely, in the central and western regions, these coefficients exhibit an increase from 2010 to 2016, followed by a decrease from 2017 to 2019. This indicates that the discrepancies in FTFP and technological progress within the eastern regions continue to widen, while the disparities within the central and western regions are gradually diminishing. When comparing horizontally, the Gini coefficients for FTFP and technical progress in western counties are found to be higher than those in the east and central regions, suggesting a higher degree of imbalance in food production and a "polarization effect" in the west. Nevertheless, the Gini coefficients for technical efficiency across disparate geographic regions are relatively modest, suggesting that the divergence in technical efficiency is not pronounced across these regions. In conclusion, it is imperative to enhance the spatial coordination and linkage mechanisms among different geographical regions and counties within the region.

Table 11 presents the intra-group Gini coefficients of county FTFP and the decomposition terms for various food functional areas. When a vertical dynamic comparison is undertaken, the Gini coefficient of county FTFP is observed to demonstrate an upward trajectory within the primary production area. However, a cyclical pattern is observed in the production and marketing balance area and the main marketing area, with fluctuations in the overall trend remaining relatively stable. The Gini coefficients of county food technological progress demonstrate a fluctuating trend in different functional areas, with a relatively stable fluctuation amplitude. Furthermore, the Gini coefficients of county food technology progress also exhibit a "rising-declining-rising" trend in different functional areas. It is noteworthy that the Gini coefficient of technical efficiency in different food functional areas experiences cyclical fluctuations of "down-up," with some years exhibiting significant volatility. A horizontal comparison of the Gini coefficients of county FTFP and technical progress in the investigated period reveals that the Balance of Production and Marketing Area exhibits the greatest difference in terms of the other two areas, namely the Main Producing Area and the Main Marketing Area. This indicates that the greatest discrepancy between county FTFP and technical progress can be observed in the Balance of Production and Marketing Area, whereas the Gini coefficients of technical efficiency are typically smaller. In general, the differences between counties within different food functional zones with regard to FTFP and its decomposition terms are on the rise. The most pronounced intra-group differences are observed in the main production and marketing balance zones.

4 Analysis of drivers of county FTFP growth

4.1 Drivers and variable selection

This paper examines the impact of county financial deepening (finas), financial self-sufficiency (govz), population density (popu), farmers' income level (income), economic development level (pgdp), and regional industrial structure (indust) on the FTFP. The variables selected and described below are as follows:

- The level of county financial deepening is measured by the county financial correlation ratio indicator, which is defined as the ratio of financial institution loans to GDP in each county area. The modern food production mode, driven by TFP, places greater emphasis on the contribution of various factors, in addition to traditional factor inputs, to the growth of food output. These include agricultural scientific and technological progress, the optimization of the factor allocation structure, the quality of factors, and so forth (Gautam and Yu, 2015). Furthermore, the process of scientific and technological research and development, as well as the rational allocation of factors and numerous other economic links, cannot be dissociated from the financial support of financial capital. Consequently, the level of financial deepening in the county area is positively correlated with the FTFP.
- The fiscal self-sufficiency of a government is gauged by the ratio of its general budget revenues to its general budget expenditures. A higher fiscal self-sufficiency of a government is indicative of greater financial self-sufficiency, which in turn implies stronger local economic strength, greater government "self-blood-creation" ability, and potentially higher government investment in the field of agricultural production. Consequently, the fiscal self-sufficiency of a government may have a positive impact on the FTFP.
- It is possible that there may be a negative correlation between population density and FTFP. This is because, as the population density increases, the land area *per capita* decreases, and the land parcels become smaller. Consequently, the characteristics of the area become less conducive to food production, and it becomes more challenging to improve the level of food yields through the economy of scale. The population density of a county is quantified by dividing the county's total population by its administrative area.
- The income level of farmers (expressed in terms of disposable income of rural residents) is related to their incentive to grow food and investment capacity. A higher level of farmers' income increases the investment of agricultural capital in the process of food production and the adoption of advanced agricultural production technology. This, in turn, positively affects the growth rate of FTFP. Nevertheless, at present, the proportion of farmers' income derived from wages has been on the rise, while that derived from agricultural production has been on the decline. This shift in income sources will inevitably result in a reduction in farmers' capital investment in food cultivation. Such a reduction will be detrimental to the application of advanced agricultural production technology and production methods, and will have a negative impact on the FTFP growth rate. Consequently, the relationship between the impact of farmers' income and FTFP is uncertain in theory.
- The level of economic development is quantified by the gross domestic product (GDP) *per capita*. As economic development progresses, the transfer of non-agricultural employment from the agricultural labor force with a high level of human capital becomes increasingly pronounced. This transfer, however, has the unintended consequence of reducing the quality of the labor force in the food planting industry. Consequently, this is not conducive to the growth of FTFP. Concurrently, the higher the level of economic development, the greater the agricultural capital investment, which in turn stimulates agricultural technology progress, thereby promoting FTFP growth. Consequently, the relationship between the impact of economic development and FTFP is uncertain in theory.
- The regional industrial structure plays a pivotal role in determining the quality of economic development and the strength of the resources received. The development of the non-agricultural sector is conducive to the deepening of the agricultural capital, but if the relationship between agriculture and industry, and urban–rural relations is improperly dealt with, it will not be conducive to the "three rural" industry. In this paper, the proportion of the added value of the secondary industry and the tertiary industry in the GDP of a county is employed as a metric for gauging the alterations in the industrial structure of the county.

4.2 Empirical analysis

4.2.1 Smoothness testing

To guarantee the accuracy of the estimated parameters in the model and circumvent the phenomenon of "pseudo-regression," it is standard practice to assess the degree of smoothness exhibited by panel data series prior to conducting regression analysis. This entails evaluating whether the panel data exhibit smoothness through unit root tests. There are two principal types of unit root tests: the LLC test and the Breitung method for homogeneous panel hypotheses, and the IPS, ADF-Fisher, and PP-Fisher methods for heterogeneous panel hypotheses. In order to ensure the robustness and persuasiveness of the results, this paper employs a number of different unit root tests, including the LLC test, the HT test, the Fisher-ADF test, and the Fisher-PP test. If the variables fail to reject the null hypothesis of the existence of a unit root in two or more tests, it can be concluded that the series is smooth. Conversely, if the variables are rejected, it indicates instability. The results of the tests are presented in Table 12. The table indicates that all variables pass the LLC test and Fisher-ADF test, while the majority of variables also pass the HT test and Fisher-PP test. Consequently, it can be concluded that all variables are stationary and can be subjected to regression analysis.

4.2.2 Empirical tests of drivers

This paper employs a random effects model along with a two-way fixed effects model (Two-way FE) for estimation. The optimal estimation model is determined through the application of the Hausman test. To mitigate the influence of data outliers on the regression results, the shrinking-tail method is employed prior to conducting the benchmark regression. The corresponding estimation results are presented in Table 13. It is observed that the Hausman test rejects the original hypothesis for all regression equations at a significance level of 5%. This indicates that the estimation results obtained from the two-way fixed effects model outperform those of the random effects model. Consequently, the analysis primarily focuses on the estimation results derived from the two-way fixed effects model.

As demonstrated by columns (2), (4), and (5) of Table 13, county financial deepening has a positive and significant impact on FTFP and technological progress at a 1% significance level. This indicates that county financial deepening exerts a considerable impact on FTFP and technological progress. Nevertheless, the estimation of technological efficiency is not significant, indicating that the impact of county financial deepening on FTFP primarily originates from its influence on food production technological progress rather than technical efficiency in food production. In general, financial savings in county areas serve as a crucial source of funds for agricultural technology innovation and technological advancement. Historically, rural areas in China's counties have faced common financial constraints and interest rate control issues, which have constrained social savings growth. The implementation of interest rate control policies has resulted in the suppression of deposit interest rates in financial institutions, which has in turn hindered the efficiency with which county residents' income is transformed into social savings. As financial reform progresses in counties, the government is gradually relaxing its interest rate control policies. The liberalization of interest rates in response to market forces is conducive to the establishment of equilibrium interest rates within the county's financial market. Consequently, there has been a considerable increase in the propensity to save among residents and the overall amount of regional savings, which has resulted in an expansion of the pool of credit funds within the county's financial system. Consequently, this enhances the supply of rural finance and credit, thereby facilitating agricultural technological innovation, transformation, and the acquisition of advanced agricultural machinery and equipment by agricultural entities. In conclusion, these financial support measures contribute to the growth of FTFP.

TABLE 12 Smoothness test results for variable data.

	LLC	HT	Fisher-ADF	Fisher-PP
GTFP	−19.7111*** (0.0000)	−15.8971*** (0.0000)	2328.5492*** (0.0000)	2991.8271*** (0.0000)
gec	−15.8294*** (0.0000)	−14.3044*** (0.0000)	2495.6069*** (0.0000)	3574.7831*** (0.0000)
Gtc	−2.5049*** (0.0000)	−47.8490*** (0.0000)	2284.5087*** (0.0000)	6513.9601*** (0.0000)
finas	−9.7418*** (0.0000)	1.8444 (0.9674)	1913.8592*** (0.0000)	1614.6836*** (0.0024)
govz	−88.0414*** (0.0000)	−18.8398*** (0.0000)	2404.2829*** (0.0000)	2726.1008*** (0.0000)
popu	−110*** (0.0000)	−12.8483*** (0.0000)	2248.6925*** (0.0000)	2137.3719 *** (0.0000)
Income	−730*** (0.0000)	8.6828 (1.0000)	1553.4296*** (0.0376)	1979.5503*** (0.0000)
pgdp	−5.9699*** (0.0000)	6.3165 (1.0000)	1786.6603*** (0.0000)	1451.8857 (0.5402)
industs	−7.2877*** (0.0000)	−6.6372*** (0.0000)	1947.9784*** (0.0000)	2534.3272*** (0.0000)

[1] The HT test reports results as Z-values, while the rest of the tests report results as statistical values, with statistical. Test p-values in parentheses; [2] T or Z statistics $p < 10$, <5, and $< 1\%$ are marked with *, **, and ***, respectively.

As illustrated in Table 13, there is a discernible correlation between the financial self-sufficiency rate and both FTFP and technological progress. Although the coefficient of food technical efficiency is positive, it did not meet the criteria for statistical significance. This indicates that the fiscal self-sufficiency variable exerts a significant influence on food production, particularly in terms of technical progress. A higher financial self-sufficiency rate is indicative of enhanced local economic strength and a government's capacity to invest more in food production in accordance with the strategy of ensuring food security. In conclusion, the financial self-sufficiency rate allows for the expansion of FTFP.

As illustrated in Table 13, the population density variable is defined as the number of individuals per unit area. The population

TABLE 13 Analysis of Drivers of County FTFP.

Equation	(1)	(2)	(3)	(4)	(5)	(6)
Method	RE	Two-way FE	RE	Two-way FE	RE	Two-way FE
Variable	FTFP		TC		TE	
finas	0.0601*** (4.20)	0.0503*** (3.15)	0.1038*** (7.42)	0.0495*** (3.27)	−0.0284*** (−13.79)	0.0016 (0.88)
govz	0.0137 (0.35)	0.0924** (1.98)	−0.0609 (−1.60)	0.0917** (2.07)	0.1017*** (23.45)	0.0082 (1.58)
popu	−3.0473*** (−6.98)	−2.2881*** (−2.97)	−3.0187*** (−7.36)	−2.3214*** (−3.18)	0.0321 (1.07)	0.0628 (0.73)
Income	0.0022 (0.18)	−0.0252 (−1.39)	0.1053*** (9.00)	−0.0282* (−1.65)	−0.0777*** (−38.24)	0.0020 (1.01)
pgdp	0.0010 (0.33)	−0.0078** (−2.15)	0.0031 (1.01)	−0.0090*** (−2.63)	0.0025*** (7.28)	0.0004 (0.87)
industs	−0.1949*** (−2.81)	−0.1890** (−2.24)	−0.0773 (−1.15)	−0.2580*** (−3.23)	−0.0230*** (−3.36)	0.0431*** (4.61)
cons	1.3815*** (25.07)	1.2965*** (18.30)	1.0589*** (20.00)	1.1393*** (16.98)	1.1805*** (223.99)	1.2112*** (154.13)
Individual fixed	No	Yes	No	Yes	No	Yes
Time fixed	No	Yes	No	Yes	No	Yes
Hausman p-value	0.000		0.000		0.000	
F-test / Wald chi2	83.86***	22.51***	517.35***	93.60***	2837.82***	4588.74***
R-squared	0.007	0.049	0.073	0.177	0.480	0.913
Sample size	7290	7290	7290	7290	7290	7290

[1] ***, ** and * denote 1, 5 and 10% significance levels, respectively; [2] Z-values or T-values of the estimated parameters are in parentheses.

density variable has a significant negative impact on both FTFP and technological progress at the 1% level of significance. This indicates that a higher regional population density is an impediment to the growth of FTFP. As population density increases, the characteristics of "many people and little land, land parcels are scattered" become more prominent in the region. These characteristics are not conducive to large-scale food cultivation, thereby impeding the realization of economies of scale. Conversely, regions with low population density may facilitate the growth of FTFP by prioritizing the scale and intensification of grain cultivation.

According to Table 13, it can be seen that the coefficient of the farmers' income variable on FTFP and technological progress is negative. Additionally, the coefficient of technological progress in food production passes the significance test at a 10% level. These findings suggest that an increase in farmers' income leads to a reduction in FTFP. Currently, farmers' wage income has become the primary component of their income structure, while income from agricultural production has declined. Consequently, farmers' capital investment in food cultivation has decreased, impeding the adoption of advanced agricultural production technology and methods. This situation has a negative effect on FTFP and technological progress.

Table 13 indicates that the level of regional economic development exerts a net substitution effect on the impact of FTFP and technological progress, which aligns with the direction of the farmers' income variable. A higher level of regional economic development is associated with a faster urbanization process and increased opportunities for farmers to earn non-farm income. This dynamic results in a continuous decline in the quantity and quality of the labor force engaged in food cultivation, as well as low profitability and high-risk attributes associated with food cultivation. Consequently, it becomes challenging to attract industrial and commercial capital to rural areas. In light of the constraints on labor and capital in food cultivation, agricultural businesses tend to adopt relatively unsophisticated management practices, which impede the growth of FTFP.

As illustrated in Table 13, the variable of industrial structure exerts a pronounced negative influence on FTFP, technological progress, and technical efficiency. The process of upgrading the regional industrial structure has the effect of further weakening the food plantation industry. As the production efficiency of the industrial and commercial sectors surpasses that of the agricultural sector, factors such as capital and talent are drawn to the non-agricultural sector, where higher returns are anticipated. Consequently, this results in a reduction in capital input for the food plantation industry, which ultimately has a negative impact on the growth of FTFP.

4.3 Discussion of environmental factors

The growth of FTFP is closely related to a number of factors, which, in addition to the economic system factors mentioned above, are influenced by climate, the state of arable land, water availability, and a number of other environmental factors. It is important to acknowledge that the lack of data on climate, natural conditions, water resources, and other pertinent factors at the county level in China presents a significant challenge in empirically analyzing the impact of these environmental factors on the FTFP in counties. Next, we will theorize the mechanisms by which these environmental factors affect FTFP.

The high degree of dependence of food production processes on climatic resources renders them susceptible to the effects of climate change. An increase in temperature results in a greater caloric requirement for food production, necessitating longer crop growing periods. Additionally, there is a northward shift in cropping system boundaries, with one- or two-crop areas being gradually replaced by two- or three-crop areas, which results in an increase in grain yields (Yang et al., 2010). However, extreme temperature changes can result in an increase in the frequency of disasters such as high temperatures and droughts, which directly impact the growth and production of food crops (Yang et al., 2022). Furthermore, the occurrence of extreme high temperatures has been observed to result in an increase in the prevalence and severity of pests and diseases, which in turn has been linked to a reduction in the viability of food crops, thereby impeding the growth of FTFP.

Cropland fragmentation refers to the spatial division of cropland owned by farmers, which is of different sizes, and the utilization of cropland is dispersed and disordered. In the case of fine fragmentation, the existence of ridges not only results in the waste of arable land resources (Chen et al., 2022), but also causes inconvenience with regard to field management. Furthermore, it restricts the large-scale operation of farmers and hinders the use of factors of production, such as agricultural mechanization, and the construction of farmland infrastructure (Zhao et al., 2023). Consequently, the fine fragmentation of arable land will result in a reduction in the efficiency with which agricultural production factors are allocated and will also lead to a decline in the technical efficiency of agricultural production.

The scarcity of water represents a significant constraint on food crop production. The scarcity of water can impede the growth and development of plants, affecting their photosynthetic processes and biomass accumulation (Gautam and Yu, 2015). This can ultimately result in a reduction in yields or even the extinction of food crops, which is detrimental to the growth of FTFP. In addition, the natural terrain is also a significant factor influencing the FTFP. Flat terrain provides optimal conditions for the implementation of mechanized farming and irrigation systems, thereby enhancing production efficiency. In contrast, complex and variable terrain may present challenges to farming operations, impede the implementation of technology, and diminish overall efficiency. Concurrently, topography serves to delineate regional climatic attributes and hydrological conditions, which in turn influence crop growth cycles and yields. These factors, in conjunction with the economic factors previously discussed, exert an influence on the overall FTFP.

5 Conclusions and policy implications

5.1 Conclusions and discussions

In this paper, the three-stage DEA-Malmquist productivity index model was employed to assess the FTFP in Chinese counties from 2009 to 2019. Subsequently, the Gini coefficient method with a fixed panel efficiency model was utilized to investigate the spatio-temporal divergence of FTFP growth in counties and its underlying drivers. The study's principal conclusions are as follows:

Firstly, the county FTFP demonstrates a fluctuating upward trend during the period under examination, with an average annual growth rate of 2.43%. This is comparable to the findings of the studies conducted by Wang et al. (2020) and Zheng and Cheng (2021) for the corresponding period. However, the average annual growth rates of FTFP and TC estimated in this paper are lower than the average annual growth rates of agricultural TFP and TC estimated in existing studies (Gautam and Yu, 2015; Gong, 2018; Yin et al., 2022). Over the past two decades, China has witnessed a surge in technological advancement and output growth in livestock, aquaculture, and horticultural plantations, including vegetables, fruits, flowers, and other crops. In contrast, technological advancement and output growth in traditional grain farming have exhibited a slower pace of advancement relative to these other sectors. Accordingly, the TFP growth rate of the food plantation sector under examination is lower than the TFP growth rate of agriculture estimated by the majority of existing studies. This finding aligns with both theoretical expectations and realistic observations. Moreover, the findings of this study exceed the mean annual growth rate of ecological total factor productivity for food, as determined by Tian et al. (2024), which was 0.98% over the period 2012–2020. This is due to the fact that the calculation of ecological total factor productivity takes into account not only the inputs and desired outputs inherent to the production process, but also non-desired outputs, such as environmental pollution and resource waste. These non-desired outputs serve to increase production costs and reduce production efficiency. In contrast, total factor productivity primarily measures production efficiency without accounting for environmental costs. Consequently, the value of ecological total factor productivity is typically lower than that of TFP when environmental factors are taken into account.

Secondly, this paper also identifies that the average annual growth rate of county FTFP in different regions is uneven. The highest average annual growth rate of county FTFP is observed in the eastern region and the main grain-producing region, at 2.75 and 3.04%, respectively. In contrast, the western region and the main grain marketing area exhibited the lowest rates, at 1.44 and 1.23%, respectively. Furthermore, the Gini coefficients of county total factor productivity and technological progress demonstrate an upward trajectory throughout the examined sample period. This indicates that the discrepancy between food total factor productivity and technological progress is still expanding among different counties. This finding aligns with the conclusions of Yin et al. (2022), who analyzed panel data from 1,173 counties in China from 2000 to 2017 and reported a widening trend in regional differences in agricultural TFP growth. In addition, the county FTFP growth is primarily driven by changes in technological progress, while the core driving role of technical efficiency is not effectively played. This is also consistent with the findings of Yue et al. (2022) and Min et al. (2023) that FTFP changes are mainly influenced by the technical progress index.

Thirdly, with regard to the driving factors, county financial deepening and financial self-sufficiency exert a considerable positive influence on FTFP, primarily through their impact on technological progress. This is consistent with the findings of Liu Y. et al. (2023), which indicate that county financial development acts with FTFP through the promotion of technological progress. The level of county population density, the degree of economic development, the income level of farmers, and the industrial structure all exert a significant negative influence on county FTFP and technological progress. This is not consistent with the findings of Liu and Xie (2016), who found that farmers' income and financial subsidies do not have a significant impact on food production. Over the course of the past four decades, the structure of farmers' income has undergone a significant transformation, shifting from a predominantly agricultural income base to a primarily wage-based income stream. This shift has also witnessed a decline in the proportion of income derived from grain cultivation, and it has constrained farmers' capacity to invest in food production. Consequently, the growth of food production efficiency is not influenced by farmers' income, and may even be hindered by it, which aligns with the current state of China's agricultural economy. Furthermore, the fiscal subsidy effect may be offset by the rising prices of production materials, resulting in a negligible impact. However, this paper's research indicates that the fiscal input can indirectly influence the growth of FTFP by promoting the advancement of agricultural technology.

In addition to the economic factors previously discussed, food productivity growth is also influenced by a number of environmental factors, including climate, the status of arable land, and the availability of water sources. This is also consistent with the findings of Mohammadi et al. (2023), Rezaei et al. (2023), and Vadez et al. (2024).

5.2 Policy implications

In light of the aforementioned research conclusions, the following insights can be derived:

Currently, there are discernible disparities in FTFP growth across counties in disparate geographic regions and grain functional areas in China. It is thus imperative to devise differentiated grain industry development strategies. On the one hand, it is imperative to vigorously develop production organization modes such as cross-area operation of agricultural machinery and agricultural socialized services. This will effectively improve the county grain production efficiency differences between regions through the common sharing of resources, specialized division of labor and collaboration, and integrated construction of infrastructure between different counties. On the other hand, the strategic positioning and development direction of the grain industry in each county must be fully defined according to the characteristics of the industrial structure, development mode, and geographical characteristics of each county. This is essential for the precise design and implementation of urban and rural factor mobility, factor reconfiguration, and food-related industrial layout, as well as the formation of the staggered development and complementary advantages of the grain industry strategy.

From the viewpoint of driving factors, financial deepening and financial self-sufficiency in counties significantly and positively affect FTFP growth by promoting technological progress. Consequently, it is imperative that counties cultivate and develop novel technologies and innovative production methods that are compatible with food production. This will reinforce the core driving function of agricultural technological innovation, transformation, and the application of achievements, thereby promoting the continuous improvement of county FTFP. Concurrently, it is imperative to persist in the county's financial market-oriented reform, prioritize the construction of a robust county financial ecology, and foster a fair, open, and secure financial environment. Concurrently, it is imperative to reinforce the notion that county financial institutions must cater to the advancement of agriculture and rural regions. Furthermore, it is essential to expedite the growth of inclusive finance within the county and enhance the accessibility of credit for rural customers with limited financial resources.

The level of population density in a county, the state of economic development, the income level of farmers, and the structure of the industrial sector have a considerable negative impact on the FTFP and technological progress of the county in question. Consequently, it is imperative to hasten the urbanization of counties, attract the remaining rural population to work and settle in cities, optimize the allocation of factors and the structure of the agricultural industry, and facilitate the transfer of rural land and the implementation of large-scale operations. Furthermore, while underscoring the necessity of industrial restructuring and economic growth, it is imperative to facilitate the transfer of sophisticated production techniques and industrial and commercial capital from the county's industrial sector to rural areas. The promotion of agriculture through industry will facilitate the deepening of agricultural capital and the overall improvement of agricultural TFP.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.scidb.cn/anonymous/dWllYWlt.

Author contributions

YL: Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft. HJ: Data curation, Validation, Writing – review & editing. JC: Resources, Formal analysis, Project administration, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. This research was funded by International Collaborative Innovation Laboratory for Science, Technology and Finance (Jinan), grant number JNSX2023078, Shandong Province Natural Science Foundation, grant number ZR2022MG045, the Key Research Topics of Shandong Province Finance Society, grant number 2024SDJR37, and The Shandong Women's University High-Level Talent Introduction Research Program, grant number 2023RCYJ05.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Aigner, D., Lovell, C. A. K., and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *J. Econ.* 6, 21–37. doi: 10.1016/0304-4076(77)90052-5

Badunenko, O., and Kumbhakar, S. C. (2017). Economies of scale, technical change and persistent and time-varying cost efficiency in Indian banking: do ownership, regulation and heterogeneity matter? *Eur. J. Oper. Res.* 260, 789–803. doi: 10.1016/j.ejor.2017.01.025

Baležentis, T., Kerstens, K., and Shen, Z. (2024). Economic and environmental decomposition of Luenberger-Hicks-Moorsteen Total factor productivity Indicator: empirical analysis of Chinese textile firms with a focus on reporting infeasibilities and questioning convexity. *IEEE Trans. Eng. Manag.* 71, 2772–2785. doi: 10.1109/TEM.2022.3195568

Baležentis, T., and Sun, K. (2020). Measurement of technical inefficiency and total factor productivity growth: a semiparametric stochastic input distance frontier approach and the case of Lithuanian dairy farms. *Eur. J. Oper. Res.* 285, 1174–1188. doi: 10.1016/j.ejor.2020.02.032

Chen, T., Yang, J. Y., and Chen, C. B. (2022). Mechanism and pathof agricultural mechanization in promoting incomeincrease:based on the separability of agriculturalproduction links. *J. Huazhong Agric. Univ.* 4, 129–140. doi: 10.13300/j.cnki.hnwkxb.2022.04.011

Fried, H. O., Lovell, C. A. K., Schmidt, S. S., and Yaisawarng, S. (2002). Accounting for environmental effects and statistical noise in data envelopment analysis. *J. Prod. Anal.* 17, 157–174. doi: 10.1023/A:1013548723393

Gao, M., and Song, H. (2014). Spatial convergence and functional area differences in the technical efficiency of food production–and the spatial ripple effect of technology diffusion. *Manage. World* 250, 83–92. doi: 10.19744/j.cnki.11-1235/f.2014.07.010

Gao, Y., and Wang, Z. (2020). Does urbanization bring increased pressure on cropland?: empirical evidence from China. *China Rural Econ.* 9, 65–85.

Gautam, M., and Yu, B. (2015). Agricultural productivity growth and drivers: a comparative study of China and India. *China Agric. Econ. Rev.* 7, 573–600. doi: 10.1108/CAER-08-2015-0094

Gong, B. (2018). Agricultural reforms and production in China: change in provincial production function and productivity in 1978-2015. *J. Dev. Econ.* 132, 18–31. doi: 10.1016/j.jdeveco.2017.12.005

Guo, B., Yu, H., and Jin, G. (2024). Urban green total factor productivity in China: a generalized Luenberger productivity indicator and its parametric decomposition. *Sustain. Cities Soc.* 106:105365. doi: 10.1016/j.scs.2024.105365

He, Y., and Qiang, Y. (2019). Research on the impact of urbanization development on the technical efficiency of food production: based on panel data from 13 Main grain producing areas in China. *China Agric. Res. Zoning* 40, 101–110. doi: 10.7621/cjarrp.1005-9121.20190314

Hu, C., Li, H., and Qu, C. (2021). Characterization of regional agricultural total factor productivity change based on spatial-temporal heterogeneous elasticity production function. *Agric. Technol. Econ.* 315, 103–114. doi: 10.13246/j.cnki.jae.2021.07.008

Lai, H., and Kumbhakar, S. C. (2018). Panel data stochastic frontier model with determinants of persistent and transient inefficiency. *Eur. J. Oper. Res.* 271, 746–755. doi: 10.1016/j.ejor.2018.04.043

Li, J. (2021). Analysis of green total factor productivity of food production in China under environmental regulation. *Southern Agric. J.* 52, 2311–2318. doi: 10.3969/j.issn.2095-1191.2021.08.032

Li, Z. Q., Li, X. Y., Sun, Q., and Ye, W. J. (2021). Can financial support for agricultural subsidies effectively enhance total factor productivity of food?: Considering the moderating role of agricultural technology environment. *J. China Agric. Univ.* 26, 236–252. doi: 10.11841/j.issn.1007-4333.2021.08.22

Liu, Y., Cui, J., Feng, L., and Yan, H. (2024). Does county financial marketization promote high-quality development of agricultural economy?: analysis of the mechanism of county urbanization. *PLoS One* 19:e0298594. doi: 10.1371/journal.pone.0298594

Liu, Y., Cui, J., Jiang, H., and Yan, H. (2023). Do county financial marketization reforms promote food total factor productivity growth?: a mechanistic analysis of the factors quality of land, labor, and capital. *Front. Sustain. Food Syst.* 7:1263328. doi: 10.3389/fsufs.2023.1263328

Liu, S., Lei, P., Li, X., and Li, Y. (2022). A nonseparable undesirable output modified three-stage data envelopment analysis application for evaluation of agricultural green total factor productivity in China. *Sci. Total Environ.* 838:155947. doi: 10.1016/j.scitotenv.2022.155947

Liu, F., Li, L., Ye, B., and Qin, Q. (2023). A novel stochastic semi-parametric frontier-based three-stage DEA window model to evaluate China's industrial green economic efficiency. *Energy Econ.* 119:106566. doi: 10.1016/j.eneco.2023.106566

Liu, H. Y., and Xie, J. Z. (2016). The effects of government subsidies, farm income and urbanization on food production efficiency. *J. Jiangxi Normal Univ.* 40:22-26+32. doi: 10.16357/j.cnki.issn1000-5862.2016.01.04

Liu, Y., and Yan, H. (2022). County financial agglomeration, factor allocation structure and food production supply: empirical evidence from Chinese counties. *Finance Trade Res.* 33, 44–56. doi: 10.19337/j.cnki.34-1093/f.2022.09.004

Luo, D. (2012). Notes on the estimation of managerial inefficiency in a three-stage DEA model. *Stat. Res.* 29, 105–108. doi: 10.19343/j.cnki.11-1302/c.2012.04.017

Min, R., and Li, G. (2012). Growth and decomposition of China's food total factor productivity under environmental constraints: an observation based on provincial panel data and serial Malmquist-Luenberger index. *Econ. Rev.* 177, 34–42. doi: 10.19361/j.er.2012.05.004

Min, R., Xie, Y. M., Huang, W. H., and Wu, Q. H. (2023). Bias of technological progress and growth path selection in China's grain production. *Stat. Decision Making* 39, 89–93. doi: 10.13546/j.cnki.tjyjc.2023.15.016

Mohammadi, S., Rydgren, K., Bakkestuen, V., and Gillespie, M. A. K. (2023). Impacts of recent climate change on crop yield can depend on local conditions in climatically diverse regions of Norway. *Sci. Rep.* 13:3633. doi: 10.1038/s41598-023-30813-7

Muftiadi, A. (2018). Food crops production efficiency analysis in Indonesia in 1971-2008. *Int. J. Econ. Policy Emerg. Econ.* 11, 282–286. doi: 10.1504/IJEPEE.2018.093952

Parichatnon, S., Maichum, K., and Peng, K. C. (2018). Measuring technical efficiency of Thai rubber production using the three-stage data envelopment analysis. *Agric. Econ.* 64, 227–240. doi: 10.17221/19/2016-AGRICECON

Peng, D., and Wen, L. (2016). Do aging and feminization of rural labor force reduce food production efficiency: a comparative analysis between north and south based on stochastic frontier. *Agric. Technol. Econ.* 2, 32–44. doi: 10.13246/j.cnki.jae.2016.02.004

Peng, C., and Zhang, C. (2020). Impact of agricultural mechanization on food production efficiency of farm households. *J. South China Agric. Univ.* 19, 93–102. doi: 10.7671/j.issn.1672-0202.2020.05.009

Rezaei, E. E., Webber, H., Asseng, S., Boote, K., Durand, J. L., Ewert, F., et al. (2023). Climate change impacts on crop yields. *Nat. Rev. Earth Environ.* 4, 831–846. doi: 10.1038/s43017-023-00491-0

Sun, K., and Kumbhakar, S. C. (2013). Semiparametric smooth-coefficient stochastic frontier model. *Econ. Lett.* 120, 305–309. doi: 10.1016/j.econlet.2013.05.001

Tian, H. Y., Liu, X., and Su, Z. H. (2024). Spatial and temporal characteristics of food ecological total factor productivity in the Yangtze River economic zone. *Chin. J. Ecol. Agric.* 32, 344–354. doi: 10.12357/cjea.20230418

Tian, X., and Wang, S. G. (2016). Analysis of environmental efficiency of grain production and its influencing factors in China. *Res. Sci.* 38, 52–63. doi: 10.18402/resci.2016.11.09

Vadez, V., Grondin, A., Chenu, K., Henry, A., Laplaze, L., Millet, E. J., et al. (2024). Crop traits and production under drought. *Nat. Rev. Earth Environ.* 5, 211–225. doi: 10.1038/s43017-023-00514-w

Wang, H., and Gao, M. (2020). Geographical differences and spatial-temporal differentiation of rice productivity in China: an empirical analysis based on the main rice producing areas. *China Agric. Sci. Technol. Bull.* 22, 1–11. doi: 10.13304/j.nykjdb.2018.0636

Wang, L., Yang, R., and Wu, B. (2020). Research on total factor productivity of agricultural production of Chinese farmers. *Manage. World* 36, 77–93. doi: 10.19744/j.cnki.11-1235/f.2020.0185

Wang, Y., Yao, X., and Zhou, M. (2013). Rural labor outflow, regional differences and food production. *Manage. World* 11, 67–76. doi: 10.19744/j.cnki.11-1235/f.2013.11.007

Wu, H., Hao, H., Shi, H., and Ge, Y. (2022). Impact of agricultural mechanization on total factor productivity of wheat and its spatial spillover effect. *Agric. Technol. Econ.* 328, 50–68. doi: 10.13246/j.cnki.jae.2022.08.006

Yang, X. G., Liu, Z. J., and Chen, F. (2010). Possible impacts of global warming on China's cropping system I. Analysis of the possible effects of climate warming on the northern boundary of China's cropping system and grain yield. *Chinese Agric. Sci.* 43, 329–336. doi: 10.3864/j.issn.0578-1752.2010.02.013

Yang, Y., Zhao, N., and Yue, T. X. (2022). Characteristics of the evolution of spatial and temporal patterns of extreme heat events in China from 1980 to 2018. *Geoscience* 42, 536–547. doi: 10.13249/j.cnki.sgs.2022.03.018

Yao, F., Zhang, F., and Kumbhakar, S. C. (2018). Semiparametric smooth coefficient stochastic frontier model with panel data. *J. Bus. Econ. Stat.* 37, 556–572. doi: 10.1080/07350015.2017.1390467

Yin, C., Li, G., and Ge, J. (2016). Food security: climate change and food productivity growth-an empirical analysis based on HP filtering and sequential DEA methods. *Res. Sci.* 38, 665–675. doi: 10.18402/resci.2016.04.09

Yin, C. J., Li, Y. N., and Ma, X. K. (2022). Regional differences and dynamic evolution of agricultural total factor productivity growth in Chinese counties. *J. Huazhong Agric. Univ.* 3, 108–118. doi: 10.13300/j.cnki.hnwkxb.2022.03.010

Yue, H., Yu, F. S., and Cai, X. Y. (2022). Research on the measurement of total factor productivity of grain in China--Malmquist-DEA analysis based on input-output. *Price Theory Pract.* 5, 122–125. doi: 10.19851/j.cnki.cn11-1010/f.2022.05.190

Zeng, Y., Lv, Y., and Liu, W. (2018). Does agricultural land transfer enhance the technical efficiency of food production: a perspective from farmers. *Agri. Technol. Econ.* 3, 41–55. doi: 10.13246/j.cnki.jae.2018.03.004

Zha, Y., Liang, N., Wu, M., and Bian, Y. (2016). Efficiency evaluation of banks in China: a dynamic two-stage slacks-based measure approach. *Omega* 60, 60–72. doi: 10.1016/j.omega.2014.12.008

Zhang, H., and Guo, X. Y. (2021). Agricultural productive services, agricultural technological Progress and Farmers' income increase: analysis based on mediating effect and panel threshold model. *Res. Agric. Modern.* 42, 652–663. doi: 10.13872/j.1000-0275.2021.0049

Zhao, H., Cai, D. H., Wang, H. L., Yang, Y., Wang, R. Y., Zhang, K., et al. (2023). Progress and prospects of research on the impact of drought disaster on food security and its response technology. *Drought Weather* 41, 187–206. doi: 10.11755/j.issn.1006-7639(2023)-02-0187

Zhao, D. D., and Zhou, H. (2020). Agricultural production agglomeration: how to improve the efficiency of food production-a re-examination based on different development paths. *Agric. Technol. Econ.* 8, 13–28. doi: 10.13246/j.cnki.jae.2020.08.002

Zheng, Z., and Cheng, S. (2021). TFP growth rate and its evolutionary trend in China's grain farming industry: 1980-2018. *China Rural Econ.* 439, 100–120. Available at: https://d.wanfangdata.com.cn/periodical/zgncjj202107006