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Solar energy development and agricultural sustainability in China: assessing the impacts of green energy adoption and technological innovation on food security

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Solar energy has recently become a significant option for countries to enhance their green energy initiatives, which can help mitigate pollution in the agricultural sector. One of the essential drivers of innovation is research and development (R&D). However, evaluations of how solar energy and R&D expenditure can impact food security and agricultural productivity are limited. Hence, this study examines the impact of solar energy, R&D investment, and green economic growth on food security and agricultural productivity in China from 2001 to 2022. This study uses the ARDL approach to explore the long- and short-run relationships between the variables. This study also employs the advanced Quantile-on-Quantile Kernel Regularized Least Squares (QQ-KRLS) method to assess the robustness of the long-run analysis results. The empirical results indicate that solar energy can significantly enhance food security and agricultural productivity. Moreover, along with R&D expenditure and green economic growth, arable land has a positive and significant impact on food security. This study confirms the long-term findings by using the QQ-KRLS estimation methods. To attain the Sustainable Development Goals, such as Goals 2, 7, and 13, policymakers should increase R&D funding for agricultural and green energy technology. Such investment is crucial for promoting food security and environmental sustainability. As the world's leading grain producer, China is facing global environmental challenges. Therefore, this study recommends the adoption of innovative climate change technologies and the development of high-temperature and drought-resistant cereal crop varieties to mitigate the adverse effects of climate change and increase food production.

KEYWORDS

agricultural sustainability, China, food security, solar energy, technological innovation

1 Introduction

Food security has become highly concerning. The availability of food in a region can influence not only the health of individuals but also the country's economic development (Deng and Zeng, 2023). However, due to the interconnection of international trade between countries, they cannot produce goods independently and may need to import some goods from other countries. Hence, factors that can affect food security are not only natural elements but also those related to global economic and political shocks (Okorie et al., 2019; Qingshi et al., 2020; Mulyo et al., 2023). One of the most prominent shocks that can cause food insecurity is externalities, which can occur due to overproduction, harming the environment and decreasing land areas and air quality through the production of high-quality agricultural products. Such shocks can impose uncertainties on countries in meeting their domestic food needs. To minimize such uncertainties, countries rely on technological advancements to develop innovative production methods and increase their agricultural productivity (Sethi et al., 2024; Sharma et al., 2025).

China is among the top countries conducting experiments with technology in the agriculture industry. The expansion of agriculture in China has continued to gain momentum. For example, China added an astonishing 93GW of solar capacity in May 2025, which is nearly equivalent to installing 100 solar panels every second (The Guardian, 2025). As of April 2025, solar energy accounted for 12.4% of China's electricity generation, nearly triple the percentage in 2020 (Ember, 2025). China makes massive investments in technology and is the global leader in research and development (R&D), in terms of its proportion to its GDP, across 112 countries, making it the fastest-growing R&D performer in the world. Moreover, in 2023, China surpassed the growth of the United States' gross domestic expenditure on R&D by 8.7% (OECD, 2025). China's central government announced that 255 billion yuan (approximately US$55 billion) in the 2025 budget will be dedicated to the development of science and technology, representing a 10% increase from the 2024 amount. Furthermore, the entire green energy industry accounted for a record 10% of China's GDP in 2024, with solar panels playing a significant role in this increase (SCMO, 2025).

With the aforementioned groundbreaking initiatives, China has established a precedent for introducing green technologies to boost its economy. However, despite the all-out push, China's substantial technology gains are experiencing industrialization-capacity constraints. Specifically, the liquefied natural gas (LNG) production sector is suffering from tightening, excess capacity, falling prices, substantial losses, and employee layoffs. In 2024, labor in the industry was reduced by nearly one third. The retirement of inefficient capacity requires a substantial amount of money, which may have negative implications on food production. For example, in Hubei's Muzi Township, agricultural product yields fell by around 80% after the farmland was repurposed for solar projects under the pretext of agrivoltaics. Solar manufacturing can harm the environment and indirectly impact agricultural land. The industrialized solar technology process produces toxic byproducts, such as silicon tetrachloride, which can render soil infertile and pose a health risk to humans. Furthermore, the massive implementation of solar panels would require a substantial amount of land, which would necessitate major transformations that may cause soil erosion and decrease farmland productivity (Luo et al., 2023; Song et al., 2024). Moreover, the mass construction of solar farms can lead to excessive land transformation, such as land disturbance, which can lead to soil erosion and farmland productivity loss (Luo et al., 2023; Song et al., 2024). China is among the forerunners of agricultural modernization. Chinese agriculture is developing rapidly, specifically, in the field of photovoltaic solar technology and research support (Deng and Zeng, 2023). Figure 1 shows that China is the top country in the world in terms of installed solar power capacity, which is higher than that of other countries combined in 2023.

Figure 2 highlights China's increase in R&D expenditure as a share of its GDP, which has helped close the gap between itself and advanced economies such as the United States and Japan. Such advancements have strengthened China's position as a technological powerhouse.

In May 2025, China installed a staggering 93GW of solar capacity, equivalent to installing nearly 100 solar panels per second. As of April 2025, solar accounted for 12.4% of China's electricity generation, which is three times the percentage in 2020. At the same time, China's gross domestic expenditure on R&D surged by 8.7% in 2023, which was supported by a central government allocation of US$55 billion for science and technology for 2025 (SCMO, 2025). Figure 3 provides the agricultural context and depicts global cereal yields for the calendar year 2023, and shows that China had intermediate cereal yields compared with the majority of the other developing regions, including the United States and some EC regions. Figure 4 presents a map of the distribution of cereals for human consumption in 2022. China occupies a central position in the transect, indicating an equilibrium zone between cereals for human food, animal feed, and industrial use. All the trends highlight the following dilemma: as China forges ahead by developing solar energy and bolstering its R&D spending, its food security will continue to be closely related to its balance between land use, productivity, and transition to renewable energy.

Previous studies examined the impact of solar technology on food security in China. For example, Hu (2024) and Xie et al. (2024) demonstrated that solar technology can improve land use efficiency and contribute to renewable energy. Meanwhile, other scholars have found that long-term investment in agricultural R&D can significantly contribute to green total factor productivity (TFP) and resource efficiency (Jin et al., 2010). Moreover, Huynh (2024), Chandio et al. (2023), and Rao et al. (2020) showed that agricultural research spending can enhance food supply stability. In contrast, Zhang et al. (2023) suggested that solar technology has a negative impact, focusing on its adverse effects on food production and cropland. The diverse findings from previous studies indicate a gap in the literature, and the actual impact has yet to be determined, necessitating further research in this area.

We aim to fill the research gap by investigating the impact of solar energy development (SEN), green economic growth, and R&D spending on food security and agricultural performance in China. Our research sample spans the period from 2001 to 2022. For model estimation, we employ the autoregressive distributed lag (ARDL) method, which enables the analysis of both short-term and

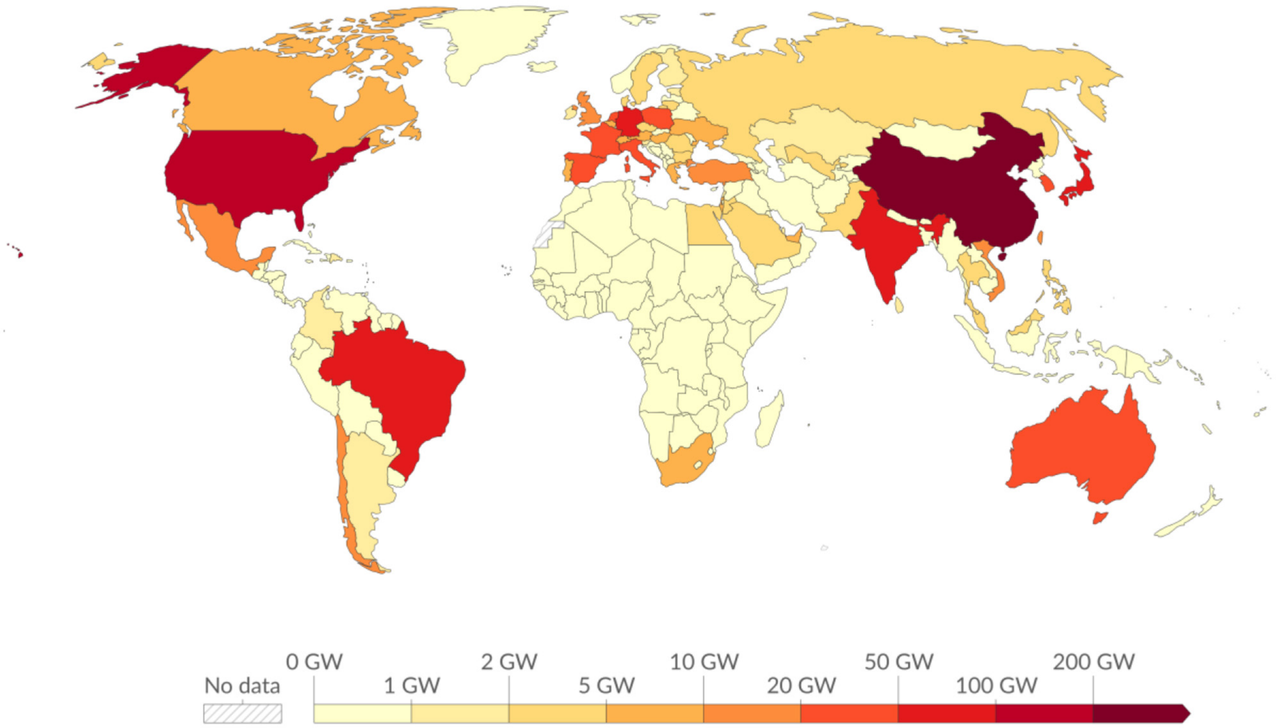

FIGURE 1
Overview of Installed solar energy capacity around the world. *Data source*: International Renewable Energy Agency (2019).

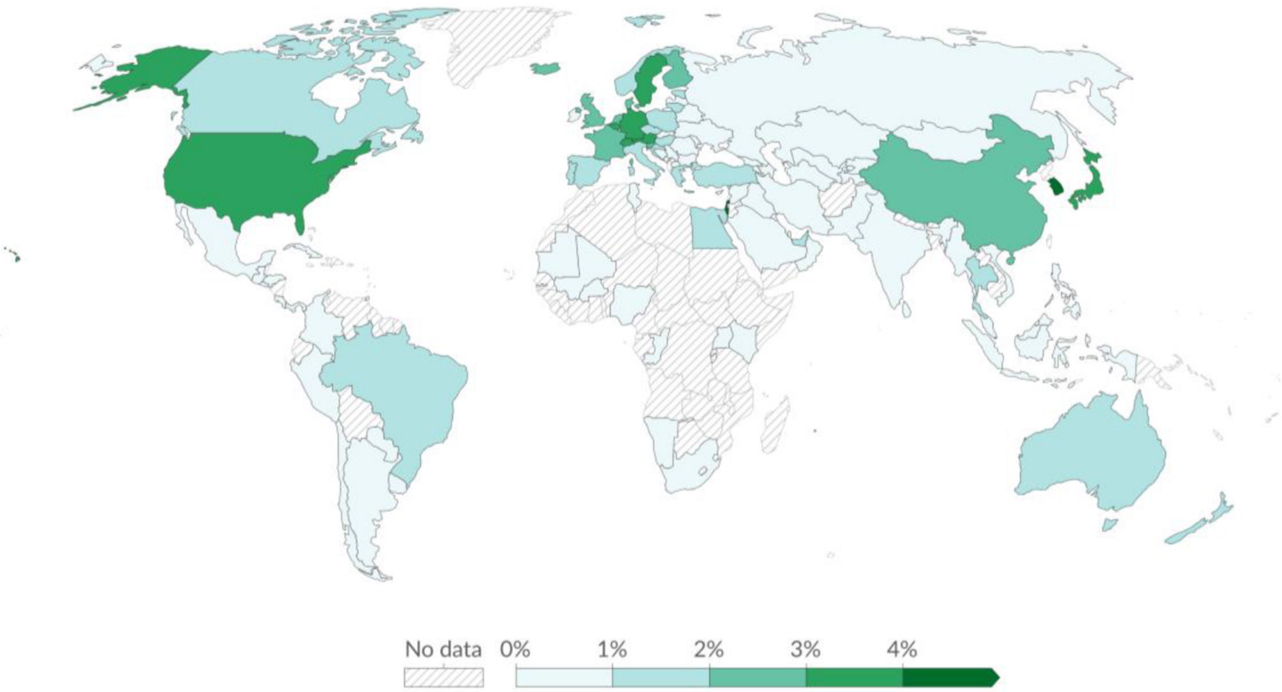

FIGURE 2
Research & development spending as a share of GDP. *Data source*: Our World in Data (2025). Data adapted from UNESCO UIS Stat Bulk Data Download Service, via World Bank. Retrieved from https://archive.ourworldindata.org/20260112-111535/grapher/research-spending-gdp.html [online resource] (archived on January 12, 2026).

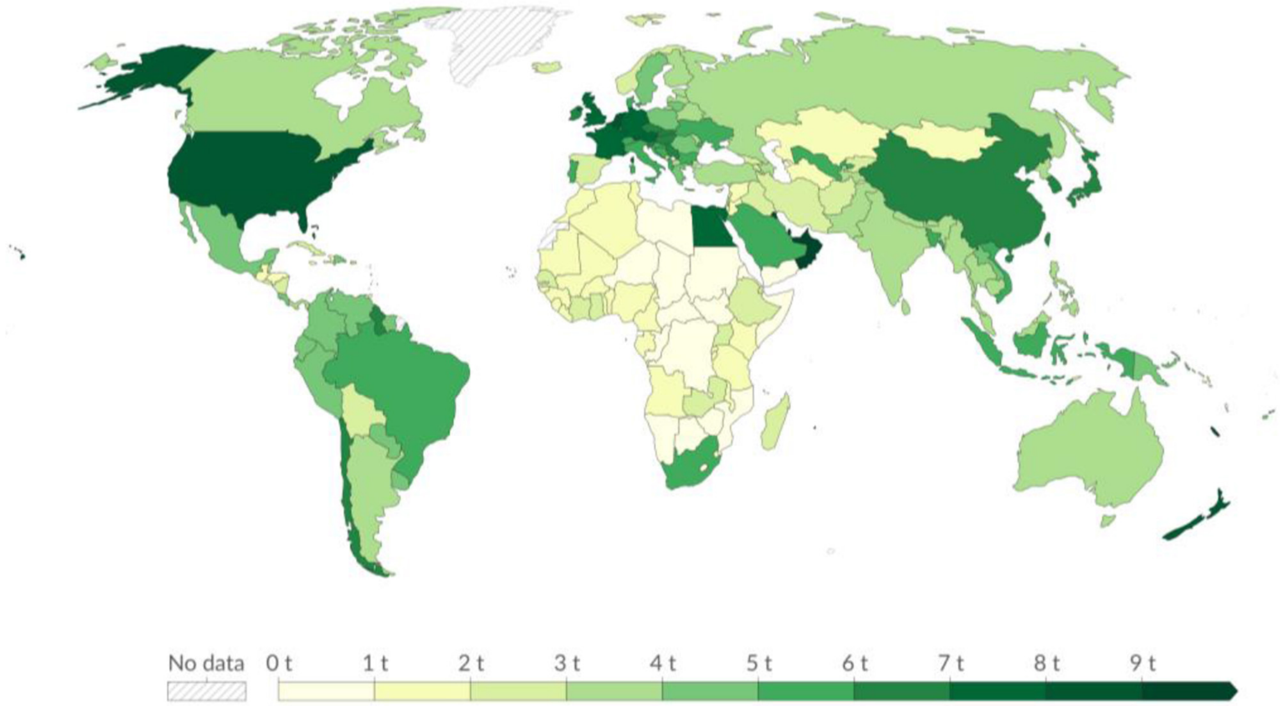

FIGURE 3
Cereal yields by region. *Data source*: Food and Agriculture Organization of the United Nations (2025) - with major processing by Our World in Data. "Cereal yields – UN FAO" [dataset]. Food and Agriculture Organization of the United Nations, "Production: Crops and livestock products" [original data]. Retrieved January 24, 2026 from https://archive.ourworldindata.org/20260116-143329/grapher/cereal-yield.html (archived on January 16, 2026).

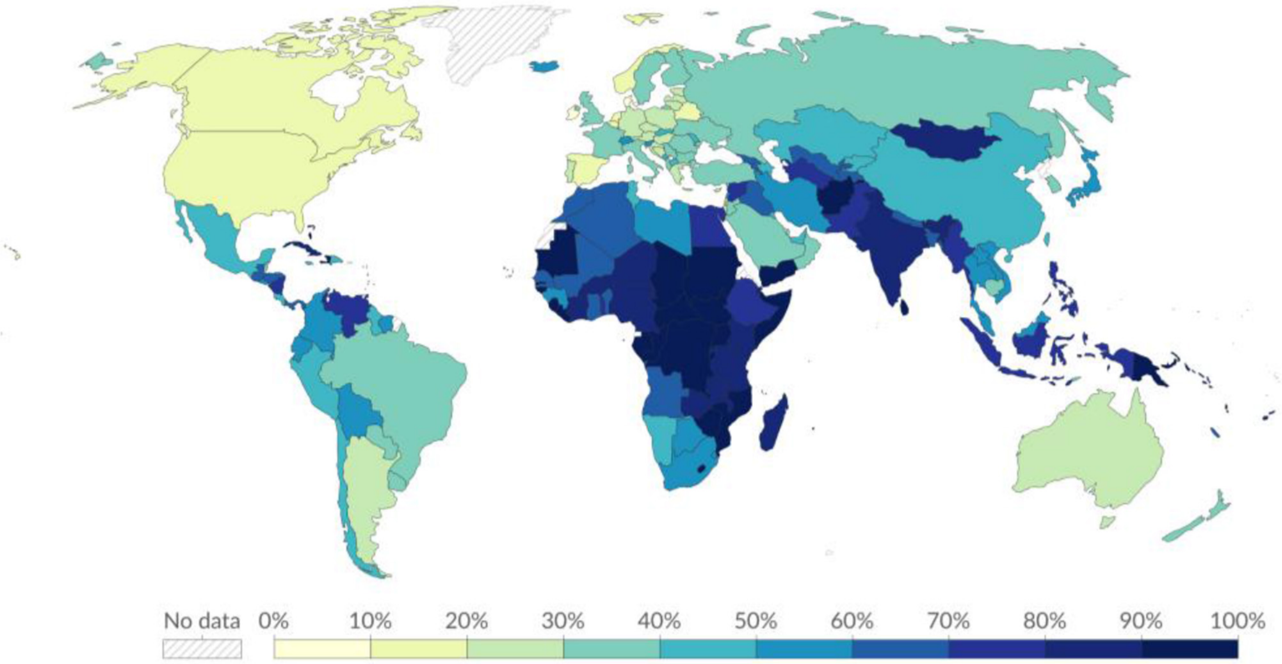

FIGURE 4
Share of cereals allocated to human food globally. *Data source*: Food and Agriculture Organization of the United Nations (2024).

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long-term impacts. For the robustness checks, we implement more advanced Quantile-on-Quantile Kernel Regularized Least Squares (QQ-KRLS) method. Given the multiple variables in the model, we present a multidimensional perspective on the issue, which has not been previously presented in the literature and thus serves as a novel contribution. The multi-perspective approach enables us to present realistic and practical policy implications on how policies and R&D can be maintained to ensure food security and allow China to achieve its green growth objectives.

This study makes several contributions to the existing literature. First, unlike previous studies, which focused on understanding the impact of solar energy, green economic growth, and R&D spending on food security separately (e.g., Salim and Islam, 2010; Kristkova et al., 2016; van Dijk et al., 2025; Hu, 2024; Xia et al., 2024), our study interacts the variables and investigates their simultaneous impact on food security. Second, our study provides a new perspective on the role of renewable energy and technological development in China's agricultural sector, amid rising tensions in land usage, environmental degradation, and food insecurity. Third, our research findings can provide policy implications that contribute to policymaking and inform future studies with new insights. In addition, based on the above background of the study, the following research questions need to be addressed:

(i) Does green energy improve food productivity and effectively reduce agricultural carbon footprints in China?
(ii) How does technological innovation mitigate the effects of climate change and increase food productivity in China?

This paper is structured as follows: Section 1 serves as the introduction, Section 2 reviews the relevant literature, Section 3 explains the methodology, Section 4 presents the analysis, and Section 5 draws conclusions and discusses policy implications.

2 Literature review

2.1 Theoretical framework

Our study is grounded in several theoretical concepts from the fields of economic growth, food security, green energy, and R&D development research. First, the theory of sustainable development (Brundtland, 1987; Sharma et al., 2025) argues that long-term economic growth should not come at the expense of the tradeoff between environmental sustainability, social welfare, and economic efficiency. The perspective considers the shift toward renewables, especially solar energy, as a solution for reducing carbon emissions, increasing energy independence, and strengthening ecological resilience (Ellabban et al., 2014). Nevertheless, sustainability emphasizes such tradeoffs; for example, competition for agricultural land for solar infrastructure, which may harm its ability to produce food (Zhang et al., 2023; Hu, 2024; Xia et al., 2024).

Second, the theory of innovation and economic growth (Salim and Islam, 2010; Sethi et al., 2024) demonstrates that R&D expenditure can increase productivity through technological progress and TFP. In agriculture, technology use can increase TFP and address environmental issues (Liu et al., 2023; Rao et al., 2020). R&D expenditure can serve as a buffer against climate change by providing adaptive technology that can increase economic resilience to shocks. This finding aligns with endogenous growth theory (Lucas, 1988), which emphasizes that innovation and knowledge accumulation are crucial factors driving long-term economic growth.

Third, the "food–energy–climate" nexus theory indicates the need for interconnections between energy transitions, climate change, and the food supply chain (Nelson et al., 2009; Ozturk, 2015; Ren et al., 2021). The implementation of solar energy technology can help reduce dependency on fossil fuels, cut carbon emissions, and mitigate climate-related risks, thereby improving the external conditions under which agricultural production takes place (Qu et al., 2024), which can contribute to stable climate conditions. However, the implementation of solar energy can crowd out land for agricultural expansion (Wei et al., 2025). We expect such efforts to enhance countries' green economic growth and enable them to utilize their resources more efficiently. However, the success of such efforts is dependent on certain factors, such as institutional quality, governance quality, and policy consistency (Lee and Song, 2024). Overall, the literature suggests that the implementation of solar energy, R&D expenditure, and green economic growth strategies can increase agricultural productivity, thereby enhancing food security (Hu, 2024; Chandio et al., 2023; Rao et al., 2020). Such interactions may become significant when macroeconomic policies are accommodating, which encourage clean production (Haftu, 2019; Olayungbo and Quadri, 2019).

2.2 Previous studies

Sharma et al. (2025) investigated the factors that can affect sustainable agriculture in Asia by focusing on greenhouse gas emissions. The analysis involved 10 leading Asian economies with the most significant agricultural share in their GDP and the highest GHG emissions and referred to annual data from 1990 to 2019. The results showed that technological innovation and renewable energy use are effective in reducing GHG emissions from agriculture in the short and long terms and thus highlighted their role in promoting environmentally friendly agricultural practices. By contrast, the results indicated that financial development can worsen emissions, and a rise in economic activity is geared toward yield growth, rather than environmental protection. Meanwhile, though globalization is positively related to emissions, it exerts no statistically significant influence. However, the role of institutional quality in reducing emissions is significant and negative, which may reflect improved regulatory enforcement systems and governance processes.

Salim and Islam (2010) investigated the long-term effects of public R&D investment and climate change on agricultural productivity in Australia by using TFP. The results showed that public R&D investment has a positive and statistically significant impact on agricultural productivity, and a significant time lag exists from investment to impact. By contrast, climate change, in the form of increasing temperatures and declining precipitation, has a statistically significant negative impact on TFP, indicating that climate variability is a central threat to future productivity. The authors also illuminated the fact that, though technological advancement through R&D can mitigate some of the negative impacts of climate change, it may not be able to fully overcome the long-term obstacles of a warming climate.

Similarly, Nelson et al. (2009) examined the long-term effect of climate change on agriculture and food security in South Asia using an integrated modeling approach that links climate forecasts, crop yield models, and economic analysis. The authors drew on the International Model for Policy Analysis of Agricultural Commodities and Trade to estimate the impact of climate change on crop yields, food prices, and calorie availability in different climate scenarios. The analysis focused on the impact of warming and changing rainfall patterns on the region's food systems by midcentury, especially for staple crops like rice and wheat, which serve as the backbone of diets and the economy in South Asia. The study concluded that climate change will result in a substantial decrease in crop yields, as reflected in calorie productivity, food prices, and food insecurity, unless adaptation measures are implemented.

R&D expenditure has also been identified as a key driver of sustainable growth. For instance, Alam and Hossain (2024) showed that the combination of economic growth, renewable energy adoption, and R&D investment can drive the trajectory of CO_2 emissions in China in a different direction; that is, R&D investment plays a crucial role in uncoupling growth from environmental degradation. Consistent with the predictions of endogenous growth theory, the results indicated that R&D investment can increase agricultural productivity and lead to the development of clean technologies and environmentally friendly production methods. The findings further corroborate those of Pickson et al. (2025), who emphasized the role of R&D investment in encouraging long-term productivity and enhancing the resilience of the food system.

From enhancing food security to promoting a greener China, attention to a new round of green agriculture practices is increasing in the food security literature, as the shift from traditional food security safeguard measures to integrated systems theory gains momentum. Deng and Zeng (2023) found that developing a mechanism of the interaction between agricultural resource use and two other sustainable development strategies (human capital accumulation and greening) is essential for ensuring food availability. In addition, Xu et al. (2025) provided spatial econometric evidence showing that, together with technological progress, environmental policies can enhance food security in the provinces and create spatial spillover benefits. The findings demonstrated the critical role of region-level governance and cooperation in maintaining the impact of climate on food energy. Meanwhile, Tian et al. (2024) showed that digital infrastructure can impose positive externalities, facilitating coordination between food production and green economic growth in China. The finding can contribute to the ongoing debate by demonstrating that digitalization can influence future green agricultural transformation. Overall, the diverse studies revealed that institutional factors, such as institutional quality, regional coordination, and technological design, can influence the relationship between technology and green economic growth.

Previous studies have explored the impact of solar energy technology on China's land use and food security. For example, Xia et al. (2024) found that agricultural technology can potentially displace cropland, leading to food insecurity. Furthermore, Lu et al. (2024) demonstrated that cropland productivity in China fluctuates periodically, highlighting the need to coordinate various stakeholders, including agricultural economists and the government, rather than focusing solely on land expansion. Moreover, Lee and Song (2024) demonstrated that land type is crucial in shaping the impact of solar technology on green economic growth. Solar PV technology is becoming more efficient, and system design is improving (Abdel-Aziz and ElBahloul, 2025). The same amount of electricity can now be produced on less land, which eases pressure on cropland (Saxena et al., 2024). Solar development on farmland can also support food production when cultivation continues. Agrivoltaic systems allow crops and electricity to be produced on the same land (Xia et al., 2024). A more reliable power supply can support irrigation, cold storage, and other farm operations (Majeed et al., 2023). In some locations, panels can reduce heat stress and slow soil moisture loss, which may help crop growth (Liu et al., 2020). Digital financial innovation supports these channels. It can improve access to credit and reduce transaction costs. This can help farmers invest in equipment and adopt productivity improving technologies. Li et al. (2023) and Qin et al. (2024) report that digital and green finance can raise agricultural total factor productivity by supporting the diffusion of efficient agrarian technology. Lee and Song (2024) argue that financial development can promote energy structure transformation. Qu et al. (2024) find that well designed financial instruments can promote renewable energy development and improve food security. At the same time, the overall effect depends on policy orientation, technology choice, and local conditions. Policies that protect cultivation, guide site selection, and enforce land management standards help solar projects work with agriculture (Zeddies et al., 2025). Technology choice matters because agrivoltaic systems differ from conventional ground mounted projects that convert farmland. Regional differences matter as well (Campana et al., 2025). Provinces vary in land scarcity, crop structure, irrigation conditions, and solar resource endowments. Solar expansion can therefore affect food production differently across regions (Qiang and Jian, 2020). Solar energy is widely regarded as a pathway to reduce emissions and enhance energy security. It may also reduce climate related risks by improving energy supply conditions for agricultural production and lowering carbon emissions (Maka et al., 2024).

2.3 Hypothesis development

Based on the overview of previous literature, the following research hypotheses are tested.

Hypothesis 1 (H1): Solar energy plays a pivotal role and significantly enhances food productivity in China.

Hypothesis 2 (H2): R&D investment mitigates the effect of climate change and increases food productivity in China.

Hypothesis 3 (H3): Sustainable economic development has a positive impact on food productivity, implying that economic development promotes food security in China.

TABLE 1 Summary of the data.

Variables	Description of the data	Sources
Food security	Food production index (2014–2016 = 100)	WDI
Agricultural sustainability	Agriculture, forestry, and fishing, value added (constant 2015 US$)	WDI
Solar energy	Installed solar capacity (Gigawatts)	WDI
R&D	Research and development expenditure (% of GDP)	WDI
Economic development	GDP per capita (constant 2015 US$)	WDI
Arable land	Arable land (% of land area)	WDI
Temperature change	Temperature change on land (°C)	FAO
Agricultural employment	Employment in agricultural sector (% of total employment)	WDI

3 Methodology

3.1 Data

This study used time series data from 2001 to 2022 and employed the ARDL technique to explore the long- and short-term relationships between the variables. This study obtained the time series data for China from the World Development Indicators and FAO. This study collected data on eight variables, namely, food security, agricultural value added, solar energy development, R&D expenditure, sustainable economic development (SED), arable land, temperature change, and agricultural employment. Table 1 provides a description of the examined variables. The summary statistics of the time series dataset are reported in Table 2. The Jarque–Bera statistic indicates that all the examined variables are normally distributed.

3.2 Econometric method

Checking the stationarity of the variables is fundamental to time series dataset analysis, as it confirms the consistency and accuracy of the econometric models. Unit root testing, also known as stationarity testing, is crucial for determining whether variables exhibit non-stationarity, as the null hypothesis suggests a unit root, whereas the alternative hypothesis proposes stationarity. Given the wide time dimension in a time series dataset, this research performed two prominent tests: an augmented Dickey–Fuller (ADF) test and a Phillips–Perron (PP) test. Both tests can determine the order of integration of each variable and confirm that none are integrated with order two, which may generate spurious results. Furthermore, this study applied the bounds testing approach developed by Pesaran et al. (2001) to explore the long-term relationship between the independent and dependent variables and the ARDL method to examine the long- and short-term impact of solar energy development, green economic growth, and R&D investment on food security and agricultural productivity. This study employed the Akaike information criterion as the method of selection. Moreover, this study checked the robustness of the long-term impact coefficients of the ARDL model by using the fully modified ordinary least squares (OLS) regression and dynamic OLS regression methods. The functional expression of the models is presented as follows:

Model 1: Food security

$$FS_t = f\left(SEN_t, RD_t, SED_t, ABL_t, TMP_t, EMP_t\right) \tag{1}$$

Model 2: Agricultural sustainability

$$AGS_t = f\left(SEN_t, RD_t, SED_t, ABL_t, TMP_t\right) \tag{2}$$

Equations (1) and (2) can be written as:

$$\begin{aligned} LFS_t &= \alpha_0 + \beta_1 LSEN_t + \beta_2 LRD_t + \beta_3 LSED_t + \beta_4 LABL_t \\ &\quad + \beta_5 TMP_t + \beta_6 LEMP_t + \varepsilon_t \end{aligned} \tag{3}$$

$$\begin{aligned} LAGS_t &= \alpha_0 + \beta_1 LSEN_t + \beta_2 LRD_t + \beta_3 LSED_t + \beta_4 LABL_t \\ &\quad + \beta_5 TMP_t + \varepsilon_t \end{aligned} \tag{4}$$

where L denotes the natural log form; FS, AGS, SEN, RD, SED, ABL, TMP, and EMP represent food security, agricultural sustainability, solar energy development, R&D expenditure, sustainable economic development, arable land, temperature change, and agricultural employment, respectively; and $\alpha_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_{5,}$ and β_6 measure the long-term elasticities of food security concerning the time trend, SEN, RD, SED, ABL, TMP, and EMP, respectively.

The ARDL technique primarily involves two fundamental steps to assess the long-term relationships between variables. An explanation of step one is presented in Equations (5) and (6) for the two models, as follows:

$$\begin{aligned} \Delta LFS_t &= \Omega_0 + \textstyle\sum_{k=1}^{p} \varphi_{1k} \Delta LSEN_{t-k} + \sum_{k=1}^{q} \varphi_{2k} \Delta LRD_{t-k} \\ &\quad + \textstyle\sum_{k=1}^{q} \varphi_{3k} \Delta LSED_{t-k} + \sum_{k=1}^{q} \varphi_{4k} \Delta LABL_{t-k} \\ &\quad + \textstyle\sum_{k=1}^{q} \varphi_{5k} \Delta TMP_{t-k} + \sum_{k=1}^{q} \varphi_{6k} \Delta LEMP_{t-k} + \chi_1 LFS_{t-1} \\ &\quad + \chi_2 LSEN_{t-1} + \chi_3 LRD_{t-1} + \chi_4 LSED_{t-1} + \chi_5 LABL_{t-1} \\ &\quad + \chi_6 TMP_{t-1} + \chi_7 LEMP_{t-1} + \varepsilon_t. \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta LAGS_t &= \Omega_0 + \textstyle\sum_{k=1}^{p} \varphi_{1k} \Delta LSEN_{t-k} + \sum_{k=1}^{q} \varphi_{2k} \Delta LRD_{t-k} \\ &\quad + \textstyle\sum_{k=1}^{q} \varphi_{3k} \Delta LSED_{t-k} + \sum_{k=1}^{q} \varphi_{4k} \Delta LABL_{t-k} \\ &\quad + \textstyle\sum_{k=1}^{q} \varphi_{5k} \Delta TMP_{t-k} + \chi_1 LAGS_{t-1} + \chi_2 LSEN_{t-1} \\ &\quad + \chi_3 LRD_{t-1} + \chi_4 LSED_{t-1} + \chi_5 LABL_{t-1} \\ &\quad + \chi_6 TMP_{t-1} + \varepsilon_t. \end{aligned} \tag{6}$$

Null Hypothesis for Model 1: Food security

$$\begin{aligned} H_0 &= \chi_1 = \chi_2 = \chi_3 = \chi_4 = \chi_5 = \chi_6 \\ H_1 &\neq \chi_1 \neq \chi_2 \neq \chi_3 \neq \chi_4 \neq \chi_5 \neq \chi_6 \end{aligned}$$

TABLE 2 Descriptive statistics.

Item	LFS	LAGS	LSEN	LRD	LSED	LABL	TMP	LEMP
Mean	4.4825	27.4061	1.4060	0.5331	8.6699	2.5155	1.2369	3.5209
Median	4.5254	27.4188	1.5194	0.6125	8.7591	2.5312	1.1765	3.5320
Maximum	4.7162	27.8320	5.9738	0.9381	9.3549	2.5595	1.9090	3.9120
Minimum	4.1658	26.9850	−3.2696	−0.0615	7.7662	2.4414	0.6250	3.1166
Std. Dev.	0.1724	0.2621	3.3619	0.2925	0.5082	0.0426	0.3218	0.2699
Skewness	−0.4223	−0.0723	0.0027	−0.4927	−0.3487	−0.6048	0.1952	0.0124
Kurtosis	1.8547	1.8189	1.3833	2.0682	1.8417	1.8108	2.5056	1.6371
Jarque–Bera	1.8564	1.2978	2.3958	1.6861	1.6756	2.6374	0.3638	1.7031
Probability	0.3952	0.5225	0.3018	0.4303	0.4326	0.2674	0.8336	0.4267

FS, food security; AGS, agricultural sustainability; SEN, solar energy; RD, research & development investment; SED, sustainable economic development; ABL, arable land; TMP, temperature; EMP, agricultural employment.

Null Hypothesis for Model 2: Agricultural sustainability

$$H_0 = \chi_1 = \chi_2 = \chi_3 = \chi_4 = \chi_5$$
$$H_1 \neq \chi_1 \neq \chi_2 \neq \chi_3 \neq \chi_4 \neq \chi_5$$

For step two, this study explored the short-term connections between the variables, which can be signified by the following error correction model in the ARDL framework:

$$\Delta LFS_t = \Omega_0 + \sum_{k=1}^{p} \varphi_{1k} \Delta LSEN_{t-k} + \sum_{k=1}^{q} \varphi_{2k} \Delta LRD_{t-k} + \sum_{k=1}^{q} \varphi_{3k} \Delta LSED_{t-k} + \sum_{k=1}^{q} \varphi_{4k} \Delta LABL_{t-k} + \sum_{k=1}^{q} \varphi_{5k} \Delta TMP_{t-k} + \sum_{k=1}^{q} \varphi_{6k} \Delta LEMP_{t-k} + \delta ECM_{t-1} + \varepsilon_t \quad (7)$$

$$\Delta LAGS_t = \Omega_0 + \sum_{k=1}^{p} \varphi_{1k} \Delta LSEN_{t-k} + \sum_{k=1}^{q} \varphi_{2k} \Delta LRD_{t-k} + \sum_{k=1}^{q} \varphi_{3k} \Delta LSED_{t-k} + \sum_{k=1}^{q} \varphi_{4k} \Delta LABL_{t-k} + \sum_{k=1}^{q} \varphi_{5k} \Delta TMP_{t-k} + \delta ECM_{t-1} + \varepsilon_t \quad (8)$$

3.3 Stability checks for models

To ensure the stability and consistency of the ARDL models, this study conducted various diagnostic tests, including CUSUM, CUSUMSQ, normality tests, heteroscedasticity tests, and serial correlation tests. The tests are essential to time series dataset analysis to evaluate the properties of the data and validate the outcomes of the estimated model.

3.4 QQ-KRLS method

Quantile Quantile Kernelized Least Squares (QQ-KRLS) method represents a cutting-edge approach that enhances the accuracy and reliability of econometric models, particularly in capturing complex relationships between variables. Its importance lies in its ability to address non-linearities and heteroscedasticity—two common challenges in economic data modeling. Unlike traditional methods, QQ-KRLS offers a more flexible and robust framework by applying kernel-based techniques to capture the underlying structures in the data without making strong assumptions about the functional form of the relationship between variables.

4 Results and discussion

4.1 Unit root testing

First, we tested the stationarity of the time series dataset by conducting two tests, namely, an ADF test and a PP test, at both the level form and the first difference form. The outcomes of the two tests are presented in Table 3. For all the examined variables, at the level form, both tests indicate non-stationarity. Moreover, LFS, LAGS, LSEN, LRD, LSED, LABL, TMP, and LEMP consistently fail to reject the null hypothesis of non-stationarity at the 0.05 level across both tests, thus showing no significant evidence of stationarity. By contrast, at the first difference, the results reveal that stationarity is achieved for all the examined variables, with both tests rejecting the null hypothesis of non-stationarity at the 1%, 5%, and 10% significance levels.

4.2 ARDL bounds cointegration testing and robustness

Second, we employed the ARDL bounds cointegration approach to examine the long-term cointegration of the variables under consideration. The estimated outcomes of the bounds cointegration test for Model 1 and Model 2 are presented in Table 4. The null hypothesis suggests that no long-term cointegration exists between the variables of Model 1 and Model 2. Hence, the alternative hypothesis for both models (LFS and LAGS) states that long-term cointegration exists for the determinants of food security and agricultural sustainability. The results show that the F-statistic values (3.6819** and 4.1451*) exceed the upper bound values at

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TABLE 3 The ADF and PP unit root test results.

Item	Augmented Dickey–Fuller unit root test statistic			
	Level		First difference	
	t-statistic	Prob.	*t*-statistic	Prob.
LFS	−2.498930	0.3241	−4.872322***	0.0048
LAGS	−1.987470	0.5742	−4.348421***	0.0134
LSEN	−2.246884	0.4398	−5.261763***	0.0025
LRD	−2.318090	0.4072	−3.799100**	0.0398
LSED	−2.055255	0.5205	−4.453959***	0.0109
LABL	−2.315012	0.4079	−5.258939***	0.0001
TMP	−2.172623	0.4792	−6.486255***	0.0002
LEMP	−1.863461	0.6354	−3.436018*	0.0747
	Phillips–Perron unit root test statistic			
	Level		First difference	
	Adj. *t*-stat	Prob.	Adj. *t*-stat	Prob.
LFS	−0.900034	0.9371	−4.919472***	0.0044
LAGS	−1.987470	0.5742	−4.504814***	0.0099
LSEN	−1.540479	0.7817	−5.309570***	0.0023
LRD	−2.350007	0.3920	−5.397077***	0.0017
LSED	−0.500627	0.9984	−4.518190***	0.0096
LABL	−2.211191	0.4598	−5.013418***	0.0040
TMP	−2.194514	0.4681	−6.407390***	0.0002
LEMP	−2.819184	0.2062	−3.451586*	0.0727

***, ** and *signify the statistical significance at the 1%, 5% and 10% levels respectively.

the 5% and 10% significance levels. Therefore, we conclude that the examined variables are cointegrated in the long term, which confirms the reliability of the long-term estimates.

Third, for the robustness checks, we employed the Johansen co-integration approach (Johansen, 1992) for the two models (LFS and LAGS). The null hypothesis of the Johansen co-integration approach assumes that there is no long-term co-integration between the variables. In contrast, the alternative hypothesis states that co-integration exists between the variables. The outcomes of the co-integration approach for both models (LFS and LAGS) are presented in Tables A1, A2. The co-integration approach confirmed the existence of a long-term co-integration relationship between the determinants of food security and agricultural sustainability.

4.3 Determinants of food security

Based on the findings of the preliminary tests and the establishment of long-term co-integration between the variables considered in Model 1 (LFS), we employed the ARDL approach for both long- and short-term estimations, which are presented in Table 5. The long-term coefficient results reveal that the main variables, namely, SEN, RD, SED, and ABL, are statistically significant at the 1% and 5% confidence levels. Our results indicate that SEN has positive and significant coefficients in both the long-term and short-term analyses. Specifically, a 1% increase in SEN can promote FS by 0.0152% and 0.0218% in the long- and short-term analysis, respectively. In economic terms, this implies that a 10% expansion in installed solar capacity is associated with an approximately 0.15–0.22% improvement in the food production index, all else being equal. Although this magnitude is modest relative to core production factors such as arable land and R&D investment, it suggests that solar energy plays a complementary role by easing energy constraints in agriculture rather than acting as a primary driver of aggregate food output. One plausible reason for the modest elasticity is that annual national indicators may average out localized productivity gains, and the effects of solar deployment may materialize through indirect and lagged channels.

Solar energy adoption can mitigate climatic risks by reducing reliance on diesel and wood, thereby reducing greenhouse gas emissions and protecting ecosystems (Shang et al., 2024). Climate risk reduction can ensure agricultural productivity and healthy environments for healthy living (Raimi et al., 2021) and hence positively affect household income (a promoter of food security). The deterioration of people's health due to poor climatic conditions will negatively impact their ability to work and increase their household income. Inadequate agricultural production is also a threat to food security. Our findings are consistent with those of previous research, such as Sethi et al. (2024) and Rehman et al.

TABLE 4 ARDL bounds test results.

Critical value bounds		
Significance	I0 Bound	I1 Bound
Model 1: LFS		
10%	2.12	3.23
5%	2.45	3.61
1%	3.15	4.43
Test statistic	Value	
F-statistic	3.6819**	
R-squared	0.6855	
Adjusted *R*-squared	0.4758	
F-statistic	3.2696**	
Prob(*F*-statistic)	0.0319	
Model 2: LAGS		
10%	2.75	3.79
5%	3.12	4.25
1%	3.93	5.23
Test statistic	Value	
F-statistic	4.1451*	
R-squared	0.7968	
Adjusted *R*-squared	0.5711	
F-statistic	3.5304**	
Prob(*F*-statistic)	0.0355	

**5% Sig; *10% Sig.

(2024), which have indicated that renewable energy technology can promote food security. Similarly, the coefficients of RD are significant and positive in the long- and short-term evaluations. Specifically, a 1% increase in RD can lead to enhancements of 0.1855% and 0.2666% in FS in the long-term and short-term analyses.

Compared with SEN, the larger elasticities for RD indicate that technological innovation and knowledge accumulation are likely to exert a more substantial leverage on food security at the national level, consistent with the notion that R&D affects yields and resilience through crop improvement and production technologies. Investment in R&D can ensure proper policy design and technological innovation to mitigate climatic risks, thereby enhancing agricultural production and ensuring food security (Garbero and Jäckering, 2021). Government-supported research institutions are working to develop high-yielding crop varieties (e.g., rice) that are resistant to pests, diseases, and extreme weather conditions. RD can also help policy initiators provide ideas and opportunities to both agricultural and non-agricultural sectors for income improvement (Kristkova et al., 2016). The findings align with those of Salim and Islam (2010) and Kristkova et al. (2016), who have revealed that RD can enhance food security. Meanwhile, SED is significant and positive, implying that a 1% increase in SED will result in an FS enhancement of 0.1335% and 0.1920% in the long-term and short-term analyses, respectively. High SED is a sign of a growing economy, which is closely linked to increased income, promoting food security through employment opportunities and healthy environments that support healthy lives. In addition, high SED can help alleviate climate risk and encourage food production, as the government can provide the necessary innovation and techniques to overcome the threats of climate change (Chandio et al., 2022). Similarly, the coefficients of ABL are significant and positive in the long- and short-term evaluations. Specifically, a 1% increase in ABL can enhance FS by 0.8648% and 1.2431% in the long- and short-term analysis, respectively.

The comparatively large elasticity of arable land underscores that land availability and quality remain fundamental constraints for food security, implying that land-use preservation and productivity-enhancing land management can yield sizeable gains relative to energy-related interventions. Farmers can grow multiple crops, which can reduce their reliance on a single food source and improve their dietary diversity, thereby addressing the problem of malnutrition. Additionally, the abandonment of farmland for non-farm employment in urban areas can be curtailed when arable land is accessible and productive. Land abandonment due to the loss of soil nutrients and other essential elements will harm agricultural productivity and food production, ultimately leading to food insecurity. The results corroborate those of Wang et al. (2019), Baig et al. (2024), and Behera et al. (2024), which revealed that access to arable land is associated with increased food production. Furthermore, TMP is negative in both the long-term and short-term evaluations, which implies that a 1% increase in TMP will result in a decrease in FS of 0.0042% and 0.0060%, respectively. Because the TMP coefficients do not reach conventional significance thresholds in the baseline specification, this negative pattern should be interpreted cautiously as suggestive rather than definitive evidence of a temperature-driven effect on aggregate food security. In practical terms, the insignificance implies that temperature change is not identified as a primary driver of FS in our baseline time-series setting, and the main policy emphasis should rely more on variables with larger and statistically robust elasticities. Such insignificant climate coefficients are not unusual when using annual, national-level aggregates, where aggregation can smooth localized and seasonal shocks and reduce statistical power. Several studies have confirmed that temperature changes can harm food security (Ahsan et al., 2020; Pickson et al., 2022; Baig et al., 2024; Behera et al., 2024; Rehman et al., 2024). Our findings are also consistent with those of the aforementioned studies.

We confirmed the statistical stability of the ARDL model by conducting CUSUM (Figure SI) and CUSUMQ (Figure S2) tests. The two figures indicate that the CUSUM and CUSUMQ test statistics fall within the critical bounds of the 5% significance level, confirming that the error correction term (ECT) in the estimated model is stable in both the short and long terms. This finding supports the robustness of the relationship between solar energy development, R&D investment, sustainable economic development, arable land, temperatures, employment, and food security in the context of China. Furthermore, Table A3 in the Supplementary file shows the lag order selection criteria for Model 1: LFS.

TABLE 5 Long and short run results for Model 1: LFS.

Variables	Coefficient	Std. error	*t*-statistic	Prob.
Long-run estimates				
LSEN	0.0152	0.0051	2.9474	0.0122**
LRD	0.1855	0.0514	3.6052	0.0036***
LSED	0.1335	0.0525	2.5395	0.0260**
LABL	0.8648	0.2015	4.2907	0.0010***
TMP	−0.0042	0.0105	−0.3984	0.6973
LEMP	−0.1369	0.1541	−0.8885	0.3917
Cons_	1.5181	0.7383	2.0561	0.0622*
Short-run estimates				
ΔLFS (−1)	−0.4375	0.2981	−1.4674	0.1680
ΔLSEN	0.0218	0.0103	2.1176	0.0558*
ΔLRD	0.2666	0.0897	2.9727	0.0116**
ΔLSED	0.1920	0.0912	2.1048	0.0571*
ΔLABL	1.2431	0.3752	3.3131	0.0062***
ΔTMP	−0.0060	0.0148	−0.4074	0.6908
ΔLEMP	0.2048	0.2613	0.7835	0.4485
ΔLEMP (−1)	−0.4016	0.1766	−2.2737	0.0421**
CointEq (−1)	−1.4375	0.2981	−4.8214	0.0004***
R-squared	0.9981			
Adjusted R^2	0.9969			
F-statistic	816.6511			
Prob(*F*-statistic)	0.0000			

***1% Sig; **5% Sig; *10% Sig.

4.4 Robustness for the food security model with core variables

To further strengthen the analysis, it is essential to highlight the significance of the FMOLS, CCR, and QQ-KRLS methods in our robustness checks. The results obtained from these alternative techniques align closely with the initial ARDL estimates, confirming the robustness of our analysis. As shown in Table 6, the main variables, SEN, RD, SED, and ABL, demonstrate a statistically significant positive relationship with FS in the long run. By incorporating QQ-KRLS, the robustness of the ARDL model's core variable findings is confirmed, providing a deeper layer of reliability to the results (see Figures S3, S4). Specifically, this technique enables a more nuanced understanding of how solar energy development (SEN), research and development (R&D), and sustainable economic development (SED) interact with food security (FS), taking into account the possibility of non-linear effects and structural shifts in the data over time. As a result, QQ-KRLS not only reinforces the consistency of the original ARDL estimates but also helps to identify the key variables that drive food security in a more refined and accurate manner.

The use of QQ-KRLS also highlights the model's capacity to handle complex data environments, where traditional methods may fall short. For instance, in dynamic systems like food security, where variables may exhibit varying degrees of influence over different periods, QQ-KRLS offers a better fit. This is crucial because food security is influenced by numerous economic, social, and environmental factors that change in response to both short-term shocks and long-term structural trends. By using QQ-KRLS, our analysis is better equipped to account for these variations, leading to more accurate and generalizable findings. Moreover, the results obtained through QQ-KRLS also help to assess the robustness of the ARDL model by providing alternative estimates that closely mirror the initial ARDL results. This alignment provides further confidence in the robustness of the relationships between SEN, RD, SED, and FS, thereby reinforcing the validity of our conclusions. The QQ-KRLS method thus emerges as a crucial tool in ensuring that the findings are not only statistically significant but also reflective of the real-world complexities.

In summary, incorporating the QQ-KRLS method enhances the overall analysis by addressing the inherent limitations of traditional econometric techniques. It enhances the reliability

TABLE 6 Robustness check for Model 1: LFS.

Variables	FMOLS			CCR		
	Coefficient	t-statistic	Prob.	Coefficient	t-statistic	Prob.
LSEN	0.0177***	8.2319	0.0000	0.0091*	1.8423	0.0867
LRD	0.1371***	5.7366	0.0001	0.2046***	3.7117	0.0023
LSED	0.1837***	8.3993	0.0000	0.1216**	2.1767	0.0471
LABL	0.9584***	10.4127	0.0000	0.6625***	3.6854	0.0024
TMP	−0.0032	−0.7120	0.4900	−0.0016	−0.1246	0.9026
LEMP	−0.0554	−0.8543	0.4096	−0.1729	−1.2847	0.2197
Cons_	0.5753	1.7739	0.1014	2.2508***	3.0923	0.0080
R-squared	0.9974			0.9969		
Adjusted R^2	0.9961			0.9956		

***1% Sig; **5% Sig; *10% Sig.

of the conclusions drawn regarding the impact of solar energy development, research, and development, as well as sustainable economic development, on food security. The consistency of results across both the ARDL and the QQ-KRLS methods highlights the robustness of these relationships, further confirming their critical role in achieving sustainable food security outcomes.

4.5 Determinants of agricultural sustainability

The long- and short-term ARDL model results for AGS are shown in Table 7. The results reveal that SEN has positive and significant coefficients in the long and short-term analyses. Specifically, a 1% increase in SEN can lead to a 0.0178% and a 0.0244% increase in AGS in the long- and short-term analysis, respectively. In practical terms, this implies that a 10% increase in installed solar capacity is associated with an approximately 0.18–0.24% rise in agricultural value added, ceteris paribus. Although the elasticity is modest relative to land-related effects, it is consistent with the view that solar energy supports agricultural performance mainly through cost-saving and reliability channels rather than through direct yield expansion at the aggregate level. Solar energy development can mitigate climate threats, as it can reduce greenhouse gas emissions (International Renewable Energy Agency, 2019). Solar technology adoption is cost-effective and can promote food production while mitigating climate risks (Ravi et al., 2016; Ghasemi and Sadeghkhani, 2025). The findings are consistent with those of Pascaris et al. (2021), Ozdemir (2022), Shah et al. (2023), and Sethi et al. (2024), which indicate that renewable energy technology can support agricultural growth. Meanwhile, SED is significant and positive in the short run but negative in the long run, which implies that a 1% increase in SED is associated with a 0.1900% decrease and a 0.3565% increase in AGS in the long- and short-term analysis, respectively. This sign suggests that while economic expansion may temporarily stimulate agricultural activity through higher investment capacity and technology adoption, longer-run structural transformation can reallocate labor and land toward non-agricultural uses, thereby weakening agricultural value added over time. High SED is a sign of a growing economy, which is closely linked to increased income, promoting food production through farm technology and educational improvements. However, an improved economy is linked with other sectoral developments. It may lead to a shift from the agricultural sector to other sectors, such as services and industry, in the long run. In addition, without effective policies, agrarian land may gradually be repurposed for nonagricultural uses, such as infrastructure, roads, and urban real estate, owing to long-term rural-urban migration. The shift is driven by a scarcity in productive farmland and the pursuit of high-paying jobs in the city (Zhang et al., 2016).

The estimated coefficient of RD is positive but not statistically significant. This finding demonstrates that a 1% increase in RD corresponds to a rise in AGS of 0.1221% in the short run and 0.0109% in the long run. By contrast, the estimation demonstrates that ABL has a positive and statistically significant impact on AGS in the short and long terms. Specifically, a 1% increase in ABL will tend to increase AGS by 1.2946% in the long run and by 1.7697% in the short run. The magnitude of the ABL elasticity is economically significant, indicating that land availability and effective land management remain binding constraints on agricultural value added; therefore, land protection and productivity-oriented land policies may yield comparatively substantial gains. The finding highlights the significance of arable land in enhancing agricultural productivity in both the short and long term. Furthermore, the finding is consistent with that of Li et al. (2016), and Yamaguchi et al. (2016) and demonstrates the positive impact of labor and capital, which are key factors in arable land management for agricultural productivity.

Over-cultivation can diminish fallowing opportunities, thereby reducing the potential to enhance soil fertility and ensure high production (Wang et al., 2019). The results corroborate those of Li et al. (2016), which showed that access to arable land is associated with increased food production. Additionally, a negative correlation exists between TMP and AGS in both the long and short terms. Specifically, a 1% increase in TMP will result in a decline in AGS of 0.0105% and 0.0144%. TMP carries a consistently

TABLE 7 Long and short run results for Model 2: LAGS.

Variables	Coefficient	Std. error	*t*-statistic	Prob.
Long-run estimates				
LSEN	0.0178	0.0051	3.4770	0.0070***
LSED	−0.1900	0.0609	−3.1197	0.0123**
LRD	0.0109	0.0581	0.1884	0.8547
LABL	1.2946	0.3444	3.7582	0.0045***
TMP	−0.0105	0.0061	−1.7213	0.1193
Cons_	25.1091	0.5456	46.0134	0.0000***
@TREND	0.0565	0.0065	8.5814	0.0000
Short-run estimates				
ΔLAGS (−1)	−0.3669	0.2346	−1.5640	0.1522
ΔLSEN	0.0244	0.0079	3.0699	0.0134**
ΔLSED	0.3565	0.1358	2.6248	0.0276**
ΔLSED (−1)	−0.2044	0.1445	−1.4146	0.1908
ΔLSED (−2)	−0.4118	0.1408	−2.9236	0.0169**
ΔLRD	0.1221	0.0731	1.6686	0.1295
ΔLRD (−1)	−0.1071	0.0841	−1.2735	0.2347
ΔLABL	1.7697	0.4902	3.6097	0.0057***
ΔTMP	−0.0144	0.0079	−1.8200	0.1021
Δ@TREND	0.0773	0.0127	6.0500	0.0002***
CointEq (−1)	−1.3669	0.2346	−5.8266	0.0003***
R-squared	0.9997			
Adjusted R^2	0.9995			
F-statistic	448.542			
Prob(*F*-statistic)	0.0000			

***1% Sig; **5% Sig.

negative sign in both the long- and short-run estimates, indicating a downward tendency; while it does not reach conventional significance thresholds in the baseline specification, the pattern remains suggestive and reflects an effect that is difficult to detect with annual national data. In statistical terms, this insignificance indicates that we cannot reject the null hypothesis of no systematic temperature effect on AGS at conventional levels in this aggregate time-series setting; hence, the negative sign should be interpreted cautiously as a directional signal rather than definitive evidence. Such a result is not unusual when using annual, national-level climate indicators, where aggregation can smooth localized and seasonal shocks and reduce statistical power. Accordingly, TMP is treated as a secondary/conditional factor in our baseline inference, and the primary conclusions and policy emphasis are drawn from variables with larger and statistically robust elasticities. Agriculture in developing countries faces significant risks due to its reliance on unpredictable global environmental conditions. Thus, the impact of climate change on food productivity should be examined. Low cereal yields and overall productivity can be attributed largely to climate change and variability (Ahsan et al., 2020; Wu et al., 2021). Climate change factors, including temperature, precipitation, and CO_2 equivalent (CO_2e), can significantly impact agricultural output in developing economies. Climate change is a global issue that affects all nations. Empirical evidence indicates that low- to middle-income emerging nations are the most vulnerable to climate change because they lack the necessary resources to combat its effects effectively. Thus, climate change poses a major threat to agricultural production and sustainable development in developing regions (Behera et al., 2024). Our results are also consistent with those of Ozdemir (2022), Rehman et al. (2024), and Chandio et al. (2025).

We confirmed the statistical stability of the ARDL model by conducting CUSUM (Figure S5) and CUSUMSQ (Figure S6) tests. The two figures indicate that the CUSUM and CUSUMSQ test statistics are within the critical bounds of the 5% significance level, confirming that the ECT in the estimated model is stable in both the short and long terms. This finding supports the robustness of the relationships between solar energy development, R&D, sustainable economic development, arable land, temperatures, and agricultural productivity in the context of China. Moreover, Table A4 in the Supplementary file shows the lag order selection criteria for Model 2: LAGS.

TABLE 8 Robustness check for Model 2: LAGS.

Variables	FMOLS			CCR		
	Coefficient	*t*-statistic	Prob.	Coefficient	*t*-statistic	Prob.
LSEN	0.0058	1.8083	0.0937*	0.0049	1.1730	0.2618
LSED	−0.1341	−2.8535	0.0136**	−0.0996	−1.2310	0.2401
LRD	0.0039	0.0908	0.9290	0.1660	1.7400	0.1055
LABL	1.3691	4.7681	0.0004**	0.6823	1.4453	0.1720
TMP	0.0022	0.4055	0.6917	0.0220	1.4218	0.1786
Cons_	24.5145	56.5425	0.0000***	25.9805	39.4763	0.0000***
@TREND	0.0566	10.5548	0.0000***	0.0426	3.7831	0.0023
R-squared	0.9991			0.9985		
Adjusted R^2	0.9987			0.9978		

***1% Sig; **5% Sig; *10% Sig.

4.6 Robustness for LAGS model with core variables

To further validate the findings of the ARDL model, robustness checks were conducted using the FMOLS, CCR, and QQ-KRLS methods within the context of the agriculture sustainable productivity model (AGS). The results obtained from these alternative techniques align closely with the initial ARDL estimates, confirming the robustness of our analysis. As shown in Table 8, the main variables, SEN and ABL, demonstrate a statistically significant positive relationship with agricultural productivity in the long run. In contrast, RD shows a positive but non-significant association with agricultural productivity, confirming the findings of the ARDL model. In addition, Figures S7, S8 present the robustness test results, which focus on the key variables of solar energy development (SEN), sustainable economic development (SED), and research and development investment (RD), in relation to agricultural productivity (AGL). The findings from the QQ-KRLS method closely align with the initial ARDL estimates, reaffirming the robustness and reliability of the analysis. The results underscore a statistically significant and positive relationship between these core variables (SEN, SED, and RD) and AGL, thereby confirming and reinforcing the conclusions drawn from the original ARDL model. Specifically, these variables play a crucial role in driving agricultural productivity, with each showing a positive contribution to improving agricultural output. The consistency of the results across different methods further strengthens the credibility of the findings and their relevance for policy and practice. The positive relationships between solar energy development (SEN), sustainable economic development (SED), and research and development (RD) with agricultural productivity (AGL) reveal important economic dynamics that link these variables to overall productivity in the agriculture sector. The integration of solar energy technologies into agricultural practices has been shown to boost agricultural productivity significantly. Solar energy can reduce reliance on conventional energy sources, lower energy costs for farmers, and support the development of sustainable irrigation systems, greenhouses, and other agricultural infrastructure. The reduction in energy costs and the increased availability of reliable energy sources for farming operations contribute directly to higher agricultural output. The positive economic effect of solar energy on agricultural productivity aligns with the growing emphasis on renewable energy solutions as part of modern agricultural strategies.

Sustainable economic development fosters an environment where agricultural practices are not only economically viable but also environmentally sustainable. Investments in infrastructure, education, technology, and market access are essential for enhancing productivity in the agricultural sector. By prioritizing sustainable practices, such as soil conservation, water management, and agricultural-ecological farming methods, SED helps maintain long-term agricultural yields. The positive relationship between SED and agricultural productivity indicates that as economies adopt more sustainable development models, they simultaneously enhance the productivity and resilience of the agriculture sector. This synergy between economic development and agriculture is vital for achieving food security and long-term growth. Investment in agricultural research and development (R&D) is one of the most direct ways to enhance agricultural productivity. R&D drives innovations in crop management, pest control, irrigation technologies, and more efficient farming techniques. As countries invest more in R&D, they equip farmers with the tools and knowledge necessary to increase yields, reduce losses, and adapt to changing environmental conditions. The positive economic impact of RD on agricultural productivity is clear, as increased R&D funding translates into better farming practices, higher efficiency, and more sustainable outputs. The positive relationship between these core variables and agricultural productivity (AGL) indicates that economic growth, technological advancements, and sustainable practices are mutually reinforcing. The model demonstrates that when countries invest in these areas, they not only improve food security but also strengthen their agricultural sectors, laying the foundation for long-term economic growth. This interconnectedness between economic factors and agricultural productivity highlights the importance of a holistic approach to policy-making that integrates energy, sustainability, and innovation into the development of the agricultural sector.

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TABLE 9 Outcomes of diagnostic tests.

Diagnostic tests	Model 1: LFS		Model 2: LAGS	
	X^2 statistics	Prob.	X^2 statistics	Prob.
Serial correlation LM test	0.628146	0.4448	0.797443	0.4875
Jarque–Bera test	0.059964	0.9704	1.855841	0.3953
Heteroskedasticity test	0.719728	0.4074	1.175250	0.2935
Ramsey reset test	0.517483	0.6151	1.530773	0.1644
CUSUM test	Stable at 5% Sig.	–	Stable at 5% Sig.	–
CUSUMSQ test	Stable at 5% Sig.	–	Stable at 5% Sig.	–

In conclusion, the robustness checks using the QQ-KRLS method confirm the validity of the initial ARDL findings, showing that solar energy development, sustainable economic development, and research and development all have a significant effect on agricultural productivity. These results provide valuable insights into the economic mechanisms that drive agricultural growth.

4.7 Diagnostic test outcomes

The results of the diagnostic tests are presented in Table 9. We conducted an ARCH test and an LM test to assess endogeneity, serial correlation, and heteroscedasticity in the model. The diagnostic tests confirmed that Model 1 (LFS) and Model 2 (LAGS) are robust, and the calculated results are reliable for policy implications.

5 Conclusion and policy implications

In this study, we aim to support China's agenda to enhance its agricultural sector, ensuring food production while mitigating environmental degradation, by examining the long- and short-term impacts of solar energy development, green economic growth, and R&D investment on agricultural sustainability and food security. Moreover, we used the ARDL and advanced QQ-KRLS approaches for the main and robustness checks. Our findings demonstrate a positive correlation between the implementation of solar energy technology, food security, and agricultural productivity in both the short and long terms. Additionally, green economic growth is positively associated with food security and agricultural productivity, and R&D investment has a positive relationship with these outcome variables.

We provide policy implications based on the obtained results and prioritize actions according to the relative strength and robustness of the estimated relationships. First, protecting and improving effective arable land should be treated as the primary lever for both food security and agricultural performance, given its large and statistically significant elasticity in the baseline estimates. This implies strengthening farmland protection zoning, tightening conversion approvals, and scaling up soil restoration and high-standard farmland programs, complemented by extension services that promote soil fertility management and sustainable land practices. Second, agricultural R&D should be scaled up with a mission-oriented focus, as R&D investment displays a robust positive association with food security. Funding should target technologies that offer direct productivity and resilience payoffs, including heat- and drought-tolerant crop breeding, water-saving irrigation, pest and disease management, and climate-smart extension and early warning systems. Third, solar energy development should be deployed in a way that complements, rather than competes with, food production. Since the estimated solar elasticity is positive but relatively modest, policy should prioritize productivity-supporting applications, such as on-farm solar for irrigation, processing, and cold-chain storage, as well as rooftop and marginal-land PV, while adopting performance-based standards for agrivoltaics to avoid the crowding-out of high-quality cropland and to ensure crop-yield outcomes. Fourth, the mixed long-run/short-run relationship between sustainable economic development and agricultural sustainability suggests the need for cross-sector policy coordination. Green growth strategies should be aligned with food-security objectives through land-use planning, compensation mechanisms, and targeted support to prevent structural shifts from undermining long-term agricultural performance.

The QQ-KRLS method, by providing a robust alternative to traditional techniques, revealed that the relationships between solar energy, green economic growth, R&D investment, food security, and agricultural productivity are not only significant but also consistent across different modeling approaches. This further confirms the reliability of the ARDL estimates and provides deeper insights into the non-linear dynamics and complexities of these variables in the context of agricultural sustainability.

Although our study provides valuable insights, it is not without limitations, which we encourage future research to address. First, our analysis focused exclusively on China as a case study. Other developing nations are also pursuing sustainable agriculture; thus, future studies can expand our evaluation from time series to panel data analysis and examine multiple countries to enhance the generalizability of our policy recommendations. Nevertheless, our study offers meaningful guidance to governments and policymakers in China and similar developing economies. Second, our study primarily examined the impact of solar energy on agricultural production and food security, without exploring its effect on other economic sectors, such as the service and industry sectors. Future research can investigate how solar energy development can impact sectors such as tourism, which may benefit from the integration of renewable. Finally, future studies could explore the moderating role of key policies, such as corruption control, institutional quality, or subsidy frameworks, in shaping the relationship between solar energy adoption and agricultural sustainability. Such analyses may yield deep policy insights to foster sustainable development.

Data availability statement

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

Author contributions

LQ: Data curation, Formal analysis, Methodology, Software, Investigation, Writing – original draft. IH: Writing – original draft, Writing – review & editing, Visualization, Validation. MA: Investigation, Writing – review & editing, Writing – original draft, Formal analysis. CL: Project administration, Funding acquisition, Visualization, Resources, Validation, Writing – original draft, Supervision, Writing – review & editing. WZ: Writing – review & editing, Validation, Visualization, Resources. AC: Conceptualization, Validation, Supervision, Writing – review & editing, Visualization, Resources, Project administration, Writing – original draft, Funding acquisition.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The author(s) declared that generative AI was not used in the creation of this manuscript.

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