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Research article

Assessing energy efficiency, regional disparities in production technology, and factors influencing total factor energy productivity change in the agricultural sector of China

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ABSTRACT

Efficiently utilizing the energy resources in the agriculture sector to produce more agricultural output with minimum environmental degradation is a shared global challenge. The Chinese government has introduced various policies aimed at enhancing energy efficiency (EE) and total factor energy productivity (TFEP) while addressing regional technological disparities in the agricultural sector. This study utilized DEA Super-SBM, Meta frontier Analysis, and the Malmquist–Luenberger index to assess energy efficiency, changes in total factor energy productivity, and the regional technology gap ratio (TGR) across 30 provinces in mainland China and three distinct regions during the period from 2000 to 2020. The findings reveal that the average EE in China's agricultural sector is 0.8492, indicating that, on average, there is a 15.08 % potential for improvement in EE growth within the sector. Qinghai (1.5828), Shanghai (1.3716), and Hainan (1.3582) are found to be the top 3 performers with the highest EE levels. The Eastern region demonstrates high excellence in EE, with a value of 1.0532. The TGR value of Zhejiang indicates the superior production technology utilized in the agriculture sector to utilize energy resources efficiently. Except for Zhejiang, the TGR of Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan is above 0.96 and near 1, indicating superior production technology in the agriculture sector of China. The Technology Gap Ratio (TGR) of China's eastern region is superior to that of the central and western regions, consistently approaching 1. This suggests that the eastern provinces possess more advanced agricultural technologies, allowing them to optimize resource utilization for maximum output. The Malmquist–Luenberger index (MLI) score of 1.103 indicates a 10.3 % growth in the total factor energy productivity of China's agricultural sector. Further analysis reveals that this growth is primarily driven by technological change (TC), with a TC value of 1.080 surpassing the efficiency change (EC) value of 1.028. Among the three agricultural regions, the eastern region exhibits the highest total factor energy productivity. Specifically, Zhejiang (1.23), Shanghai (1.197), Liaoning (1.184), and Hebei (1.147) are identified as the top performers in total factor energy productivity growth in China's agricultural sector. Additionally, the Kruskal-Wallis test confirmed statistically significant differences in EE and TGR among the three regions.

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1. Introduction

The agricultural sector plays a crucial part in the overall economic development of a Country. The agricultural sector ensures food security by providing a consistent and reliable food supply. Additionally, it is a significant source of employment for a considerable proportion of the population, thereby contributing to economic growth and development [1]. Moreover, agriculture is an essential source of income for farmers and laborers, further enhancing their livelihoods and overall well-being. A resilient agricultural sector catalyzes rural development, mitigating the influx of individuals into urban regions and fostering enhancements in rural infrastructure [2,3]. The agricultural sector in top-producing countries often plays a crucial role in generating export revenues, earning foreign reserves, and providing raw materials for other industries [4,5]. Innovative farming practices create economic progress, facilitate technical improvements, and contribute to environmental sustainability [6,7]. China's agricultural sector is one of the world's largest and most diverse, defined by its vastness, crop variety, and modernization efforts. It is the biggest global producer of rice and wheat [8]. Land reforms, particularly the Household Responsibility System, have empowered individual farmers and enhanced agricultural output. The sector has diversified to fulfil the dietary needs of its enormous population, although rural-to-urban migration has led to labor shortages in some places [9]. Environmental problems, such as soil degradation and water scarcity, have encouraged a shift toward sustainable farming practices. China's agricultural policies influence global food markets, and the government promotes food security through strategic reserves and self-sufficiency in critical staples [10]. Moreover, the impact of energy efficiency on CO2 emissions is more noticeable in provinces with higher quantiles, which can be attributable to significant differences in financing for research and development and investments in staff [11].

Implementing innovative and sustainable farming practices is crucial in improving China's agricultural production efficiency. These practices enhance productivity by utilizing advanced technologies and implementing precision agriculture techniques to tackle the challenging task of providing sustenance to a vast global population effectively [12]. Moreover, Sustainable practices are of utmost importance in environmental preservation, as they are crucial in mitigating concerns such as soil pollution and water scarcity [13]. The optimization of energy usage is an essential input within the agricultural sector and is of paramount importance due to a multitude of factors. The utilization of automated farming, irrigation, and transportation in agriculture has been found to impact production, substantially increasing efficiency [14]. It contributes to the economic sustainability of the agricultural sector by reducing operational costs. Furthermore, optimizing energy usage is crucial in reducing the environmental consequences of resource-intensive agricultural methods, preserving valuable resources, and decreasing pollution [15]. Implementing emission reduction strategies and adopting energy conservation practices actively contributes to endeavors to mitigate climate change [16]. In addition, implementing energy-efficient methods fosters innovation, empowers rural communities, strengthens global trade competitiveness, and serves as a foundation for long-term sustainability [17]. Studies show a direct correlation between the size of a farm and its Fuel Use Efficiency (FUE). On average, for every 1 % increase in farm size, there is a 0.2 % rise in FUE. This highlights the environmental advantages of larger farms [18].

Modern technologies are pivotal in transforming the agriculture industry through substantial enhancements in energy efficiency and reducing carbon emissions [19]. The implementation of precision agriculture, facilitated by advanced technology such as GPS-guided machinery and drones, enables the targeted allocation of resources, resulting in a reduction in energy consumption and a simultaneous increase in crop yields [20]. Innovative irrigation systems, enhanced by automation and soil moisture sensors, effectively optimize water utilization, preserving energy and crucial water resources [21]. Further, incorporating renewable energy resources, such as photovoltaic panels and wind turbines, enables agricultural establishments to produce environmentally friendly energy autonomously, thereby diminishing their dependence on non-renewable energy sources and mitigating greenhouse gas emissions [22]. Moreover, sophisticated machinery featuring highly efficient engines and optimized design elements reduces fuel usage [23]. Using data analytics and biotechnology provides valuable insights and facilitates the development of crop types that necessitate reduced resource consumption, significantly contributing to enhancing energy efficiency [24]. Waste-to-energy systems boost the conversion of agricultural residues into bioenergy, thereby effectively resolving concerns related to sustainability and emissions [25]. Numerous agricultural countries increase the renewable energy share in total energy consumption in agriculture to reduce the environmental impact [26].

The Chinese government has adopted a comprehensive strategy to improve energy efficiency within the agricultural sector, with a particular emphasis on diminishing the utilization of fossil fuels, augmenting the proportion of renewable energy sources, and improving agrarian technology [27]. A significant approach entails advocating for using sustainable energy sources, such as solar panels and biogas technology, to produce environmentally friendly energy for diverse agricultural practices. Simultaneously, China has substantially invested in technological advancements such as precision agriculture and innovative irrigation systems [28]. These initiatives involve the usage of data and automation to optimize the utilization of resources effectively. Efforts to mitigate reliance on fossil fuels encompass several strategies, such as promoting the utilization of electric-powered farm machinery and investigating the potential of biofuels derived from agricultural waste [29].

Furthermore, the government has tried to establish uniformity and compatibility in agricultural technologies to minimize variations in production techniques across different regions [30]. The dissemination of knowledge and implementation of training programs play a pivotal role in promoting the widespread adoption of energy-efficient methods, hence facilitating a sense of consistency and standardization across diverse agricultural regions within the country. The integrated projects exemplify China's dedication to implementing sustainable and energy-efficient techniques within the agriculture industry [31].

However, the extent to which the Chinese government's initiatives to enhance energy efficiency (EE), promote total factor productivity growth, and reduce regional production technology heterogeneity in the agricultural sector have been successful remains unclear and merits thorough investigation. This study addresses this gap by employing the DEA Super-SBM model to assess the EE of the agricultural sector across 30 mainland Chinese provinces from 2000 to 2020. This assessment identifies the level of EE within China's agricultural sector over the study period and distinguishes the provinces that are most efficient in agricultural energy utilization. In the second stage, Meta-frontier analysis is used to evaluate the technology gap ratio (TGR) among China's three agricultural regions—east, center, and west—thereby assessing the heterogeneity in production technology across these regions and the effectiveness of government efforts to reduce it over time. The third stage utilizes the Malmquist–Luenberger index to measure changes in total factor energy productivity (TFEPC) within China's agricultural sector, determining whether there has been growth or decline in TFEP over the study period and identifying whether efficiency change or technology change is the primary driver of TFEPC. Finally, the Kruskal-Wallis test is applied to ascertain statistically significant differences among the three agricultural regions of China in terms of EE, TGR, and TFEPC, thereby reinforcing the study's findings. The structure of the study is as follows: Section 2 provides a comprehensive literature review, Section 3 details the methodology, Section 4 discusses variable selection and data collection, Section 5 presents the results and discussion, and Section 6 covers the conclusions and policy implications.

2. Literature review

The importance of energy efficiency in agriculture is crucial as it significantly affects both economic and environmental sustainability. The implementation of energy-efficient technologies by farmers can lead to substantial reductions in operational expenses, thereby enhancing the economic sustainability of their agricultural enterprises [32]. Furthermore, the decrease in energy consumption reduces greenhouse gas emissions, thereby mitigating the sector's impact on climate change [33]. Concurrently, enhanced energy efficiency facilitates the preservation of resources by encouraging responsible utilization of water, reduction of waste, and sustainable management of land [34]. Fundamentally, placing a high priority on energy efficiency within the agricultural sector is a crucial stride toward fostering a farming future that is both robust and environmentally responsible [35]. Numerous research studies employed DEA to gauge the energy efficiency in the agriculture sector of different countries and regions.

Latruffe et al. [36] examine the disparities in technological efficiency, productivity change, and technology gaps within the dairy, cereal, oilseed, and protein crops (COP) sectors in France and Hungary from 2001 to 2007. The study employed national Farm Accountancy Data Network (FADN) data. It utilized Data Envelopment Analysis (DEA) to assess and evaluate the efficiency levels of farms operating under their respective technology and a meta frontier. The study's results suggest that, on average, the technological efficiency of COP farms in France was higher than that of their Hungarian counterparts. However, no statistically significant difference was observed in the technical efficiency of dairy farms between the two countries.

Nevertheless, while analyzing the meta-technology ratios derived from the meta frontier, it was observed that Hungarian technology exhibited higher levels of productivity in both the dairy and COP sectors, with a notable emphasis on COP output. Bogoviz et al. [37] provide a critical analysis of Russia's energy efficiency policies in the agricultural sector between 2008 and 2016. The study evaluates federal-level papers and indicators from the Ministry of Energy, concluding that Russia's energy sector policies are lacking and fail to fully utilize its potential for energy efficiency.

Wysokiński et al. [38] found that Contemporary agricultural practices are extensively dependent on external energy sources, primarily derived from non-renewable sources. This reliance contributes significantly to the generation of greenhouse gases and the destruction of the environment. Therefore, it is evident that a distinct imperative exists to augment energy efficiency and modify the composition of energy sources. The research aims to assess agriculture's economic and energy efficiency in European Union (EU) member states. It will be achieved by analyzing the energy consumption per employee or hectare of agricultural land utilized. This study examines the changes in energy consumption within the agrarian sector of the European Union (EU) and its constituent member states, using data sourced from Eurostat. Shi et al. [39] argued that redirecting crop straw use from cooking, heating, and open burning to bioenergy production can prevent the release of 122 million metric tons of greenhouse gas emissions. Furthermore, substituting fossil fuels with bioenergy can cut 34–86 million metric tons of emissions. This emphasizes the importance of bioenergy as a crucial approach for sustainable straw use. Moreover, using a multi-regional input-output model in research demonstrates that alterations in demand and consumption patterns play a substantial role in increasing carbon emissions. Conversely, enhancements in energy efficiency have been effective in reducing these emissions, emphasizing the necessity for sustainable policy interventions [40].

Demydenko et al. [41] investigate the relationship between energy efficiency in crop production and the carbon monoxide balance in the Cherkasy region's agro-industrial complex. Specifically, the study focuses on the transition from using manure to utilizing by-products as organic fertilizer throughout the period spanning from 1956 to 2020. Through the application of information-analytical and mathematical-statistical techniques, the investigation uncovered a correlation between enhanced energy efficiency and a reduction in the production of humus from organic fertilizers. The relative contribution of CO2 emissions from manure and residues to humus displays variability, with waste as a more significant source. Abbas et al. [42] investigate a concerning trend in Pakistan regarding the productivity of maize yield and energy input, particularly the significant input sources. The ensemble technique gives an average efficiency score of 59.67 %, suggesting the possibility of achieving energy savings. Significantly, this approach addresses limitations in efficiency reporting compared to individual models. The results of this study provide valuable insights that might inform decision-making processes, particularly about resource conservation and the enhancement of energy efficiency in maize production in Pakistan. These numerous studies employed the DEA to gauge the EE in different industries and sectors [43–53].

Previous research studies have explored energy efficiency in many countries and industries, but there is a significant lack of studies that explicitly investigate energy efficiency in China's agriculture sector. This study aims to fill this void by utilizing DEA methodology to assess energy efficiency in various provinces of China. It enhances the existing body of knowledge by offering valuable perspectives on the energy efficiency situation in China's agricultural sector and pinpointing possible avenues for enhancement. Further, the technological heterogeneity in different agricultural regions of China is evaluated. In addition, this research goes beyond past studies by considering regional differences and factors that affect the overall energy productivity shift in China's agriculture sector. The thorough analysis aims to provide significant insights that might guide policy measures to enhance energy efficiency and sustainability in China's agricultural sector.

3. Methodology

3.1. Super-SBM model with bad outputs

Tone [54] introduced a non-radial Data Envelopment Analysis (DEA) model based on the super Slack-Based Measure (SBM), which facilitates the evaluation of efficiency from both input and output perspectives. Unlike radial DEA models, the super SBM model includes slack variables, offering significant advantages in addressing the limitations of radial measurements and effectively differentiating among efficient decision-making units (DMUs). Building on this, Tone [55] advanced the model by developing the Super-Efficiency SBM, which was the first to incorporate undesirable outputs into the SBM framework. This enhancement allows for a more thorough and accurate assessment of efficiency. The model is defined as follows:

The input-output matrix has the formulas $X = [x_1 \cdots x_n] \in R^{m\times n}$, $Y^{nd} = \left[y_1^d \cdots y_n^d\right] \in R^{s_1\times n}$, and $Y^u = \left[y_1^A \cdots y_n^{ut}\right] \in R^{s_2\times n}$. Below is the equation of the super-efficient SBM model with bad output.

$$\rho^* = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(\frac{\overline{x}}{x_{ik}}\right)}{\frac{1}{(s_1+s_2)}\left(\sum_{r=1}^{s_1}\frac{\overline{y^d}}{y_{rk}^d}+\sum_{t=1}^{s_2}\frac{\overline{y^u}}{y_{rk}^u}\right)} \tag{1}$$

$$\text{s.t.}\begin{cases} \overline{x} \geq \sum\limits_{j=1,4k}^{n} x_{ij}\lambda_j; i = 1,2,\cdots m \\ \overline{y^d} \leq \sum\limits_{j=1,\neq k}^{n} y_{rj}^d\lambda_j; r = 1,\cdots,s_1 \\ \overline{y^{u\mu}} \geq \sum\limits_{j=1,\neq k}^{n} y_{tj}^u\lambda_j; t = 1,\cdots,s_2 \\ \lambda_j \geq 0, j = 1,2,\cdots n, j \neq 0 \\ \overline{x} \geq x_{ik}; y^d \leq y_{rk}^d; \overline{y^\mu} \geq y_{dk}^u \end{cases}$$

In Equation (1), the slack variables for input, desirable output, and undesirable output are represented as as $\overline{x}, \overline{y^d}$ and $\overline{y}^u$, respectively. The weight vector is denoted by λj, and ρ^* serves as the estimate of the optimal value. When ρ^* is greater than or equal to 1, the decision-making unit (DMU) is considered efficient.

3.2. Meta-frontier model

The Meta-frontier Model allows for more precise evaluations of DMU efficiency across different groups. To ensure fair comparisons, it is recommended to compare DMUs within the same group, as they have equal access to technology. The Technology Gap Ratio (TGR) can be employed to gauge the extent of technological development among different groups. TGR can be specifically presented for a particular group to assess their technological advancement [56,57].

$$TGR = \frac{MAEE}{GAEEi} \tag{2}$$

The assessment evaluates the Energy Efficiency (EE) of all Decision-Making Units (DMUs). In equation (2), *GAEEi* denotes the agricultural energy efficiency of DMUs within a specific group, while MAEE represents the Meta-agriculture Energy Efficiency of DMUs at a particular technical level. The Technology Gap Ratio (TGR) employs a distance metric to determine a meta-frontier technology's proximity to a specific group's frontier technology [58]. TGR is commonly used to evaluate regional differences. A TGR value 1 indicates no technological gap between the group and the meta-frontier.

3.3. Malmquist–Luenberger index

However, the DEA model has limitations in analyzing dynamic changes in energy efficiency, as it can only evaluate technical efficiency (TE) within a fixed period. To examine variable productivity, the Malmquist index serves as a valuable tool. Chung et al. [59] adapted the Malmquist index into the Malmquist-Luenberger index (MLI) by incorporating an undesirable directional distance function. The MLI includes distinct components: the efficiency component (EC) and the technology component (TC) [60]. The change in the MLI from time t to t+1 is as follows in equation (3):

$$ML^{t+1} = \left\{ \frac{\left[1 + \overrightarrow{D_0^t}\left(x^t, y^t, b^*; y^t, -b^t\right)\right]}{\left[1 + \overrightarrow{D_0^t}\left(x^{t+1}, y^{+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)\right]} \times \frac{\left[1 + \overrightarrow{D_0^{t+1}}\left(x^t, y^t, b^t; y^t, -b^t\right)\right]}{\left[1 + \overrightarrow{D_0^{t+1}}\left(x^{t+1}, y^{t+1}, b^{++1}; y^{t+1}, -b^{s+1}\right)\right]} \right\}^{1/2} \tag{3}$$

$$EC^{x+1} = \frac{1 + \overrightarrow{D_0^t}\left(x^t, y^t, b'; y^t, -b^2\right)}{1 + \overrightarrow{D_0^{t+1}}\left(x^{t+1}, y^{t+1}, b^{+1}; y^{k+1}, -b^{t+1}\right)} \tag{4}$$

$$TC^{4+1} = \left\{ \frac{\left[1 + \overrightarrow{D_0^{t+1}}\left(x^t, y^t, b^t, y^t, -b^t\right)\right]}{\left[1 + \overrightarrow{D_0^t}\left(x^t, y', b^t; y^t, -b'\right)\right]} \times \frac{\left[1 + \overrightarrow{D_0^{t+1}}\left(x^{t+1}, y^{++1}, b'^{+1}; y^{t+1}, -b^{t+1}\right)\right]}{\left[1 + \overrightarrow{D_0'}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{++1}\right)\right]} \right\}^{\frac{1}{2}}$$

here, x, y, and b denote input, desired, and undesirable output, respectively. The distance functions during time intervals t and t+1 are represented by (D 0 t) $\overrightarrow{D_0^t}\left(x^2, y^r, b^r; y^t, -b^t\right)$ and $\overrightarrow{D_0^{t+1}}\left(x^{s+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)$ respectively (see equation (4)). Under the technical conditions of the t+1 period, the distance function for the t+1 period is $\overrightarrow{D_0^t}\left(x^{s+1}, y^{s+1}, b^{t+1}; y^{s+1}, -b^{t+1}\right)$, and under the t+1 technical conditions, the *t* period distance function is $\overrightarrow{D_0^{t+1}}\left(x^t, y^t, b^t; y^t, -b^t\right)$(*see equation* 5). An ML value greater than 1 indicates an increase in total factor productivity, while $ML = 1$ ML = 1 signifies no change, and ML < 1 indicates a decline. Similarly, an EC value greater than 1 denotes growth in efficiency, EC = 1 implies no change, and $EC < 1$ EC < 1 signifies deterioration. Finally, a TC value greater than 1 represents technological advancement, TC = 1 indicates constancy, and TC < 1 suggests decline.

3.4. Kruskal–Wallis test

The Kruskal-Wallis test is highly valuable in statistical analysis since it is a non-parametric method and is not reliant on the assumptions typically needed by parametric tests, making it more robust. Unlike tests such as the *t*-test or ANOVA, this method does not make assumptions about the normality of the data. As a result, it is appropriate for analyzing ordinal data and situations where the sample sizes are not equal. The adaptability of this method is enhanced by its capacity to handle circumstances in which the assumption of homogeneity of variances is violated, making it applicable to many experimental designs. With broad applicability across various disciplines, from biology to social sciences, this method yields results that are easily understood through the use of a p-value, which indicates the presence of significant differences between groups. In addition, while assessing overall differences, it is necessary to conduct post-hoc studies such as Dunn's test to discover specific inequalities between groups. Significantly, its dependence on rankings instead of raw data values makes it resistant to outliers, hence improving its reliability in actual research settings. The Kruskal-Wallis test is a powerful tool that allows for thorough comparisons between groups, while also addressing typical statistical assumptions and problems [56]. For this study, we utilize the Kruskal-Wallis test to identify statistically significant variations among the three Chinese regions concerning average EE, TGR, and MLI. The hypotheses are delineated as follows:

H01. The EE of the agriculture sector is the same in three different Chinese regions.

H02. The TGR of the agriculture sector is the same in three different Chinese regions.

H03. The MLI of the agriculture sector is the same in three different Chinese regions.

4. Data collection and variable selection

Data for the agricultural sector of 30 mainland provinces in China, excluding Tibet, from 2000 to 2020 are gathered from various sources, including China's Rural Statistical Yearbook, China Statistical Yearbook, and China Energy Statistical Yearbook (refer to Table 1).

Table 1
Input-output variables used for EE and energy productivity estimation of the agriculture sector.

Inputs	Outputs
Labor: Total number of employees working in the agriculture sector in that year (10,000 people)	Expected output value-added of the agriculture sector (100 million yuan)
Capital: Capital stock of the agriculture sector (ten thousand yuan)	Carbon dioxide emissions (10,000 tons) in the agriculture sector: Undesired output
Energy: Total energy consumption of each province (10,000 tons of standard coal) for the agriculture sector	

5. Results and discussion

Section 5 presents the change in energy efficiency, technology gap ratio, and energy productivity in China's agriculture sector.

5.1. Energy efficiency evaluation of the agricultural sector in China (2000–2020)

Using the DEA super-SBM model, this study assessed the energy efficiency of China's agriculture sector by examining various inputs and outputs from 2000 to 2020. The findings reveal that the average energy efficiency (EE) of China's agriculture sector is 0.8492. This suggests that, on average, there is still a 15.08 % potential for improving EE growth within the sector. Such improvement could be achieved through either reducing inputs or increasing outputs in China's agriculture sector. Further elaborating the results study in Fig. 1, it found that the EE of the agriculture sector was higher in the year 2020 with an average EE = 0.9163; in 2012, it was found to be 0.9133, while in 2019, its value was 0.8917. On the contrary, the EE was found to be lowest in the study years of 2002 with an average EE = 0.7857; in 2008, it was 0.8123, while in 2009, it was found to be 0.815. Results illustrate that although there were many fluctuations in the EE, a continuing inclining trend was noticed over the study period, which was close to the highest value of the study period in 2020. The analysis suggests that there has been a notable increase in energy efficiency within the agriculture sector in China over time, and there is still room for future improvements. The results of this study can provide valuable insights for developing policies and initiatives that aim to enhance resource utilization and foster sustainable practices within the agriculture industry. Advanced technologies like precision farming tools and innovative equipment maximize resource use in agriculture, improving energy efficiency. Renewable energy sources like solar and wind power can reduce non-renewable use. Upgrades to energy-efficient equipment and water-efficient irrigation systems boost efficiency. Sustainable agricultural methods like crop rotation and diversification minimize resource use. Energy audits and farmer sustainability education are essential for continuous development. Innovative, energy-efficient technology can be adopted faster with government policies, incentives, and research and development. Supply chain optimization and waste management also reduce energy use. Collaboration and knowledge sharing among farmers and stakeholders help create an energy-efficient agriculture sector [61].

Fig. 2 presents the average EE level of the agriculture sector of each Chinese province over the study period. Results indicate that Qinghai (1.5828), Shanghai (1.3716), and Hainan (1.3582) are found to be the top 3 performers with the highest EE level in 30 inland Chinese provinces. Except this, the EE of Hainan, Jiangsu, Guangxi, Shandong, Hunan, Fujian, Sichuan, Guangdong, and Ningxia is over 1, indicating that these provinces perform better in terms of energy efficiency in the agriculture sector. Beijing, Hebei, Henan, Jiangxi, Liaoning, Anhui, Zhejiang, Tianjin, Jilin, Hubei, and Chongqing EE is between 0.60 and 1. Finally, the EE of Shaanxi, Guizhou, Yunnan, Xinjiang, Heilongjiang, Inner Mongolia, Gansu, and Shanxi is between 0.22 and 0.60. The results of this study reveal a significant discrepancy in energy efficiency among various provinces in China. It highlights the necessity of implementing focused approaches to enhance agricultural sustainability and optimize resource utilization in particular areas [62].

This study investigates the regional variations in energy efficiency levels within China's agricultural sector, specifically focusing on categorizing provinces into three distinct regions: East, Central, and West. According to the data presented in Table 2, it can be observed that the Eastern area demonstrates a high level of excellence in the field of EE, with a value of 1.0532. It denotes the achievement of efficient energy utilization in the agricultural sector, characterized by minimum resource inefficiencies and the implementation of superior operational approaches. The Western region exhibits a higher EE level of 0.7797 compared to the Central region's 0.7147, suggesting proficient utilization of resources and operational effectiveness. The differences in environmental efficiency (EE) across regions can be attributed to climate, soil conditions, agricultural techniques, and disparities in economic growth. The benefits of the Eastern area can be ascribed to its utilization of advanced technologies, superior infrastructure, and elevated levels of economic development. Various tactics can be employed to improve energy efficiency in currently less efficient regions. These strategies encompass the transfer of technology, provision of training, development of infrastructure, support of policies, and

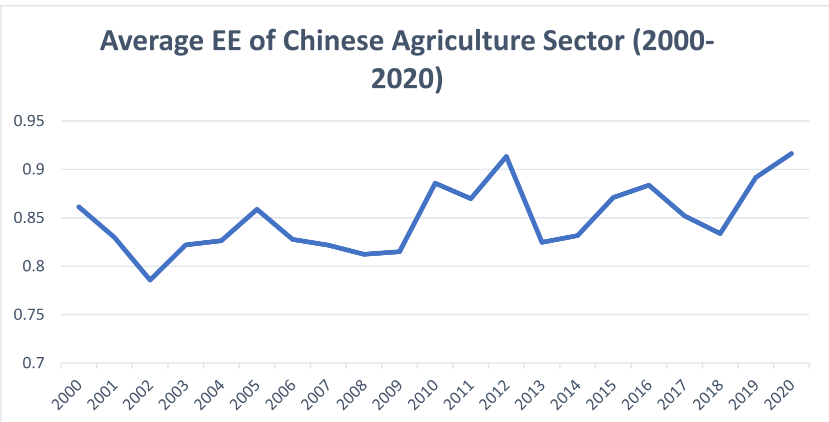

Fig. 1. Average EE trends in China's agriculture sector over the study period (2000–2020).

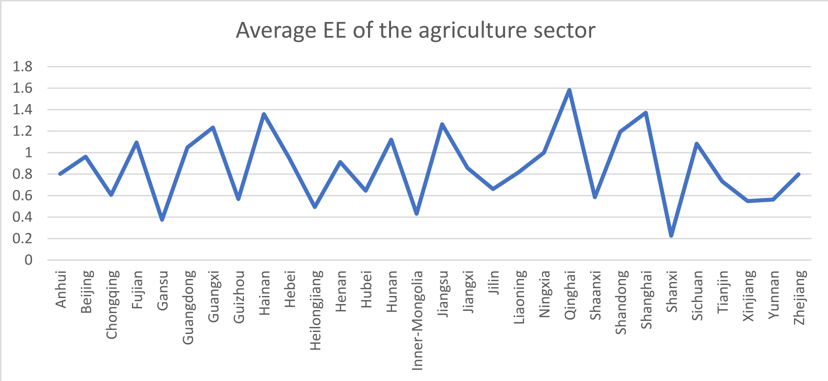

Fig. 2. Average EE of the agriculture sector in different Chinese provinces.

Table 2
Average EE in three different agricultural regions of China.

Years	East	Central	West
2000	1.104	0.757	0.723
2001	0.957	0.787	0.745
2002	1.048	0.612	0.697
2003	1.021	0.647	0.798
2004	1.034	0.709	0.736
2005	1.08	0.697	0.799
2006	1.042	0.677	0.764
2007	0.994	0.688	0.783
2008	1	0.669	0.768
2009	0.986	0.73	0.729
2010	1.084	0.798	0.775
2011	1.002	0.773	0.834
2012	1.073	0.79	0.877
2013	1.013	0.715	0.746
2014	1.072	0.704	0.719
2015	1.109	0.683	0.821
2016	1.111	0.764	0.776
2017	1.055	0.699	0.802
2018	1.021	0.674	0.806
2019	1.146	0.699	0.83
2020	1.166	0.737	0.846
Average	**1.0532**	**0.7147**	**0.7797**

implementation of targeted research and extension services. By considering these criteria, regions with lower efficiency can strive to enhance energy efficiency in the agricultural sector, making a valuable contribution to the goals of sustainability and production [63].

5.2. Meta-frontier analysis results of the agricultural sector in China

The agriculture industry's energy efficiency (EE) in different regions of China is significantly impacted by the variety of regional production technologies. Diverse agricultural practices, technologies, and production methods are adopted by other areas, influenced by their distinct environmental conditions, available resources, and levels of economic development. The variations mentioned can affect the agricultural industry's overall energy efficiency, as different technologies may exhibit varying energy intensity levels. Those who possess advanced irrigation systems, precise farming technologies, and efficient machinery are more likely to demonstrate higher levels of energy efficiency in comparison to those who rely on conventional or less advanced agricultural practices. Table 3 explains the results of meta frontier analysis. GEE is the group energy efficiency of a particular province.

Similarly, the MEE is the meta energy efficiency of the province in the meta group of all 30 provinces. These two columns present the performance of a particular DMU in the meta frontier and then in a specific group. Finally, TGR is the technology gap ratio of a particular province. It illustrates the technological gap of a DMU from its group to the Meta-technology of all provinces under consideration. Qinghai, Shanghai, Hainan, Jiangsu, and Guangxi were found to be the top performers in the MEE. Qinghai, Sichuan, Henan, Hainan, and Shanghai were the best performers in group EE over the study period. The GEE of Henan (1.4379) province is at its highest level in the central region. At the same time, Heilongjiang was the least efficient, with an average value of 0.8916. Hainan performs at an optimum GEE level of 1.4065 in the eastern region.

While Zhejiang was found to be the least efficient, with a GEE of 0.7977. Finally, Qinghai (1.698) is the highest position in the

Table 3
GEE, MEE and TGR in Chinese provinces (2000–2020).

Region	Province	GEE	MEE	TGR
Central	Anhui	1.1245	0.802	0.7177
East	Beijing	1.0043	0.9624	0.9571
West	Fujian	1.2211	1.0937	0.9157
East	Gansu	0.5361	0.3754	0.7811
West	Guangdong	1.0629	1.0483	0.9873
East	Guangxi	1.3788	1.2328	0.8969
West	Guizhou	0.9109	0.5676	0.6763
West	Hainan	1.4065	1.3582	0.965
East	Hebei	1.0319	0.9485	0.9366
East	Henan	1.4379	0.9127	0.6286
Central	Heilongjiang	0.8916	0.4929	0.5801
Central	Hubei	0.9707	0.6451	0.6793
Central	Hunan	1.3459	1.1213	0.837
Central	Jilin	1.1331	0.6612	0.5845
West	Jiangsu	1.271	1.2635	0.9947
East	Jiangxi	1.3077	0.8564	0.6654
Central	Liaoning	0.8171	0.8161	0.9988
Central	Inner-Mongolia	1.0038	0.431	0.4332
East	Ningxia	1.0367	1	0.9673
West	Qinghai	1.698	1.5828	0.9341
West	Shandong	1.3313	1.1945	0.899
West	Shanxi	1.065	0.2263	0.2471
East	Shaanxi	0.6665	0.5846	0.9008
East	Shanghai	1.3805	1.3716	0.9936
Central	Sichuan	1.5763	1.0836	0.6909
West	Tianjin	0.8154	0.7323	0.9175
East	Xinjiang	1.0914	0.5492	0.5025
West	Yunnan	0.6125	0.5631	0.9274
West	Zhejiang	0.7977	0.7977	1.0000
East	Chongqing	0.8476	0.6064	0.7183

Western region. However, the Gansu is the least efficient, with a GEE of 0.5361. A TGR of 1 indicates the superior technology of any DMU. In Table 3, the last column presents the TGR of each province. Results illustrate that the TGR value of Zhejiang indicates the superior production technology utilized in the agriculture sector to utilize energy resources efficiently. Except for Zhejiang, the TGR of Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan is above 0.96 and near 1, indicating superior production technology in the agriculture sector of China.

Moreover, Fig. 3 indicates that the average TGR of China's eastern region is superior to that of the central and western regions. It is always near to 1 and indicates that the eastern provinces have the more advanced agricultural technology to utilize the resources to get optimum output. The western region is ranked second in production technology advancement, while the agricultural production technology of the central region is the most inferior of the three regions. The impact of regional variations in production technology on energy efficiency outcomes within China's agricultural sector is significant. The energy intensity levels fluctuate due to the variable adoption of agricultural techniques, technology, and production methods across different locations. Environmental conditions and levels of economic development influence these variations. Provinces that utilize new technologies demonstrate higher levels of energy efficiency, whereas those that rely on conventional practices may experience a relative lack of progress in this regard. The insights

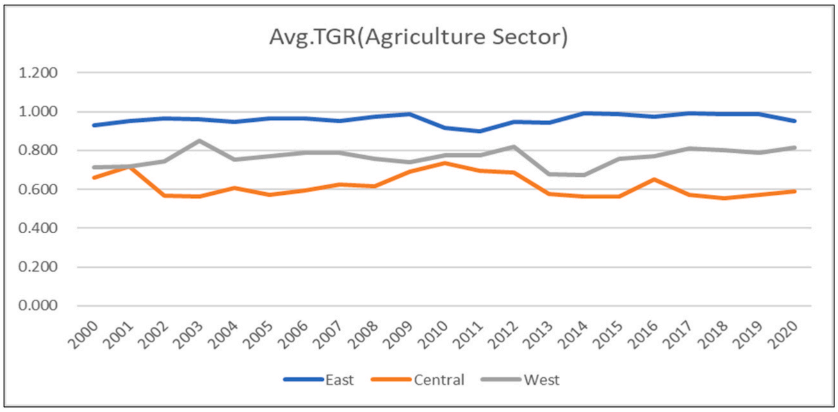

Fig. 3. Average TGR in three different regions of China.

derived from the meta-frontier analysis results presented in Table 3 highlight the significance of Group Energy Efficiency (GEE), Meta Energy Efficiency (MEE), and Technology Gap Ratio (TGR). Zhejiang province exhibits a technology gap ratio (TGR) of 1, suggesting the exploitation of modern agriculture technology.

In contrast, other provinces such as Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan demonstrate TGR values above 0.96, suggesting superior production technology implementation. The imperative to enhance overall energy efficiency (EE) in the agriculture sector necessitates the reduction of production technological heterogeneity. Various strategies, including technology transfer, training programs, research and development, and policy support, can significantly reduce technological disparity [64].

Policymakers and stakeholders must give precedence to projects that promote the transfer of innovative technologies, provide education to farmers in less efficient regions, allocate resources towards region-specific technological solutions, and enforce policies that encourage the adoption of energy-efficient techniques. The significance of these tactics shown by the TGR values accentuates the imperative of technological progress in various geographical areas. Fig. 3 provides more evidence supporting the notion that the Eastern region's average Total Growth Rate (TGR) is higher, suggesting the presence of more sophisticated agricultural technology. The Western region is positioned as the second-ranked region in terms of advancements in industrial technology. Still, the Central region exhibits a comparatively lower level of progress in this regard. The attainment of a more universally efficient and sustainable agriculture sector in China necessitates implementing coordinated endeavors to reduce the technology disparity across different regions [65].

5.3. *Malmquist –Luenberger index results of the agricultural sector in China*

By applying the Malmquist-Luenberger index (MLI) on data spanning 2000 to 2020 from 30 Chinese provinces, this study estimates the dynamic variation in total factor energy productivity growth within China's agriculture sector. Table 4 presents an average MLI score of 1.103 for the agriculture sector of Chinese provinces, indicating a 10.3 % growth in total factor energy productivity over the study period. Further analysis reveals that this growth in MLI is primarily attributed to technological change (TC), with a value of 1.080, surpassing the efficiency change (EC) value of 1.028. The TC value suggests a growth of 0.8 % over the study period, while the EC value indicates a growth of 0.28 %. These findings underscore the significance of technological progress in driving the increase in

Table 4
MLI, EC, and TC in 30 Chinese provinces and 3 regions.

Region	Province	MLI	EC	TC
Central	Anhui	1.074	1.007	1.067
	Henan	1.106	0.993	1.141
	Heilongjiang	1.098	1.021	1.061
	Hubei	1.116	1.049	1.064
	Hunan	1.112	1.021	1.094
	Jilin	1.122	1.009	1.117
	Jiangxi	1.097	1.042	1.047
	Shanxi	1.102	1.037	1.08
Ave. Central		**1.103**	**1.022**	**1.084**
East	Beijing	1.053	1.008	1.054
	Fujian	1.107	1.006	1.098
	Guangdong	1.116	1.025	1.107
	Hainan	1.076	1.015	1.064
	Hebei	1.147	1.036	1.116
	Jiangsu	1.098	1.002	1.091
	Liaoning	1.184	1.05	1.139
	Shandong	1.106	0.987	1.122
	Shanghai	1.197	1.152	1.053
	Tianjin	1.063	1.05	1.078
	Zhejiang	1.23	1.061	1.171
Ave. East		**1.125**	**1.036**	**1.099**
West	Gansu	1.066	1.016	1.068
	Guangxi	1.068	1.013	1.056
	Guizhou	1.093	1.070	1.025
	Inner- Mongolia	1.105	1.045	1.058
	Ningxia	1.116	1.000	1.116
	Qinghai	1.036	1.000	1.035
	Shaanxi	1.050	1.003	1.052
	Sichuan	1.082	1.005	1.084
	Xinjiang	1.090	1.003	1.085
	Yunnan	1.062	1.056	1.012
	Chongqing	1.116	1.067	1.051
Ave. west		**1.0800**	**1.025**	**1.058**
Ave. all		**1.103**	**1.028**	**1.080**

total factor energy productivity change across various dimensions. Technological progress is vital in improving energy efficiency, enabling the creation of the same results with less energy consumption.

Furthermore, technological advancements drive innovation in energy sources, identifying and implementing cleaner and more environmentally friendly options [66]. Innovative technology and industry automation enhance energy efficiency by dynamically changing usage in response to real-time demand and supply. Data analytics enhances understanding energy use patterns by offering significant information [67]. The integration of renewable energy sources, enabled by technological advancements, enhances the sustainability and productivity of the energy sector. Advanced technologies additionally minimize energy wastage by creating efficient appliances, machines, and processes. Moreover, technology facilitates adjusting to evolving energy needs, promoting a flexible and effective energy distribution system. In essence, the ongoing advancement of technology not only enhances overall energy efficiency but also supports worldwide initiatives for environmental preservation, tackling the issues presented by climate change [68].

Further examination of the regional Malmquist-Luenberger index (MLI) results reveals significant variations in total factor energy productivity across China's agricultural regions. The study identifies the Eastern region as the top performer, boasting the highest total factor energy productivity among the three regions. With a MLI score of 1.125, indicating a growth of 12.5 %, this region's achievement is primarily attributed to a technological growth rate of 0.99 %. In comparison, the central agricultural sector of China experienced a total factor energy productivity increase of 10.3 % over the study period. Similar to the Eastern region, the growth in MLI is predominantly driven by technological advancement, with a growth rate of 0.84 %. On the other hand, the western agricultural sector of China ranks third, with a total energy productivity growth of 0.80 % over the study period. Like the Eastern and central regions, the main determinant of MLI growth in the western region is technological advancement, with a growth rate of 0.58 %. The analysis of regional MLI outcomes underscores notable disparities in total factor energy productivity across China's agricultural regions, with the Eastern region emerging as the top performer. It achieved an excellent MLI score of 1.125, suggesting a significant gain of 12.5 percent throughout the research period. The main factor driving this impressive performance is mostly ascribed to technical advancement, which makes a major contribution, accounting for 0.99 percent of the whole rise.

A significant increase of 10.3 percent in total factor energy productivity is noted in China's central agricultural sector, which is consistent with the pattern seen in the eastern region. In the same way, technological progress is essential for this expansion, accounting for 0.84 percent of the total MLI score. Despite being ranked third in growth at 8.0 percent, the Western agricultural sector shows a commendable gain. Similar to the other regions, technical advancement has led to an increase in the overall MLI, which accounts for 0.58 percent of the growth. The regional differences highlight the critical role of technological improvements in influencing overall energy productivity, offering valuable information for policymakers and stakeholders as they navigate the varied agricultural environments in China [69]. A comprehensive approach is necessary to tackle the variations in total factor energy productivity development among the three agricultural areas in China. A critical approach is to promote the transfer of technology and knowledge sharing, enabling regions with higher productivity to teach modern agricultural practices to regions with lower output. Simultaneously, allocating resources to enhance infrastructure, such as energy-efficient buildings and transport systems, can establish a fairer basis for the wider use of technology. Providing more resources to conduct research and development activities specifically focused on each region is essential. It will enable the customization of technologies to address the distinct requirements of each part, ultimately reducing the technological disparity. It is recommended to introduce training programmers and capacity-building initiatives to improve the technical expertise of farmers and stakeholders in regions with lower productivity. Aligning national and regional policies can simplify regulatory procedures and offer uniform assistance for implementing technology. Moreover, providing subsidies and financial aid to farmers in less productive areas might help mitigate the expenses associated with implementing energy-efficient technologies and motivate their adoption. Encouraging collaboration within regions, promoting customized technical solutions, and establishing vital monitoring and evaluation procedures to minimize regional differences and encourage sustainable growth in China's agricultural landscape [70].

Finally, Table 4 also compares the MLI growth of the different agricultural sectors of 30 Chinese provinces. Results indicate that Zhejiang (1.23), Shanghai (1.197), Liaoning (1.184), and Hebei (1.147) are the top performers in total factor productivity growth in the agricultural sector of China. Results further elaborate that all these 4 provinces belong to the eastern region of China. The determinant of MLI growth in all these 4 provinces is technological advancement. Further, Jilin (1.122) from Central is the top MLI scorer, while Ningxia (1.116) in Western China witnessed the highest growth in total factor energy productivity. Qinghai (1.036) from Western China, Shaanxi (1.05) from Western China, and Beijing (1.053) from Eastern China are the lowest performers in MLI growth over the study period. These results indicate that in most provinces, the efficiency change is less than technological change. By analyzing the growth of agricultural sectors in 30 Chinese provinces using MLI, specific recommendations can be developed to improve total factor energy productivity. Provinces in the Eastern area, namely Zhejiang, Shanghai, Liaoning, and Hebei, have achieved notable success primarily due to technological developments. To emulate their achievements, other provinces should prioritize implementation.

Furthermore, it is advisable to promote inter-regional collaboration activities to ease the exchange of optimal methods and strategies. As demonstrated by Jilin's highest MLI score, Provinces in the Central area necessitate customized assistance for the adoption of technology and the development of capabilities [71]. In the Western region, particularly in provinces such as Ningxia that demonstrate promising growth, it is imperative to prioritize improving resource efficiency and adopting sustainable practices. Provinces like Qinghai, Shaanxi, and Beijing, which have had slower MLI growth (Multidimensional Livelihood Index), should prioritize enhancing efficiency and advancing technology. It is crucial to align policies with national goals and implement incentives to enhance energy productivity increases. Regular monitoring and evaluation methods would allow provinces to improve plans, thus achieving a more equitable and effective agriculture sector throughout China [72].

5.4. Statistical significance difference

Sections 5.1, 5.2, and 5.3 of the study reveal notable differences in average energy efficiency (EE), total factor growth rate (TGR), and Multilateral Instrument (MLI) scores across the agriculture sectors of the three Chinese regions, indicating heterogeneity among them. However, determining the statistical significance of these differences is crucial for the research community. To address this, the study employed the Kruskal-Wallis test to evaluate the significance of variations in EE, TGR, and MLI among all three agricultural regions of China. The results are presented in Table 5 and Figs. A1, A2, and A3. The significance level for the first hypothesis is 0.037, below the conventional threshold of 0.05, indicating a significant difference in EE among the regions. Thus, the null hypothesis is rejected, suggesting a statistically significant disparity in EE levels across all three agricultural regions. Similarly, the significance level for the second hypothesis is 0.001, also below 0.05, indicating a significant statistical difference in TGR among the regions. Conversely, the significance level for the third hypothesis is 0.067, exceeding 0.05, suggesting that MLI across all three regions does not exhibit statistically significant differences.

These findings, presented in Table 5 and Figs. A1, A2, and A3, offer valuable insights into the variation of average EE, TGR, and MLI scores within the agricultural sectors of the three Chinese regions, demonstrating the robustness of utilizing the Kruskal-Wallis test to assess statistical significance in such disparities. The test results indicate a noteworthy gap in EE and TGR among the three locations, with p-values of 0.037 and 0.001, respectively, below the traditional significance level of 0.05. These findings suggest that the differences in EE and TGR are statistically significant, supporting the conclusion that these regions' agricultural sectors function at varying efficiency and growth levels. Conversely, the findings of the MLI analysis indicate a significance level of 0.067, which is barely above the threshold of 0.05. It suggests no statistically significant difference in MLI across the three regions [48].

6. Conclusions and policy implications

The agricultural sector in China plays a crucial role in the country's economic development, food security, employment, and rural infrastructure due to its extensive size, diverse range of crops, and continuous efforts towards modernization. To effectively manage the requirements of a large population, combat labor shortages caused by movement from rural to urban areas, and handle environmental issues, it is crucial to implement creative and sustainable agricultural methods. The Chinese government is actively enhancing energy efficiency in agriculture by reducing fossil fuel consumption, promoting renewable energy sources, and advancing agrarian technologies. This includes promoting sustainable energy sources such as solar panels, biogas technologies, and investments in precision agriculture and innovative irrigation systems to enhance resource use efficiency. Efforts to decrease dependence on fossil fuels encompass the promotion of electric-powered farm machinery and the investigation of biofuels derived from agricultural waste. In addition, the government seeks to standardize agricultural technologies to reduce regional disparities in production methods. Knowledge dissemination and training initiatives facilitate the broader adoption of energy-efficient techniques. China's commitment to sustainable practices in agriculture is evident through these integrated initiatives. However, the government's actual achievement in improving energy efficiency, total factor productivity growth, and reducing regional production technology heterogeneity in the agricultural sector requires additional investigation.

The study investigates variations in energy efficiency (EE), technological gap ratio (TGR), and total factor energy productivity change (TFEPC) across 30 provinces and three distinct regions in China, revealing significant discrepancies. The study assesses the statistical significance of differences in EE and TGR among these regions by applying the Kruskal-Wallis test. The findings indicate that the average EE of China's agriculture sector is 0.8492, suggesting that, on average, there is a 15.08 % potential for improving EE growth within the sector. This improvement could be achieved by reducing inputs or increasing outputs in China's agriculture sector. Notably, the EE of the agriculture sector peaked in 2020, with an average EE of 0.9163. Results further indicate that Qinghai (1.5828), Shanghai (1.3716), and Hainan (1.3582) are found to be the top 3 performers with the highest EE level in 30 inland Chinese provinces. The Eastern region demonstrates high excellence in EE, with a value of 1.0532. It denotes the achievement of efficient energy utilization in the agricultural sector, characterized by minimum resource inefficiencies and the implementation of superior operational approaches. The Western region exhibits a higher EE level of 0.7797 compared to the Central region's 0.7147, suggesting proficient utilization of resources and operational effectiveness.

Meta-frontier analysis shows that Qinghai, Shanghai, Hainan, Jiangsu, and Guangxi were the top performers in the MEE. Qinghai, Sichuan, Henan, Hainan, and Shanghai were the best performers in group EE over the study period. The GEE of Henan (1.4379) province is at its highest level in the central region. At the same time, Heilongjiang was the least efficient, with an average value of 0.8916. Hainan performs at an optimum GEE level of 1.4065 in the eastern part. At the same time, Zhejiang was the least efficient, with a GEE of 0.7977. Finally, Qinghai (1.698) is in the highest position in the Western region. However, the Gansu is the least efficient, with

Table 5
Kruskal Wallis test results.

Hypothesis Test Summary				
Null Hypothesis Test Sig. Decision				
1	The EE of the agriculture sector is the same in three different Chinese regions.	Independent-Samples Kruskal– Wallis Test	0.037	Reject
2	The TGR of the agriculture sector is the same in three different Chinese regions.		0.001	Reject
3	The MLI of the agriculture sector is the same in three different Chinese regions.		0.067	Retain

a GEE of 0.5361. Results further illustrate that the TGR value of Zhejiang indicates the superior production technology utilized in the agriculture sector to utilize energy resources efficiently. Except for Zhejiang, the TGR of Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan is above 0.96 and near 1, indicating superior production technology in the agriculture sector of China.

Moreover, Fig. 3 indicates that the average TGR of China's Eastern region is superior to that of central and western areas. It is always near to 1, meaning that the eastern provinces have the more advanced agricultural technology to utilize the resources for optimum output. The western region is ranked second in production technology advancement, while the agricultural production technology of the central region is the most inferior of the three regions.

The Malmquist-Luenberger index (MLI) score of 1.103 indicates a 10.3 % growth in total factor energy productivity within China's agricultural sector. Further analysis reveals that this increase in MLI is primarily driven by technological change (TC), with a value of 1.080, surpassing the efficiency change (EC) value of 1.028. The TC value suggests a growth of 0.8 % over the study period, while the EC value indicates a growth of 0.28 %. The significance of technological progress in driving the increase in total factor energy productivity change is notable across various dimensions. The total factor energy productivity of the Eastern region surpasses that of all other agricultural regions, with an MLI score of 1.125, indicating a growth of 12.5 %. This growth is primarily attributed to technological advancement, with a rate of 0.99 %. Similarly, the central agricultural sector of China witnessed a 10.3 % increase in total factor energy productivity over the study period, with MLI growth primarily driven by technological advancements of 0.84 %. Conversely, the western agricultural sector of China ranks third, with a total factor energy productivity growth of 0.80 % over the study period. Like the Eastern and central regions, the primary determinant of MLI growth in the western region is technological advancement, with a growth rate of 0.58 %.

Analyzing regional MLI outcomes reveals notable disparities in total factor energy productivity across China's agricultural areas. Moreover, the analysis of MLI growth across the agricultural sectors of 30 Chinese provinces identifies Zhejiang (1.23), Shanghai (1.197), Liaoning (1.184), and Hebei (1.147) as the top performers in total factor productivity growth. Interestingly, all these provinces belong to the eastern region of China, with technological advancement being the key determinant of MLI growth. Additionally, Jilin (1.122) from the central region emerges as the top MLI scorer, while Ningxia (1.116) in western China exhibits the highest total factor energy productivity growth. Conversely, Qinghai (1.036) and Shaanxi (1.05) from western China, along with Beijing (1.053) from eastern China, are identified as the lowest performers in MLI growth over the study period. The Kruskal-Wallis test results demonstrate a statistically significant difference between EE and TGR in the three Chinese agricultural regions, while MLI is not significantly different among the regions.

The study's findings indicate several policy implications for improving China's agriculture industry's effectiveness and long-term viability. Policymakers should prioritize a customized strategy due to significant regional energy efficiency and technical innovation differences. Provinces with lower efficiency levels can benefit from region-specific interventions, such as customized research and development grants and technology transfer initiatives, which can cater to their specific needs. In addition, the government needs to continue its admirable focus on developing sustainable energy sources such as solar panels and biogas technologies. Continuing incentives, such as subsidies and tax benefits, can promote wider adoption. Implementing standardized agricultural technologies is crucial in addressing regional variations in production methods. Creating and enforcing national standards is necessary to establish consistent procedures, promote effectiveness, and facilitate knowledge sharing. It is crucial to tackle environmental issues related to agriculture, and rules and incentives should encourage the adoption of eco-friendly technologies such as precision agriculture and innovative irrigation systems. Enhancing farmers' ability to embrace contemporary and effective technology is imperative through educational programs and extension services, contributing to human capital development. Finally, it is crucial to establish a comprehensive monitoring and evaluation system at both regional and national levels to effectively evaluate the performance of policies, identify areas that need development, and ensure continuous advancement in the agricultural sector. Integrating these policy implications into the broader agricultural development agenda will advance China's progress toward sustainable and efficient practices in all regions. The study's use of data at the province level may hide specific trends in localized areas, necessitating a more detailed investigation at the sub-regional level.

Furthermore, the data's temporal cut-off may overlook recent advancements, necessitating more frequent updates. The study's concentration on a particular group of variables excludes essential elements, such as socio-economic circumstances and policy intricacies, restricting the investigation's thoroughness. The idea that provinces are homogeneous oversimplifies the complex agricultural environment, and so it is necessary to investigate the variances within smaller regions. Subsequent investigations could utilize a longitudinal methodology to monitor alterations and evaluate the direct influence of particular agricultural policies on energy efficiency and productivity. Augmenting quantitative data with qualitative methods, such as interviews, can provide more profound insights into the determinants that shape farmers' decision-making. Furthermore, investigating the impact of climate change on agricultural methods and performing a comparison examination with other nations encountering comparable difficulties would offer significant standards for policy formulation. Conducting a study at the farm level would provide a clearer understanding of the specific dynamics at play, which would help make more precise policy suggestions.

Optimizing resource allocation is essential, with policies emphasizing encouraging the adoption of modern technologies and precision agriculture to enhance energy efficiency and productivity. It is crucial to address regional differences by implementing customized methods that consider various agricultural regions' distinct characteristics and requirements. Furthermore, providing government assistance through subsidies, training initiatives, and incentives can significantly enhance the sustainability of the agricultural industry by encouraging the adoption of energy-efficient technologies. Supporting the uptake of new technologies among farmers and agricultural practitioners is practical and beneficial. Implementing automated irrigation systems, integrating renewable energy sources, and embracing other technological advancements have the potential to optimize efficiency and mitigate environmental impacts. Offering training and guidance to farmers on the benefits and implementation of energy-efficient practices is essential to improve the overall efficiency of the sector. Investing in rural infrastructure, such as energy-efficient transportation and storage systems, is critical to reducing post-harvest losses and improving the supply chain.

This study lays a solid foundation for future agricultural efficiency and sustainability research. It is suggested that future studies include longitudinal analyses to investigate the long-term impacts of policy changes and technological advancements on agricultural energy efficiency. Such research can provide valuable insights for enhancing the resilience and sustainability of the agricultural sector. Comparative studies across different countries or areas could provide more profound insights into the efficacy of different agricultural methods and policies. Furthermore, researching climate change's influence on energy efficiency and production in agriculture could yield significant insights for devising adaptive measures to alleviate detrimental consequences.

Data availability

Data is collected from China's Rural Statistical Yearbook, China Statistical Yearbook, and China Energy Statistical Yearbook. Data is freely available at: http://www.shujuku.org/tag/and https://www.stats.gov.cn/sj/ndsj/

CRediT authorship contribution statement

Xiaomei Luan: Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rizwana Yasmeen:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis. **Wasi Ul Hassan Shah:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

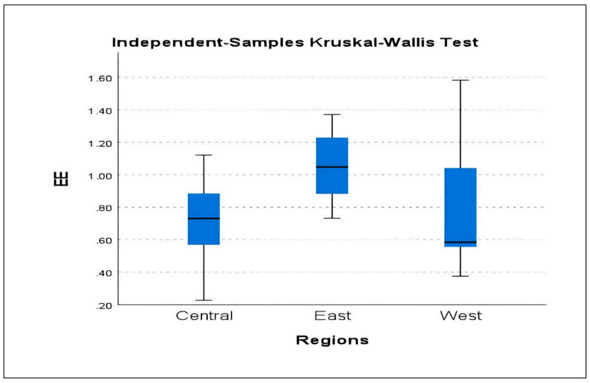

Fig. A1. Average EE distribution of the agriculture sector in three different regions of China.

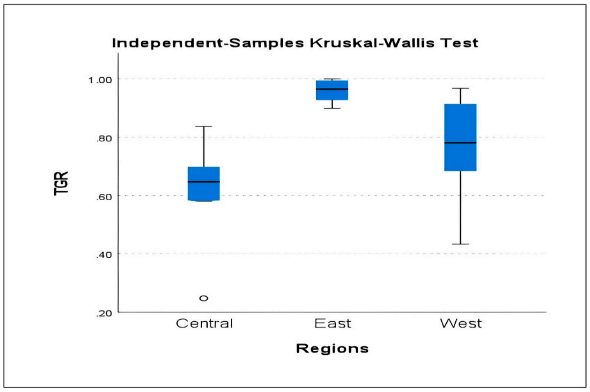

Fig. A2. Average TGR distribution of the agriculture sector in three different regions of China.

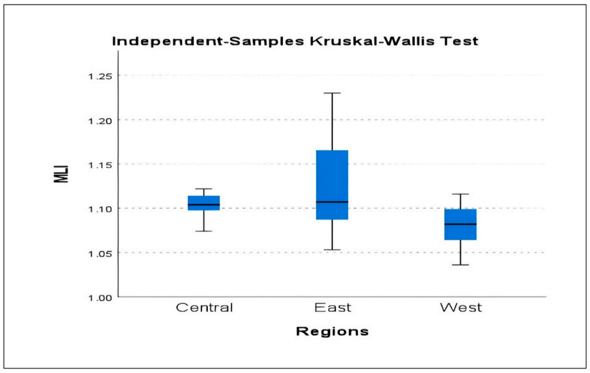

Fig. A3. Average MLI distribution of the agriculture sector in three different regions of China.

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