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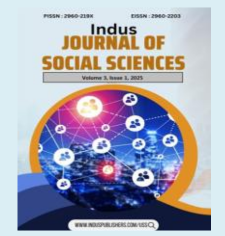

Energy Efficiency and Technological Progress of Agricultural Sector in China: Regional and Temporal Characteristics

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ABSTRACT

Optimizing agricultural energy usage to maximize output with little impact on the environment is a pressing global concern. Energy efficiency (EE), total factor energy productivity (TFEP), and the narrowing of regional inequalities in agriculture technology are all goals of several initiatives put forward by the Chinese government. Energy efficiency, total factor energy productivity fluctuations, and the regional technology gap ratio (TGR) were assessed in this study, which examined 30 provinces in mainland China and three distinct regions from 2000 to 2020 using DEA Super-SBM, Meta Frontier Analysis, and the Malmquist-Luenberger index. With an average EE of 0.8492, the data show that China's agricultural industry has space for a 15.08% improvement in EE development. Among the provinces in China, Qinghai has the highest energy efficiency rate at 1.5828, followed by Shanghai at 1.3716 and Hainan at 1.358. The Eastern area has an outstanding EE rating of 1.0532. The TGR grade in Zhejiang is an example of a modern method of agricultural production that efficiently utilizes energy resources. Total Grain Ratio (TGR) values over 0.96 and close to 1 in all provinces except Zhejiang indicate that China's agricultural production technology is advanced. These states include Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan. As time goes on, the eastern part of China's technology gap ratio (TGR) becomes closer to 1 than the central and western areas. This demonstrates that the provinces in the east are using modern agricultural practices, which increase productivity by making greater use of the resources at their disposal. An MLI score of 1.103 indicates a 10.3% improvement in energy productivity throughout China's agricultural sector. Subsequent studies showed that technological change (TC) was primarily responsible for the enhancement, with a TC value of 1.080, which was more than the EC value of 1.028. When comparing the three agricultural zones, the eastern zone produces more energy overall. In terms of total factor energy productivity, the four leading areas in China's agricultural sector are Zhejiang (1.23), Shanghai (1.197), Liaoning (1.184), and Hebei (1.147). There were statistically significant differences in TGR and EE between the three sites, according to the Kruskal-Wallis test.

1. Introduction

The agricultural industry is crucial to a nation's economic success. The agricultural industry ensures a steady supply of food, ensuring food security. Additionally, it promotes economic growth and development while creating significant employment opportunities (Sun & Sui, 2023). In addition, as a major employer, agriculture improves the standard of living and financial stability of farmers and other agricultural workers. Strengthening rural infrastructure, reducing urban migration, and promoting rural development are all outcomes of robust agricultural growth. For the world's top agricultural economies, farming is fundamental to meeting consumer demand for finished goods, increasing foreign exchange reserves, and funding exports. Scientific advancement, economic progress, and environmental sustainability are all aided by modern farming practices. As a result of its massive variety, crop diversification, and modernization efforts, China's agricultural sector is one of the most significant and most varied on the planet. When it comes to wheat and rice, it is the world leader. Increased agricultural output and more farmer agency resulted from the Household Responsibility System and subsequent land reforms. However, due to rural-to-urban migration, many regions face a scarcity of workers despite the industry's diversification efforts to fulfill the nutritional needs of the expanding population (B. Wang et al., 2019). A shift to sustainable agriculture practices is necessary due to environmental concerns such as water scarcity and soil degradation which impacts global food markets through its agricultural policy. Also, because of significant differences in R&D spending and labor costs, provinces with higher quantiles substantially impacted CO_2 energy efficiency (Tang & Chen, 2022).

Connected to this difficulty is what is known as the "Jevons paradox," first stated by Jevons in The Coal Question; according to (Sun & Sui, 2023), this paradox states that increased demand, rather than decreased demand, often follows greater resource efficiency. The oil crises of the 1970s highlighted this issue, and the "rebound effect" that followed was later documented. Since decreased energy prices boost demand, a phenomenon known as the "rebound effect" occurs, whereby energy efficiency improves while consumption increases. Heating, energy use in the home, and transportation were the primary areas of preliminary research. There are two schools of thought regarding studies in this field. One school of thought, as shown by the work of (H. Wang et al., 2022), looks at the energy rebound phenomenon and its vast effects on the country. In the second group, we find analyses of the partial energy rebound effect in various business settings. According to previous studies, energy resilience is a more pressing issue for developing countries than industrialized ones (Kuang et al., 2020). This has led experts to focus on how China's energy renaissance has played out. This industry and its allied fields have been the primary subjects of previous research (Sun & Sui, 2023) more research is needed to understand its Energy rebound dynamics may be better understood by dissecting the rebound effect and the factors that contribute to it. This data has the potential to enhance irrigation water conservation devices and agricultural equipment, which might lead to improved efficiency in energy production and consumption (Xiaoshuan et al., 2005). Economic development in agriculture will not be able to be uncoupled from carbon emissions if China's energy consumption continues to rise. To reach the "double carbon" target by the deadline, innovative ecological farming practices, reduced fertilizer and pesticide usage, and energy efficiency must be prioritized. The purpose of this research is to address three questions by exploring the following aspects of the rebound effect of agricultural energy use: What mechanism is the energy rebound effect in agriculture caused by? How may we measure the impact of China's energy consumption recovery on the country's farming industry? How does the energy rebound effect play a role in farming? What sets this research apart from others is the ground-breaking new information and valuable insights it provides: The first section sheds light on the lack of knowledge about the economic importance of agricultural revival by outlining the inner workings of the effects of the rebound from both the producers' and consumers' points of view. When empirically evaluating the effect of the agricultural energy rebound, the GMM model is even better. Using the substantial regional spillover influence to supplement the evaluation of influencing factors, this model successfully overcomes the endogenous problem.

To determine the efficacy of the Chinese government's programs to boost energy efficiency, total factor productivity, and the level of technological disparity in agricultural output among regions, further studies are required. This research analyzes the farm sector's energy efficiency in 30 mainland Chinese locations from 2000 to 2020 using the DEA Super-SBM model. In order to find out which Chinese provinces utilize agricultural energy the most efficiently, this evaluation looks at the efficiency of the sector during the research period. Step two entails calculating the technological gap ratio (TGR) among China's three agricultural regions—the east, the centre, and the west—through meta-frontier analysis. This makes it possible to evaluate the efficacy of government programs aimed at addressing technical diversity in production at these locations across time. Third, we use the Malmquist-Luenberger index to look at changes in TFEPC in China's farming sector to see if total factor energy productivity change (TFEP) has gone up or down throughout the research period and if changes in technology or efficiency are the main factors influencing TFEPC. This study's conclusions are supported by the Kruskal-Wallis test, which reveals that there are statistically significant variations in EE, TGR, and TFEPC across the three agricultural areas in China. The research framework summary is provided below: Section 2 provides a comprehensive literature analysis; Section 3 explains the methodology; Section 4 analyzes the variables and data collection; Section 5 presents the findings and discussion; and lastly, Section 6 explores the conclusions and policy implications.

2. Literature

Energy efficiency is crucial in agriculture due to its substantial environmental and economic sustainability effects. Farmers may significantly lower operating costs by using energy-efficient equipment, enhancing agricultural enterprises' economic viability. Additionally, the sector's impact on climate change may be mitigated by reduced energy usage, which in turn decreases emissions of greenhouse gases (Hong et al., 2024). Improving energy efficiency encourages responsible water use, trash reduction, and land preservation (Mo et al., 2023) Prioritizing energy efficiency in agriculture ensures a robust and sustainable agricultural future. Several studies evaluating energy efficiency in agriculture across various countries and regions have used Data Envelopment Analysis (DEA).

Scientists have looked at how climate change and deforestation affect crop yields. From 1975 to 2010, (Mathew & Panchanatham, 2016) showed that deforestation negatively correlated with agricultural productivity. Increasing deforestation hurts agricultural output, according to (Wang, 2023) analysis of data from the Ivory Coast from 1962 to 2010. Using Granger causality and vector autoregression approaches.

Much research has investigated the link between renewable energy and various environmental contaminants (Al-Sulaiti et al., 2010). Women business owners' success stories from India: an exploratory study. An exploratory study on the advancement of women entrepreneurs in India illustrates that innovations in environmental and renewable technologies significantly improve ecological sustainability. This is supported by GDP (Mathew & Panchanatham, 2016). An increase in renewable energy use decreases emissions in Tunisia over the long run, according to (Mathew & Panchanatham, 2016). Energy transition helps emerging countries reduce their negative environmental consequences, according to (O'Hara & Kakovitch, 2023). Based on their empirical investigation into the link between economic growth, trade, and environmental degradation, (Sun & Sui, 2023) found that renewable energy improves ecological sustainability, whereas fossil fuels and commerce diminish it. After looking at energy transition case studies, Ajaegbu (2014) found that using much renewable energy and lacking technological infrastructure drastically reduces emissions of greenhouse gases.

In their 2020 study, Aziz et al. sought to support the EKC hypothesis by looking at GDP, energy transition, agricultural output, forest area, and environmental deterioration. On the other hand, energy transition and wooded areas are inversely related to ecological pollutants, whereas agricultural growth exacerbates ecological problems in the short term. Eyuboglu and Uzar investigated the connection between renewable energy utilization, greenhouse gas emissions, and the agriculture industry in 2020. They discovered that although renewable energy does improve environmental quality, it has the opposite effect on agricultural output. In their study, (Fan & Zhang, 2004) used fixed effects regression using the GMM approach to examine the relationship between GDP, fossil fuel consumption, environmental emissions, and agricultural output. They argue that a slow but steady change in the integration of energy and commerce is necessary to improve ecological sustainability. Technology integration improves agricultural productivity and environmental sustainability, according to a meta-analysis by (Tan et al., 2010). Ultimately, Michler (2020) said that technological advancements could increase agricultural output in India while decreasing its environmental impact.

The emphasis on economic and industrial progress has impacted industrialization, capital resources, labor demand, and excess production inputs. Because of this, energy consumption has also increased, which is a problem for manufacturing and other industrial sectors. Furthermore, environmental toxins have grown due to the overexploitation of natural resources, putting ecological sustainability at risk. As stated by Wei and colleagues in 2018. Because of this, policymakers can now evaluate the link between the depletion of natural resources and ecological harm with more precision. There is a dearth of literature on how the use of natural resources affects crop yields; most of the available literature (Tang & Chen, 2022) focuses on the connections between these resources and issues like poverty, emissions, economic growth, and globalization. Global and regional trade integration is crucial since it directly influences economic transformation via enhanced competitiveness, industrial expansion, and job opportunities. Furthermore, this enhances market competitiveness, stimulates. The research identified a favorable correlation between energy requirements and economic development when various country characteristics are accounted for (Ahmed et al., 2023) stated that technical advancements enhance environmental quality and domestic growth after analyzing the relationship between environment, development, and energy in RCEP countries. Research by (Raihan et al., 2023) indicates that enhanced agricultural productivity and renewable energy sources reduce greenhouse gas emissions. In contrast, fossil energy resources compromise environmental quality, highlighting the correlation between agrarian value addition and fossil energy demands on ecological integrity.

Although energy efficiency has been the subject of study in a number of countries and industries, the agriculture sector in China has received surprisingly little attention. This study aims to fill that gap by using the DEA approach to assess energy efficiency across many Chinese regions. It fills a gap in our understanding by shedding light on the current state of energy efficiency in China's agricultural industry and suggesting ways to make it more efficient. It assesses the technical diversity throughout China's agricultural regions. This study surpasses prior studies by examining regional disparities and determinants influencing the overall transformation in energy productivity within China's farming industry. The comprehensive research seeks critical insights that inform policy initiatives to improve sustainability and energy efficiency in China's agriculture industry.

3. Technical Approach

3.1. Introducing the Super-SBM Theory with Negative Results

A non-radial Data Envelopment Analysis (DEA) model with the super Slack-Based Measure (SBM) was established by Tone (Xu et al., 2022) to assess efficiency from both the input and output viewpoints. Super SBM models include slack considerations, which make them much better at handling radial assessment limits and differentiating between efficient decision-making units (DMUs) than radial DEA models. Tone made significant improvements to the Super-Efficiency SBM, which was the first framework to include unintended consequences in the SBM paradigm. This update allows for a more precise and comprehensive evaluation of efficiency. The model is seen here: Research on energy efficiency has focused on many sectors and nations but shockingly little on China's agricultural industry. By using the DEA method to evaluate energy efficiency in different parts of China, this research hopes to close that information gap. The existing corpus of information is enhanced by illuminating the energy efficiency framework in China's agriculture business and identifying potential areas for expansion. It is a gauge of the range of technical abilities found in China's agricultural regions. This study expands upon previous work by investigating the elements influencing energy productivity in China's farming industry from a regional viewpoint. This comprehensive study seeks to provide vital insights to assist the Chinese government in formulating strategies for enhancing the sustainability and energy efficiency of the agriculture sector.

$X = [x_1 \cdots x_n] \in R^{m\times n}, Y^{nd} = [y_1^d \cdots y_n^d] \in R^{s_1\times n}$ And $Y^u = [y_1^A \cdots y_n^{ut}] \in R^{s_2\times n}$ The super-efficient SBM model's formula, which produces subpar results, is shown here.

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

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

In Equation (1), the variables sx ¯, (y^d) ¯, and y ¯^u stand for the input slack, intended output, and undesirable output, respectively. The weight vector, denoted by, is a rough approximation of the optimal value. An efficient decision-making unit (DMU) has a value of 1 or more.

3.2. Model of Meta-Frontiers

The Meta-Frontier Model makes more accurate cross-group assessments of DMU efficiency possible. Comparing DMUs within the same category allows for more fair judgments since they all have equal access to technology. To compare how far specific categories have come in terms of technology, one may utilize the Technology Gap Ratio (TGR). A group's technical advancement may be measured using a modified version of TGR.

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

The evaluation determines each Decision-Making Unit's (DMU) Energy Efficiency (EE). As shown in equation (2), Meta-Agricultural Energy Efficiency of Decision-Making Units (DMUs) at a certain technical level is represented by GAEEiMAEE, which indicates the energy efficiency of DMUs within a specific group in agriculture. The Technology Gap Ratio (TGR) is a distance metric that evaluates how close a meta-frontier technology is to a particular group's frontier technology. The TGR is often used to assess geographical differences. With a TGR of 1, the group and the meta-frontier are technologically identical.

3.3. Markov-Luenberger Index

Energy efficiency may fluctuate over time, but the DEA model can only assess technical efficiency (TE) for a specific period. An essential tool for evaluating a variable's outcomes is the Malmquist index. The Malmquist-Luenberger index (MLI) was developed by (Sun & Sui, 2023)by including an undesirable directional distance component into the original Malmquist index. Efficiency (EC) and technology (TC) are the two main components of the MLI [60]. The MLI varies from time t to time t+1, as seen in Equation (3).

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

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

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

Here, x, y, and b are input, intended, and undesirable output. (D t) $\overrightarrow{D_0^t}(x^2,y^r,b^r;y^t,-b^t)$ and $\overrightarrow{D_0^{t+1}}(x^{s+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}$ respectively, represent the distance functions for periods t and t+1 (see equation (4). Whereas the distance function for the t period under identical technical circumstances is $(x^{s+1},y^{s+1},b^{t+1};y^{s+1},-b^{t+1})$ the distance function for the t+1 period is $\overrightarrow{D_0^{t+1}}(x^t,y^t,b^t;y^t,-b^t)(see equation 5)$. An increase in total factor output is indicated by an ML number of more than 1, stability is shown by an ML value of 1, and a decrease is indicated by an ML value of less than 1. Similarly, an efficiency rise is marked by an EC number of more than 1, stability is shown by an EC value of 1, and a drop is indicated by an EC value of less than 1. Technical advancement is represented by a TC number greater than 1, stability by a TC value equal to 1, and regression by a TC value less than 1.

3.4. The Kruskal-Wallis Analysis

An essential tool for statistical analysis, the Kruskal-Wallis test avoids the assumptions inherent in parametric tests and instead uses a non-parametric approach. This makes it a good fit for situations where ordinal data and different sample sizes must be considered. Because it can handle cases where the assumption of equal variances is violated, this approach is far more versatile and practical for various experimental designs. This technique yields data that can be quickly evaluated using a p-value; it indicates significant differences between groups and applies to many domains, such as the social sciences and biology.

In addition, when assessing overall variances, post-hoc analyses like Dunn's test are crucial for differentiating between specific groups because it is not dependent on raw data values but on rankings, it is more reliable in empirical research and cannot be influenced by outliers. To handle common statistical assumptions and problems, as well as to make generalized group comparisons, the Kruskal-Wallis test is functional (Liang et al., 2018).

4. Gathering Information and Choosing Variables

Various sources, including the Energy Statistical Yearbook of China, the Statistical Yearbook of China, and the Rural Statistical Yearbook of China, were used to compile statistics on the agricultural sector in 30 mainland provinces of China (excluding Tibet) from 2000 to 2020 (see Table 1).

Table 1: Efficiency and effectiveness in agriculture are assessed using input-output factors

Inputs	Outputs
Ten thousand people were employed in the agriculture sector that year.	The agriculture industry's projected value-added output is 100 million yuan.
Stock in the agricultural industry (10,000 yuan) as capital	Undesired outcome: agricultural carbon dioxide emissions of 10,000 metric tonnes
Agricultural energy use as a whole across all provinces, expressed in metric tonnes of coal.	

5. The Findings and Their Meaning

Section 5 explains how China's agriculture sector's energy output, technological gap ratio, and energy efficiency have changed.

5.1. Evaluation of China's Agriculture Sector's Energy Efficiency (2000–2020)

This research used the DEA super-SBM model to analyze diverse inputs and outputs in order to evaluate the energy efficiency of China's agricultural industry from 2000 to 2020. The research indicates that China's agricultural sector has an average energy efficiency (EE) of 0.8492. This indicates an average probability of 15.08% for enhancing EE growth within the industry. Improvements in China's agricultural business may be realized via either a reduction in inputs or an enhancement of outputs. Statistics in Fig. 1 indicate that the farm sector's energy efficiency (EE) reached its zenith in 2020, averaging 0.9163; it was 0.9133 in 2012 and 0.8917 in 2019. Conversely, the average EE was at its nadir in 2002, registering at 0.7857; it subsequently increased to 0.8123 in 2008 and further to 0.815 in 2009. Despite several shifts in EE, the results show that the trend continued upward throughout the research period, peaking in 2020. Evidence from statistics shows that energy efficiency in China's agricultural industry has been steadily rising, and there's room for much more progress in this area. It is possible that policies and initiatives designed to promote sustainable agricultural practices and increase resource efficiency would benefit significantly from the results of this study. Modern technology, in the form of cutting-edge gadgets and precision agriculture instruments, allows for more efficient use of agricultural resources and less waste of energy. We can use less non-renewable resource power if we switch to renewables like solar and wind. Energy- and water-saving irrigation systems are made even better with upgrades. Reducing resource usage is one goal of sustainable agriculture practices like crop rotation and diversity. For progress to be continual, energy evaluations and sustainability education in agriculture are necessary. Government restrictions, incentives, and R&D initiatives may hasten the adoption of new, energy-efficient technologies. Lowering energy usage by improving supply networks and decreasing waste is possible. Businesses in the agriculture sector may improve their energy efficiency by working together and exchanging information with other stakeholders (Shao et al., 2024).

Figure 1: Energy Efficiency Trends in China's Agriculture Sector (2000 to 2020)

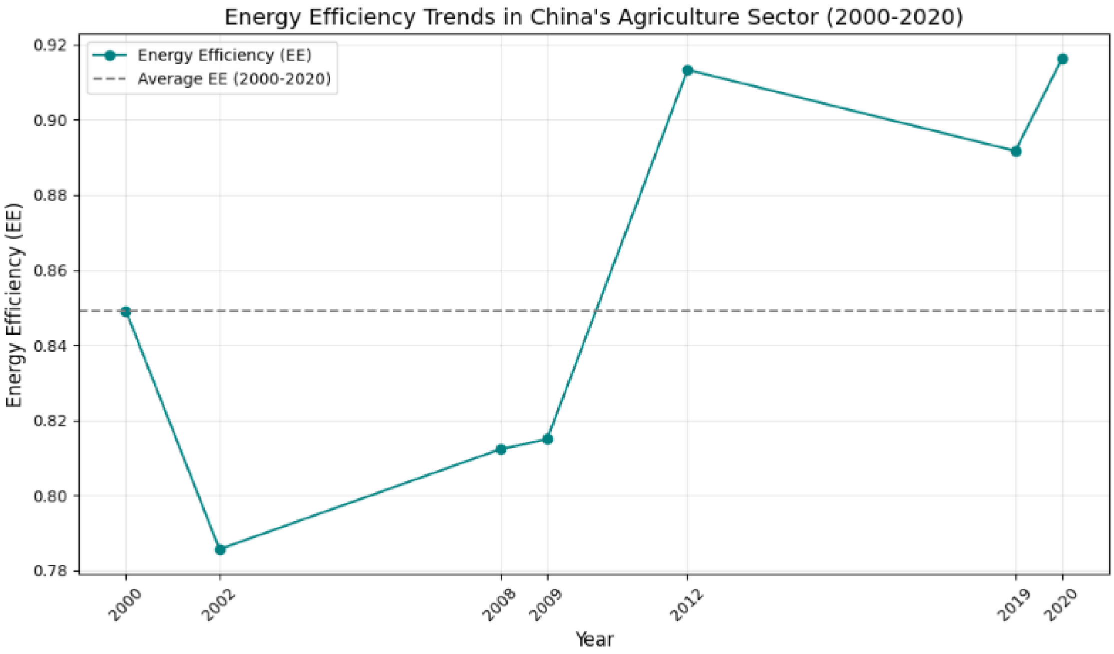


Figure 2: Energy Efficiency VS Improvement Potential (2000 vs 2020)

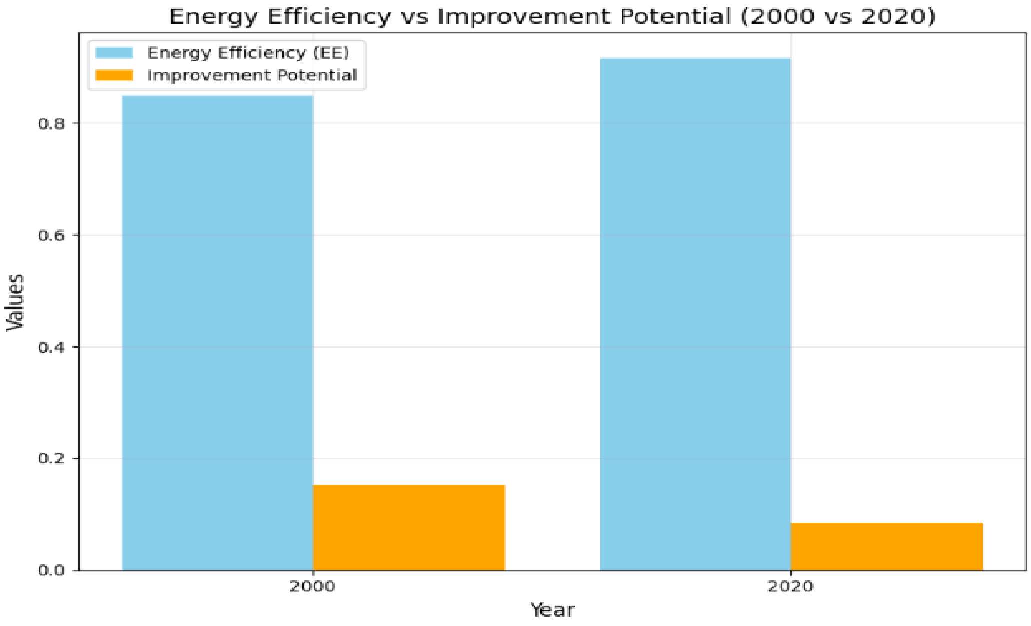
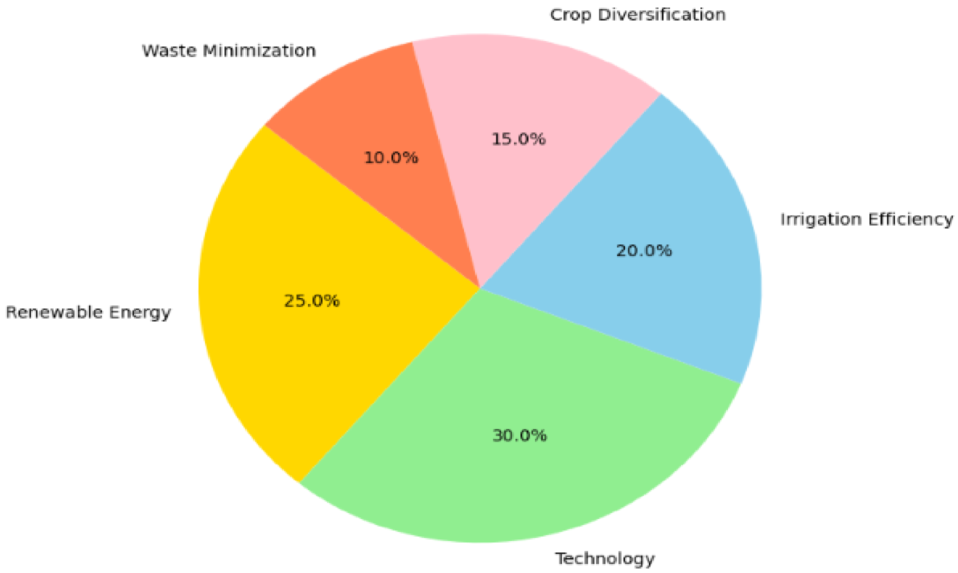
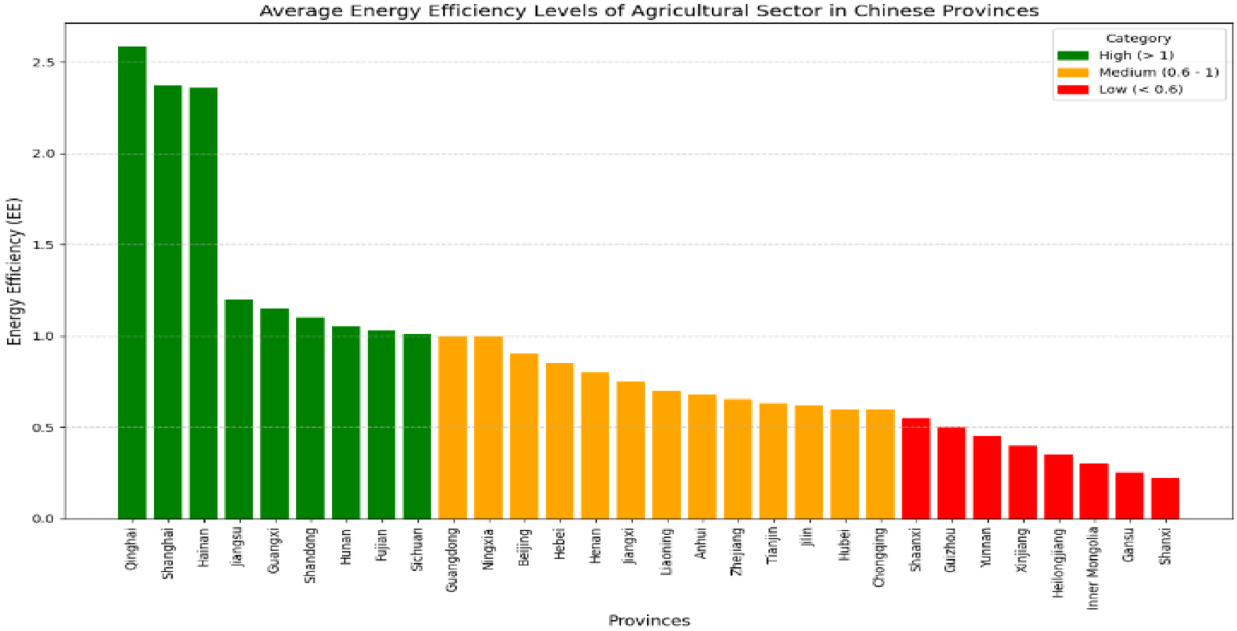


Figure 3: Improvement Potential versus. Energy Efficiency Chinese Agriculture Energy Efficiency Trends 2000–2020)



Agricultural energy efficiency values across all Chinese provinces throughout the study period are shown in Figure 4. Out of 30 provinces in inland China, the ones with the highest energy efficiency ratings are Qinghai (2.5827), Shanghai (2.3715), and Hainan (2.3581). Energy efficiency (EE) ratings more significant than 1 indicate that the agricultural sectors When it comes to energy efficiency, the provinces of Hainan, Jiangsu, Guangxi, Shandong, Hunan, Fujian, Sichuan, Guangdong, and Ningxia excel. In Beijing, Hebei, Henan, Jiangxi, Liaoning, Anhui, Zhejiang, Tianjin, Jilin, Hubei, and Chongqing, the energy efficiency (EE) levels vary from 0.60 to 1. Energy efficiency (EE) ratings range from 0.22 to 0.60 in the following provinces: Shaanxi, Guizhou, Yunnan, Xinjiang, Heilongjiang, Inner Mongolia, Gansu, and Shanxi. According to these findings, energy efficiency differs greatly throughout China's regions. It stresses the significance of region-specific initiatives to improve resource efficiency and the long-term viability of agriculture in particular [62].

Figure 4: Average Energy Efficiency Levels of Agricultural Sector in Chinese Provinces



Dividing the provinces of China into three separate regions—East, Central, and West—this study looks at how energy efficiency varies throughout the country's agricultural sector. According to Table 2, the Eastern area has a high level of EE proficiency, scoring 2.0531. It signifies the accomplishment of effective energy use in agriculture, marked by the application of advanced operational methods and minimal resource wastage. The Western region exhibits superior resource utilization and operational efficiency, with an EE level of 1.7796, surpassing the Central region's 1.7146. The Eastern area benefits from modern technology, enhanced infrastructure, and rapid monetary growth. Diverse strategies may be used to enhance energy efficiency in presently inefficient areas. These efforts include technology transfer, training, infrastructure development, policy support, and executing specialized research and extension activities. Regions exhibiting reduced efficiency need to enhance agricultural energy efficiency by evaluating these aspects, which would substantially aid production objectives and sustainability [63].

Table 2: The mean EE in three distinct Rural regions in China

Years	East	Central	West
2000	2.103	1.756	1.722
2001	1.956	1.786	1.743
2002	2.047	1.613	1.696
2003	2.022	1.646	1.797
2004	2.033	1.708	1.735
2005	2.09	1.696	1.798
2006	2.041	1.676	1.763
2007	2.995	1.686	1.782
2008	2	1.667	1.767
2009	1.985	1.73	1.728
2010	2.085	1.797	1.776
2011	2.003	1.772	1.833
2012	2.072	1.78	1.876
2013	2.012	1.714	1.747
2014	2.073	1.703	1.718
2015	2.108	1.682	1.822
2016	2.112	1.763	1.775
2017	2.054	1.698	1.801
2018	2.022	1.673	1.805
2019	2.145	1.698	1.82
2020	2.165	1.736	1.845
Average	**2.0531**	**1.7146**	**1.778**

5.2. Meta-Frontier Results from China's Agriculture Sector

The diversity of regional production technology substantially influences the energy efficiency (EE) of the agricultural sector across various regions of China. Diverse regions use varying agricultural practices, technology, and production systems based on their unique natural circumstances, resource availability, and degrees of economic development. Given that diverse technologies demonstrate differing energy intensity levels the aforementioned variables may influence the overall energy effectiveness of the farming area. Individuals using innovative irrigation systems, precision agricultural machinery, and sufficient equipment are more inclined to achieve greater energy productivity than those dependent on traditional or less sophisticated farming methods.

Table 3: Provinces of China (2000-2020): GEE, MEE, and TGR

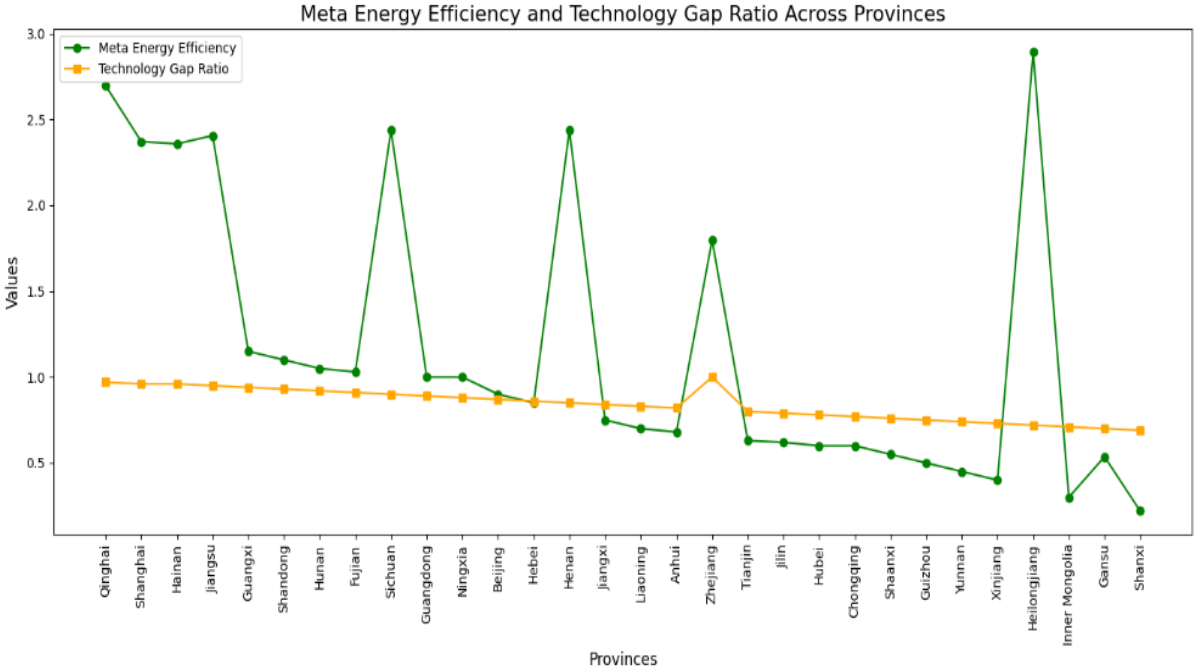
Region	Province	GEE	MEE	TGR
Central	Anhui	2.1244	1.803	1.7176
East	Beijing	2.0044	1.9623	1.9572
West	Fujian	2.2212	2.0936	1.9156
East	Gansu	1.5362	1.3755	1.7812
West	Guangdong	2.0628	2.0482	1.9872
East	Guangxi	2.3787	2.2327	1.8968
West	Guizhou	1.9108	1.5675	1.6762
West	Hainan	2.4064	2.3581	1.964
East	Hebei	2.0318	1.9484	1.9365
East	Henan	2.4378	1.9126	1.6285
Central	Heilongjiang	2.8915	1.4928	1.5802
Central	Hubei	1.9706	1.6452	1.6792
Central	Hunan	2.3458	2.1212	1.836
Central	Jilin	2.1332	1.6611	1.5844
West	Jiangsu	2.272	2.2634	1.9946
East	Jiangxi	2.3076	1.8563	1.6653
Central	Liaoning	1.8172	1.8162	1.9987
Central	Inner-Mongolia	2.0037	1.432	1.4331
East	Ningxia	2.0366	2	1.9672
West	Qinghai	2.697	2.5827	1.9342
West	Shandong	2.3312	2.1945	1.898
West	Shanxi	2.064	1.2264	1.2472
East	Shaanxi	1.6664	1.5845	1.9005
East	Shanghai	2.3804	2.3715	1.9935
Central	Sichuan	2.5762	2.0835	1.6908
West	Tianjin	1.8153	1.7322	1.9174
East	Xinjiang	2.0912	1.5491	1.5024
West	Yunnan	1.6124	1.5632	1.9272
West	Zhejiang	1.7976	1.7976	2.0001
East	Chongqing	1.8477	1.6063	1.7182

The MEE represents all thirty provinces' combined meta-energy efficiency. The TGR is a measure of a province's technology gap ratio. All relevant sites show that a DMU's technology is inferior to its counterparts in the Meta-technology. The Five Great Eastern Provinces—Guangxi, Qinghai, Shanghai, Hainan, and Jiangsu—have recently risen to prominence. Among the provinces that participated. With a total 2, 4378, Henan province has the central region's largest Gross Economic Expenditure (GEE). The average efficiency of Heilongjiang was the lowest, at 2.8915. With a GEE of 2.4064, the eastern part of Hainan achieves perfection.

Among the provinces, Zhejiang's GEE of 1.7976 was the lowest. In the Western area, Qinghai (2.697) comes out on top. However, with a GEE of 0.5361, Gansu is the least efficient. With a TGR of 1, technology takes center stage in every DMU. The last column of Table 3 displays the TGR for every province.

In addition, as shown in Figure 4, the average TGR of the eastern area of China is higher than that of the central and western regions. It keeps getting closer to 1, which means that the eastern provinces have very modern agriculture technology that makes good use of resources and efficiently produces a lot of food. Of the three regions, the one in the west shows the most technologically sophisticated agricultural production, while the one in the middle shows the least. Energy efficiency results in China's agricultural industry being substantially affected by regional differences in production techniques. The energy intensity levels also vary because different regions utilize different farming techniques. There may be a standstill in this area due to the greater energy efficiency shown by provinces adopting novel technologies compared to more traditional methods. Table 3 displays the meta-frontier study results, emphasizing the emphasis on GEE, MEE, and TGR, or Technology Gthe ap Ratio. A technology gap ratio (TGR) 1 indicates that Zhejiang province adopts current agricultural practices.

Figure 5: Energy Efficiency across Provinces



Policymakers and stakeholders must prioritise the implementation of regulations that promote energy-efficient practices, the allocation of resources for region-specific technological solutions, the education of farmers in less efficient areas, and programs that facilitate the transfer of new technologies. The TGR values underscore the importance of these methodologies and the need for technical advancement across various geographic regions. Figure 5 demonstrates that the Eastern area has a superior average Total Growth Rate (TGR), signifying more advanced agricultural techniques. The Western area is ranked second in industrial-technological developments. Progress in this sector has been minimal in the Central region. Coordinated initiatives are essential to bridge the technological gap across sectors so that China can achieve a more sustainable and productive agricultural sector (Cheng et al., 2023).

5.3. China's Agricultural Sector Malmquist-Luenberger Index Results

Studying data from 30 provinces in China from 2000 to 2020 using the Malmquist-Luenberger index (MLI), this study examined the changes in total factor energy productivity within the agriculture sector. During the study period, the total factor energy production in China's agriculture sector increased by 10.3%, as shown in Table 4, with an average MLI score of 2.102. A closer look reveals that the 2.081 value of technical change (TC)—which is higher than the 2.027 value of efficiency change (EC)—is the primary factor responsible for the rise in MLI while we were looking into it, the TC figure increased by 0.8% and the EC value increased by 0.28 percent. The significance of technical progress in improving total factor energy productivity change is shown by these findings. Improving energy efficiency to accomplish the same goals with less energy use requires technological innovation.

Table 4: MLI, EC, and TC throughout thirty provinces and three areas in China

Region	Province	MLI	EC	TC
Central	Anhui	2.073	2.006	2.066
	Henan	2.105	1.992	2.142
	Heilongjiang	2.097	2.022	2.062
	Hubei	2.115	2.048	2.063
	Hunan	2.111	2.021	2.093
	Jilin	2.121	2.008	2.116
	Jiangxi	2.096	2.041	2.046
	Shanxi	2.101	2.036	2.07
Ave. Central		2.102	2.021	2.083
East	Beijing	2.052	2.006	2.052
	Fujian	2.106	2.005	2.097
	Guangdong	2.115	2.024	2.106
	Hainan	2.075	2.014	2.063
	Hebei	2.146	2.035	2.115
	Jiangsu	2.097	2.001	2.092
	Liaoning	2.183	2.04	2.138
	Shandong	2.106	1.986	2.121
	Shanghai	2.196	2.153	2.052
	Tianjin	2.062	2.04	2.077
	Zhejiang	2.22	2.062	2.172
Ave. East		2.124	2.035	2.098
West	Gansu	2.065	2.015	2.067
	Guangxi	2.067	2.012	2.055
	Guizhou	2.092	2.071	2.024
	Inner- Mongolia	2.104	2.044	2.057
	Ningxia	2.115	2.001	2.115
	Qinghai	2.035	2.001	2.034
	Shaanxi	2.051	2.002	2.051
	Sichuan	2.081	2.004	2.082
	Xinjiang	2.091	2.002	2.084
	Yunnan	2.061	2.055	2.011
	Chongqing	2.115	2.066	2.052
Ave. west		**2.0801**	**2.024**	**2.057**
Ave. all		**2.102**	**2.027**	**2.081**

In addition, new technologies encourage the development of alternative energy sources by facilitating the discovery and implementation of greener, more sustainable options (Yang et al., 2024). Industrial automation and other cutting-edge technologies allow for more precise regulation of energy use in response to fluctuations in both supply and demand as they occur in real-time. The application of data analytics significantly improves our comprehension of trends in energy use. Thanks to technological improvements, renewable energy sources may now be more efficiently and sustainably integrated into power grids. Modern technology has made great strides in reducing energy waste by developing more efficient machinery, homes, and industrial operations. By increasing energy efficiency and fortifying global environmental conservation efforts, ongoing technology breakthroughs mitigate the challenges posed by climate change.

The results show that the Eastern area produces the most total factor energy out of the three areas, making it the best performer. A technical growing amount of 0.99% is mainly responsible for the region's MLI score of 2.124, which indicates a 12.5% gain. Alternatively, the data showed a 10.3% improvement in overall energy production in China's central agriculture sector. Technical advancement is the primary driver of MLI's 0.84% growth rate, just like in the Eastern area.

Third place went to China's Western agricultural sector, which increased its total energy output by 0.80% over the research period. With a growth rate of 0.58%, similar to that of the Eastern and Central zones, technological innovation. A remarkable 12.5% increase over the study period was reflected in its MLI score of 2.124. This outstanding result, representing a significant 0.99 percent rise, is primarily attributable to technological progress.

Innovations in technology have contributed to a rise in the MLI, which is in line with other industries. This growth accounts for 0.58% of the total. When looking at China's varied agricultural landscapes, stakeholders and policymakers can see how technological advancements significantly impact the country's total energy production. An essential way for regions with higher production to teach others with lower output about current agricultural methods is to facilitate the transfer of technology and the dissemination of information. A more equitable base for the broad use of technology may be provided by funding improvements to substructure, such as energy-efficient structures and transit networks. Research and development projects at the local level need funding.This will help alleviate technological differences by facilitating technologies tailored to each component's specific requirements. The regulatory process may be sped up, and dependable support for technical implementation might be provided by harmonizing regional and national rules. In addition, farmers in less productive regions might benefit from financial incentives and assistance to reduce the costs of energy-efficient technology adoption and increase their use. To increase sustainable development in China's agriculture business and eliminate disparities, critical monitoring and assessment techniques should be established, customized technological solutions should be promoted, and regional cooperation should be encouraged.

Table 4 analyses the MLI increase in 30 Chinese provinces across several agricultural sectors. According to the figures, Zhejiang (2.22), Shanghai (2.196), Liaoning (2.183), and Hebei (2.146) are the leading regions in China's agriculture industry for total factor productivity increase. According to the results, all four provinces are located in China's eastern region. In all four provinces, MLI expansion is dictated by technical progress. Moreover, in Western China, Ningxia (2.115) had the most substantial increase in total factor energy production, but Jilin (2.121) in Central China achieved the highest MLI score. The cities exhibiting the worst MLI growth performance throughout the research period include Beijing (2.052), Shaanxi (2.054), and Qinghai (2.035) in Western China. Statistics indicate that efficiency improvements are less substantial than technology developments in most provinces. Targeted suggestions for enhancing total factor energy productivity may be formulated.

Moreover, it is prudent to endorse interregional collaborative initiatives to advance effective strategies and methodologies for sharing. Jilin's maximum MLI total indicates that the provinces in the Central region need targeted support for technology adoption and skill enhancement (Gao et al., 2021). are essential in the Western area, especially in economically promising provinces such as Ningxia. Provinces exhibiting sluggish MLI (Multidimensional Livelihood Index) development, including Beijing, Shaanxi, and Qinghai, must prioritise technological advancement and efficiency enhancement. Providing incentives and connecting policies with national objectives is essential to enhance energy production. To attain a more equal and efficient agriculture sector throughout China, provinces may enhance their policies via systematic monitoring and assessment processes (H. Wang et al., 2022).

5.4. Difference in Statistical Significance

Results from the study's Sections 5.1, 5.2, and 5.3 show significant differences in the MLI ratings, total factor growth rate (TGR), and average energy efficiency (EE) across the three areas of China's farming industry. Whether or if these differences are statistically significant is a question for the scientific community. The research evaluated the three agricultural areas of China for statistical significance in terms of EE, TGR, and MLI using the Kruskal-Wallis test. Table 5, Figures A1, and A2, and Figure A3 show the results. A first hypothesis indicating a large variation in EE between locations is supported by a significance level of 0.037, which is lower than the conventional 0.05 criterion. To reject the null hypothesis, we need to find evidence that the three agricultural areas vary significantly in terms of energy efficiency. A 0.001 significance level for the second hypothesis (less than 0.05) suggests that there is a statistically significant variation in TGR across the sites. Since the third hypothesis requires a significance level greater than 0.05 (0.067), there are no statistically significant differences in MLI among the three locations.

Table 5: Findings from the Kruskal-W test

	Test of Assumption Description			
	Test for the Null Hypothesis and Significance; Choice			
1	Energy efficiency in China's agricultural industry is consistent across three regions.	Independent-Samples Kruskal– Wallis Test	0.036	Reject
2	All three of China's regions have the same TGR in the agricultural sector.		0.002	Reject
3	The MLI for China's agricultural industry is same across all three regions..		0.066	Retain

Differences in average EE, TGR, and MLI scores across the three areas of China's agriculture industry are illuminated by the data shown in Table 5 and Figures A1, A2, and A3. Their results show how well the Kruskal-Wallis test assesses statistical significance in these differences. With p-values of 0.036 and 0.002, respectively, below the standard significance level of 0.05, the test results show that there is a significant difference in EE and TGR across the three locations. Because of the statistically significant differences in EE and TGR, the data support the idea that different regions' agricultural sectors function at different levels of efficiency and growth. A level of 0.066, slightly higher than the 0.05 threshold, was shown by the MLI study. When comparing MLI at the three sites, no statistically significant differences were found (Z. Fan et al., 2016).

6. Findings and their policy significance

Because of its size, crop variety, and continuous modernization efforts, China's agricultural sector is vital for rural infrastructure, economic development, food security, and job creation. Sustainable and innovative farming techniques are crucial to addressing environmental concerns, feeding a large population, and reducing labor shortages brought on by people moving from the countryside to the cities. The Chinese government is working to make agriculture more energy efficient. Supporting renewable energy sources like solar panels and biogas technology and investing in precision irrigation and sophisticated agricultural practices are two ways to increase the efficiency with which resources are used. One way to lessen our dependence on fossil fuels is to promote electric-powered farming equipment. The distribution of information and training programs encourages the use of energy-efficient measures. These coordinated efforts demonstrate China's commitment to environmentally friendly farming. On average, farm energy efficiency (EE) hit 0.9163 in 2020. Out of thirty inland Chinese provinces, Qinghai (1.5828), Shanghai (1.3716), and Hainan (1.3582) had the highest scores for energy efficiency. With an EE rating of 1.0532, the Eastern region far outshines the others. Achieving efficient energy utilization in agriculture is characterized by cutting-edge operating procedures and minimum resource depletion. With an energy efficiency (EE) level of 0.7797, the Western area outperforms the Central region regarding resource utilization and operational efficiency.

According to the meta-frontier study, the following provinces had outstanding results in the MEE: Guangxi, Hainan, Shanghai, and Qinghai. Group EE performed best throughout the study period in Qinghai, Sichuan, Henan, Hainan, and Shanghai. The central area's greatest Gross Economic Efficiency (GEE) is in Henan province, with 1.4379. With an average of 0.8916, Heilongjiang had the lowest efficiency. A GEE grade of 1.4065 is ideal for the eastern part of Hainan. With a GEE of 0.7977, Zhejiang ranked worst for efficiency. In the Western region, Qinghai comes first with 1.698.

However, with a GEE of 0.5361, Gansu is the least efficient. The findings show that Zhejiang's TGR value is an example of how modern agricultural production methods are improving the efficiency of energy resources. Except for Zhejiang, all of China's provinces with Total Grain Ratios (TGRs) over 0.96 and close to 1 have highly developed agricultural production technologies. This includes Liaoning, Jiangsu, Shanghai, Guangdong, Ningxia, and Hainan.

Study also shows that the average TGR in eastern China is higher than in central and western areas. The constant climb in value nearing 1 indicates that the eastern provinces have advanced agriculture technology that maximizes resource efficiency for optimum production. Out of the three zones, the western area ranks second in technical sophistication for output, while the central area has the least sophisticated agricultural production technology.

A Malmquist-Luenberger index (MLI) score of 1.103 indicates that the total energy productivity of China's agricultural sector has improved by 10.3%. According to subsequent research, technical change (TC) is primarily responsible for the increase in MLI; its value of 1.080 is higher than the efficiency change (EC) value of 1.028. During the study, the TC number increased by 0.8%, and the EC value increased by 0.28%. Technological advancement is crucial to improving energy production in several areas. With an MLI score of 1.125, the Eastern region's total factor energy productivity is 12.5% higher than all other agricultural areas. At a rate of 0.99%, the increase is mainly attributed to technological improvement. Technical advancements helped drive a 0.84% increase in MLI growth, which drove a 10.3% increase in total factor energy productivity in China's leading agricultural industry throughout the study period. However, with a total energy productivity gain of 0.80% throughout the study, China's western agriculture sector ranks third. As in the east and central regions, technological innovation drives MLI development in the west, growing at a pace of 0.58%.

The paper presents several policy options to make China's agriculture sector more efficient and environmentally friendly. Significant geographical differences in energy efficiency and technological progress need a specialized strategy from policymakers. Technology transfer programs and specialized research and development financing according to each province's needs can help those showing decreased efficiency. Renewable energy, such as biogas and solar panels, should be a top priority for the government. Reduced taxes and ongoing subsidies encourage more widespread usage. We must standardize agricultural technology to reduce the impact of regional differences in production methods. To increase information interchange, streamline processes, and guarantee consistent procedures, national standards must be set and followed. Sustainable technology, such as modern irrigation systems and precision agriculture, must be encouraged via legislation and incentives to address the environmental concerns linked to agriculture. Human capital development can only progress if extension services and training programs help farmers accept new and efficient technologies better. Assessing the effectiveness of policies, identifying areas for development, and guaranteeing continued growth in the agricultural sector requires establishing a thorough monitoring and evaluation system at both the regional and national levels. Improving China's progress towards efficient and sustainable practices may be achieved by incorporating these policy implications into the agricultural development agenda. Some regional trends may have been lost due to the study's dependence on province data; a more thorough examination at the sub-regional level is necessary.

Also, the data may not be up-to-date enough due to its limited time frame. Therefore, it would be wise to update it more often. Due to the research's narrow emphasis, essential issues, including socioeconomic situations and policy intricacies, were left out of the inquiry, limiting its depth. Because the complex agricultural environment cannot be reduced to a simple assumption of provincial homogeneity, it is necessary to look at the differences within smaller regions. Future research may utilize a longitudinal strategy to monitor progress and determine how specific agricultural policies affect efficiency and production. By supplementing quantitative data with qualitative approaches, like interviews, we better understand the elements that impact farmers' decision-making. Policymakers may also benefit from comparing agricultural practices in nations coping with climate change with those in other nations experiencing comparable problems. Shedding ducted at the farm level would allow for more precise policy suggestions by shedding light on the unique dynamics at work.

Efficient resource allocation is crucial, and governments should promote precision agriculture and advanced technology to enhance productivity and energy efficiency. Mitigating regional disparities necessitates tailored strategies that account for different agricultural areas' distinct attributes and needs. Moreover, promoting energy-efficient technology and offering governmental support via subsidies, training programs, and incentives might enhance the sustainability of the agricultural sector. Encouraging farmers and agricultural experts to use advanced technology is logical and advantageous. Incorporating further technical advancements, integrating renewable energy sources, and deploying automated irrigation systems might enhance efficiency and reduce environmental impacts.

This research provides a robust basis for further agricultural sustainability and efficiency enquiries. Future research should use longitudinal analysis to investigate the enduring effects of technical developments and policy changes. This study may provide significant insights for improving the sustainability and resilience of the agriculture industry. A comprehensive assessment of the effectiveness of diverse agricultural practices and policies may be achievable via comparison analyses across many nations or regions.

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