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Spatiotemporal Trends and Determinants of Cultivated Land Ecological Efficiency in China

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Abstract: As one of the most important developing countries, China faces the dual pressures of declining cultivated land area and deteriorating land quality. Under these conditions, improving cultivated land ecological efficiency (CLEE) has become essential for overcoming resource constraints and ensuring food security. This study utilizes panel data from 31 provinces in China covering the period from 2000 to 2022. CLEE is measured employing a global benchmark EBM-DEA model incorporating undesirable outputs (carbon emissions). Kernel density estimation and σ-convergence analysis are used to characterize the dynamic distribution features of CLEE, and a panel Tobit regression model is applied to identify its key influencing factors. The results show that the national CLEE exhibits a continuous upward trend, with an accelerated improvement stage after 2015. While regional disparities persist, a convergence trend is observed: the eastern region maintains a leading position, the central region demonstrates the highest growth rate, and the western and northeastern regions show steady yet relatively lagging improvements. Kernel density analysis reveals a transition of the efficiency distribution from bimodal to unimodal, with the main peak continuously shifting to the right. The Tobit regression results indicate that urbanization rate, per capita cultivated land resources, multiple cropping index, and rural electrification level have significant positive impacts on CLEE, whereas the proportion of dryland, agricultural cropping structure, and area of crops affected by disasters exert significant negative effects. Based on the research findings, this study proposes optimization strategies such as implementing differentiated regional development policies, strengthening agricultural infrastructure, and optimizing cultivated land utilization methods to promote green transformation. These strategies provide empirical evidence to support the formulation of targeted policies, the improvement of cultivated land use efficiency, and the promotion of sustainable agricultural development in China and other resource-constrained developing countries.

Keywords: cultivated land ecological efficiency; EBM model; kernel density estimation; Tobit model; carbon emissions

1. Introduction

As a fundamental natural resource for human survival, cultivated land not only provides the material and spatial foundation for food production but also serves as a strategic resource for ensuring global food security, maintaining ecological balance, and upholding social stability. However, conventional agricultural practices have often prioritized economic gains at the expense of the environment and natural resources [1], resulting in a series of problems such as land degradation [2], water scarcity [3], and ecosystem imbalance [4]. Against the backdrop of continuous global population growth and increasing food demand [5], cultivated land resources are facing mounting pressures. Recent statistics reveal that the global per capita cultivated land area has declined from 0.45 ha in 1961 to 0.21 ha [6], representing a reduction of 50% and highlighting the increasing scarcity of this essential resource.

As the world's most populous developing country, China supports 22% of the global population with only 7.5% of the world's cultivated land [7]. This structural imbalance renders the protection of cultivated land resources in China particularly prominent and complex. The Chinese government has attached great importance to cultivated land protection, implementing a series of strict protection policies and establishing the "1.8 billion mu red line" as an inviolable threshold [8]. Nevertheless, China's cultivated land resources are subject to dual pressures of both quantity reduction and quality degradation. On the one hand, data indicate that China's cultivated land area decreased from 2.031 billion mu in 2009 to 1.918 billion mu in 2019, representing a net reduction of 113 million mu over a decade [9]. On the other hand, the excessive use of chemical fertilizers and pesticides in agricultural production has led to deterioration in land quality [10], with the restoration cost of the cultivated land ecological environment estimated at several trillion yuan [11]. Under the dual constraints of decreasing area and degrading quality, the traditional extensive development model—reliant on expanding cultivated land area to boost agricultural output [12]—has become unsustainable. Consequently, enhancing cultivated land use efficiency has become a crucial strategy for overcoming resource and environmental constraints and safeguarding food security [13]. As a comprehensive indicator, cultivated land ecological efficiency (CLEE) measures the relationship between economic output and ecological environmental impact during cultivated land utilization, fully reflecting the sustainability level of land use and providing a scientific basis for evaluating and optimizing cultivated land use patterns [14].

Prior studies on cultivated land ecological efficiency have encompassed multiple spatial scales ranging from the global to the provincial level [15,16], and have employed diverse measurement approaches, such as principal component analysis (PCA), entropy weighting methods, and stochastic frontier analysis (SFA) [12]. Among these, Data Envelopment Analysis (DEA) is the most widely applied [17,18]. However, conventional DEA models do not account for slack variables and assume proportional changes in inputs and outputs, which presents certain limitations [19]. Traditional research on CLEE has mainly focused on maximizing economic output, often neglecting undesirable outputs such as carbon emissions and non-point source pollution generated during agricultural production. According to IPCC assessment reports, agriculture is one of the major sources of global greenhouse gas emissions, with emissions from agriculture, forestry, and other land uses accounting for 23% of total anthropogenic GHG emissions [20], and carbon dioxide constituting as much as 75% of this total. In the process of cultivated land utilization and agricultural production, the application of fertilizers and pesticides is the primary source of carbon emissions, representing a significant share of total agricultural carbon emissions [21]. In order to fully account for undesirable outputs and avoid misleading conclusions, numerous scholars have begun to incorporate carbon emissions as undesirable outputs in efficiency evaluation frameworks [22,23]. These studies have made important contributions to enriching methodological systems for evaluating cultivated land use efficiency.

Despite recent advances in the study of green efficiency, two key gaps remain in this field. First, there is a relative lack of in-depth analysis regarding the dynamic evolution and regional disparities of cultivated land ecological efficiency; most studies remain at the level of static comparisons, without revealing changing patterns in the distribution of efficiency. Second, most determinant analyses rely on ordinary least squares (OLS) regression and fail to account for the bounded nature of efficiency values, potentially leading to estimation bias.

In the context of China's economic transition to a "new normal" and the elevation of ecological civilization as a national strategic priority, investigating the spatiotemporal evolution of CLEE and its influencing factors is of significant theoretical and practical value for promoting the green transformation of agriculture and fostering a modern society in which humanity and nature coexist harmoniously. This study aims to: (1) depict the trajectory of provincial-level CLEE in China from 2000 to 2022 using the global benchmark EBM-DEA and kernel density estimation; and (2) quantify the effects of economic, resource, and risk-related factors through a panel Tobit model.

This paper makes three main contributions: First, it integrates the "global benchmark EBM—kernel density—Tobit" analytical chain, enabling an integrated approach to efficiency measurement, distributional comparison, and mechanism testing, thereby enriching the evaluation paradigm of cultivated land ecological efficiency. Second, by utilizing 23 years of national provincial-level data, it dynamically characterizes the staged evolution and regional development trends in CLEE. Third, the study quantitatively analyzes the positive and negative effects of driving factors, providing actionable policy insights for region-specific interventions and targeted improvements of CLEE. The findings not only offer important guidance for optimizing land protection and low-carbon agriculture policies in China but also provide valuable experience for other developing countries facing land resource constraints in their pursuit of higher land use efficiency and sustainable agricultural development.

2. Materials and Methods

2.1. EBM-DEA Model with Undesirable Outputs

Traditional DEA models, such as CCR and BCC, assume proportional changes in inputs and outputs, which deviate from actual production processes [19]. To overcome this limitation, Tone proposed the slack-based measure (SBM) model, which is non-radial and non-oriented, allowing for non-proportional adjustments in inputs and outputs and accommodating undesirable outputs. However, the objective function of the SBM model minimizes the efficiency value of the decision-making unit by maximizing the slack variables of inputs and outputs, which contradicts the shortest path principle desired by decision-makers. To address this issue, Tone and Tsutsui developed a hybrid model based on SBM, namely the epsilon-based measure (EBM) model [24], which simultaneously incorporates both radial and non-radial features. In the EBM model, the radial feature refers to the simultaneous contraction or expansion of inputs and outputs in the same proportion, while the non-radial feature allows for adjustments in different proportions. Therefore, the EBM model can be regarded as a generalized form of both the radial DEA model and the non-radial SBM model. By introducing a balancing parameter between radial and non-radial characteristics, the EBM model retains the advantages of SBM in handling non-proportional changes and undesirable outputs, while also providing a more rational projection path.

To ensure cross-period comparability, this study adopts the global benchmark approach proposed by Pastor and Lovell [25], which uses the production frontier across all observation periods as a unified reference. Assume there are n decision-making units (DMUs), denoted as DMUj (j = 1, 2, ..., n); each DMU has m types of inputs, denoted as x_i (i = 1, 2, ..., m), s types of outputs denoted as y_r (r = 1, 2, ..., s), and p types of undesirable outputs denoted as b_g (g = 1, 2, ..., p). The non-oriented global benchmark EBM model incorporating undesirable outputs is formulated as:

$$
\begin{aligned}
&\gamma^* = \min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{\omega_i^- s_i^-}{x_{ik}}}{\varphi + \varepsilon_y \sum_{r=1}^{q} \frac{\omega_r^+ s_r^+}{y_{rk}} + \varepsilon_b \sum_{t=1}^{p} \frac{\omega_t^{b-} s_t^{b-}}{b_{tk}}} \\
&s.t. \sum_{j=1}^{n} x_{ij}\lambda_i + s_i^- = \theta x_{ik},\ i = 1, \ \dots m \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \varphi y_{rk},\ r = 1, \ \dots s \\
&\sum_{j=1}^{n} b_{tj}\lambda_j + s_t^{b-} = \varphi b_{tk},\ t = 1, \ \dots p \\
&\lambda \geq 0,\ s_i^- \geq 0,\ s_r^+ \geq 0,\ s_t^{b-} \geq 0
\end{aligned} \tag{1}
$$

where b_{tk} represents the t-th undesirable output of the k-th DMU, s_t^{b-} denotes the slack variable for undesirable outputs, ε_b indicates the importance of the non-radial component of undesirable outputs in efficiency calculation, and ω_t^{b-} represents the relative importance of each undesirable output indicator, satisfying $\sum_{t=1}^{p} \omega_t^{b-} = 1$. γ^* is the calculated efficiency value, ranging from 0 to 1, where a higher value indicates greater relative efficiency of the DMU. When γ^* equals 1, it indicates that the DMU is relatively technically efficient compared to other DMUs and is located on the production frontier. The closer γ^* is to 1, the higher the relative efficiency of the DMU; conversely, the closer γ^* approaches 0, the lower the relative efficiency of the DMU.

2.2. Kernel Density Estimation

Kernel density estimation is a non-parametric method for estimating the probability density function of random variables. This approach provides smooth estimates of the distribution shape and density patterns of sample data, thereby overcoming the discontinuity and roughness issues inherent in traditional histograms due to their fixed bin widths. The method has been widely applied in economics, statistics, and resource management, and is particularly suitable for analyzing the distributional characteristics and temporal evolution trends of CLEE.

Commonly used kernel functions include the Epanechnikov kernel, Gaussian kernel, and triangular kernel, among others. The Gaussian kernel, owing to its favorable mathematical properties and its resemblance to the normal distribution, is the most widely adopted in practical applications.

Its specific form is shown in Equation (2):

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}u^2} \tag{2}$$

where $u = \frac{x - x_i}{h}$ represents the standardized distance between the sample data point x and the estimation point x_i divided by the bandwidth h. The bandwidth h in kernel density estimation is a critical parameter determining the smoothness of the estimated curve. An excessively small bandwidth leads to an overly "rugged" curve, while an excessively large bandwidth results in over-smoothing that obscures the true data structure. The Silverman rule provides an objective approach for bandwidth selection, balancing the trade-off between bias and variance. The application value of kernel density estimation in cultivated land efficiency analysis is reflected in four aspects: (1) Peak position (horizontal axis location): the rightward shift of the main peak indicates an overall improvement in efficiency levels, reflecting the effectiveness of agricultural modernization, technological progress, and policy support; conversely, a leftward shift suggests efficiency regression; (2) Curve shape (peak height and width): a tall and narrow peak indicates high concentration of efficiency values around the mean, suggesting relatively balanced development across regions; a flat and wide curve reflects substantial dispersion and pronounced regional heterogeneity; (3) Number of peaks: a unimodal distribution indicates relatively uniform efficiency across regions; a bimodal or multimodal distribution reveals polarization, with provinces clustering into distinct efficiency groups (e.g., high-efficiency and low-efficiency clusters), signaling unbalanced regional development; (4) Tail characteristics: a long right tail indicates the presence of a few exceptionally high-efficiency provinces that raise the overall level but also suggest large efficiency gaps; a long left tail reflects the persistence of low-efficiency "troughs" that drag down the overall performance. The shortening of both tails indicates convergence, with the gap between leading and lagging regions narrowing. By analyzing the dynamic evolution of these characteristics in kernel density functions, we can systematically reveal the spatiotemporal evolution patterns of CLEE and identify key stages of structural transformation, thereby providing a scientific basis for differentiated policy formulation.

2.3. σ-Convergence Analysis Method

σ-convergence analysis is an important method for examining the changing trend of regional disparities in cultivated land ecological efficiency. Its core concept lies in assessing whether efficiency gaps among different regions gradually diminish over time, thereby indicating convergence across regions. To quantitatively characterize such disparities and their dynamic trends, we typically employ two statistical indicators: standard deviation and coefficient of variation. The standard deviation measures the dispersion of efficiency levels across regions relative to the mean, while the coefficient of variation further eliminates the influence of changes in the mean, thereby providing a more accurate reflection of the relative magnitude of efficiency differences. The formulas for the standard deviation and coefficient of variation of CLEE are as follows:

$$S_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Y_{it} - \overline{Y}_t)^2} \tag{3}$$

$$CV_t = \frac{1}{\overline{Y}_t}\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(Y_{it} - \overline{Y}_t)^2} \tag{4}$$

In the above formulas, Y_{it} denotes the cultivated land ecological efficiency of city i in Anhui Province in year t; $\overline{Y}_t$ represents the average CLEE of all cities in year t; $N(1，2，3 \cdots 16)$ refers to the number of cities in Anhui Province; S_t denotes the standard deviation in year t; and CV_t is the coefficient of variation in year t. As time progresses, if both the standard deviation and the coefficient of variation exhibit a downward trend, it indicates that the dispersion among the samples is decreasing, illustrating the presence of σ-convergence. Conversely, an upward trend indicates σ-divergence.

2.4. Tobit Regression Model

As a censored dependent variable bounded within the [0, 1] interval and with a substantial number of boundary observations (efficiency values of 1), CLEE poses challenges for conventional OLS regression, which would yield biased parameter estimates. The Tobit model [26] addresses this issue by applying maximum likelihood estimation to handle censored data, thus effectively resolving the selectivity bias arising from a bounded dependent variable and ensuring consistent and unbiased estimates. For panel data, the Tobit model mainly includes mixed effects and random effects specifications [27]. Given that the fixed effects Tobit model cannot provide consistent and unbiased estimators when incorporating time dummies [28,29], this study employs a random effects panel Tobit model, which is specified as follows:

$$\begin{cases} y^* = \alpha + \beta x + \varepsilon, & y^* > 0 \\ 0, & y^* \leqslant 0 \end{cases} \tag{5}$$

where y^* is the dependent variable vector; α is the intercept term; β is the vector of parameters to be estimated; x is the vector of independent variables; and ε is the random error term.

2.5. Selection of Variables and Data Description

2.5.1. Variables Used to Measure CLEE

The utilization of cultivated land resources primarily targets agricultural production and constitutes a complex system often involving multiple inputs and outputs. Martin et al. considered agricultural labor and production materials as input indicators [30]; YougbarÃ et al. employed cultivated land area and labor inputs as inputs, with crop output as an output indicator [17]; Gu et al. additionally included fertilizer use as an input metric [31,32]; Theodoros noted that pesticide application is crucial in agricultural production and significantly impacts the evaluation of agricultural ecological efficiency [33]; Luo et al. incorporated agricultural plastic film, considering its environmental pollution, as an input indicator [34]; Kuang et al. introduced total power of agricultural machinery and irrigated area as inputs, acknowledging their indispensable role in modern agricultural production and their potential to contribute to greenhouse gas emissions [13]. As research has deepened, scholars have increasingly recognized that some undesirable outputs are inevitable in cultivated land utilization and agricultural production processes, and neglecting undesirable outputs may yield misleading results in efficiency assessment [35,36]. Existing literature demonstrates that both agricultural production infrastructure and production processes can directly or indirectly induce carbon emissions [37,38]. According to IPCC assessment reports, the frequency and intensity of certain extreme weather and climate events have increased due to global warming and are expected to continue increasing under moderate to high emission scenarios. As a major source of greenhouse gas emissions, agriculture, forestry, and other land uses account for 23% of total anthropogenic greenhouse gas emissions globally [20], with carbon dioxide comprising as much as 75% of the total. In cultivated land use and agricultural production, the processes involving fertilizers and pesticides are primary sources of carbon emissions, making up a significant proportion of total agricultural emissions [21].Given the significant greenhouse gas emissions linked to cultivated land use, many scholars have incorporated greenhouse gases—particularly carbon emissions—as undesirable outputs in evaluation frameworks [39,40].

Based on the above theoretical developments and empirical experiences, this study develops a comprehensive evaluation index system comprising three dimensions: inputs, desirable outputs, and undesirable outputs. The input indicators follow the logic of "land–labor–capital–material inputs" and include: (1) cultivated land area (10,000 ha), reflecting the scale of land input; (2) number of agricultural employees (10,000 persons), indicating labor input intensity; (3) total power of agricultural machinery (10,000 kW), representing the level of capital and technology inputs; (4) quantities of chemical fertilizers applied (10,000 tons), pesticide use (tons), and agricultural plastic film use (10,000 tons), measuring the intensity of material inputs. The desirable output is represented by gross agricultural output value (100 million CNY), comprehensively reflecting the economic benefits of land use. The undesirable output is measured by carbon emissions from cultivated land use (10,000 tons), calculated by summing activity levels multiplied by emission factors (see Equation (4)). The index system is detailed in Table 1.

Table 1. Input–Output Index System for Cultivated Land Ecological Efficiency.

Category	Indicator	Variable & Description	Unit
Input indicators	Cultivated land input	Cultivated land utilization area	10,000 ha
	Labor input	Number of agricultural production labor force	10,000 persons
	Fertilizer input	Amount of chemical fertilizers applied	10,000 tons
	Plastic film input	Amount of agricultural plastic film used	10,000 tons
	Pesticide input	Amount of pesticides used	tons
	Agricultural machinery input	Total power of agricultural machinery	10,000 kW
Desirable output	Gross agricultural output	Gross agricultural output value	100 million CNY
Undesirable output	Carbon emissions	Carbon emissions from cultivated land use	10,000 tons

Current studies primarily consider sources of carbon emissions such as tillage, chemical fertilizers, pesticides, agricultural plastic film, irrigation, and the use of agricultural diesel fuel. Based on previous research [13,41], this study summarizes the emission factors in Table 2. The calculation formula for carbon emissions is shown in Equation (4):

$$E = \sum_{i=1}^{n} Ei = \sum_{i=1}^{n} TiCi \tag{6}$$

E denotes the total agricultural carbon emissions; *Ei* represents the total carbon emissions from different agricultural inputs; *Ti* indicates various carbon sources; *Ci* denotes the corresponding emission factors.

Table 2. Main emission factors of major carbon sources.

Carbon Source	**Tillage (kg/ha)**	**Chemical Fertilizer Application (kg/ton)**	**Agricultural Plastic Film Use (kg/ton)**	**Pesticide Use (kg/ton)**	**Agricultural Diesel Use (kg/ton)**	**Irrigated Cultivated Area (kg/ha)**
Emission Factor	3.126	895.6	5180	4934	593	25

2.5.2. Variables that Influence the Disparity of CLEE

To systematically identify the determinants of CLEE, this study draws on the existing literature and selects seven variables from four dimensions: level of economic development, rural infrastructure, resource endowment and natural disasters, and cultivated land utilization patterns.

(1) This study measures regional economic development level using the urbanization rate (the proportion of urban permanent residents in the total population). Urbanization can have a bidirectional impact on CLEE: its positive effects are reflected in industrial support for agriculture, technological spillovers, and improved mechanization [42]; its negative effects are manifested in the loss of agricultural labor, occupation of high-quality cultivated land, and land abandonment [43].

(2) Rural electrification level, measured by the natural logarithm of rural electricity consumption, is used as a proxy for rural infrastructure. Generally, access to electricity facilitates agricultural mechanization and the modernization of irrigation systems, enhances labor productivity, improves living conditions for farmers, and supports the dissemination of advanced technologies [44].

(3) For resource endowment and natural disasters, three variables are selected: per capita cultivated land resource, proportion of dry land, and crop disaster area. Per capita cultivated land resource is defined as the ratio of cultivated land area to agricultural employment population; adequate per capita land facilitates large-scale operations and mechanization, thereby increasing land output and efficiency [45], while scarcity of cultivated land may lead to overexploitation and constrain intensive development. The proportion of dry land (%) is measured as the share of dry land in total cultivated land area; dry land is generally characterized by harsher production conditions, weaker disaster resistance, and lower yield stability, which usually have negative implications for CLEE [46]. Crop disaster area is represented by the natural logarithm of affected area; natural disasters can potentially cause direct yield losses and damage rural infrastructure, thereby suppressing cultivated land use efficiency [47].

(4) Regarding cultivated land utilization, this study focuses on two variables: multiple cropping index and agricultural cropping structure. The multiple cropping index, defined as the ratio of total sown area to cultivated land area, reflects the level of intensive land use; higher values indicate more effective utilization of sunlight and thermal resources, increased output per unit area, and greater factor turnover efficiency, thus representing higher levels of intensification [48]. Cropping structure is measured by the share of grain sown area in total sown area; the effect of this variable may also be bidirectional: a higher grain share is conducive to food security but is associated with lower short-term economic returns [49], while an increased share of cash crops may improve income and efficiency [50], but must balance resource alignment and food security. The direction of impact may vary under different resource and market conditions and thus requires empirical identification.

2.5.3. Research Area and Data Source

This study takes 31 provincial-level administrative units in mainland China (excluding Hong Kong, Macao, and Taiwan) as the research area, using provinces as decision-making units (DMUs) and constructing a balanced panel dataset spanning 2000–2022. For the purposes of regional comparison and policy interpretation, the sample is divided into four major regions following the common classification of the National Bureau of Statistics: the Eastern region (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), Central region (Shanxi, Anhui, Jiangxi, Henan, Hubei, Hunan), Western region (Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang), and Northeastern region (Liaoning, Jilin, Heilongjiang). This spatial taxonomy captures regional heterogeneity in natural endowments, agricultural foundations, and factor allocation, thereby facilitating the analysis of temporal trends and regional disparities in CLEE. The sample period covers the pivotal phase of intensive agricultural modernization and green development policies in China since the start of the 21st century, allowing comprehensive depiction of long-term evolutionary trends. Data sources mainly include the China Statistical Yearbook (2001–2023), the respective provincial statistical yearbooks, and the CEIC database, among other authoritative statistical platforms, ensuring data consistency and traceability. Occasional missing values for a few years were imputed using linear interpolation. Descriptive statistics for the relevant indicators are presented in Table 3.

Table 3. Descriptive statistics of relevant variables.

Variable Type	Indicator (Unit)	Symbol	Mean	Std. Dev.
Input indicators	Cultivated land area (10,000 ha)	I_1	384.68	301.74
	Total power of agricultural machinery (10,000 kW)	I_2	2834.70	2714.58
	Amount of chemical fertilizers applied (10,000 tons)	I_3	171.05	136.52
	Amount of agricultural plastic film used (10,000 tons)	I_4	3.80	3.87
	Amount of pesticides used (tons)	I_5	49,560.49	41,414.19
	Number of agricultural employees (10,000 persons)	I_6	469.06	374.19
Desirable output indicator	Gross agricultural output value (100 million CNY)	O_1	1334.33	1269.05
Undesirable output indicator	Carbon emissions from cultivated land use (10,000 tons)	O_2	24.10	17.93
Determinant variables	Urbanization rate (%)	UR	0.507	0.168
	Rural electrification level	REL	13.607	1.542
	Per capita cultivated land resource (ha/person)	PCCLR	1.053	0.800
	Proportion of dry cultivated land area (%)	PDCLA	0.460	0.251
	Disaster area of affected crops	DAAC	13.115	1.631
	Multiple cropping index	MCI	1.418	0.513
	Agricultural planting structure (%)	APS	0.657	0.136

3. Results and Discuss

3.1. Calculation and Comparison of CLEE

The inputs, desirable outputs, and undesirable outputs of each provincial-level administrative unit (DMU) were input into the MAXDEA software, and the non-oriented EBM model was employed to measure the CLEE for 31 provincial-level administrative units in China from 2000 to 2022. To facilitate the observation of spatiotemporal evolution, annual CLEE change curves for China and the four major regions were plotted based on the measurement results (see Figure 1).

From an overall perspective, CLEE in China exhibited a sustained upward trend from 2000 to 2022, rising from 0.269 in 2000 to 0.877 in 2022—an increase of 2.26 times, with an average annual growth of 0.026. This overall progress reflects the synergistic effects of agricultural modernization, technological advancement, and policy support, providing crucial backing for national food security and promoting the sustainable development of agriculture.

By region, the eastern area has maintained a leading position, increasing from 0.325 to 0.977, benefitting from a robust economic foundation, high technology adoption rates, and well-developed infrastructure. The central region had the lowest starting point (0.175), but showed relatively rapid growth, reaching 0.865 in 2022—an increase of approximately 3.94 times. This reflects significant achievements and potential in policy support and technology introduction. The western region rose from 0.290 to 0.842, achieving steady improvement under natural constraints through moderate-scale management and characteristic agriculture. The northeast increased from 0.188 to 0.709, showing relatively slow progress; as a traditional agricultural area, it still has considerable room for improvement, necessitating further efficiency gains through optimizing cropping structure and strengthening technological applications.

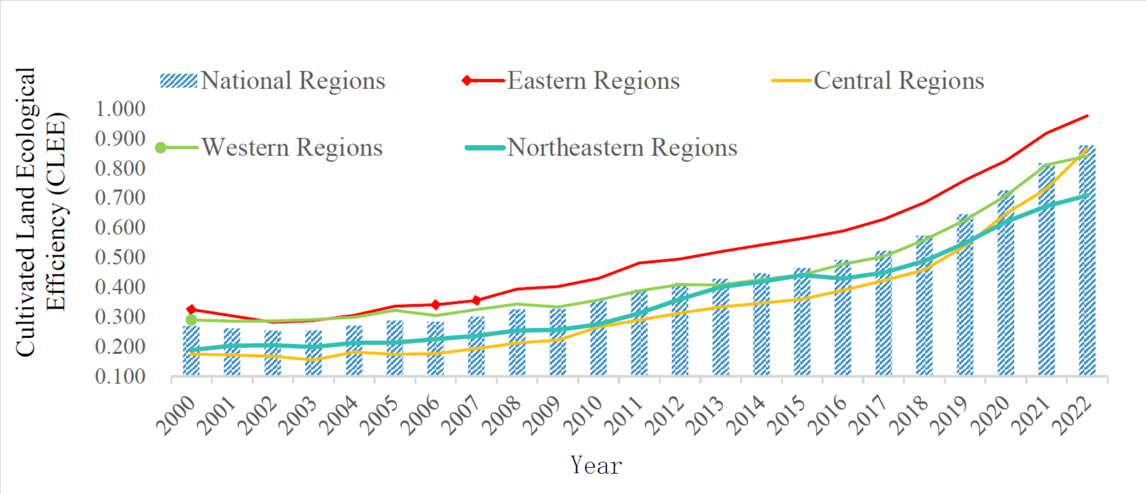

Figure 1. Changes in cultivated land ecological efficiency in China and its major regions.

According to the rate and magnitude of efficiency changes, the period from 2000 to 2022 can be divided into three distinct phases: (1) 2000–2010: Slow Improvement Phase. Both the national average and the four major regions saw limited efficiency gains, with an average annual increase of approximately 0.009. During this phase, agricultural mechanization and modernization were still in the initial and ramp-up stages, and related policy and technology dissemination were being launched and refined; (2) 2010–2015: Acceleration Phase. The national average annual increase reached about 0.022, with particularly notable progress in the central and western regions. Key drivers included accelerated agricultural modernization, the spread of high-yield and high-quality crop varieties, improved mechanization, and the adoption of precision agriculture technologies; (3) 2015–2022: Rapid Take-off Phase. During this period, CLEE at the national and regional levels entered a stage of rapid growth, with the national average annual increase rising to 0.059 (6.8 times that of the 2000–2010 phase).

Although substantial progress has been made nationwide in CLEE, regional disparities remain. In 2022, the national average efficiency reached 0.877, still falling short of the optimal value of 1, indicating the persistence of efficiency losses and room for improvement in cultivated land use. The gap between the eastern region and the central, western, and northeastern regions has narrowed, but significant differences in infrastructure, resource endowment, and development level persist. Reflecting on the period from 2000 to 2022, the marked improvement in CLEE highlights the remarkable achievements of China's agriculture. In the future, further efforts are required to optimize agricultural structure, promote green and sustainable development, intensify technological innovation and policy support, and continuously enhance CLEE to realize high-quality agricultural development.

3.2. Analysis of the Distributional Characteristics of Cultivated Land Ecological Efficiency

Cultivated land resources form the foundation for food production and sustainable agricultural development. Against the backdrop of rapid industrialization and urbanization, improving CLEE has become a key driver for achieving high-quality agricultural development. This section utilizes kernel density estimation to investigate the dynamic evolution of CLEE across 31 provinces in China from 2000 to 2022. By characterizing the trajectories of efficiency distribution and dissecting the evolution of regional disparities, this analysis provides important practical implications for formulating evidence-based policies on cultivated land protection and management, and for promoting green and efficient agricultural development.

To comprehensively capture the trends in CLEE, this study employs equidistant sampling with 2000 as the base year and five-year intervals, selecting six time points: 2000, 2005, 2010, 2015, 2020, and 2022 for analysis. Using Stata 16 software, kernel density estimation curves were generated for the CLEE of 31 provinces in each selected year, visually displaying their distributional patterns and dynamic evolution. The horizontal axis of the kernel density curves represents efficiency values, while the vertical axis indicates kernel density. The relevant results are depicted in Figure 2.

According to the kernel density estimation results, the main peak of CLEE distribution was located in the lower efficiency range during 2000–2010, indicating a generally low national efficiency level. After 2015, the main peak shifted markedly to the medium-high efficiency range, reflecting a significant improvement in CLEE from 2015 to 2022, which could be attributed to the ongoing progress of agricultural modernization as well as technological advancements driving rapid increases in agricultural mechanization and informatization, thus effectively facilitating improvements in CLEE. In the vertical dimension, the kernel density curves also underwent changes: from 2005 to 2015, the peak value decreased and the curve became notably flatter, signaling a divergence in CLEE. In 2020 and 2022, the curve's peak rose again; although the tails at both ends did not fully converge, the distribution as a whole exhibited a certain degree of agglomeration.

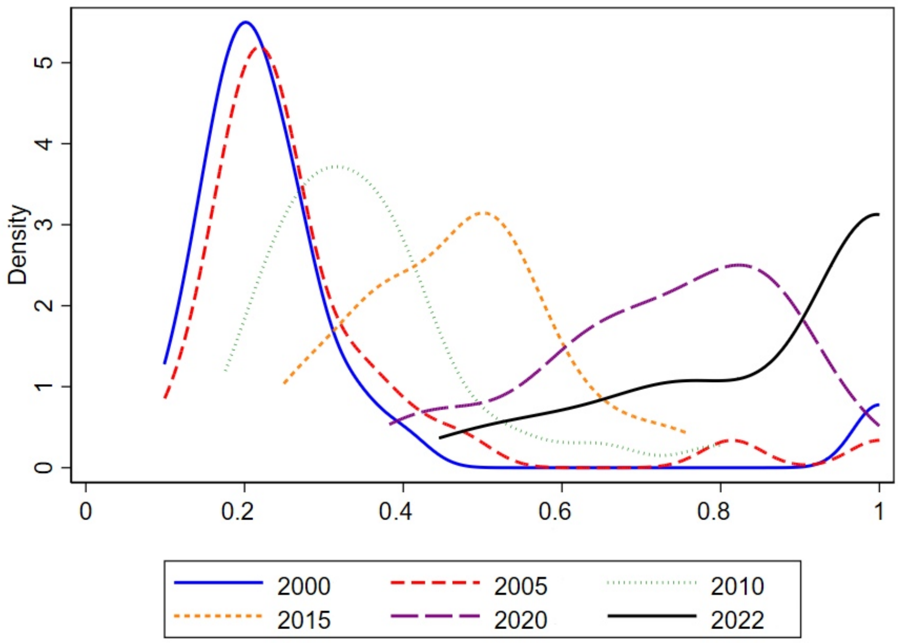

Figure 2. Kernel density analysis results of cultivated land ecological efficiency in China.

To further analyze the changing trends of CLEE in different subregions of China, kernel density estimation was separately conducted for the eastern, central, and western regions. The northeastern region was excluded from separate kernel density analysis due to its small number of provinces.

Through analysis of Figure 3, it can be observed that the eastern region's CLEE followed a transformation path from "low-level dispersion" to "high-level concentration." In terms of the main peak position, the primary peak was located in the low-efficiency interval during 2000–2010, but shifted markedly to the high-efficiency range after 2015, reflecting an overall leap in efficiency. This transformation could be attributed to optimized resource allocation and improved institutional environment driven by economic development. Changes in curve shape reveal the dynamic evolution of intra-regional disparities: from 2000 to 2015, the curves were flat with relatively low peaks, indicating substantial interprovincial efficiency differences. During 2020–2022, the curve became sharply peaked and unimodal, with tails on both sides greatly shortened, signaling an accelerated convergence of internal efficiency. Particularly after 2015, the curve became slim and tall, displaying pronounced convergence, suggesting that coordinated regional development strategies may have effectively narrowed interprovincial efficiency gaps. The long right-hand tail during 2000–2015 indicates that a few high-efficiency provinces raised the overall level, while the shortened left-hand tail after 2015 and the sharp reduction in the area of the low-efficiency range indicate the gradual elimination of efficiency "troughs" in the eastern region. The underlying drivers of these changes could include: (1) rapid economic growth providing a solid material and technological foundation for agricultural modernization; (2) progress in agricultural science and technology facilitating the optimized allocation and intensive use of production factors; (3) continual improvement of cultivated land protection systems, creating a favorable institutional environment for efficiency enhancement; and (4) regional integration strategies promoting technology diffusion and knowledge sharing, thus accelerating the catch-up process in lagging areas.

Based on Figure 4, For the central region, judging from the shifts in the main peak of the kernel density curves, the primary peak was in the low-efficiency interval (0.1–0.3) during 2000–2010, but significantly moved to the higher efficiency range (0.3–0.9) after 2015, indicating a marked improvement in CLEE overall. According to the efficiency calculation results, the average CLEE in the central region ranged from 0.175 to 0.266 during 2000–2010, and rapidly increased to 0.360–0.865 after 2015. Between 2000 and 2010, the curve was sharply peaked and positioned to the left, indicating that overall CLEE was low but with relatively small interprovincial disparities. In 2015, the main peak shifted rightward and became somewhat flatter, with longer tails on both sides, reflecting a rise in overall CLEE accompanied by growing disparities between provinces. From 2020 to 2022, the curve shifted further to the right and the tails elongated, suggesting continued improvement in CLEE as well as an increasing dispersion and widening differences among provinces. Over the entire study period, the distribution of CLEE in the central region evolved from "low-level concentration" to "high-level dispersion." Potential contributors to this evolution could include: (1) the implementation of the Central China Rising strategy, injecting fresh impetus into the region's economic and social development; (2) advancements in market-oriented allocation reform of production factors, improving resource allocation efficiency; and (3) progress in agricultural technology and modernization, raising cultivated land ecological efficiency.

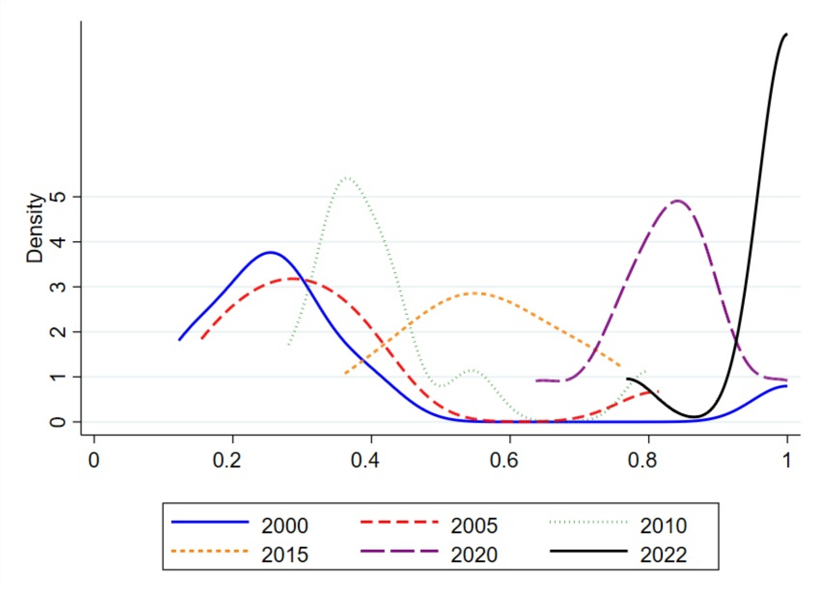

Figure 3. Kernel density analysis results of cultivated land ecological efficiency in Eastern China.

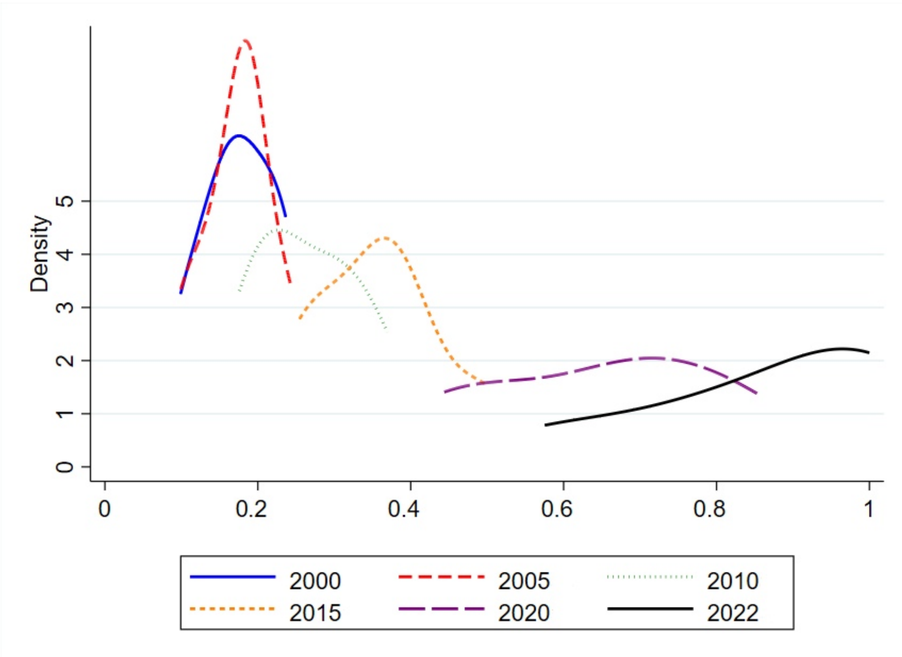

Figure 4. Kernel density analysis results of cultivated land ecological efficiency in Central China.

As shown in Figure 5, in the western region, the kernel density curves consistently shifted to the right. In 2000 and 2005, the main peak was located within the 0.2–0.4 efficiency range; by 2010, it had moved to the 0.3–0.4 range; in 2015, it further shifted to the 0.4–0.5 range; and by 2020 and 2022, the main peak had entered the high-efficiency range of 0.7–0.9. Comparing the shapes of the kernel density curves over the years reveals that during 2000–2005, the curves had a long right tail and displayed a bimodal pattern, indicating substantial dispersion.

After 2010, the curves became increasingly peaked, reflecting a trend toward concentration, with narrowing efficiency disparities among regions and a shift toward more balanced development.

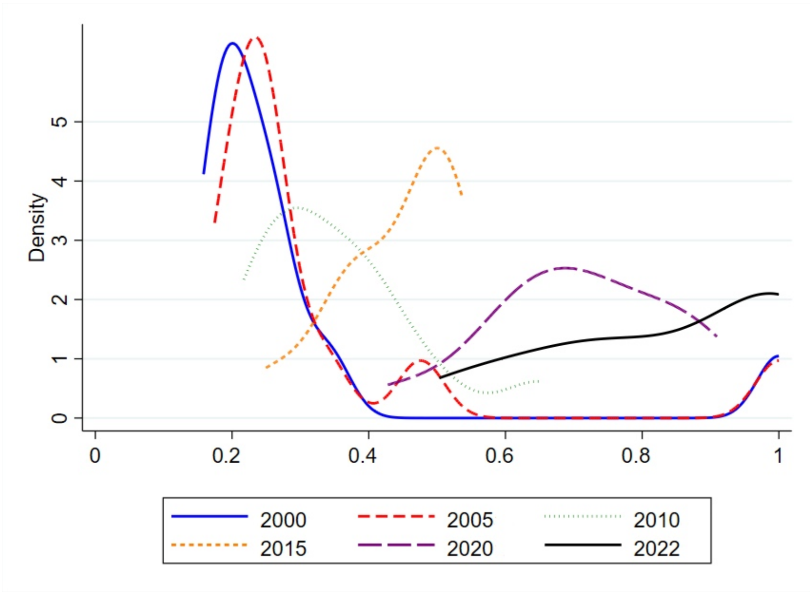

Figure 5. Kernel density analysis results of cultivated land ecological efficiency in Western China.

3.3. Results of σ-Convergence Analysis

The calculated trend of the coefficient of variation for national cultivated land ecological efficiency in China from 2000 to 2022 is illustrated is illustrated in Figure 6.

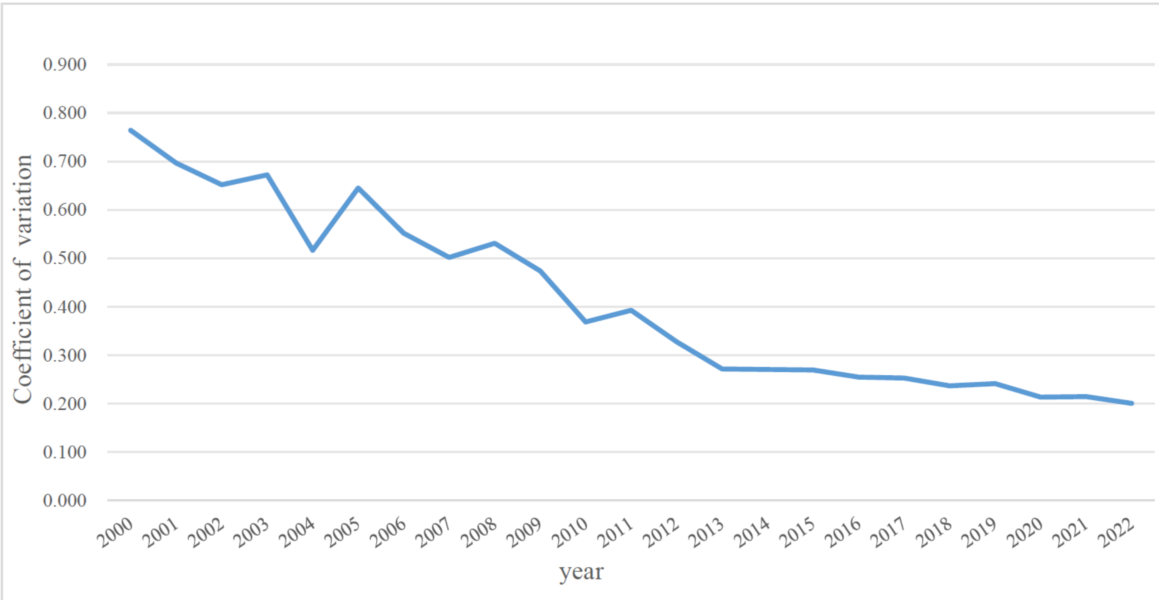

Figure 6. Fluctuations in the coefficient of variation of national CLEE.

It can be observed that the coefficient of variation for national CLEE declined markedly from 0.764 in 2000 to 0.201 in 2022, indicating significant σ-convergence. This suggests an overall narrowing of regional disparities and a trend toward more balanced allocation of cultivated land resources.

This process can be divided into three stages: a rapid decrease from 2000 to 2004 (0.764 decreased to 0.517), a fluctuating decline from 2004 to 2009 (0.517 decreased to 0.474), and a sustained decrease after 2009 (0.474 decreased to 0.201).The sustained convergence since 2009 may be mainly attributed to two factors: first, increased national support for agricultural modernization, which improved production conditions in the central and western regions and narrowed the gap with the eastern region; and second, the development of region-specific, high-efficiency agriculture, which has facilitated the optimization of cultivated land resource allocation.

Based on the calculated coefficients of variation and trend charts for CLEE in the eastern, central, western, and northeastern regions of China from 2000 to 2022 (Figure 7), it is evident that the differences in CLEE across regions have exhibited distinct patterns of change.

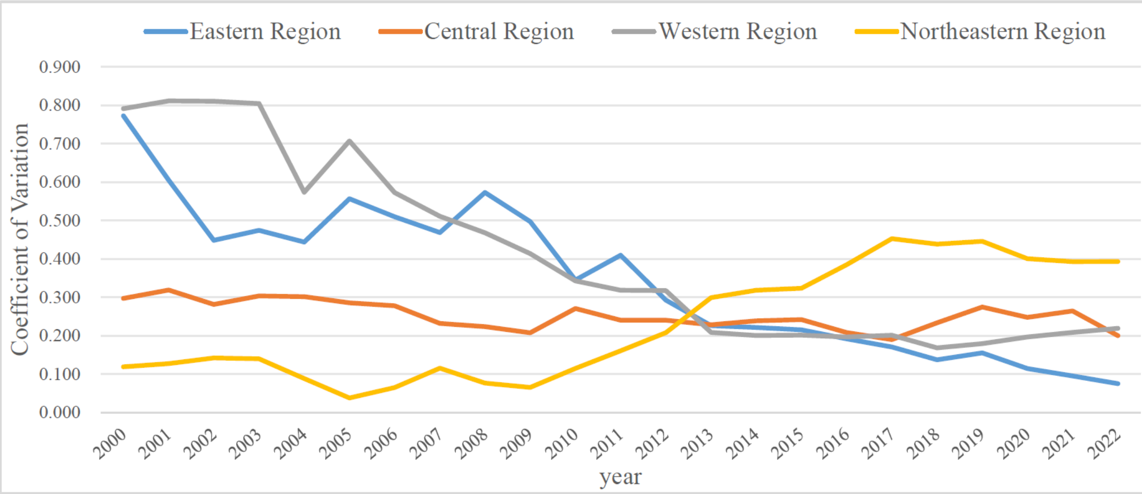

Figure 7. Fluctuations in the coefficient of variation of CLEE in each sub-region of China.

From a regional perspective, the four major regions exhibit distinct characteristics:

In the eastern region, the coefficient of variation decreased from 0.773 to 0.075, indicating a pronounced σ-convergence. This can be attributed to the region's higher levels of economic development, agricultural modernization, and close interregional cooperation. In the western region, the coefficient of variation dropped from 0.791 to 0.219, also demonstrating clear convergence, likely as a result of ongoing national agricultural support policies that have promoted efficiency convergence among provinces. In the central region, the coefficient of variation declined during 2000–2010 but subsequently fluctuated upward, reaching 0.200 after 2010, suggesting that the trend of convergence was unstable. In the northeastern region, the coefficient of variation increased from 0.119 to 0.393, displaying σ-divergence, which may be related to the widening disparities in production conditions among Heilongjiang, Jilin, and Liaoning provinces due to extreme weather events.

3.4. Influencing Factors of the Disparity of CLEE

This study employed the LR test to assess the appropriateness of the model. The LR test results strongly reject the null hypothesis (Prob ≥ chibar^2 = 0.000), supporting the choice of a random effects panel Tobit model over a pooled Tobit model. For comparative purposes, alongside the random effects panel Tobit regression, we also estimated a random effects OLS model and a pooled Tobit model. Model 1 represents the random effects OLS specification, Model 2 corresponds to the pooled Tobit model, and Model 3 is the random effects panel Tobit model. The regression results are presented in Table 4 below.

The estimation results of Model 3 indicate that all seven explanatory variables pass the significance tests, with signs consistent with theoretical expectations, thereby supporting the validity of the study's theoretical framework. The detailed interpretation is as follows:

Economic development & infrastructure: UR has a coefficient of 0.599 (significant at 1%), the largest among all variables, suggesting that its positive effects (industrial support for agriculture, technological spillovers, mechanization) currently outweigh its negative effects (loss of agricultural labor, land occupation). This implies that, at this stage of development, UR plays a dominant role in promoting CLEE by optimizing factor allocation and facilitating technology diffusion. REL has a coefficient of 0.0223 (significant at 5%). Although modest in magnitude, its mechanism is clear—it improves efficiency by enabling the substitution of machinery for manual labor and enhancing irrigation systems, providing an economics-based rationale for upgrading rural power grids.

Resource endowment & natural conditions: PCCLR has a coefficient of 0.142 (significant at 1%), confirming the efficiency advantages of large-scale operations, but the relatively small magnitude suggests it needs to be complemented by technological progress. PDCLA exerts the strongest negative effect (−0.355, significant at 1%), highlighting the rigid constraints of adverse natural conditions—dry land yields less, has poorer stability, and limits the scope for mechanization and intensification. DAAC has a coefficient of −0.0734 (significant at 1%), capturing multiple negative impacts of disasters: in addition to direct yield losses, they disrupt production continuity and increase operational uncertainty, which can discourage long-term investment and cause cumulative efficiency losses.

Table 4. Regression results of cultivated land ecological efficiency in China.

Variable	Model		
	1	2	3
REL	0.0183	0.0190	0.0223 **
	(0.020)	(0.018)	(0.010)
UR	0.527 ***	0.142	0.599 ***
	(0.113)	(0.173)	(0.057)
PCCLR	0.132 ***	0.0922 ***	0.142 ***
	(0.039)	(0.033)	(0.015)
DAAC	−0.0774 ***	−0.0962 ***	−0.0734 ***
	(0.011)	(0.018)	(0.007)
PDCLA	−0.111	0.0456	−0.355 ***
	(0.124)	(0.111)	(0.106)
MCI	0.0793 ***	0.0930 ***	0.0759 ***
	(0.021)	(0.031)	(0.018)
APS	−0.275	−0.257	−0.354 ***
	(0.168)	(0.214)	(0.091)
_cons	0.915 ***	1.289 ***	0.930 ***
	(0.275)	(0.316)	(0.186)
N	713	713	713

Note: Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Land use practices: MCI has a coefficient of 0.0759 (significant at 1%), confirming the positive role of intensive use, though its relatively small magnitude suggests that excessive multiple cropping under current technological conditions may risk soil fertility depletion and increased pest/disease incidence. APS shows a significant negative effect (−0.354, significant at 1%), comparable in magnitude to PDCLA, revealing a structural trade-off in Chinese agriculture between "food security" and "economic efficiency." While grain crops are essential for national security, they offer relatively low economic returns. This result provides empirical support for applying differentiated subsidy policies to balance security and efficiency objectives.

Overall, the empirical results align with theoretical expectations and yield three additional key insights: (1) Technological and institutional factors (UR and REL) have surpassed resource endowment as the primary drivers of efficiency improvement; (2) Natural constraints (PDCLA and DAAC) remain critical bottlenecks for CLEE, requiring targeted interventions through engineering and technological measures; and (3) Adjusting cropping structures (APS) entails deep-seated trade-offs, calling for innovative policy instruments that can reconcile food security with economic efficiency.

4. Conclusions and Policy Implications

4.1. Conclusions

Drawing on panel data from 31 Chinese provinces over the period 2000–2022, this study measured CLEE using an EBM-DEA model that incorporates undesirable outputs, depicted its dynamic evolution via kernel density estimation, and identified key determinants through Tobit regression analysis. The main conclusions are as follows:

First, CLEE in China has exhibited a sustained upward trajectory, but substantial room for improvement remains. The national CLEE increased from 0.269 in 2000 to 0.877 in 2022, with an average annual growth of 0.027. Notably, the post-2015 period marked an acceleration phase, with the annual rate of increase reaching 6.8 times that of the earlier phase. This remarkable progress reflects the combined effects of accelerated agricultural modernization, wider adoption of green production technologies, and intensified policy support. Nevertheless, the current efficiency level remains 12.3% below the production frontier, indicating considerable potential for further gains through factor allocation optimization and technological advancement.

Second, while pronounced regional disparities persist, a convergence trend is emerging. The eastern region has consistently maintained a leading position (reaching 0.977 in 2022); the central region, although starting from the lowest base, recorded the fastest growth (a 3.94-fold increase); and the western and northeastern regions improved steadily but remain relatively lagging. Kernel density analysis reveals that the efficiency distribution has transitioned from a bimodal to a unimodal pattern, with the primary peak shifting steadily rightwards and the number of low-efficiency provinces declining significantly. This suggests a narrowing of interregional efficiency gaps, although uneven development remains an issue.

Third, multiple factors jointly drive improvements in CLEE. Tobit regression results indicate that UR, PCCLR, MCI, and RELexert statistically significant positive effects on CLEE, whereas PDCLA, APS, and DAAC have significant negative impacts. These findings underscore the importance of advancing CLEE through an integrated approach that combines technological progress, structural optimization, and risk management.

4.2. Policy Implications

Based on the above conclusions, the following policy recommendations are proposed:

(1) Implement differentiated regional development strategies to foster coordinated improvement. The eastern region should leverage its advantages in technological innovation to establish modern agricultural demonstration zones, explore frontier models such as smart agriculture and precision farming, and drive development in the central and western regions through technology transfer and experience sharing. The central region should capitalize on its plains to accelerate agricultural mechanization and large-scale farming, consolidating its role as the primary grain-producing area. The western region should focus on improving dryland production conditions by promoting water-saving irrigation technologies and drought-resistant varieties, and developing specialty ecological agriculture. The northeastern region should strengthen black soil protection, optimize cropping structures, and fully harness the production potential of its commercial grain bases.

(2) Strengthen agricultural infrastructure to enhance resilience. Expedite the upgrading of rural power grids to increase the electrification level of agricultural production. Advance the construction of high-standard cultivated land, improve water conservancy facilities, and establish comprehensive monitoring and early-warning systems for agricultural meteorological disasters. Expand the coverage of policy-based agricultural insurance to reduce the impacts of natural disasters on production, thereby providing a stable environment for efficient land use.

(3) Optimize cultivated land use practices to drive green transformation. Increase the multiple cropping index in accordance with local conditions, while moderately adjusting cropping structures under the premise of ensuring food security. Promote technologies such as soil testing and formulated fertilization, integrated water and fertilizer management, and green pest control to reduce chemical fertilizer and pesticide usage. Strengthen the recycling system for agricultural plastic films, advance the resource utilization of crop straw, and build a low-carbon circular model for cultivated land use.

4.3. Limitations and Future Research

This study has several limitations. First, due to data availability constraints, the analysis relies on provincial-level panel data, which may mask intra-provincial heterogeneity; future research could employ county-level or farm household microdata for more granular insights. Second, the efficiency measurement primarily incorporates carbon emissions as the sole undesirable output, without fully accounting for other ecological indicators such as non-point source pollution and soil degradation, which may result in estimation bias.

Future research could be extended in several directions: (1) incorporating spatial econometric models to examine spatial correlations and spillover effects of CLEE, thereby uncovering interregional interaction mechanisms; (2) applying dynamic DEA or the Malmquist productivity index to decompose efficiency change into technological progress and technical efficiency components, identifying the primary drivers of improvement; (3) integrating machine learning methodologies to develop predictive models of efficiency, offering forward-looking references for policy formulation.

Author Contributions

M.L.: conceptualization, methodology, software, validation, formal analysis and resources; Y.L.: investigation; Y.L. and F.Y.: data curation; Y.L., F.Y. and C.Z.: writing—original draft preparation; H.C.: writing—review and editing; Z.Z.: visualisation; M.L.: supervision, project administration and funding acquisition. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used DeepSeek to assist with translation and language polishing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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