Measurement, Distribution Characteristics and Regional Differences Analysis of Eco-efficiency Development in Tobacco Planting Zone

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Abstract: The positive development of ecological efficiency is of great significance for the high quality synchronization development of economy and ecological environment. In order to study the temporal and spatial distribution dynamics and regional differences of the ecological efficiency of tobacco planting zone in China, the Super-SBM model was used to calculate the ecological efficiency of provincial tobacco planting zone in China from 2005 to 2019 from economic perspective, and the kernel density function, Gini coefficient, σ convergence and Markvo transition matrix were used to analyze the dynamics of spatial distribution and regional differences in this paper. The research results show that: (1) China's overall ecological efficiency exhibits a U-shaped curve, i.e., decreased first and then increased. (2) The overall difference in eco-efficiency of tobacco planting zone is large, which is mainly originated from the inter-regional differences and hypervariable density. (3)The eco-efficiency development of tobacco planting zone in China does not have the characteristics of convergence, resulting in differences in spatial distribution. (4) The national and regional eco-efficiency of tobacco planting zone has the greatest transfer probability from year t to year t+1 in the same level of eco-efficiency.

Key words: Ecological efficiency of tobacco planting zone; Super-SBM; Gini Coefficient; Markov chain

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INTRODUCTION

At present, as a driving force for the harmonious coexistence between man and nature, the building of beautiful country, the service of people's livelihood, and the achievement of sustainable and highquality development, ecological system with its improvement in quality and stability has attracted the attentions of governments in the world.During the recent 40 years of long-term rapid economic and social development, the great achievements in economy, sci-tech and other fields of all countries have resulted in the consumption of abundant natural resources, and serious global ecological environment pollution, especially in the tobacco planting zone, such as global warming, smog, water pollution, heavy metals contaminated soil, etc., thus affecting people's physical and mental health in all countries.The environmental performance index published by Yale University shows the serious pollution in all over the world [1]. In the background of undetermined economic policy, China as a developing country in a critical period of economic and social development is a tobacco planting country, it is urgent to comprehensive measure eco-efficiency level to accelerate high-quality social developmentand promote global green development.

As an important concept developed by OECD in 1998 to express the relationship between economic development and ecological development, the term ecological efficiency firstly proposed by Schaltegger and Stum[2] specifically refers to that obtain certain economic output by taking resources and capital as input, but with less production of negative environmental impact. In order to explore the relationship between economic and ecological development, some pioneering studies have been focusing on the spatial-temporal changes and influencing factors of eco-efficiency. For example, Hashim et al. analyzed the eco-efficiency differences of East China, Central and West China[3]. Dong et al. built ecological efficiency evaluation model to measurethe eco-efficiency level of China, and analyzethe difference of regions[1]. Yasmeen et al. found that the eco-efficiency in the EastChina is higher than that in the Central China and West China from 2008 to 2018, as well as the positive impact of environmental regulation on China's eco-efficiency[4]. Moreover, Han et al. evaluatedthe eco-efficiency central plains urban agglomeration in China from 2003 to 2016, showing that the eco-efficiency is higher in the North China and the South China, but lower in the middle[5]. Wang et al. analyzed the reasons of environmental regulation affecting the difference of ecological efficiency of urban agglomeration [6]. The literature review shows that most studies on China' eco-efficiency are conducted on the East, Central and Western China, economic regions [7], and industrial parks [8], or cities [9] and urban agglomerations [10, 11], but few studies take the six geographic regions of tobacco planting as decision-making units (DMU). With the gradual revocation of administrative regions in the process of national development, six geographic regions of tobacco planting still have the regional characteristics in economy and culture, so it is of practical significance for the balanced development and improvement of eco-efficiency to study the development level and change law of ecological efficiency and the differences in six geographical regions.

As we have known, tobacco is an important economic crop[12,13], however, large-scale tobacco planting would destroy the natural resource system of the land,inducing the transformation of productive land into wasteland.Specifically, the longer growth and maturity period of tobacco can consume more soil nutrients. Moreover, large amounts of chemical fertilizers can also make the soil compact for production. When tobacco is processed and cured, 1 hm2 of tobacco leaves consumes 3 hm2 of woodland. A large number of trees have been felled and a large number of soils have been compacted, which will lead to serious soil erosion and environmental problems. On the other hand, the roasting process for tobacco produces hazardous gas such as CO_2 and CO, which can affect air quality. Also, it is notable that flue-cured tobacco is in particular cultivated more concentrated.

The tobacco planting is widely distributed in China, from about 75° to 134° east longitude and from18° to 50° north latitude, covering 907 zones in 23 provinces. The main plant areas include Yunnan, Guizhou, Henan, Hunan, Sichuan, Hubei, Chongqing, etc. Compared with flue-cured tobacco, the plantingzones of sun-cured tobacco are relative dispersed, in which Guangxi, Xijiang, Hunan, and Hubei have larger plant area.As another important tobacco sort, the planting area of burley tobacco is the largest in Hubei, followed by Chongqing, Yunnan, Sichuan, and Hunan. Moreover, oriental tobacco is cultivated mainly in Yunnan,Zhejiang, Xinjiang, and Hubei. Thus, the ecological efficiency of tobacco planting zone can be seriously affected by the tobacco planting. Though the ecological civilization construction drives the development and upgrading of tobacco related industry, Chinais bound to cause a certain degree of environmental pollution, and some ecological and environmental problems have been gradual exposedwith excessive pursuit of economic development, especially in the tobacco planting zone. The study of eco-efficiency of tobacco planting zone in China would help practicingthe concept of green ecological development, accelerating the exploration of environmental protection and resource conservation with technological innovation, and making green development an important way to improve quality and efficiency for tobacco industry.

The current eco-efficiency evaluation is mostly conducted by data envelopment analysis (DEA) which was firstly proposed in 1978[14]. As a nonparametric estimation method, DEA method can avoid the impact of subjective factors by its characteristics of simplified algorithm and less error [15], and has the strong advantages in dealing with the same type of decision-making unit (DMU) with multiple input and multiple output. Based on the continuous expansion and optimization of DEA model, the more targeted CCR, BCC, SBM and other models have been developed to achieve the better application in the research of medical treatment [16], finance [17], ecological environment [18, 19] and other fields. The existed literature are mainly on the ecological suitability evaluation of tobacco planting areas, there are few results on the eco-efficiency evaluation of tobacco planting areas from the economic perspective. In this paper, the undesirable output-based Super-SBM model was adopted to study on the eco-efficiency measurement and analysis by taking 30 provinces in China as DMU when the return on scale is variable. At the same time, the temporal and spatial evolution and distribution characteristics as well as the regional differences of China's provincial eco-efficiency about tobacco planting in the six geographic regions werefurther explored, so as to deeply reveal the difference source and transfer laws of inter-regional and intra-regional eco-efficiency by introducing statistical analysis methods such as kernel density function, Gini coefficient and Markov chain, which may provide somenew research interest and reference for the development of eco-efficiency in China and other countries.

RESEARCH METHOD AND DATA SOURCES

Research method

Construction of index system

The newest planting zone division of tobacco in China was carried out in 2003 under the leadership of the National Tobacco Monopoly Administration. There are two division types, i.e., ecological type division and regional division. According to the general principles of ecological type zones, flue-cured tobacco planting zones was usually divided into 4 areas according to the flue-cured tobaccoecological suitability.On the other hand, the regional division adopts the secondary zoning system, 5 first-level tobacco plantingzones and 26 second-level tobacco planting zones been divided. To compute the eco-efficiency development level of tobacco planting zone, the eco-efficiency evaluation index system which can be found in Table 1 on the basis of the input-output framework in this study is established by referring to the eco-efficiency evaluation indexes in the previous studies 20-27. The input includes three primary indexes, namely, labor force, capital and resource, while the output includes two primary indexes, namely, desirable output and undesirable output.

Table 1
Eco-efficiency evaluation index system and the computational methods

Index system	Primary index	Secondary index
Input	Labor input	Urban unit employment/10 thousand people
	Capital input	Total investment in fixed assets/100 million yuan
	Resource input	Energy consumption (coal consumption/10 thousand tons)
		Water consumption (Total water supply/100 million tons)
		Land resource (Built-up area/ square kilometer)
Output	Desirable output	Total GDP/100 million yuan
	Undesirable output	Sulfur dioxide emissions/10 thousand tons

	Carbon dioxide emissions/ton
	Total wastewater discharge/10 thousand tons

Evaluation model

On the basis of DEA, SBM has been further proposed to solve the deviation and influence caused by radial and angle selection. However, in practical applications, there exist some cases unable to be compared with each othersince the decision efficiency of multiple units valued as 1. Consequently, Super-SBM model was developed by the combination of DEA model and SBM model[28], which contains undesirable output linear programming formula as Eqs. (1) and (2),

$$\min \rho = \frac{1\text{-}\ \frac{1}{n}\sum_{i=1}^{n}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1} s_r^+ \Big/ y_{rk} + \sum_{t=1}^{q_2} s_t^{b-} \Big/ y_{tk}\right)} \tag{1}$$

$$s.t.\begin{cases} x_k = X\lambda + s^-, y_k = Y\lambda - s^+, b_k = b\lambda + s^{b-} \\ \lambda, s_i^-, s_r^+, s_t^{b-} \geq 0 \end{cases} \tag{2}$$

in which, ρ = Eco-efficiency value;

n = Number of input indicators;

q_1 = Number of desirable output indicators;

q_2 = Number of undesirable output indicators;

x_{ik} = The i–th input indicator of the k–th decision unit;

y_{rk} = The r–th output indicator of the k–th decision unit;

y_{tk} = The t–th output indicator of the k–th decision unit;

X, Y and b = input-output vector matrix;

λ = weight vector;

s_i^-, s_r^+ and s_t^{b-} = slack variables of input and output.

Analysis method

Convergence analysis

In this paper, the variation coefficient method was used in the convergence test conducted on China's regional eco-efficiency (i.e., σconvergence)[29], with the specific formula as follows:

$$\sigma = \frac{\overline{x}_i}{\mu_i} \tag{3}$$

in which,

$\overline{x}_i$ =The mean value of regional eco-efficiency value in the i–th year;

μ_i =The standard deviation of regional eco-efficiency value in the i–th year.

Regional eco-efficiency model

For computing the regional eco-efficiency index, the linear weighting model will be constructed through computing the entropy weighting of each indicator. The detailed calculated formulas of the regional eco-efficiency index can be used the following Eqs. (3)-(9).

Entropy method for determining the weight of each province

Firstly, the characteristic specific weight pij of the j–th province's eco-efficiency within the region in the i–th year is calculated as follows:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{4}$$

where, xij denotes the eco-efficiency of the j–th province within the region in the i–th year.

Secondly, we calculate the entropy value of the j–th province within the region by the following formula:

$$e_j = -k\sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right) \tag{5}$$

where, k is usually chosen as lnm.

Thirdly, the information utility value of the j–th province within the region can be computed as follows:

$$g_j = 1 - e_j \quad (6)$$

Finally, we can obtain the weight of the j–th province within the region as follows:

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \quad (7)$$

Model for calculating the regional eco-efficiency

In this paper, the eco-efficiency REEki of the k-th region in the i-th year will be calculated by the following linear weighting model:

$$REE_{ki} = \sum_{j=1}^{n} x_{ij} \times w_j \quad (8)$$

where, xij denotes the eco-efficiency of the j–th province within the region in the i–th year.

Kernel density function

In this study, we will use the kernel density estimation method to analyze the distribution shape of the regional eco-efficiency. The kernel density estimation is a non-parametric method which is usually used to analyze distribution characteristics of samples by using continuous density curves[30]. Assume that x is a random variable, then the probability density function f(x) can be estimated by the following formula:

$$f(x) = \frac{1}{ph} \sum_{i=1}^{p} K\left(\frac{y_i - \bar{y}}{h}\right) \quad (9)$$

where, p=Number of samples, h=Bandwidth, yi denotes the independently distributed observations, $\bar{y}$ denotes mean value, the Kernel density function K(·) is usually chosen as the following Gaussian kernel function:

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \quad (10)$$

Gini coefficient

Since the Gini coefficient is usually used to analyze income or wealth distribution as an important tool, Dagum decomposed Gini coefficient also called Dagum's Gini coefficient as within-group inequality, the net contribution of between-group inequality and the intensity of the "transvariation" between subgroup to measure inequality difference between and within subgroups[31]. In this study, we will use Dagum's Gini coefficient to measure the inter-regional and intra-regional differences of regional the co-efficiency index as well as hypervariable density, the detailed calculation formulasare listed as follows:

$$G = \frac{\sum_{i=1}^{k}\sum_{m=1}^{k}\sum_{j=1}^{n_i}\sum_{r=1}^{n_m}\left|y_{ij} - y_{mr}\right|}{2n^2\mu}, \mu_m \le \cdots \le \mu_i \le \cdots \le \mu_k \quad (11)$$

$$G_{ii} = \frac{\sum_{j=1}^{n_i}\sum_{r=1}^{n_i}\left|y_{ij} - y_{ir}\right|}{2n_i^2\mu_i} \quad (12) \qquad G_{im} = \frac{\sum_{j=1}^{n_i}\sum_{r=1}^{n_m}\left|y_{ij} - y_{mr}\right|}{n_i n_m(\mu_i + \mu_m)} \quad (13) \qquad G = G_w + G_{nb} + G_l,\ G_{gb} = G_{nb} + G_l,$$

$$G_w = \sum_{i=1}^{k} G_{ii} p_i s_i \quad (14)$$

$$G_{nb} = \sum_{i=2}^{k}\sum_{m=1}^{i-1} G_{im}(p_i s_m + p_m s_i) D_{im} \quad (15) \qquad G_l = \sum_{i=2}^{k}\sum_{m=1}^{i-1} G_{im}(p_i s_m + p_m s_i)(1 - D_{im}) \quad (16)$$

$$D_{im} = \frac{d_{im} - p_{im}}{d_{im} + p_{im}} \quad (17)$$

in which,

G=Overall Gini coefficient of eco-efficiency reflecting the relative difference of provincial eco-efficiency;

yij= The i–th regional eco-efficiency in the j–th province;

k=Number of regions;

n=Number of provinces;

μ=Mean value ofeach regional eco-efficiency, which is conducted with sorting;

Gii= Gini coefficient of the i–th region;

Gim=Gini coefficient between the i–th region and the m-th region;

Dim=Relative impact of eco-efficiency between the i–th region and the m-th region;

dim=The difference of eco-efficiency between regions, that is, the mathematical expectation for the aggregation of sample values of all yij－ymr>0 in the i–th region and the m-th region;

pim=The mathematical expectation for the aggregation of sample values of all ymr－yij>0 in the i–th region and the m-th regions.

Markov transition matrix

With the calculation of transition probability by Markov chain[32], the transition probability of Markov chain in the i-th state at the time t and in the j-th state at the time t+1 can be defined as:

$$P_{ij} = P\left(X_{t+1} = j \mid X_t = i\right) \quad (18)$$

According to the Cohort method, the transition probability of gradualchange from the i-th state to the j-th state during the study period is as follows:

$$P_{ij} = \frac{\sum_{t=0}^{T} N_{it} P_{ijt}}{\sum_{t=0}^{T} N_{it}} \quad (19)$$

in which,

N_{it} =Number of the provinces with the transition from the i-th state at the year t to the j-th state at the year t+1 during the study period;

N_i = Number of all the provinces in the i-th state during the study period.

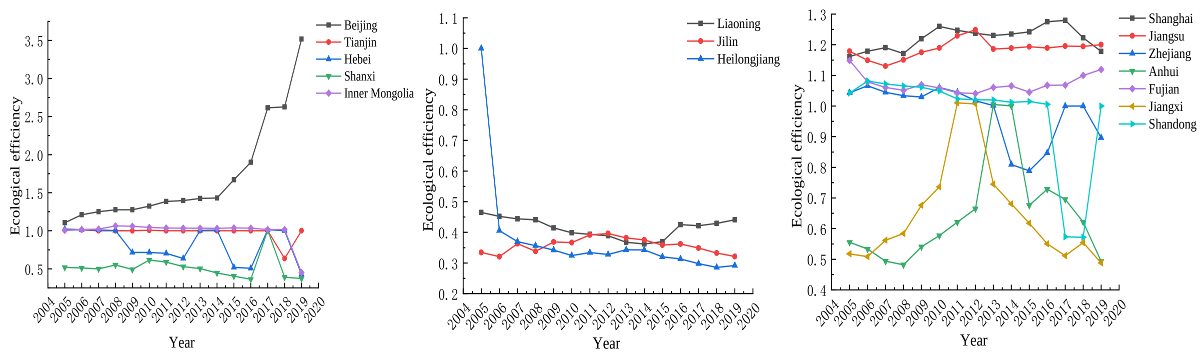
Data sources

In this study, we focus on the eco-efficiency study of tobacco planting zone in 30 provinces, cities and autonomous regions except Tibet owing to the serious loss of partial data in Tibet.The secondary indexes were acquired from the data published by National Statistics Bureau, in which the carbon dioxide emission was comprehensively calculated from the carbon dioxide produced by raw coal, crude oil and natural gas as well as cement production. The missing data were completed by trend forecasting, and the missing data of individual indicators in other provinces were completed by interpolation method.

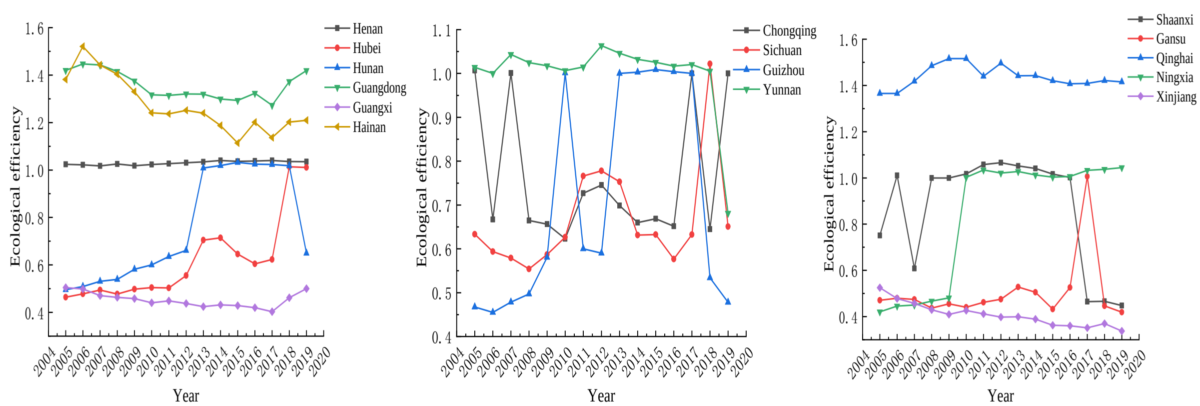
RESULTS AND DISCUSSIONS

Temporal and spatial characteristicsanalysis of eco-efficiency

The eco-efficiency wascalculated by using MATLB fordifferent regions from 2005 to 2019, and the eco-efficiency of all provinces, cities and autonomous regions were further averaged. Overall, the sorting of provinces/municipalities with the efficiency value greater than 1 from high to low is Beijing, Qinghai, Guangdong, Hainan, Shanghai, Jiangsu, Fujian, Henan and Yunnan. Furthermore, the calculation results from 2005 to 2019 were mapped by six geographic regions, as shown in Fig. 1. In the region of North China, Beijing has the yearly increasing eco-efficiency, with the highest reaching 3.5192 in 2019, the eco-efficiency of Tianjin and Inner Mongolia without big difference stabilizes around 1, Hebei has the great variation of eco-efficiency, while Shanxi has the lowest eco-efficiency in this region.In the region of Northeast China, the eco-efficiencies of the three provinces are lower than 0.5 from 2005 to 2019 except the reaching of 1 in 2015 by Heilongjiang, indicating the overall low eco-efficiency. According to the calculated eco-efficiency, the region of East Chinacan be divided into three categories. As shown in Fig.1c, the eco-efficiencies of Shanghai and Jiangsu fluctuate around 1.2, serving as the highest in East China.The eco-efficienciesof Shandong and Zhejiang fluctuate around 1.0, in which the local eco-efficiency of Zhejiang shows a "U"-shaped trend from 2013 to 2017.Moreover, the eco-efficiencies of Anhui and Jiangxi show an inverted "U"-shaped trend.In the region of Central South China, there is obvious difference in the eco-efficiency among provinces. Guangdong and Hainan possess the overall higher eco-efficiency,while Guangxi possesses the lowest eco-efficiency(Fig. 1d). The eco-efficiency of Henan stabilizes between 1.0-1.1. Hunan possesses a lower eco-efficiency with an increasing trend from 2005 to 2012, however,the eco-efficiency suddenly decreased down to 0.6495 in 2019. The eco-efficiency of Hubei also shows an increasing trend with a local peak in 2014. In Southwest China, except that Yunnan with a large decline in 2019 has the stable eco-efficiency greater than 1, the provincial eco-efficiency fluctuates greatly and is mostly lower than 1.0 (Fig.1e). In Northwest China, Qinghai with high eco-efficiency fluctuates around 1.4, Gansu and Xinjiang both have the low eco-efficiency, and Shaanxi and Ningxia with the stable eco-efficiency respectively in 2008-2016 and 2009-2019 fluctuate around 1.0 (Fig.1f). To improve each region's eco-efficiency level, agricultural production technologies should be promoted, such as tobacco rotation, soil and water conservation, biological control, and plastic film recycling. Furthermore, the recycling tobacco leaf development system will make green, efficient, high-quality, and sustainable the characteristics of the development of the tobacco industry, which may promote green, high-end, and distinctive tobacco agricultural production.



(a) North China (b) Northeast China (c)EasternChina



(d) South China(e) Southwest China (f) Northwest China

Fig.1 The regional eco-efficiency of China's six geographic regions from 2005 to 2019

Convergence analysis of eco-efficiency

As shown in Fig.2, the results of σ convergence analysis on national and regional variation coefficientscalculated by Eq. (3) show that the variationcoefficient of South China is higher than the national variation coefficient in 2006-2012 and then lower than the national variation coefficient level in 2013-2019, exhibiting a decreasing evolution trend. On the other hand, there is obvious convergence trend for eco-efficiency. In the region of Northwest China, the variation coefficient is basically higher than the national level from 2005 to 2019 (except for 2005, 2017 and 2019), showing the " ascend-descend- ascend" change tendency, without the obvious convergence of eco-efficiency variation. The variation coefficient ofNorthwest China with a growing volatility from

2005 to 2019 is higher than national level by a large increase in 2014-2019, while the variation coefficients of Northeast China, East China and Southwest China are lower than the national level. In the regions of Northeast China, East China and Southwest China, the change of regional ecological efficiency has a certain convergence in the early stage, but shows an expansion trend in the later stage, indicating that the eco-efficiency development in each region shows a divergent trend.

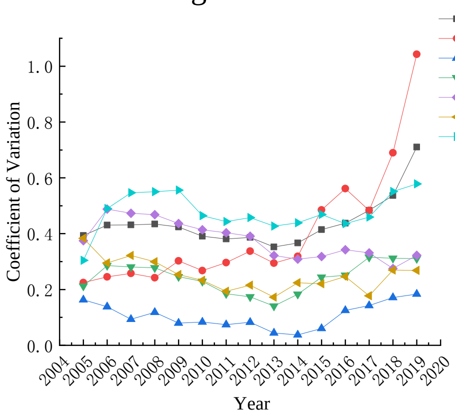


Fig.2 2005-2019 regional σ convergence curve

ANALYSIS OF ECO-EFFICIENCY DEVELOPMENT

National eco-efficiency evolution

The kernel density curve can comprehensively and objectively display the national eco-efficiency development. Figure 3 shows that the national eco-efficiency kernel density curve movestowards right, has the obvious phenomena of double peaks, and exhibits right tailing characteristics in 2005-2015, implying the positive development of national eco-efficiency. However, there still existsthe certain polarization phenomenon. The gap between front crest and peak valleygradually decreased, and polarization situation weakened as time goes on. In 2015-2019, the eco-efficiency with the tendency to move left has a slight protrusion on the right side of double peaks, thus indicating the right skew trend of overall eco-efficiency of the whole country, but the eco-efficiency of some provinces has excellent development, with the increased gap of eco-efficiency between provinces.

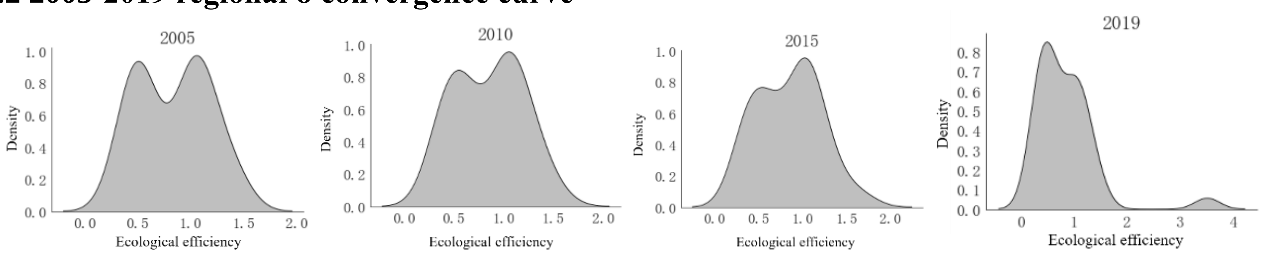


Fig.3 National Eco-efficiency Kernel Density Curve from 2005 to 2019

Development differences of regional eco-efficiency

In term of Eqs. (4)-(9), the eco-efficiency value of each region from 2005 to 2019 was computed, and the kernel density curves were drew on the basis of calculated results (Fig.4). The deference of the kernel density curve of eco-efficiency between the Northeast China and the North China is largest in Fig. 4.The kernel density curve of eco-efficiency in the North China has the obvious phenomenon of three peaks, and the eco-efficiency value of North Chinais mostly lower than 1.0 during the period of 2005-2019 since the height of main peak is less than 1.0, and the frequency of eco-efficiency within the range of 1.0-1.2 is higher than that of the eco-efficiency value exceeding 1.2. While the kernel density curve of eco-efficiency in the Northeast Region is characterized bysingle-peak evolution, and the crest with ecological efficiency below 0.4 is much higher than that with ecological efficiency of 0.6. Both the kernel density curves of East China and Central South China are characterized by single-peak evolution with the peak value of crest basically at the same level. Moreover, relative to the Central South China, the wave crest of East China is more to the right, indicating that the East China has higher eco-efficiency from 2005 to 2019 than that of the Central South China. Besides the similar width of the two kernel density curves, the more obviousphenomenon of double peaks in the Northwest China and the higher main peak in the Southwest China indicate that the greatly different eco-efficiency between the two regions from the year 2005 to 2019.

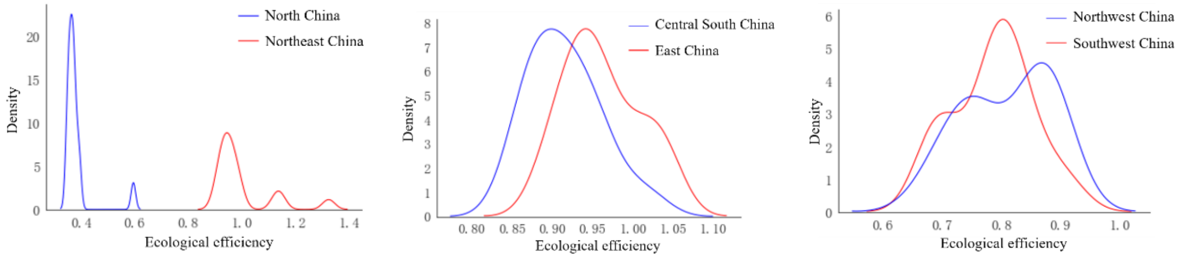


Fig.4 Regional Eco-efficiency Kernel Density

Difference analysis of regional eco-efficiency

After the exploration on national and regional eco-efficiency development by kernel density function, the Dagum Gini coefficient and its decomposition (referring to Eqs. (11)-(17)) are used to analyze the eco-efficiency, so as to further clarify the spatial difference and source of causing eco-efficiency development difference.

Spatial differences and sources of six geographic regions

The overall eco-efficiency spatial differences and sources of the six geographic regions in China from 2005 to 2019 are listed in Table 2, showing the "growth - decline - growth"trend of overall Gini coefficient. It can be found that the overall Gini coefficientdevelops stability with the changes between 0.20-0.25 from 2005 to 2017 (except 2013). The maximum value of 0.3208 in 2019 of the overall Gini coefficient indicates that the difference of regional eco-efficiency value is the largest in 2019, with the overall regional spatial difference showing an expanding evolution.Except for 2005, 2010, 2015 and 2016, the inter-regional differences in all years have the largest contribution to spatial differences, followed by the hypervariable density contribution, while the intra-regional difference has the smallest contribution rate. The inter-regional difference from 2005 to 2019 with its contribution rate in the range of 34.25%-52.59% is similar to the spatial difference in the aspect of change trend, whose contribution to regional difference reaches the highest in 2017. The intra-regional difference with small change from 2005 to 2019 barely has the impact on spatial difference, with the contribution rate changing between 12.80%-14.92%. The hypervariable density with the contribution rate changing between 33.72%-51.52% keeps the same change trend with spatial differences, but has the strong volatility in change from 2014 to 2019. Then, it can be deduced that the inter-regional difference and hypervariable density act as the main sources for the spatial differences of national eco-efficiency. Moreover, the analysis results of Gini coefficient is consistent with the convergence analysis of regional eco-efficiency, that is, the difference in regional eco-efficiency development is increasing gradually.

Table 2
Overall differences and sources of ecological efficiency from 2005 to 2019

Year	Overall	Intra-region		Inter-region		Hypervariable density	
		Source	Contribution rate (%)	Source	(%) Contribution rate (%)	Source	Contribution rate (%)
2005	0.2195	0.0328	14.92	0.0762	34.70	0.1106	50.37
2006	0.2389	0.0335	14.01	0.1050	43.97	0.1004	42.02
2007	0.2389	0.0330	13.82	0.1054	44.12	0.1005	42.06
2008	0.2423	0.0338	13.94	0.1088	44.91	0.0997	41.15
2009	0.2391	0.0335	14.01	0.1039	43.43	0.1018	42.56
2010	0.2213	0.0309	13.94	0.0912	41.20	0.0993	44.85
2011	0.2163	0.0287	13.27	0.1014	46.88	0.0862	39.85

2012	0.2197	0.0294	13.38	0.0971	44.21	0.0932	42.41
2013	0.1951	0.0250	12.80	0.0901	46.20	0.0800	41.00
2014	0.2049	0.0273	13.35	0.0896	43.75	0.0879	42.91
2015	0.2325	0.0331	14.23	0.0796	34.25	0.1198	51.53
2016	0.2420	0.0353	14.57	0.0839	34.66	0.1228	50.77
2017	0.2395	0.0328	13.69	0.1259	52.59	0.0807	33.72
2018	0.2724	0.0382	14.01	0.1307	47.97	0.1036	38.02
2019	0.3208	0.0457	14.24	0.1402	43.71	0.1349	42.05

Intra-regional differences of six geographic regions

The Gini coefficients of eco-efficiency in the six geographic regions from 2005 to 2019 are listed in theTable 3.According to the mean values from large to small, the Gini coefficient of regional eco-efficiency obeys the sequence that of Northwest China > Central SouthChina > North China > EastChina > Southwest China > Northeast China. With the largest inter-regional difference in Northwest China, there is a small gap of inter-regional eco-efficiency average difference between the Central South China and the North China, in which, the Central South Chinashows the decline trend and small fluctuation range, with its Gini coefficient decreased by 16.77% from 2005 to 2019. The North China has a growing trend, and the growth rate is large and more fluctuating from 2014 to 2019, with the largest difference in 2019, with a Gini coefficient of 0.4756, and a 98.23% increase in 2005 -2019. The average difference in ecological efficiency between the regions in the East China and the Southwest China is relatively smaller, with the Gini coefficient decreasing by 7.51% and 20.81% in the two regions from 2005 to 2019, respectively.Both of the Gini coefficients for East China and Southwest China have the change tendency of decreasing first and increasing, that is, the difference in ecological efficiency between regions decreases first and then expands. The Northeast Chinahas a small intra-regional variation and a more balanced ecological efficiency development from 2005 to 2019.

Table 3
The Gini coefficient of regional eco-efficiency in the region from 2005 to 2019

Year	North China	Northeast China	East China	Central South China	Southwest China	Northwest China
2005	0.1018	0.2466	0.1419	0.2507	0.1612	0.2458
2006	0.1179	0.0743	0.1411	0.2610	0.1573	0.2510
2007	0.1273	0.0456	0.1419	0.2528	0.1707	0.2448
2008	0.1239	0.0603	0.1413	0.2513	0.1545	0.2801
2009	0.1686	0.0428	0.1297	0.2381	0.1215	0.2857
2010	0.1483	0.0454	0.1222	0.2281	0.1171	0.2503
2011	0.1635	0.0355	0.0925	0.2233	0.1033	0.2408
2012	0.1857	0.0409	0.0883	0.2180	0.1143	0.2503
2013	0.1512	0.0237	0.0741	0.1777	0.0921	0.2346
2014	0.1627	0.0202	0.1016	0.1693	0.1162	0.2409
2015	0.2634	0.0314	0.1375	0.1720	0.1139	0.2550
2016	0.3000	0.0678	0.1422	0.1878	0.1288	0.2395
2017	0.1948	0.0772	0.1772	0.1790	0.0796	0.2517
2018	0.3423	0.0915	0.1701	0.1403	0.1423	0.2879
2019	0.4756	0.0942	0.1671	0.1803	0.1420	0.3035
Mean value	0.2018	0.0665	0.1312	0.2086	0.1277	0.2575

Inter-regional differences of six geographic regions

As shown in Fig.5 and Table 4, the inter-regional Gini coefficient of eco-efficiency from 2005 to 2019 reflects the differences among the six geographic regions, so we can divide the regions into two categories on the basis of the differences by taking 0.3 as the boundary. The first category is North China-Northeast China, Northeast China-Central SouthChina, Northeast China-East China, Northeast China-Southwest China, and Northeast China-Northwest China. In this category, the Northeast China are all included, indicating that the Northeast China is greatly different from other regions in eco-efficiency development, with the average Gini coefficient up to 0.4491. Especially, the difference between NortheastChina and North China is the largest from 2017 to 2019, andreached as high as 0.5776 in 2017.Moreover, the difference between Northeast China and Eastern China is also large, with the average Gini coefficient of 0.4360. The second category is North China-East China, North China-CentralSouth, North China-Southwest China, North China-Northwest China, Eastern China-Central SouthChina, Eastern China-Southwest China, East China-Northwest China, Central SouthChina-Southwest China, Central SouthChina-Northwest China, and Southwest China-Northwest China. In this category, the differences between North China and other regions show a sudden increase from the year 2018 to 2019, with the Gini coefficients all higher than 0.4, while the Gini coefficients among other regions are stable and fluctuate between 0.1-0.3 from 2005 to 2019. With the small differences among North China-EastChina, East China-Central SouthChina, and East China-Southwest China, their average values of Gini coefficients are all lower than 0.2.

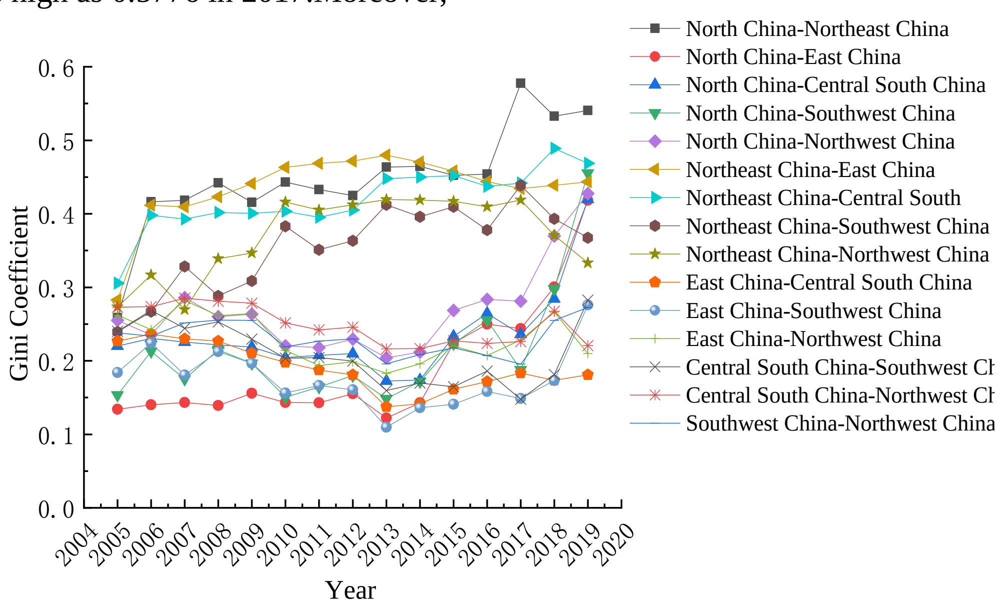


Fig. 5 Gini coefficient between regions of eco-efficiency from 2005 to 2019

Table 4
Average value of Gini coefficient between regions of eco-efficiency from 2005 to 2019

Region	North China	Northeast China	East China	Central South China	Southwest China	Northwest China
North China						
Northeast China	0.4491					
East China	0.1905	0.4360				

Central South China	0.2348	0.4192	0.1898		
Southwest China	0.2125	0.3549	0.1749	0.2089	
Northwest China	0.2676	0.3710	0.2286	0.2486	0.2308

Analysis of state transition

In order to further explorethetobacco planting zone's eco-efficiency transition law of the whole country and the six geographic regions, Markov transition matrix was usedin our study. Before the calculation of Markov transition matrix, it is necessary to carry on eco-efficiency classification.Since the eco-efficiency difference of different regions is great, the eco-efficiency was classified into five categories based on quintiles to decreasing the gap in the data amount of different categories.The five categories are defined as the lowest level (-0.4644), the lower level (0.4644-0.6577), the medium level (0.6577-1.0149), the higher level (1.0149-1.1181) and the highest level (1.1181-), which conforms to the essence of eco-efficiency. After the classification, the calculation results of Markov transition matrix according to the formula are listed in Table 5, where the rows and columns respectively represent the states of this region in t-th and t+1-th years. The study on the national eco-efficiency transition shows that the transition probabilities from the lowest level in the t-th year to the lowest, the lower, the medium, the higher and the highest levels in the t+1-th year are 0.9136, 0.0741, 0.0123, 0.0000 and 0.0000, respectively.As shown in Table 5, the same-type eco-efficiency transitions of all provinces in China have the largest probabilities, the probability of the transitions from the lower level to the medium level is 21.43%, and the probability of the transitionsfrom the medium level to the lower level is 16.67%.On the basis of these results, it can be deduced the slight fluctuation state of national eco-efficiency, without the obvious increasing or decreasing trend.Similar to the whole country, North China, Eastern China, Central SouthChina and Northwest China have the largest probability in the same-level transition, in which, in North China, the transition probability from the highest level is up to 1, while the transition probabilities from the lowest level to the medium level and from the lower level to the medium level are 25.00% and 23.08%, respectively, indicating the trend of eco-efficiency in North China to develop towards a higher level. In Northeast China, its lower eco-efficiency value pushes the transition probabilities from the lowest and the medium levels to the lowest level to be 1, while other transition probabilities are all 0, indicating that the Northeast China with poor eco-efficiency development will develop towards the lowest level next year. In EastChina, the transitions from the lower level to the medium level and from the medium level to the lower level with their respective probabilities of 16.67% and 14.29% indicate the fluctuation in eco-efficiency development of EastChina, without significant increase or decrease. In Central South China, the transitions from the lowest level to the lower level, from the lower level to the medium level, from the medium level to the lower level and from the medium level to the higher level with their respective probabilities of 16.67%, 15.00%, 20.00% and 20.00% indicate the increasing trend of the overall eco-efficiency development in Central SouthChina. In Southwest China, different from other regions, the transition probability from the lowest level to the lower level is 1, while the transitions from the lower level to the medium level, from the medium level to the lower level and from the higher level to the medium level with their respective probabilities of 29.41% 27.78% and 25.00% indicate that the eco-efficiency development in Southwest China has the trend of concentration on the medium level, without significant increase and decrease. In Northwest China, the transition probabilities from the lower level to the lowest and the medium levels, from the medium level to the lower and the higher levels, and from the higher level to the medium level are 25.00%, 25.00%, 22.22%, 22.22% and 20.00%, indicating that the unstable eco-efficiency development in Northwest China has strong volatility.

Table 5
The full sample and sub-regional ecological efficiency Markov transition probability matrix from 2005 to 2019

Region	Level	Lowest	Lower	Medium	Higher	Highest
Overall	Lowest	0.9136	0.0741	0.0123	0.0000	0.0000
	Lower	0.0714	0.7024	0.2143	0.0119	0.0000
	Medium	0.0595	0.1667	0.6905	0.0833	0.0000
	Higher	0.0114	0.0227	0.0682	0.8523	0.0455
	Highest	0.0000	0.0000	0.0120	0.0843	0.9036
North China	Lowest	0.7500	0.0000	0.2500	0.0000	0.0000
	Lower	0.0769	0.6923	0.2308	0.0000	0.0000
	Medium	0.0833	0.1250	0.7500	0.0417	0.0000
	Higher	0.0625	0.0000	0.0625	0.8125	0.0625
	Highest	0.0000	0.0000	0.0000	0.0000	1.0000
Northeast China	Lowest	1.0000	0.0000	0.0000	0.0000	0.0000
	Lower	0.0000	0.0000	0.0000	0.0000	0.0000
	Medium	1.0000	0.0000	0.0000	0.0000	0.0000
	Higher	0.0000	0.0000	0.0000	0.0000	0.0000
	Highest	0.0000	0.0000	0.0000	0.0000	0.0000
East China	Lowest	0.0000	0.0000	0.0000	0.0000	0.0000
	Lower	0.0000	0.8333	0.1667	0.0000	0.0000
	Medium	0.0000	0.1429	0.8571	0.0000	0.0000
	Higher	0.0000	0.0000	0.0645	0.9032	0.0323
	Highest	0.0000	0.0000	0.0000	0.0345	0.9655
Central South China	Lowest	0.8333	0.1667	0.0000	0.0000	0.0000
	Lower	0.0500	0.8000	0.1500	0.0000	0.0000
	Medium	0.0000	0.2000	0.6000	0.2000	0.0000
	Higher	0.0000	0.0500	0.0000	0.9000	0.0500
	Highest	0.0000	0.0000	0.0000	0.0370	0.9630
Southwest China	Lowest	0.0000	1.0000	0.0000	0.0000	0.0000
	Lower	0.0588	0.5882	0.2941	0.0588	0.0000
	Medium	0.0000	0.2778	0.6111	0.1111	0.0000
	Higher	0.0000	0.1250	0.2500	0.6250	0.0000
	Highest	0.0000	0.0000	0.0000	0.0000	0.0000
Northwest China	Lowest	0.8571	0.1429	0.0000	0.0000	0.0000
	Lower	0.2500	0.5000	0.2500	0.0000	0.0000
	Medium	0.2222	0.1111	0.4444	0.2222	0.0000
	Higher	0.0000	0.0000	0.2000	0.8000	0.0000
	Highest	0.0000	0.0000	0.0000	0.0000	1.0000

The predictedresults on the distribution probability of eco-efficiency grade in the whole country are listed in Table 6. Taking 2019 as benchmark, the provinces with the lowest-level eco-efficiency account for the largest proportion in 2020, followed by the provinces with the highest-level eco-efficiency, implying the greatly unbalanced eco-efficiency development in the whole country, with the large gap among provinces.While by 2025, the proportions of provincial eco-efficiency development from the lowest level to the highest leveldecrease successively, which are 30.29%, 19.14%, 18.51%, 16.66% and 15.40% respectively, demonstrating the decreased imbalance for the overall eco-efficiency in China. To improve the ecological efficiency level, the tobacco industry should be developed based onthe concept of green development. In the production process, enterprises should reduce the waste of energy and materials, and reduce the emission of pollutants to improve the local environment.

Table 6
Distribution probability of China's eco-efficiency grades in2019, 2020 and 2025

Year	Lowest	Lower	Medium	Higher	Highest
2019	0.3000	0.2000	0.2000	0.0667	0.2333
2020	0.3010	0.1975	0.1920	0.0955	0.2139
2025	0.3029	0.1914	0.1851	0.1666	0.1540

CONCLUSIONS AND DISCUSSIONS

Conclusions

In this paper, the provincial eco-efficiency of tobacco planting zone in China measured by using Super-SBM is divided according to the six geographic regions for further exploration and analysis. The regional eco-efficiency for all the provinces is measured and calculated by the creative combination of entropy method and kernel density function, and then the regional eco-efficiency in the time dimension and the provincial eco-efficiency in the national spatial dimension are taken as samples to respectively draw the kernel density curves, so as to explore the evolution and distribution characteristics of eco-efficiency development in China. In addition, after the further exploration on the imbalance and trend of temporal and spatial development of national and regional eco-efficiency by using the Gini coefficient decomposition andσconvergence test, this paper uses Markov transition matrix to explore the transition law of eco-efficiency, so as to provide research basis for the prediction on future eco-efficiency. The main conclusions are listed as follows:

(1) The mean value-based sorting of provincial eco-efficiency in China is as follows: Beijing ＞ Qinghai ＞ Guangdong ＞ Hainan > Shanghai > Jiangsu > Fujian > Henan > Yunnan > Inner Mongolia > Zhejiang > Tianjin > Shandong > Shaanxi > Ningxia > Hebei > Chongqing > Hunan > Guizhou > Sichuan > Jiangxi > Anhui > Hubei > Shanxi > Gansu > Guangxi > Liaoning > Xinjiang > Heilongjiang > Jilin, and the weakened polarization phenomenon is accompanied with the trend of overall eco-efficiency to firstly decrease and then increase, without the convergence characteristics, but with good eco-efficiency development in individual provinces.

(2) The analysis on the obvious gap of eco-efficiency development in the six geographic regions from the perspectives of inter-regional Gini coefficient and convergence shows that with the enhanced overall spatial difference in the region, the inter-regional differences are the main source of differences, while the lower eco-efficiency of Northeast China itself is the major cause for its great difference with other regions, the eco-efficiency growth in North China enlarges its difference with other regions, and the difference of eco-efficiency among other regions is small, without the characteristics of convergence.

(3) Among the eco-efficiency transition probabilities of the whole Country and all regions shown in the results of Markov transition matrix, except for the transition probability of the lowest-level eco-efficiency in Southwest China, the same-level transitions in all regions have the largest probability, the main reason is that the tobacco planting area in Southwest China is the bigger produce region in China. The eco-efficiency development of tobacco planting zone in North China and Central South China has the trend of growth, that in East China and Northwest China has volatility, that in Northeast China has the trend of decline, and that in Southwest China is towards the medium level as a whole. The prediction on eco-efficiency in 2020 and 2025 finds that the national eco-efficiency development with the increased difference is at a lower level.

Discussions

The results of deep research on the distribution dynamics and regional differences of eco-efficiency about tobacco planting in 30 provinces, cities and autonomous regions by using the kernel density function, Dagum’s Gini coefficient, convergence analysis and Markov transition matrix can confirm and complement each other to a certain extent, whose greatly practical significance can provide some basis for further research. With the overall good eco-efficiency development in China shown in the analysis of the above results, it is still necessary to focus on the transformation of development mode, the tobacco planting zone should make efforts to save energy, reduce harmful gas emissions, and reduce carbon emissions during the entire process of tobacco production, thus conforming to the green development concept of the current society, and promoting the coordinated development among regions to reduce the regional eco-efficiency difference. From the evaluation system framework in this paper, we should minimize the unexpected emissions of sulfur dioxide, carbon dioxide and wastewater, that is, reduce the emissions of pollutants, as well as air pollution emissions, a green environment should also be created by clean baking, water and fertilizer conservation, soil. At the same time, the strengthening inter-regional cooperation in technology and talents for tobacco production and other various fields, improving resource utilization by production technology improvement and so on may be used to enhance the local GDP, so as to improve regional eco-efficiency level by maximizing the desirable output.

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