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Research article

Spatiotemporal differences, dynamic evolution and trend of cultivated land use efficiency: Based on three food functional areas

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ABSTRACT

China's agricultural development has entered a period of transition, and improving the cultivated land use efficiency (CLUE) is of great significance for guaranteeing national food security. Based on the province panel data in China from 2000 to 2021, this research calculates the cultivated land use efficiency, and uses the Dagum-Gini coefficient, Kernel density estimation, and Markov chain to conduct an in-depth analysis of CLUE's regional variations and distribution dynamics in three food functional areas (TFA) of China. The study results showed that the trend of CLUE was characterized by "increasing levels and decreasing absolute differences," not only in the whole country but also in the TFA. The inter-regional variation among TFA is gradually narrowing, and the cross-group degree of inter-regional variation is on the rise. The upward probability of CLUE was more effective than the probability of a transitionary change, and the mutual influence of CLUE between neighboring cities would lead to spatial convergence in the level of CLUE in the long term. Therefore, improving CLUE in China's TFA should not only grasp the regional differences in CLUE but also actively utilize the spatial spillover effects among functional regions to realize the cross-regional synergistic development of cropland utilization efficiency in China.

1. Introduction

Cultivated land, as a crucial factor in stabilizing food production, stands at the forefront of ensuring food security in China. However, the inefficient problem using of cultivated land is becoming increasingly severe in rapidly urbanizing and industrializing China. To scientifically plan cultivated land resources and increase grain production, the State Council of China divided 31 provinces into 13 main producing areas (MPA), seven main marketing areas (MMA), and 11 balanced production-marketing areas (BPMA) in 2001 [1]. For different food functional areas, the government put forward additional requirements. The MPA should continue to focus on food production [2]. The BPMA should continue to maintain basic self-sufficiency in food. The MMA should improve food self-sufficiency while ensuring the scope of grain cultivation. Under the impetus of many national policy instruments, China's CLUE has increased, providing a material basis for guaranteeing the supply of agricultural products. However, simply ensuring no reduction in area is still not enough to achieve the goal of increased production. Although China has had good grain harvests for nearly two decades, it is essential to note that significant grain crops' potential productivity is already high. Therefore, we should focus more on improving the CLUE to ensure the food supply.

The essence of CLUE is the economic and social benefits obtained from agricultural production in terms of cultivated area units. It

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has the capability to directly indicate the allocation of various production factors in agricultural activities [3], providing a more precise and objective assessment of the sustainable development status of cultivated land utilization. Improving the CLUE is the best way to achieve increased food production and ensure food security when food security is facing severe challenges in China. By reviewing existing literature, it becomes evident that various scholars have investigated the spatiotemporal evolution characteristics and distributional variances of CLUE from a multidimensional research perspective. A literature survey highlights the analyses conducted by different scholars on the distribution differences in CLUE [4,5] and their exploration of the spatiotemporal evolution of CLUE from a multidimensional standpoint [6,7]. By analyzing the distributional characteristics at the provincial level, the researchers identified clear spatial disparities among Chinese provinces [8–10]. The spatial and temporal patterns of subdivided regions such as the Northeast [11], the Yellow River Basin [12,13], and the Yangtze River Economic Belt [14–16] have also been the focus of scholars' discussions [17]. Xiao et al. analyzed regional differences in CLUE at the level of individual provinces [18–20]. Some scholars have also explored the CLUE in MPA [21–24]. In general, there are obvious differences in the trend of CLUE over time and spatial distribution in different regions. The spatiotemporal features of CLUE are intricately linked to various elements, including the geographic environment, regional economic progress, and policy orientation. Exploring the differences in CLUE in different regions provides an important reference for regional agricultural development strategies. Although existing studies have made important contributions to the CLUE, fewer investigations have delved into CLUE from the TFA standpoint. The synchronized advancement of distinct food functional areas can contribute to achieving comprehensive national food security. By fully utilizing the advantages of each region, it ensures the stability of China's food supply and improves China's food security. This study aims to further complement and deepen this research area to fill the gaps in existing research. For the measurement of CLUE, the two most common methods currently used in the academic community are Data Envelopment Analysis [25–27] and the utilization of Stochastic Frontier Analysis [28–30]. While the SFA method is extensively utilized for measuring CLUE, it is more suitable when the study environment is more complex and the influence of external random factors is significant. Given the dataset and research objectives of this study, the DEA method allows for a more direct and explicit comparison of CLUE between provinces. Traditional DEA models, such as the BBC and CCR models, are employed for the efficient evaluation of units of the same type using multiple inputs and multiple outputs. Nevertheless, measuring their efficiency becomes somewhat inaccurate in the presence of non-zero slack in inputs or outputs. To address these issues, Tone [31] constructed the super-efficient SBM model [32–36]. This model effectively addresses the issue of all DMU efficiencies being 1, which complicates the differentiation between efficient DMUs. Hence, this approach is selected for measurement in the present study.

From the actual situation, there are differences between land factor inputs, output levels, and CLUE in TFA? Is the story of CLUE higher in the main production areas that bear more national food security tasks? What are the characteristics and changing trends of CLUE in different functional areas? Clarifying the above question is vital to achieving the targeted development of CLUE in TFA. As a result, after explaining the importance of exploring the regional differences in CLUE, the super-efficient SBM model is employed to assess the CLUE of 30 provinces in China from 2000 to 2021. Following that, an in-depth analysis of regional disparities in CLUE among Three Food Functional Areas (TFA) in China, along with an examination of the sources of these differences and the dynamic evolution of their future development, is conducted using Dagum's Gini coefficient, Kernel estimation, and Markov chain. Ultimately, the study consolidates key findings and proposes specific policy recommendations and future research directions based on these outcomes.

The potential contributions of this study are as follows: First, the study thoroughly investigates CLUE within China's TFA. Past research efforts may have predominantly concentrated on the national-level assessment of CLUE, paying less attention to the differences among various functional areas. Through this detailed study, the paper is expected to uncover the characteristics as well as sources of differences in these regions. This will provide a more precise basis for formulating differentiated agricultural policies [37]. Second, it provides strategic recommendations for synergistic development among SFA. In addition to examining the current status of CLUE, this study places emphasis on forecasting future development trends and identifying potential opportunities for synergy. By identifying the interactions between different functional areas and the mutual impacts of CLUE, this paper provides valuable insights for the development of cross-regional collaboration and resource-sharing strategies. This has important practical implications for balancing regional development, promoting resource complementarity among functional areas, and enhancing food security.

2. Materials and methods

2.1. Research area

Following the reform and opening up, notable transformations have occurred in the landscape of food production, with a gradual northward shift in the center of gravity. To scientifically plan the national cultivated land resources [38] and guarantee the safe production of food, the country has proposed food functional areas, and 31 provinces in China were divided into MPA, MMA, and

Table 1
Food functional areas in China.

Food functional areas	Provinces
MPA (13)	Hunan, Heilongjiang, Shandong, Sichuan, Jilin, Jiangsu, Liaoning, Jiangxi, Inner Mongolia, Hebei, Henan, Anhui, Hubei
MMA (7)	Beijing, Guangdong, Tianjin, Fujian, Shanghai, Hainan, Zhejiang
BPMA (11)	Shanxi, Shaanxi, Ningxia, Qinghai, Xinjiang, Gansu, Guangxi, Tibet, Guizhou, Chongqing, Yunnan

BPMA [39]. The delineation is shown in Table 1.

The MPA mainly refers to those areas with rich natural resources and superior cultivated land endowment, which have a favorable impact on agricultural production. They are mainly located in northeast, north, central, and east China [40]. The MMA refers to those areas with weak cultivated land resources, poor natural conditions, and less agricultural land, mainly in some coastal and economically developed areas. The BPMA refers to those provinces between the MPA and the MMA [1], which have better natural conditions and richer agricultural resources. Although their contribution to China's grain production is limited, they can meet their production and consumption needs and roughly achieve balanced production and marketing.

2.2. Indicators selection

To better measure the CLUE in each province, combined with the research of scholars such as Bing Kuang and Haibin Han [21,33], this paper selects the indicator data from input and output perspectives. Firstly, six input factors are selected. Grain acreage represents land input, agricultural workers represent labor input (Utilizing the available data, the count of agricultural workers in this study is determined by the formula: the number of people engaged in agriculture, forestry, and fisheries multiplied by the total value of agricultural production, divided by the total value of agricultural, forestry, and fisheries production.), total powers of agriculture machinery represent agricultural machinery input, consumption of chemical fertilizer by pure represents fertilizer input, consumption of agricultural plastic film represents agricultural film input, consumption of pesticide use represents pesticide input. Secondly, rural output value and total grain production are selected to represent two output factors. Indicators selection as in Table 2.

2.3. Research methods

This study is dedicated to exploring the current status, regional differences, and dynamic evolution in CLUE of TFA. Therefore, four methods are selected to investigate the problem in depth.

2.3.1. Super-SBM model

The super-efficient SBM model, an extension of data envelopment analysis (DEA), is employed to evaluate variations in the relative efficiency of decision-making units, such as provinces, operating under identical conditions. The model measures the CLUE by calculating the ratio of inputs to outputs to determine the efficiency value for each province. The model can be expressed as:

$$\rho = \min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{s}\sum_{k=1}^{s}\frac{\overline{y_k}}{y_{k0}}};\ \text{s.t.}\quad \overline{x_i} \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j, \forall i;\ \overline{y_k} \leq \sum_{j=1,\neq 0}^{n}\lambda_j y_j, \forall k;\ \overline{x_i} \geq x_{i0}, 0 \leq \overline{y_k} \leq y_{k0}, \lambda_j \geq 0, \sum_{j=1,\neq 0}^{n}\lambda_j = 1, \forall i, j, k, \tag{1}$$

in equation (2), with each province serving as an individual decision-making unit.

m is the input (land, labor, machinery, agricultural film, pesticide and fertilizer inputs) for each province, s is the output, and $\overline{x_i}$, $\overline{y_k}$ is the slack input and output variables.

2.3.2. Dagum–Gini Coefficient

The Dagum Gini coefficient serves as an indicator of inequality in income or wealth distribution, with a scale from 0 (representing perfect equality) to 1 (representing perfect inequality). In this study, we use it to analyze the unequal distribution of CLUE across TFA. A higher value of this coefficient signifies increased inequality in CLUE among regions, while a low value indicates a higher degree of parity. The Dagum Gini coefficient provides insights into the variations within, between, and across regions. Specific formula setting as:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{i=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\overline{y}}, \tag{2}$$

in equation (2), G represents the overall Gini coefficient of CLUE in China; k is the number of functional zones, with k = 3 in this formula; j and h represent different provinces, cities, and autonomous regions within the functional zones; $n_j(n_h)$ is the number of

Table 2
Indicators selection.

Indicator Type	Indicators	Description of Indicators
Input	land input	grain acreage (10^4ha)
	agricultural film input	consumption of agricultural plastic film (t)
	labor input	agricultural workers (10^4 people)
	fertilizer input	consumption of chemical fertilizer by pure (10^4t)
	machinery input	total powers of agriculture machinery (10^4kw)
	pesticide input	consumption of pesticide use (t)
Output	economic benefits output	agricultural output value (10^8yuan)
	social benefits output	total grain production (10^4t)

provinces within the j(h) functional zone; $y_{ji}(y_{hr})$ is the CLUE of the i(r) province, city, or autonomous region within the j(h) functional zone; $\overline{y}$ is the national average of CLUE.

Dagum–Gini Coefficient for all regions (G) is decomposed into three components: intra-regional variation (G_w), inter-regional variation ((G_{nb}), and *trans*-variation density (G_t). The formulas and relationships are as follows:

$$G = G_w + G_{nb} + G_t, \tag{3}$$

See Dagum [41] et al. for specific formulas.

2.3.3. Kernel density estimation

The Kernel density estimation method is used to analyze the distribution and dynamics of cropland utilization efficiency. This approach addresses the shortcomings of the two methods described above, which effectively depicts the distribution of CLUE by constructing a kernel density curve, thus visualizing the trend and distribution pattern of the data over time, and we are able to understand the inter-regional differences and temporal evolution from another perspective.

2.3.4. Markov chain

The Markov chain analysis method offers insights into the long-term evolution and potential future scenarios of CLUE. Unlike the Kernel density estimation approach, which analyzes distribution patterns and dynamics, the Markov chain method predicts future changes in CLUE, aiding in the development of future projections and policy decisions. It focuses on the dynamic behaviors of variable distributions and their progression over time. By categorizing CLUE into N distinct classes, a transition probability matrix P of size N*N is constructed. This matrix, with Pij representing the likelihood of transitioning from class i at time t-1 to class j at time t, uncovers the dynamic progression trends of CLUE within the TFA, offering a comprehensive view of its evolutionary patterns.

2.4. Data sources

This text has collected agricultural input-output data from 30 provinces in China from 2000 to 2021, excluding Hong Kong, Macao, and Taiwan regions. Additionally, considering the model's sensitivity to outliers, data from the Tibet region has been temporarily removed. The data used in the study all come from the "China Statistical Yearbook" and the "China Rural Statistical Yearbook". In addition, the money-type data covered in the text are all based on the 1978 base period and have been made constant using the corresponding price indices.

3. Results

3.1. Process results

The MaxDEA software is utilized for the analysis of the CLUE of China (The formula is shown in equation (1)), covering the period from 2000 to 2021. The findings are presented in Table 3.

From the results of China's CLUE measurement, the efficiency from 2001 to 2021 ranges from 0.903 to 1.027 (Table 3), and cultivated land resources are effectively utilized, with a relatively high level of overall efficiency. However, it is important to note the fact that CLUE declines from 1.027 in 2000 to 0.963 in 2021, a decrease of 6.26%. Specifically, the changes in China's CLUE are mainly divided into four periods (Fig. 1). The first stage is the period of substantial decline (2000–2003), in which the CLUE is in a stage of substantial decline. Since the 21st century, China's industrialization and urbanization have accelerated, and significant encroachment on farmland has led to a substantial reduction in the extent of cultivated land. In addition, Jixia Li point out that misallocation of cropland and redundancy of resources occurred during this period due to management and other reasons [42], which also had an impact on efficiency. The second stage is the period of significant fluctuation (2003–2009), during which the overall volatility of China's CLUE level was large, mainly due to the impact of natural disasters such as the heavy rainfall in 2006 and the snowstorm in the

Table 3
Results of CLUE in China from 2000 to 2021.

year	efficiency	year	efficiency
2000	1.027	2011	0.955
2001	0.951	2012	0.955
2002	0.933	2013	0.936
2003	0.928	2014	0.926
2004	0.967	2015	0.903
2005	0.952	2016	0.924
2006	0.930	2017	0.929
2007	0.975	2018	0.944
2008	0.971	2019	0.964
2009	0.994	2020	0.967
2010	0.985	2021	0.963

Source: Calculated through software.

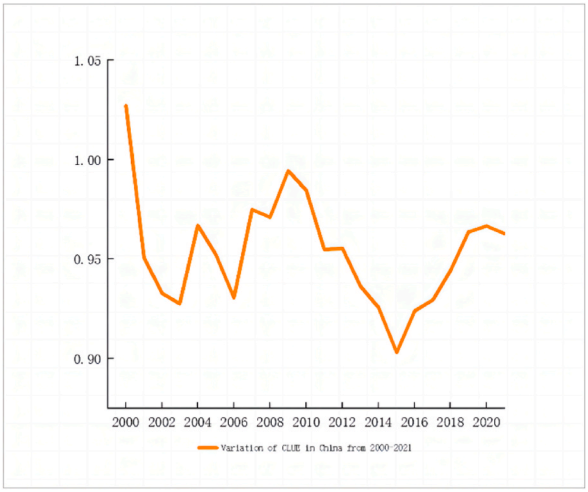

Fig. 1. Variation of CLUE in China from 2000 to 2021.
Source: Calculated through software.

south of China in 2008, which drastically reduced the grain output and caused the overall fluctuation of efficiency to be large. While technological advances can improve the CLUE, the impact of natural disasters remains significant [43]. The third stage is the period of steady decline (2009–2015), in which the efficiency values show an overall steady downward trend. This could be linked to emerging issues in Chinese agriculture, including increasing labor expenses and the shift of workers from rural to urban regions, resulting in a diminished workforce for farming activities. Moreover, the efficiency of agricultural production on a scale was impacted by the unpredictability associated with land lease durations [44]. The fourth stage is a period of steady rebound (2015–2021), during which China has increased its investment in agricultural research, such as the application of new breeding technologies, smart agricultural equipment, and the promotion of precision agriculture technologies, all of which have significantly improved the CLUE.

Regarding the outcomes of CLUE from different functional areas (Fig. 2), the results of CLUE show that CLUE in MMA > CLUE in MPA > CLUE in BPMA. From the perspective of inputs and outputs, the urbanization process in the sales area is generally faster, non-agricultural land use is increasing, and the area of cultivated land per person is significantly below China's average [45]. So the relative inputs in MMA are lower, but the total value of agricultural output in the MMA is likely to come from higher value-added agricultural products, whereas in MPA, although the total food production is large, the total value of output is likely to be less than that in MMA, due to food crops typically commanding lower market prices compared to cash crops. Therefore, the MMA obtains higher outputs with fewer inputs, and its CLUE is rather higher than that of the MPA. On the other hand, the MPA possess a substantial amount of cultivated land; however, due to their relatively underdeveloped economic status, at the same time, they bear more tasks of food production and have more intense use of cultivated land. Farm refinement is not as good as in the primary marketing areas. So, the CLUE in it is rather lower.

3.2. Regional differences in CLUE

This paper adopts the Dagum Gini coefficient (The formula is shown in equation (2) and (3)) to measure and decompose the

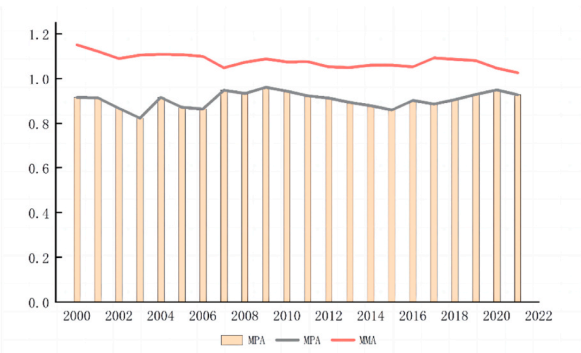

Fig. 2. Variation of CLUE in TFA from 2000 to 2021.
Source: Calculated through software.

regional disparities in CLUE among the TFA from 2000 to 2021. Given the extensive size of the table, it is included in an appendix (appendix1) at the conclusion of the article.

3.2.1. Intra-regional variation

Viewing CLUE from a nationwide standpoint (Fig. 3), the mean Gini coefficient for China's CLUE between 2000 and 2021 stands at 0.136, which is smaller overall, showing more obvious fluctuations and a certain downward trend. The overall regional imbalance in CLUE is gradually being improved. Specifically, it declined from 0.148 in 2001 to 0.124 in 2021, a decline of only 0.024, a relatively small rate of decline. This primarily stems from the significant disparities in agricultural development resources across different areas, making the diminishment of regional CLUE discrepancies a prolonged endeavor. Looking at CLUE within TFA (Fig. 3), the internal differences in the BPMA are large, and their Gini coefficients all exceeded the overall national Gini coefficient in the period under examination, indicating that the differences in CLUE within the BPMA are large, and are an important aspect leading to the large national CLUE [46]. The provinces within the BPMA exhibit significant disparities in terms of natural resource allocation, geographical positioning, and economic development stages, so their internal differences are large. Intra-regional variation in CLUE in MPA have shown a fluctuating upward trend over the past decade, and more monitoring efforts are needed to prevent them from expanding further. On the other hand, intra-regional variation in CLUE in the MMA are lower than the overall Gini coefficient for the country as a whole, and also lower than that in MPA and BPMA. This is mainly due to the fact that most of the MMA are areas where cultivated land resources are scarce but where talent and technology are concentrated, and where the overall CLUE is higher and the differences are smaller.

3.2.2. Inter-regional variation

Data analysis shows that the levels of CLUE between TFA in China are significantly different, and the average value of Dagum's Gini coefficient across functional zones for the period 2001–2021 shows this trend: MMA - BPMA > MPA - BPMA > MPA -MMA. Specifically, the large gap in CLUE between MMA and BPMA may be explained by the fact that MMA may be more advanced in terms of agricultural technology and management, for example, the adoption of modern agricultural technology, precision agriculture, and highly efficient irrigation systems, which have improved the CLUE, whereas BPMA may be relatively backward in these aspects. Observing the trend of variation between regions among the various groups, the Gini coefficients are all decreasing. That indicates that inter-regional variation among the TFA is gradually decreasing. The government and state authorities are increasingly focusing on achieving a balanced enhancement of CLUE across TFA. National food security is no longer solely reliant on the MPA.

3.2.3. Sources of variation and decomposition

Considering their impact as shown in Table 4, the average G_t value from 2000 to 2021 stood at 39.13%. Additionally, the mean value of the G_w was found to be 32.27%, while the mean value of G_{nb} was observed to be 28.60%. Among them, intra-regional variation measures the difference in CLUE between provinces within the TFA. G_{nb} measures the pure difference between provinces with high and low efficiency. *Trans*-variation density indicates the role that the overlap among subgroups plays in the total variance [47], i.e., the presence of some high-efficiency municipalities in an inefficient region with greater cropland use efficiency than some inefficient municipalities in a high-efficiency region.

The contribution from variations between regions is showing a downward trend, from 30.98% in 2000 to 15.87% in 2021, while the contribution of *trans*-variation density is on an upward trend, gradually rising from the original 37.29%–49.69%, representing nearly half of the overall total and emerging as a primary factor in the disparities observed in CLUE, while the contribution of intra-regional variation has basically remained unchanged (Fig. 4). The significant increase in the contribution of *trans*-variation density reveals an increase in the number of outliers in CLUE between regions, and this widening difference may be due to uneven agricultural development, with some provinces being able to make better use of resources and technology, while other regions may be limited by natural

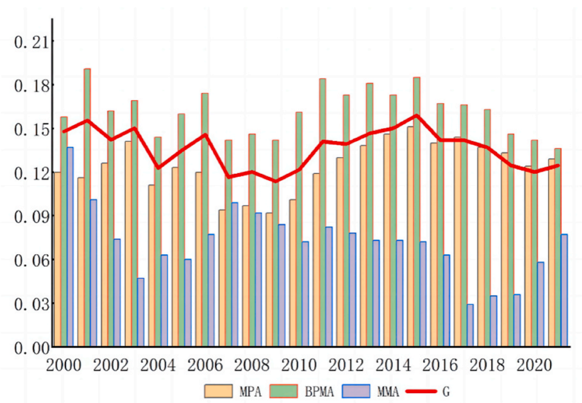

Fig. 3. Variation Gini coefficient of intra-regional variation in CLUE.
Source: Calculated through software.

Table 4
Variation Gini coefficient of inter-regional variation.

year	BPMA | MPA	MMA | MPA	BPMA | MMA	year	BPMA | MPA	MMA | MPA	BPMA | MMA
2000	0.147	0.152	0.169	2011	0.159	0.119	0.16
2001	0.171	0.134	0.207	2012	0.158	0.122	0.141
2002	0.150	0.140	0.165	2013	0.168	0.130	0.145
2003	0.164	0.162	0.152	2014	0.171	0.144	0.144
2004	0.133	0.116	0.139	2015	0.178	0.154	0.162
2005	0.15	0.135	0.135	2016	0.161	0.128	0.145
2006	0.156	0.143	0.171	2017	0.163	0.136	0.143
2007	0.124	0.106	0.134	2018	0.157	0.125	0.142
2008	0.130	0.111	0.137	2019	0.143	0.114	0.117
2009	0.123	0.101	0.133	2020	0.137	0.105	0.115
2010	0.139	0.102	0.132	2021	0.137	0.118	0.116

Source: Calculated through software.

conditions, market access, or policy support. Intuitively, if one reduces the efficiency of regions with higher average CLUE and raises the efficiency of regions with lower CLUE, one can reduce the overall Gini coefficient by shrinking inter-regional variation [48]. Indeed, when subsamples overlap, this can lead to an increase in the intra-regional Gini coefficient, a decrease in the net variation between regions, and heightened inequality within the intersecting sections of the regions, so that the overall Gini coefficient rises rather than falls. Based on this, each functional area's coordinated development should be strengthened to improve the CLUE level in China. The MMA appropriately expands the cultivated land area to ensure the CLUE does not decline. The MPA should focus more on improving the CLUE to bolster food production and safeguard food security.

3.3. Distribution dynamics of CLUE

The positioning of the kernel density curve for period sample data alone can signify the CLUE's magnitude, with the peaks' height and breadth indicating CLUE's concentration level within that range. The quantity of peaks illustrates the sample data's polarization, whereas the curve's elongation, or its trailing extent, illustrates the distance between cities with the highest or lowest CLUE and the rest. A more pronounced trailing suggests a greater disparity within the region. Vertically comparing kernel density curves from various timeframes within the same area reveals the dynamic progression of CLUE's distribution features in that region. Meanwhile, a horizontal analysis of curves from different regions highlights the variances in CLUE evolution paths. Using the Kernel density estimation method, depth analysis in the position, pattern, flexibility, and polarization of CLUE in China as a whole and in TFA (Fig. 5).

In terms of distribution position, a rightward shift in the curve's distribution position occurs in the whole country, in MPA as well as in BPMA, showing an overall improvement in CLUE. This trend may stem from the progress of agricultural technology, effective land management policies and agricultural support measures at the national level. Conversely, the curve for MMA moved right and then left, suggesting that this region has undergone intricate variations in CLUE through the years. As urbanization advances, the MMA may face a reduction in the area of cultivated land and changes in land use, but at this time the traditional perception of the importance of agriculture has not yet been fully transformed [49], so the remaining cultivated land may receive more inputs and attention, and these elements might temporarily result in an elevation of CLUE. Yet, as urbanization progresses, the diminishing cultivated area, the shift of agricultural workers to non-agricultural sectors, and ecological pressures could cause a decrease in CLUE.

In terms of distribution dynamics, the curve of CLUE in China from 2000 to 2021 has a tendency of rising wave peaks and narrowing widths. In terms of TFA, the trend seen in the kernel density estimation curve for CLUE within MMA aligns with the national pattern,

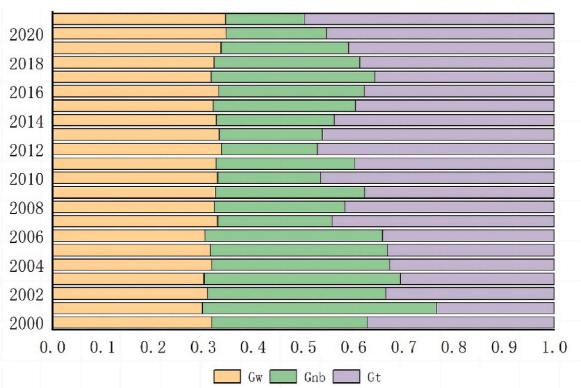

Fig. 4. Sources of variation and their contribution.
Source: Calculated through software.

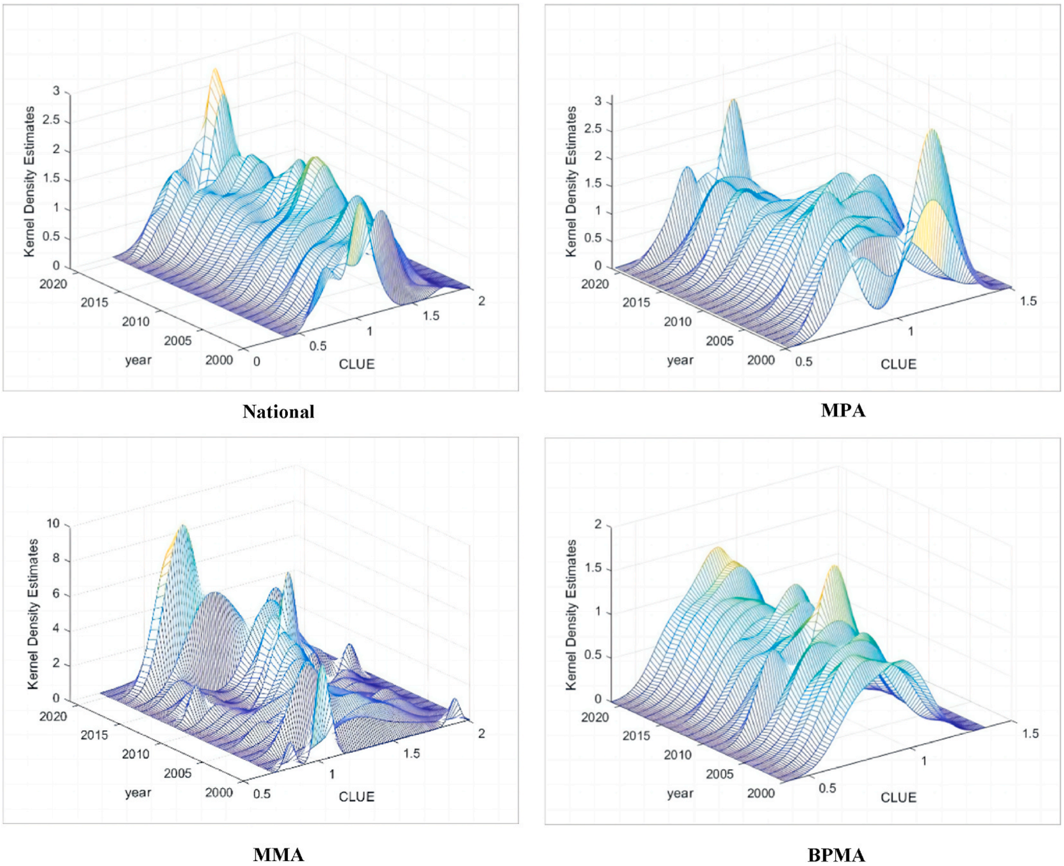

Fig. 5. Kernel density curves of CLUE for China and TFA.
Source: Calculated through software.

showing that the absolute disparity in CLUE levels in MMA is steadily decreasing. In contrast, the relative values of the crests in MPA and BPMA are expanding, indicating that the differentiation of CLUE between these two functional areas is obvious, which may be caused by a combination of uneven application of technology, differences in management practices, inconsistencies in the effects of policy implementation, and changes in market conditions [47]. These common problems suggest that, in order to improve the CLUE in these regions, a more balanced and integrated strategy is needed to ensure the effective allocation and utilization of technologies, policies and resources.

In terms of distribution ductility, the curve of CLUE in the whole country from 2000 to 2021 shows the phenomenon of right trailing, especially after 2005, the change of right trailing is obvious, and the right trailing phenomenon of MPA, MMA and BPMA is basically consistent with that of the whole country, among which there is the phenomenon of left trailing in MPA in part of the year, and the change of right trailing is obvious after 2015, and overall trailing phenomenon is slowed down, which shows that the CLUE in part of provinces in this region is low, which in turn pulls down the value of the overall CLUE.

In terms of distribution polarization, the bipolar or multipolar trend of the curve reveals the differences in CLUE between different regions. The whole country, MPA and BPMA all show a “double-peak” pattern, while the MMA shows a “multi-peak” state, suggesting that CLUE within the region is trending towards multi-polarization. In general, whether analyzed from the perspective of the whole country or the three food functional areas, the overall trend of CLUE had shown characteristics such as “leveling up and narrowing absolute differences,"

3.4. Evolution trend of CLUE

3.4.1. Traditional Markov chain

To further investigate the transfer pattern of CLUE in China, this paper uses the CLUE of TFA from 2000 to 2021 to measure the probability matrix of transfer of CLUE status in China under different time spans by the Markov chain method. According to previous studies, the CLUE was classified into four categories: low efficiency (LE), medium-low efficiency (MLE), medium-high efficiency (MHE), and high efficiency (HE) [42], and the period T was set as 1–5 years. Table 5 presents the probability matrix of transfer within the research period.

The figures on the main diagonal represent the likelihood of the CLUE level remaining unchanged in each province, while the numbers on the off-diagonal lines show the probabilities of a lateral shift in CLUE levels across the provinces. From the data in Tables 5 and it can be analyzed:

(1) The probabilities on the diagonal were greater than other positions. It indicates that the development trend of CLUE in each province is more stable when the influence of spatial factors is not considered, and cross-transfer between provinces of differing levels proves to be challenging.
(2) As time increases, the probability that the provinces will remain unchanged is gradually decreasing. For example, from low-low = 0.870, medium-low-mid-low = 0.729, medium-high-mid-high = 0.701, high-high = 0.856 in T/T+1 lagged period down to low-low = 0.652, medium-low-mid-low = 0.492, medium-high-mid-high = 0.504, and high-high = 0.705 in the T/T+5 lag period. It shows that the ability of the provinces to maintain the status quo at the level of CLUE has decreased. In other words, the convergence trend of CLUE in each province diminishes with time, and mobility increases gradually.
(3) From the results in the table, it can be observed that the probability of an increase in the level of CLUE was greater than that of a downward shift in the level. In other words, there was a greater inertia of upward shift [50]. In addition, transfers of CLUE typically happen between adjacent efficiency levels, except for the transfer from MLE to MHE in the T/T+5 lag period. That is to say, the transfer of CLUE in each province is slow, and it is difficult to achieve cross-domain leaps. It also reflects that improving CLUE requires matching economic development level and agricultural production technology.

3.4.2. *Spatial Markov chain*

While the conventional Markov chain method effectively illustrates the temporal evolution of CLUE, it operates under the assumption that regions are independent, overlooking the spatial correlations among them. To further reveal the spatial transfer pattern of CLUE in China, and to judge whether the efficiency level of “neighboring” regions affects the efficiency transfer in the region, this section will use a spatial Markov chain that incorporates spatial neighboring weights into the time for analysis. The transfer probability matrix is shown in Table 6. The results show that:

(1) The transfer of CLUE does not exist in isolation but is affected by the CLUE in surrounding provinces. Disregarding the geospatial context, the probability of transitioning from LE to MLE at T/T+1 was 13.0%. In contrast, when considering the proximity to provinces with different levels of CLUE, the probability of transferring LE to MLE was 7.4%, 13.9%, 15.8%, and 0.00% when the efficiency of neighboring provinces was LE, MLE, MHE, and HE. This indicates that the level of CLUE in neighboring provinces impacts the CLUE level in this province. Therefore, it is necessary to consider spatial factors’ influence on CLUE’s transfer pattern.
(2) “Neighbors” with high-efficiency levels (i.e., neighboring provinces with higher levels of CLUE than this province) will promote the probability of transfer to higher efficiency levels. In contrast, “neighbors” with low-efficiency levels will have a dampening effect. It reflects the positive spillover effect of provinces with higher levels of CLUE on surrounding provinces.
(3) With the continuous time lag, the effects on the upward and downward shift of the level type of CLUE in neighboring provinces under the same spatial lag type are asymmetric, and the probability of an upward shift of CLUE under different spatial lag types increases.

To guarantee the robustness of the spatial Markov chain outcomes, this study integrates both the spatial distance matrix and the

Table 5
Traditional Markov transfer probability matrix for CLUE.

lag period	categories	LE	MLE	MHE	HE
T/T+1	LE	0.870	0.130	0.000	0.000
	MLE	0.097	0.729	0.168	0.006
	MHE	0.013	0.162	0.701	0.123
	HE	0.000	0.013	0.131	0.856
T/T+2	LE	0.808	0.179	0.013	0.000
	MLE	0.109	0.680	0.204	0.007
	MHE	0.041	0.152	0.662	0.145
	HE	0.000	0.020	0.132	0.849
T/T+3	LE	0.740	0.220	0.040	0.000
	MLE	0.158	0.590	0.223	0.029
	MHE	0.044	0.185	0.578	0.193
	HE	0.000	0.034	0.199	0.767
T/T+4	LE	0.676	0.268	0.049	0.007
	MLE	0.197	0.530	0.220	0.053
	MHE	0.063	0.164	0.578	0.195
	HE	0.000	0.051	0.196	0.754
T/T+5	LE	0.652	0.273	0.068	0.008
	MLE	0.211	0.492	0.234	0.063
	MHE	0.083	0.174	0.504	0.240
	HE	0.000	0.070	0.225	0.705

Source: Calculated through software.

Table 6
Spatial Markov transfer probability matrix for CLUE.

T/(T+1)	categories	LE	MLE	MHE	HE	T/(T+5)	categories	LE	MLE	MHE	HE
LE	LE	0.926	0.074	0.000	0.000	LE	LE	0.739	0.261	0.000	0.000
	MLE	0.083	0.583	0.250	0.083		MLE	0.167	0.250	0.500	0.083
	MHE	0.000	0.091	0.818	0.091		MHE	0.000	0.143	0.714	0.143
	HE	0.000	0.000	0.000	1.000		HE	0.000	0.000	0.000	1.000
MLE	LE	0.861	0.139	0.000	0.000	MLE	LE	0.620	0.304	0.065	0.011
	MLE	0.097	0.731	0.172	0.000		MLE	0.264	0.514	0.167	0.056
	MHE	0.025	0.225	0.575	0.175		MHE	0.149	0.209	0.328	0.313
	HE	0.000	0.020	0.168	0.812		HE	0.000	0.101	0.247	0.652
MHE	LE	0.842	0.158	0.000	0.000	MHE	LE	0.706	0.118	0.176	0.000
	MLE	0.122	0.780	0.098	0.000		MLE	0.167	0.528	0.222	0.083
	MHE	0.000	0.056	0.861	0.083		MHE	0.000	0.143	0.750	0.107
	HE	0.000	0.000	0.094	0.906		HE	0.000	0.000	0.263	0.737
HE	LE	0.000	0.000	0.000	0.000	HE	LE	0.000	0.000	0.000	0.000
	MLE	0.000	0.667	0.333	0.000		MLE	0.000	0.500	0.500	0.000
	MHE	0.000	0.148	0.815	0.037		MHE	0.000	0.105	0.684	0.211
	HE	0.000	0.000	0.167	0.833		HE	0.000	0.000	0.500	0.500

Source: Calculated through software

economic geography matrix into the analysis of the spatial Markov chain over various time spans, after considering the influence of spatial and economic factors, the CLUE among provinces still shows obvious spatial correlation, so the results have a certain degree of stability. Due to space limitation, the relevant results are put into the appendix (appendix2, appendix3) for testing.

4. Conclusions and recommendations

4.1. Conclusions

This study evaluated the CLUE of 30 provinces in China over the period 2000–2021, utilizing the super-efficient SBM model. It then examined the regional disparities in CLUE among TF and their underlying reasons via the Dagum Gini coefficient. Ultimately, it undertook a comprehensive analysis of the dynamic evolution of CLUE in China through kernel density estimation and Markov chain methods. The study's findings can be summarized as follows:

(1) China's overall CLUE value is high, but the efficiency value is slightly decreasing in fluctuation. Regarding CLUE in three food functional areas, CLUE in MMA > CLUE in MPA > CLUE in BPMA. However, the high efficiency of MMA may be due to the fact that its total agricultural output value may come more from high value-added agricultural products, and it obtains higher outputs with fewer inputs, and its CLUE is rather higher than that of MPA.
(2) The unbalanced development phenomenon still existed among the three food functional regions during the study period. Yet, there was a general trend towards diminished regional disparities, and the imbalance has seen some mitigation. The inter-regional variation among TFA is gradually narrowing, and the influence on the overall differences is gradually weakening. However, the cross-group degree of inter-regional variation is on the rise. Based on this, to enhance China's overall CLUE, it is crucial to bolster the coordinated development across all functional areas, and the MMA should ensure that the CLUE does not decline by appropriately expanding the cultivated land area, while the MPA should place greater emphasis on enhancing the CLUE.
(3) The kernel density estimation results showed that the overall trend of CLUE exhibits the characteristics of "increasing level and decreasing absolute difference," both from the perspective of the whole country and the three food functional areas. The traditional Markov chain results showed that the development trend of CLUE in each province was relatively stable. Still, with the increase of time, the probability of maintaining the same level gradually decreased, and the probability of shifting the level of CLUE upward was greater than that of shifting it downward. The results of the spatial Markov chain further demonstrated a significant spatial correlation effect of CLUE in China, and the interaction of CLUE between neighboring provinces will lead to spatial convergence of CLUE in the long term.

4.2. Recommendations

In response to the results of the study, this paper argues that, firstly, maximizing the potential of production regions is essential, by delineating the variances in cultivated land resources, agricultural production capabilities, and economic growth levels across each functional sector. Exploiting the unique benefits of each area, customizing approaches to align with local requirements, and mobilizing resources internationally are crucial steps to amplify efficiency. Second, strengthen the synergistic development under the spatial correlation effect. The government should pursue relevant policies to promote inter-regional coordinated development, which may include establishing inter-regional mechanisms for agricultural technology exchange and cooperation, promoting inter-regional economic integration, and establishing common agricultural markets between provinces. Finally, infrastructure development should be strengthened and the level of agricultural science and technology should be enhanced. Governments should support research and development and innovation in agricultural science and technology, including biotechnology, smart agricultural equipment, precision irrigation and fertilizer use technology.

Although this study has made significant progress, there is still potential for further refinement and enhancement. The High Level Panel of Experts on Food Security and Nutrition (HLP) proposes that the definition of food security should also encompass aspects of accessibility and sustainability, which is not yet fully reflected in this study when selecting indicators for assessing the efficiency of CLUE. Subsequent studies can be supplemented and improved on the basis of existing studies, so as to integrate the multidimensional and deep-rooted factors of food security into the assessment system, continuously optimize and improve the evaluation model, and reflect the situation of cropland utilization in a more scientific and comprehensive way.

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CRediT authorship contribution statement

Xintong Dong: Writing – original draft, Resources, Methodology, Investigation, Formal analysis. **Shuai Liu:** Writing – review & editing, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix

Appendix1

Table 7
Decomposition of Dagum-Gini coefficient of CLUE in China from 2000 to 2021

year	G	G_w	G_{nb}	G_t	Intra-regional			Inter-regional			Contribution		
					MPA	BPMA	MMA	BPMA|MPA	MMA|MPA	BPMA|MMA	G_w	G_{nb}	G_t
2000	0.148	0.047	0.046	0.055	0.120	0.158	0.137	0.147	0.152	0.169	31.72%	30.98%	37.29%
2001	0.156	0.046	0.073	0.037	0.116	0.191	0.101	0.171	0.134	0.207	29.83%	46.69%	23.48%
2002	0.142	0.044	0.051	0.048	0.126	0.162	0.074	0.150	0.140	0.165	30.94%	35.50%	33.56%
2003	0.150	0.045	0.059	0.046	0.141	0.169	0.047	0.164	0.162	0.152	30.13%	39.21%	30.66%
2004	0.123	0.039	0.044	0.040	0.111	0.144	0.063	0.133	0.116	0.139	31.72%	35.49%	32.79%
2005	0.135	0.042	0.048	0.045	0.123	0.160	0.060	0.150	0.135	0.135	31.42%	35.23%	33.35%
2006	0.146	0.044	0.052	0.050	0.120	0.174	0.077	0.156	0.143	0.171	30.33%	35.47%	34.21%
2007	0.117	0.038	0.027	0.052	0.094	0.142	0.099	0.124	0.106	0.134	32.89%	22.82%	44.29%
2008	0.120	0.039	0.031	0.050	0.097	0.146	0.092	0.130	0.111	0.137	32.22%	26.05%	41.72%
2009	0.114	0.037	0.034	0.043	0.092	0.142	0.084	0.123	0.101	0.133	32.51%	29.68%	37.82%
2010	0.122	0.040	0.025	0.057	0.101	0.161	0.072	0.139	0.102	0.132	32.93%	20.52%	46.55%
2011	0.141	0.046	0.039	0.056	0.119	0.184	0.082	0.159	0.119	0.160	32.60%	27.62%	39.78%
2012	0.139	0.047	0.027	0.066	0.130	0.173	0.078	0.158	0.122	0.141	33.65%	19.14%	47.21%

(*continued on next page*)

Table 7 (*continued*)

year	G	G_w	G_{nb}	G_t	Intra-regional			Inter-regional			Contribution		
					MPA	BPMA	MMA	BPMA|MPA	MMA|MPA	BPMA|MMA	G_w	G_{nb}	G_t
2013	0.147	0.049	0.030	0.068	0.138	0.181	0.073	0.168	0.130	0.145	33.22%	20.56%	46.22%
2014	0.150	0.049	0.035	0.066	0.146	0.173	0.073	0.171	0.144	0.144	32.62%	23.53%	43.85%
2015	0.159	0.051	0.045	0.063	0.151	0.185	0.072	0.178	0.154	0.162	31.96%	28.42%	39.62%
2016	0.142	0.047	0.041	0.054	0.140	0.167	0.063	0.161	0.128	0.145	33.03%	29.11%	37.86%
2017	0.142	0.045	0.046	0.051	0.144	0.166	0.029	0.163	0.136	0.143	31.55%	32.68%	35.77%
2018	0.137	0.044	0.040	0.053	0.137	0.163	0.035	0.157	0.125	0.142	32.14%	29.06%	38.80%
2019	0.125	0.042	0.032	0.051	0.133	0.146	0.036	0.143	0.114	0.117	33.57%	25.42%	41.01%
2020	0.120	0.041	0.024	0.055	0.124	0.142	0.058	0.137	0.105	0.115	34.53%	20.07%	45.40%
2021	0.124	0.043	0.020	0.062	0.129	0.136	0.077	0.137	0.118	0.116	34.44%	15.87%	49.69%

Appendix 2

Table 8
Spatial Markov transfer probability matrix for CLUE (Spatial distance matrix)

T/(T+1)	categories	LE	MLE	MHE	HE	T/(T+5)	categories	LE	MLE	MHE	HE
LE	LE	0.895	0.105	0.000	0.000	LE	LE	0.625	0.375	0.000	0.000
	MLE	1.000	0.000	0.000	0.000		MLE	1.000	0.000	0.000	0.000
	MHE	0.000	0.000	0.000	0.000		MHE	0.000	0.000	0.000	0.000
	HE	0.000	0.000	0.000	0.000		HE	0.000	0.000	0.000	0.000
MLE	LE	0.862	0.138	0.000	0.000	MLE	LE	0.661	0.268	0.063	0.009
	MLE	0.080	0.761	0.152	0.007		MLE	0.183	0.530	0.226	0.061
	MHE	0.016	0.169	0.677	0.137		MHE	0.102	0.204	0.459	0.235
	HE	0.000	0.015	0.131	0.854		HE	0.000	0.071	0.205	0.723
MHE	LE	1.000	0.000	0.000	0.000	MHE	LE	0.500	0.000	0.500	0.000
	MLE	0.154	0.615	0.231	0.000		MLE	0.500	0.200	0.200	0.100
	MHE	0.000	0.130	0.783	0.087		MHE	0.000	0.063	0.625	0.313
	HE	0.000	0.000	0.118	0.882		HE	0.000	0.091	0.364	0.545
HE	LE	0.000	0.000	0.000	0.000	HE	LE	0.000	0.000	0.000	0.000
	MLE	0.000	0.000	1.000	0.000		MLE	0.000	0.000	1.000	0.000
	MHE	0.000	0.143	0.857	0.000		MHE	0.000	0.000	0.857	0.143
	HE	0.000	0.000	0.167	0.833		HE	0.000	0.000	0.333	0.667

Appendix3

Table 9
Spatial Markov transfer probability matrix for CLUE (Economic distance matrix)

T/(T+1)	categories	LE	MLE	MHE	HE	T/(T+5)	categories	LE	MLE	MHE	HE
LE	LE	0.500	0.500	0.000	0.000	LE	LE	0.625	0.375	0.000	0.000
	MLE	0.000	0.375	0.625	0.000		MLE	1.000	0.000	0.000	0.000
	MHE	0.000	0.097	0.774	0.129		MHE	0.000	0.000	0.000	0.000
	HE	0.000	0.111	0.444	0.444		HE	0.000	0.000	0.000	0.000
MLE	LE	0.866	0.134	0.000	0.000	MLE	LE	0.661	0.268	0.063	0.009
	MLE	0.097	0.766	0.129	0.008		MLE	0.183	0.530	0.226	0.061
	MHE	0.023	0.216	0.625	0.136		MHE	0.102	0.204	0.459	0.235
	HE	0.000	0.010	0.126	0.864		HE	0.000	0.071	0.205	0.723
MHE	LE	0.889	0.111	0.000	0.000	MHE	LE	0.500	0.000	0.500	0.000
	MLE	0.095	0.667	0.238	0.000		MLE	0.500	0.200	0.200	0.100
	MHE	0.000	0.100	0.867	0.033		MHE	0.000	0.063	0.625	0.313
	HE	0.000	0.000	0.047	0.953		HE	0.000	0.091	0.364	0.545
HE	LE	1.000	0.000	0.000	0.000	HE	LE	0.000	0.000	0.000	0.000
	MLE	0.500	0.500	0.000	0.000		MLE	0.000	0.000	1.000	0.000
	MHE	0.000	0.000	0.600	0.400		MHE	0.000	0.000	0.857	0.143
	HE	0.000	0.000	0.400	0.600		HE	0.000	0.000	0.333	0.667

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