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Spatiotemporal Pattern and Driving Mechanism of Cultivated Land Use Transition in China

Feifei Jiang, Fu Chen *, Yan Sun, Ziyi Hua, Xinhua Zhu and Jing Ma

School of Public Administration, Hohai University, Nanjing 211100, China; jff@hhu.edu.cn (F.J.); suny@hhu.edu.cn (Y.S.); huastacey@hhu.edu.cn (Z.H.); 20110033@hhu.edu.cn (X.Z.); jingma2022@hhu.edu.cn (J.M.)
* Correspondence: chenfu@cumt.edu.cn; Tel.: +86-025-8378-7368

Abstract: In the past 20 years, the global economy has undergone tremendous changes with rapid industrialization and urbanization. Cultivated land is an important spatial carrier for human production and life, and its use pattern also changes with socioeconomic development. Natural, economic, social, and policy factors jointly drive the cultivated land use transition (CLUT). However, the spatiotemporal pattern and evolution characteristics of the CLUT at the national scale have not yet been clarified in China. Factors that play a leading role in the transition are also unclear. To this end, this paper explores the spatiotemporal evolution characteristics of the CLUT at a national scale and analyzes the main drivers and spatial differentiation rules of the transition based on relevant data from 31 provincial units on the Chinese mainland from 2000 to 2019. The results show that: (1) The CLUT in China from 2000 to 2019 had obvious stage characteristics. (2) The coordination degree of the CLUT was enhanced overall. Areas with a higher degree of coordination presented a spatial distribution pattern of small agglomeration and large dispersion, while low-level areas were distributed in spots. (3) Different drivers had various effects on the CLUT. The topography played an inhibitory role in the transition, and its influence showed obvious differences between the east and west regions. The effect of the construction land demand index shifted from inhibition to promotion, while the effects of the gross agricultural economic output and the total power of agricultural machinery in the transition were insignificant.

Keywords: cultivated land use transition; spatiotemporal differentiation; coupling and coordination; geographically weighted regression model

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1. Introduction

Cultivated land is an important cornerstone of agricultural production. In the 21st century, global cities continue to expand rapidly [1]. Excess urban expansion of the city causes the mass loss of high-quality farmland, directly threatening global food security. Especially in economically underdeveloped areas such as Asia and Africa, grain pressure and shortages of cultivated land become unavoidable practical problems. In addition, a modern economy and rapid development lead to a rigid growth in global grain demand [2,3]. Meanwhile, the competition for cultivated land resources in industry, agriculture, and other fields is increasingly fierce, which further aggravates the human-land conflict. Poor cultivation and management also cause prominent problems, including overuse, abuse, soil degradation, environmental pollution, and so on. These problems hinder the realization of sustainable development goals (SDGs) [4]. Moreover, the world is currently in the post-epidemic era. Combined with the impacts of sudden events such as extreme climate change and geopolitical conflicts [5], the stability of the global grain system is being severely challenged. Thus, the CLUT is not only the core issue of land use and cover change (LUCC), but also an urgent need to respond to the increasingly complex situation of cultivated land protection in the world.

The concept of land use transition (LUT) was first proposed by British scholars when studying forest cover changes in underdeveloped countries [6]. LUT refers to the trend variations or transitions of land use morphology driven by socioeconomic transition and innovation during the corresponding period [7,8]. Early studies mainly focused on the forest land use transition and gradually expanded to the transition of other types of land with the deepening of the research [9–12]. Since cultivated land is the most basic agricultural resource, research on the CLUT has continued to receive high attention from academic circles. Some scholars conducted relevant studies on the CLUT based on different regional scales and perspectives. Guan et al. [13] analyzed the spatial transition of farmland use in Kyushu, Japan, from the perspective of spatial morphology, mainly focusing on changes in the quantity and spatial pattern of cultivated land. Song et al. [14] and Zhang et al. [15] have constructed a theoretical analysis framework for the multifunctional transition of farmland use and proposed an optimization path for the multifunctional use of farmland. Zhang et al. [16] explored the spatiotemporal pattern and trend variations of the CLUT in different regions of Africa and found that the CLUT had obvious spatiotemporal differentiation characteristics. Ketema et al. [17] assumed that economy, technology, system, and location were the potential drivers of the CLUT in Europe, but the impact of labor force change and social culture were easily overlooked. Ke et al. [18] constructed a research framework for the green transition of farmland use and conducted an empirical analysis on the example of Hubei Province, China. Moreover, in the context of rapid urbanization, several studies have also explored the coupling relationships among CLUT, economic development [19], rural construction [20], and grain output [21]. However, most of the existing studies focused on a single perspective, such as spatial transition and functional transition, lacking innovative and multiple perspectives. Meanwhile, existing research has given greater consideration to the process, characteristics, and driving factors of the CLUT, while insufficient regard has been given to the effect and optimization regulation of the transition. At present, it can be inferred that the field of CLUT still exists with an enormous development space in the aspects of empirical evaluation, method innovation, impact exploration, etc. Therefore, it is particularly important to promote the development of transition research to a higher and deeper level.

China has the largest population in the world, as well as the largest food production and consumption. Over the past 20 years, with the rapid advancement of industrialization and urbanization in China, occupying a large amount of farmland for non-agricultural construction has become a common phenomenon in developed regions [22]. At the same time, integrated urban-rural development and the flow of geographical factors have also caused prominent issues such as non-agriculturalization [23], non-grain [24], marginalization, and fragmentation of cultivated land [25,26], which seriously threaten the grain security of China. In the context of the severe situation, the academic community called for a reconsideration of the use of cultivated land resources. At the beginning of the 21st century, Long [27] introduced relevant theories of LUT into China and improved them according to the current situation of land use management in China. Related research results were significant for the sustainable use of cultivated land resources and national food security. Moreover, intensive study on the CLUT was also conducive to coordinating the protection of cultivated land resources, high-quality economic development, and ecological civilization construction, which attracted wide attention from society and government.

Due to the late start of research on the LUT in China, there were few direct studies on the topic of CLUT, whereas the relevant researche mainly focused on themes of driving mechanisms and morphology transition. As everyone knows, China has a vast territory with diverse natural, economic, and social elements. Thus, although previous studies of driving mechanisms have involved many scales, such as provinces, cities, counties, and river basins, it is still crucial to clarify the transition process and its spatial heterogeneity at the national scale. In addition, cultivated land use is a complex system composed of multiple elements that interact and influence each other. These elements are interwoven according to certain rules and principles. They together constitute the overall function and structure of cultivated land use. However, few scholars have studied the coupling and coordination relationships between different elements. Since human-land conflict is prominent in China, the analysis of the CLUT is inseparable from the in-depth analysis of the coupling influence of the changes in various cultivated land use elements within the human-land system. Based on this, this study took the perspective of cultivated land use morphology as the starting point. Then, the coupling coordination degree model was used to explore the spatiotemporal pattern of the CLUT in China from 2000 to 2019, and the coupling coordination types were further divided. Finally, by identifying the main driving factors of the utilization transition and their spatial differentiation, the study proposed some corresponding policy recommendations, aiming to provide decision-making references for the protection and optimal utilization of cultivated land.

2. Materials and Methods

2.1. Research Framework

The diagnosis of cultivated land use morphological change is the basis for understanding the CLUT and is also the key to investigating the spatiotemporal pattern of the CLUT [28], which requires profound and intensive research. At present, there are two main classifications of cultivated land use morphologies. One classification is dominant and recessive morphologies [29–31]. The dominant morphology corresponds to the quantity, usage structure, and spatial layout of cultivated land, while the recessive morphology refers to the socio-economic utilization attributes under the interaction between people and land, including quality, ownership, management style, input-output, and function. The other classification is spatial, functional, and model morphologies [32–35]. The spatial morphology mainly reflects the quantitative change and structural transition, and the functional morphology characterizes the production, living, and ecological effects of cultivated land use, while the model morphology includes the inherent input and management style of cultivated land. Generally speaking, both dominant and spatial morphologies emphasize the spatiotemporal changes in the quantity or structure of the cultivated land, with similar connotations [19]. However, the recessive, functional, and model morphologies have slightly different emphasis. The recessive morphology has a richer connotation, emphasizing not only the multifunctional expression and management model but also the quality and ownership changes of cultivated land [36]. Nevertheless, there are certain blind spots in the quantitative research on recessive morphological change caused by the discontinuity of quality monitoring time and a lack of ownership information [37]. Obviously, the dominant and recessive forms are more suitable for the mechanism research of CLUT and are not suitable for the empirical analysis. In view of this, this study conducts empirical research on CLUT in China from the perspectives of spatial morphology transformation, multifunctional morphology transformation, and model morphology transformation.

Driving factors of cultivated land use morphology change mainly include natural and socio-economic drivers [38,39] (Figure 1). Regional disparity could lead to major factors of differentiation in different regions [40]. Natural factors, such as topography, climate, and hydrology, are the foundation of the cultivated land use morphology change [41], and they show a significant impact on the macroscale or mesoscale research area with less disturbance by human activities [42]. Socio-economic factors are the core driving force. Several studies have shown that, under the influence of institutions and policies, the response of individuals or groups to the economy is the deep-seated driving factor of the cultivated land use morphology change [43,44]. Therefore, based on previous literature and considering geographical location factors, this article constructs an analysis framework for the driving factors of CLUT from four aspects: nature, economy, society, and institution.

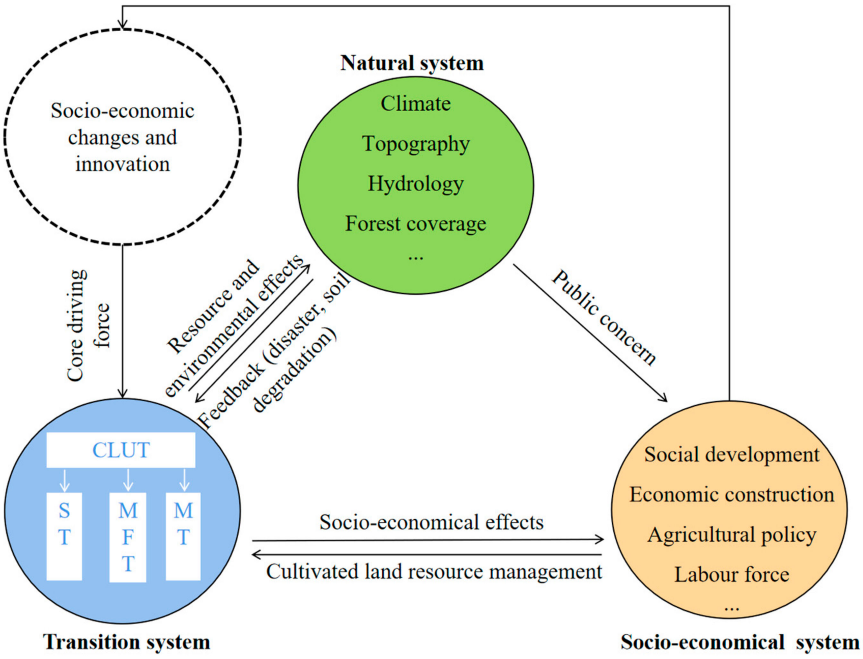

Figure 1. Analysis framework of the CLUT.

2.2. Index System and Data Sources

2.2.1. Index System

The Delphi method is a subjective and qualitative method that can gather diverse perspectives and reach consensus on complex themes or issues [45]. It has been widely applied in agriculture [46], the economy [47], and the environment [48]. This method involves conducting multiple rounds of surveys on the opinions of experts on the questions raised in the questionnaire, repeatedly soliciting, summarizing, and modifying. Finally, they are summarized into a consensus among experts, which serves as the predicted result [49]. In the process of collecting and analyzing expert feedback, quantitative statistical analysis methods are used to statistically process the data, and the obtained results present stability and reliability [50]. Therefore, this paper adopted the Delphi method to establish an evaluation index system. In this study, 15 professors and associate professors from Chinese universities engaged in research on farmland protection and agricultural policy were selected for consultation. They have more than 10 years of teaching experience and field practice experience.

Under the analysis framework proposed above, three target layers and seven factor layers were first identified. Target layers included spatial transformation, multifunctional transformation, and model transformation. Factor layers included quantity, structure, production function, living function, ecological function, resource conservation, and spatial intensification. Then, based on this, evaluation indicators (indicator layer) belonging to different factor layers were selected, and finally, the evaluation indicator system of CLUT was formed at three levels: the target layer, the criterion layer, and the indicator layer.

According to the results of the first round of consultation (Table 1), grain sown area and grain economy ratio were merged into the proportion of non-grain sown area. Additionally, the average scores of the importance of cultivated land per capita, proportion of paddy fields, crop output per hectare, ratio of agricultural output to GDP, labor force per hectare, and organic fertilizer use were <4, which were deleted. Meanwhile, the average scores of the operability of landscape fragmentation, agricultural technicians per hectare, and agricultural plastic film use were <4, and they were also deleted.

Table 1. Results of the first round of expert consultation.

Index Layer	Importance		Operability	
	$\bar{x} \pm s$	CV	$\bar{x} \pm s$	CV
Cultivated land area	4.467 ± 0.516	11.561%	5.000 ± 0.000	0.000%
Cultivated land per capita	3.717 ± 1.059	28.496%	4.667 ± 0.516	11.066%
Multiple crop index	4.450 ± 0.809	18.187%	4.667 ± 1.506	18.060%
Grain-sown area	4.367 ± 1.388	11.229%	4.000 ± 0.894	22.361%
Grain economy ratio	4.217 ± 1.114	18.450%	4.583 ± 1.429	19.875%
Landscape fragmentation	4.000 ± 0.894	29.814%	1.750 ± 0.880	50.305%
Proportion of paddy fields	2.750 ± 1.084	39.417%	4.000 ± 0.894	22.361%
Grain output per hectare	4.600 ± 0.800	17.391%	4.167 ± 0.753	18.067%
Crop output per hectare	3.633 ± 0.753	20.719%	4.333 ± 0.816	18.842%
Agricultural economic output per hectare	4.000 ± 0.632	15.811%	4.667 ± 0.816	22.268%
Ratio of agricultural output to GDP	3.167 ± 0.753	23.772%	4.250 ± 1.255	29.529%
Per capita share of grain	4.242 ± 0.755	17.806%	4.083 ± 1.357	14.013%
Proportion of agricultural employees	4.375 ± 0.802	18.339%	4.150 ± 0.418	11.155%
Labor force per hectare	2.983 ± 0.873	29.254%	2.667 ± 1.033	38.730%
Agricultural technicians per hectare	4.000 ± 0.787	23.861%	1.750 ± 0.880	50.305%
Chemical fertilizer pollution per hectare	4.067 ± 1.061	24.759%	4.217 ± 1.021	22.233%
Agricultural plastic film use	4.150 ± 0.731	29.855%	1.750 ± 0.758	43.331%
Unit irrigation level	4.167 ± 1.098	20.163%	4.083 ± 0.917	24.754%
Proportion of water-saving irrigation area	4.067 ± 1.108	17.235%	4.033 ± 1.329	16.912%
Total power of agricultural machinery per hectare	4.250 ± 0.758	17.842%	4.667 ± 1.862	19.821%
Energy consumption per hectare	4.350 ± 1.173	19.457%	4.083 ± 0.665	21.900%
Organic fertilizer use	2.817 ± 1.150	40.816%	2.017 ± 0.895	44.398%
Proportion of facility agricultural land	4.217 ± 1.167	24.674%	4.033 ± 0.753	19.638%

Based on the results of the first round of consultation, the second round of consultation questionnaires were sorted out to conduct expert consultation. The final results showed that the importance and operability scores of all three-level indicators were >4, and the coefficient of variation was <0.25. After completing two rounds of the Delphi method, this study identified 3 first-level indicators, 7 second-level indicators, and 13 third-level indicators for the comprehensive evaluation of CLUT (Table 2).

Table 2. Comprehensive evaluation index system of the CLUT.

Target Layer	Rule Layer	Index Layer	Index Interpretation	Attribute	Weight
Spatial transition	Quantity	Cultivated land area	/	+	0.1395
	Structure	Multiple crop index	Crop-sown area/cultivated land area	+	0.0592
		Proportion of non-grain-sown area	Non-grain sown area/total crop sown area	−	0.0484
Multifunctional transition	Production function	Grain output per hectare	Total grain output/grain sown area	+	0.0683
		Agricultural economic output per hectare	Total crop economic output/cultivated land area	+	0.0908
	Living function	Per capita share of grain	Total grain output/total population	+	0.0547
		Proportion of agricultural employees	Agricultural population/total population of the labor force	+	0.0725
	Ecological function	Chemical fertilizer pollution per hectare	Total amount of chemical fertilizer application/cultivated land area	−	0.1029
		Unit irrigation level	Effective irrigated area/grain output	+	0.0863
Model transition	Resource saving	Proportion of water-saving irrigation area	Water-saving irrigation area/cultivated land area	+	0.0698
		Total power of agricultural machinery per hectare	Total power of agricultural machinery/cultivated land area	+	0.0679
		Energy consumption per hectare	Total agricultural energy consumption/cultivated land area	−	0.0971
	Spatial intensification	Proportion of facility agricultural land	Facility agricultural land area/cultivated land area	+	0.0425

Note: "+", positive indicators; "−", negative indicators.

2.2.2. Data Sources and Processing

The time series of the database in this study were the years 2000–2019. The land use data came from the China land and resources statistical yearbook published by the Ministry of Natural Resources of China. The terrain data was provided by the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 25 May 2023). ArcGIS 10.2 was used for spatial analysis and processing. The socioeconomic data was obtained from statistical yearbooks of various provinces and cities in China, statistical communiqués of national economic and social development, and relevant government portals. Considering the unavailability of data, the Taiwan Province of China, HKSAR, and Macao SAR were not included in the scope of this study. In addition, the maps in this study were based on the standard map with the figure number GS(2019)1719, which was downloaded from the standard map service website of the Ministry of Natural Resources of China (http://bzdt.ch.mnr.gov.cn/, accessed on 12 May 2023).

2.3. Study Methods

2.3.1. Indicator Weight Calculation

The analytic Hierarchy Process (AHP) method is a reliable, rigorous, and robust method widely used for determining indicator weights [56–58]. The hybrid approach used by combining AHP with common weighting methods requires less expert judgment than the AHP method, providing more accurate rankings and weighting [59]. This paper combined AHP and the entropy weight method. During the hierarchical analysis, the study once again invited the 15 Delphi experts mentioned earlier to form an AHP expert group to jointly complete the ranking of the importance of each indicator.

The weights calculated can be corrected through the combined empowerment method, which can overcome the shortcomings of the single method of subjective weighting or objective weighting to the greatest extent [60]. The final result can not only demonstrate subjective human intervention but also highlight the objective indicator weight so as to make the indicator weight more scientific. The calculation formula is as follows:

$$W_j = \frac{\sqrt{\alpha_j \omega_j}}{\sum_{j=1}^{n} \sqrt{\alpha_j \omega_j}} \quad (1)$$

where W_j is the weight value of the indicator after combination weighting; α_j represents the weight value of the indicator calculated using AHP; and ω_j represents the weight value of the indicator calculated using the entropy weight method.

2.3.2. Evaluation of Comprehensive Measurement and Coupling Coordination Degree of the CLUT

1. Comprehensive degree of the transition

The transition index of the subsystem was calculated by adding the product of the indicator layer weight and the standardized value of each indicator. The comprehensive degree of the transition can be obtained by summing the transition indexes of subsystems according to the target layer weight. The calculation formulas are as follows:

$$ST(s) = \sum_{i=1}^{m} (\alpha_i \cdot s_i) \quad (2)$$

$$MFT(x) = \sum_{j=1}^{m} (\beta_j \cdot x_j) \quad (3)$$

$$MT(g) = \sum_{k=1}^{m} (\lambda_k \cdot g_k) \quad (4)$$

$$T = \alpha \times ST(s) + \beta \times MFT(x) + \lambda \times MT(g) \tag{5}$$

where $ST(s)$, $MFT(x)$, and $MT(g)$ are respectively spatial transition index, multifunctional transition index, and model transition index; T is the comprehensive degree of the CLUT; α_i, β_j, and λ_k represent the index layer weight; s_i, x_j, and g_k are indicators that represent the characteristics of spatial transition, multifunctional transition, and model transition after using range normalization; α, β, and λ represent the target layer weight.

2. Coupling degree of the transition

During the transition process, there will be interactions and impacts of different intensities among the three subsystems. This study used the methods of studying coupling system models in physics to construct an evaluation model for the coupling degree of the CLUT [61]. The coupling function is as follows:

$$C = \frac{3 \times \{ST(s) \times MFT(x) \times MT(g)\}^{1/3}}{ST(s) + MFT(x) + MT(g)} \tag{6}$$

where C is the coupling degree of the transition.

3. Coordination degree of the transition

This study focused on both the interaction degree among the three subsystems and the coordination status of the three. Therefore, the study introduced a coordination model to effectively measure the interaction and development status of the three subsystems [62]. The specific calculation formula is as follows:

$$D = \sqrt{C \times T} \tag{7}$$

where D is the coordination degree of the transition, C is the coupling degree of the transition, and T is the comprehensive degree of the transition.

Given the complexity of the comprehensive degree, coupling degree, and coordination degree of the CLUT, this study referred to the previous research results [18] and used the manual breakpoint method to classify the indexes in order to better understand the coordinated development status of the transition in different regions. The classification criteria are as shown in Table 3.

Table 3. Grade classification of indexes.

Transition Index	Index Level	Criteria
Comprehensive degree of the transition	Primary stage	[0.00, 0.41)
	Intermediate stage	[0.41, 0.47)
	Advanced stage	[0.47, 1.00]
Coupling degree of the transition	Low level	[0.00, 0.93)
	Medium level	[0.93, 0.96)
	High level	[0.96, 1.00]
Coordination degree of the transition	Low level	[0.00, 0.62)
	Medium level	[0.62, 0.67)
	High level	[0.67, 1.00]

2.3.3. Construction of a Minimum Data Set (MDS) Based on the Principal Component Analysis (PCA)

PCA is widely used in identifying the main drivers of cultivated land use change. This method can reduce data redundancy, but it only considers the factor loading of a variable on a principal component (PC). Reducing the number of evaluation indicators can also result in the loss of partial cultivated land use change information contained in the indicators. To avoid this defect, this study introduced the norm value as an important reference for constructing MDS [63]. The norm value is calculated as follows:

$$N_{ik} = \sqrt{\sum_{i=1}^{k} (U_{ik}^2 \lambda_k)} \quad (8)$$

where N_{ik} is the combined loading value of the i-th variable on the first k PCs with eigenvalue ≥ 1, U_{ik} is the factor loading value of the i-th variable on the k-th PC, and λ_k is the eigenvalue of the k-th PC.

2.3.4. Geographic Weighted Regression (GWR) Analysis

GWR introduces the spatial relationship on the basis of traditional global regression, which can reflect the relationship between variables changing and the spatial position by establishing the local regression variance at each point in the spatial range [64]. Therefore, in this study, GWR was chosen to explore the spatial differentiation characteristics of drivers in different regions. The model is constructed as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (9)$$

where (u_i, v_i) is the spatial coordinate of the i-th observation point; β_k (u_i, v_i) is the k-th regression parameter on the i-th observation point; β_0 is the regression constant of the i-th observation point.

3. Results

3.1. Classification of Cultivated Land Use Stages in China from 2000 to 2019

Based on the weight calculation in Table 1, the comprehensive score trend chart of cultivated land use in China from 2000 to 2019 was drawn by weighting and summing the index values of each indicator (Figure 2). It can be seen that the comprehensive score had obvious stage characteristics. During 2000–2006, the comprehensive score of cultivated land use showed a trend of rapid decline, and its average score was 0.43. During 2006–2013, the comprehensive score began to fluctuate upwards, with an average score of 0.48. During 2013–2019, the curve fluctuation was relatively small, and the average score was 0.57. To sum up, the change in cultivated land use in China from 2000 to 2019 can be roughly divided into three periods: 2000–2006, 2006–2013, and 2013–2019.

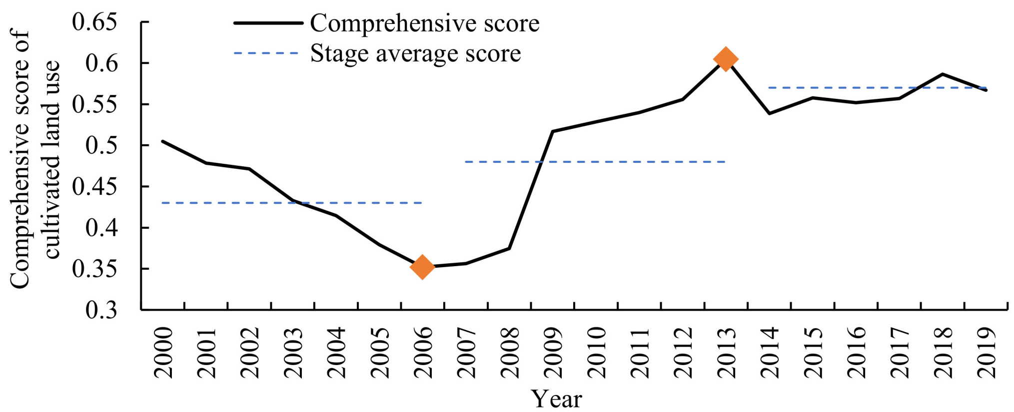

Figure 2. Comprehensive score of the CLUT in China from 2000 to 2019. The orange diamonds represent the minimum (2006) and maximum (2013) comprehensive scores of cultivated land use in China from 2000 to 2019, respectively.

3.2. Characteristics and Trends of the CLUT in China from 2000 to 2019

Figure 3 shows that the spatial transition index experienced drastic changes over the whole period 2000–2019, showing a tendency toward "slow decrease–rapid increase–relative stability". The mean value increased from 0.323 to 0.819 in the first stage. The multifunctional transition index went through a process of decreasing first and then increasing, with a decreasing trend from 2000 to 2006 and an increasing trend from 2006 to 2019. Its mean value decreased from 0.466 to 0.435. From the perspective of individual functions, the production function transition index rose rapidly, and its mean value increased from 0.033 to 0.275 in the first stage. However, the living function transition index declined to varying degrees in three stages, with the mean value decreasing from 0.160 to 0.126. The ecological function transition index experienced a process of decreasing first and then increasing, with a decreasing trend from 2000 to 2013 and an increasing trend from 2013 to 2019. Its mean value decreased from 0.274 to 0.034. The above results show that the production function of cultivated land use was gradually enhanced, while the living function was weakened little by little. Meanwhile, ecological function was in a slow recovery stage. In addition, the model transition index presented a variation trend of "slow decrease–rapid increase–slow decrease", but it achieved overall growth. The mean value increased from 0.367 to 0.621.

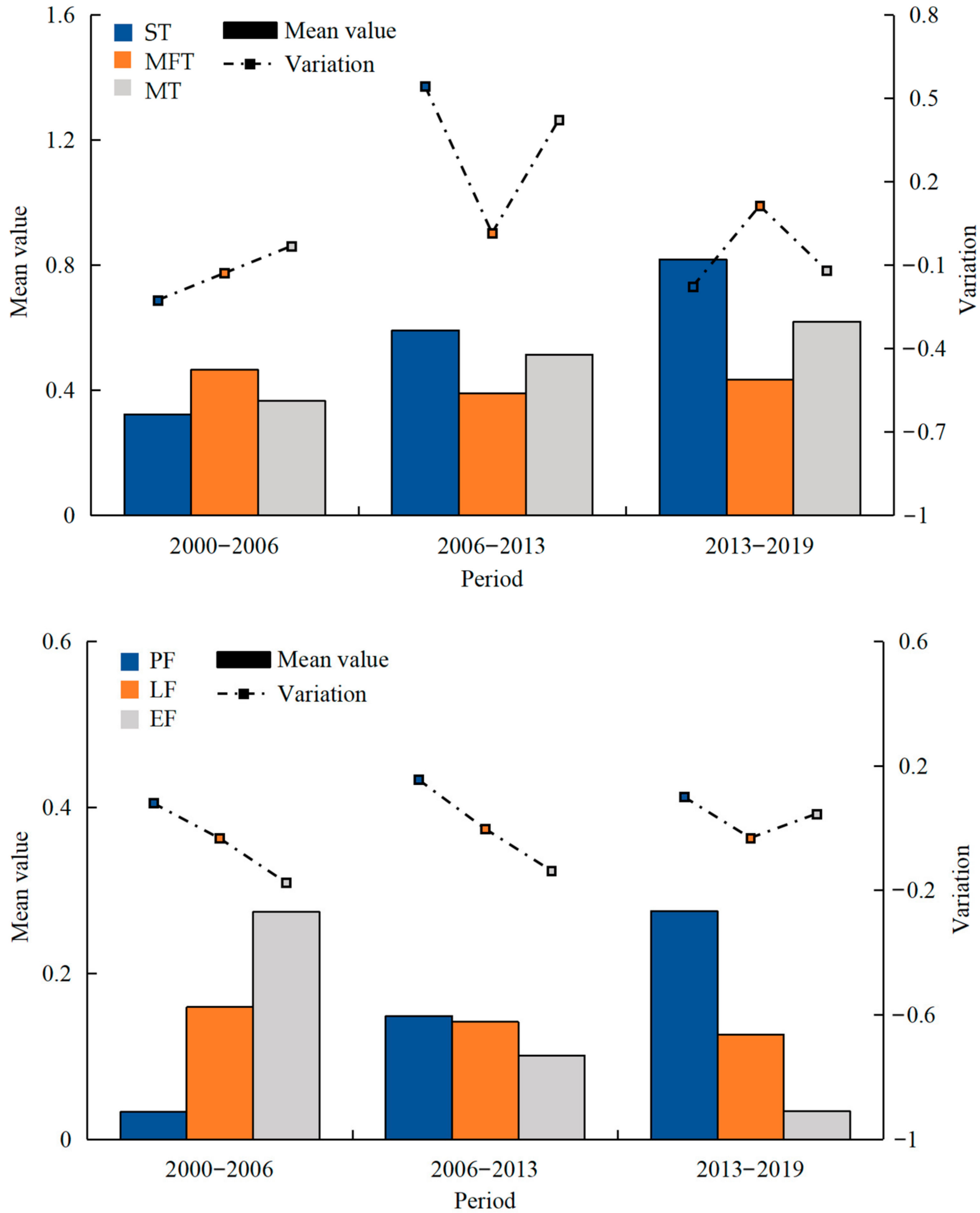

Figure 3. Stage characteristics of the CLUT in China from 2000 to 2019. ST, spatial transition; MFT, multifunctional transition; MT, model transition; PF, production function; LF, living function; EF, ecological function.

3.3. Evaluation of Comprehensive Measurement and Coupling Coordination of the CLUT in China

During 2000–2006, the comprehensive degree of the transition showed a feature of low in the south and high in the north. Eight units were in the advanced stage, with a mean of 0.492. The distribution pattern of small agglomeration and large dispersion in intermediate-level regions across the country accounting for 45.2%, and its mean was 0.442. Areas that were in the primary stage were distributed in spots, with a mean of 0.394. The coupling degree results of the three subsystems were relatively high, with a mean of 0.965, indicating that the overall interaction was strong. 67.7% of units were at the high level, with a mean of 0.975. The coordination degree of the three subsystems was at a medium level, with an average value of 0.650.

During 2006–2013, the comprehensive degree of the transition was improved compared with the previous stage, and their average value rose to 0.462. 45.2% of the units were at the advanced stage, showing a spatial pattern of small agglomeration and large dispersion. Areas in the primary stage accounted for 12.9%, generally developing from dispersion to aggregation. The coupling degree of the transition presented an enhanced trend, with an average value of 0.974. 87.1% of the units were at the high level, and its average value was 0.979. The coordination degree of the transition also showed an enhanced trend, with the average value rising to 0.670.

During 2013–2019, the comprehensive degree of the transition began to slow down, and its average value dropped to 0.450. Areas that were in the advanced stage were mainly distributed in a strip pattern in the whole region, gathering in "Jiangsu–Shanghai–Zhejiang–Fujian–Guangdong". The average value of the regions that were in the intermediate stage increased compared with the previous stage, and the areas in the primary stage were characterized by punctate distribution. The coupling degree of the transition showed a further enhanced trend. Except for Xinjiang and Beijing, 29 provincial units were all at the high level. The coordination degree of the transition declined, and its average value fell to 0.661% (Figure 4)

3.4. Drivers of the CLUT and Their Spatial Differentiation

3.4.1. Construction of MDS Based on PCA

From the four aspects of the natural environment, economic construction, social development, and agricultural policy, eight indicators were preliminarily selected (Table 4). Based on the PCA, the eigenvalues of 8 indicators were determined, and there were three principal component eigenvalues ≥ 1, with a cumulative contribution rate of 71.17%. Firstly, all the indicators were grouped according to the factor loading, and then the indicators with an absolute value of the factor loading less than 0.55 in the three principal components were excluded. According to the norm value and correlation between the indicators, four evaluation indicators of topography, gross agricultural economic output, total power of agricultural machinery, and construction land demand index were finally selected.

3.4.2. Spatial Autocorrelation Test of Dependent Variables

Analyzing whether the dependent variable has spatial autocorrelation is the basis for constructing the GWR model. The study used ArcGIS 12.0 to calculate the Global Moran's I to test whether there is a significant spatial autocorrelation of the coordination degree of the CLUT in the three stages. The results are shown in Table 5. Through analysis, the Z-scores of the three stages were all greater than 2.04, and the *p*-values were all less than 0.1, indicating a confidence level of over 90% between the results of spatial autocorrelation and the actual situation. Meanwhile, all the results of Global Moran's I were close to 1, showing that the dependent variable was spatially clustered and the spatial autocorrelation was positive.

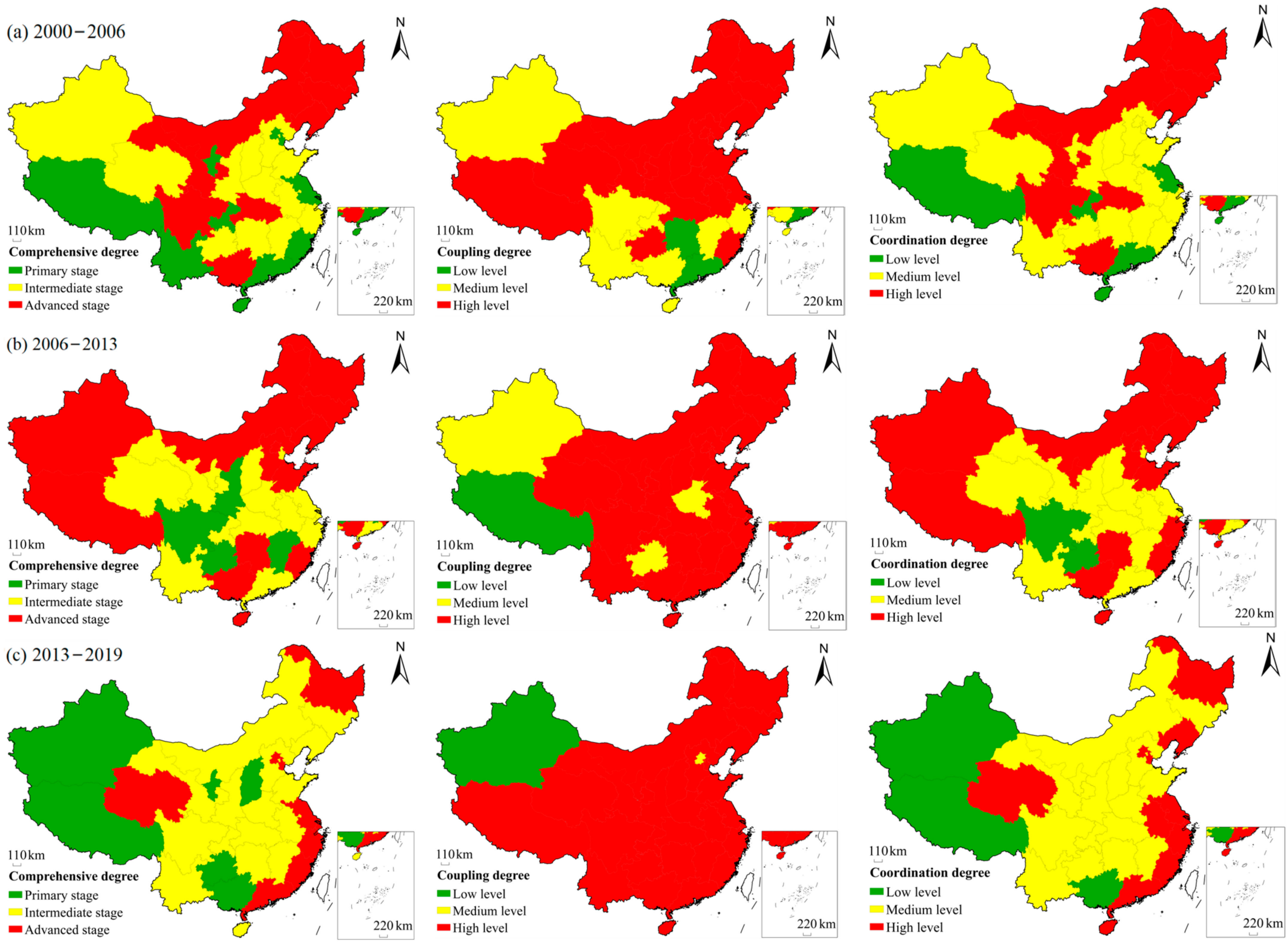

Figure 4. Spatial distribution of the comprehensive evaluation results of the CLUT in China from 2000 to 2019. (**a**) Phase 1, 2000–2006; (**b**) Phase 2, 2006–2013; (**c**) Phase 3, 2013–2019.

Table 4. Factor loading matrix, common factor variance, and norm value.

Indicator	Group	PC1	PC2	PC3	Norm Value
Slope	1	−0.741	−0.317	−0.027	4.133
Topography	1	−0.825	−0.082	−0.028	4.271
Construction land demand index	1	−0.688	−0.016	0.558	4.325
Gross agricultural economic value	2	0.085	0.87	−0.147	4.414
Per capita GDP	2	0.239	0.789	0.331	4.381
Urbanization rate	2	−0.466	0.564	−0.364	4.038
Disposable income of the rural household	3	0.246	0.35	0.757	3.995
Total power of agricultural machinery	3	0.243	0.370	0.790	4.157
Eigenvalue		2.824	2.216	1.366	
Variance contribution rate/%		31.372	24.620	15.178	
Cumulative contribution rate of the principal components/%		31.372	55.993	71.710	

Table 5. Results of the spatial autocorrelation test for the dependent variable.

Period	2000–2006	2006–2013	2013–2019
Global Moran's I	0.2876	0.2853	0.2875
Z-score	2.1341	2.0418	2.1681
p-value	0.0328	0.0412	0.0353

3.4.3. GWR Model Test

Before constructing the GWR model, it is necessary to verify whether the combination of multiple independent variables is redundant. If there is a serious collinearity problem between independent variables, the model may be unstable and unreliable. This study used SPSS 22.0 to conduct correlation tests on evaluation indicators, and the test results are shown in Table 6. It can be seen that the correlation coefficients between independent variables at different stages were all less than 0.722, indicating that there was no serious collinearity problem among independent variables.

Table 6. Correlation coefficient table of the evaluation indexes.

2000–2006	**Topography**	**Gross Agricultural Economic Output**	**Total Power of Agricultural Machinery**	**Construction Land Demand Index**
Topography	1.000			
Gross agricultural economic output	−0.286	1.000		
Total power of agricultural machinery	−0.237	0.715	1.000	
Construction land demand index	−0.554	−0.182	−0.301	1.000
2006–2013	Topography	Gross agricultural economic output	Total power of agricultural machinery	Construction land demand index
Topography	1.000			
Gross agricultural economic output	−0.250	1.000		
Total power of agricultural machinery	−0.193	0.721	1.000	
Construction land demand index	−0.553	−0.092	−0.208	1.000
2013–2019	Topography	Gross agricultural economic output	Total power of agricultural machinery	Construction land demand index
Topography	1.000			
Gross agricultural economic output	0.283	1.000		
Total power of agricultural machinery	0.056	0.278	1.000	
Construction land demand index	−0.537	−0.272	0.075	1.000

If the regression model lacks key explanatory variables, it can lead to misspecification of the regression model. Therefore, this study needs to conduct a spatial autocorrelation test on the residuals of the regression results to determine whether the residuals are randomly distributed. If the residuals are clustered, it indicates that the construction of GWR model parameters is problematic and explanatory variables need to be increased or decreased. The Moran's I, Z-score, and *p*-value calculated by ArcGIS 12.0 are shown in Table 7. It can be seen that the spatial distribution of residuals in each stage showed a certain degree of randomness.

Table 7. Spatial autocorrelation test results of residuals.

Period	2000–2006	2006–2013	2013–2019
Moran's I	0.1296	0.0668	−0.1215
Z-score	1.4938	0.9164	−0.8219
p-value	0.1352	0.3594	0.4111

The Akaike information criterion (AIC) was used to evaluate the fitting effect of the GWR model in this study. The fitting coefficients R^2 and R^2 adjusted can be used to measure the fitting degree of the model. The larger the R^2, the better the fitting effect of the model. As can be seen from Table 8, the goodness of fit of the constructed GWR model in three stages was 57%, 58%, and 53%, respectively, all exceeding 52%.

Table 8. GWR model goodness of fit test results.

Period	2000–2006	2006–2013	2013–2019
R^2	0.57	0.58	0.53
R^2 Adjusted	0.48	0.48	0.41

3.4.4. Analysis of Driving Factors for CLUT

1. Topography

The topography mainly played an inhibitory role in the CLUT. During 2000–2006, the impact of the topography on the CLUT in different regions was various, and the promoting impact mainly occurred in the central and eastern regions, while the inhibiting impact occurred in the western regions. The main reason might be that the topography in western China is complex and diverse, and the topography has relatively great restrictions on agriculture. During 2006–2013, the spatial distribution pattern of regression coefficients changed greatly. Coefficient in the whole domain were all negative, and the influencing degree gradually increased from west to east. The main reason might be the rapid development of the social economy and the further increase in land development intensity. Meanwhile, with the lack of standardized guidance for people's land development and utilization activities, a large amount of cultivated land has been converted into non-agricultural construction land, while the quality of the cultivated land has also declined. The increasingly fragile ecological environment led to a further increase in the constraints of natural environmental conditions on the CLUT. During 2013–2019, the regression coefficients of the topography in the whole region began to be both positive and negative again. Compared with the spatial distribution of the regression coefficients from 2000 to 2006, the coefficient distribution pattern of the two stages was basically the same (Figure 5).

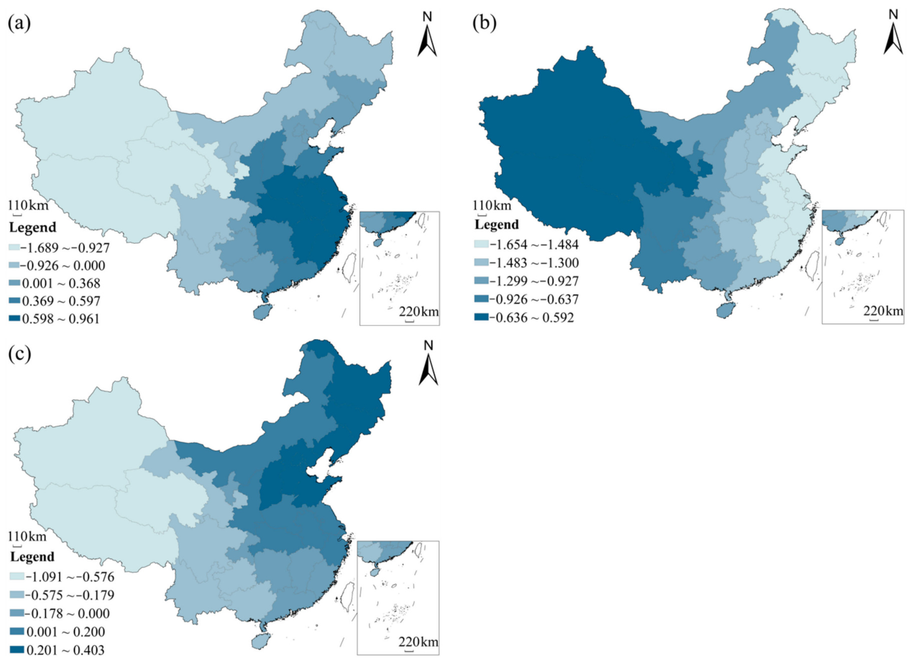

Figure 5. Spatial distribution of topography regression coefficients from 2000 to 2019. (**a**) Phase 1, 2000–2006; (**b**) Phase 2, 2006–2013; (**c**) Phase 3, 2013–2019.

2. Gross agricultural economic output

The gross agricultural economic output had a certain inhibitory effect on the transition, but it was indistinctive. During 2000–2006, the degree of the positive effect gradually increased from the northwest end to the internal region, and the degree of the negative effect gradually increased from the internal region to the southeast end. The reason for this spatial distribution pattern might be the difference in regional economic development. Richer areas had low enthusiasm for agricultural development, which hampered the CLUT to some extent, while poorer areas were mainly dominated by traditional agriculture, and the cultivated land has always been given a crucial role. During 2006–2013, the negative effect became weaker than that in the previous period and showed a significant north-south difference. During 2013–2019, the negative effect of the gross agricultural economic output also existed, and the effect continued to weaken. The spatial distribution characteristics gradually changed from the north-south difference to the east-west difference (Figure 6).

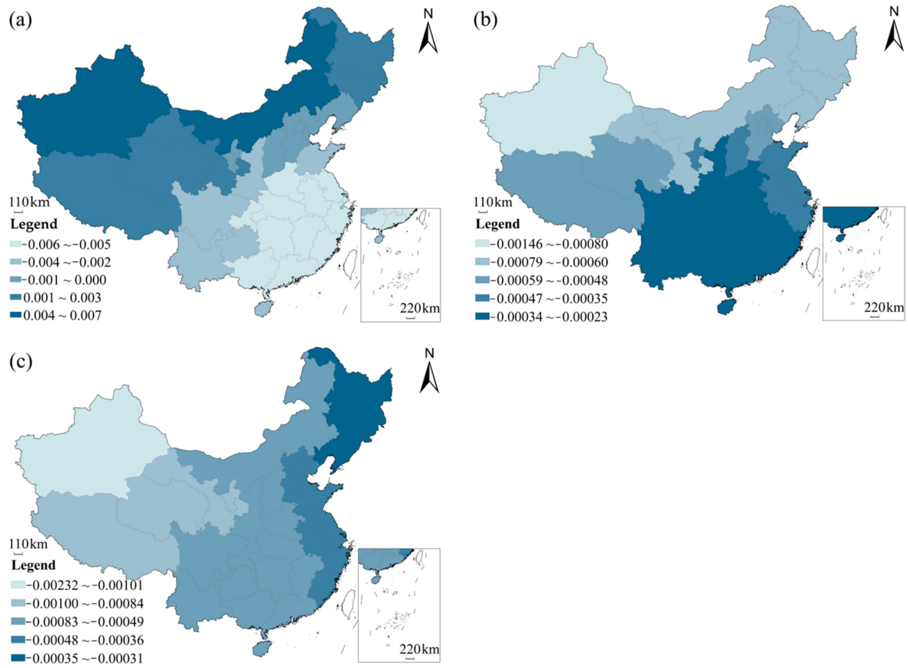

Figure 6. Spatial distribution of gross agricultural economic output regression coefficients from 2000 to 2019. (**a**) Phase 1, 2000–2006; (**b**) Phase 2, 2006–2013; (**c**) Phase 3, 2013–2019.

3. Total power of agricultural machinery

The total power of agricultural machinery promoted the CLUT, but the effect was inapparent. During 2000–2006, the regression coefficients showed a development trend of high in the south and low in the north. The reason might be that the small land area and high degree of dispersion in southern China led to the backward development of large and medium-sized agricultural machinery, while the development of agricultural mechanization in the northern plains of China was at the leading level nationwide, relying on the advantages of geographical conditions and planting scale. Thus, the development of agricultural mechanization had a stronger impact on the CLUT in southern China. During 2006–2013, the total power of agricultural machinery played a positive role in 87% of the areas. One of the main reasons for this kind of spatial distribution pattern was the comprehensive promotion and substantial investment of the central government in agricultural mechanization. During 2013–2019, regression coefficients in the whole region were all positive, but the average value of coefficients decreased compared with the previous stage, indicating that the force of the total power of agricultural machinery on the transition weakened in this stage (Figure 7).

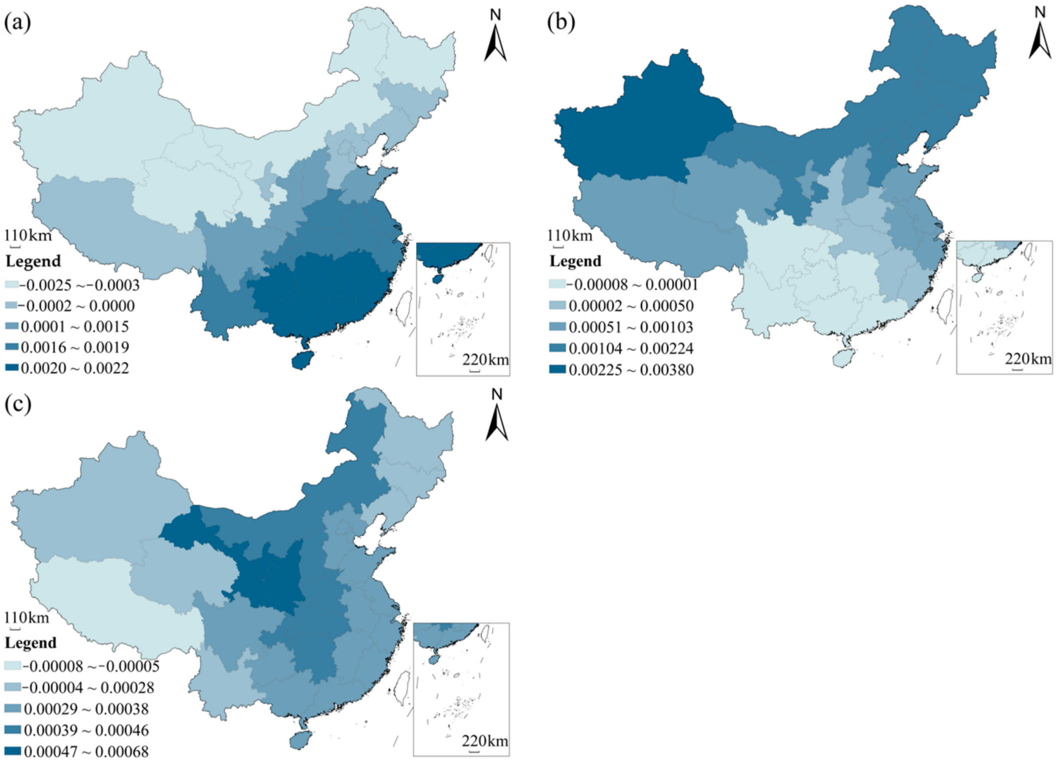

Figure 7. Spatial distribution of total power of agricultural machinery regression coefficients from 2000 to 2019. (**a**) Phase 1, 2000–2006; (**b**) Phase 2, 2006–2013; (**c**) Phase 3, 2013–2019.

4. Construction land demand index

The overall effect of the construction land demand index on the transition changed from inhibition to promotion, and its influencing degree was the most significant among the four factors. The growth of the construction land demand index was generally consistent with the regional economic development pattern. During 2000–2006, there was an intense negative correlation between the construction land demand index and the CLUT. Regression coefficients in the whole region were all negative, and the influencing degree gradually increased from southeast to northwest. The main reasons for this spatial difference might be the continuous implementation of the western development strategy and the slow urbanization in parts of eastern China. During 2006–2013, the positive coefficients were mainly concentrated in the northwest, and the reason might be that the increased investment in land consolidation and reclamation funds as well as comprehensive agricultural development funds in western areas alleviated the conflict between economic construction and farmland protection. The negative coefficients were mainly concentrated in Central China, South China, and East China, and the negative influence in southeast coastal areas was deeper than that in inland areas, probably because of the less cultivated land resources in coastal areas as well as the extension and expansion of urban and rural construction in the process of economic development. During 2013–2019, the construction land demand index showed a strong effect on promoting the transition, and its effect gradually weakened from east to west, which might benefit from the amelioration of the farmland protection policy system at this stage (Figure 8).

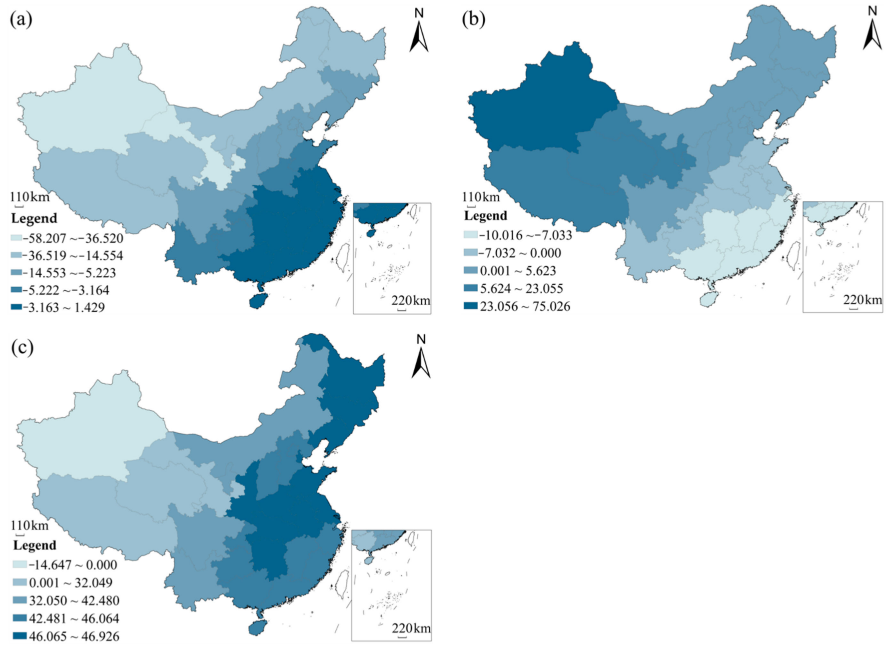

Figure 8. Spatial distribution of construction land demand index regression coefficients from 2000 to 2019. (**a**) Phase 1, 2000–2006; (**b**) Phase 2, 2006–2013; (**c**) Phase 3, 2013–2019.

4. Discussion

The spatiotemporal evolution pattern and driving mechanism of CLUT are the hot topics in the field of cultivated land use research in China. The research results indicate that the spatial structure, functional intensity, and management model of cultivated land use are closely related to the cultivated land use morphology, which has strong explanatory significance for the CLUT. The change in cultivated land use morphology is the result of socio-economic development and the transformation of cultivated land use modes in China's modernization process. On one hand, China's industrialization and urbanization development have led to changes in the traditional elements of cultivated land use. In order to meet major development needs, such as food security, high-quality agricultural development, and rural revitalization, cultivated land utilization is shifting towards a more efficient direction, and spatial differences are also narrowing. On the other hand, the spatial distribution and coupling coordination of CLUT constantly evolve and change over time. The impact of natural conditions, socio-economic factors, and land policies on the CLUT varies greatly over different periods. Analyzing the spatiotemporal differences in the impact of different factors on the CLUT can provide a basis for scientific management and control of cultivated land resources. Research also suggests that China should start with the following aspects to promote efficient transformation of cultivated land use and achieve agricultural modernization in the future:

(1) Take multiple measures to promote comprehensive land remediation across the entire region. Resource endowment is the foundation of the CLUT. At present, the negative effect of the topography is more intense in western China, mainly due to the complex terrain, fragile ecological environment, relatively poor cultivated land resources, and high degree of cultivated land fragmentation. Comprehensive land consolidation is of great significance for the improvement of terrain constraints and large-scale operations. It has become an important level for high-quality agricultural development and rural revitalization in China. However, the following two points should be paid attention to: Firstly, it is necessary to fully utilize advanced scientific technology and management methods. On one hand, we can use advanced technologies such as mechanical deep planting, buried drip irrigation, soil testing, fertilizer distribution, or drone spraying to control plant diseases and insect pests and standardize the planting. On the other hand, equipment such as aerial drones and ground sensors can be used to

establish remote control and three-dimensional monitoring systems. Secondly, we need to strengthen the dominant position of farmers in the consolidation process. We should fully respect the wishes of farmers, understand their practical demands, and encourage them to actively learn the skills of modern agricultural production, which can provide an internal driving force for the transition.

(2) Actively support and guide the cross-regional operation of agricultural machinery. The total power of agricultural machinery played a role in promoting the CLUT, but its effect continued to weaken with time, and problems of regional and structural imbalance were prominent due to the inefficient allocation of agricultural machinery resources. Since the implementation of agricultural preference policies such as agricultural machinery purchase subsidies, the number of agricultural machines in China has continued to expand. Agricultural machinery is abundant in some areas, but as far as the country is concerned, there are still many areas lagging behind. Therefore, actively guiding the cross-regional operation of agricultural machinery can effectively promote the allocation of agricultural machinery resources. In recent years, the income from the cross-regional operation of agricultural machinery has decreased. In order to effectively reduce the burden on farmers, we should increase targeted subsidies for agricultural machinery oil and further innovate value-added services such as green channels for agricultural machinery refueling, agricultural preference commodity counters, convenient service desks for agricultural machinery, etc. In addition, the operation link should be appropriately widened to promote the transition from traditional harvest to whole-process management, specialization, and one-stop service.

(3) Implement the responsibility of cultivated land protection and form a joint cultivated land protection system. The construction land demand index played a certain role in promoting the CLUT, mainly thanks to the strict cultivated land protection system. Although the central government has issued the strictest policies and systems around the control, construction, and incentives of cultivated land, there is a lack of a strong incentive mechanism for the triple protection of cultivated land. To this end, we should refine the trinity protection scope of cultivated land, divide the evaluation threshold based on the characteristics the resource background and create an intelligent, dynamic supervision platform to provide support for farmland improvement and differentiated management. Meanwhile, elements related to farmland protection should be included in the scope of supervision, such as strict supervision of chemical fertilizers, pesticides, and other inputs, as well as farmland ecosystem and biodiversity protection. Moreover, it is necessary to explore the establishment of a horizontal and vertical linkage compensation mechanism for farmland protection to reduce the risk of environmental damage caused by cross-regional supplementary farmland and stimulate the spiritual and material effects of the subjects responsible for farmland protection [65].

Although this study can comprehensively reflect the level and characteristics of the CLUT, which is significant for empirical research, the cultivated land use system is a complex giant system with open characteristics, and the indicator system for structure, function, and model transformation still needs to be improved. Especially as the tasks and goals of China's cultivated land protection will change over time, it is necessary to continuously adjust the evaluation indicator system to adapt to the changes in China's food security situation. In addition, the analysis of the spatiotemporal evolution characteristics of CLUT is only a preliminary result. Based on the significant differences between regions, in-depth analysis of the regional suitability and applicability of CLUT should be the content that needs further deepening research in the future.

5. Conclusions

The cultivated land use in China has great potential for transition, but there are still great development obstacles. From the perspective of time, although the average indices of multifunctional transition and model transition of cultivated land use in China increased continuously, they were much lower than the average index of spatial transition. Therefore, more attention should be paid to the multifunctional transition and model transition of the cultivated land. The spatial distribution characteristics of CLUT in China gradually changed from north-south differences to east-west differences, and the low-value areas were distributed in spots, while the high-value areas mainly showed strip-like distribution. In addition, the coupling degree of the three subsystems of spatial transition, multifunction transition, and model transition was high, indicating that the overall interaction was strong, but the imbalance phenomenon was increasingly prominent. Therefore, the future regulatory strategy of CLUT should fully consider regional differences and link the internal elements of the cultivated land use system with the external environment. Finally, it is also necessary to coordinate the development relationship among the three subsystems to promote the scientific transition of cultivated land use and the efficient development of agriculture.

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