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Analysis of the Spatial-Temporal Characteristics and Driving Factors of Cultivated Land Fragmentation Under the Expansion of Urban and Rural Construction Land: A Case Study of Ezhou City

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Abstract: A systematic understanding of the spatial-temporal evolution patterns of cultivated land fragmentation (CLF), its driving factors, and its relationship with the expansion of urban and rural construction land is essential for identifying strategies to mitigate CLF in rapidly urbanizing regions. This study combined landscape fragmentation with ownership fragmentation, analyzing CLF through three dimensions: resource endowment, spatial concentration, and convenience of utilization, with eight selected indicators. By comparing village-level data from 2013 to 2022, we explored the key drivers of CLF and its conflicts with urban and rural construction land expansion. The findings indicate a clear spatial variation in village-level CLF in Ezhou, characterized by low fragmentation in the northwest and northeast, and high fragmentation in the southwest and central regions. This pattern is in contrast to Ezhou's economic development, which decreased progressively from east to north and south. Over the study period, village-level CLF in Ezhou evolved from being primarily moderately and relatively severely fragmented to predominantly severely and relatively severely fragmented, with an overall declining trend and more pronounced polarization. At the same time, the CLF within the village region demonstrated notable spatial clustering features, with a rapid increase observed between 2013 and 2022. It was also discovered that CLF is driven by various factors, with the main influences being the proportion of construction land, land use intensity, and population density. Cultivated land is the main source of both urban construction land (UCL) and rural construction land (RCL), with average contribution rates of 46.47% and 62.62%, respectively. This research offers empirical evidence for rapid urbanization and serves as a critical reference for rural revitalization and coordinated urban–rural development, with potential guidance for future policy formulation and implementation.

Keywords: cultivated land fragmentation; expansion of urban and rural construction land; driving factors; random forests

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1. Introduction

Cultivated land fragmentation (CLF), as a global land use phenomenon, has garnered significant attention, particularly in transitional economies and developing countries due to its prevalence and complexity [1,2]. Studies in the Central Asian republics indicate that urban expansion has resulted in a significant loss of carbon sequestration, particularly because the development of agricultural land into construction land has led to substantial carbon loss, thereby intensifying the fragmentation of cultivated land [3]. Evidence from the Central Plain urban cluster in China similarly shows that urban expansion has caused a large portion of cultivated land to be repurposed for new urban developments, causing regional cultivated land fragmentation to rise and ecosystem service functions to significantly deteriorate [4]. Nationally, the loss of cultivated land in traditional agricultural areas is also seen to be largely caused by the growth of construction land [5]. The continual expansion of urban boundaries into rural areas during this urbanization process not only reflects the trend of urban sprawl, but also presents serious obstacles to food security and the sustainable use of land [6–8]. As high-quality cultivated land in China often overlaps with urban land, the excessive expansion of non-agricultural land has further exacerbated the CLF issue [9]. Food security, the sustainable development of the rural economy, and the improvement in farmers' incomes are all adversely affected by this situation. It not only challenges the optimal allocation of land resources, but also significantly undermines the economies of scale in agricultural production by reducing the output efficiency per unit of land [10,11]. Therefore, in order to investigate solutions to mitigate CLF, a methodical examination of the spatial features and contributing causes of CLF under the effect of urban and rural development land is essential [12,13]. This study not only provides scientific evidence of the adverse impact of urbanization on cultivated land resource utilization, but also offers empirical support for local governments in formulating land use planning and policy, thereby promoting a more rational allocation of land resources.

Traditional CLF research focuses on the micro level, analyzing from the perspective of farm household economics. In this context, the primary contributing factors are identified as the number of plots, average plot size, and average household cultivated land [14–17]. A case study conducted in Poland indicates that the documentation of cadastral data, especially the allocation of ownership shares for cultivated land, is essential for assessing cultivated land fragmentation [18]. Furthermore, the fragmentation of household cultivated land results in a disordered and scattered allocation of land resources, hindering the synergy between plots and economies of scale, thus affecting agricultural production efficiency and the overall effectiveness of land use [19]. However, such studies typically rely on costly surveys and interviews, limiting the feasibility of large-scale CLF measurements. Effective data support and technical tools have been made available with the development of medium-to-high-resolution remote sensing technology, enabling the precise evaluation of problems like insufficient operational scale, spatial fragmentation, and inconvenient farming conditions at the national or regional level [20,21]. Advances in landscape ecology have also promoted the widespread application of multi-dimensional structural indicators such as patch density, shape index, and spatial aggregation, which are often used to measure the degree of cultivated land refinement [22–24]. Research on CLF at the regional level and a thorough evaluation system are progressively taking shape [25]. A study on CLF in 25 Central and Eastern European countries through multiple dimensions such as property rights, resource availability, and fragmentation of farming activities suggests that highly fragmented land ownership and usage rights tend to constrain agricultural and rural economic development [26]. By creating a thorough fragmentation index employing landscape indices and principal component analysis, researchers have started to investigate the spatiotemporal variations in agricultural landscape fragmentation in China at the urban level [27]. Numerous previous studies have demonstrated that although the total area of cultivated land in China is relatively large, the per capita cultivated land area is comparatively small, and its spatial distribution exhibits significant unevenness. This fragmentation pattern of the agricultural landscape has led to issues such as an unclear distribution of land rights among farmers and difficulties in land use at the regional level [28]. Thus, future studies should not only keep concentrating on the multifaceted effects of CLF, but also incorporate the latest developments in remote sensing technology and landscape ecology to build a more comprehensive and integrated CLF evaluation framework, better addressing the challenges of cultivated land resource management and agricultural sustainability.

The demand for construction land and its conflict with cultivated land during urbanization remains a major challenge for countries and regions worldwide [29]. Research conducted in Inciralti, Turkey, revealed that urban expansion significantly affects agricultural land, leading to the gradual transformation of substantial areas of permanent irrigation, dryland farming, and berry plantations into urban land [30]. Meanwhile, the Thrace region has determined the optimal spatial locations for urban and industrial development areas by analyzing land cover changes and cultivated land fragmentation, thereby safeguarding the integrity of cultivated land [31]. In order to maintain ecological balance and guarantee national food security, the Chinese government has implemented a number of strict regulations to protect cultivated land [32] including the Basic Cultivated Land Protection System, the Cultivated Land Occupation-Compensation Balance Policy, land-use regulation, and the "Cultivated land Red Line" Protection System, aimed at ensuring food security and ecological balance, but these measures still face significant challenges in coping with the tension over cultivated land resources caused by rapid urbanization [33]. The horizontal growth of cities in plain areas and its impact on landscape ecological risks are the primary subjects of current study on the relationship between urban expansion and CLF [34]. By utilizing elevation and slope indices to depict gradients, studies have looked into how urbanization affects land use patterns and the environment as well as how it may jeopardize food security by reducing the amount of cultivated agricultural area [35,36]. However, studies focusing on landscape changes in rural areas during urbanization remain relatively scarce [37–39]. This is especially true for villages surrounding key urban development areas, which are often the main regions where agricultural land is turned into land for construction. Furthermore, the majority of previous research has failed to consider the impact of urban growth from both urban and rural construction land—known as the "Rural–Urban Conversion Landscape", on CLF. It is generally believed that urban construction land exerts a stronger erosive effect on cultivated land compared to rural construction land. Evidence from Hangzhou suggests that the moderate expansion of urban construction land has facilitated the improvement in intensive land use in townships, whereas the excessive expansion of rural residential land has resulted in substantial losses of cultivated land in rural areas [40]. Other studies have pointed out that rural construction occupies a land area that is 22.4% larger than urban construction; however, urban construction land is superior to rural construction land in terms of the efficiency of cultivated land usage. Particularly in regions with substantial differences in urban–rural development, the influence of rural construction land on CLF could be more extensive and significant [41,42]. This is because expansion in urban fringe areas tends to exacerbate the fragmentation of cultivated land, while intensive development in central areas tends to mitigate this trend. Therefore, further research on the combined impacts of rural and urban construction land on CLF during urbanization will help optimize land use policies.

To summarize, considering Ezhou City as a key commercial grain base in Hubei Province with a rapidly developing urban economy, this study comprehensively examined landscape fragmentation and ownership fragmentation. It selected eight locally representative indicators based on three dimensions—resource endowment, spatial concentration, and convenience of utilization—an as evaluation framework. Through spatial autocorrelation analysis, the research investigated the spatial aggregation characteristics of CLFI at the village level, identifying spatial hotspots of high and low aggregation, while also validating driving factors and exploring the impact mechanisms between urban and rural construction land and cultivated land. The results will contribute empirical insights for identifying pathways to alleviate CLF and facilitate coordinated urban–rural development.

2. Material and Methods

2.1. Study Area

Ezhou City is situated next to the southern bank of the middle Yangtze River in the eastern portion of Hubei Province, between longitudes 114°32′–115°05′ and latitudes 30°00′–30°06′ (Figure 1). To the west, Ezhou City borders Wuhan; to the east, it adjoins Huangshi; and to the north, it is near the Yangtze River. As a member of the Wuhan-Ezhou-Huangshi urban agglomeration, Ezhou City is an essential part of Wuhan's new city development and is a major node in the center of the Yangtze River urban cluster. Ezhou is recognized as one of Hubei

Province's key grain-producing areas, significantly contributing to the production of crops like rice and wheat. Nevertheless, Ezhou's cultivated land area declined from 61,572.03 hectares in 2013 to 45,722.89 hectares in 2022, a total decrease of 15,849.14 hectares. As urbanization and industrialization progress rapidly, the phenomenon of cultivated land loss has intensified, exacerbating cultivated land fragmentation and highlighting the growing conflict between urban and rural land use.

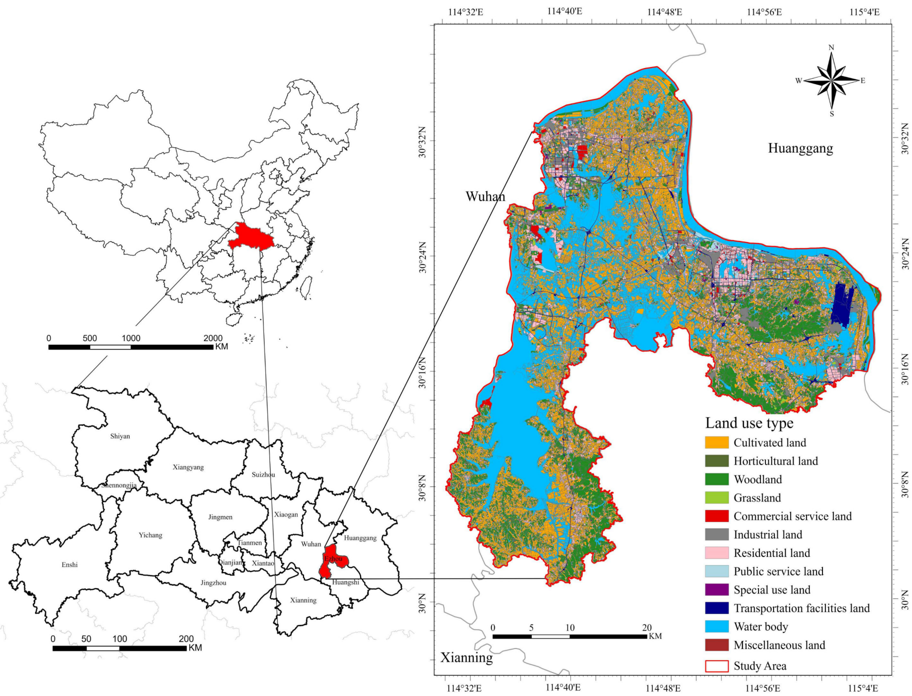

Figure 1. Current land use status of Ezhou City.

The year 2013 marked a pivotal year for substantial changes in China's land use policies. That year, significant amendments were made to the Land Administration Law, enhancing the protection measures for cultivated land, especially regarding its conversion and occupation, thus markedly raising the awareness of land loss. Simultaneously, associated policies specified the requirements for balancing occupied and restored cultivated land, highlighting how important it is to carry out appropriate restoration in addition to any occupation in order to preserve the amount and caliber of cultivated land. The preservation and sensible use of cultivated land have been greatly impacted by the implementation of these regulations.

The fragmentation of cultivated land in Ezhou City not only reflects local features, but also serves as a representative case of the rapid urbanization process occurring in small- and medium-sized cities. This example highlights the shared challenges encountered by many regions, especially in the context of balancing urban expansion with agricultural preservation. Consequently, a detailed investigation into the fragmentation of cultivated land in Ezhou City will not only enhance our understanding of the local land management challenges, but also offer critical references and insights for land management practices throughout China in the context of fast urbanization.

2.2. Data Sources

This study examined 24 townships and 313 administrative villages in Ezhou City. The data employed comprised land use change survey data, administrative boundary vector data, and household population data, as detailed in Table 1. According to the classification procedures, the data from the Third National Land Survey were used to merge the categorization data for the current land use status. To ensure uniformity in data magnitude, an extreme value normalization technique was used to standardize all data, scaling each to the range [0, 1] for ease of further research.

Table 1. Data sources of this study.

Data Types	Data Names	Data Sources
Land use data	Ezhou City land use changing investigation data (2013, 2022)	Ezhou City land use changing investigation database
Socioeconomic data	Ezhou YearbookEzhou Statistical Yearbook	Ezhou Bureau of Statistics
Administrative division	Administrative division data for China and for Ezhou City's administrative structure.	Resource and environment data cloud platform (http://www.resdc.cn; accessed on 27 June 2024)
Topographic data	DEM	

2.3. Selection of Evaluation Indicators

This research integrated traditional landscape fragmentation metrics with property fragmentation-related metrics to develop a CLF assessment framework [43,44]. Specifically, eight key indicators were chosen: patch density, per household cultivated land area, aggregation index, mean nearest neighbor distance, shape index, land patch accessibility, production convenience, and per household cultivated land patch number.

2.3.1. Resource Endowment

(1) Patch density (PD) represents the number of patches per unit area. Patch density provides an intuitive measure of the degree of cultivated land fragmentation; as the density decreases, the relative area of patches increases, facilitating large-scale agricultural production and advanced mechanization, thus functioning as a negative indicator.

$$\mathrm{PD} = \mathrm{N}/\mathrm{A} \tag{1}$$

(2) Per household cultivated land patch number (PCN) represents the quantity of cultivated land patches managed by each household; a larger PCN indicates a higher degree of fragmentation, serving as a negative indicator.

$$\mathrm{PCN} = \mathrm{N}/\mathrm{F} \tag{2}$$

(3) Per household cultivated land area (PCA) represents the area of cultivated land patches managed by each household. A larger PCA indicates a lower degree of cultivated land fragmentation in the area, while a smaller PCA signifies a higher degree of fragmentation, serving as a positive indicator.

$$\mathrm{PCA} = \mathrm{A}/\mathrm{F} \tag{3}$$

2.3.2. Spatial Concentration

(1) The aggregation index (AI) indicates the spatial concentration of cultivated land patches within the boundaries of the administrative village. A higher aggregation index indicates a greater concentration of cultivated land resources in the area and a lower degree of cultivated land fragmentation, serving as a positive indicator.

$$\mathrm{AI} = [1 + \sum_{\mathrm{i}=1}^{\mathrm{N}} \frac{\mathrm{P_i} \ln(\mathrm{P_i})}{2\ln(\mathrm{N})}] \times 100 \tag{4}$$

(2) The mean nearest neighbor distance (MNN) reflects the distribution of cultivated land patches across different topographical regions. A larger mean nearest neighbor distance indicates a greater average distance between cultivated land patches, resulting in a more dispersed distribution of patches and a higher degree of fragmentation, while a smaller value reflects a more concentrated distribution and a lower degree of fragmentation, serving as a negative indicator.

$$\mathrm{MNN} = \sum_{i=1}^{N} \frac{w_i}{N} \tag{5}$$

2.3.3. Convenience of Utilization

(1) The shape index (SI) is employed to assess the regularity of the shapes of cultivated land patches. A shape index that approaches 1 signifies that the cultivated land patches have a more regular shape, resembling squares or circles, thus increasing their usability; conversely, as the shape index moves further away from 1, it indicates that the shapes of the cultivated land patches become increasingly irregular, potentially taking on more complex forms, which is considered a negative indicator.

$$\mathrm{SI} = \sum_{i=1}^{n} \left[\left(\frac{0.25P_i}{\sqrt{A_i}} \right) \times \left(\frac{A_i}{A} \right) \right] \tag{6}$$

(2) Land patch accessibility (LPA) represents the distance from cultivated land to roads within a defined region. An increasing LPA signifies a greater degree of cultivated land fragmentation in the village, which is considered a negative indicator.

$$\mathrm{LPA} = \sum_{i=1}^{N} \frac{f_i}{N} \tag{7}$$

(3) Production convenience (PC) represents the distance from cultivated land to the closest residential area within a defined region. An increased PC signifies a higher level of cultivated land fragmentation in the village, which is considered a negative indicator.

$$\mathrm{PC} = \sum_{i=1}^{N} \frac{d_i}{N} \tag{8}$$

The indicator results for all cultivated land patches in Ezhou City were derived from Formulas (1) to (8). While the patch density, per household cultivated land patch number, per household cultivated land area, and land patch accessibility results are associated with administrative villages, and the mean nearest neighbor distance, aggregation index, production convenience, and shape index correspond to cultivated land patches, in order to maintain consistency in the evaluation results, an area-weighted approach was utilized to calculate the weighted averages of mean nearest neighbor distance, aggregation index, production convenience, and shape index indicators for the administrative villages, using the area of cultivated land patches within each village administrative region, yielding the village-level fragmentation indicators for the mean nearest neighbor distance, aggregation index, production convenience, and shape index. The formulas for calculating the fragmentation indicators under area weighting are as follows:

$$I_a = \frac{I_{ab} \cdot S_{ab}}{\sum_{b=1}^{n} S_{ab}} \tag{9}$$

Note: N stands for the number of cultivated land patches within an administrative village, A refers to the area of cultivated land in the village, F indicates the total number of farmers' households in various administrative villages, w_i represents the distance between cultivated land patches, P is the total perimeter of the cultivated land patches, f_i indicates the distance from a cultivated land patch to the nearest road, and d_i denotes the distance from the i-th cultivated land patch to the nearest residential area, I_a denotes the fragmentation index for administrative village a, and I_{ab} refers to the fragmentation index of patch b. In this context, a indicates the administrative village unit, b signifies the cultivated land patch, n represents the number of cultivated land patches within village a, and S_{ab} is the area of patch b.

2.4. Analytical Methods

2.4.1. Weight Calculation for Indicators

In order to guarantee the reliability and impartiality of the assessment findings, this study performed a collinearity test following the standardization of the evaluation indicators to confirm the scientific rigor and accuracy of the assessment results. Ultimately, by combining the entropy method with the CRITIC approach, weights were allocated to each indicator to ensure a rational distribution of weights (Table 2), improving the reliability and applicability of the evaluation framework.

Table 2. Weight table of the evaluation indicators for cultivated land fragmentation in Ezhou City.

Standard Level	Index Level	Quantitative Method	Weight Coefficient	VIF
Resource endowment	Patch density	PD = N/A	0.0722	1.578
	Per household cultivated land patch number	PCN = N/F	0.0846	2.906
	Per household cultivated land area	PCA = A/F	0.2581	2.203
Spatial concentration	Mean nearest neighbor distance	$\mathrm{MNN} = \sum_{i=1}^{N} \frac{w_i}{N}$	0.0625	1.433
	Aggregation index	$\mathrm{AI} = \left[1 + \sum_{i=1}^{N} \frac{P_i \ln(P_i)}{2\ln(N)}\right] \times 100$	0.2561	2.873
Convenience of utilization	Shape index	$\mathrm{SI} = \sum_{i=1}^{n} \left[\left(\frac{0.25P_i}{\sqrt{A_i}}\right) \times \left(\frac{A_i}{A}\right)\right]$	0.0888	1.173
	Land patch accessibility	$\mathrm{LPA} = \sum_{i=1}^{N} \frac{f_i}{N}$	0.0978	1.303
	Production convenience	$\mathrm{PC} = \sum_{i=1}^{N} \frac{d_i}{N}$	0.0799	1.949

(1) Entropy weighting method

One common objective weighing technique is the entropy weight method. Its fundamental idea is to measure each indicator's uncertainty or information content by computing its information entropy, which establishes the indicators' relative relevance. The following are the precise steps:

Determine the i-th evaluation unit's percentage of the j-th indicator value:

$$Y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}} \tag{10}$$

Determine the indicator's information entropy:

$$e_j = -k \sum\nolimits_{i=1}^{n} \left(Y_{ij} \times \ln\left(Y_{ij}\right)\right) \tag{11}$$

$$K = \frac{1}{\ln(n)} \tag{12}$$

Determine each indicator's coefficient of variation:

$$d_j = 1 - e_j \tag{13}$$

Determine the indicator's weight value:

$$w_j = d_j / \sum_{i=1}^{m} d_j \tag{14}$$

In the formula, Y_{ij} denotes the weight of the j-th indicator value for the i-th evaluation unit, X'_{ij} denotes the value of the j-th metric in the i-th evaluation unit, e_j represents the information entropy of the indicator, d_j signifies the coefficient of variation for the indicator, w_j indicates the weight of the indicator, n denotes the total number of evaluation units, and m represents the total number of evaluation indicators.

(2) CRITIC

The CRITIC approach scientifically determines the weight values by utilizing the correlation between the data and the standard deviation. It effectively demonstrates the objective characteristics of the CLF quantification process [45]. The precise steps are as follows:

Calculate the data variability:

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{15}$$

$$S_j = \sqrt{\frac{\sum_{i=1}^{n}(x_{ij} - \bar{x}_j)^2}{n-1}} \tag{16}$$

Calculate the conflict between indicators:

$$R_j = \sum_{i=1}^{p}(1 - r_{ij}) \tag{17}$$

Calculate the amount of information:

$$C_j = S_j \sum_{i=1}^{p}(1 - r_{ij}) = S_j \times R_j \tag{18}$$

Calculate the weights of the indicators:

$$W_j = \frac{C_j}{\sum_{j=1}^{p} C_j} \tag{19}$$

In the formula, S_j represents the standard deviation of the j-th indicator, x_{ij} denotes the value of the j-th metric in the i-th evaluation unit, R_j denotes the correlation coefficient between indicators i and j, r_{ij} indicates the conflict of the j-th indicator with other indicators, C_j represents the amount of information contained in the j-th indicator, and W_j is the weight of the evaluation indicator.

2.4.2. Calculation of CLFI

Considering that individual methods may be affected by the data characteristics, averaging helps to mitigate biases from method selection, resulting in more stable outcomes and improving the adaptability of the evaluation model to various data types. This study averaged the entropy weights and CRITIC values for each evaluation indicator, multiplied these averages by the standardized values of the original data, and summed the resulting products to derive the comprehensive evaluation value of cultivated land fragmentation for each administrative village in Ezhou City.

$$CLFI = \sum_{i=1}^{M} W\prime_j \times r_{ij} \tag{20}$$

In the formula, CLFI represents the comprehensive evaluation value of cultivated land fragmentation for the i-th evaluation unit, $W\prime_j$ is the weight of the j-th indicator, r_{ij} denotes the value of the i-th indicator in the i-th evaluation unit, and M is the total number of evaluation units. Using the above method, the cultivated land fragmentation index for different administrative villages can be calculated, with values ranging from [0, 1]. A higher index value indicates a lower degree of cultivated land fragmentation.

2.4.3. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is a crucial statistical technique commonly utilized in geography, spatial science, and environmental science to measure the correlation and spatial structure of variables within geographic space. This method detects the clustering, dispersion, and potential distribution patterns of geographic phenomena by analyzing the distribution patterns of spatial data, thereby uncovering the spatial heterogeneity of variables in particular regions. This approach not only elucidates the distribution characteristics of geographic phenomena, but also establishes a scientific foundation for a deeper understanding of complex spatial interactions.

In this study, spatial autocorrelation analysis was employed to assess the spatial clustering characteristics of CLFI at the village level in Ezhou City for 2013 and 2022, aiming to reveal the evolution patterns of CLFI in the region and its impact on regional land use patterns. This analysis not only aids in identifying spatial hotspots of high and low clustering, but also provides empirical evidence for optimizing land use and formulating cultivated land protection strategies, contributing to theoretical support for decision-makers in land management amidst rapid urbanization.

2.4.4. Random Forest

The random forest model, introduced by Leo Breiman and Adele Cutler in 2001, is an ensemble learning technique [46]. The model aims to improve the overall predictive accuracy by constructing multiple decision trees, and training and predicting on selected samples. The core concept involves aggregating the prediction results of several weak learners (specifically, decision trees) to form a strong learner. This integration method not only boosts the performance of the model, but also increases its stability and robustness.

Leveraging these advantages, this study thoroughly examined the driving forces behind the geographic differences in CLF using the random forest model. The study will explore how social and natural factors influence CLF, utilizing the feature importance ratings to quantify the relative contributions of each element. Such analysis not only supports the understanding of the spatial characteristics of CLF with data, but also establishes a scientific basis for the development and optimization of land management policies.

2.4.5. Urban–Rural Land Use Transfer

In order to present a more complete assessment of how construction land development impacts cultivated land resources, this study computed the expansion rates and intensities of urban construction land (UCL) and rural construction land (RCL), accounting for the development status of both urban and rural construction land. Furthermore, by assessing the rate and intensity of the cultivated land loss, the study quantified the degree of cultivated land degradation, offering data support for developing effective land management and conservation policies. The equations are as follows:

$$R_{Bui\ lt-up} = (N_1 - N_2)/N_2 \times 1/T \times 100\% \tag{21}$$

$$I_{Buiilt-up} = (N_1 - N_2)/A \times 1/T \times 100\% \tag{22}$$

In the formula, $R_{Built-up}$ represents the rate of expansion of construction land in urban and rural areas; $I_{Built-up}$ denotes the expansion intensity of urban and rural construction land; N_1 is the construction land area in urban and rural areas at the conclusion of the study; N_2 is the construction land area in urban and rural areas at the outset of the study; and A is the overall area of the research region.

$$R_{\text{Cultivated land}} = (N_1 - N_2)/N_2 \times 1/T \times 100\% \quad (23)$$

$$I_{\text{Cultivated land}} = (N_1 - N_2)/A \times 1/T \times 100\% \quad (24)$$

In the formula, $R_{\text{Cultivated land}}$ represents the loss rate of cultivated land; $I_{\text{Cultivated land}}$ denotes the loss intensity of cultivated land; N_1 is the cultivated land area at the end of the study; N_2 is the cultivated land area at the baseline of the study; and A is the overall area of the research region.

3. Results and Analysis

3.1. Temporal and Spatial Distribution Characteristics of CLF

According to the CLF evaluation index system for Ezhou City, the cultivated land fragmentation index (CLFI) for villages was derived by assessing the cultivated land resource endowment (RE), spatial concentration (SC), and convenience of utilization (CU). The index was classified into five categories using equal intervals: lowest ($\leq$0.4091), Lower (0.4091–0.4917), medium (0.4917–0.5743), higher (0.5743–0.6568), and highest ($\geq$0.6568). A higher CLFI indicates a lower degree of cultivated land fragmentation, while a lower CLFI signifies a more severe degree of fragmentation (Table 3).

Table 3. Comprehensive statistics of indicators for 2013.

Contents	RE	SC	CU	CLFI
Maximum value	0.3618	0.2984	0.2461	0.7394
Minimum value	0.0841	0.0130	0.0782	0.3265
Mean value	0.1654	0.1081	0.1935	0.4671
Share of villages at the lowest level	21.41%	21.73%	2.24%	9.27%
Share of villages at the lower level	63.90%	51.76%	4.15%	66.13%
Share of villages at the medium level	11.18%	17.57%	15.02%	20.13%
Share of villages at the higher level	1.60%	6.71%	54.31%	4.15%
Share of villages at the highest level	1.92%	2.24%	24.28%	0.32%

The results for 2013 are presented in Figure 2. From the perspective of resource endowment, differences in cultivated land across villages in Ezhou City were relatively minor, with poor quality cultivated land and no distinct distribution characteristics. Regarding spatial agglomeration, significant differences were observed, with a general pattern of higher values in the west and lower values in the east. Mild and moderate fragmentation areas were concentrated in Tujianao Town, Donggou Town, and Changgang Town, while severe fragmentation was mainly found at the city's edges. The majority of villages in Ezhou City were classified in high usage convenience zones, with only Tujianao Town showing some low-value zones. In summary, the CLFI for Ezhou City in 2013 ranged from a maximum value of 0.7394 to a minimum of 0.3265, with an average of 0.467. The fragmentation of cultivated land in villages was mainly characterized by severe and moderate fragmentation.

The results for 2022 are depicted in Figure 3. In terms of cultivated land resource endowment, there were pronounced spatial differences among villages in Ezhou City. High-value zones were predominantly located in the central-western and southwestern regions, whereas low-value areas were concentrated around the development zones. The spatial distribution of villages in Ezhou City mirrorred the resource endowment pattern, with high-value areas concentrated in Donggou Town and Changgang Town, while low-value areas were sporadically distributed at the city's edges. Concerning usage convenience, the majority of villages in Ezhou City exhibited good cultivated land usage conditions, with overall minimal spatial variation. In summary, the CLFI for Ezhou City in 2022 ranged from a maximum of 0.7221 to a minimum of 0.2807, with an average of 0.4536 (Table 4). The fragmentation of cultivated land in villages was primarily classified as severe and moderate.

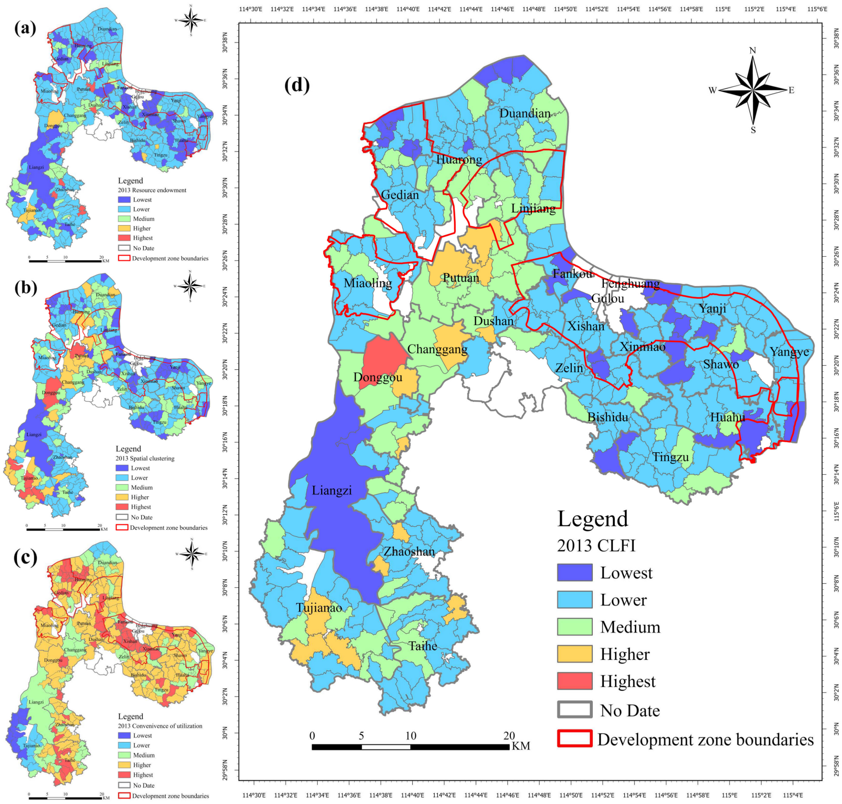

Figure 2. Evaluation map of Ezhou City for resource endowment (**a**), spatial concentration (**b**), convenience of utilization (**c**), and CLFI (**d**) in 2013.

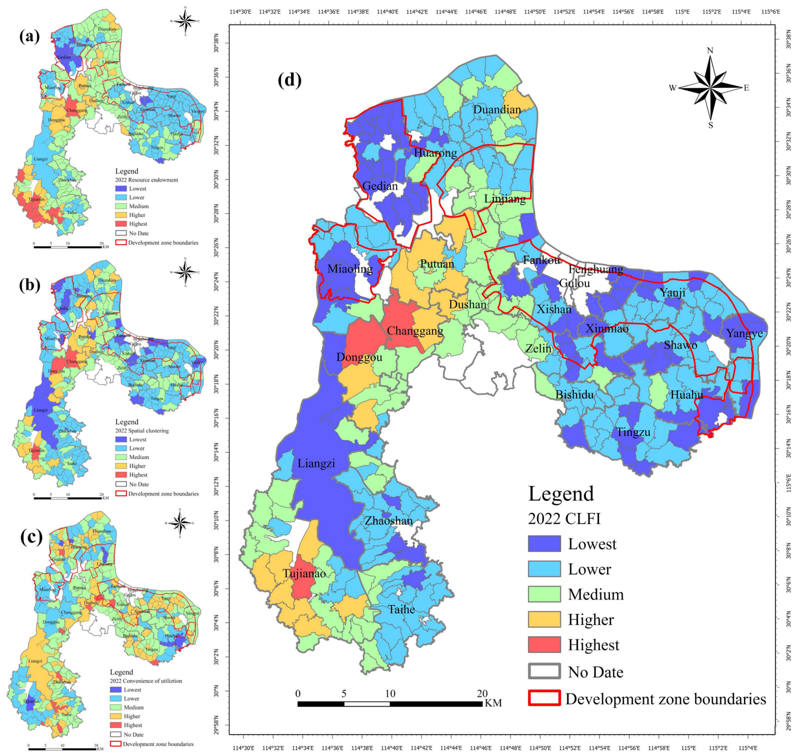

Figure 3. Evaluation map of Ezhou City for resource endowment (**a**), spatial concentration (**b**), convenience of utilization (**c**), and CLFI (**d**) in 2022.

Table 4. Comprehensive statistics of indicators for 2022.

Contents	RE	SC	CU	CLFI
Maximum value	0.3222	0.3073	0.2248	0.7221
Minimum value	0.0798	0.0037	0.0865	0.2807
Mean value	0.1836	0.1105	0.1596	0.4536
Share of villages at the lowest level	6.39%	11.82%	1.60%	27.48%
Share of villages at the lower level	39.30%	58.15%	20.13%	43.13%
Share of villages at the medium level	41.53%	22.04%	44.09%	14.06%
Share of villages at the higher level	9.27%	7.03%	29.07%	14.38%
Share of villages at the highest level	3.51%	0.96%	5.11%	0.96%

The following conclusions were derived from calculating the annual average change rates of CLFI for each village in Ezhou City (Figure 4). Between 2013 and 2022, significant changes in the CLFI were observed across villages in Ezhou City. The change rates for villages were concentrated between −1.5% and 1.5%, with an average annual change rate of −0.3%. Data indicated that 65.81% of villages had an annual average CLFI change rate less than 0, whereas 34.19% had an annual average CLFI change rate greater than 0. Villages with a substantial increase in CLFI were found in Changgang Town in Echeng District, Tujianao Town and Liangzi Town in Liangzi Lake District, and certain villages in Duandian Town in Huarong District. Villages with a notable decrease in CLFI were situated in Gedian Town and Miaoling Town in Huarong District, and some villages in Huahu Town and Tingzu Town in Echeng District.

Data from Ezhou City's cultivated land fragmentation index (CLFI) revealed that overall fragmentation has intensified in recent years, and the polarization trend has become more pronounced. This observation indicates that the spatial distribution and utilization structure of cultivated land resources have experienced profound changes due to the dual drivers of urbanization and industrial development. Specifically, the proportions of both mildly and severely fragmented areas have increased, emphasizing spatial differences in land use across regions during urban and rural development.

Regarding spatial distribution, low-CLFI zones were primarily clustered around the development area and Liangzi Town, while high-CLFI zones were concentrated near state-owned farms in Changgang and Donggou Towns. This pattern of differentiated distribution illustrates the diversity and complexity in land use changes accompanying urbanization. As an economic growth hub, the development area has seen intensified population and industrial clustering effects, spurring numerous infrastructure and real estate developments, leading to a reduction in cultivated land and heightened fragmentation. Concurrently, Ezhou's economic development and industrial restructuring policies are typically implemented preferentially in these high-demand zones to support industrial layout and urban growth. Driven by policy, former agricultural land has gradually been converted to industrial, commercial, or residential uses, thus creating low CLFI values (indicating high fragmentation) in the development zones. This trend not only highlights the increased pressure on cultivated land protection in economically developing areas, but also the potential for policy biases to have a lasting impact on the spatial characteristics of cultivated land.

In 2018, to promote ecological civilization, Ezhou City enacted the "Ezhou Lake Protection Ordinance" to enhance the protection of ecologically sensitive areas. This ordinance specifies that in the administrative zones around Liangzi Lake, no further industrial enterprises will be permitted, except for innovative and high-tech firms, while also broadening the restrictions on livestock and expanding mountain protection zones. These ecological policies, by imposing strict development limitations, have mitigated excessive land development and cultivated land conversion around Liangzi Lake, markedly raising its CLFI since 2013, suggesting lower fragmentation, although it is still relatively low on a citywide scale. This outcome suggests that robust ecological protection measures have led to a more stable and sustainable land use pattern around Liangzi Lake. Despite an increase in CLFI to a relatively high level, ecological protection policies have not fully mitigated cultivated land fragmentation in the urbanization process. The stabilized fragmentation trend offers valuable insights for land management and ecological policies in other comparable ecologically sensitive areas. In contrast, state-owned cultivated land serves to safeguard national food security, maintain agricultural production stability, and drive the development of state-owned farms or agricultural projects. Due to its defined ownership, legal protection, and regulatory policies, the land use remains stable. In the face of urbanization pressures, the land in these areas has not been extensively converted or developed, keeping the fragmentation index relatively stable. The stability of state-owned cultivated land suggests that government control and protective policies for state-owned land can effectively minimize fragmentation fluctuations, maintaining a relatively manageable land use condition, which positively contributes to optimizing land use structures and preserving agricultural land.

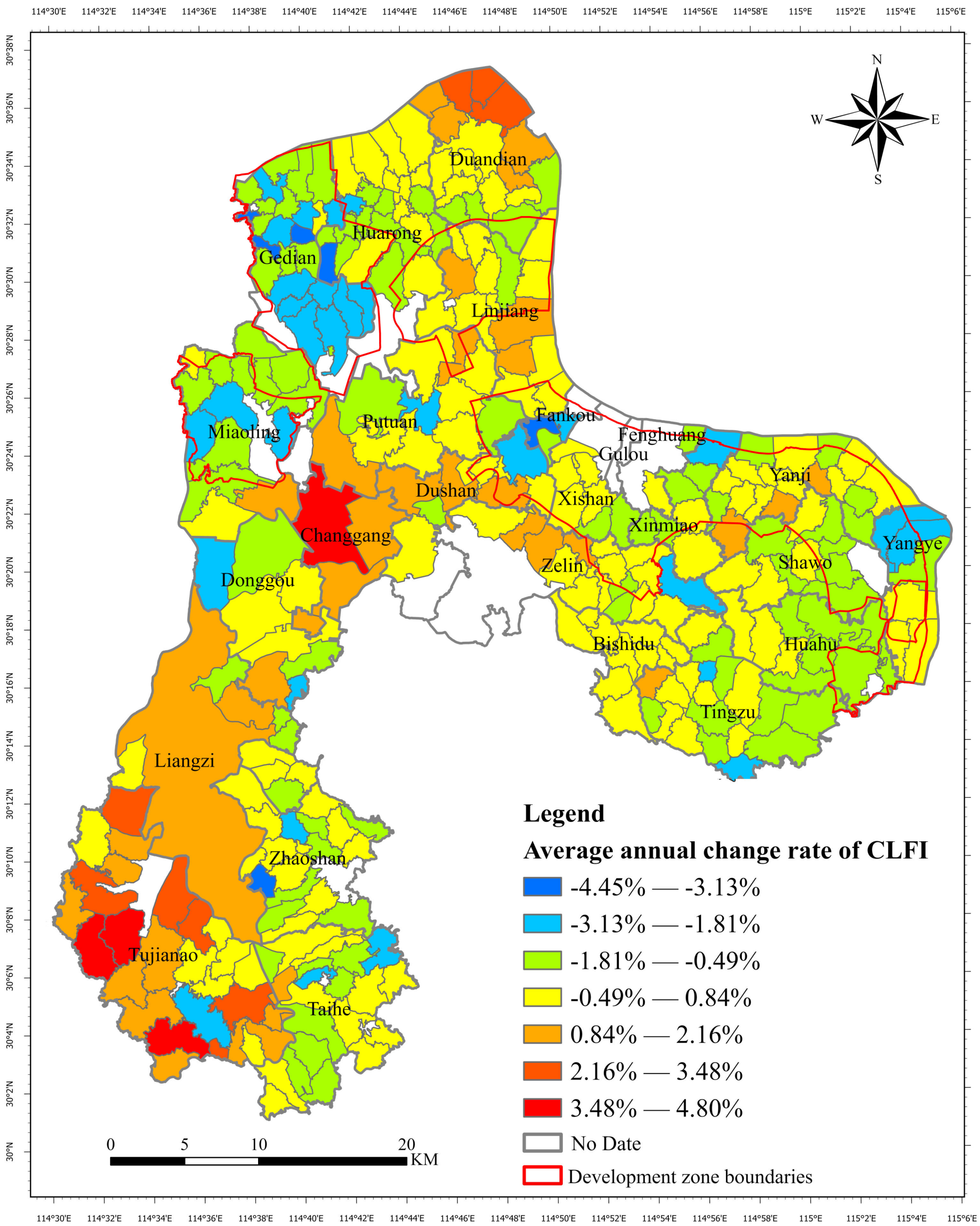

Figure 4. Annual average change rates of CLFI from 2013 to 2022 and their spatial distribution.

Overall, the fragmentation of cultivated land in Ezhou City exhibited a spatial distribution pattern with lower values in the northwest and northeast regions, and higher values in the southwest and central areas. This characteristic stands in stark contrast to Ezhou's economic development pattern, which declined from east to north and south, highlighting the complex interplay between economic development and cultivated land fragmentation. Urban expansion and land redistribution often accompany economic development, with cultivated land fragmentation reflecting land resource impacts during this process. This reverse spatial distribution highlights urbanization's uneven effects across different regions of Ezhou, especially notable between central urban areas and ecological zones, underscoring the lasting influence of urbanization on land use structures. In summary, this study elucidates trends, spatial characteristics, and driving mechanisms of cultivated land fragmentation in Ezhou under the dual policies of urbanization and ecological protection, offering critical scientific evidence for land resource optimization and ecological policy development in similar regions.

3.2. Spatial Clustering Characteristics of CLF

In order to gain a deeper understanding of the spatiotemporal changes of CLF in Ezhou City between 2013 and 2022, this study employed both global and local spatial autocorrelation analyses. Based on the data presented in Table 5, the global Moran's I values for CLFI at the village level in Ezhou City for 2013 and 2022 demonstrated significant positive correlations at the 1% significance level. This implies that the CLF in rural areas of Ezhou City exhibits distinct spatial clustering characteristics, with a pronounced upward trend between 2013 and 2022.

Table 5. Global Moran's I analysis of single factors for CLF in 2013 and 2022.

Year	Type	Moran's I	Z-Value	*p*-Value
2013	RE	0.090	2.624	0.001
	SC	0.395	10.517	0.001
	CU	0.623	16.880	0.001
	CLFI	0.324	9.076	0.001
2022	RE	0.708	18.844	0.001
	SC	0.400	10.897	0.001
	CU	0.250	6.739	0.001
	CLFI	0.639	17.091	0.001

The outcomes of the local spatial autocorrelation analysis are depicted through LISA maps (Figures 5 and 6). From 2013 to 2022, the clustering and random distribution patterns of CLFI at the village scale in Ezhou City generally remained relatively stable. In 2013, high-high clustering areas, indicative of high value concentrations, were primarily located in Putuan Township, Changgang Town, Donggou Town, and Tujianao Town in the central and western regions; low-low clustering areas, indicative of low value concentrations, were mainly found in parts of Tingzu Town, Xinyao Town, Zelin Town, and Gedian Town. High-low aggregation zones and low-high aggregation zones encompassed fewer villages, leading to more fragmented spatial characteristics. In 2022, high-high clustering areas were primarily located in Putuan Township, Changgang Town, Donggou Town, Tujianao Town, and Dushan Town; low-low clustering areas were mainly concentrated in Gedian Town, Fenghuang Sub-District, and Xinyao Town; low-high clustering areas were predominantly found in Liangzi Town.

These results suggest that between 2013 and 2022, the CLFI exhibited a generally stable spatial distribution pattern at the village level. The distribution characteristics of the clustering types in most villages and towns (namely high-high and low-low clusters) were consistent, suggesting that the spatial aggregation pattern of CLFI is temporally stable. Additionally, the concentrated spatial distribution of clustered areas may indicate the polarization effect resulting from urban expansion, especially driven by development zones and central urban districts, leading to a greater concentration of low-low clusters. Concurrently, as a result of policies aimed at ensuring food security and promoting comprehensive tourism development, the CLFI in the villages around southern Putuan Township and state-owned farms exhibited stable growth, leading to the gradual formation of a more concentrated high-high cluster.

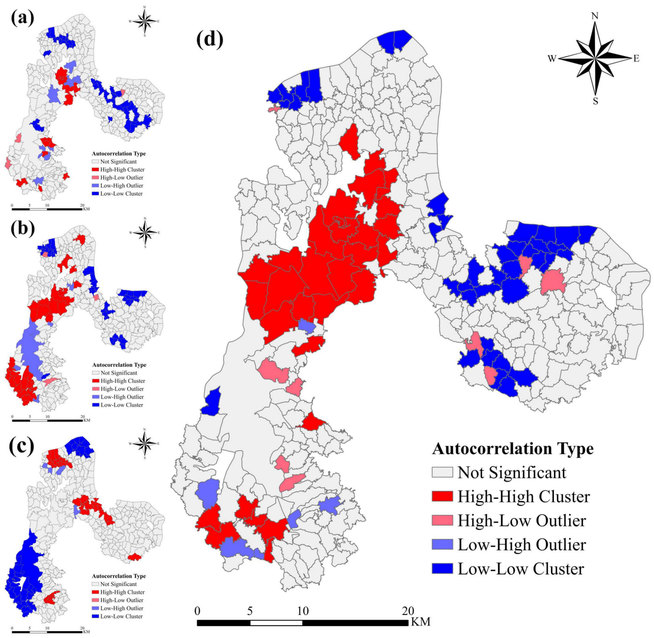

Figure 5. The local Moran's I map for Ezhou City in 2013, resource endowment (**a**), spatial concentration (**b**), convenience of utilization (**c**), and CLFI (**d**).

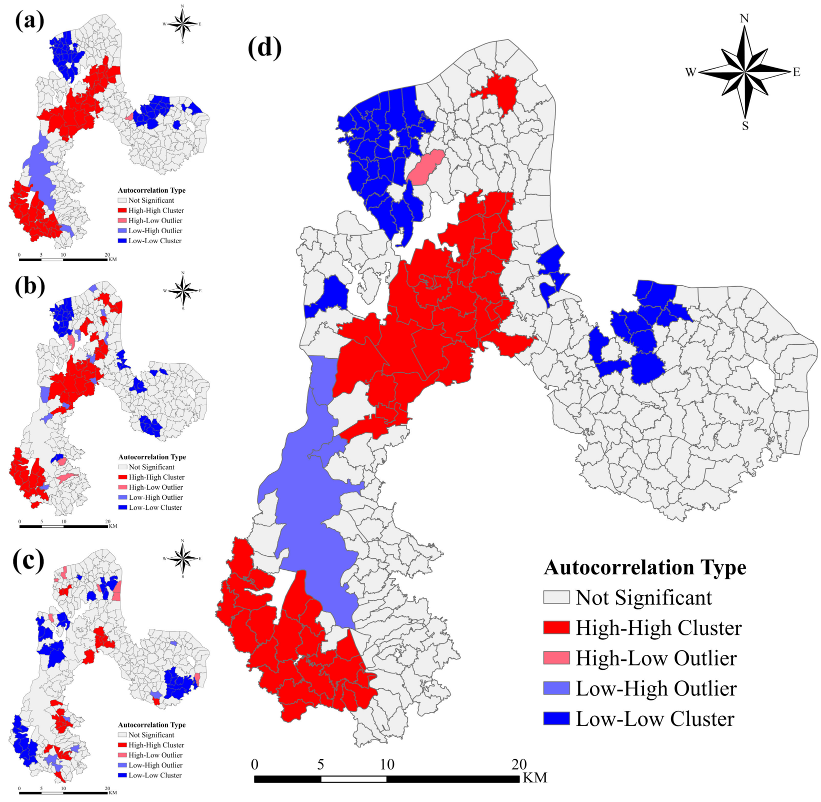

Figure 6. The local Moran's I map for Ezhou City in 2022: resource endowment (**a**), spatial concentration (**b**), convenience of utilization (**c**), and CLFI (**d**).

3.3. Actors Driving Spatial Variation in CLF

This research combined data accessibility with the representativeness of indicators, selecting seven potential indicators as independent variables from both natural and social perspectives, which were validated using a random forest model (Table 6). As illustrated in Figure 7, the importance ranking of the factors influencing CLF in Ezhou City is as follows: proportion of construction land > land use intensity > population density > average patch area > slope > water network density > elevation. Among these, the proportion of construction land, land use intensity, and population density were identified as critical factors.

Table 6. Driving factors of CLF.

Type	Driving Factors	Hypotheses on the Relationship with CLF	Mean Value	Standard Error
Natural factors	Slope	Slope may affect the utilization of cultivated land.	1.7806	2.1076
	Elev	Elevation may influence the distribution of cultivated land.	33.98	24.61
	Water network density	Water network density may influence the usability conditions of cultivated land.	0.0571	0.0857
	Average patch size	Could influence the mechanization of agricultural practices and the scale of operations on cultivated land.	2.4880	1.8300
Social factors	Population density	Population density may influence the management of cultivated land at scale.	7.0395	3.6642
	Proportion of built up land	Proportion of built up land may influence land conversion and segmentation.	0.2366	0.1833
	Land use intensity	Land use intensity may potentially affect the availability of cultivated land.	2.8267	0.4194

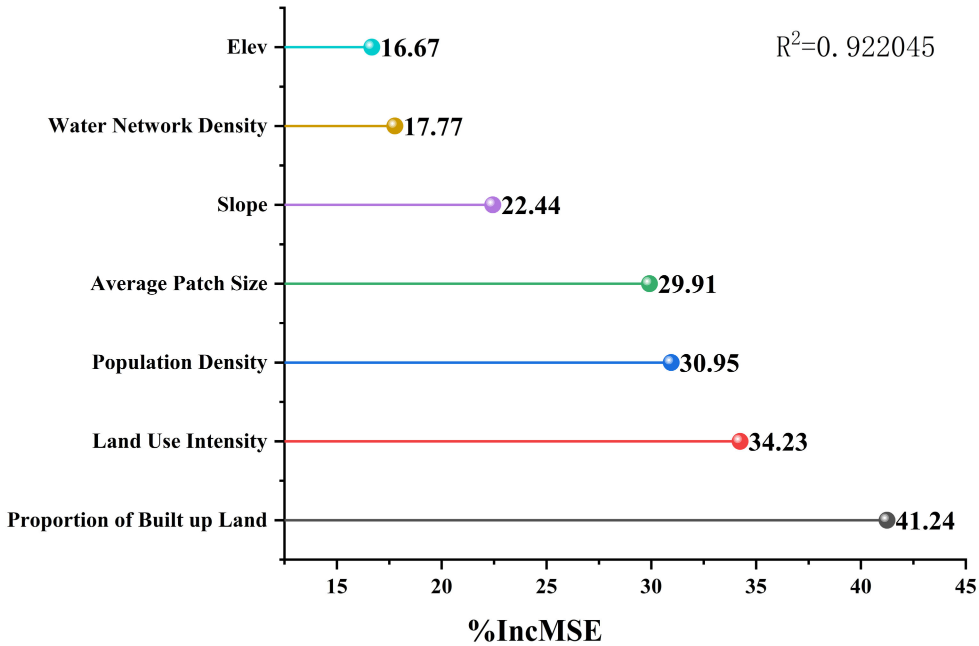

Figure 7. Significance of the driving factors for cultivated land fragmentation in Ezhou City.

Ezhou City has a flat terrain with minimal topographical variation, and the eastern and southern regions consist of vast plains, covering approximately 45% of the city's total area. According to topographical analysis, the elevation differences among the villages in the city are minimal, with a maximum height of 188.54 m, a minimum of 15.6 m, and an average elevation of 33.9 m. This topographical feature provides a relatively stable foundation for cultivated land use; however, it also implies that the variations in elevation among different villages have no significant impact on cultivated land fragmentation. Furthermore, Ezhou City is endowed with abundant and evenly distributed water resources, with a water area of 51,193.02 hectares, which accounts for approximately one-third of the city's total area. This uniform distribution of water resources provides favorable conditions for agricultural irrigation; however, it also indicates that natural factors such as elevation, water network density, and slope have relatively minor driving effects on cultivated land fragmentation.

The ongoing rise in the share of construction land throughout the urbanization process signifies that a significant portion of land previously allocated for agricultural purposes is being repurposed for residential, commercial, and industrial functions. This transformation not only undermines the continuity of cultivated land, but also divides formerly contiguous agricultural fields into smaller plots to meet the new construction requirements. In the development areas of Ezhou City, the need for large-scale industries has led to the occupation of extensive organized cultivated land, with only a limited number of fragmented plots being restored as cultivated land, thereby exacerbating the fragmentation of cultivated land in the surrounding areas. Areas characterized by intensive land use frequently require the partitioning of large agricultural parcels to satisfy diverse functional and usage needs. This fragmentation results in a greater disaggregation of cultivated land, hindering the scaling of agricultural enterprises, increasing the farmers' operational costs, and perhaps having an effect on the sustainability and efficiency of agricultural production. Additionally, with the progression of urbanization, there is a gradual concentration of population in development zones and core urban areas, resulting in a significant surge in land demand. This trend forces cities to consistently expand construction land and enhance the land utilization intensity to meet the escalating demands of population growth and economic activities. Consequently, in the context of cultivated land fragmentation in Ezhou City, the proportion of built-up areas, land use intensity, and population density have exerted considerable influence. Figure 8 demonstrates that between 2013 and 2022, regions with high values for construction land proportion, land use intensity, and population density were predominantly located in the development zone, whereas low-value areas were found in the southern and fringe areas of the city, characterized by lower levels of urbanization and weaker economic development. Comparisons revealed that socio-economic factors had a markedly greater impact on the fragmentation of cultivated land in the villages of Ezhou City during the urbanization process than natural factors. This discovery highlights the complex interrelationship between land use and urbanization, underscoring the need to take socioeconomic development considerations into account when developing policies for urban planning and land management.

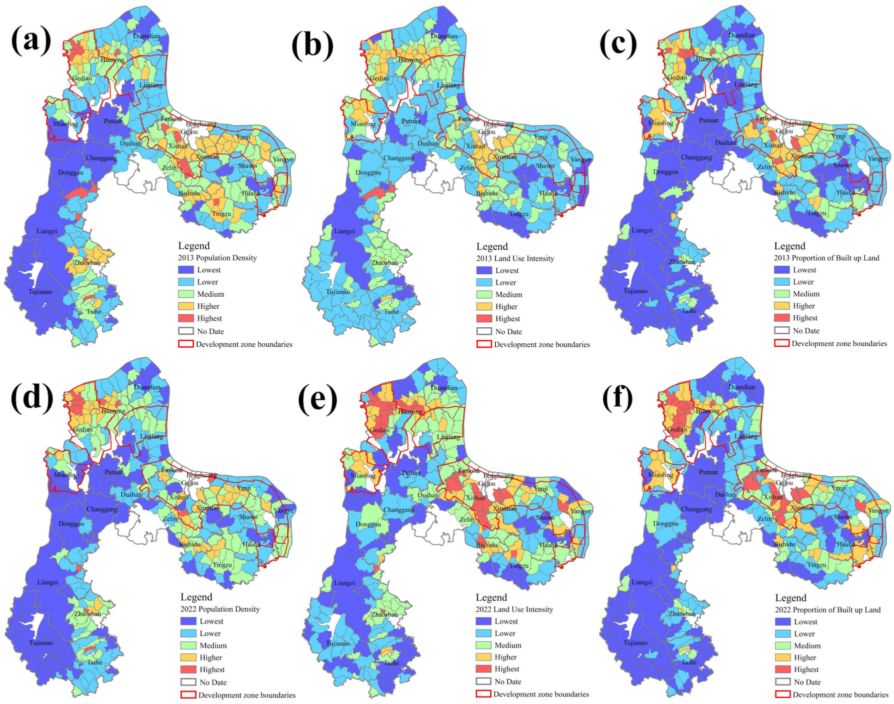

Figure 8. Spatial characteristics of key driving factors of CLF for 2013 and 2022: population density (**a**,**d**), land use intensity (**b**,**e**), and proportion of built-up land (**c**,**f**).

In conclusion, the fragmentation of cultivated land in Ezhou City is influenced not only by natural conditions, but also directly results from urbanization and socio-economic transformations. Future studies should investigate ways to reconcile land development with the preservation of cultivated land during the urbanization process, thereby promoting sustainable land use and ecological equilibrium.

3.4. Trends in the Transfer of Urban–Rural Construction Land and Cultivated Land

The analysis of land use change (Figure 9) showed that from 2013 to 2022, the proportion of UCL in the total area of the study area rose from 5.72% to 8.36%, with cultivated land contributing an average of 46.47% to this expansion. This high conversion rate indicates that a large area of contiguous high-quality cultivated land has been occupied, leading to the formation of fragmented small plots. Urban expansion typically focuses on flat, accessible cultivated land, which leads to the division of areas that are suitable for large-scale cultivation into isolated and scattered plots. The subsequent infrastructure development further disrupts the connectivity of cultivated land, limiting the application of agricultural mechanization, increasing the difficulty of land utilization, and intensifying the fragmentation of cultivated land. While the proportion of RCL in the total area has decreased (from 7.85% to 6.92%), cultivated land still constitutes the main source of RCL, accounting for 62.62% of the inflow to RCL. The manner of rural construction land expansion is quite scattered and widespread, which has further intensified the fragmentation of cultivated land. The expansion of RCL not only directly influences the spatial structure of cultivated land, causing it to be divided into smaller plots, but also changes the micro-pattern of land use in rural areas, resulting in cultivated land being increasingly surrounded or intermixed with irregular built-up areas, which restricts the possibilities for land consolidation.

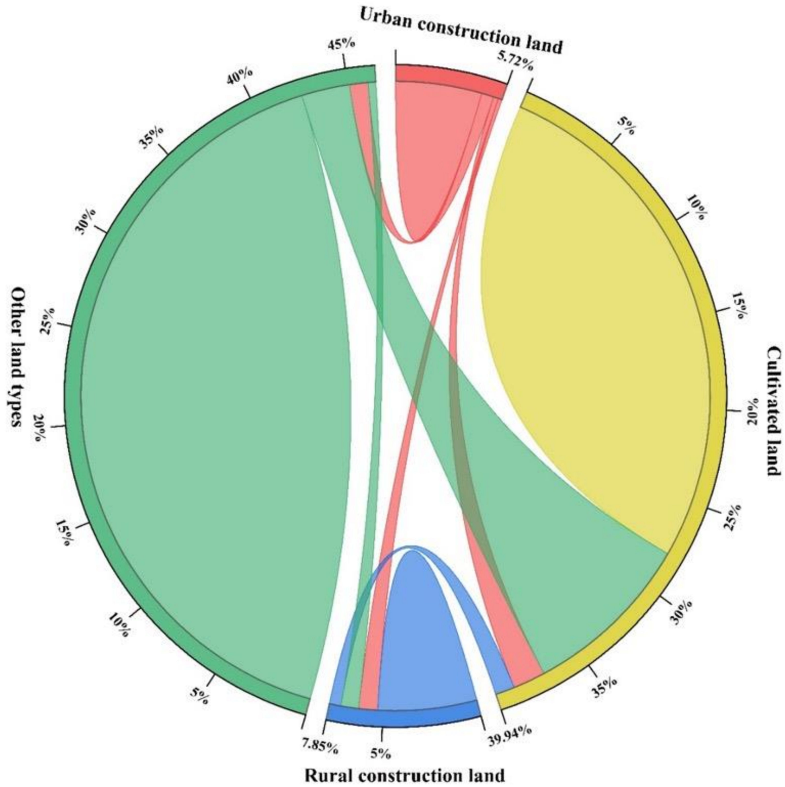

Figure 9. Chord diagram of land use changes in Ezhou from 2013 to 2022.

Figure 10 shows that between 2013 and 2022, Ezhou City experienced an expansion rate of 162.94% for UCL with an expansion intensity of 19.42%; an expansion rate of −2.05% for RCL with an expansion intensity of −0.16%; and an expansion rate of −2.86% for cultivated land with an expansion intensity of −1.13%. The slower expansion rate of RCL relative to UCL was due to land transfer and the rapid urbanization-driven industrial adjustments in Ezhou City. The primary contributor to UCL expansion was cultivated land, followed by RCL.

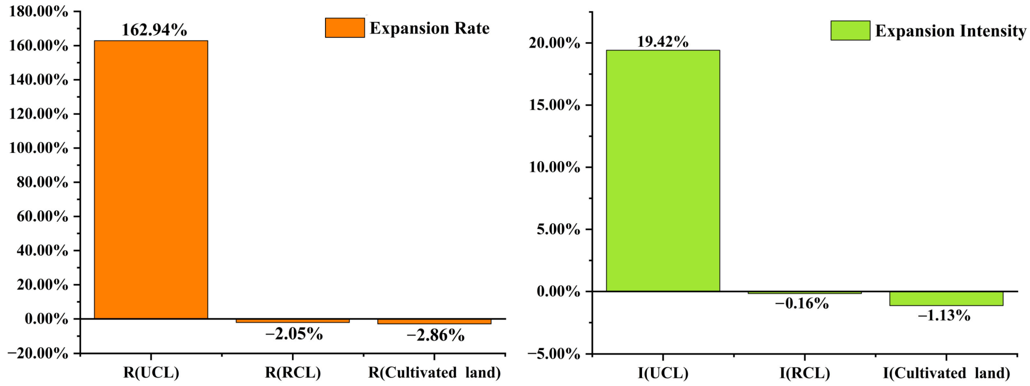

Figure 10. Expansion changes in UCL, RCL, and cultivated land from 2013 to 2022.

In general, UCL has been a key factor in the fragmentation of cultivated land in Ezhou City. The growth of UCL exacerbates the trend of land fragmentation by directly converting extensive cultivated land into high-intensity urban development. With the rapid urbanization in Ezhou City, the growing demand for infrastructure, housing, and public services has resulted in the spatial fragmentation of cultivated land into smaller parcels to meet the space requirements of these new developments. For instance, the laying of roads and other infrastructure has disrupted previously consolidated cultivated land parcels, further undermining the conditions for agricultural mechanization and intensification, increasing the costs of agricultural operations and decreasing the production efficiency, thus exacerbating land fragmentation. Despite a slower expansion rate compared to UCL, the influence of RCL on the fragmentation of cultivated land should not be underestimated. During the urban–rural integration process, a dynamic transformation relationship exists between RCL and UCL, especially with the increasing trend of RCL converting to UCL, suggesting that under urban expansion pressures, the demand for rural construction land is increasingly shifting toward urban areas. The expansion of RCL in rural areas is often characterized by discontinuous and irregular scattered patterns, which directly influence the spatial distribution of cultivated land, leading to the greater fragmentation of agricultural land. The expansion of RCL not only disrupts the integrity of cultivated land, but also renders the original agricultural landscape structure more complex and fragmented, further impacting the efficiency of agricultural management and the feasibility of resource integration.

4. Discussion

4.1. Analysis of Spatial Variability of CLF and Comparison

Evidence from the Wuhan metropolitan region shows that the average level of CLF is greater in mountainous and hilly areas compared to plains. In the low hill and plain regions, socio-economic factors serve as the primary determinants of CLF [47], consistent with the results observed in Ezhou City. Being part of the Wuhan metropolitan area, Ezhou City's land management can derive important lessons from the experiences of Wuhan. Furthermore, this study's findings concur with those of Xiaoran and Li Wenbo [48]. Studies have shown that the expansion of urban areas in China, especially in central regions, leads to the extensive transformation of adjacent cultivated land into non-agricultural land, especially pronounced in eastern counties. Furthermore, cultivated land in the urban outskirts frequently worsens during land use changes, making urban fringe hotspots for cultivated land fragmentation. The study revealed different impact patterns of urban and rural construction land on CLF, further confirming the substantial influence of construction land expansion on cultivated land fragmentation. Specifically, the fragmentation of cultivated land in the urban periphery was exacerbated by pressures from non-agricultural uses. As urban expansion progresses, cultivated land in these areas is increasingly transformed into construction land for commercial, industrial, and other purposes, intensifying the problem of cultivated land fragmentation. In comparison, rural areas, while also impacted by construction land expansion, exhibit different fragmentation patterns and extents than those observed in urban peripheries. In rural regions, extensive construction land is redirected to urban development and other uses, absorbing adjacent cultivated land to accommodate rural housing demands. According to these distinct spatial impact features, the irrational expansion of urban and rural construction land in Ezhou City has markedly intensified the fragmentation of cultivated land within villages, with regionally distinctive impacts. Additionally, a comparative analysis of models revealed that researchers employed a geographically weighted regression model to investigate CLF factors, yielding an R^2 of 0.606 [49], which is notably lower than the R^2 of 0.922 achieved with the random forest model used in this study. The random forest model, in contrast to the geographically weighted regression model, offers more accurate and robust analytical outcomes, showcasing superior predictive power. The high R^2 value demonstrates that the random forest model excels in capturing and interpreting the complex factors affecting CLF, thereby providing a more dependable foundation for predicting and analyzing CLF issues in the research area.

4.2. Integrated Effects of CLF During Urban Expansion

The study findings suggest that between 2013 and 2022, the CLF in Ezhou City overall intensified, and the polarization phenomenon has become increasingly significant. Areas exhibiting a greater average annual growth rate of the CLFI were situated near the state-owned farms in the central region and around Tujianao Town in the south, and these regions also demonstrated the highest land quality and lowest levels of cultivated land fragmentation. This observation may be associated with the crucial function of state-owned cultivated land in safeguarding national food security, leading to its relatively lower susceptibility to encroachment by construction land amid urban expansion. Furthermore, because of its clearly defined land ownership and legal protection, the CLFI has shown a consistent increase. As the hub of comprehensive tourism in the Liangzi Lake area, Tujianao Town actively consolidates parcels and organizes land, improves the infrastructure levels and has achieved the least degree of cultivated land fragmentation. Relatively speaking, the Gedian Development Zone and the central urban area, as key regions for economic growth in Ezhou City, demonstrate notable effects of population and industrial concentration. In order to satisfy the needs of economic development and urban expansion, substantial high-quality cultivated land has been allocated for non-agricultural construction, resulting in the severe fragmentation of cultivated land. The study of driving factors has shown that during the urban expansion process in Ezhou City, the proportion of construction land, land use intensity, and population density were the primary influences on the level of cultivated land fragmentation in the area; that is, areas with higher construction land proportions, increased land use intensity, and greater population density experience more severe levels of cultivated land fragmentation.

A significant number of studies have indicated that the rapid advancement of urbanization has resulted in serious cultivated land fragmentation and obstructed the progress of mechanized agriculture. However, cultivated land fragmentation does not only have negative impacts [50–52]. Previous studies have indicated that CLF within manageable limits can indirectly improve the stability of agricultural production, enhance crop production diversity, and also bolster the resilience of agricultural systems against climate change and natural disasters [53]. Moreover, fragmented land patterns can, to some extent, alleviate potential conflicts between land ownership and usage rights, providing greater flexibility and maneuverability for cultivated land transfer [54]. Therefore, when assessing the impact of land fragmentation, it is essential to go beyond a single perspective of economic benefits and conduct a comprehensive analysis from multiple dimensions including agricultural production, landscape ecology, and land management, in order to weigh its pros and cons and develop more effective land management strategies that achieve the goal of coordinated agricultural and urban–rural development.

4.3. Policies and Recommendations for Controlling CLF

Against the backdrop of Ezhou City's rapid economic growth, it is crucial to simultaneously achieve sustainable agricultural development and mitigate the fragmentation of cultivated land. To effectively tackle the challenges brought about by cultivated land fragmentation, increase land use efficiency, and strengthen agricultural productivity, this research presents three policy recommendations. These suggestions are intended to provide a theoretical basis for the formulation of land management and agricultural policies, thereby facilitating regional sustainable development.

(1) Optimize the spatial configuration of cultivated land. In regions experiencing severe fragmentation around the development zone and Liangzi Town, it is essential to scientifically consolidate the scattered small plots of cultivated land into appropriately sized units to enhance agricultural production efficiency. Furthermore, for the development zone, compensation mechanisms may be developed according to the actual ecological circumstances of the region and businesses to retain or restore cultivated land within their development projects, minimizing the encroachment on agricultural resources. In regions of slight fragmentation in state-owned farms and less economically developed areas in the south, attention should be directed toward expanding the scale of cultivated land and enhancing the production capacity of the consolidated land, thereby facilitating spatial intensification. Facilitating the balanced development of regional economies can be undertaken by ensuring the sustainable development of cultivated land resources.

(2) Establishment of permanent basic cultivated land and population redistribution. The Gedian Development Zone and the central urban area represent regions with the highest proportion of construction land, the greatest land use intensity, and the highest population density. It is suggested that the overall land use plan explicitly delineate a protection zone for permanent basic cultivated land. Furthermore, the development of new urbanization in neighboring towns should be advanced, effectively directing the population and industries to transfer in an orderly manner to small and medium-sized towns and industrial parks, thereby relieving population pressure in the central urban area and promoting the transfer and employment of surplus rural labor. This comprehensive strategy not only helps to relieve the socio-economic pressures in development areas, but also aids in achieving sustainable regional development.

(3) Optimizing the urban–rural development framework. In the economically developed eastern and northern regions where the average annual change rate of CLFI is negative, it is advisable to designate ecological protection areas or integrated development zones to foster a compact urban growth pattern while preventing the excessive outward expansion of urban boundaries. In the southern regions with poorer economic conditions but continuous improvement in CLFI, we suggest that the development of green infrastructure is advanced including ecological roads and green space systems. These initiatives should be implemented with the aim of fostering sustainable regional economic development while safeguarding the integrity of cultivated land. By means of strategic planning and construction, it is possible to optimize the spatial arrangement of urban and rural areas, thereby improving the efficiency of land use and the quality of the ecological environment.

4.4. Constraints and Future Directions

Although this study offers significant empirical evidence, it still has several limitations. First, the analysis centered on Ezhou City as a singular case, which may partially restrict the applicability of the findings to other areas with varying socio-economic and environmental contexts. Furthermore, although the random forest model demonstrated significant effectiveness in identifying key factors, it did not adequately capture the complex dynamic relationships among these factors over time. Future studies may investigate the spatiotemporal variations of CLF under varying urbanization pressures by incorporating longitudinal data across multiple regions.

5. Conclusions

This research provides a systematic assessment of the levels of CLF in Ezhou City for the years 2013 and 2022. It analyzed the spatial clustering characteristics and employed a random forest model to investigate the key factors and mechanisms by which urban and rural land expansion impacts CLF. The results demonstrated notable spatial disparities in the fragmentation of cultivated land across Ezhou City, with lower levels observed in the northwest and northeast regions and higher levels in the southwest and central areas, providing a stark contrast to the decreasing trend of economic development from east to north and south within Ezhou City. Throughout the study period, CLF evolved from being primarily characterized by moderate and severe fragmentation to being predominantly classified as severely and extremely fragmented, exhibiting an overall decline but with a more pronounced trend of polarization. The research further highlights the pivotal role of social factors in influencing CLF in Ezhou City, demonstrating that construction land proportion, land use intensity, and population density exert a significantly greater impact on CLF compared to natural factors such as slope and elevation. Numerically, the total area of cultivated land converted to UCL exceeded that converted to RCL. However, the average contribution of cultivated land within RCL was proportionately greater than in the UCL, highlighting the significant role of RCL in fulfilling basic rural demands through cultivated land conversion. Especially in rural areas, the appropriation and transformation of cultivated land have intensified the fragmentation phenomenon. Through the case study of Ezhou City, this research highlights the significance of urban–rural coordinated development and cultivated land protection in the context of urban expansion, offering empirical evidence.

Author Contributions: K.F. conducted data analysis, performed experiments, and drafted the manuscript. H.G. was responsible for reviewing and supervising the manuscript. L.Q. performed experimental validation and data management. J.G. designed this study and provided final approval for the submitted version. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The land use data utilized in this study is obtained from the Ezhou City Land Use Change Investigation Database, which is classified. If necessary, requests for information can be made to the corresponding author as appropriate.

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Conflicts of Interest: The authors assert that there are no conflicts of interest.

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