

Article

Spatial–Temporal Pattern of Urban Land Green Use Efficiency and Its Influencing Factors in Guizhou Province, China, Based on County Units

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Abstract: Urban land is an important and indispensable support for urban development. However, the continued development of urbanization and industrialization has given rise to many problems, increasing the burden of urban land and leading to inefficient urban land use. The study of urban land green use efficiency (ULGUE) helps to explore the path to alleviate urban land-use pressure and enhance the land green utilization efficiency, and provides important decision-making references for urban greening construction and development. In this paper, 88 districts and counties in Guizhou Province were taken as the research units. Then, their efficiency values and spatial–temporal evolution characteristics were analyzed by applying the non-expected output super-efficiency SBM model, the kernel density estimation method, and spatial autocorrelation analysis, respectively. In order to identify its influencing factors, the main correlation analysis was carried out using the Tobit model. The research findings are summarized as follows: (1) From the time-series evolution characteristics, the ULGUE among the 88 county cities in Guizhou Province had obvious polarization characteristics. In terms of the numbers, there was a gradual downward trend in the number of high-efficiency cities. (2) Based on the spatial evolution characteristics, there was a positive correlation in the ULGUE among county cities in Guizhou Province, and the high- and low-value areas were comparatively more widely located in the central–east and west sides of Guizhou Province, respectively. (3) Among the factors influencing the level of the ULGUE, the level of economic development, industrial structure upgrading, and environmental regulation mainly played a positive facilitating role, while the material standard of living of the population, the GDP content, the green development level, government financial support, and the population size played a negative inhibiting role. The study of the ULGUE in Guizhou Province provides ideas for urban construction and is of great significance for the green transformation of urban development. At the same time, it can provide a reference for China’s western development.

Keywords: urban land green use efficiency; characteristics of spatial–temporal evolution; influence factors; non-expected output super-efficiency SBM model



Citation: Xu, Z.; Chen, H.; Song, W. Spatial–Temporal Pattern of Urban Land Green Use Efficiency and Its Influencing Factors in Guizhou Province, China, Based on County Units. *Land* **2024**, *13*, 2140. <https://doi.org/10.3390/land13122140>

Academic Editor: Thomas W. Sanchez

Received: 14 November 2024

Revised: 4 December 2024

Accepted: 6 December 2024

Published: 9 December 2024



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1. Introduction

Significant progress has been made in urban development. Urban land, serving as a spatial platform facilitating the interaction of factors, is a crucial urban resource imbued with substantial value for urban development [1–3]. The continuous expansion of its spatial extent and the increasing efficiency of the utilization of its effective area have an impact on production practices [4]. Massive land reclamation for rapid urbanization [5] brings with it the risk and possibility of resource depletion [6]. The landscape of land utilization has also undergone transformation amidst rapid urbanization [7]. At a macroscopic level, the urban areas are growing rapidly. There has been a sudden and dramatic increase in both the size and number of cities [8]. Urban areas are encroaching on non-urban landscapes, including

forests [9], habitats [10], farmland [11], cropland [12], etc. Non-urban land is gradually being squeezed out. The disorderly expansion and rough utilization of urban building land have exerted immense pressure on land resources [13], leading to an unscientific and irrational urban land-use structure [14,15]. The unchecked escalation in demand for finite land resources has precipitated a myriad of urban challenges, including urban inundation, ecological degradation [16], city heat island effect [17], carbon emissions [18], pollution [19], landscape fragmentation [20], distorted spatial configurations, among others. Environmental challenges are ubiquitous [21]. Moreover, the foregoing is sufficient to demonstrate that urban development is constrained by land resources. Urban green spaces and the greening of land use are closely linked to human well-being [22] and can provide richer ecosystem services [23]. In addition, greening urban spaces contributes to sustainable urban development [24]. Therefore, it is necessary to give full play to the functions of urban green space. Guided by green development, promoting green land transition has become a major way to alleviate the pressure on urban land use [25], effectively mitigate the problems associated with urbanization [26], and achieve sustainable development [27]. Therefore, the key to achieving a comprehensive green transformation is to improve the urban land green use efficiency (ULGUE). Conducting in-depth research on the ULGUE has become an important research topic.

As a pivotal strategy for addressing the issue of land overexploitation, the concept of green land use embodies the integration of exploitation, conservation, and sustainable development. Scholars have introduced the notion of the ULGUE as a synthesis of green development principles and land utilization practices [28–30]. In scholarly discourse, the ULGUE is delineated as the economic yield derived from urban land utilization within specific production technological parameters [31,32]. While minimizing input costs and environmental impacts, its objective is to maximize social, economic, and ecological benefits. Emphasizing both economic and social returns, the ULGUE places a distinct focus on its environmental benefits, particularly in safeguarding the ecological landscape. Aligned with the pursuit of high-quality development, vigorously promoting urban land green use and enhancing the ULGUE stand as crucial components for driving economic growth, ensuring social well-being, and safeguarding ecological integrity in urban areas. Undoubtedly, it is imperative to achieve the efficient and environmentally friendly utilization of urban land.

As a result, researchers are paying increasing attention to the study of the ULGUE. Research in this area has yielded rich results. In terms of the study methodology, with the gradual development of relevant research, the research of the ULGUE has formed a relatively mature theoretical basis. In particular, it is gradually developing towards empirical analysis [33]. The evolution of the research methodology has been marked by a shift towards increased scientific rigor and sophistication. Moving beyond simple single-indicator measurements, researchers have embraced multi-indicator comprehensive evaluations, employing techniques such as the stochastic production frontier model [34], entropy method [12], and data envelopment analysis (DEA) [35]. This evolution has also led to a heightened awareness of the ecological impacts stemming from urban land use [36], including issues like industrial wastewater discharge [37]. Ecological losses were also a focus of attention when constructing the evaluation indicator system. However, the impact of the external environment is not taken into account in the traditional DEA method. Consequently, the non-expected output super-efficient SBM model, which can be enhanced to address non-desired outputs, has emerged as the predominant method for analyzing the ULGUE [38]. The model takes into account negative environmental losses arising from economic activities. Different areas have been studied based on this model [39,40]. Additionally, tools like the Theil index [41] and kernel density estimation (KDE) [42] have been utilized to explore the regional differences and temporal evolution patterns of the ULGUE. Among them, the KDE model can be used to analyze differences in time series presented by specific geographic phenomena. Scholars often use this model to analyze the characteristics of the ULGUE presented in the time series [28,43], and exploratory spatial data analysis (ESDA) [39] has been employed to uncover its spatial characteristics. ESDA

can be used to analyze the spatial correlation and clustering characteristics of research objects [30]. Specifically, spatial autocorrelation is analyzed from a global perspective. Visual analysis of aggregation features can be performed from a local perspective. Existing studies mostly use spatial autocorrelation analysis to determine whether clustering exists and to analyze the distribution of hot and cold spots [25]. In general, the above methods have their own characteristics and provide a scientific reference for the study of the ULGUE.

Currently, countries are working on sustainable development. The Sustainable Development Goals (SDGs) provide ideas for the selection of indicators of urban land-use efficiency (ULUE). In line with the SDGs, the ULUE can be expressed as the ratio of the rate of land consumption to the rate of population growth in urban space [44]. Of this, land is mainly the area occupied by built-up areas. Based on the above ratios, some scholars have measured urban land-use efficiency on a global scale, using the country as the basic unit [45]. Their research provides ideas for sustainable urban development. Changes in the ULUE in Portugal can also be explained [46]. Increasing land consumption and declining population have led to a decrease in its efficiency. In terms of influencing factors, the ULGUE is affected by a number of factors. Masini et al. analyzed the factors influencing the ULUE in terms of population, landscape, and land characteristics using European metropolises as the study area [47]. Urban sprawl can have a negative impact on the land-use efficiency [48]. Different patterns of sprawl also affect the ULUE [49]. Inward orientation reduces per capita land consumption, which, in turn, regulates the ULUE. There are also studies that point to gaps in the implementation of leasing policies as a possible cause of inefficient land use in Ethiopian cities [50]. Zitti et al. suggest that the high ULUE in southern Europe is related to factors such as integrated land use and mixed-use buildings [51]. They consider that the key to improving the ULUE is sustainable land management adapted to local conditions. The relationship between city size and urban land-use efficiency was explored by Guastella et al. [52]. They argued that administrative fragmentation may lead to inefficient land use. Complex land policy implementation processes, inefficient land transfer markets [50], and land hoarding [53] can also lead to inefficient urban land use. There is also a relationship between the land-use efficiency and future climate [54]. Improving the land-use efficiency has the potential to avert global warming. Urban land policies also affect the ULUE [55], mainly represented by land lease policies. In summary, scholars have performed in-depth explorations on the evaluation indicators, influencing factors, and research methods of the ULGUE.

The research scope surrounding the ULGUE has diversified over time, encompassing a broader array of subjects and locations. For China, studies now delve into various types of cities [56,57], as well as typical provinces [58–60]. Scholars have also investigated the relationship between urban agglomerations and the ULGUE [61,62]. However, the scope and scale of research on the ULGUE is still relatively macroscopic. It is more concentrated at the national level and in major watersheds, including the Yangtze River Delta, prefecture-level cities, the Yellow River Basin, among others [43,63–65]. Consequently, there remains a notable gap in the research concerning typical provinces and cities in western China. This study selects Guizhou Province, which is dominated by plateaus and mountainous terrain, as the research area in order to enrich the relevant research.

Through the combination of the results in the existing literature, it is found that the research related to the ULGUE started relatively late but has an important status, and this research topic has both academic and practical value. Scholars have conducted specific research around the research methodology, evaluation indices, and influencing factors of the ULGUE. Regarding the study methodology, the super-efficiency SBM model stands out as the established methodology for assessing the ULGUE. In addition, only a few scholars have used environmental factors as one of the efficiency evaluation indicators. As economic development shifts from “high speed” to “high quality”, environmental losses have become a major concern in the urban land-use process. Incorporating environmental losses into the evaluation index system makes the evaluation of the ULGUE more in line with the requirements of green, sustainable, and high-quality development. Therefore, the

super-efficiency SBM model, which includes non-desired outputs, is also introduced to measure the efficiency of green land use in urban areas. Regarding the influencing factors, scholars at home and abroad have specifically analyzed them from various aspects. They can be summarized into five aspects, including the economy, policy, society, population, and the land itself. In the study area, research on the ULGUE has predominantly centered on economically developed coastal regions and cities, with less emphasis on the western regions. This imbalance may influence the exploration of spatial development characteristics related to the ULGUE. Regarding the study scale, the existing literature is mostly based on the city and state scale to study the ULGUE. That said, empirical studies on the ULGUE in county cities are still relatively scarce. County cities are an important part of China's urban system and play an important role in China's economic and social development. They are not only the main implementers of national policies, but also play a key role in promoting the local economy, social governance, and cultural heritage. Studying the green land-use efficiency of county cities not only helps to improve the economic and environmental benefits of land resources, but also helps to realize the goal of the sustainable development of the society.

Consequently, we selected Guizhou Province as the case study area in this study. Moreover, the super-efficiency SBM model including non-desired outputs was adopted to measure the ULGUE in 88 districts and counties in Guizhou Province from 2013 to 2022. In order to describe the time-series evolving pattern of the ULGUE in Guizhou Province, the KDE method will be applied. Concurrently, the spatial autocorrelation analysis method will be applied to unveil its spatial evolutionary characteristics. With regard to the influencing factors, the Tobit model was used for specific analyses. The primary target of the study is to offer practical insights and guidance for the sustainable and green development of Guizhou Province through an investigation of the ULGUE. Specifically, the main objectives of this study are threefold. Firstly, an indicator system is constructed based on the input–output perspective, and the current situation is grasped by measuring the ULGUE of 88 districts and counties in Guizhou Province. Secondly, the spatial and temporal evolution characteristics of the ULGUE in Guizhou Province are analyzed based on the results of the efficiency measurement. Finally, the main factors affecting the ULGUE in Guizhou Province are analyzed in terms of economy, society, environment, government, as well as population. The purpose of this paper is to provide practical paths and guidance for sustainable and green urban development based on the study of the ULGUE. Figure 1 depicts the essential phases of the writing process employed in this study.

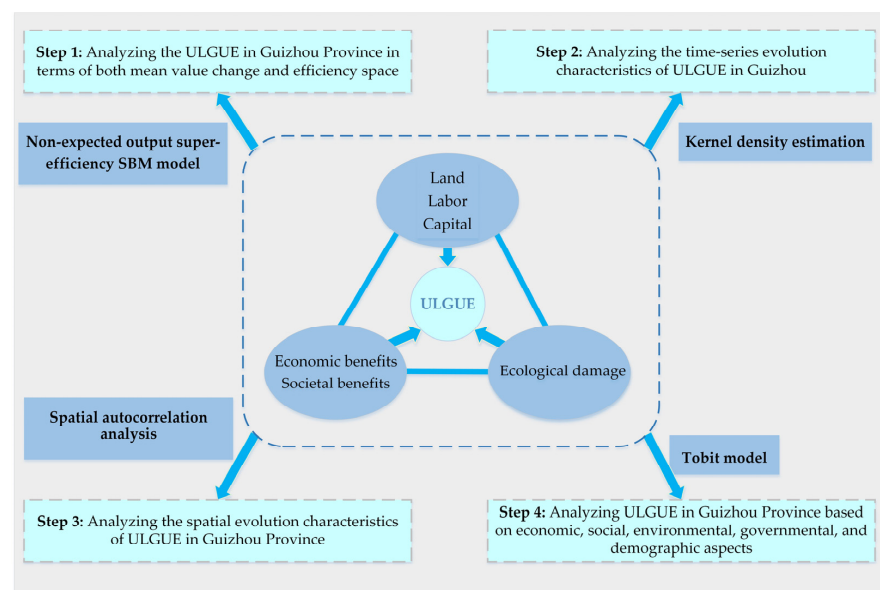


Figure 1. Flowchart for the efficiency analysis in Guizhou Province.

2. Materials and Methods

2.1. Research Area

Guizhou Province is situated on the Yunnan-Guizhou Plateau (Figure 2). By the end of 2023, Guizhou Province had 88 districts and counties with a resident population of 38.65 million. As a typical mountain karst area, Guizhou Province is the only province in China without a plain, and its average altitude is 1100 m. Most of Guizhou Province is plateau and mountainous areas. Of this, 92.5% of the area is covered by mountains and hills. As a transport hub in southwest China, Guizhou Province is an important transit area for the northwestern and southwestern provinces and regions to the coast. It is worth noting that the province of Guizhou is one of the few regions that has realized high-speed access to all counties. In addition, Guizhou Province is also known as “eight mountains, one water, one field”, which is a typical karst landscape with serious rocky desertification in some areas [66,67]. The special topography and geomorphology make land resources in Guizhou Province even more scarce.

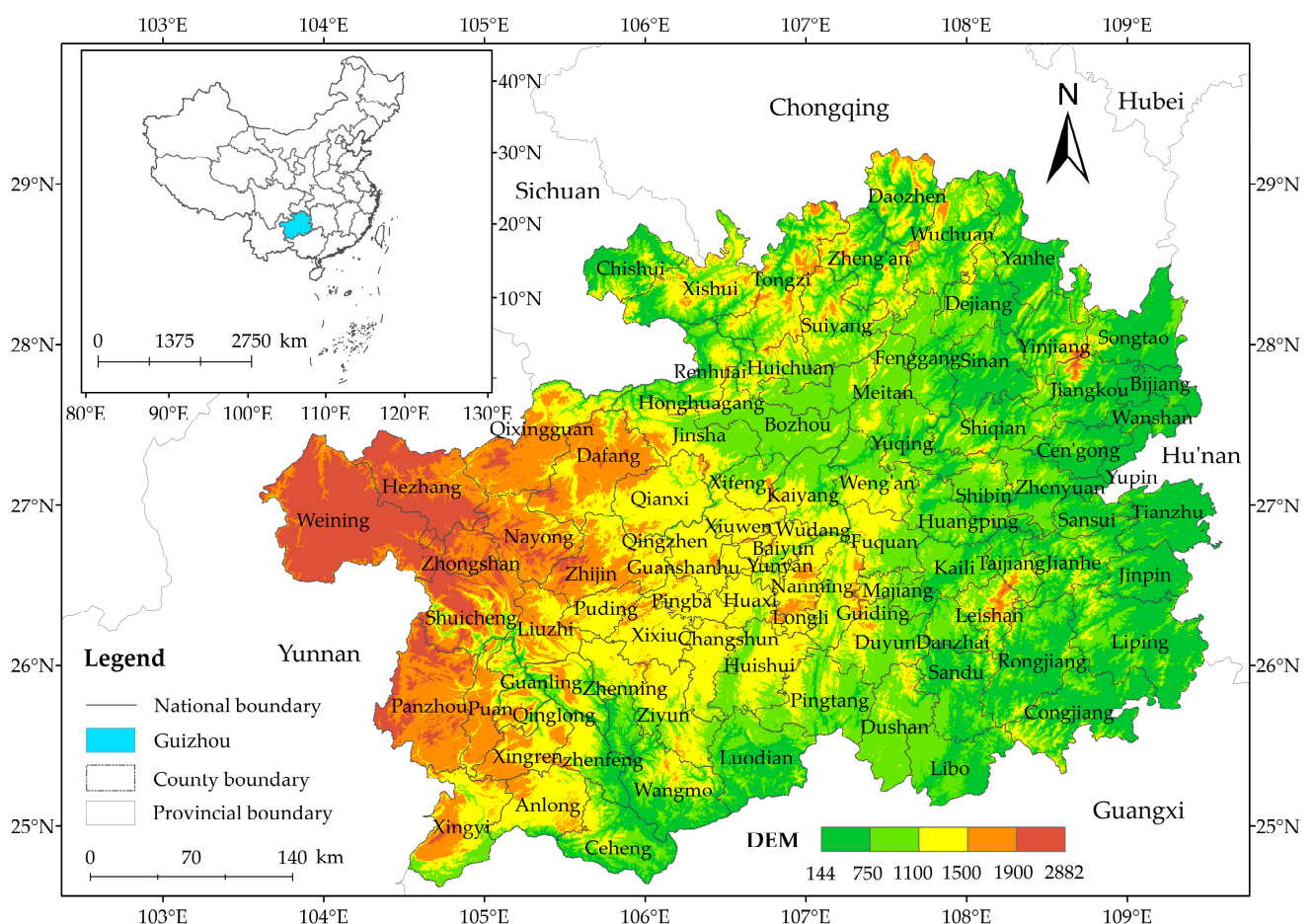


Figure 2. Study area.

The Opinions of the State Council on Supporting Guizhou's Innovative Approach to the Development of Western China in the New Era states that Guizhou Province should actively build an advanced area of ecological civilization construction. Simultaneously, the State supports Guizhou Province in seizing new opportunities with digital empowerment, working diligently to attain brand new achievements in ecological construction and progressively stepping out of the green development path with Guizhou Province characteristics. As a new highland of the inland open economy, analyzing the ULGUE in Guizhou Province is highly relevant to scientifically regulating the utilization structure of

urban land. Undoubtedly, this endeavor will play a pivotal role in advancing land greening initiatives in Guizhou Province and amplifying its ecological benefits.

2.2. Methods

2.2.1. Non-Expected Output Super-Efficiency SBM Model

DEA represents a methodology that employs linear programming techniques for the purpose of ascertaining the relative efficiency of production units or analogous decision-making units (DMUs) [68]. DEA has the capability to comprehensively take into account the interplay between input and output factors [69]. Therefore, DEA is widely used to measure the ULGUE. However, the traditional DEA often falls short in adequately considering the impact of non-desired outputs, leading to less precise evaluation results [70]. Tone introduced a non-radial SBM model incorporating non-expected outputs through slack variables for the first time [71]. This innovation compensates for errors stemming from slack variables, enhancing the effectiveness of evaluating efficiency issues involving non-expected outputs. To better identify effective decision-making units and address information loss challenges, Tone proposed an ultra-efficient SBM model integrating undesired outputs [72]. This model incorporates non-desired output elements in the calculations, ensuring a more accurate assessment of the ULGUE under non-desired output constraints. Assuming the presence of t input variables, m effective decision-making units, b_1 desirable outputs, and b_2 unexpected outputs, the mathematical model can be expressed as follows [27]:

$$\min(\gamma) = \frac{1 - \frac{1}{t} \sum_{i=1}^t \left(\frac{\bar{z}}{z_{ik}} \right)}{1 + \frac{1}{b_1 + b_2} \left(\sum_{s=1}^{b_1} \frac{\bar{y}^v}{y_{sk}^v} + \sum_{q=1}^{b_2} \frac{\bar{y}^\theta}{y_{qk}^\theta} \right)}$$

$$s.t. \begin{cases} \bar{x} \geq \sum_{j=1, \neq 0}^m z_j \lambda_j, j = 1, \dots, t \\ \bar{y}^v \leq \sum_{j=1, \neq 0}^m y_{sj}^v \lambda_j, s = 1, \dots, b_1 \\ \bar{y}^\theta \leq \sum_{j=1, \neq 0}^m y_{sj}^\theta \lambda_j, q = 1, \dots, b_2 \\ \bar{z} \geq z_k, \bar{y}^v \leq y_k^v, \bar{y}^\theta \geq y_k^\theta \\ \lambda \geq 0, \sum_{j=1, \neq 0}^m \lambda_j = 1 \end{cases} \quad (1)$$

where γ represents the value of the ULGUE; i , s , and q are the elements in the inputs, desired outputs, and undesired outputs, respectively; z , y^v , and y^θ denote the input indicators, desired output indicators, and non-desired output indicators, respectively; z_{ik} , y_{sk}^v , and y_{qk}^θ denote the elements in the input matrix, the elements in the desired output matrix, and the elements in the undesired output matrix of the k th decision unit, respectively; λ_j is the weight vector of the j th decision unit. When the efficiency value is less than or equal to 0.2, it is considered to be inefficient; an efficiency value of 0.2–0.4 is considered to be lower; an efficiency value of 0.4–0.6 is considered to be moderately efficient; efficiency values lying between 0.6 and 0.8 are considered to be more efficient; an efficiency value greater than 0.8 is considered to be highly efficient.

2.2.2. Kernel Density Estimation (KDE)

KDE is employed to derive continuous probability density profile functions, effectively mitigating subjectivity issues and enhancing the accuracy of the estimation results [73,74]. Additionally, insights gleaned from the function graph can aid in discerning the time-series evolution of the ULGUE [60]. Specifically, information such as the number of wave peaks, curve shift, trailing situation, and the height of the main peak of the kernel density curve are used to analyze the time-series evolution characteristics of the ULGUE in Guizhou Province. The specific formula is the following [75]:

$$f(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x_i - x}{h}\right) \quad (2)$$

In Equation (2), the total sample size is n ; the bandwidth is denoted by h ; x_i is the ULGUE; the kernel function is $K(x)$. As a general rule, more commonly used in the study of the ULGUE is the Gaussian kernel function. So, it was selected in this study for the subsequent calculation.

2.2.3. Spatial Autocorrelation Analysis

(1) The spatial autocorrelation of the entire study area can be comprehensively analyzed through the global spatial autocorrelation [76], which is a spatial analysis method. The presence of spatial autocorrelation in the efficiency values can be determined from the Moran's I and p -values. Based on this foundation, the global spatial autocorrelation of the ULGUE in Guizhou Province was gauged through the global Moran's I . The following formula can be used to calculate the metric [30]:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (3)$$

In Equation (3), n represents the number of cities; x_i and x_j signify the efficiency values for each city; $\bar{x}$ is the mean value of the observation; S^2 indicates the sample variance; the symbol w_{ij} specifically represents the spatial weight matrix. Additionally, the spatial proximity weight matrix is predominantly utilized for methodological operationalization. The specific choices are as follows: In the first step, a distance-based spatial weight matrix was constructed. This matrix quantifies the spatial relationships between samples by calculating the distances between geographic entities. In the second step, spatial autocorrelation analysis was performed using the k -neighborhood algorithm. This algorithm is effective in capturing the localized features between samples. In this, we specified k values from 0 to 20, performed several verifications, and finally determined the neighborhood number k to be 5. I denotes the global Moran's I . As a general rule, it accepts values in the range $(-1, 1)$. If I is closer to 1, this can indicate that the positive spatial correlation is more pronounced; if I is closer to -1 , this may be an indication that the negative spatial correlation is more pronounced. Additionally, when $I = 0$, it signifies a random spatial distribution.

(2) Local spatial autocorrelation identifies the clustering and dispersion characteristics within local spaces by quantifying the similarity in the efficiency values among neighboring cities. This measurement is computed by using the following formula:

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{S^2} \quad (4)$$

In the formula, the exact meaning can be found in Equation (3). If $I_i > 0$, it suggests the clustering of similar values among the local neighboring units; if $I_i < 0$, it indicates the clustering of dissimilar values among the local neighboring units; if $I_i = 0$, this implies a random spatial distribution in the surrounding area. This analysis can be further classified into the following four types of local clustering: high-value aggregation (HH), low-value heterogeneous aggregation (LH), high-value heterogeneous aggregation (HL), and low-value aggregation (LL).

2.2.4. Tobit Model

The Tobit model, constructed mainly by Tobin, is a better solution to the problem of restricted dependent variables [77]. This applies especially to cases where there is a left-truncated or right-truncated dependent variable. The model is designed for analyzing dependent variables with both discrete and partially continuous characteristics. And it is based on the maximum likelihood estimation method, which effectively circumvents the computational bias that may arise from the traditional model when dealing with this kind of data. Therefore, the reliability and accuracy of the results are, to some extent, guaranteed. The efficiency values measured in this paper are all greater than 0 and there is a left truncation. Consequently, the Tobit model was chosen in this paper to analyze the

relevant factors affecting the ULGUE in Guizhou Province. The expression of the model is as follows [75]:

$$Y_i = \begin{cases} Y_i^* = \beta_0 + \sum_{i=1}^n \beta_i X_i + \varepsilon_i, & Y_i^* > 0 \\ 0, & Y_i^* \leq 0 \end{cases} \quad (5)$$

where Y_i is the interpreted variable, X_i is the explanatory variable, β_0 denotes the constant term, β_i is the estimated coefficient of this model, n denotes the number of explanatory variables, and ε_i denotes the random error term.

2.3. Indicator Selection and Data Sources

2.3.1. Indicator Selection

This study is guided by the philosophy of green development. Adhering to the principles of comprehensiveness, scientific rigor, a systematic approach, and data operability, this study, guided by green development theory and drawing insights from the existing literature, has meticulously selected indicators to assess the ULGUE in Guizhou Province. These indicators, categorized under input and output perspectives (Table 1), have been chosen with careful consideration. The indicators were standardized prior to the measurement in order to eliminate the effect of magnitude.

Table 1. Indicators for evaluating the ULGUE.

Target Level	Layer of Factor	Layer of Indicator	Description	Unit	Data Sources
Inputs	Land	Built-up area [45,78]	+	km ²	https://essd.copernicus.org accessed on 19 June 2024
	Labor	Number of persons employed in secondary and tertiary industries [79]	+	10,000 persons	https://www.guizhou.gov.cn accessed on 1 June 2024
	Capital	Investment in fixed assets [80]	+	CNY 100 million	https://www.guizhou.gov.cn accessed on 1 June 2024
Expected outputs	Economic benefits	Value added of secondary and tertiary industries [42]	+	CNY 100 million	https://www.guizhou.gov.cn accessed on 1 June 2024
	Societal benefits	Per capita disposable income of urban residents [43]	+	CNY	https://www.guizhou.gov.cn accessed on 1 June 2024
Unexpected outputs	Ecological damage [75]	Industrial wastewater emissions	-	10,000 tons	https://hgk.guizhou.gov.cn accessed on 10 June 2024
		Industrial sulfur dioxide emissions	-	ton	https://hgk.guizhou.gov.cn accessed on 10 June 2024
		Industrial solid waste emissions	-	10,000 tons	https://hgk.guizhou.gov.cn accessed on 10 June 2024

Note: “+” and “-” represent the direction of the indicator’s effect on ULGUE. Where “+” represents positive direction and “-” represents negative direction.

Land is an important spatial carrier for urban development. To better reflect the utilization of urban land resources in Guizhou Province during the study period, the built-up area was chosen to characterize the land input.

Human beings are the main body of land use and play a subjective initiative in the process of land use. Considering that this study mainly explores the ULGUE from an urban perspective, the secondary and tertiary industries are chosen to characterize the labor input.

The development and utilization of urban land cannot be carried out without substantial financial support. Financial inputs can reflect the intensity of the development of urban land resources. An increase in the scale of investment will also increase the economic benefits of land use. Therefore, fixed assets are selected as the capital inputs.

The secondary and tertiary sectors are the main economic activities of the city. The value added of urban secondary and tertiary industries can better reflect the economic output of urban land use. Therefore, the value added of the secondary and tertiary sectors was chosen to characterize the economic efficiency.

Social outputs reflect the social gains that people receive as a result of the urbanization process. In this paper, we use the urban disposable income per capita characterization.

Guizhou Province is one of the major mineral resource provinces in China. Abundant resources support industrial development in Guizhou Province. In the process of industrial production, it is very easy to produce environmental pollution. Therefore, the environmental pollution indicators were selected mainly in terms of the waste gas and waste generated by industrial production.

Scholars have used a wealth of indicators to evaluate the ULGUE. Limited by the availability of data, this paper selected the above indicators for the evaluation and analysis.

2.3.2. Data Sources

The study selected 88 districts and counties in Guizhou Province as the study case area, and collected relevant socio-economic data from 2013 to 2022, mainly from the China County Statistical Yearbook, Guizhou Provincial Statistical Yearbook, and municipal and state statistical yearbooks. For some data not available in the yearbooks, they were obtained through district and county statistical bulletins on national economic and social development. Among them, the built-up area data were calculated in ArcGIS 10.8 using the land cover dataset produced by professors from Wuhan University [81]. Detailed information is provided in Table 1. Data on the non-expected outputs were obtained from the Guizhou Provincial Macroeconomic Database. In addition, individual missing data were filled in using interpolation.

3. Results and Analysis

3.1. Efficiency Measurement Results

In this study, the ULGUEs in the 88 districts and counties in Guizhou Province during 2013–2022 were measured using iDEA Ultra Software. The box-and-line diagram is plotted as shown in Figure 3. Based on the median position, the median is lower for all years except for 2018, when the median ULGUE was in the middle. This indicates that the ULGUE in Guizhou Province in the past ten years showed a negative skewed distribution characteristic. There is an uneven distribution of efficiencies with a relatively large number of low values in the distribution of the efficiency values. From the upper and lower quartiles, the upper quartile of the ULGUE in Guizhou Province during the study period is almost on a line, while the lower quartile shows a curve. This indicates that the distribution of the data in the high-value area of the ULGUE in Guizhou Province is relatively concentrated and shows low variability. The data in the lower value range, on the other hand, have greater dispersion and more pronounced differences. This led to large fluctuations in the second half of the data. Meanwhile, the 2016–2018 quartile spacing is relatively small, and the rest of the years have large quartile spacing. This reflects the high degree of discrete ULGUEs in Guizhou Province in 2013–2015 and 2019–2020.

As can be seen from Figure 4, the average curve of the ULGUE in Guizhou Province as a whole shows an ‘inverted U’ shape, i.e., the average value of the ULGUE value demonstrated the development trend of slowly increasing–stable development–slowly decreasing. Therefore, the whole can be divided into the following three phases: (1) A slow improve-

ment phase (2013–2016), in which the average value of the ULGUE increased from 0.6510 to 0.7426. The green transformation presented a good development situation of steady progress and steady improvement. (2) A phase of stable development (2017–2018), with the average value of efficiency remaining around 0.74. At this stage, the province earnestly implemented the spirit of the 19th National Congress of the CPC and the important speech of General Secretary Xi Jinping at the Guizhou delegation, which insisted on guarding two bottom lines, that is, a special emphasis on development and ecology, and continued to improve the ecological environment. (3) A downward trend phase (2019–2022), where the average efficiency value decreased from 0.7446 to 0.6136. Desired outputs such as economic and social benefits increased during this period. This suggests that the inefficient use of urban land resulted from the continued expansion of building land. It also increased the environmental pressures to some extent.

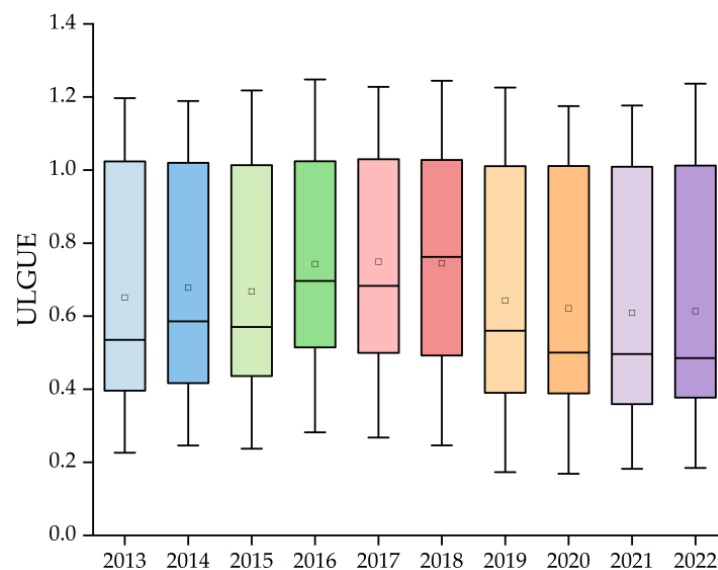


Figure 3. Distribution of the ULGUE in counties in Guizhou Province, 2013–2022.

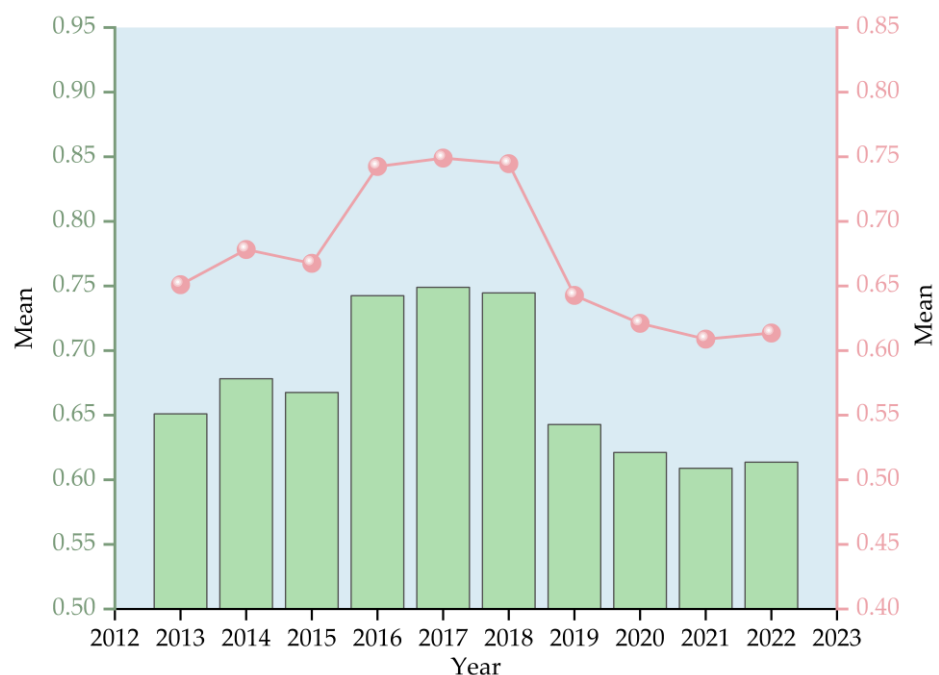


Figure 4. Average value of the ULGUE in Guizhou Province counties during 2013–2022.

As can be seen in Table 2, the extreme variance increased from 0.97 in 2013 to 1.05 in 2022 during 2013–2022. The standard deviation, while not varying much overall, is still fluctuating and changing. This shows that, as cities continue to develop, the gap in the ULGUE between cities shows a tendency to widen. However, this widening of the difference is not obvious when judged only from the extreme values and standard deviations.

Table 2. Descriptive statistics of the ULGUE in Guizhou Province counties during 2013–2022.

Years	Obs.	Mean	Max	Min	Var.	Std. Dev.
2013	88	0.650964	1.196952	0.226395	0.970557	0.312069
2014	88	0.678183	1.188810	0.245854	0.942956	0.294612
2015	88	0.667570	1.217610	0.237205	0.980405	0.284685
2016	88	0.742552	1.248016	0.282190	0.965827	0.264539
2017	88	0.748923	1.227664	0.267638	0.960026	0.277095
2018	88	0.744626	1.244466	0.246297	0.998169	0.296101
2019	88	0.642703	1.225881	0.173159	1.052722	0.300950
2020	88	0.621158	1.751190	0.168753	1.582437	0.306956
2021	88	0.608950	1.176488	0.182345	0.994143	0.306867
2022	88	0.613562	1.236247	0.184441	1.051806	0.313082

Based on the method of the natural breakpoint within ArcGIS10.8, this study has specifically divided the ULGUE of the 88 districts and counties in Guizhou Province into the following five intervals: (0,0.2] for a low efficiency, (0.2,0.4] for a lower efficiency, (0.4,0.6] for a medium efficiency, (0.6,0.8] for a higher efficiency, and greater than 0.8 for a high efficiency (Figure 5). As a whole, the number of cities in the 88 districts and counties of Guizhou Province with high ULGUE values was gradually decreasing. Cities with higher efficiency values demonstrated an increasing and then decreasing trend in the numbers. Furthermore, it reached its lowest value in 2022. For cities with medium efficiency values, there was a slow increasing trend in its number. In terms of cities with lower efficiency values, its number changed less in 2013, 2019, and 2022, except for a significant decrease in 2016. And for cities with low efficiency values, it remained essentially the same. Of these, the decrease in more efficient and efficient cities was mainly transformed into medium-efficient cities. Concerning the spatial distribution, lower-efficiency value and low-efficiency value cities were mostly distributed in the areas west of Guizhou Province. Specifically, Bijie, Liupanshui, and Qianxinan were more widely distributed, and Zunyi also had more than a small portion, such as Qianxi, Jinsha, Puding, Weining, Shuicheng, Liuzhi, Xingyi, Chishui, Xishui, and Tongzi counties. Cities with medium efficiency values were nearly evenly distributed across cities (states), such as Hezhang, Qixingguan, Fuquan, Dejiang, Sinan, Sansui, Tianzhu, Congjiang, and other counties. The higher and more efficient values were mainly located in the central–eastern and northern areas. It mainly included southern Zunyi, Guiyang, and Qiannan, such as Daozhen, Wuchuan, Meitan, Yuqing, Yanhe, Kaiyang, Guanshanhu, Yunyan, Nanming, Longli, Shibing, Ceheng, Wangmu, Luodian, Libo, and other counties and districts.

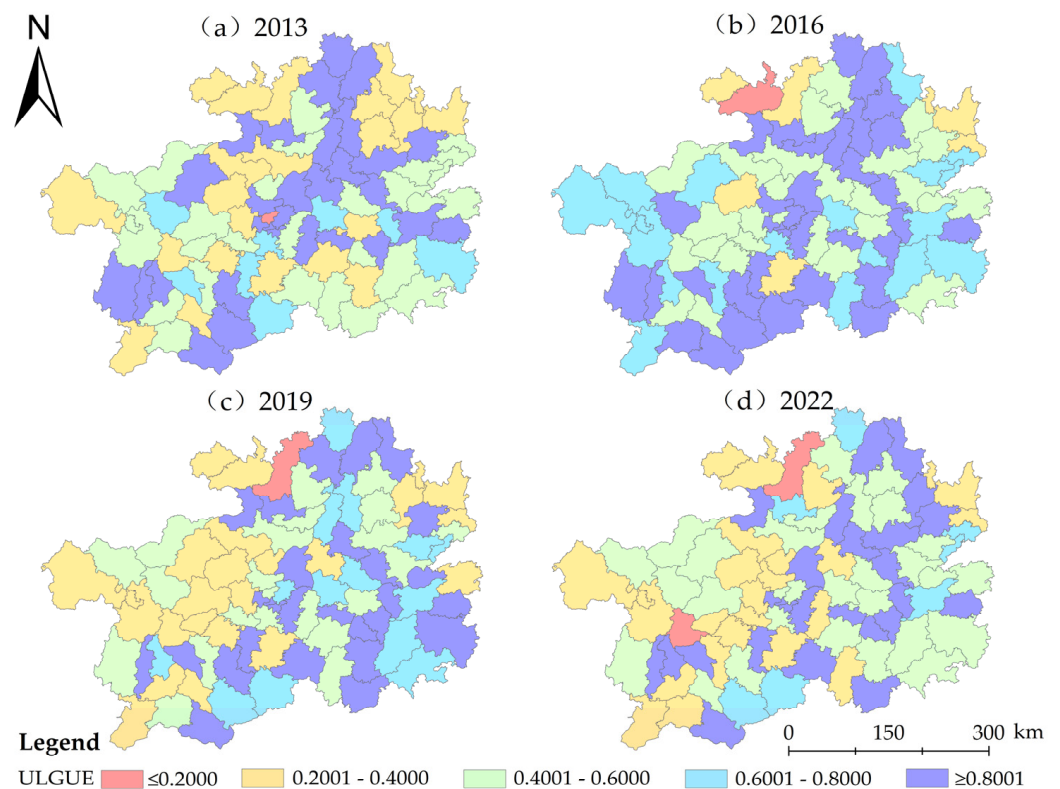


Figure 5. Distribution of the ULGUE in Guizhou Province counties during 2013–2022.

3.2. Characterization of the Dynamic Evolution of the Time Series

In this section, the kernel density graphs are plotted with the help of Matlab2018 and Eviews10 to visualize and analyze the temporal evolution characteristics of the 88 districts and counties in Guizhou Province in 2013, 2016, 2019, and 2022, respectively, from the whole area and local area perspectives.

3.2.1. Characterization of the Evolution of the Global Time Series

This section describes the time-series evolutionary characteristics of the ULGUE in counties within Guizhou Province from a global perspective. In this study, we will plot data from four selected years in kernel density plots to specifically characterize the evolution of the ULGUE in Guizhou from a time-series perspective for detailed analysis (Figure 6).

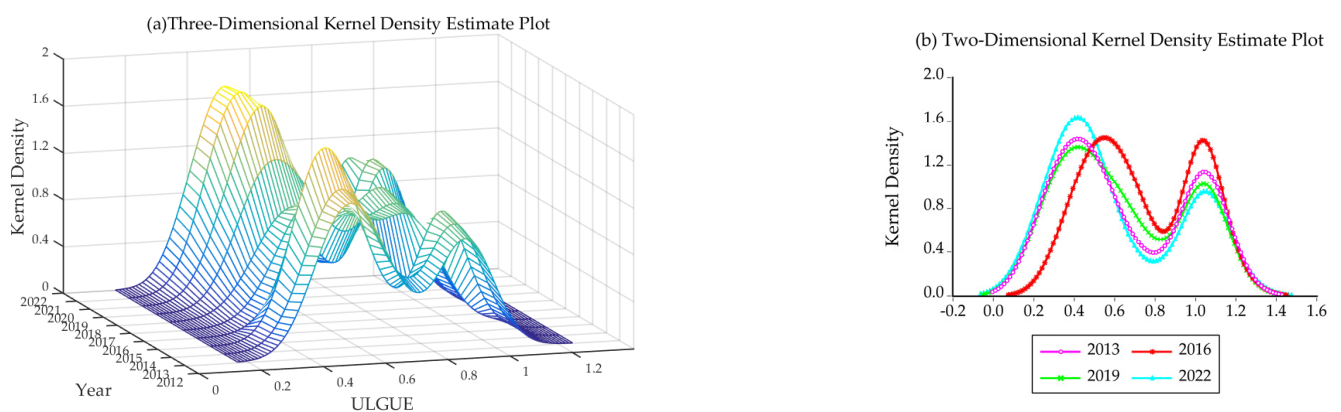


Figure 6. Kernel density estimation of the ULGUE in the whole area of Guizhou Province during 2013–2022.

The results indicate the following: (1) Regarding the shifting position of the curve, there was a shift to the right in 2013–2016 and a shift to the left in 2017–2022, and the distance to the left was greater than the distance to the right. This shows that the ULGUE of the counties in Guizhou Province presents an evolutionary feature of slow improvement followed by continuous decline. (2) In terms of the shape change, the left and right trailing tails were nearly the same length in all years except 2016, when the right trailing tail was significantly longer than the left. This suggests that, quantitatively, there were more high-value areas than low-value areas in 2016, while, in other years, there was little difference between the number of high-value and low-value areas. However, the right-hand side of the trailing tail thins slowly in 2022, suggesting that the number of high-value districts has declined during this period. (3) Looking at the peaks, we can clearly see that there is a clear bimodal coexistence in 2013–2022. This situation suggests that the ULGUE in Guizhou Province has been polarized from 2013 to 2022. (4) In terms of the elevation of the dominant summit, there is a slight increase in the peak kurtosis in 2013–2016, a more substantial decrease in 2017–2019, and a significant elevation in 2020–2022. This shows that the difference in the ULGUE among the cities in Guizhou Province presents the characteristic of narrowing and then expanding, and then narrowing again.

In conclusion, as a whole, the ULGUE in Guizhou Province from 2013 to 2022 showed a gradually declining tide. The cities in the high-efficiency districts declined in number and showed obvious polarization, but the difference in the ULGUE between cities was gradually narrowing.

3.2.2. Characterization of the Dynamic Evolution of Local Time Series

The local scale is able to analyze the ULGUE in different regions of Guizhou Province from a regional perspective. The Qianzhong City Cluster is an important fulcrum of China's 'Two Horizontal and Three Vertical' urbanization strategy pattern, a key area of the new round of the western development strategy, and a power source and growth pole for promoting the high-quality development of Guizhou Province. Therefore, as a key urbanization area with concentrated development conditions in Guizhou Province, it is an important support for the construction of the National Ecological Civilization Pilot Area. Based on this, this section will be discussed specifically in terms of the Qianzhong Urban Agglomeration and other districts and counties (Figure 7).

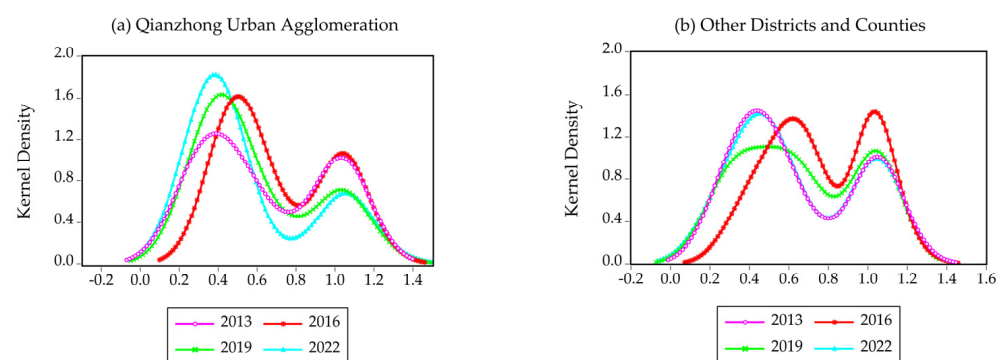


Figure 7. Kernel density estimation of the ULGUE in the bureau of Guizhou Province during 2013–2022.

The results indicate the following: (1) In terms of the shifts in the curve position, the Qianzhong Urban Agglomeration and the other districts and counties are shifted to the right from 2013 to 2016, and, in the next shift in the curve position, they were moved to the left from 2017 to 2022. This indicates that the ULGUE in the Qianzhong Urban Agglomeration and other districts and counties in the study period shows a tendency to increase and then to decrease, among which the kernel density curve of Qianzhong Urban Agglomeration has a larger leftward shift, which indicates that the value of its efficiency

had a larger change. (2) Regarding the shape change, the right side of the kernel density curve of the Qianzhong Urban Agglomeration had a slightly longer trailing tail than the left side, while the left side of the other districts and counties had a longer trailing tail. This shows that, quantitatively, cities with high efficiency values are slightly more than cities with low efficiency values in the Qianzhong Urban Agglomeration, while other districts and counties have a higher number of cities with low efficiency values. (3) From the number of waves, the Qianzhong City Cluster and other districts and counties had obvious double-peak coexistence phenomena during the study period, and there were obvious polarization characteristics in the efficiency among cities. (4) Regarding the height of the main peak, the height of the main peak of the Qianzhong Urban Agglomeration increased sharply in 2013–2016, leveled off in 2017–2019, and rose again in 2020–2022, while the other districts and counties continued to decline in the peak kurtosis of the main peak in 2013–2019, and showed an upward trend in 2020–2022. This indicates that the difference in the ULGUE among cities in the Qianzhong City Cluster is decreasing year by year, while the difference in the ULGUE among cities in other districts and counties shows an evolutionary characteristic of expanding first and then decreasing.

In conclusion, under the comprehensive effect of socio-economic development, land development, and utilization, the ULGUE in Guizhou Province presents differentiated time-series evolution characteristics in different areas and time periods.

3.3. Characterization of the Evolution of Spatial Patterns

3.3.1. Characterization of the Evolution of Global Spatial Correlation Patterns

This section measures the global Moran's I of the ULGUE within Guizhou Province from 2013 to 2022 by using GeoDa. The specific results are shown in Table 3. During the study period, the global Moran's I of the ULGUE of the 88 districts and counties within Guizhou Province was negative in three years and positive in seven years. In this case, the Moran's I for the positive seven years is within the significance level test. This indicates that the ULGUE of the counties in Guizhou Province in these seven years shows a positive spatial autocorrelation.

Table 3. Global Moran's I of the ULGUE in Guizhou Province, 2012–2021.

Years	Moran's I	p -Values	z -Values
2013	−0.005870	0.31	0.2203
2014	0.013840 *	0.09	1.3188
2015	0.013256 *	0.09	1.2558
2016	−0.000263	0.34	0.3505
2017	−0.006520	0.42	0.1377
2018	0.034182 *	0.09	1.4417
2019	0.082920 **	0.02	3.4583
2020	0.052993 **	0.02	2.4992
2021	0.042467 **	0.03	2.1842
2022	0.036067 *	0.09	1.3746

Note: * and ** indicate significance at the 10% and 5% levels, respectively.

Adding to that, the changes in the global Moran's I of the ULGUE in the 88 districts and counties in Guizhou Province during the study period years are shown in Figure 8. Among them, the Moran's I changed from negative to positive in 2013–2015, and passed the 10 per cent significance level test in both 2014 and 2015. There was a decrease in 2015 compared to 2014, indicating that the ULGUE of the 88 counties in Guizhou Province showed a positive spatial correlation in this period, but this positive correlation is weakening. The Moran's I was negative and did not pass the test in 2016–2017, indicating that there was no significant spatial correlation between the ULGUE in the 88 districts and counties in Guizhou Province during these two years. The Moran's I of the ULGUE of the 88 districts and counties in Guizhou Province from 2018 to 2022 are all positive, all of them pass the test of significance, show a trend of change from increase to decrease and back again, and reach the peak in

2019. There is a significant positive spatial autocorrelation of the ULGUE in the 88 districts and counties in Guizhou Province during this period, but this correlation starts to gradually weaken after 2019.

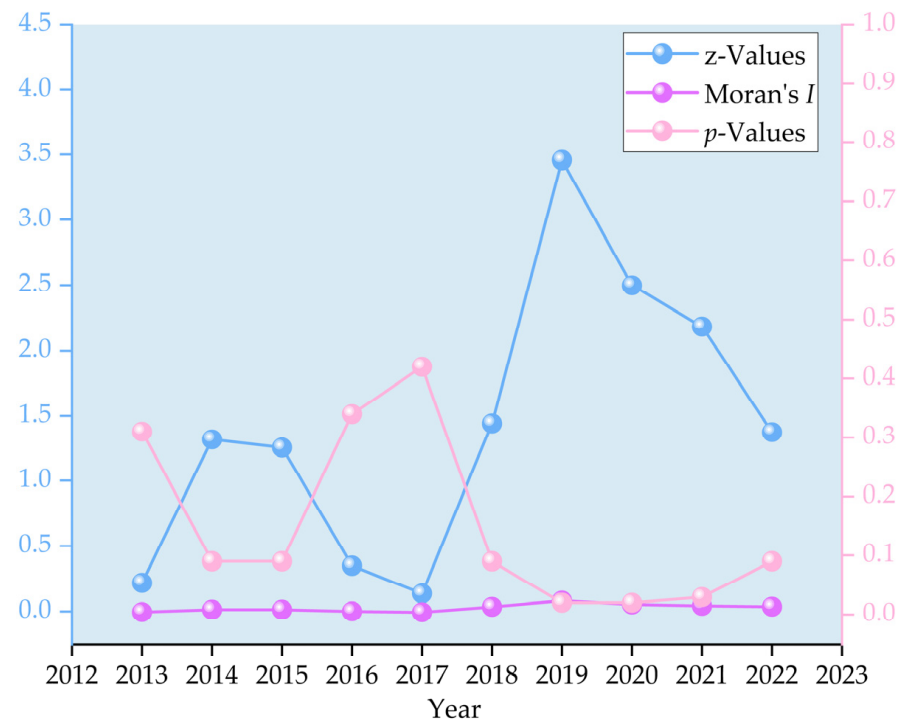


Figure 8. Change in the global Moran's I of the ULGUE in Guizhou Province counties during 2013–2022.

3.3.2. Characterizing the Evolution of Local Spatial Association Patterns

From the above global Moran index results, it can be seen that, although there is a positive spatial dependence on the ULGUE in counties in Guizhou Province at the macro-level, it is not possible to identify the specific characteristics at the local level. Therefore, local spatial autocorrelation analysis methods are needed to identify their relevant features on the local spatial pattern. For this reason, this study specifically mapped the LISA clustering of the ULGUE in the 88 districts and counties in Guizhou Province on a localized spatial basis (Figure 9).

As a whole, the spatial agglomeration of the ULGUE values of the 88 districts and counties in Guizhou Province was not high in 2013 and 2016, and the degree of agglomeration was significantly enhanced in 2019 and 2022. Among them, the two types of aggregation, “high-value aggregation” and “low-value aggregation”, are mainly characterized by concentrated and continuous distribution; the two types of aggregation, “low-value heterogeneous” and “high-value heterogeneous” aggregation, are characterized by scattered and fragmented distributions. From a specific point of view, the “high-value aggregation” type is largely located in the central and eastern cities of Guizhou Province, covering Zunyi, Tongren, Guiyang, Qiannan, and other places, such as Kaiyang, Weng'an, Fuquan, Danzhai, Sandu, Pingtang, Shibing, Taijiang, Jianhe, Liping, and other counties (districts and cities). The “low-value aggregation” type mainly focuses on the western part of Guizhou, such as Qixingguan, Dafang, Zijin, Nayong, Hezhang, Weining, Zhongshan, Liuzhi, Shucheng, Panzhou, Xingren, Zhenfeng, and other counties (districts and cities). The “low-value heterogeneous” type occurs in Xishui, Songtao, Huangping, Zhenyuan, Sansui, Luodian, Dushan, Duyun, and Congjiang counties (districts and cities), while the “high-value heterogeneous” type occurs mainly in Guanshanhu District and Guanling County.

In summary, from the local spatial perspective, the ULGUE in the 88 districts and counties in Guizhou Province shows a spatial distribution pattern of “high–high value and low–low value aggregation, and low–high value and high–low value fragmentation”.

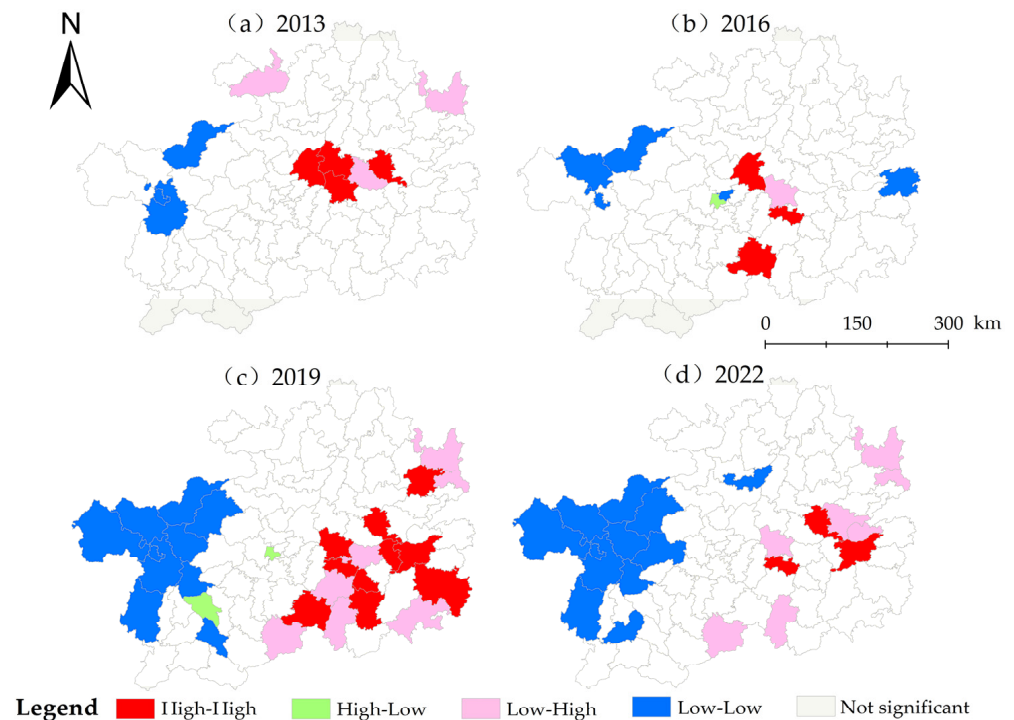


Figure 9. LISA agglomeration map of the ULGUE in Guizhou Province counties during 2013–2022.

4. Impact Factor Analysis

4.1. Selection of Impact Factors

The ULGUE is affected by economic, social, demographic, and ecological factors. As a result, this paper, on the basis of the reference to relevant literature research, selected eight relevant indicators from five aspects, such as economy, society, environment, government, population, etc., to specifically construct the evaluation index system affecting the ULGUE in Guizhou Province (Table 4). In order to eliminate the effect of heteroskedasticity, we obtained logarithms for the level of economic development, the material standard of living of the population, and the size of the population.

Table 4. Influence factors of the ULGUE in Guizhou Province counties during 2013–2022.

Influencing Factors	Specific Indicators	Characterization Method	Unit	Data Sources
Economics	X ₁ : Level of economic development [30]	GDP per capita	yuan	https://www.guizhou.gov.cn accessed on 1 June 2024
	X ₂ : Upgrading of the industrial structure [30]	Value added of tertiary industry/value added of secondary industry	%	https://www.guizhou.gov.cn accessed on 1 June 2024
Social	X ₃ : Material standard of living of the population	Total retail sales of consumer goods	10,000 yuan	https://www.guizhou.gov.cn accessed on 1 June 2024
	X ₄ : GDP content	Urban disposable income per capita/GDP per capita	%	https://www.guizhou.gov.cn accessed on 1 June 2024

Table 4. Cont.

Influencing Factors	Specific Indicators	Characterization Method	Unit	Data Sources
Environmental	X ₅ : Level of green development	Industrial wastewater discharge/value added of secondary industry	%	https://hgk.guizhou.gov.cn https://www.guizhou.gov.cn accessed on 10 June 2024
	X ₆ : Environmental regulation [82]	Comprehensive utilization rate of general industrial solid waste	%	https://hgk.guizhou.gov.cn accessed on 10 June 2024
Government	X ₇ : Government financial support [43]	General public budget expenditure/GDP	%	https://www.guizhou.gov.cn accessed on 1 June 2024
Population	X ₈ : Size of population [2]	Total population at the end of the year	10,000 persons	https://www.guizhou.gov.cn accessed on 1 June 2024

In general, the presence of more severe multicollinearity among the explanatory variables may lead to bias in the model measurements. Therefore, in order to address the problem of biased results due to explanatory variables, a reasonable multiple covariance test is required for the linear relationship between the explanatory variables. The test results are shown in Table 5 below. This study specifically used the variance inflation factor test to obtain a VIF value of less than 10 for each of the influencing factors. It shows that there is no significant multicollinearity between the eight indicators of the influencing factors selected in this study, which meets the requirements for the use of the Tobit model.

Table 5. VIF test results.

Variable	VIF	1/VIF
X ₁ : Level of economic development	5.56	0.179724
X ₃ : Material standard of living of the population	5.05	0.198030
X ₇ : Government financial support	1.81	0.552983
X ₄ : GDP content	1.61	0.621647
X ₅ : Level of green development	1.50	0.665091
X ₂ : Upgrading of the industrial structure	1.31	0.762071
X ₈ : Size of population	1.17	0.854047
X ₆ : Environmental regulation	1.02	0.983227
Mean VIF	2.38	

4.2. Analysis of Regression Results

According the panel data of the ULGUE values and the influencing factors for each county in Guizhou Province from 2013 to 2022, the Tobit regression results were specifically measured with the help of Stata17. The LR test results show a *p*-value of 0.000. Therefore, this paper mainly uses the random effects model in the Tobit model for the subsequent analysis, as shown in Table 6.

From the above Table 6, the following can be observed: (1) The economic development level contributes positively to the improvement of the ULGUE in Guizhou Province. It shows that, when the level of economic development increases, it will improve the ULGUE in Guizhou Province to some extent. (2) Upgrading the industrial structure has a clear positive impact on improving the ULGUE in Guizhou Province. That is to say, optimizing the industrial structure and achieving transformation and upgrading can better enhance the level of the ULGUE. (3) The material standard of living of the population inhibits the ULGUE in Guizhou Province. As the material standard of living of the residents increases, the ULGUE will instead decrease. (4) The GDP content plays a negative role in improving

the ULGUE in Guizhou Province, i.e., an increase in the GDP content will instead lead to a decrease in the level of the ULGUE. (5) The green development level also plays a significant negative role, mainly because the relevant major industries in Guizhou Province are still dominated by resource-based industries such as coal and phosphate mining. There is also greater resistance to their transformation and upgrading, and they have not yet fully realized intensive and green utilization. Therefore, the enhancement effect of the level of green development on the ULGUE within Guizhou Province has not yet been formed. (6) With regard to environmental regulation, it mainly plays a positive influence role on the ULGUE in Guizhou Province. This suggests that governments at all levels in Guizhou Province have introduced a series of policies on environmental protection and integrated management. This has resulted in better changes in the way that resources are invested, thus improving the quality of the ecological environment. As a result, it greatly improves the ULGUE of county cities in Guizhou Province. (7) Government financial support plays an inhibitory role on the ULGUE in Guizhou Province. Government policy direction affects the efficiency of green land use. Government investment in land to promote its own economic development may lead to the ineffective utilization of land resources. (8) Population size negatively affects the ULGUE in Guizhou Province. This is mainly due to the fact that the larger population size creates a certain pressure on urban land use. It is the excessive pressure that leads to a shortage of land resources in the city, which, in turn, leads to a decrease in its ULGUE.

Table 6. Tobit regression results.

Explanatory Variables	Coefficient	Std. Err.	z-Values	p-Values
X ₁ : Level of economic development	0.0923 *	0.0508	1.82	0.069
X ₂ : Upgrading of the industrial structure	0.0273	0.0191	1.43	0.153
X ₃ : Material standard of living of the population	−0.2992 ***	0.0477	−6.26	0.000
X ₄ : GDP content	−0.0754 ***	0.0236	−3.19	0.001
X ₅ : Level of green development	−0.1751 ***	0.0209	−8.38	0.000
X ₆ : Environmental regulation	0.0318 *	0.0174	1.82	0.069
X ₇ : Government financial support	−0.0365	0.0260	−1.41	0.160
X ₈ : Size of population	−0.0119	0.0154	−0.77	0.440
_cons	0.8538 ***	0.0426	20.04	0.000
sigma_u	0.2361 ***	0.0187	12.59	0.000
sigma_e	0.1681 ***	0.0042	39.79	0.000
Loglikelihood	668.37 ***	<i>LR test(P)</i>		0.000
Wald chi2(8)	156.86 ***			0.000

Note: * and *** indicate significance at the 10% and 1% levels, respectively.

5. Discussion

5.1. Main Discussion

We collected panel data from nine cities in Guizhou Province for the period 2012–2021 in this study. Building upon this dataset, we employed the super-efficiency SBM model, which includes non-expected outputs under the assistance of iDEA Ultra data envelopment analysis, to measure the ULGUE in Guizhou Province during the specified period. Subsequently, an intuitive representation of the ULGUE features is presented in time and space using GeoDa and ArcGIS 10.8.

5.1.1. Measurement of ULGUE in Guizhou Province

Existing studies more often take prefecture-level cities as the research unit and analyze the ULGUE from a municipal perspective. At the same time, fewer studies have specifically analyzed cities in western China. Therefore, this paper sinks the research unit to the county scale and analyzes it from a more micro-perspective, so that the research object is more in-depth and specific. Consistent with related studies [82], the ULGUE in Guizhou Province shows a fluctuating growth trend. Although it has experienced an upward

and then downward trend of change, the overall level is in the upper middle range. The possible reason is that Guizhou Province carried out the working concept with environment and development, and strengthened the development of the economy while attaching importance to ecological environmental protection. At the same time, Guizhou Province has better natural resources. Higher vegetation cover brings greening advantages, but it is not enough on its own merits. How to continuously guard the two bottom lines of development and ecology, and realize the transformation of urban land to green and low-carbon use, is an important issue that is urgently in need of resolution.

5.1.2. Characteristics of Time-Series Evolution of ULGUE in Guizhou Province

The ULGUE in Guizhou Province has been multi-polarized. This is consistent with previous findings [25]. Differences in the level of development within Guizhou Province have led to an unbalanced development pattern of the ULGUE. Guiyang and Zunyi are cities with relatively high levels of economic development and better infrastructure. The cities of Bijie and Liupanshui, on the other hand, mainly develop coal as well as coal chemical industries, which are relatively polluted. The combined effects of the development level and industrial structure have led to the multiploidization of the ULGUE in Guizhou Province. At present, Guizhou Province is deeply implementing the Great Ecological Strategy Action to build a national ecological civilization pilot area. It is believed that, under the concept of green and sustainable development, the ULGUE in Guizhou Province will be improved to some extent.

5.1.3. Spatial Evolution Characteristics of ULGUE in Counties in Guizhou Province

From the spatial autocorrelation analysis of the whole area, the ULGUE in Guizhou Province shows a positive correlation. Unhesitatingly, this correlation is gradually diminishing. These conclusions align with the research findings of various scholars [75,82,83]. From a localized perspective, the high-value aggregation types are mainly distributed in the central and eastern parts of the country, varying around the central city. The low-value agglomeration type, on the other hand, is mainly located in the western part of Guizhou Province. This phenomenon is primarily attributable to the existence of a spatial spillover effect, which manifests between neighboring cities in the context of their geospatial distribution. Similarities in natural resource endowment, economy, social development, and many other factors have led them to learn and absorb each other's advantageous experience, and to have frequent exchanges with each other. At the same time, it is known from the first law of geography [84] that this spatial spillover effect diminishes as the distance between individual cities increases.

5.1.4. Influencing Factors of ULGUE in Guizhou Province

Among the relevant influencing factors, the level of economic development plays a major contributing role. This is consistent with the findings of Sun et al. [30]. The increase in the level of economic development has helped to optimize the industrial layout. This allows for the full utilization of land. At the same time, industrial development has gradually shifted from industry to services, reducing environmental pollution. Therefore, it has a promoting effect on the ULGUE. Industrial structure upgrading mainly plays a positive role in promoting the ULGUE in Guizhou Province. This result is consistent with the study by Xue et al. [75]. It may be that, therefore, the value added of the secondary sector has a greater positive impact on the ULGUE than environmental damage. The positive role played by environmental regulation is consistent with previous studies [82]. Environmental regulation makes enterprises pay more attention to green and low-carbon development in the production process, thus promoting the improvement of the ULGUE. It has been argued that population size contributes to the ULGUE [75]. Some scholars have also suggested an inhibitory effect [2]. This paper argues that there is a negative impact of population size. While an increase in the urban population brings with it an abundant labor force, it also brings with it problems such as housing and transportation. This will increase the demand

for urban land. The level of green development has a dampening effect. It may be due to the fact that the problem of high pollution emissions in the current industrial development in Guizhou Province has not yet been effectively solved.

The findings reveal notable disparities in the ULGUE across Guizhou Province, yet an overall trend towards improvement is evident. Moreover, the spatial correlation of the ULGUE in the province demonstrates a significant positive relationship, indicating a mutual influence among neighboring cities. In response to these outcomes, it is imperative to devise a properly informed urban land-use plan and to bolster environmental regulations. Furthermore, enhancing the capacity for urban ecological governance in Guizhou Province is essential to enable the sustainable utilization of urban land. Last, but not least, the tailored land-use plan should be implemented according to the specific conditions of each city, leveraging the positive spillover effects of high-efficiency cities.

5.2. Policy Recommendations

Combined with the above main conclusions, for the promotion of the ULGUE in the counties of Guizhou province, all parties still need to focus on the following work.

(1) Leveraging spatial spillovers between cities. Giving full play to the spatial spillover effect that exists among high-efficiency cities, and actively promoting interaction and cooperation with low-efficiency cities. In this way, common development synergies will be formed to narrow the development differences between counties and promote balanced development among cities in each county. Specifically, Guiyang Guian can be used as a development pole core. As the core city, its leading role should be strengthened to promote the modernization and development of the Qianzhong City Cluster, as well as to give full play to its radiating effect, so as to realize the coordination and unity of the multi-dimensional benefits of urban land. While enhancing the economic and social benefits, this also pays full attention to the ecological benefits.

(2) Optimizing the strength of all types of government regulation. In terms of government planning, the strict planning and control of urban land use can help to enhance its ULGUE. Regarding financial support, government financial support for the ULGUE should be increased. It should also improve the urban infrastructure in counties with low efficiency values in Guizhou Province. With regard to the ecological environment, ecological protection and early-warning mechanisms must be established. A coordinated socio-economic-ecological development pattern should be formed on the basis of strengthened environmental regulation.

(3) Promote the green transformation of the industrial structure. Industrial structure upgrading and transformation is having a significant positive impact on the ULGUE in counties within Guizhou Province. Therefore, Guizhou Province should perform a good job in the undertaking of industrial transfer in the eastern part of China, give full play to its own natural resource endowment, and actively promote the traditional industry greening, low-carbon transformation, and upgrading. In parallel, Guizhou Province should give full play to its inherent excellent ecological environmental conditions. Looking at the specifics, it is necessary to grasp the two bottom lines, that is, the development and ecology that have been emphasized, and actively implement the green development strategy so as to achieve industrial-scale and green development.

5.3. Restrictions

By delving into the measurement of the ULGUE in Guizhou Province, this study delves into its temporal-spatial evolution characteristics and agglomeration types, thereby enhancing the understanding of the ULGUE. Nonetheless, the study is not without its limitations. On the one hand, in this paper, the study period only includes the period from 2013 to 2022, and lacks data before 2013, which can be supplemented in the future by conducting relevant research. On the other hand, Guizhou Province has not counted the foreign direct trade volume of county-level cities for the time being. Due to the unavailability of data, this paper does not consider the impact of the foreign trade level

on the ULGUE when selecting the indicators of the ULGUE influencing factors. In the future, we will further explore the ULGUE in Guizhou Province from more perspectives and analyze its influencing factors in various aspects.

6. Conclusions

Main Conclusions

This study specifically measured the ULGUE in Guizhou Province and tracked its spatial–temporal evolution and influencing factors.

(1) From the average value, the mean value of the ULGUE for the 88 districts and counties in Guizhou Province showed an overall decreasing trend, specifically from 0.6510 to 0.6136. The overall trend of change first rises and then falls, and there is a great deal of variability in the ULGUE between cities in various counties.

(2) Viewed from the perspective of time-series evolving characteristics, there are obvious polarization characteristics in the ULGUE in the 88 district and county cities in Guizhou Province, but the efficiency difference between the county cities is gradually smaller. Additionally, cities with high efficiency values are gradually decreasing. This is mainly due to the decline in the ULGUE in county cities, except for the Qianzhong Urban Agglomeration. Overall, there are more high-value areas in the Qianzhong Urban Agglomeration than in other counties.

(3) From the spatial evolution characteristics, the ULGUE in Guizhou Province in 2014–2015 and 2018–2022 shows certain positive spatial correlations. This positive spatial autocorrelation begins to taper off after peaking in 2019. The two aggregation types, ‘high value and low value’, are concentrated in the eastern, western, and central parts of Guizhou Province, respectively. In contrast, the two types of ‘low-value depressions and high-value occurrences’ are scattered and few in number.

(4) In terms of the main influencing factors, the level of economic development, the industrial structure upgrading, and environmental regulations have a positive contribution to the improvement of the ULGUE in counties in Guizhou Province. In contrast, residents’ material living standards, the GDP content, the level of green development, government financial support, and the population size mainly have a negative dampening effect.

Author Contributions: Conceptualization, H.C., Z.X., and W.S.; methodology, H.C.; software, H.C.; validation, H.C.; formal analysis, H.C.; resources, Z.X. and W.S.; data curation, H.C.; writing—original draft preparation, H.C.; writing—review and editing, Z.X. and W.S.; visualization, H.C.; supervision, Z.X. and W.S.; project administration, Z.X.; funding acquisition, Z.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the “Research on the Livelihood Diversification of Farm Household and Land Marginalization in Guizhou Karst Area” project of the Youth Fund for Humanities and Social Sciences Research of the Ministry of Education, grant number 18YJC630216.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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