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Direct and Spillover Effects of Urban Land Expansion on Habitat Quality in Chengdu-Chongqing Urban Agglomeration

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Abstract: Urban land expansion has dramatically changed the spatial distribution patterns and functional structure of habitats. Previous studies on the spatial externality effect of urban land expansion on the habitat quality of urban agglomerations are still insufficient. With the use of remote sensing and statistical data from 2000 to 2018, this study explored the evolutionary relationship between urban land expansion and habitat quality in the Chengdu-Chongqing urban agglomeration (CUA) using the bivariate local autocorrelation method and spatial Durbin model. Partial differential equation decomposition of the local and spatial spillover effects was implemented to investigate the marginal effects of the influencing factors. The highlights of the results are as follows: CUA's urban land increased by 2890.42 km^2 from 2000 to 2018, mainly caused by urban encroachment over farmland and grassland. New urban lands were situated primarily in the main urban districts of Chengdu and Chongqing; urban expansion intensity slowed to 7.64% in 2010–2018, declining by 53.95% from 2000 to 2010. The average habitat quality decreased to 0.905, and two "ring-shaped decline areas" were formed around the main urban areas of Chengdu and Chongqing. "Low-High" and "Low-Low" clusters were the main associations between urban land expansion and habitat quality changes. The impact of urban land expansion on local habitat quality changed from insignificant to negative, while its spatial spillover effects over adjacent areas have increased the negative environmental externalities to habitat quality in adjacent areas through spatial spillovers. Our findings provide evidence for urban agglomerations such as CUA that are still being cultivated to carry out cross-city joint protection strategies of habitat quality, also proving that habitat quality protection should be an integration of urban expansion regulation, natural adaptation and socioeconomic adjustment.

Keywords: urban land expansion; habitat quality; spatial spillover effect; spatial regression model; Chengdu-Chongqing urban agglomeration (CUA)

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1. Introduction

Habitat quality can express regional biodiversity by assessing the extent of various urban habitat or vegetation types and the degradation levels of each of these types. To a certain extent, habitat quality can directly provide the functional strengths and weaknesses of regional ecosystems. The destruction and degradation of natural ecosystems are the primary causes of global biodiversity loss [1,2]. Due to rapid urban expansion, the fragmentation, degradation, and transformation of habitats impair vital ecosystem functions by reducing biomass and altering nutrient cycling and have profound impacts on global biodiversity [3,4]. By 2100, the global population is expected to grow to 10.88 billion (WPP2019), while the urban land area will increase by 1.8–5.9 times [5]. The explosive growth in urban population and land use would accelerate the decline in habitat quality, resulting in the loss of about 11 to 33 million hectares of natural habitat [6]. Such losses would be extremely detrimental to the implementation of the Future Earth strategy and the UN's Convention on Biological Diversity (CBD). China is one of the main countries with unprecedented urbanization and major conservation challenges. China is experiencing unprecedented urbanization, with 47.5% of the world's total new urban land area from 2000 to 2018, resulting in a sharp decline in biodiversity, habitat fragmentation and degradation, and numerous ecological problems [7]. These problems have become major obstacles for China in realizing the Post-2020 Global Biodiversity Framework set during the CBD COP15. To achieve China's Sustainable Development Goals (SDGs) by 2030, particularly SDG 11 (sustainable cities) and SDG 15 (sustainably managing habitat and halting biodiversity loss), a greater understanding of how urban land expansion affects the rate, scale, and spatial distribution of habitat quality loss is crucial.

Quantifying the spatio-temporal response of habitat quality on urban land expansion is of great value for optimal urban land management and ecological security protection. Previous studies have had significant differences in analyzing the impact of urban land expansion on habitat quality. Some focused on the negative effects of urban land expansion on habitat quality [8]. For example, Yang (2021) and Wang et al. (2022) found that urban land use expansion has changed the spatial pattern and functional elements of regional habitats, profoundly affecting the material and energy flows between habitat patches and playing a leading role in habitat quality decline [9,10]. They concluded that improving urban land use efficiency should be an important strategy to prevent and control habitat degradation. Some explored the regional heterogeneity of the impact of urban land expansion on habitat quality. For example, Feng et al. (2018) concluded that habitat degradation usually occurs in the functional expansion areas around cities and plain-mountain junctions, while the urban core's habitat quality usually improves gradually due to residential demand for habitat environment. Others have looked into how urban land expansion morphology affects habitat quality [11]. Dai et al. (2018) found that the fragmented spatial layout of built-up lands and increased morphological irregularities are the main negative factors contributing to habitat degradation in Changsha City. In addition, the changes in habitat quality in the future process of urban land expansion have also been investigated by some scholars [12]. Through simulation studies, Li et al. (2022) predicted that urban land expansion will accelerate the transformation and degradation of habitats and lead to biodiversity loss, especially among vertebrates [6]. Li et al. (2022), Gao et al. (2022), and Liu et al. (2022) also analyzed future changes in habitat quality in response to urban expansion from different regions [13–15]. However, given that previous studies have largely focused on cities, special terrain areas, or global perspectives, significant research gaps remain, particularly on the coercive effects of urban land expansion on habitat quality in urban agglomeration areas under the background of ecological integration construction.

More importantly, a large number of studies have analyzed the driving effects of urban land expansion on habitat quality using map visual analysis, coupled coordination model, and linear regression models, creating difficulties in quantifying the error effects of geospatial differences and limiting the practical value of the resulting estimates [16–18]. To address this issue, spatial regression models have been used in exploring the interactions between urban land expansion and ecological factors (e.g., carbon emissions and PM2.5 concentrations) [19]. For better analysis, driving effects are usually divided into local direct effects and spatial spillover effects [20]. For a long time, the spillover effect of urban land expansion on habitat quality in adjacent areas has been seriously underestimated, that is, the external impact of urban land expansion has been relatively under-considered in previous studies, which is obviously a lack of support for joint actions of regional habitat governance.

As highly integrated collections of cities, urban agglomerations have become important vessels of urbanization and urban land expansion in China. The Chengdu-Chongqing urban agglomeration (CUA) is one of the most important urban systems in China's existing urban agglomeration hierarchy, the others being the urban agglomerations of Beijing-Tianjin-Hebei, Guangdong-Hong Kong-Macao Great Bay Area, Yangtze River Delta, and the middle reaches of the Yangtze River (Figure 1). According to the China Statistical Yearbook, CUA is one of the core regions of China's economy, population, and technology, accounting for 6.20% of GDP and 6.81% of the population in 2018. The region, having rich natural resources and abundant wildlife (e.g., cliff cypress, silver fir, ginkgo and golden monkey), is an important treasure trove of biodiversity in China. However, the rapid development of the industrial economy and population agglomerations have led to accelerated urban expansion and the conversion of grasslands and forests into construction lands, putting significant pressure on wildlife habitats and biodiversity [21]. Additionally, while the "Ecological Environment Protection Plan of Chengdu-Chongqing Twin Cities Economic Circle" by the regional government has been recently established to strengthen biodiversity investigation and monitoring in ecologically sensitive areas, understanding the impact mechanisms of urban land expansion on the habitat quality in the CUA has been limited.

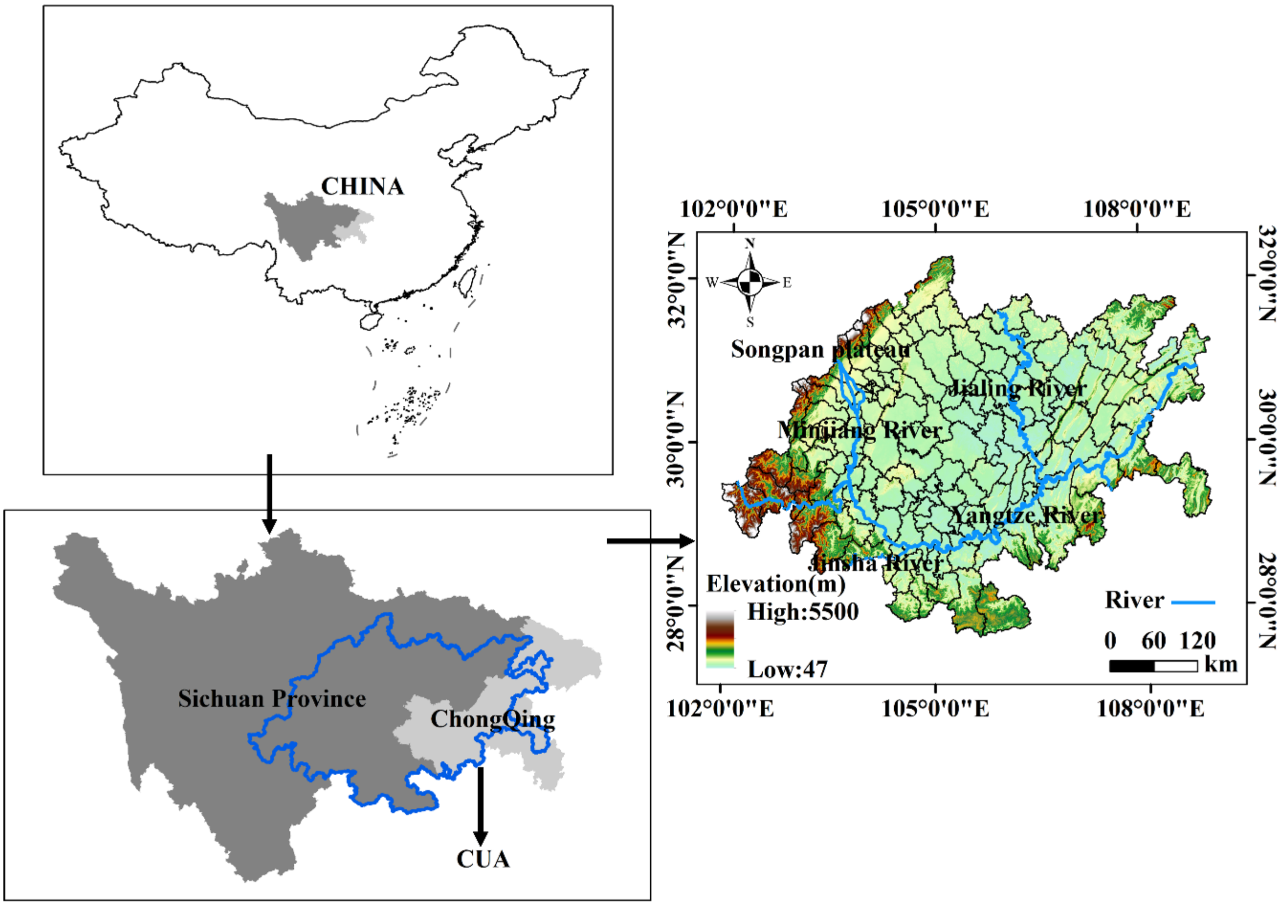

Figure 1. The geographical location of CUA.

In summary, previous studies have made substantial contributions in exploring the effects of urban land expansion on habitat quality, providing useful references for regional ecological security protection and urban land management. However, the discussion on urban land expansion and habitat quality in the context of rapid urbanization is far from settled due to the following reasons: (1) the impact mechanism of urban land expansion on habitat quality has largely been overlooked at the urban agglomeration level; (2) the spatial externality of the urban land expansion on habitat quality has long been neglected; (3) to our knowledge, there has been no study exploring the impact mechanism of urban land expansion on habitat protection in CUA. To fill these knowledge gaps, this study explored the differentiated mechanisms of the local direct and spatial spillover effects of urban land expansion on habitat quality in the CUA. Google Earth Engine (GEE) geographic cloud platform was used to obtain the urban land expansion data from 2000 to 2018, and the InVEST-Habitat Quality model was applied to describe the spatio-temporal distribution and trend changes in habitat quality. The bivariate local spatial autocorrelation method was used to analyze the spatial correlation between urban land expansion and habitat quality, while the Spatial Durbin model evaluated the spatial externalities of the impact of urban land expansion on habitat quality. It is worth mentioning that these research paths were realized using administrative and geographical grid levels to increase the study's objectivity.

2. Study Area, Methods and Data

2.1. Study Area

CUA has emerged as a critical platform for China's western development strategy, providing vital support in the development of the Belt and Road Initiative [22]. CUA is centered in Chongqing and Chengdu and includes Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, and Ziyang. To ensure study refinement and adequacy of the sample size in the regression analysis, the regression analysis of our study was conducted at the county level, resulting in a total of 142 samples (Figure 1).

2.2. Methods

The research methods used are shown in Figure 2, and they were used to investigate the effects of urban expansion intensity on habitat quality in the CUA.

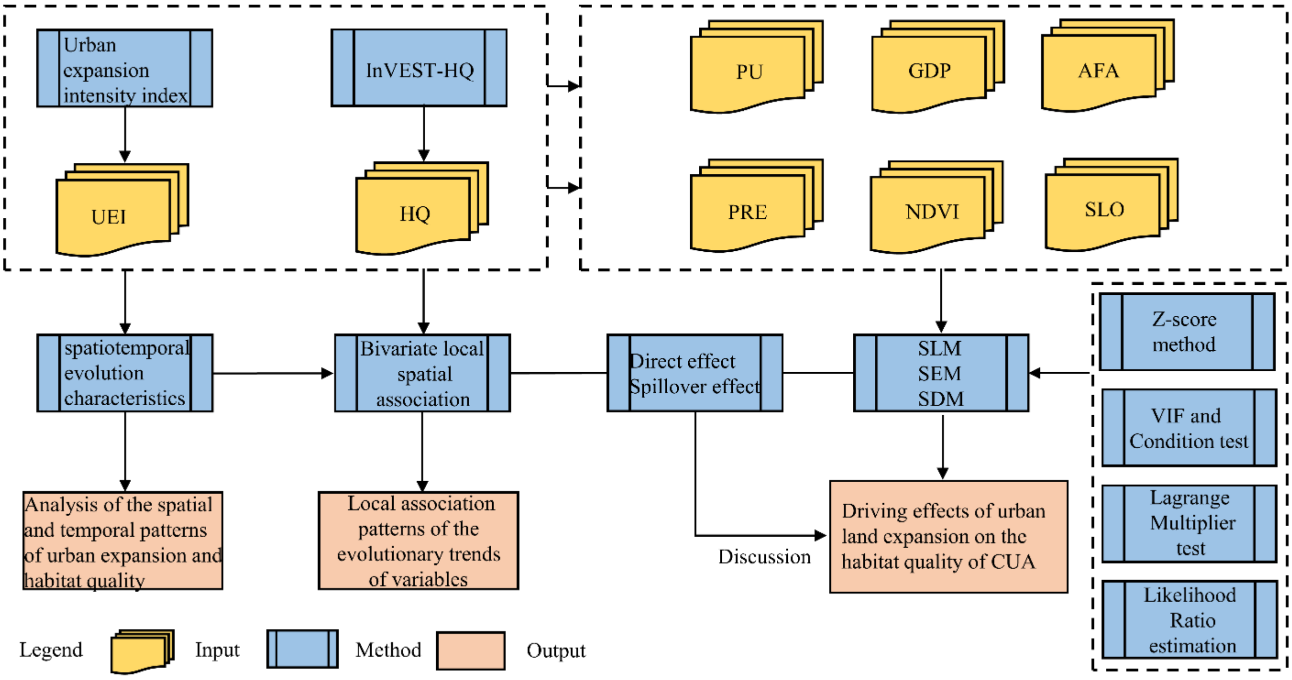

Figure 2. Study Flowchart (the original meaning of abbreviations, see Abbreviation for detail).

2.2.1. Urban Land Expansion Intensity Index

The urban land expansion intensity index is used to characterize the expansion degree of urban areas in the CUA. This index can measure the state of expansion of a region at varying stages and compare the development intensities of different regions at same stages [23]. The calculation formula is as follows:

$$UEIn = \frac{A_n^{t2} - A_n^{t1}}{A_n^{t1} \times \Delta t} \times 100\% \tag{1}$$

where UEI_n is the urban land expansion intensity index of the nth study unit; A_n^{t1} and A_n^{t2} are the urban land areas at nodes t_1 and t_2, respectively; Δt is the interval year from t_1 to t_2.

2.2.2. InVEST-Habitat Quality Model

Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) is a model system developed by the U.S. Natural Capital Project team for valuing ecosystem services and their economic value to support ecosystem management and decision-making [24,25]. Among them, the Habitat Quality (HQ) module evaluates the biodiversity of the study area through the level of habitat degradation and suitability, reflecting the potential ability of the ecosystem to provide living and breeding conditions for species [26]. Habitat quality measurement includes two aspects: habitat degradation and habitat suitability. The former refers to the disturbance intensity of the threat source to the habitat, while the latter refers to habitat suitability.

The HQ module measures the habitat degradation degree with various parameters (e.g., threat source, threat source sensitivity, and distance between habitat and threat source) using the following equations:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} r_y \left(\frac{\omega_r}{\sum_{r=1}^{R} \omega_r} \right) \times i_{xy} \beta_x S_{jr} \tag{2}$$

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{r\max}} \right) \text{(if it is linear decay)} \tag{3}$$

$$i_{rxy} = \exp\left(\frac{-2.99 d_{xy}}{d_{r\max}} \right) \text{(if it is exponential decay)} \tag{4}$$

where D_{xj} is the degree of habitat degradation; R is the number of threat sources; Y_r is the grid number of threat sources; ω_r is the weight of threat source; r_y is the stress value of grid y; i_{rxy} is the stress level of grid y to grid x; β_x is the accessibility of threat source to grid x; S_{jr} is the sensitivity of the habitat type j to the threat source r; d_{xy} is the Euclidean distance of the habitat to the threat source; d_{rmax} is the maximum disturbance radius of the threat source r to the habitat.

The degree of habitat degradation (D_{xj}) and the habitat suitability are then used for the comprehensive evaluation of habitat quality, see the equation:

$$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}^z}{D_{xj} + k^z} \right) \right] \tag{5}$$

where Q_{xj} is the habitat quality index, the larger the value, the better the regional habitat quality and biodiversity service function; H_j is the habitat suitability of land-use type j; k is the half-saturation constant, which is half of the maximum degradation degree; z is the normalization constant, which is generally taken as 2.5 with reference to the previous studies by scholars [26].

As for the threat source, it is generally believed that the higher the degree of human utilization, the higher the threat to the habitat, and the greater the impact on the surrounding habitat biodiversity and ecosystem. Therefore, in this study, the areas of intensive human activities, such as farmland and urban land, were considered the main threat source areas. Bare lands, such as saline soils, barren grounds, and sandy lands, were also set as habitat threat factors for their poor ecological conditions and erosive effects on external habitats and the stability of surrounding ecosystems [27]. It is generally believed that the more pristine and complex the ecosystem, the higher the habitat suitability. Land-use types such as forest land, grasslands, and water areas were considered habitats in the study. The maximum impact distance and weight of each threat factor and the suitability and sensitivity of each habitat type were set according to the InVEST operation manual and the parameter settings of previous habitat quality studies in different regions of China (see Tables 1 and 2).

Table 1. Threat source and their maximum impact distance and weight.

Threat Source	The Maximum Influence Distance/km	Weight	Space Decline Type
Farmland	4	0.3	Exponential decay
Urban land	10	1	Exponential decay
Bare land	3	0.1	Exponential decay

Table 2. Habitat suitability of land-use types and the sensitivity to threat factors.

Land Use Type	Habitat Suitability	Threats		
		Farmland	Urban Land	Bare Land
Farmland	1	0.5	0.65	1
Forest land	1	0.6	0.8	1
Grassland	0.75	0.5	0.55	1
Water area	1	0.6	0.75	1
Urban land	0	0	0	0
Bare land	0	0	0	0

2.2.3. Spatial Driving Effect Analysis

Bivariate spatial autocorrelation methods and spatial regression models were used to analyze the spatial association patterns and driving effects of urban expansion and habitat quality changes, respectively. Among them, bivariate spatial autocorrelation is an extension of traditional spatial autocorrelation analysis, used to test the spatially coupled correlation between two variables [28]. In different regions, the response of habitat quality to urban land expansion generally has local non-stationarity, which can be reflected and identified using the bivariate LISA map. Based on the Multivariate LISA tool of GeoDa 1.4.6, a bivariate local spatial autocorrelation method was employed to quantify the local variability of the association between urban land expansion and habitat quality in the CUA. The calculation formula for the bivariate Moran's I is:

$$I_{kl}^{i} = \frac{x_k^i - \overline{x}_k}{\sigma_k} \cdot \sum_{j=l}^{n} \left(W_{ij} \frac{x_l^i - \overline{x}_l}{\sigma_l} \right) \tag{6}$$

where W_{ij} is the spatial weight matrix; x_k^i is the observation value k of study unit i; x_l^i is the observation value l of study unit j; σ_k and σ_l are the variances of x_k and x_l. The value range of I is between $[-1, 1]$. Values greater than 0 indicate positive correlations, in which similar variables tend to be clustered in space. Values less than 0 suggest negative correlations, in which similar variables tend to be discrete.

The spatial regression model can be used to further illustrate the local direct and spatial spillover effects of independent variables. There are mainly three common spatial regression models. The Spatial Durbin Model (SDM) integrates the ability of two methods (Spatial Error Model (SEM) and Spatial Lag Model (SLM)) to quantify the exogenous and endogenous interaction effects of variables and classifies the driving effects of urban land expansion on habitat quality into local direct effects and spatial spillover effects [29]. The SDM formula is as follows:

$$Yit = \rho WYit + \beta Xit + \theta WXit + \varepsilon it \tag{7}$$

where Y_{it} is the explained variable of region i in period t, expressed as increments in habitat quality; X_{it} is the explanatory variable of region i in period t, including urban land expansion and control variables; ρ, β, and θ are the parameters to be estimated; ε is the random disturbance term of the normal distribution; W is the spatial weight matrix; WY is the spatial lag dependent variable; WX is the spatial lag independent variable. Based on previous studies practice and the comparison of model operation results, the queen contiguity method and Euclidean distance were used to construct a spatial weighting matrix that reflects the spatial structure and location relationship of the data [27].

To improve the scientificity of the model operation, the following preprocessing steps were performed on the variable data. First, normalization of variable data (Z-score method) was performed while maintaining a normal distribution to improve the comparability of regression coefficients. Second, Variance Inflation Factor (VIF) and Condition index were used to test for possible multicollinearity among explanatory variables. Third, tests were conducted to evaluate the necessity of spatial regression and the rationality of model selection before constructing the SDM models of habitat quality drivers [21,29]. The Lagrangian Multiplier (LM) was used to test the necessity of incorporating spatial effects into the regression model. The Likelihood Ratio estimation (LR) was used to assess whether the SDM model can be reduced to SLM or SEM, that is, whether SDM can integrate the measure advantages of SLM and SEM. In analyzing the driving effects, the SDM model was used to divide the spatial regression effects into total effects, local direct effects, and spatial spillover effects using partial differential equations (P.D.E), focusing on the spatial characteristics of the driving effects of urban land expansion on habitat quality [30].

2.3. Data Source

Details of the variables used in this paper can be found in Table 3. The required data were obtained from the following sources:

Table 3. Variable category.

Variable Category	Variable	Abbreviation	Unit
Socioeconomic	Urban expansion intensity index	*UEI*	%
	Population urbanization level	*PU*	%
	GDP	*GDP*	yuan
	Agricultural fertilizer application	*AFA*	t
Natural	Habitat quality	*HQ*	-
	Slope	*SLO*	°
	Average annual precipitation	*PRE*	mm
	Normalized Difference Vegetation Index	*NDVI*	-

Land cover data. Land cover was determined using the global land cover dataset for 1992–2020 from the European Space Agency (ESA-CCI) (http://due.esrin.esa.int/globcover/) (accessed on 20 June 2021). With a 300 m resolution, the dataset has an overall accuracy of 75.38%, among which the user accuracy of urban land is 88%, which has a good interpretation effect on the current situation of regional land use. Using the land-use classification system of the Intergovernmental Panel on Climate Change (IPCC) and previous studies, the dataset was adjusted on the GEE geographic cloud platform and merged into six general categories: farmland, forest land, grassland, water area, urban land, and bare land [31].

Socio-economic data. In addition to urban land expansion, regional habitat quality has been shown to be associated with socio-economic factors such as economic development, urban population size, and food production [25,32,33]. Accordingly, on the basis of considering the prevalence of variables and existing research, GDP (*GDP*), population urbanization level (*PU*) and agricultural fertilizer application (*AFA*) were used to indicate the error effect of regional economic level, urban population size and food production [34]. These socio-economic data were acquired mainly from the "Statistical Yearbook of Sichuan Province" and the "Statistical Yearbook of Chongqing city" at the county and district levels.

Natural control variables. Indicators such as slope, precipitation, and Normalized Difference Vegetation Index (NDVI) have also been shown to have important effects on habitat quality [33,35]. Therefore, we included natural factors such as slope (*SLO*), precipitation (*PRE*), and NDVI (*NDVI*) as control variables in the model. The slope data had a 30 m spatial resolution and were derived from the GDEMV2 DEM digital elevation product of the Computer Network Information Center of the Chinese Academy of Sciences (http://www.gscloud.cn) (accessed on 15 January 2022). Spatial distribution data of precipitation were obtained from the spatial dataset of meteorological conditions provided by the National Earth System Science Data Center (https://www.resdc.cn/) (accessed on 20 January 2022). The NDVI dataset was derived from satellite remote sensing such as SPOT/VEGETATION and MODIS, and the vegetation cover distribution data were obtained through mosaic and projection transformation (https://www.resdc.cn/data.aspx?DATAID=343) (accessed on 30 January 2022).

3. Results

3.1. Spatio-Temporal Evolution Characteristics of Urban Land Expansion

3.1.1. Changes in Land Use Structure

Using the statistical analysis in ArcGIS (see Figure 3), farmland and forest land were the main land-use types in the CUA from 2000 to 2018, accounting for more than 95% of the region. Urban lands can be found in the plains and riverside areas of the middle of the urban agglomeration, concentrated mainly in the central regions of Chengdu and Chongqing. Table 4 summarizes the area transition matrix for the different land-use types at different periods. From 2000 to 2018, urban land expanded the most, increasing by 2890.42 km^2, equivalent to 170.82%. Forest land increased by 752.78 km^2, growing by 1.92%, while farmlands declined by 2.88% (4074.74 km^2). The increase in urban lands was caused mainly by encroachment into farmlands and grasslands and was particularly pronounced from 2010 to 2018 when 1511.36 km^2 of farmland was converted into urban land, accounting for 1.08% of the total area of farmland in 2005.

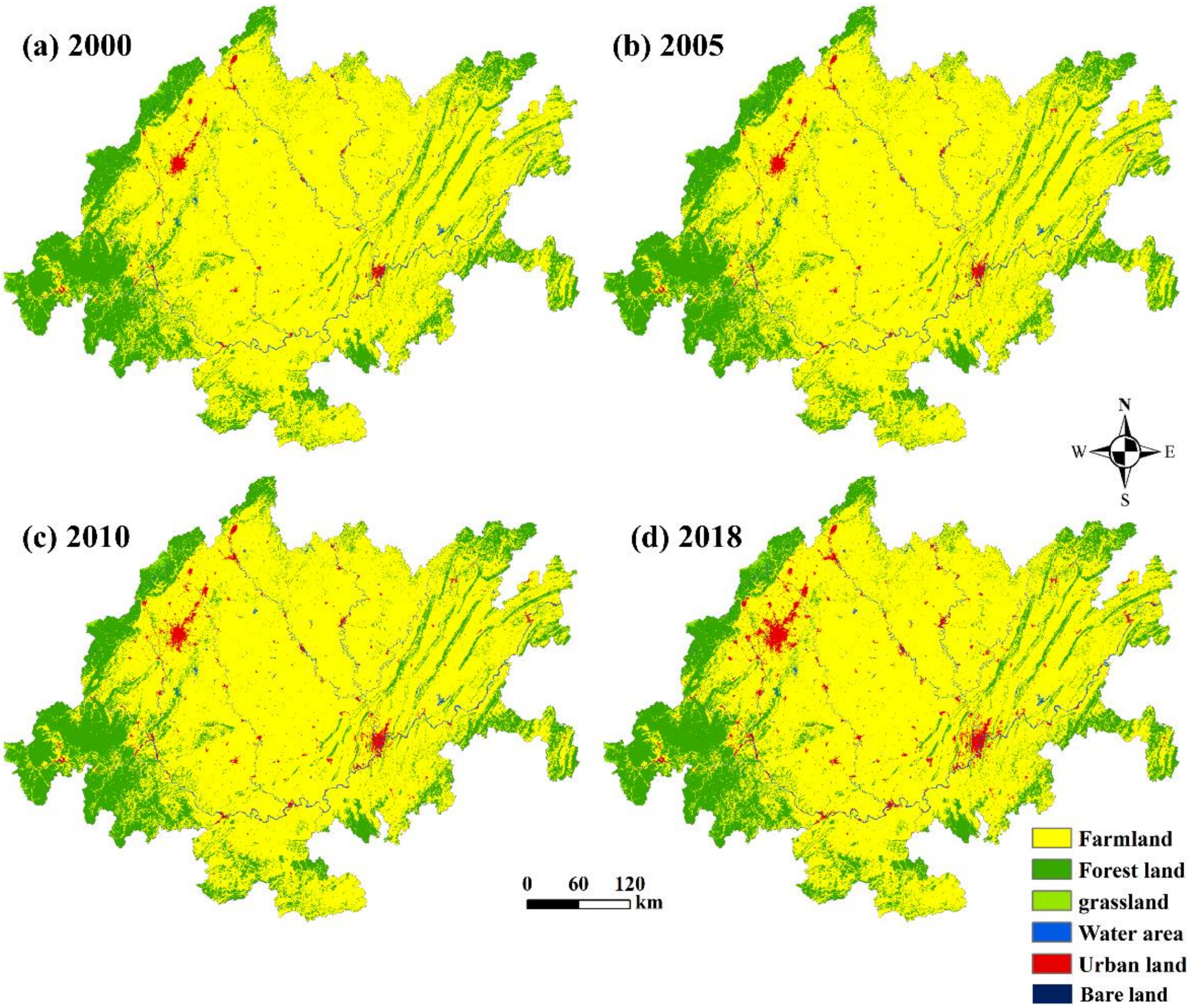

Figure 3. Distribution and evolution of land-use types in CUA from 2000 to 2018.

Table 4. The transition matrix of land-use types (km^2).

Year	Land Use Types	Farmland	Forest Land	Grassland	Water Area	Urban Land	Bare Land
2000–2005	Farmland	140,507.95	461.76	0.00	0.00	360.65	0.00
	Forest land	169.78	38,876.04	19.36	1.82	1.24	0.00
	Grassland	1.74	6.29	579.74	0.00	20.44	0.00
	Water area	0.00	0.00	0.00	2167.31	7.12	0.00
	Urban land	0.00	0.00	0.00	0.00	1691.90	0.00
	Bare land	0.00	0.00	0.00	0.00	0.00	0.00
2005–2010	Farmland	139,770.18	21.93	6.21	5.05	876.11	0.00
	Forest land	146.53	39,068.57	105.33	19.94	3.72	0.00
	Grassland	0.08	0.17	572.13	0.08	26.64	0.00
	Water area	0.00	0.00	0.00	2152.26	16.88	0.00
	Urban land	0.00	0.00	0.00	0.00	2081.35	0.00
	Bare land	0.00	0.00	0.00	0.00	0.00	0.00
2010–2018	Farmland	137,546.19	842.93	1.57	14.73	1511.37	0.00
	Forest land	78.52	38,972.76	7.53	15.47	16.38	0.00
	Grassland	0.08	5.30	651.56	2.23	24.49	0.00
	Water area	0.00	0.00	0.00	2152.09	25.23	0.00
	Urban land	0.00	0.00	0.00	0.00	3004.70	0.00
	Bare land	0.00	0.00	0.00	0.00	0.00	0.00

3.1.2. Spatio-Temporal Distribution Characteristics of Urban Land Expansion Intensity

Figure 4 shows the evolution of urban land expansion in the CUA. During the study period, the core areas of urban land expansion were in the main urban areas of Chengdu and Chongqing, while urban land expansion in small and medium-sized cities, such as Zigong, Luzhou, and Deyang, was relatively limited. Urban land expansion had a "Core-Periphery" gradient expansion pattern, and the extent of urban land expansion was most prominent from 2010 to 2018 compared to previous periods.

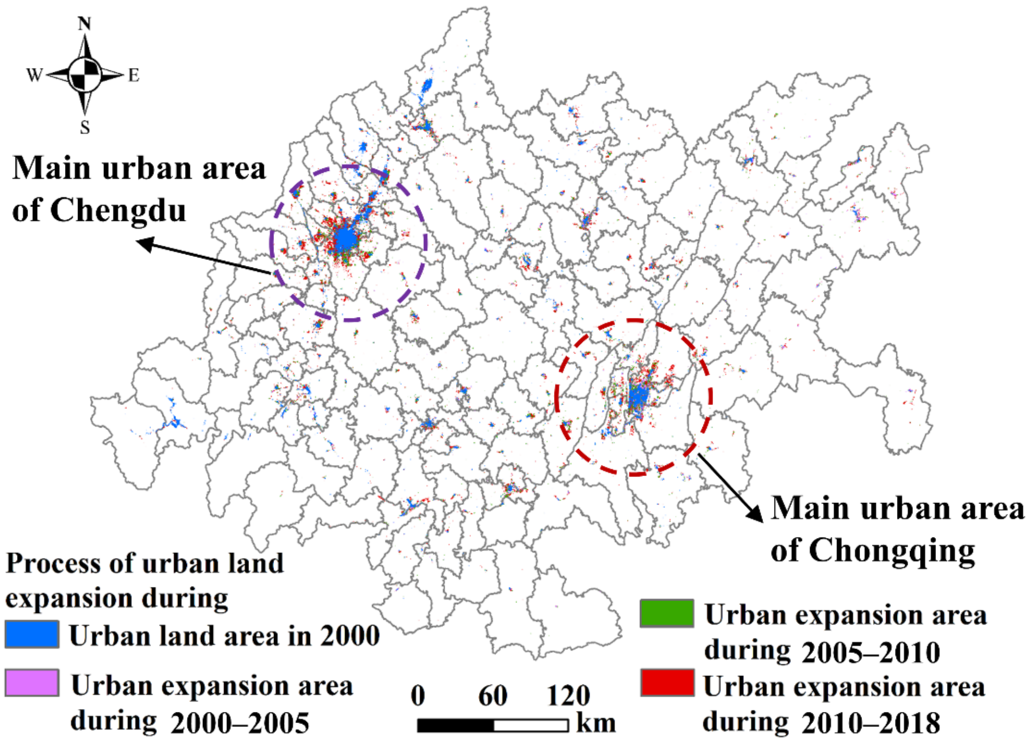

Figure 4. The process of urban land expansion from 2000 to 2018.

The overall urban land expansion of the CUA showed a slowing trend. Compared with 2000–2010, the average UEI index of the urban agglomeration dropped to 7.64% in 2010–2018, decreasing by 53.95% (Figure 5). The spatial distribution pattern of the UEI changed significantly during the 19-year research period. We classified the UEI index of the CUA region into five levels from "V-I" based on the natural breakpoint classification with nodes of 5%, 15%, 50% and 100%. From 2000 to 2010, 34.51% and 38.73% of county units were in levels IV and III in the UEI index. Level IV areas were concentrated in Leshan, Meishan, Neijiang, and southern Chongqing counties, while the Level III areas were situated mainly in Ziyang, Luzhou, and western Chongqing counties. From 2010 to 2018, the urban land expansion rates in many counties generally slowed down, possibly due to restrictive policies on regional land development. Cities classified as Level IV became dominant, accounting for 53.52% of all county-level units, followed by Class V, which comprised 40.85%. In addition, the UEI index distribution also significantly changed between 2000–2005 and 2005–2010, evolving from a configuration of "low-speed in the west and high-speed in the east" into a scattered distribution of low-speed expansion areas (V-level).

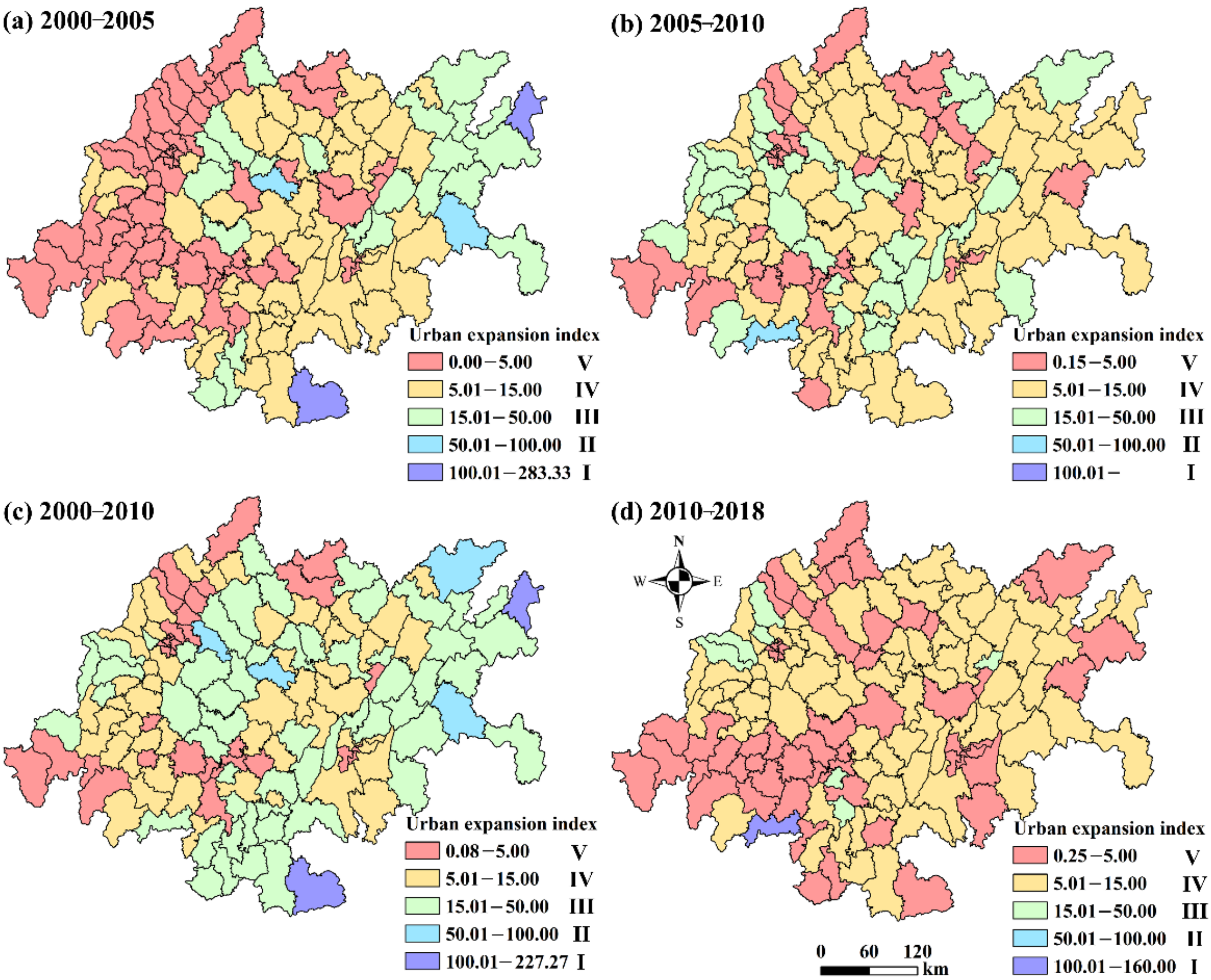

Figure 5. Spatio-temporal distribution pattern of UEI from 2000 to 2018.

3.2. Spatio-Temporal Evolution Characteristics of Habitat Quality

Figure 6 presents the evolution of the spatio-temporal distribution of habitat quality in the CUA. Habitat quality deteriorated at the administrative level for the given research period, with the average HQ index decreasing by 4.03%, from 0.943 in 2000 to 0.905 in

2018. Spatially, the habitat quality in the CUA exhibited pronounced regional differences. High-value areas were clustered in the Jiajin Mountain, Daliang Mountain, and Qionglai Mountain in the southwest, including the cities of Ya'an, Leshan, and Yibin, which have relatively low economic development levels. The low-value areas in Chengdu and Chongqing expanded considerably during the study period, their central urban districts of Jinjiang, Chenghua, Wuhou, and Yuzhong had the lowest habitat quality in the urban agglomeration.

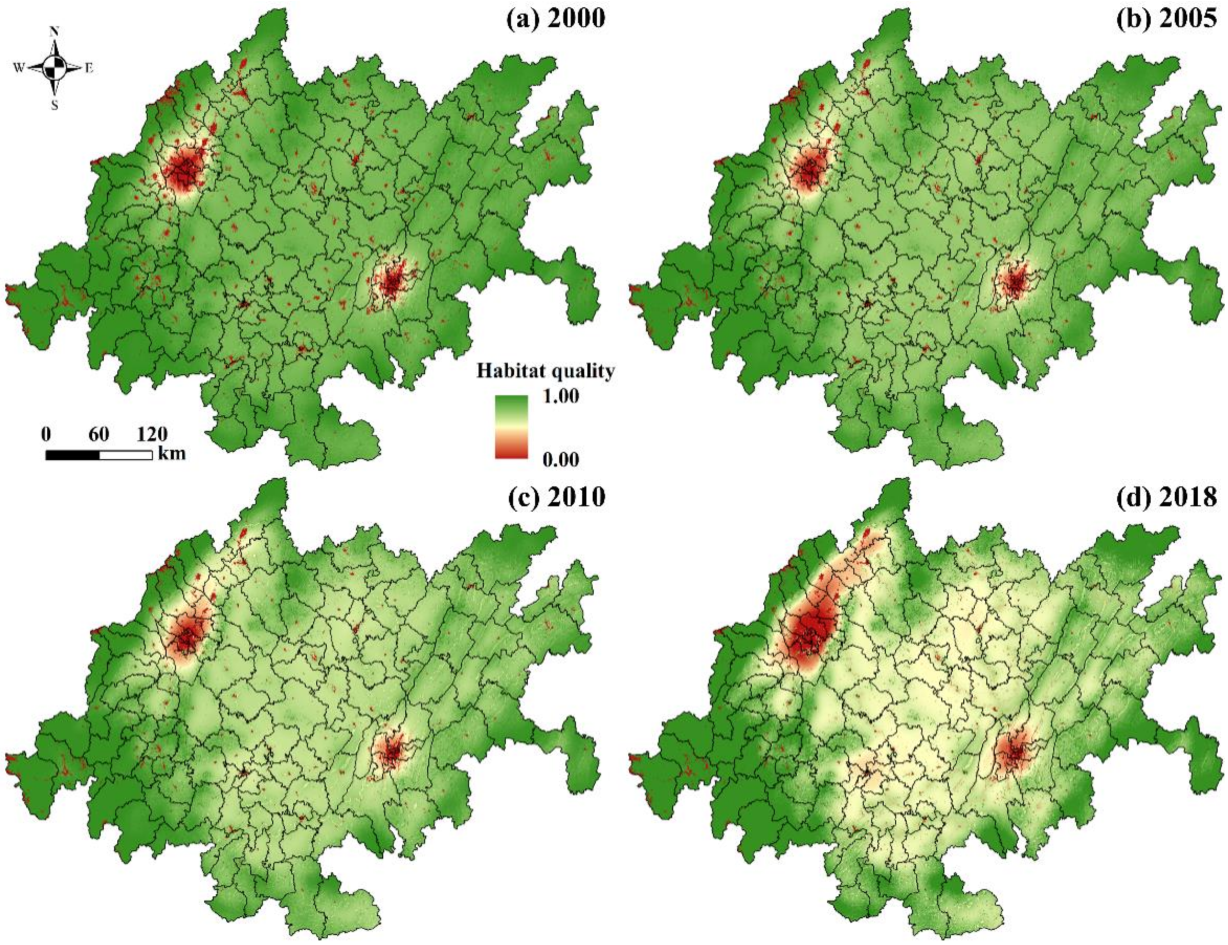

Figure 6. Spatio-temporal distribution pattern of habitat quality from 2000 to 2018.

We then analyzed the trend in habitat quality by subtracting the habitat quality at different periods (see Figure 7). The most significant decline in habitat quality was due to the peripheral expansion of the main metropolitan centers; in particular, two areas with considerable reduction in habitat quality developed around the main urban areas of Chengdu and Chongqing in a ring-shaped formation. Habitat quality in the marginal areas (e.g., southwestern and southeastern mountainous areas) significantly improved, particularly in the administrative regions of Mabian County, Ebian County, Junlian County, Xuyong County, and Qianjiang District. In addition, the area of "ring-shaped decline areas" with declining HQ values and habitat growth areas both had slow growths, increasing the structural complexity of the habitat system in the CUA.

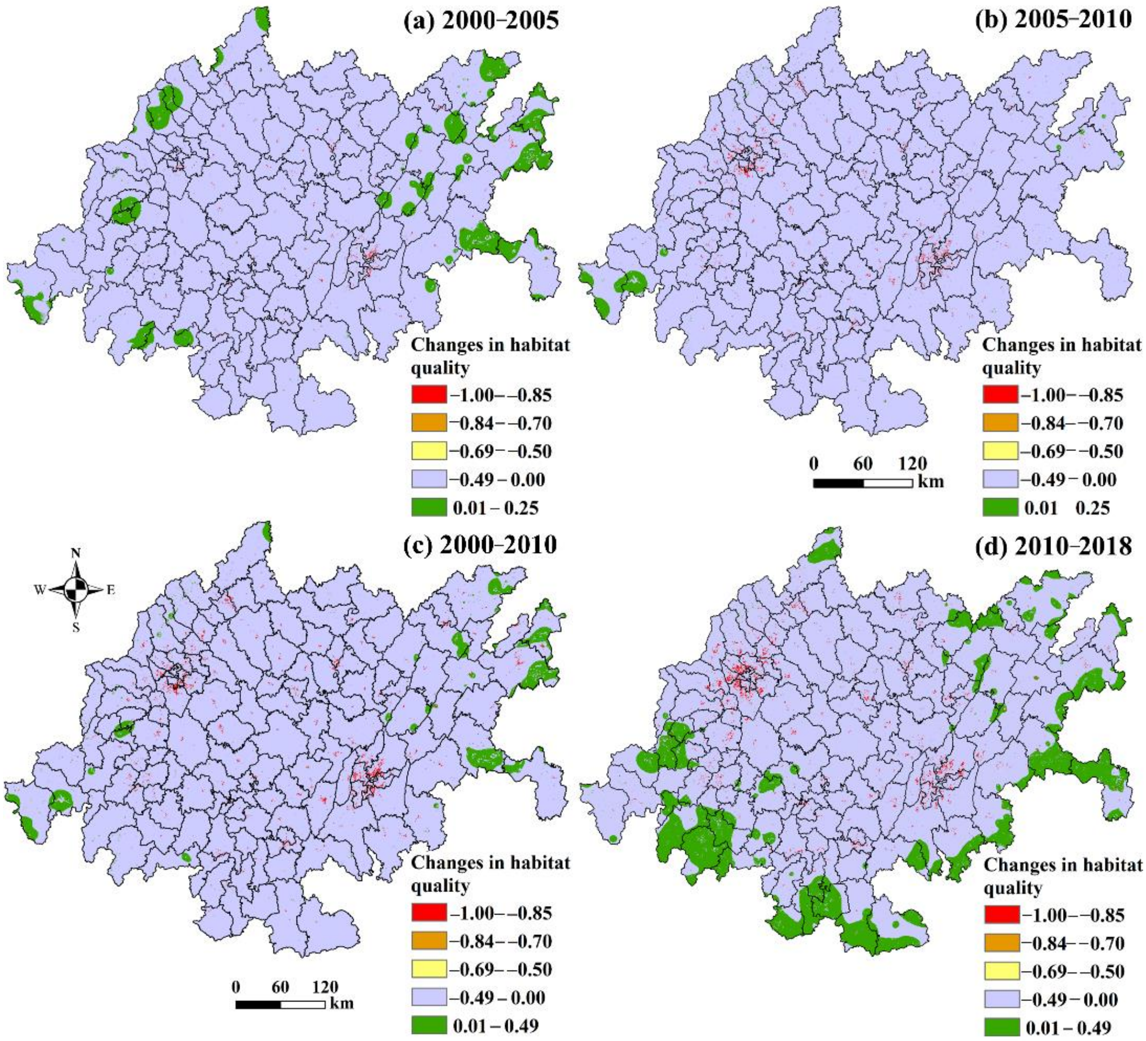

Figure 7. Spatial distribution changes in habitat quality from 2000 to 2018.

3.3. Driving Impacts of Urban Land Expansion on Habitat Quality

3.3.1. Bivariate Spatial Autocorrelation between Urban Land Expansion and Habitat Quality

The spatial analysis tool of the GeoDa platform was used to calculate the global spatial autocorrelation index Moran's I for urban land expansion and habitat quality changes. The Moran's I index for urban land expansion and habitat quality changes was 0.120 for 2000–2010 and 0.019 for 2010–2018. Since Moran's I indexes were low and exhibited a downward trend, the values cannot strongly prove a positive correlation between urban land expansion and habitat quality. This means that further analysis of the local variability of association is needed through bivariate local autocorrelation.

The investigation emphasizes that "Low-High" negative correlation and "Low-Low" positive correlation are the main agglomeration types associated with urban land expansion and habitat quality changes in the CUA (Figure 8). From 2000 to 2010, the negative correlation cluster regions accounted for 6.34% of the total area were formed by southwestern counties, such as Shimian County, Hanyuan County, Xuzhou District. Indicating the urban development intensity in these areas was relatively weak, while the habitat quality and regional ecological conservation efforts were great. "Low-Low" positive correlation cluster regions accounted for 11.27% of the total area and were consistent with the old urban areas of Chengdu and Chongqing, such as Chenghua District, Jiangjin District. This may be related to the early infrastructure construction that destroyed the natural habitat of the old urban areas, but the current urban construction space tends to be saturated. "High-High" positive correlation cluster regions accounted for 4.93% of the total area were formed by some southwestern mountainous counties, such as Xinjing County and Gulin County, which may be associated with the high-quality ecological base of these areas but the rapid acceleration of urban construction in recent years. As the new urban area of Chengdu and Chongqing, Longquanyi District, Beibei District, Yubei District, and Bishan District undertake the function of relieving the pressure of land demand in the old urban area, forming "high-low" negative correlation cluster.

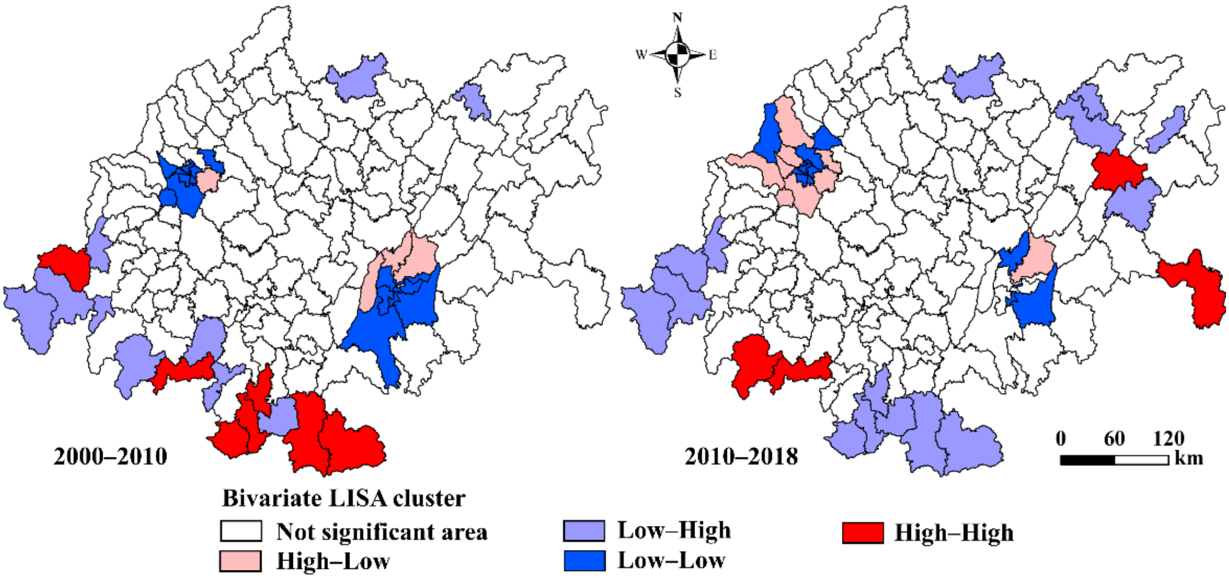

Figure 8. The spatial distribution of bivariate LISA between urban expansion and habitat quality in 2000–2018.

The number of counties with cluster types "Low-High" or "High-Low", where urban land expansion is negatively correlated with habitat quality, increased from 9.15% in 2000–2010 to 16.90% in 2010–2018. This means that the adversarial relationship between urban land expansion and habitat quality has become more prominent and that reconciling the relationship between urban development and ecological protection is extremely important. With the growth in land-use demand in old cities due to rapid population agglomeration, new cities around Chengdu and Chongqing (e.g., Chongzhou City, Pengzhou City, and Pidu District) have become new "High-Low" negative correlation cluster areas, accounting for 6.34% of the total area. "Low-high" cluster areas increased to 10.56%, and the newly added areas included northern and southern counties in the CUA, such as Kaizhou District, Xuyong County, and Gulin County. In comparison, correlated clusters of "Low-Low" and "High-High", where urban land expansion and habitat quality have a positive correlation, shrank to 8.45% and 2.82%, respectively. The results suggest that the phenomenon of deviation from the fundamental conflict situation of "urban land expansion-habitat quality" in the global autocorrelation analysis is gradually disappearing.

3.3.2. Further Analysis of the Driving Effect of Urban Land Expansion on Habitat Quality

Based on the data preprocessing results (i.e., logarithmization of variables, normalization, and multiple co-linearity tests), the LM tests for both spatial lags and spatial errors rejected the original hypothesis at 1% significance level, confirming the necessity of introducing geospatial elements into the regression model. The study then evaluated whether SDM can be reduced to SLM or SEM using the LR test. The results showed that both LR-SLM and LR-SEM rejected the null hypothesis of "no spatial lag" and "no spatial error" at 1% confidence level. Based on the preprocessing results, the SDM model was selected as the best fitting model to evaluate the driving effect of urban land expansion on habitat quality. The SDM estimation and test results are shown in Table 5.

Table 5. Empirical results of Ordinary Least Squares (OLS) and spatial Durbin model (SDM).

Variables	Ordinary Least Squares		Spatial Durbin Model	
	2000–2010	2010–2018	2000–2010	2010–2018
ln(*UEI*)	−0.023	−0.123	−0.029	−0.114 **
ln(*PU*)	−0.06	−0.259 **	−0.286 ***	−0.303 ***
ln(*GDP*)	−0.236 ***	−0.006	0.007	0.058
ln(*AFA*)	0.121 *	0.153 ***	0.021	0.073
ln(*SLO*)	0.087	0.131 **	0.257 ***	0.461 ***
ln(*PRE*)	0.066	0.218 ***	0.064	0.265
ln(*NDVI*)	1.223 ***	1.108 ***	−0.389 **	0.239
$W \times$ ln(*UEI*)			−0.01	−0.084
$W \times$ ln(*PU*)			0.008	0.282
$W \times$ ln(*GDP*)			−0.376 ***	−0.300 *
$W \times$ ln(*AFA*)			0.004	0.102
$W \times$ ln(*SLO*)			−0.328 **	−0.529 ***
$W \times$ ln(*PRE*)			−0.021	−0.225
$W \times$ ln(*NDVI*)			1.819 ***	0.364
R^2	0.430	0.681	0.675	0.775
sigma^2	0.014	0.014	0.008	0.008

Note: * statistical significance at 10% level; ** statistical significance at 5% level; *** statistical significance at 1% level.

The regression results show that the effect of urban land expansion on habitat quality is not significant from 2000 to 2010, while the effects of population urbanization level and NDVI are significantly negative and the effect of slope is significantly positive. In addition, compared to OLS regressions, SDM also highlights the negative spillover effects of GDP and slope on habitat quality and the strong positive spillover effects of NDVI under the influence of spatial factors (Table 5, column 3). The impact of urban land expansion on habitat quality was significantly negative from 2010 to 2018, while the negative impact of population urbanization level was rapidly enhanced (Table 5, column 4). While the results lay the foundation and offer important inspiration, they may only provide a basic picture for the "urban land expansion-habitat quality" story. According to LeSage and Pace (2010) and Du et al. (2019), the SDM coefficients neither reflect the marginal nor the total effects of the independent variables. Instead, they require further decomposition into local direct effects, spatial spillover effects, and total effects by partial differential equations (P.D.E) to comprehensively understand the effects of urban land expansion on habitat quality.

Using partial differential equations, the direct (local) and indirect (spillover) effects were decomposed, and the results are shown in Table 6. Except for 2000, urban land expansion has a significant negative impact on habitat quality in both local and adjacent areas, and the intensity of the impact is increasing rapidly. From 2000 to 2010, the local direct effect of urban land expansion is not significant, but the spillover effect on neighboring areas is significantly negative with a regression coefficient of −0.011 (Table 6, columns 1 and 3). The direct and spatial spillover local effects of urban land expansion were significantly negative from 2010 to 2018, with regression coefficients of −0.135 and −0.317, respectively (Table 6, column 2 and 4). There are several important economic implications of these findings. First, the direct effect shifted from insignificant to negative, while the negative impact of spillover effects increased. This suggests that the influence of urban land expansion on habitat degradation in local and adjacent areas has gradually increased, and the reason will be discussed in Section 4. Second, comparing effect intensities, the negative externality of urban land expansion on habitat quality was more prominent in adjacent areas than in local areas. In addition, regardless of the period, the total effect of urban land expansion was negative and significant. This means that the spatial spillover effect dominates over local direct effects, and therefore, as a whole, urban land expansion reduces regional habitat quality (Table 6, columns 5 and 6). In this sense, the results provide evidence for the need to integrate the conservation and restoration of habitats and the regional coordination of urban land expansion in planning and land resource management.

Table 6. Decompositions of the local, spatial spillover, and total effects for the variables.

Variables	Local Direct Effects		Spatial Spillover Effects		Total Effects	
	2000–2010	**2010–2018**	**2000–2010**	**2010–2018**	**2000–2010**	**2010–2018**
ln(UEI)	−0.028 (−0.801)	−0.135 ** (−2.011)	−0.011 * (−1.231)	−0.317 * (−1.755)	−0.039 * (−1.326)	−0.452 *** (−3.978)
ln(PU)	−0.286 *** (−4.540)	−0.289 *** (−3.194)	0.004 (0.041)	0.240 (0.605)	−0.281 *** (−2.905)	−0.048 (−0.110)
ln(GDP)	0.005 (−0.628)	0.024 (0.312)	−0.382 *** (−4.118)	−0.548 (−1.404)	−0.377 *** (−4.891)	−0.524 (−1.190)
ln(AFA)	0.020 (0.395)	0.091 * (1.858)	0.003 (0.036)	0.281 (1.527)	0.024 (0.256)	0.373 * (1.825)
ln(SLO)	0.255 ** (2.503)	0.423 *** (4.229)	−0.333 *** (−2.513)	−0.573 *** (−2.942)	−0.077 (−1.103)	−0.149 (−0.914)
ln(PRE)	0.069 (0.457)	0.252 (1.560)	−0.026 (−0.149)	−0.165 (−0.634)	0.042 (0.917)	0.086 (0.540)
ln(NDVI)	−0.379 * (−1.875)	0.306 (1.433)	1.833 *** (8.468)	0.993 *** (3.189)	1.454 *** (20.053)	1.300 *** (5.621)

Note. T values are in parentheses. * statistical significance at 10% level; ** statistical significance at 5% level; *** statistical significance at 1% level.

There were also interesting results regarding the impact of socio-economic factors on habitat quality, particularly the geographically heterogeneous driving effects of population urbanization GDP. Specifically, population urbanization from 2000 to 2018 threaten local habitat quality, but the effect on adjacent areas was not significant. It can be interpreted that the high concentration of urban population increases the demand for local infrastructure and physical resources, thus creating negative effects on natural habitats [36]. GDP did not have a significant effect on local habitat quality in 2000–2010, but significantly weakened habitat quality in adjacent areas. One possible explanation is that although GDP implies natural resource depletion, housing construction, and green space encroachment, environmental regulation policies and green production technologies offset the negative effects on local habitat. However, in the context of regional integration, local economic construction is likely to generate resource siphoning to adjacent areas, threatening the habitat quality of adjacent areas [37]. Moreover, to verify the phenomenon just described, in addition to using the queen contiguity matrix, the SDM based on the other spatial weight matrix were implemented to confirm the validity of the findings. The confirmatory test results suggest that the research findings were robust and that no abrupt change in the above index system was observed, thus ensuring the robustness and reliability of the model. In addition, the R^2 of the queen contiguity estimation results is better, which also shows the suitability of the selection of the matrix.

4. Discussion

This section discusses the potential mechanisms through which urban land expansion affects the habitat quality of the CUA, especially the different levels of impact on the habitat quality of local and adjacent areas. In addition, the research proposes policy applications, shortcomings and future prospects based on the above.

4.1. Spatial Responses of Local and Adjacent Habitat Quality to Urban Land Expansion

Previous studies have argued that urban land expansion has two main effects on habitat quality. First, urban land expansion reduces public green spaces and landscape diversity in urban ecosystems, adversely impacting habitat integrity and environmental self-renewal [38,39]. Second, economic growth and population agglomeration may increase dependence on natural resources and accelerate their depletion. They may increase the growth of impervious areas and vegetation fragmentation, damage urban ecosystem service functions, and decrease the ecological product value, putting greater pressure on ecological habitats [24,40]. In our study, habitat quality was found to have different levels of responses to urban land expansion in local and adjacent areas, highlighting the role of spatial externalities in urban land expansion.

In terms of local direct effects, urban land expansion had a non-significant impact in 2000–2010 and became negative in 2010–2018. The former is consistent with the phenomenon in bivariate spatial autocorrelation analysis that the number of cities with a negative correlation between urban land expansion and habitat quality were relatively few (9.15%) in the early part of the research period. A possible explanation is that given the extensive mountainous forests with excellent ecological bases and high habitat quality in the southwestern, southeastern, and western CUA, the increased difficulties of area development may generate some initial buffer on the adverse environmental effects of urban expansion, resulting in a non-significant regression coefficient [21]. For example, the NDVI in 2018 for the southwestern mountainous cities of Ya'an (slope = 20°) and Leshan (slope = 13°) were 0.84 and 0.83, while the NDVI for central cities of Chengdu (slope = 5°) and Nejiang (slope = 5°) were 0.67 and 0.75. The Lower NDVI and slope are related to urban ecosystems and construction difficulty, which influence the intensity of negative ecological effects of urban land expansion. The latter may be related to the degradation of buffer effect and the increased of urban development intensity. Over time, mountainous areas with high ecological quality may gradually lose their buffer protection from the adverse effects of urban land expansion [41]. Additionally, despite the rapid decline in the UEI indexes of urban agglomerations, demands for urban land expansion and its intensity to habitat transformation would further intensify, supported by modern construction technologies and socio-economic development needs [42,43]. In particular, due to various national strategies, such as China's Western Development Strategy, the Yangtze River Economic Belt, and the construction of the Chengdu-Chongqing Urban Agglomeration, more demand of infrastructure construction and residential housing are developed in the CUA area, increasing the inward utilization intensity of urban lands [21].

In terms of spatial spillover effects, the adverse effects of urban land expansion on habitat quality have significantly increased in adjacent areas. This could be due to the networking of cross-urban linkages and the demonstration effect of urban land development [44]. On the one hand, along with the development of integrated networks of urban agglomerations, supply pressures on building materials (e.g., cement and wood) required for urban construction are released in the surrounding areas due to unified regional markets and differences in natural endowments, threatening the habitat quality of neighboring cities [26,45]. On the other hand, some measures, such as demolition and relocation of rural houses, land transfer, and the removal of counties and establishment of districts by the local governments, may obscure the actual connotation and extent of urban land expansion. These measures promote tax revenue growth and increase urbanization, producing demonstration effects of land finance management within urban agglomerations and contributing to habitat fragmentation and degradation in neighboring cities [46,47]. Given the influence of these two aspects, urban land expansion has a significant adverse impact on the habitat quality of neighboring cities, the intensity of which even exceeds the role of local urban development and construction.

4.2. Policy Implications

Since the first official draft of the Global Biodiversity Framework was issued, countries around the world have made great efforts to maintain domestic species diversity and control habitat quality. The fifteenth meeting of the Conference of the Parties to the Convention on Biological Diversity (COP15) in Kunming brought the attention of international conservation organizations and individuals to China's habitat protection efforts. This study explored the interaction between urban land expansion and habitat quality in the CUA, providing new insights to support optimal regional urban land expansion and habitat conservation management. Based on the research results, we believe that there is still some work to be done for promoting the sustainability of habitat protection in the CUA and the overall optimization of urban land expansion.

First, policymakers and environmental organizations would have to coordinate and balance the needs for urban growth and habitat protection to develop long-term and sustainable development strategies that consider prevailing land use conditions, landscape types, and economic development in the urban agglomerations. Policies and measures should focus on improving the utilization rate of urban land stock, formulating reasonable paths for optimizing urban land expansion based on regional habitat quality levels, promoting more compact spatial layouts and geometric forms of construction lands, and mitigating habitat fragmentation caused by urban land expansion. Urban plans and strategies should be aimed toward the rational and optimal allocation of urban ecological resources and alleviating pressures on environmental resources caused by urban land expansion, economic development, and population agglomeration. For example, strengthening the construction of urban green corridors, open spaces, urban greenways and park cities to achieve unity between the urban expansion and the ecological needs of residents. Second, more attention should be given to the spillover effects of urban land expansion on habitat quality in adjacent areas. Policymakers should strengthen inter-regional capacity for joint action on habitat protection and management based on the "Ecological Environment Protection Plan of Chengdu-Chongqing Twin Cities Economic Circle" and minimize the adverse mediating effects of regional trade on the environment [48–50]. Cross-regional cooperation in the rational allocation and utilization of land resources should be given more attention, especially to strengthen the coordination of regional ecological restoration and management and achieve high-quality ecological city clusters that encourage wellness and are suitable for business.

4.3. Research Limitations and Future Prospects

There are some limitations in this study that should be considered when interpreting the results. First, the threat sources, habitat suitability, and sensitivity of each land-use type in the habitat quality accounting were made uniform and identical and did not consider spatial geographic differences. In the future, the scientificity of the correlation coefficient value set should be improved based on regional ecological surveys and the InVEST operation manual recommendations. Second, this paper focused on the spatio-temporal evolution and prevailing relationships between urban land expansion and habitat quality but did not tackle future development paths. Subsequent studies can implement other approaches (e.g., the CA-Markov model, FLUS and PLUS) to simulate future development scenarios in urban expansion and habitat quality to improve the perspective and practical reference value of the research.

5. Conclusions

In the 21st century, land-use change has become one of the most influential factors in the ecological environment. Urban land expansion is a key link between human activities and the natural environment, and the impact of landscape pattern changes caused by urban land expansion on regional habitat quality cannot be ignored. This paper investigated the spatio-temporal distribution of urban land expansion and habitat quality in the CUA and analyzed the driving effect of urban land expansion on habitat quality from a spatial perspective. The P.D.E method was used to further explore the local direct effects, spatial spillover effects, and total effects of urban land expansion on habitat quality.

The main findings are as follows: (1) Urban lands in the CUA are scattered along the plains and rivers in the middle of the urban agglomeration, increasing by 2890.42 km^2 from 2000 to 2018, mainly due to urban encroachments over farmlands and grasslands. (2) The urban land expansion exhibited a "Core-Periphery" gradient expansion pattern, with core areas situated in the main urban districts of Chengdu and Chongqing. Urban expansion has generally slowed, and the average UEI index dropped to 7.64% in 2010–2018, decreasing 53.95% compared to 2000–2010. (3) The overall habitat quality dropped to 0.905 by 2018, a decrease of 4.03%. The high-value regions of habitat quality were concentrated in the mountainous cities in the southwest, while two major "ring-shaped decline areas" for habitat quality were formed around the main urban districts of Chengdu and Chongqing. (4) "Low-High" (with negative correlation) and "Low-Low" (with positive correlation) clusters were the main associations between urban land expansion and habitat quality changes. In 2010–2018, county units with negative correlation cluster types have significantly increased, indicating that the dichotomy between urban expansion and habitat quality has become more pronounced. (5) The impact of urban land expansion on local habitat quality shifted from insignificant to negative, while the negative externalities on the habitat quality of adjacent areas have been continuously enhanced. Differential effects of population urbanization level and GDP on habitat quality in local and adjacent areas were also found in this investigation.

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Abbreviations

Original meaning of abbreviations.

Abbreviations	**Original Meaning**
UEI	Urban expansion intensity index
PU	Population urbanization level
GDP	Gross Domestic Product
AFA	Agricultural fertilizer application
HQ	Habitat quality
SLO	Slope
PRE	Average annual precipitation
NDVI	Normalized Difference Vegetation Index
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLM	Spatial Lag Model
LM	Lagrangian Multiplier
LR	Likelihood Ratio estimation
VIF	Variance Inflation Factor
CUA	Chengdu-Chongqing urban agglomeration

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