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Investigating the Impacts of Urbanization on Vegetation Net Primary Productivity: A Case Study of Chengdu–Chongqing Urban Agglomeration from the Perspective of Townships

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Abstract: As an emerging national strategic urban agglomeration in China, the changing trend of vegetation net primary productivity (NPP) and the impact of the urbanization level (UL) on carbon cycle functions in the Chengdu–Chongqing urban agglomeration (CUA) have received increasing attention. Previous studies have largely overlooked externalities and the heterogeneity of urbanization effects, and urbanization has also been analyzed in isolation (with focus being on land and population urbanization). In this study, the spatial evolution of NPP was evaluated from 2000 to 2020 at the township level (3859) using multivariate remote sensing data and a comprehensive index (UL) that included population urbanization, land urbanization, and economic urbanization. Bivariate spatial autocorrelation, spatial Durbin models, and geographically weighted regression models were used to analyze the spatial externalities of urbanization impacts and assess the global and local effects. The results show that the region's mean NPP increased by 177.25 g*c/m^2 (annual growth of 1.59%), exhibiting a distribution of "low in the middle and high in the periphery" and low-value clustering along major traffic arteries and rivers. Low-value-NPP areas were mainly located in urban centers, while the high-level areas were in the mountainous region (in the southwest and southeast) and significantly expanded over time. Negative correlation clusters were the main clustering types between the UL and NPP; the "High-Low" negative correlation clusters accelerated outward from the urban centers of Chengdu and Chongqing. Overall, urbanization had negative direct and spillover effects on NPP, exhibiting spatial non-stationarity of the negative driving effect within the urban agglomeration. The results indicate the need to strengthen regional ecological joint governance and adopt more place-based urbanization optimization strategies. This study offers new insights to help to reduce the constraining effects of urbanization on vegetation productivity and ecological functions from the perspectives of population agglomeration, land expansion, and industrial construction.

Keywords: urbanization; vegetation net primary productivity; spatial Durbin model; geographically weighted regression; Chengdu–Chongqing urban agglomeration (CUA)

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1. Introduction

As an important component of the terrestrial carbon cycle, vegetation net primary productivity (NPP) has been shown to be an important indicator for expressing the carbon sequestration capacity, regional productivity, sustainability, and even the evolutionary process of ecosystems [1]. The increasing decoupling between anthropogenic activities and natural systems has attracted international attention, given that in the first two decades of the 21st century, global urban lands have expanded by 117.49%, from 239,000 km^2 to 519,800 km^2, significantly impacting vegetation productivity and ecological security [2]. Human activities, mainly urbanization, have accelerated the structural transformation of land use and the fragmentation of landscape patterns, reshaping vegetation cover systems and climate–carbon cycles [3,4]. Balancing the relationship between urbanization and NPP and reducing the adverse ecological effects of urbanization on vegetation cover are crucial in achieving the goals of human well-being, attaining sustainable city construction (Goal11, SDG), maintaining ecosystem carbon cycles (Goal13, SDG), and ecosystem conservation (Goal15, SDG) [5,6].

Scholarly interest in this topic has not been limited to international cooperative governance programs, such as International Geosphere-Biosphere Program (IGBP), Kyoto Protocol (KP), The Paris Agreement, and the 26th United Nations Climate Change Conference (COP26). A large number of case studies on the responses of NPP to urbanization processes have been conducted [7,8]. For example, Pei et al. (2022) found that significant increases in NPP in urban built-up might be highly correlated with urban green cover and urbanization. Liu et al. (2021) concluded that global urban expansion from 2000 to 2010 detracted from terrestrial NPP 22.4 Tg-C per year, offsetting 30% of climate-driven NPP growth [1]. However, previous studies have largely analyzed urbanization in isolation, rarely considering the driving effects of comprehensive urbanization on NPP as an integrated system covering multiple elements, such as population agglomeration, land expansion, and economic development [9,10]. As a result, the impact of urbanization on NPP remains unclear, especially given the considerable heterogeneity in regional human activity intensity, urban expansion intensity, and urban development, resulting in significant disparities in the driving effects measured considering single and combined dimensions.

The transboundary and local effects of urbanization on NPP have also largely received insufficient attention. On the one hand, numerous studies have investigated the direct coercive effects of urbanization on NPP in terms of land use transition and population agglomeration [11–13]. For example, Chang et al. (2020) found that the average NPP of built-up areas is generally lower than that of non-urban areas in the same year, highlighting the negative impact of urbanization on regional vegetation cover systems [14]. Zhou et al. (2021) suggested that human activities, mainly urban expansion, directly partially offset the NPP gain from climate change [10]. The transboundary effects of urbanization have been increasingly analyzed, especially in terms of carbon emissions, ecosystem health, and ecosystem services [15–17]. However, the spatial spillover effects of urbanization on NPP have remained largely unexplored, limiting the development of needed strategies for joint ecological governance and synergistic urban planning. On the other hand, methods such as least squares regression, environmental Kuznets curves (EKCs), and Pearson correlation coefficients have been widely used to assess the driving effects among systems [18]. In recent years, spatial regression models have also been employed to quantify and evaluate the driving influences of NPP in a geospatial sense [19]. Few have combined the results of global estimates with regional analyses based on geographically weighted regression (GWR) or spatio-temporal geographically weighted regression (GTWR) to observe the differentiated effects of urbanization on the global and local scales. This is obviously disadvantageous to developing systematic and differentiated urbanization optimization and environmental protection plans.

The Chengdu–Chongqing urban agglomeration (CUA) is an emerging pole among the five national strategic urban agglomerations in China [20]. According to National Bureau of Statistics of China, the CUA accounted for 6.20% and 6.81% of China's total GDP and population in 2018, playing an important role in the country's macroeconomic development [21]. The urbanization rate of the CUA has also increased from 50.10% in 2000 to 66.71% in 2018. However, some environmental problems have emerged due to urbanization, such as urban haze pollution, increased carbon emissions, habitat fragmentation, and shrinking vegetation cover systems [22]. While a number of environmental policies have been implemented in recent years to conserve and protect vegetation systems in the CUA, research on NPP response to CUA's rapid urbanization has been limited, restricting the understanding and evaluation of urbanization mechanisms on regional carbon cycling and environmental sustainability.

In summary, existing studies have made outstanding contributions to understanding the spatial dependency pattern of NPP and its response to urbanization. However, the discussion of the driving effects of urbanization on NPP is far from being resolved. (1) Few studies have explored the impact of urbanization on NPP by taking urbanization as a multi-dimensional system covering population, land, and economy. (2) The global estimates and local impacts of urbanization on NPP are yet to be integrated, making it difficult to provide targeted support for regional NPP optimization strategies. (3) Given that the response mechanism of NPP to urbanization varies from place to place, there have been limited studies exploring the driving mechanism of urbanization in the CUA. To fill these research gaps, we analyzed the spatial evolution of NPP in the CUA at the township level from 2000 to 2020 using MODIS-17A3HF images. We used the spatial Durbin model (SDM) and GWR models to estimate the global and local effects of urbanization (i.e., population, land, and economy) on NPP and utilized Partial Differential Equations (PDEs) to further investigate the local direct and spatial spillover effects of urbanization.

The highlight of our study is the exploration of the impact of comprehensive urbanization on NPP; in particular, the externalities and spatial non-stationarity of this impact are discussed. To the best of our knowledge, this has rarely been discussed in previous studies, and no studies have focused on the application of this topic in the CUA. This is necessary for the development of ecological management and ecological restoration projects in the context of rapid urbanization in the region, while the discussion based on the impact of externalities can likely provide support for regional ecological joint management and urbanization synergistic optimization paths. Moreover, it may provide new perspectives on emerging urban agglomerations in aid of sustainable urban development.

2. Study Area, Methods, and Data Sources

2.1. Study Area

Located in the upper reaches of the Yangtze River waterway, the CUA has a complex and diverse topography dominated by plains, hills, and mountains. The area has a subtropical monsoon climate with rich vegetation and excellent ecology (Figure 1). The CUA is an important segment of China's national economic system, with the total GDP rising from CNY 493.19 billion in 2000 to CNY 5365.48 billion in 2018; its urbanization rate also increased from 50.10% in 2000 to 66.71% in 2018. Given the region's rapid urbanization and economic importance, understanding the CUA's evolution and the response mechanism of NPP is crucial in developing policies and strategies that would promote the twin goals of environmental conservation and economic progress. With Chengdu and Chongqing as the core, the CUA encompasses 16 cities (i.e., Chengdu, Chongqing, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, and Ziyang) and is composed of 3589 townships. In order to improve the refinement of the study and enrich the regression model sample, our study was conducted at the township level.

2.2. Methods

Bivariate spatial autocorrelation was used to quantify the correlation effects of urbanization and NPP. The SDM and GWR models were then used to analyze the global and local effects of urbanization on NPP. The framework of the study is shown in Figure 2.

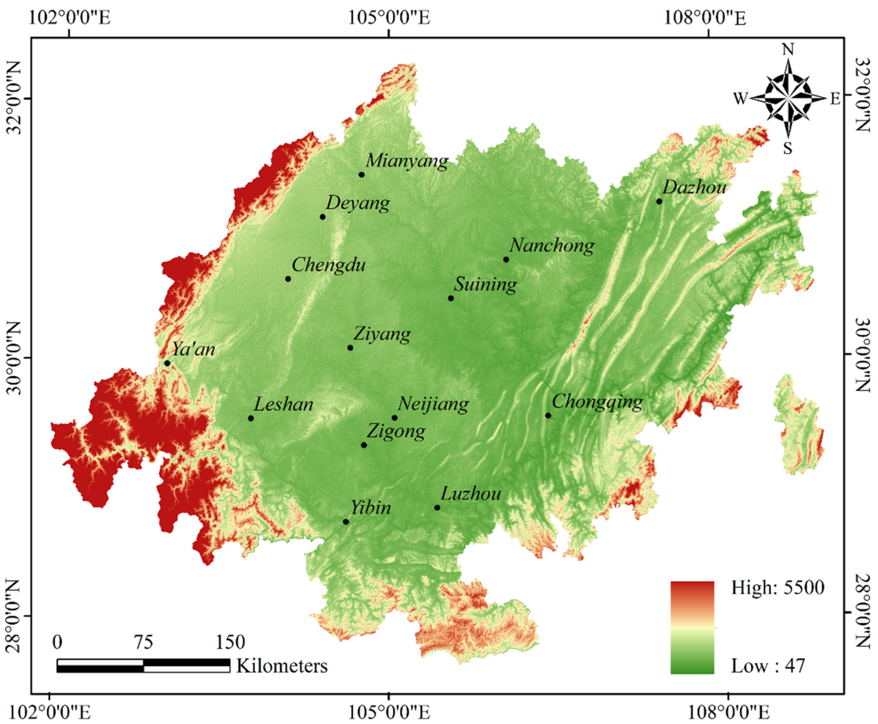

Figure 1. Study area.

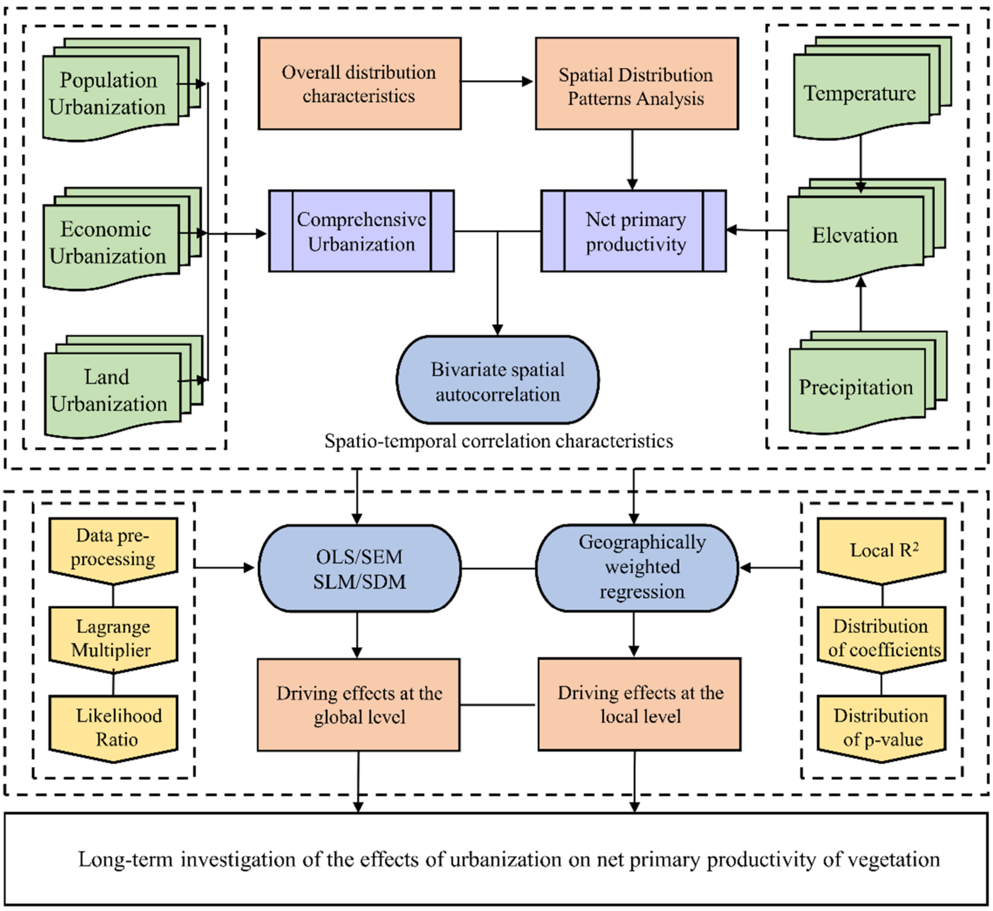

Figure 2. Technical route of this research.

2.2.1. Comprehensive Urbanization Level (UL) Accounting

Urbanization is an integrated process that includes several subsystems, such as urban population agglomeration, built-up area expansion, and socio-economic development. In this study, regional urbanization was analyzed as an integrated system of population urbanization (PU), land urbanization (LU), and economic urbanization (EU) based on practices and recommendations from previous research [23–25]. Based on Chen et al. (2022), we extracted the data of population, land, and economic urbanization; then, the extreme value method was used to standardize the urbanization index of different dimensions. The standardized results were summed and averaged to obtain the final regional comprehensive urbanization level (UL). The calculation formula is:

$$x_{ij}{}' = \frac{x_{ij} - \min\{x_{1j}, \cdots, x_{nj}\}}{\max\{x_{1j}, \cdots, x_{nj}\} - \min\{x_{1j}, \cdots, x_{nj}\}} \tag{1}$$

$$UL_i = \frac{x_{iPU} + x_{iLU} + x_{iEU}}{3} \tag{2}$$

where $x_{ij}{}'$ is the standardized value of the jth indicator of study unit i; x_{iPU}, x_{iLU}, and x_{iEU} are the standardized values of the PU, LU, and EU of study unit i, respectively; and UL_i is the integrated urbanization level of study unit i [23].

2.2.2. Bivariate Spatial Autocorrelation

Bivariate spatial autocorrelation was employed to analyze the geospatial correlation between the UL and NPP [26]. Local bivariate spatial autocorrelation is an extension of the traditional spatial autocorrelation analysis and is often used to test the possibility of local correlation properties between two systems with different spatial locations. The calculation formula is:

$$I_{UL\sim NPP} = \frac{UL_i - \overline{UL}}{\sigma_{UL}} \cdot \sum_{j=l}^{n} \left(W_{ij} \frac{NPP_j - \overline{NPP}}{\sigma_{NPP}} \right) \tag{3}$$

where W_{ij} is the spatial weight matrix; UL_i and NPP_j are the UL and NPP of units i and j, respectively; and σ_{UL} and σ_{NPP} are the variances of the UL and NPP, respectively. Generally, bivariate spatial autocorrelation LISA plots can be classified into four cluster types: High–High, High–Low, Low–High, and Low–Low, where High–High and Low–Low indicate that urbanization and NPP are positively correlated and clustered in local areas; for example, High–High means that the urbanization of a place is high and that NPP is also relatively high, and this phenomenon shows the clustering tendency in local space. High–Low and Low–High indicate that urbanization and NPP are negatively correlated and clustered in local areas; for example, High–Low means that the urbanization of a place is high and that NPP is relatively low, and this phenomenon shows the clustering tendency in local space.

2.2.3. Spatial Regression Analysis

Spatial regression models were used to investigate the spatial driving effects of urbanization on NPP. Among them, the SDM is used to monitor the overall driving effect of urbanization on NPP from a global perspective. The method is an extension of the spatial lag and spatial error models, integrating the quantitative advantages of both for exogenous and endogenous interaction effects of variables, and can be used to decompose the driving effects into direct and spillover effects based on PDEs [27]. The formula is as follows:

$$NPP_{it} = \rho WNPP_{it} + \beta(UL_{it} \sim PRE_{it}) + \theta W(UL_{it} \sim PRE_{it}) + \varepsilon_{it} \tag{4}$$

where NPP_{it} is explanatory variable NPP for region i in period t; UL_{it}~PRE_{it} are the explanatory variables for region i in period t, containing the key explanatory variable UL and other control variables; ε is the random disturbance term of the normal distribution; ρ, β, and θ are the parameters to be estimated; W is the spatial weight matrix; WY is the spatial lagged dependent variable; and WX is the spatial error independent variable.

Logarithmization and normalization were used to eliminate the influence of variable heteroskedasticity, and the variance inflation factor (VIF) was used to determine possible multicollinearity. We referred to Du et al. (2021) and Wei et al. (2021) to verify the need to use spatial effects and spatial Durbin models using Lagrange multipliers (LM) and likelihood ratio estimation (LR), respectively [28,29]. The GWR model focuses on the effect of spatial heterogeneity in local areas on the overall regression fitting and is often used to test individual spatial variations in regression coefficients [30]. The local variation effect of the UL on NPP was computed on the GWR tool of the ArcGIS platform using the following model:

$$NPP_{it} = \rho WNPP_{it} + \beta(UL_{it} \sim PRE_{it}) + \theta W(UL_{it} \sim PRE_{it}) + \varepsilon_{it} \quad (5)$$

where (u_i, v_i) are the geographic location coordinates of region i; β_i is the geospatial location function of region I; and UL_i~PRE_i are the explanatory variables for region i, containing the key explanatory variable UL and other control variables.

2.3. Data Sources

In this study, NPP was the dependent variable, and the data were taken from the MOD17A3 global net primary productivity product provided by NASA. The UL was the key explanatory variable, encompassing population, land, and economic urbanization. Drawing on the studies by Peng et al. (2021) and Wang et al. (2021), these indicators were quantified in terms of the ratio of urban population to the total population, the ratio of urban land to the total area, and GDP density, respectively [24,27]. The data were obtained from LandScan Global Vital Statistics Analysis Database, and the land use remote sensing dataset and GDP density spatialized dataset provided by Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences, respectively. Supported by the studies by Yue et al. (2022), Wang et al. (2016), and Sun et al. (2016), we selected elevation, temperature, and precipitation as control variables [31–33]. These data were mainly from Geospatial Digital Cloud Platform of Chinese Academy of Sciences and National Earth System science Data Center [34]. Table 1 summarizes the basic attributes and data sources used in this study.

Table 1. Data sources for the various parameters.

Data Type	Variable	Unit	Data Name	Data Source	Spatial Resolution
Socioeconomic	Population urbanization (PU)	%	LandScan spatial grid datasets for 2000, 2010, and 2020	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences (http://www.resdc.cn) (accessed on 7 February 2022)	1 km
	Land urbanization (LU)	%	Land use data for 2000, 2010, and 2020	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences (http://www.resdc.cn) (accessed on 7 February 2022)	30 m
	Economic urbanization (EU)	CNY/km^2	GDP density grid datasets for 2000, 2010, and 2020	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences (http://www.resdc.cn) (accessed on 7 February 2022)	1 km

Table 1. *Cont.*

Data Type	Variable	Unit	Data Name	Data Source	Spatial Resolution
Natural	Elevation (ELE)	m	DEM digital elevation data	Geospatial Digital Cloud Platform of Chinese Academy of Sciences (http://www.gscloud.cn/sources/index) (accessed on 20 March 2022)	90 m
	Average annual precipitation (PRE)	mm	China's monthly precipitation data for 2000, 2010, and 2020	National Earth System Science data (http://www.geodata.cn/) (accessed on 20 March 2022)	1 km
	Average annual temperature (TEM)	°C	China's monthly temperature data for 2000, 2010, and 2020	National Earth System Science data (http://www.geodata.cn/) (accessed on 20 March 2022)	1 km
	Net primary productivity (NPP)	g^*c/m^2	NPP data from MODIS-MOD17A3	MODIS-17A3HF data products are available on the NASA website (https://modis.gsfc.nasa.gov/) (accessed on 20 March 2022)	500 m

3. Results

3.1. Spatio-Temporal Evolutionary Pattern of NPP

Based on the ArcGIS platform, NPP was summed and averaged over 21 years, and the spatial distribution map of the mean NPP from 2000 to 2020 was obtained (Figure 3a). The results indicated that the NPP of CUA was geographically and spatially distributed; the main urban areas of Chengdu and Chongqing served as low-value cores, exhibiting a distribution pattern of "low in the middle and high in the surroundings". The reason could be that the main urban areas had a strong population concentration and high urban development intensity, resulting in high levels of urban landscape fragmentation and impervious surface coverage. Compared with remote mountainous regions with a relatively low human footprint, urban development can have profound changes to the surface structure and ecosystem functions (Figure 3b). The results also showed significant clustering of low-value-NPP areas along railroads, roads, and waterways, which may be linked with settlement location preferences and the long history of development along transportation routes. In addition, the overall NPP level of the urban agglomeration showed a fluctuating upward trend from 2000 to 2020, with the NPP reaching its highest value in 2019 (640.59 g^*c/m^2) (Figure 3c). The mean NPP increased from 451.76 g^*c/m^2 in 2000 to 629.01 g^*c/m^2 in 2020 at an annual growth rate of 1.59%. This suggested that the CUA's vegetation and associated ecosystem functions were restored to some extent during the study period.

Figure 4 was generated with the ArcGIS zoning statistics tool and interpolation technique. The township-level NPP values were classified into five categories (i.e., low, relatively low, ordinary, relatively high, and high) using natural breakpoints to better assess the spatial evolution trend. The results showed that NPP values exhibited a continuous growth trend, increasing from 397.71 g^*c/m^2 in 2000 to 470.61 g^*c/m^2 in 2010 and then to 575.87 g^*c/m^2 in 2020. In terms of spatial evolutionary trends, a low-value area gradually formed with the CUA's urban center as the core, and two low-level areas in the main urban areas of Chengdu and Chongqing spread outward over time. The low-level areas in Suining, Guang'an, and Nanchong gradually shrank over time, while the high-level areas in the southwest and southeast mountains continued to expand.

3.2. Spatio-Temporal Correlation Effects of UL and NPP

The global Moran's I values at the township level were −0.357, −0.468, and −0.409 in 2000, 2010, and 2020 (p-value = 0.0001), indicating a significant negative spatial autocorrelation between the UL and NPP. Figure 5 shows the bivariate local correlations between the UL and NPP for 2000, 2010, and 2020. "Low-High" was the main clustering type, but it decreased over time from 15.60% in 2000 to 13.88% in 2020 (Table 2). Compared with positively correlated clusters that significantly declined (from 7.83% in 2000 to 3.82% in

2020), the proportion of negatively correlated cluster townships remained stable, averaging 21.38% during the study period; this suggested widespread spatial conflict between the UL and NPP. The results indicate an urgent need to adjust urbanization paths to reduce constraints on regional vegetation ecological security and maintain carbon cycle functions.

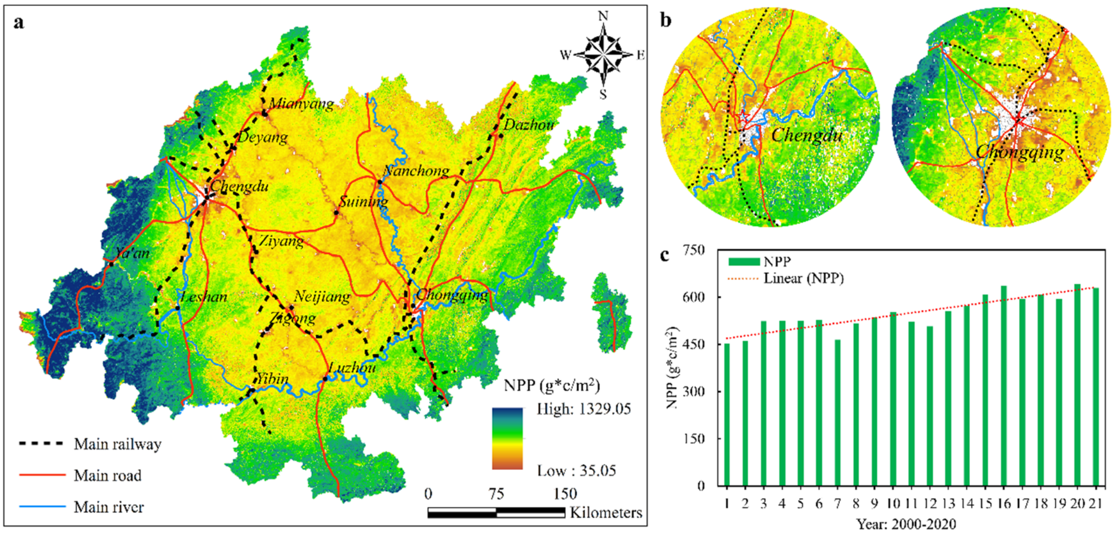

Figure 3. Average NPP distribution of CUA: 2000–2020 (**a**), NPP distribution of core cities (**b**), and temporal evolution trend of NPP (**c**).

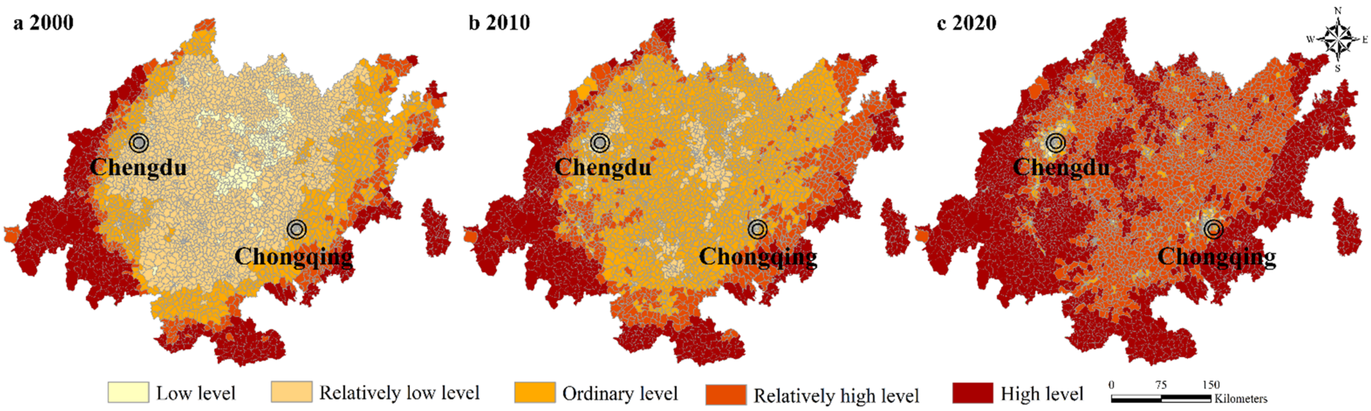

Figure 4. Spatial distribution pattern of NPP in CUA in 2000, 2010, and 2020.

Table 2. Percentage of bivariate spatial autocorrelation cluster types.

Cluster Type	2000	2010	2020
High–High	1.56%	1.17%	1.70%
Low–Low	6.27%	1.34%	2.12%
Low–High	15.60%	15.24%	13.88%
High–Low	6.21%	6.74%	6.46%

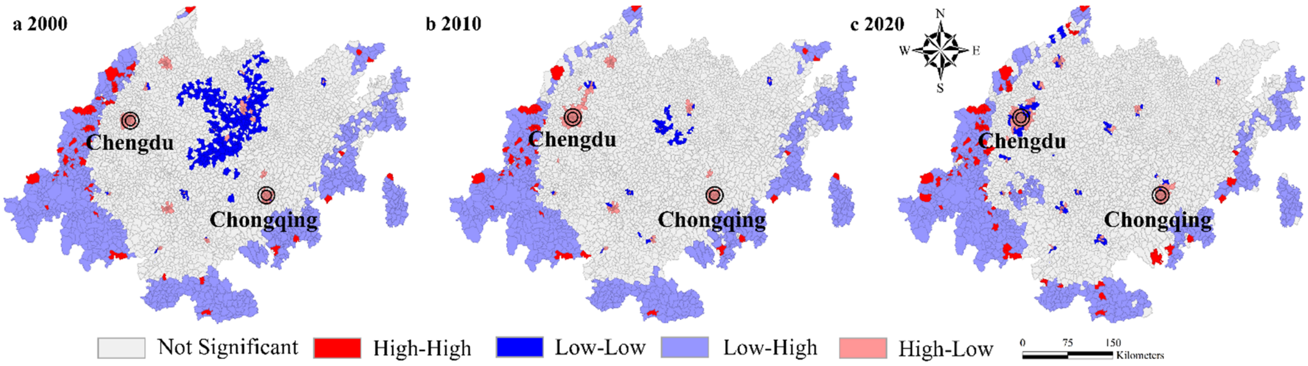

Figure 5. Bivariate spatially correlated clusters of UL and NPP in CUA.

In terms of spatial evolution, in 2000, the "High-Low" negatively correlated cluster was concentrated in the main urban areas of Chengdu and Chongqing, while the "Low-High" negatively correlated cluster was widely distributed in the mountainous areas in the southwest and southeast. Compared with the high-intensity urban centers of Chengdu and Chongqing, these mountainous areas have an excellent natural base, complex topography, and relatively minimal human footprint, resulting in low urbanization levels and a well-established vegetation ecological system. There were fragmented "High-High" positively correlated clusters found in the marginal mountainous areas. This may have been due to the fact that while some mountainous cities in the CUA may have large population concentrations and high urbanization levels in their urban centers, their excellent natural ecosystems could have offset some encroaching effects of urbanization construction on NPP. In 2010 and 2020, the bivariate spatial correlation structure evolved steadily, with the "High-Low" negatively correlated clusters extending outward from the main urban areas of Chengdu and Chongqing, while the "Low-Low" clusters concentrated in Suining, Guang'an, and Nanchong in 2000 shrank and converged to 1.70% in 2020.

3.3. Global and Local Estimation of the Impact of UL on NPP

3.3.1. Spatial Regression Results on the Global Scale

After logarithmization and normalization, all variables passed the VIF test. The LM test for spatial lag and spatial error, LR-SLM, and LR-SEM significantly rejected the original hypothesis at the 1% confidence level. Based on the results, the SDM was selected to fit the driving effects of the UL on NPP. As shown by the regression results in Table 3, there was an increasingly negative effect of urbanization on NPP as the absolute value of the UL regression coefficient increased. Altitude showed a positive correlation with NPP, but the intensity gradually weakened over time. There was a negative correlation between temperature and NPP, which gradually increased.

Referring to LeSage (2010) and Wei (2021), the regression effect of the UL was further decomposed into direct and spillover effects using PDEs to measure the impact of variable externalities [29,35]. The UL had significant negative direct and spillover effects on NPP, and the strength of the effect intensified throughout the study period. Compared with 2000, the elasticity coefficients of the direct and spillover effects of the UL in 2020 jumped by 73.53% and 26.85%, respectively. This meant that the UL exhibited increasingly strong negative effects on NPP, both locally and in adjacent areas. In addition, the UL's spillover effects were consistently more intense than its direct effect. For example, the spillover effect in 2020 was −1.002, considerably stronger than the local direct effect (−0.118). In this sense, our study not only confirms the negative impact of urbanization on regional vegetation ecosystems but also substantiates the need for joint ecological management.

Table 3. Estimation results of spatial Durbin model.

Variable	2000	2010	2020
UL	−0.045 *** (−8.980)	−0.056 *** (−19.478)	−0.066 ** (−2.179)
ELE	−0.003 (−0.385)	0.204 *** (9.036)	0.022 * (1.850)
TEM	−0.016 ** (−2.191)	−0.037 * (−1.751)	−0.070 ** (−2.594)
PRE	0.002 (0.425)	0.017 (0.936)	−0.013 (−1.372)
W*UL	−0.016 *** (−2.593)	−0.059 *** (−6.987)	−0.103 *** (−10.398)
W*ELE	0.061 *** (6.003)	0.045 *** (3.474)	0.059 *** (3.750)
W*TEM	0.011 (0.808)	−0.004 (−0.248)	0.004 (0.257)
W*PRE	−0.003 (−0.256)	0.009 (0.494)	0.008 (0.422)
Direct effect (UL)	−0.068 ** (−1.707)	−0.073 *** (−13.259)	−0.118 *** (−2.673)
Spillover effect (UL)	−0.733 *** (−8.455)	−0.852 *** (−4.432)	−1.002 *** (−2.788)
R-suqared	0.536	0.664	0.522

Notes: *, **, and *** indicate the significance at the confidence levels of 10%, 5%, and 1%, respectively.

3.3.2. Spatial Regression Results on the Local Scale

In the GWR estimation, the adjusted R^2 values were 0.567, 0.626, and 0.731 in the three periods; the Sigma values were 0.133, 0.122, and 0.137, and the AICc values were −4219.725, −4659.477, and −3979.206, respectively. The results demonstrated that the driving effect of the UL on NPP was characterized by significant local non-stationarity in the geographic space, validating the rationality and necessity of investigating the driving effects from a local perspective. Over time, this non-stationarity pattern gradually shifted towards homogeneity (Figure 6). Specifically, the UL coefficients in the GWR model showed a negative driving effect consistent with the SDM analysis of the entire urban agglomeration. In 2000, NPP in Chongqing city, Xuanhan county, and Shimian county was impacted the strongest by UL, while that in Nanchong, Dazhou, Guang'an, Suining, and Ziyang received the weakest impact. In 2010, the low-level clusters in the northern part became fragmented, and NPP in Gulin, Gongxiang, and Fengdu counties was the most affected by the UL. In 2020, low-value areas further contracted to the main urban areas of Dazhou, while NPP in other areas mostly suffered a negative impact to the same extent (regression coefficient between −1.499 to −0.850), with the strongest negative impact being found in Fengdu County, Fuling District, Yunyang County, and Kaizhou District.

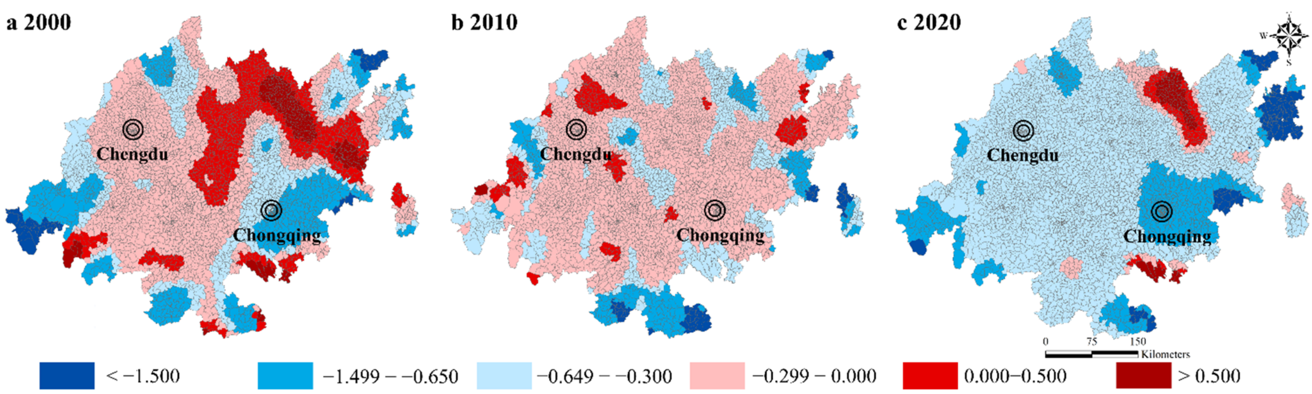

Figure 6. Spatial distribution pattern of regression coefficient of UL.

4. Discussion

4.1. Differences in Global Estimates and Local Effects of Urbanization Impact on NPP

Previous studies have supported the notion that urbanization considerably affects regional NPP [36]. However, most studies have centered their analysis around a single dimension (e.g., population, land, or economic urbanization). For example, Qiao et al. (2018) concluded that rapid urban expansion, which leads to increased built-up and urban development, is the main reason for the decline in NPP [37]. Since urbanization is highly complex, involving multiple elements, such as population concentration, land expansion, and economic growth, it would not be objective to quantify urbanization's ecological impact through a single indicator [38,39].

Our study evaluated how comprehensive urbanization (i.e., population, land, and economic urbanization) impacted NPP in the CUA for providing a more comprehensive perspective on how urban development affects vegetation ecological functions [40]. The findings not only highlight the contributions of urbanization to the derogation of NPP but also reveal its widespread negative spillover impact on adjacent areas, with continually growing intensity. The direct shocks from local urban construction activities, and regional integration can be used to explain these phenomena [41]. Increased population and economic urbanization could intensify resource utilization, encroaching over environmental lands and disrupting ecological systems, while land urbanization could significantly transform the land-use structure, converting critical carbon sinks (e.g., forests and grasslands) into impervious surfaces, which could limit regional carbon cycle capacity and other ecosystem functions [42]. In addition, resource consumption from population migration, economic construction, and land urbanization, supported by regional integration, may generate synergistic effects on the consumer markets of neighboring cities, indirectly leading to cross-regional ecological consumption [43]. This generates a realistic value that it is necessary to pay more attention to the intra-regional transmission effects of rough resource consumption behaviors in urbanization processes, and the joint governance of vegetation production capacity and ecological protection should be given more consideration.

In addition to the global effects, the intrinsic variability of the urbanization effects on NPP was considered when analyzing the driving effect at the township level. The results indicate a local non-stationarity feature of the driving effect. The spatial heterogeneity of the ecological effects of urbanization could be related to variations and differences in the natural base, economic level, population size, urban construction, and environmental regulations among regions [23,43]. For example, as shown in Figure 6, Chonqing's urbanization had a stronger negative impact on NPP in 2000 and 2020, mainly due to the city's high-intensity production and urban expansion threatening the ecological carrying capacity, limiting the ecological functions and productivity of its vegetation (in 2020, Chongqing townships exceeded the average population, economic, and land urbanization levels by 31.61%, 73.51%, and 28.24%, respectively). In comparison, the impact of urbanization on NPP was relatively weak in Dazhou and Ziyang, which could have been related to the ecological management of their local governments [44]. In Dazhou, for example, numerous environmental measures and strategies, such as the ecological benefit compensation fund, forest planting activities, and environmental protection plans, have been implemented, which have greatly restrained the adverse effects of anthropogenic activities on vegetation ecosystems. This generates a socio-economic value that indicates the need for more targeted vegetation restoration and ecological management, targeted according to regional and local urban conditions and the ecological base, promoting sustainable urban development, resource use efficiency, and environmental conservation.

4.2. Policy Implications, Study Limitations, and Future Research

Our study confirms a fluctuating upward trend of NPP in the CUA from 2000 to 2020. However, the NPP values did not uniformly increase across the urban agglomeration, especially since we found low-value-NPP areas in the urban centers of Chengdu and Chongqing. The upward trend also did not corroborate the ineffectiveness of the impact of urbanization, similar to the findings of Pei et al. (2015) [5]. In fact, our results emphasize the constraints and weakening effect of rapid urbanization on NPP. Possible mechanisms for the divergence of negative urbanization effects and NPP growth trends from the urban agglomeration perspective may be related to ecological resilience. The superior vegetation cover systems and carbon sequestration capacity in southwest China due to the high-quality ecological substrate contribute to increase an area's ecological resilience from the adverse impact of urbanization. In contrast, the rapid expansion of impervious surfaces in urban centers can disrupt ecological resilience and constrain ecosystem functions, particularly vegetation carbon cycling [45–47]. This has led to an overall upward trend of NPP despite the encroachment of urbanization. Based on this, there is still some work worthy of attention on the maintenance of vegetation ecosystems in the urbanization process.

Green development should be the core of urban planning and design. Ecological corridors and urban parks should be incorporated into city plans, and considerable vegetation cover should be maintained in urban districts to minimize the anthropogenic impact on ecosystem functions. Strategies should be adopted toward more efficient land use, and proper control and management of undeveloped land should be implemented to mitigate the negative ecological effects of urban expansion. For population urbanization, green consumption and environmental protection should be promoted, focusing on people-oriented conservation strategies. In terms of economic urbanization, resource allocation and use should be further optimized, emphasizing green industrial transformation and low-carbon production processes to reduce excessive consumption and promote long-term sustainability. To address the negative spillover effects of urbanization, regional joint ecological governance should be promoted, and ecological information sharing and monitoring between agencies and local governments should be further strengthened. Policymakers should optimize the urbanization paths of urban agglomerations from an overall perspective and encourage cooperation to support industrial low-carbon transformation, integrated urban–rural low-carbon development and regional green ecological space governance, which would reduce urbanization constraints on NPP. Considering the regional variability of the impact of urbanization on NPP, place-based ecological management policies should be adopted. Ecological management strategies should be developed based on local environmental, population, and economic conditions.

There are some shortcomings in this study that should be considered when interpreting the results. The drive effect analysis was based on a regression model that used cross-sectional data; this meant that the status of the drive effect could only be observed at one point, and its evolution could not be evaluated. Future studies should try to adopt spatial panel regression models, such as the spatial panel Durbin model (SPDM) and GTWR, to measure the mechanism of the stage-specific urbanization effects on NPP. The driving mechanisms of NPP caused by activities within urbanization (e.g., industrial construction, transportation, population migration, housing construction, etc.) were also not further quantified, although we discussed their effects. In the future, we will focus on the integrated driving mechanisms of urbanization-related socioeconomic indicators on NPP based on the availability of data.

5. Conclusions

Previous studies have rarely considered the driving effect of comprehensive urbanization on local and neighborhood NPP and have largely overlooked the regional variability of driving effects. This study analyzed the spatio-temporal evolution of NPP in the CUA at the township level from 2000 to 2020, developing comprehensive indicators that combined population, land, and economic urbanization and evaluating global and local urbanization impacts based on SDM and GWR models.

Some interesting conclusions were drawn: (1) From 2000 to 2020, the average NPP increased by 177.25 g^*c/m^2 at an annual growth rate of 1.59%, showing a spatial distribution pattern of "low in the middle and high in the surroundings". There were also significant low-value agglomerations found along major traffic arteries and rivers. (2)

The low-value-NPP areas exhibited a clear tendency to distribute in urban central areas. Low-value agglomerations were found in the main urban areas of Chengdu and Chongqing that spread outward, while high-value areas located in the mountainous areas in the southwest and southeast accelerated expansion. (3) Negative correlation was the main spatial correlation between the UL and NPP. The "Low-High" negative correlation cluster was the most abundant cluster type and could mainly be found in the southwest and southeast mountainous areas of the CUA. (4) The UL had a significant negative driving effect on NPP in both local and neighboring areas. The results indicated local non-stationarity characteristics of the driving effect and the prevalence of negative urbanization shocks. Based on the research results and the concept of "people-land harmony", new insights and strategies are proposed for the synergistic management of regional ecology and the optimization of population, economy, and land urbanization. Overall, compared with previous studies on the association effect of urbanization and NPP, our study not only verifies that a progressively stronger negative spatial externality effect of urbanization is prevalent in the adjacent areas. More importantly, the adoption of place-specific ecological governance strategies and urbanization optimization paths is supported in the GWR analysis.

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