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Research Article

Comprehensive Assessment of the Effect of Urban Built-Up Land Expansion and Climate Change on Net Primary Productivity

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Urbanization is causing profound changes in ecosystem functions at local and regional scales. The net primary productivity (NPP) is an important indicator of global change, rapid urbanization and climate change will have a significant impact on NPP, and urban expansion and climate change in different regions have different impacts on NPP, especially in densely populated areas. However, to date, efforts to quantify urban expansion and climate change have been limited, and the impact of long-term continuous changes in NPP has not been well understood. Based on land use data, night light data, NPP data, climate data, and a series of social and economic data, we performed a comprehensive analysis of land use change in terms of type and intensity and explored the pattern of urban expansion and its relationship with NPP and climate change for the period of 2000–2015, taking Zhengzhou, China, as an example. The results show that the major form of land use change was cropland to built-up land during the 2000–2015 period, with a total area of 367.51 km^2 converted. The NPP exhibited a generally increasing trend in the study area except for built-up land and water area. The average correlation coefficients between temperature and NPP and precipitation and NPP were 0.267 and 0.020, respectively, indicating that an increase in temperature and precipitation can promote NPP despite significant spatial differences. During the examined period, most expansion areas exhibited an increasing NPP trend, indicating that the influence of urban expansion on NPP is mainly characterized by an evident influence of the expansion area. The study can provide a reference for Zhengzhou and even the world's practical research to improve land use efficiency, increase agricultural productivity and natural carbon sinks, and maintain low-carbon development.

1. Introduction

As an important part of the global carbon cycle, the terrestrial biosphere is affected by urban expansion and climate change [1–3]. The trend of global terrestrial net primary productivity (NPP) is still uncertain [4]. In the context of climate change, the threat of rapid global urbanization to terrestrial ecosystem productivity, environment, livelihoods, and food security has gradually become one of the most critical issues in the world [5, 6]. The net primary productivity refers to the amount of organic matter accumulated by green plants in unit time per unit area [7, 8]. It is an important indicator in the determination of the carbon source, carbon sink health, and sustainable development of ecosystems and is the main factor regulating ecological processes. It also helps in assessing the carrying capacity of

ecosystems [9–11]. Terrestrial vegetation provides a great deal of food, fuel, and building materials for human beings; therefore, in the context of global change, more and more researchers are beginning to pay attention to the trend of NPP in terrestrial ecosystems [12].

With the rapid growth in the world economy, urbanization is increasing. Urbanization is a complex process involving population transfer, land use change, urban function change, and urban form [13, 14]. Urbanization-induced changes may have a significant impact on the ground and thus affect the structure and function of ecosystems, as well as regional climates [15–17]. Therefore, studying the response of NPP to urban expansion and climate change can provide a better understanding of the function of ecosystems, which is important for balancing the relationship between development and environment and for the rational use of natural resources [18–20]. The NPP is an important ecological indicator for judging sustainable development and can help assess the carbon budget of terrestrial ecosystems [9, 21, 22]. The NPP has been widely used to monitor the state of carbon cycles in regions of different sizes [23–25]. Changes in NPP over a specific period can help quantify vegetation growth, which is related to the amount of vegetation and the environment in which it grows. Different models have been used to enrich the research results provided by NPP trends, primarily at a global level [26, 27], at a national level [28], and in ecosensitive areas [22, 29]. By comparing annual and seasonal NPP estimates from 15 global models in latitude zones and biomes, Cramer et al. [26] found that NPP estimates vary over time and space. Most previous research studies have been conducted at the global, national, or other macrolevels; studies at the city level are limited. The impact of urbanization on terrestrial ecosystems has been assessed based on the NPP indicator [30–32]. In addition, model estimation is a convenient method for determining NPP, as field measurements require significant human and material resources and data on urban areas, which are difficult to obtain. With the development of remote sensing technology, the surface information of any region can be comprehensively and continuously obtained [26, 33]. To analyze the impact of urban expansion on NPP in the past few decades, a long-term NPP time series with a high time resolution is required. The spatial distribution of NPP in urban areas can be determined using data from the moderate resolution imaging spectroradiometer (MODIS), with proven accuracy. The spatial changes in NPP in urban areas can thus be better reflected.

The response of NPP to urban expansion and the factors influencing NPP have been widely studied [34, 35]. Most studies have shown that urban landscape and land use changes lead to carbon loss [36] and that land use changes have a negative impact on urban NPP [37]. However, these studies employed two time nodes when quantifying the impact of land use change on NPP and only few studied the spatialization of land expansion by urbanization and the impact of land expansion on NPP from a time and space perspective. Several scholars have relied on DMSP/OLS night light data to carry out a wide range of spatial research,

such as those on population migration [38], anthropogenic carbon emissions [39, 40], and night lighting data particularly for determining built-up land and other aspects for a wide range of applications [41, 42], with good results. However, these studies were limited to the time period from 1992 to 2013; only few scholars have connected MODIS and NPP-VIIRS (Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-Orbiting Partnership (Suomi NPP) spacecraft) to simulate urban expansion [43]. Appropriate time series updates are thus required. The factors influencing NPP include land use change, vegetation, climate, and topography. Although the factors influencing NPP have been widely studied, particularly the correlation between NPP and climate factors, the studies have primarily focused on a single dynamic change perspective. In other words, the correlation between climate change and NPP change was analyzed by establishing a relationship between them, with few comprehensive studies on the impact of land expansion combined with climate factors on NPP. Therefore, quantifying the impact of human activities and climate change on NPP is an important step in formulating sustainable development of urban ecosystems in the context of climate change and human activities.

Henan province is located in central China, has a temperate continental climate, and is suitable for multicrop growth. This province is known for its agriculture, grain, and population. Zhengzhou is the capital of Henan province and is China's national center. In recent years, with the change in national policies, urbanization and industrialization have been taking place at a rapid rate, leading to an increase in the number of urban areas and population explosion. The urban landscape in Zhengzhou has undergone rapid changes, which has affected the local ecological environment. In this study, we used relevant data to analyze the response of NPP to urban expansion and climate change in Zhengzhou during the period of 2000–2015. We provide a reference for urban land use and ecological environment development in the regional centers of developing and agricultural countries. This study can fill the gaps discussed above, including broadening the time series of night lighting data, innovatively combining two kinds of night lighting data to simulate the change of urban construction land, and comprehensive studies on the impact of land expansion combined with climate factors on NPP. Strong data and new method will enhance the accuracy compare with previous studies. Detailed contents of this research include the following: (1) analysis of land use type changes and NPP changes; (2) analysis of the relationships between NPP and climate factors; (3) analysis of changes in land use intensity and urban built-up area; (4) exploration of the impact of urban built-up land on NPP change.

2. Materials and Methods

2.1. Study Area. Zhengzhou is the capital of Henan province, bordering the Yellow River in the north (Figure 1). It is located at $112°42'–114°14'$E and $34°16'–34°58'$N. The region has a warm temperate continental climate, with an annual precipitation of approximately 639.2 mm and an average
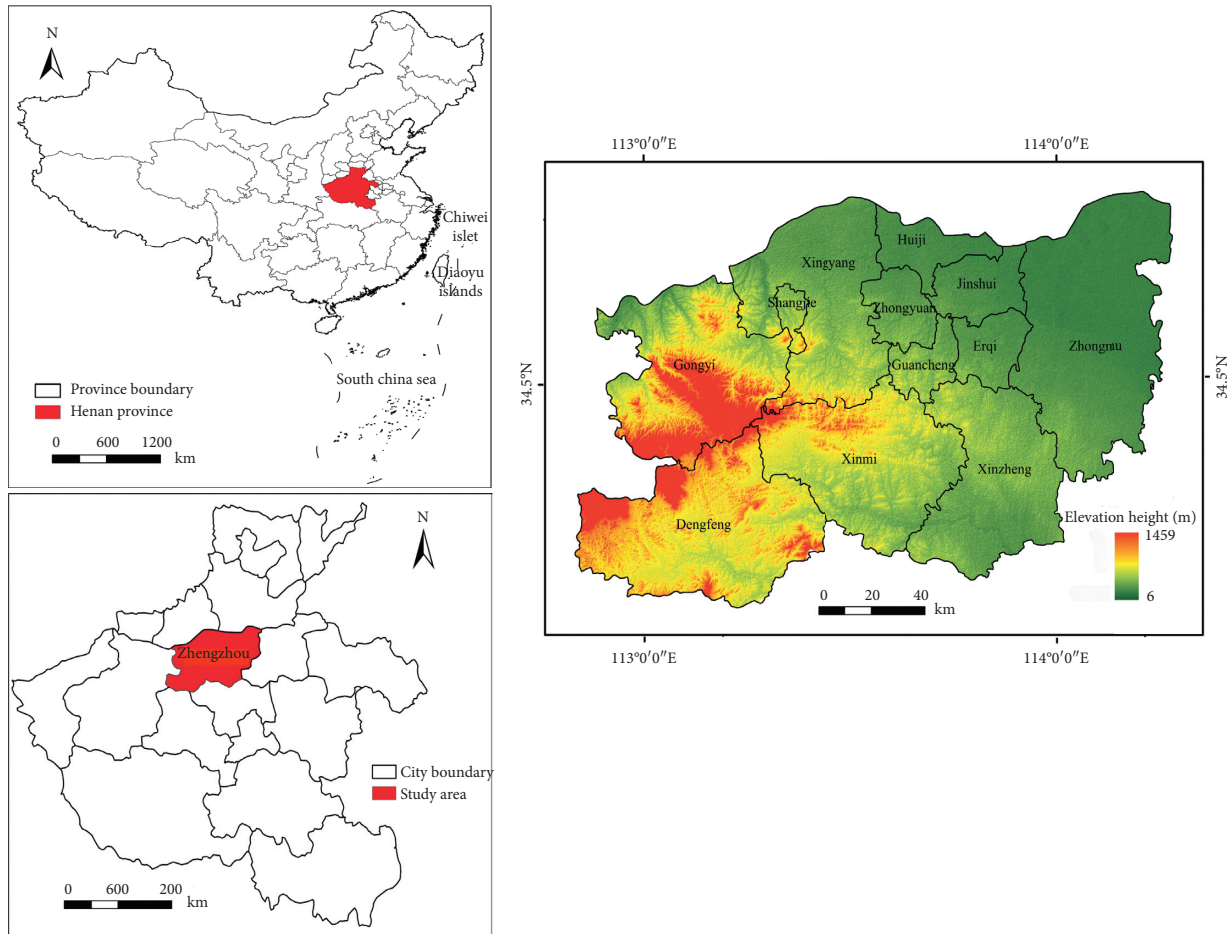
Figure 1: The location of study area.

annual temperature of 14.2°C. The dominant striped vegetation is the temperate deciduous evergreen mixed broad-leaved forest belt, and the distribution of the flora is in the middle north temperate zone and east Asia. By 2018, Zhengzhou had a total area of 7446 km², a built-up land area of 830.97 km², a total population of 101.36 million, and a total GDP of 101.433 billion yuan. In recent years, due to policy guidance, urbanization in Zhengzhou has been accelerating, and the urbanization rate in 2018 reached the top of the national rate of growth, at 1.59%. This rapid urbanization process is accompanied by several urban land development projects; land use change is thus inevitable.

2.2. Data Sources. The datasets used in this study and data preprocessing conducted are as follows:

(1) The land use data for 2000, 2005, 2010, and 2015 in period of 2000–2015 were derived from the Resource and Environment Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). The socioeconomic data were derived from the statistical yearbook of Henan Province and Zhengzhou City (Henan statistics bureau Henan general team of investigation under the NBS, 2001–2016; Zhengzhou statistics bureau Zhengzhou general team of investigation under the NBS, 2001–2016). The climate data between 2000 and 2015 in Zhengzhou was extracted from the whole 745 meteorological stations, which were obtained from the China meteorological data network (http://data.cma.gov.cn/).

(2) The MODIS NPP data for the period of 2000–2015 were downloaded from the Numerical Terradynamic Simulation Group (NTSG) of the University of Montana (http://www.ntsg.umt.edu/). In general, the accuracy of MODIS NPP estimates has been proven to be consistent with the NPP observed on-site [44]. The dataset is in TIF format with a resolution of 30 arcsec (approximately 1 km). We extracted the Chinese NPP from the global map and excluded nonvegetation areas.

(3) Night lighting data for the period of 2000–2015 and DMSP-OLS night stable light (NSL) data for the period of 2000–2013 were obtained from NASA's (http://ladsweb.nascom.nasa.gov) data archiving and distribution system. The stable light data include lights from cities, towns, and other places with

persistent light sources, with the background noise eliminated. The NPP-VIIRS NSL data for the period of 2014–2015 were obtained from the National Environmental Information Center website (https://www.ngdc.noaa.gov). Prior to data processing, the monthly average data of 2014 and 2015 from January to December were combined into annual data through ENVI 5.1. NPP-VIIRS NSL data processing included noise cancellation and continuity correction of OLS night light data using DMSP-OLS.

First, the DMSP-OLS night light data of 2013 were extracted as a dark background mask, and the mask was then used to remove unexpected noise from the NPP-VIIRS night lighting data for 2014 and 2015.

Second, according to Li et al. [45], the average light value (DN) of the NPP-VIIRS night light data is exponentially correlated with the DN value of DMSP-OLS night light data. Accordingly, we can obtain the corrected NPP-VIIRS night light data. The formula is as follows:

$$Y = a * X_b. \tag{1}$$

After further processing, equation (1) can be converted to the following:

$$X = e^{((\ln Y - \ln a)/b)}. \tag{2}$$

Here, Y represents the DN value of DMSP-OLS night light data, X represents the DN value of NPP-VIIRS night light data, and a and b are coefficients.

(4) The temperature and precipitation data in the 2000–2015 time series were derived from the Resource Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/doi/doi.aspx?doiid=32).

2.3. Methods

2.3.1. NPP Trend Analysis.
The trend of change in NPP at the cell level is analyzed and predicted using a one-way linear regression analysis, and the formula is as follows:

$$\text{Slope} = \frac{n \times \sum_{i=1}^{n} i \times \text{NPP}_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} \text{NPP}_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i^2\right)}. \tag{3}$$

Here, n represents the number of years ($n = 16$), NPP_i is the NPP for year i ($i = 1, 2, 3, \ldots, 16$), and *slope* is the slope for the NPP at the individual cell level of the slope. If the slope > 0, an increasing trend is indicated; the greater the value, the more evident the increasing trend. If the slope < 0, a decreasing trend is indicated; the lower the value, the more evident the decreasing trend.

2.3.2. Correlation Analysis.
The trend of change in NPP and the temperature and precipitation correlation coefficient on the space-time scale can be calculated using the Pearson correlation coefficient method. The correlation coefficient (R_{xy}) is calculated as follows:

$$R_{xy} = \frac{\sum_{i=1}^{n} \left[(x_{ij} - \overline{x}_j)(y_{ij} - \overline{y}_j) \right]}{\sqrt{\sum_{i=1}^{n} (x_{ij} - \overline{x}_j)^2 \sum_{i=1}^{n} (y_{ij} - \overline{y}_j)^2}}. \tag{4}$$

Here, n is the year serial number, x_{ij} is the value of the NPP in the first year of the j cell, and x_j is the average of the NPP j cell over 16 years, i.e., from 2000 to 2015. Similarly, y_{ij} is the value of the first j cell of temperature or precipitation, and y_j is the average of the first j cell of temperature or precipitation over the 16 years of 2000–2015. To check the validity of the model, a p-test was used, and the tendencies were classified into 3 categories: highly significant, significant, and no significant change.

2.3.3. Urban Built-Up Land Expansion Simulation.
It is of great significance to understand the spatial expansion trend of urban built-up land for guiding the rational expansion of urban land [46–51]. Night light data is a common kind of remote sensing data analyzing the city scale [52–54]. The average night light data constitute a cloudless composite map generated by the DN value for each time period, with a spatial resolution of 1 km. The night lighting data from DMSP-OLS provides a tool for monitoring urban sprawl from time and space perspectives [55, 56]. The city area is determined by the threshold of the DN. If the DN of the region is greater than the threshold, the region is defined as a city. Different scenarios for the total urban area are obtained by changing the threshold of DN. When the simulated total urban areas are close to each other, the threshold of DN is noted in the urban land use census data and applied to the process of measuring urban expansion. The recorded nighttime light image data were used as an indicator of urban expansion.

2.3.4. Land Use Intensity.
In recent years, Zhengzhou has experienced rapid urbanization, with a significant growth in economic development, leading to an increase in population and resource consumption. The land use intensity has changed dramatically. In this study, seven indicators were selected to measure the change in land use intensity: urban population, GDP, industrial output, agricultural output, fixed asset input, quantity of shipments, and electricity consumption.

3. Results

3.1. Changes in Land Use Types.
To determine the land use change in Zhengzhou during the period of 2000–2015, the land use transfer matrix for the period was obtained (Table 1). Table 1 shows that the transfer of cropland to built-up land is the main form of land use transfer; the area is approximately 367.51 km^2, accounting for approximately 51.08% of the total land use transfer area. Water area is the second largest type of land occupied by cropland in addition

TABLE 1: Land transfer matrix between 2000 and 2015 (km^2).

2000	2015						
	Cropland	Forest	Grassland	Water area	Built-up land	Unused land	Total
Cropland	**4475.95**	30.89	33.07	103.77	367.51	0.14	5011.32
Forest	32.37	**709.01**	9.20	1.89	11.27	0.16	763.89
Grassland	31.52	11.08	**645.12**	1.36	3.32	0.00	692.39
Water area	19.99	2.06	0.47	**166.54**	11.69	0.00	200.76
Built-up land	43.28	0.89	0.87	1.84	**801.72**	0.03	848.62
Unused land	0.09	0.15	0.05	0.10	0.43	**2.61**	3.42
Total	4603.19	754.06	688.77	275.50	1195.94	2.94	**7520.41**

to built-up land, with an area of approximately 103.77 km^2; the water area increases significantly. Cropland is not only the main type of land transfer out but also the main land receiver, with grassland and built-up land being transferred to areas of 32.37 km^2, 31.52 km^2, and 43.28 km^2, respectively.

Figures 2(a) and 2(b) show the spatial distributions of the type of unchanged land and the type of transferred land in Zhengzhou City during the period of 2000–2015. Figure 2(a) shows that cropland was the main land use type in Zhengzhou and was spread throughout the region. The built-up land was concentrated in the central and northern regions in the form of small patches scattered in some parts. Ecological land was mainly distributed in the western part of the region in the form of large patches, and the water area was mainly distributed at the borders of the city in the northern area in the form of a ribbon. According to the land transfer situation (Figure 2(b)), eight land use types were selected in the order from highest to lowest use to show the spatial distribution of land use transfer; the total area of the eight land transfer types accounted for 92.07% of the total area of the land transfer. Among them, the transfer from cropland to built-up land was mainly distributed in the central urban area, as a result of urban land expansion. The transfer from cropland to water area was mainly distributed around the land along the waters.

3.2. Changes in NPP of 2000–2015. Figure 3(a) shows that the NPP in general was distributed in areas other than the built-up land and water area, showing a generally increasing trend. Among them, the low value of NPP was mainly distributed in the eastern, southwestern, and southern border areas of Zhengzhou City in the form of small patches, and the areas with a high NPP value were mainly distributed throughout the city in the form of large patches. As shown in Figure 3(b), the value of the NPP slope ranges from negative to positive; the slope value represents the change in NPP itself in the period of 2000–2015. The positive values indicate an increasing trend in NPP, whereas negative values indicate a decreasing trend in NPP. The NPP growth area was mainly concentrated in the southern and northwestern regions of Zhengzhou, wherein the growth trend was stronger in some parts of central southern area. The NPP with a downward trend was mainly distributed in the areas surrounding the development of built-up land, which were concentrated in

the northern and northeastern regions of Zhengzhou City. The average slope of the NPP trend of 2000–2015 was 0.55, indicating that the NPP value in Zhengzhou showed an overall increasing trend.

3.3. Relationships between NPP and Climate Factors. Based on the relevant analysis, the correlation coefficient map of precipitation, temperature, and NPP was obtained, as shown in Figures 4(a) and 4(b). The p-value tests indicated that only a small percentage of the areas passed the $p > 0.05$ significance test for both negative and positive correlations of both precipitation and temperature (Figures 3(c) and 3(d)). Overall, the average phase relationship values (R) of precipitation and temperature are 0.267 and 0.020, respectively. Figure 4(a) shows the distribution of the coefficient R between precipitation and NPP for the period of 2000–2015, in which positive values account for 96.38% and negative values account for 3.62%. The positive coefficient indicates that precipitation has a positive correlation with NPP, that is, the increase in precipitation can promote the growth of NPP to some extent. The positive values were observed in most parts of the city in the form of large patches, wherein the high values of the positive coefficient were mainly observed in the central and northwest regions. The negative values, which represent a negative correlation between precipitation and NPP values, were primarily observed throughout the region in the form of small patches. Figure 4(b) shows the distribution of the correlation coefficient between temperature and NPP for the period of 2000–2015, with positive values accounting for 56.57% and negative values accounting for 43.43%. The positive values indicate a positive correlation between temperature and NPP, that is, an increase in temperature promotes the increase of NPP to a certain extent. The positive values are observed mainly in the form of small patches in most areas of the whole region, with higher positive values concentrated in the eastern and central areas. The negative values indicate a negative correlation between temperature and NPP, that is, an increase in temperature will inhibit the growth of NPP to a certain extent. They are primarily observed in the western and northwest areas in the form of small patches and in the form of large plaques that are densely distributed in the central and central northern areas.
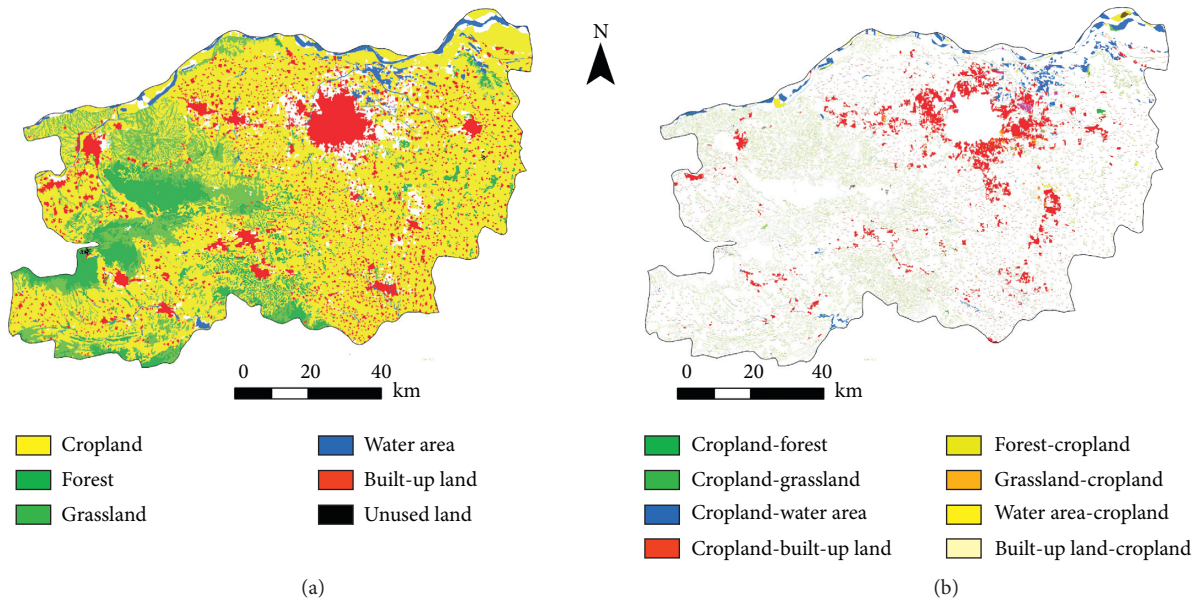
Cropland   Water area   Cropland-forest   Forest-cropland

Forest   Built-up land   Cropland-grassland   Grassland-cropland

Grassland   Unused land   Cropland-water area   Water area-cropland

Cropland-built-up land   Built-up land-cropland

(a)   (b)

FIGURE 2: Spatial distribution of land without changes in land use type (a) and transferred land (b).

−0.51 ~ −0.03   0.25 ~ 0.34   −0.65 ~ −0.21   0.01 ~ 0.11

−0.02 ~ −0.00   0.35 ~ 0.46   −0.20 ~ −0.08   0.12 ~ 0.22

0.01 ~ −0.24   0.47 ~ 0.83   −0.07 ~ 0.00   0.23 ~ 0.55

(a)   (b)

Highly significant   Highly significant

Significant   Significant

Nonsignificant   Non-significant

(c)   (d)
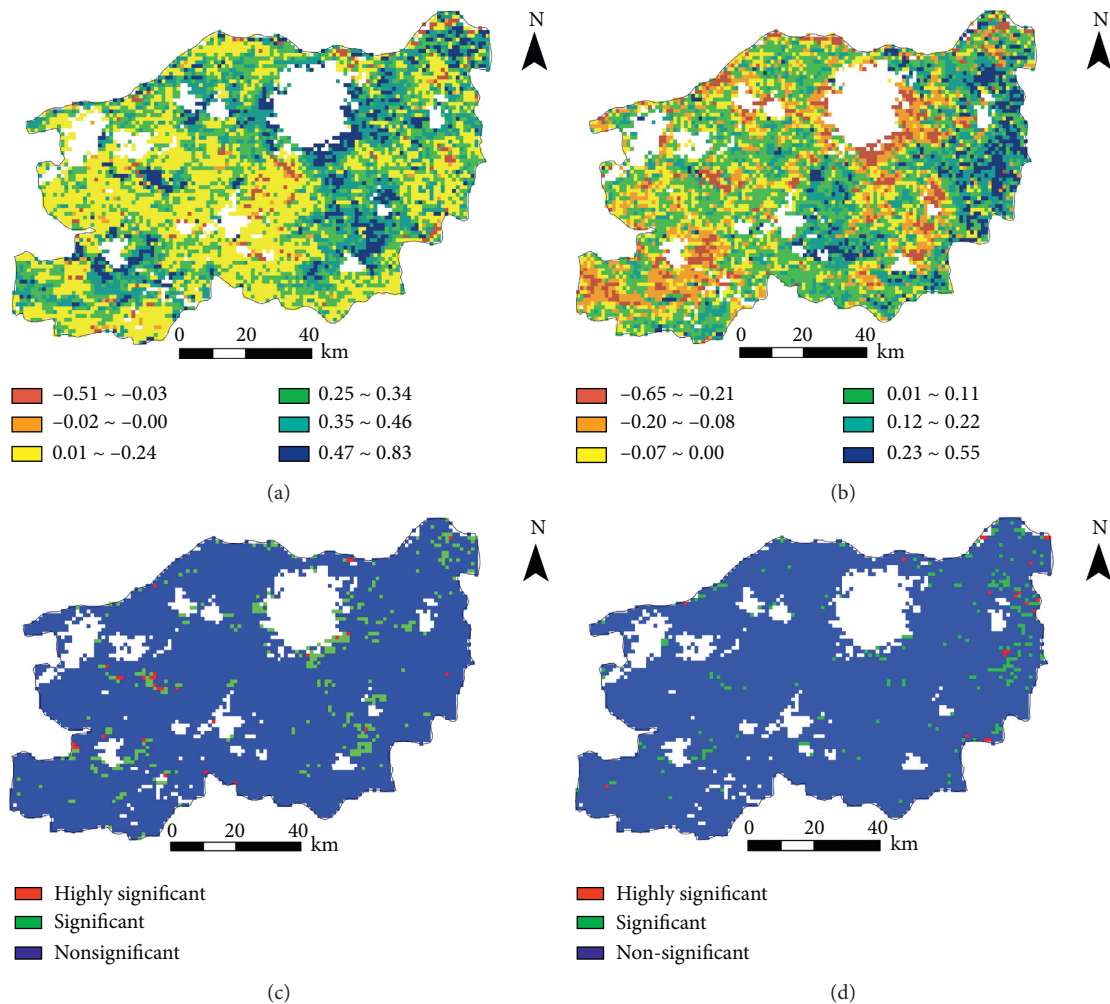
FIGURE 3: Correlation coefficients and significance tests between (a, c) NPP and precipitation and (b, d) NDVI and temperature. Highly significant, significant (+), and nonsignificant areas are shown in (c) and (d), where the positive correlations between NDVI and precipitation and temperature are significant at the 99% and 95% confidence levels, and the nonsignificant positive and negative correlations.
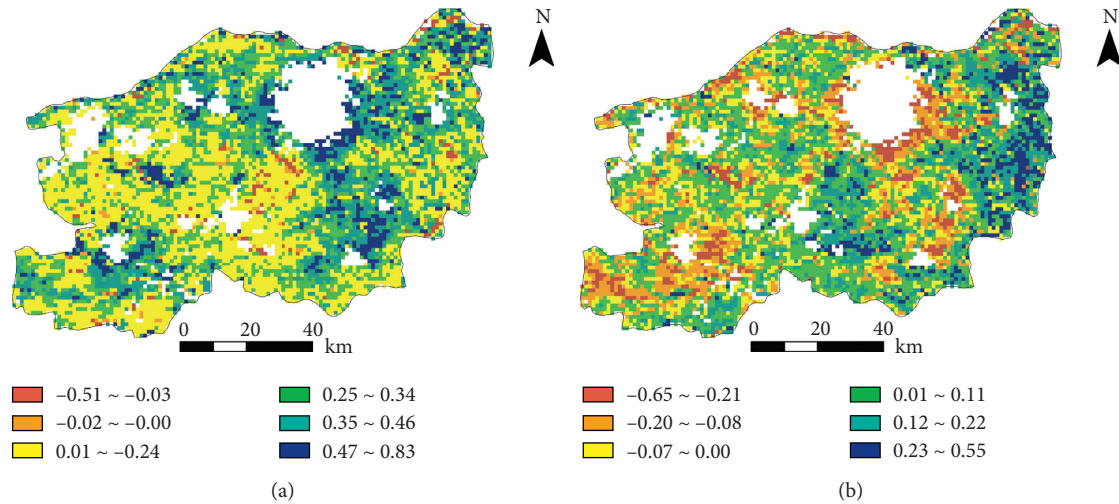
FIGURE 4: Spatial distribution of the correlation coefficients between NPP and precipitation (a) and temperature (b).

3.4. Change in Land Use Intensity and Urban Built-Up Area. Land use intensity can reflect the rates of energy emissions and socioeconomic development to a certain extent, and it has been documented that socioeconomic development indicators can be a good indicator of land use intensity [57, 58]. We selected seven main indicators to reflect the land use intensity of Zhengzhou City and calculated the ratio between typical years to analyze the changing trends (Table 2). According to Table 2, the total population increased steadily from 2000 to 2015, but the growth amount was greater, and the growth rate showed a steady downward trend. The increase in GDP was most pronounced, increasing from 73.802 billion yuan to 731.152 billion yuan. Both industrial output and agricultural output increased significantly, particularly in ratios of 2.99% and 1.75%, respectively, between 2005 and 2010. From 2000 to 2015, the fixed asset investment increased from 25.839 billion yuan to 628.80 billion yuan, and the increase during the period of 2005–2010 was the highest compared with the changes during different time periods. The quantity shipped increased significantly overall, from 15,781.00 million tons to 24,639.00 million tons, but decreased during the period of 2005–2010 by a ratio of 0.87.

Figure 5 show the distribution of urban built-up land in the typical years ranging from 2000 to 2015 in Zhengzhou. From a spatial point of view, the urban built-up land was mainly distributed in the central and northern parts of the city, which are the most developed parts of the urban economy. Urban built-up land expanded around the northern part of the city during the period of 2000–2015, and the area of urban built-up land increased gradually, with the fastest growth reported in the period of 2010–2015.

3.5. Impact of Urban Built-Up Land on NPP Change. Figure 6 shows the relationship between NPP and urban built-up land expansion. The correlation between NPP and urban built-up land expansion was relatively strong, with

more areas showing a positive correlation. The areas with negative NPP value were mainly distributed in the expansion area of the central city, indicating that the expansion of urban built-up land inhibits the NPP. The areas with positive values were distributed in most parts of the region, indicating that the impact of urban expansion on NPP is mainly concentrated in the expansion areas.

4. Discussion

The rapid expansion of urban areas has significantly affected regional ecosystems, making it extremely important to quantify the impact of urban expansion and climate change on NPP. Using land use data, night light data, NPP data, climate data, and a series of socioeconomic data, we explored the expansion of urban built-up land in Zhengzhou City during the period of 2000–2015 and the response of NPP to urban expansion and climate change. The study provides a reference for land managers to formulate land policies towards low carbon and sustainable development.

Built-up land expansion is the main form of land use change in Zhengzhou and is quite common in China, as the country is undergoing rapid urbanization. However, the land use changes in China and those in Europe [59, 60], the United States [61], Australia [62], and other developed countries that have completed the process of urbanization are different. As Zhengzhou is located in the region with a general population and economic level, cropland and ecological land are the main land use types, and land use transformation is more characteristic, compared with the northwest, inland areas, and other underdeveloped areas of China. Cropland being occupied by built-up land is the main change in land use types that occurs in Zhengzhou, which is mainly due to the social and economic development. This result is consistent with previous studies on land use change [63, 64]. From 2000 to 2015, the population increased to 9.569 million, and the urbanization rate in Zhengzhou increased from 55.1% to 69.7%. To accommodate more urban

TABLE 2: Change in land use intensity index in Zhengzhou during the period of 2000–2015.

	Urban population/10,000	GDP/hundred million	Industrial output/ hundred million	Agricultural output/hundred million	Fixed assets/hundred million	Quantity shipped/tons	Electricity consumption/100 million kWh
2000	259.11	738.02	1080.24	73.18	258.39	15781.00	78.7
2005	424.13	1660.60	2489.33	126.22	820.00	23750.00	140.6
2010	551.00	4040.89	7452.60	221.43	2756.98	20636.00	356
2015	666.91	7311.52	15531.27	276.58	6288.00	24639.00	352
2000–2005	1.64	2.25	2.30	1.72	3.17	1.50	1.79
2005–2010	1.30	2.43	2.99	1.75	3.36	0.87	2.53
2010–2015	1.21	1.81	2.08	1.25	2.28	1.19	0.99
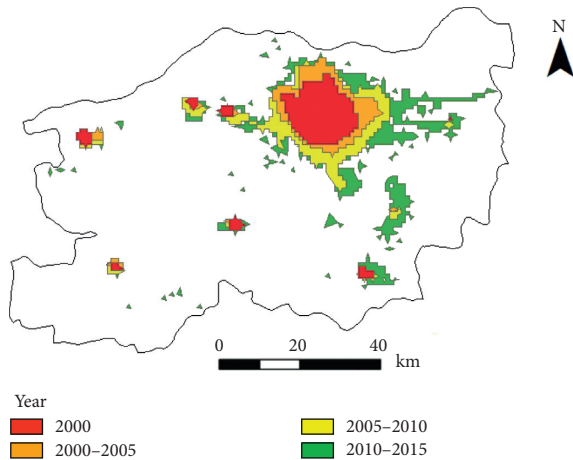
FIGURE 5: Urban built-up land sprawl during the period of 2000–2015, as detected using night-time light data.
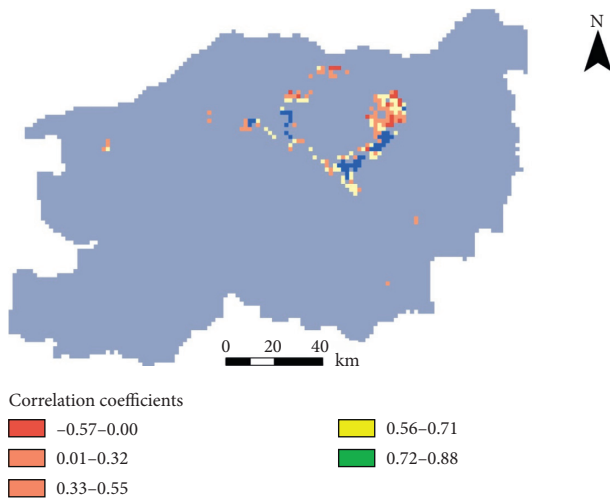

FIGURE 6: Spatial distribution of the correlation coefficients between NPP and night-time light data.

residents and under the influence of the growing real estate market [65], urban areas expanded rapidly during the study period. Although the population in rural areas has been significantly reduced, idle rural settlements are widely distributed, and land consolidation can take a long time. As cropland accounts for more than 80% of the area in Zhengzhou and is distributed in various places, the expansion of urban land requires the occupation of a large area of cropland. The spatial distribution of land transformation, shown in Figure 2, proves our conclusion that socioeconomic development is the main driving force of change in land use type. The economic level of Zhengzhou city shows a characteristic growth from center to periphery, and the land use change shows the same trend. In other words, the land circulation in the developed areas of the urban economy is more intensive.

Zhengzhou has experienced rapid urbanization in recent years, not only bringing about a growth in the economy and mass population, capital, and technology but also leading to a rapid increase in land use intensity. In this study, to represent land use intensity, we selected seven indicators, which showed a strong correlation between land use intensity and economic development level. The land use intensity gradually enhanced with the growing economy, which can be attributed to the regional differences in economic and natural resources between different periods. The differences in the economy and resources are consistent with the study conducted by Yang et al. [66], which showed that urban land use intensity increases with the increase in the level of urbanization. According to our research, the change in land use intensity has a significant effect on NPP. The areas with high land use intensity usually exhibit high levels of economic development and lower NPP values because such areas always have a large proportion of artificial vegetation and land, which can also explain the lower NPP values. In addition, areas with more natural and seminatural land use tend to have lower land use intensity [67], where cropland, forests, and grasslands account for a large proportion. With ecological land being increasingly occupied, policies and measures to promote intensive land use should be implemented to adjust land use intensity and to match the socioeconomic situation with the local condition [68]. Besides socioeconomic conditions, climate change [69], ecological conditions, and crop structures affect land use intensity to some extent.

Second, to correct and integrate the two types of night light data from different sources, we performed an exponential regression between MODIS-OLS night light data for 2013 and NPP-VIIRS night light data for 2014 and 2015 after noise processing and then obtained the revised NPP-VIIRS night light data. The reliability of this method has been verified [39, 70]. In spatial simulations of energy-related carbon emissions, the night light data obtained from DMSP-OLS and NPP-VIIRS are suitable for simulating urban land

expansion, and there is an innovation in the integration of the two types of data and the updating of time series. The urban expansion simulated by night light data effectively reflected the land change distribution in Zhengzhou from 2000 to 2015, which also can be attributed to the economic development and urban functional planning.

Compared with previous studies, the NPP simulation performed in this study has several advantages. The NPP estimates from MODIS have been validated to be consistent with the NPP values observed in the field [44, 71]. Exist studies show that, for urban system, the MODIS NPP still has a good application [72, 73]. As a result, the NPP simulations in previous studies have been validated, although more field observations are required for further research to improve the NPP simulation models for China (particularly in the west, where the density of field observations is low). The effects of global warming were widely demonstrated in China during the period of 2000–2015, with regions experiencing a rise in temperature accounting for 52.99% of that for the whole country. Although an increase in temperature can promote NPP to a higher extent than an increase in soil respiration, higher temperatures can also contribute to steaming and drought, leading to low vegetation productivity [74], particularly in an environment with insufficient water supply. In addition, a continuous increase in temperature will lead to increased soil respiration [75, 76] and decrease the NPP. Continued global warming will ultimately damage carbon sequestration in terrestrial ecosystems. Therefore, in China, reducing carbon emissions is urgently required for green, low-carbon development. Zhengzhou, which is an emerging and fast-growing city, should respond positively to the country's call for low-carbon green development. Moderate precipitation conditions are essential for vegetation growth; if the precipitation is too high or too low, vegetation growth will be affected, thus reducing NPP. For example, rainfall can increase cloud cover and thus reduce solar radiation, which is critical for vegetation growth [77]. Further water supply may create an aerobic environment in the root area, reduce soil nutrients [78], and inhibit vegetation growth. With the increase in temperature and a decrease in precipitation, ecological pressure will increase under primitive fragile environmental conditions [79, 80]. However, rising temperatures may also cause other ecological problems, such as melting glaciers, extreme climate, and disease, which require enhanced ecological protection. Owing to extreme weather conditions, the precipitation in Zhengzhou city has been insufficient in recent years, and water resources are relatively scarce. Precipitation is a key factor for the growth of vegetation. The government should strengthen ecological protection.

For the effect of urban built-up land expansion on NPP, the impact of urban built-up land expansion on NPP may be positive or negative, depending on socioeconomic and biophysical factors [81, 82]. The results in this study show there is negative relationship between urban built-up land and NPP at edge of the urban expansion areas, which means that the urban built-up expansion can damage the vegetation productivity in some extent. This is because with the continuous expansion of built-up land, the composition and quantity of vegetation decreased, then the net primary productivity of vegetation will decrease, which is consistent with the existing study [83]. While on the other areas, the relationships between urban built-up land and NPP are positive on the whole. The negative impact of urban expansion on NPP will disturb carbon balance to some extent. In addition, in Zhengzhou, human activities, such as desertification, loss of agricultural use, and deforestation, hamper green development; most of these activities may also disrupt the carbon balance. Therefore, government departments should take effective environmental protection measures to strictly prohibit such activities.

5. Conclusions

Unlike previous studies, this study first simulated urban expansion from night light data by integrating the night light data obtained from DMSP-OLS and NPP-VIIRS and explored the response of NPP to urban expansion and climate change. This study can serve as a reference for urban green development.

We found that cropland is the main land use type in Zhengzhou City, and from 2000 to 2015, the land transfer of cropland to built-up land was the main pattern of land use change, with a total area of 367.51 km^2 being converted; this was common in most cities of China. Areas other than the built-up land and water area exhibited a generally increasing NPP trend; these areas were mainly distributed in the southern and northwest regions of Zhengzhou. Areas around the development of built-up land exhibited a downward trending NPP. Both precipitation and temperature had obvious effects on NPP. The average correlation coefficients between temperature and NPP and precipitation and NPP were 0.267 and 0.020, respectively, indicating that an increase in temperature and precipitation can promote NPP, despite significant spatial differences. Land use intensity gradually increased with economic growth. In terms of urban expansion, Zhengzhou expanded into the central city, and urban built-up expansion was mainly distributed in the central and northern parts of the city. From 2000 to 2015, most expansion areas exhibited an increasing NPP trend, indicating that the influence of urban expansion on NPP is mainly characterized by the evident influence of the expansion area.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The funding sources had no role in the study design, data collection, analysis or interpretation, or the writing of this manuscript.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Pengyan Zhang and Wenlong Jing designed and carried out the study. Yanyan Li, Dan Yang, and Yu Zhang participated

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