Study on the Evolution of Urban Spatial and Temporal Patterns in Sichuan Province from the Perspective of Nighttime Light Data

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Abstract

A timely and accurate understanding of spatial-temporal evolution patterns and the development status of cities is essential for effective urban planning. This study utilized NPP/VIIRS nighttime light (NTL) data from 2012 to 2021 to extract the built-up areas of 34 prefecture-level and county-level cities in Sichuan Province. Key indicators, including the urban center of gravity, standard deviation ellipse, expansion speed, expansion intensity, fractal dimension, and compactness, were employed to analyze urban spatial patterns across three stages. The findings reveal that the urban center of gravity in Sichuan Province shifted from northeast to southeast, with cities dispersed in the northwest-southeast direction and clustered in the northeast-southwest direction. Prefecture-level cities generally exhibited high or medium speed to lower development levels, evolving towards relatively low and low intensity expansion, while county-level cities expanded more slowly at low intensity. Furthermore, better-developed cities are primarily located in the eastern region of Sichuan. Throughout the study period, outlying expansion was the predominant urban expansion model, and the spatial evolution of cities demonstrated considerable diversification. This research offers valuable insights into the sustainable development and planning of cities in Sichuan Province.

Keywords

Urban built-up areas, nighttime light, NPP/VIIRS, temporal and spatial evolution, sichuan province.

1. Introduction

Cities are the focal points of human habitation and they form the foundation of modern human life. Urbanization represents the transformation of nature by humans, as well as changes and improvements in people's lifestyles and productivity levels. Since the implementation of the reform and opening-up policy, China has begun the process of high-speed urbanization. According to the National Bureau of Statistics of China, by the end of 2023, the urbanization rate of the resident population was 66.16%, which was 48.24 percentage points higher than the urbanization rate of 17.92% in 1978 [1]. Current studies have shown that rapid urbanization exacerbates ecological environmental problems, such as resource depletion and environmental fragility, exerting pressure on the ecological environment[2], [3]. Comprehending the dynamic changes in cities and addressing problems arising from urbanization is crucial for sustainable development. The built-up area is the most densely populated and economically active region of the city, and its boundary identification is a fundamental study to support the study of urban geography. In addition, its dynamic changes reflect the expansion of the city, providing a reference for the planning and regulation of the city [4], [5].

Remote sensing images have been extensively employed for monitoring urban development due to their fast update, wide range of viewpoints, and strong objectivity. Among the outer space imageries, the nighttime light (NTL) data has emerged as a reliable source for distinguishing the intensity of human activities in built-up areas and non-built-up areas. It has become one of the most widely used data sources in the extraction of urban built-up areas (UBAs). The urbanization level can be better measured by calculating the light index, especially for areas lacking statistical data [6]. The Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) was initially employed as a widely used NTL product for monitoring city expansion, providing valuable records of global nightscapes from 1992 to 2013 [7]. However, this product suffers from oversaturation and spillover effects [8]. Subsequently, a new generation of NTL composites derived from the National Polar-Orbiting Partnership-Visible Infrared Imaging Radiometer Suite (NPP/VIIRS) has been developed, with significant improvements in sensor calibration and spatial resolution compared to DMSP/OLS [9], [10]. Another novel NTL dataset is obtained from the Luojia 1-01 satellite launched in 2018, which features a spatial resolution of 130m and holds great potential for modeling socio-economic parameters [11]. Unfortunately, this product has not been available since 2019.

As for identifying the boundaries of UBAs using NTL images, the most commonly used methods include the empirical threshold method, mutation detection method[12], and reference comparison method [13], [14]. However, some scholars argue that the empirical thresholds lack sufficient scientific basis and stability [8]. Additionally, the optimal thresholds obtained through mutation detection are not generalizable [15]. In contrast, the reference comparison method uses statistical data or remote sensing images as references according to the specific study area. This method allows the dynamic optimal thresholds to extract urban boundaries. It accounts for small cities, prevents overestimating actual areas, and indicates spatiotemporal changes in urbanization levels [16], thus offering significant advantages in extraction accuracy. This approach has been successfully practiced to monitor changes in UBAs in the Shandong Peninsula Urban Agglomeration [17], as well as in the three most developed urban agglomerations in China [16].

The current studies have predominantly examined the urbanization process in large cities and urban clusters with well-developed infrastructure and higher nighttime light intensity, such as the Yangtze River Economic Belt urban agglomeration [18], [19], the Pearl River Delta urban agglomeration [20], [21], the Beijing-Tianjin-Hebei urban agglomeration [22], [23], and large cities[24], [25], while medium-sized and small cities receive limited attention. In 2016, the State Council of the People's Republic of China approved the Chengdu-Chongqing City Cluster Development Plan, and the study of the coordinated development between major cities in this area became a hot spot. Scholars have extracted the UBAs of the Chengdu-Chongqing city cluster and explored the spatial pattern evolution and the driving force behind the changes [26], [27], [28], [29]. However, little attention is given to county-level cities. Due to the deficiency of studies on urbanization at county and township levels, it is crucial to explore new methods and strategies for gaining a more comprehensive understanding of the spatial transformation process within small and medium-sized cities. This study aims to take the Sichuan Province as a case study and utilize the NPP/VIIRS data from 2012-2021 to comprehensively analyze the characteristics and patterns of the spatial patterns of urban development at the prefecture and county levels. It is hoped that the research can inform urban management and regional development practices.

2. Materials

2.1. Study Area

Sichuan Province, renowned for its abundant natural tourism resources and robust economy in western China, will be selected as a case study. Situated in the southwestern region of China, the province is also known as the Land of Abundance. It covers an area of 486,000 square kilometers, ranking fifth in China, with 21 cities (states) and 183 counties(districts). It is bordered by five provinces (Guizhou, Yunnan, Qinghai, Gansu, and Shanxi), one municipality (Chongqing), and one autonomous region (Tibet). As of the end of 2023, Sichuan's resident population was 83.68 million. The GDP of this province exceeded 6 trillion yuan, representing a 6% increase compared to 2022. This placed it as the sixth-largest contributor (4.8%) to China's overall GDP and the leading province in western China [30].

The urban system in this province has gradually formed a four-level pattern: one megacity city (Chengdu), large cities such as Mianyang, Nanchong, and Luzhou, medium-sized cities like Neijiang, Suining, Meishan, and Leshan, and small cities including Guanghan, Jiangyou and Langzhong etc. Only Chengdu has a population of more than 2 million, while most other cities are small and medium-sized with a population of less than 1 million people. Furthermore, most cities (91.43%) are in the eastern part of the province, with only 5 cities in the western part. Despite improvements in urban development, the urbanization rate of this province remains lower than the national average. Considering the unbalanced and inadequate development in the region, it is essential to know the situation of urban expansion and improve the quality of urban development.

2.2. Data

The NPP/VIIRS Black Marble VNP46A4 product is an annual synthetic product [31] and can be obtained from the National Aeronautics and Space Administration (NASA) website (available at https://ladsweb.modaps.eosdis.nasa.gov/). Firstly, imageries from the study area spanning 2012-2021 were collected and underwent preprocessing, including format conversion, band extraction, image mosaicing, reprojection, and cropping. Then, the maximum values within the airport area for each year were used as thresholds to remove data outliers. Finally, the NTL data set with a spatial resolution of 500 meters within the study area was obtained for the continuous work. Vector data, such as administrative district maps, were sourced from the National Center for Basic Geographic Information (https://www.ngcc.cn/ngcc/html/1/index.html). Information on areas of the built-up region of cities was obtained from the Sichuan Provincial Bureau of Statistics (https://tjj.sc.gov.cn/) and the statistical yearbook published by each city. Due to the limited data in statistical yearbooks, Shehong City, Longchang City, and Huili City were excluded from the study. We collected 34 cities, including 18 prefecture-level and 16 county-level cities. Additionally, the built-up area statistics for Maerkang City and Kangding City could be only obtained from 2015 to 2021, while the study period for other cities was from 2012 to 2021.

3. Methods

3.1. UBAs Extraction

This study focuses on the identification of the UBAs in Sichuan Province from 2012 to 2021. To more accurately track urban development over the study period, the years are divided into 3 distinct periods (2012-2015; 2015-2018; 2018-2021). The reference comparison method, based on dichotomy analysis [3], is employed to extract built-up areas of each city using data from the statistical yearbooks. The extraction process is shown in Figure 1.

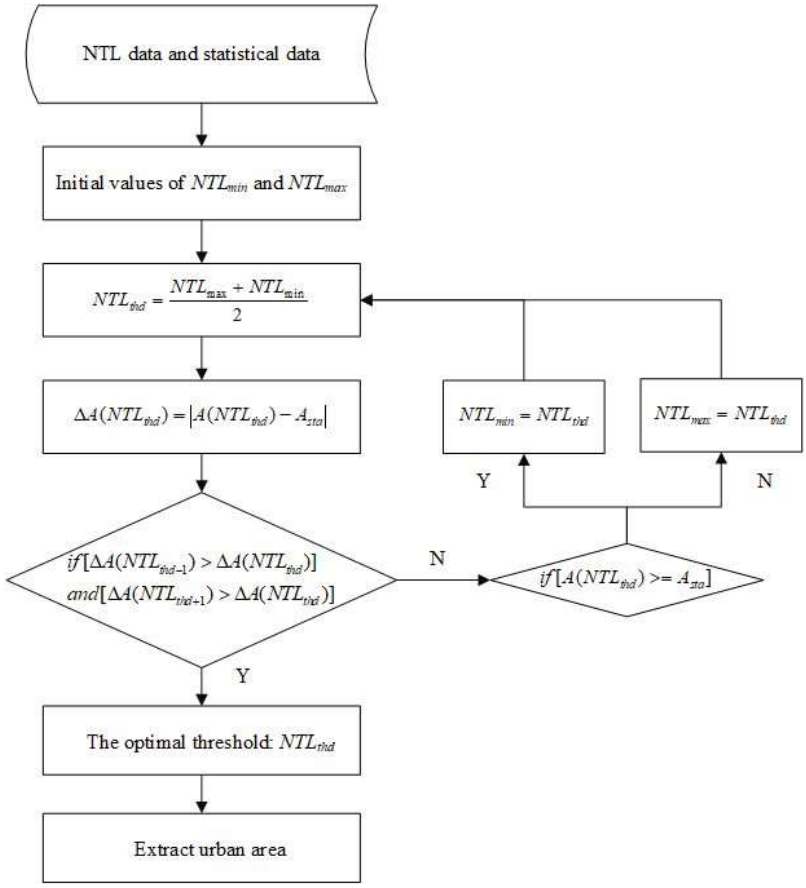


Figure 1. The flow chart for extracting urban areas

Where NTL_{max} and NTL_{min} are the maximum and minimum values from the NTL data, NTL_{thd} is the threshold for the specific NTL image; NTL_{thd-1} stands for the value of NTL intensity that is closest but smaller than NTL_{thd}, and NTL_{thd+1} represents the value of NTL intensity that is closest but larger than NTL_{thd}; $A(NTL_{thd})$ denotes the built-up area extracted at the threshold NTL_{thd}; $Area_{sta}$ is the urban area data from the statistical yearbook; ΔA is the discrepancies between $A(NTL_{thd})$ and $Area_{sta}$. Initially, the NTL threshold will be set at half of the minimum and maximum NTL intensity of an image from one year in a specific region. Then, according to the difference between the calculated and statistical data, the minimum NTL or maximum NTL value will be replaced by this NTL threshold. This iterative process will continue until the difference reaches the minimum, at which point the current threshold is considered optimal. Finally, UBAs will be extracted by applying the dynamic optimal thresholds for each area over different periods. The relative error is calculated as follows:

$$R = \frac{A(NTL_{thd}) - A_{sta}}{A(NTL_{thd})} \tag{1}$$

where R is the relative error.

The extracted data is then converted into vector format to calculate the areas and perimeters of each city. Meanwhile, relative errors between the results of the built-up areas extracted from the Sichuan Province and the results of the statistical yearbook of the corresponding periods are also determined. It's worth noting that the term "built-up area" refers to the developed and constructed region within the city administrative area [32], therefore data from townships within the area are not included in the calculation.

3.2. Direction of Urban Evolution

3.2.1. Gravity Center

The gravity center of the urban is the average X-coordinate and Y-coordinate of all elements in the area, which is used to measure the degree of unbalanced development within the city. The calculation formula is as follows:

$$X = \frac{\sum_{i=1}^{n} x_i \times DN_i}{\sum_{i=1}^{n} DN_i}, \quad Y = \frac{\sum_{i=1}^{n} y_i \times DN_i}{\sum_{i=1}^{n} DN_i} \tag{2}$$

where X and Y are the coordinates of the gravity center of the city, x_i and y_i are the latitude and longitude coordinates of the ith pixel, respectively. DN_i is the nighttime light intensity of the ith pixel, and n is the total number of pixels in the region.

Distance of Gravity Center Moving

The distance of the gravity center moving represents the distance that the gravity center of the city has shifted in a specific year relative to the base year, calculated using the following formula:

$$D = \sqrt{(X_j - X_k)^2 + (Y_j - Y_k)^2} \tag{3}$$

where X_j, Y_j, and X_k, Y_k represent the latitude and longitude coordinates of the gravity center of the city for two different periods, respectively.

3.2.2. Velocity of Center Gravity Moving

The velocity of center gravity characterizes how quickly or slowly it shifts in a specific time and is calculated as follows:

$$V = \frac{L}{T} \tag{4}$$

where L is the distance of the gravity center moving and T is the time interval.

3.2.3. Standard Deviation Ellipse

The standard deviation ellipse (SDE) measures the general pattern of a changing phenomenon and can reflect the evolution patterns of a discrete urban area. It defines the axes of the ellipse by calculating the standard distances in the x and y directions. The center of the ellipse represents the barycenter of the spatial distribution of urban areas. The rotation angle of the ellipse and the standard deviation [33] are calculated as follows:

$$\tan\theta = \frac{A + \sqrt{A^2 + B^2}}{B}, \quad A = \sum_{i=1}^{n}(x_i - X)^2 - \sum_{i=1}^{n}(y_i - Y)^2, \quad B = 2\sum_{i=1}^{n}(x_i - X)^2(y_i - Y)^2 \tag{5}$$

$$\sigma_x = \sqrt{\frac{2\sum_{i=1}^{n}\left[(x_i - X)\cos\theta - (y_i - X)\sin\theta\right]^2}{n}}, \quad \sigma_y = \sqrt{\frac{2\sum_{i=1}^{n}\left[(x_i - X)\sin\theta - (y_i - X)\cos\theta\right]^2}{n}} \tag{6}$$

where X,Y are the coordinates of the center of gravity of the city, and x_i , y_i are the coordinates of the ith pixel, and σ_x , σ_y are the standard deviations of the X and Y axes of the ellipse.

3.3. Urban Expansion Index

3.3.1. Urban Expansion Speed

The urban expansion speed (UES) can indicate the growth rate of a given UBAs over time, representing the scale and trend of urban expansion, and it is calculated by the formula:

$$UES = \frac{A_2 - A_1}{(t_2 - t_1) \times A_1} \tag{7}$$

where A_1, A_2 represent the built-up area of a city in t_1 and t_2 year, respectively.

3.3.2. Urban Expansion Intensity

The urban expansion intensity (UEI) can measure the strength of urban expansion in built-up areas. It is the ratio of urban expansion area to the total land area within a certain time and is calculated as follows:

$$UEI = \frac{A_2 - A_1}{(t_2 - t_1) \times A_T} \tag{8}$$

where A_T indicates the total area of the administrative district.

3.3.3. Urban Expansion Pattern Metrics

a) Compactness

Compactness is a crucial indicator of urban shape, describing the degree of aggregation of urban space, and is represented by a value that falls within the range [0,1]. A higher compactness value indicates that the city plane shape is closer to a circle, implying less influence from external forces. It describes the degree of spatial agglomeration within the city. The formula [6] for calculating the compactness C is:

$$C = 2\sqrt{A\pi} / P \tag{9}$$

where P and A represent the perimeter and area of the built-up region of the city, respectively.

b) Fractal Dimension

The fractal dimension is typically applied to examine the spatial morphology of an object and represents the degree of irregularity in the boundaries of the urban built environment. As cities expand, the fractal dimension tends to become more complex. Its evolution reflects the phase and direction of urban development. The formula for calculating the fractal dimension F is [6]:

$$F = \frac{2\ln(P/4)}{\ln A} \tag{10}$$

3.4. Pattern Types of Urban Evolution

We applied the natural breaks method to classify the expansion speed of cities into four categories: slow, low, medium, and high expansion. Similarly, the expansion intensity was categorized into four groups: low intensity, relatively low intensity, relatively high intensity, and high intensity. The fractal dimension was also employed to depict the urban spatial expansion pattern. An increase in a city's fractal dimension over a specific period indicates a more complex shape, typically reflecting an outlying urban spatial expansion pattern. In contrast, a simplification of the city boundary suggests edge expansion, while a stable fractal dimension implies inward filling (infilling) [36]. Additionally, based on urban spatial expansion patterns over three periods, cities were classified into four types: (a) stable (the expansion type remains consistent across all three periods), (b) changing-stable (the expansion type differs in the first period but remains consistent in the last two periods), (c) stable-changing (the expansion type is consistent in the first two periods but differs in the last period), and (d) changing (the expansion type changes across all three periods). Using these classifications, we mapped the evolution of urban spatial patterns in Sichuan Province.

4. Analysis of Results

4.1. UBAs Extraction Accuracy

The highest relative error (absolute value) in the accuracy of extracting built-up areas in Sichuan Province's cities from 2012 to 2021 was observed in Kangding, with a value of -13.33%, while the lowest was in Dazhou, at 0.01%. The average relative error across all cities was 4.05%, with prefecture-level cities averaging 3.13% and county-level cities 5.09%. Additionally, the average relative error of each city over the 10 years remained consistently below 8%, indicating a level of accuracy suitable for subsequent research.

4.2. Direction of Urban Evolution

The urban spatial patterns in Sichuan Province experienced significant changes from 2012 to 2021, as shown in Table I. The gravity center of the urban area, initially located southeast of Chengdu, shifted eastward over time (see Figure 2). The distance and velocity of this movement initially decreased and then increased, with the major axis of the ellipse showing a decreasing trend, while the minor axis continued to grow. The azimuth angle fluctuated, increasing from 26.48° to 28.00°, indicating a "northeast-southwest" orientation. During the first study period, the gravity center shifted to the northeast, with the movement distance, velocity, and major axis length reaching their maximum values compared to other periods. Subsequently, the gravity center continued moving northeast at a rate of 1.47 km per year, accompanied by changes in the ellipse's axes and azimuth angle. By the end of the study period, the center of gravity had shifted southeast, with both the major and minor axes of the ellipse increasing and the azimuth angle decreasing.

The center of gravity of the cities has shifted in a "northeast-northeast-southeast" direction, reflecting the rapid development of cities in the eastern part of the study area, which has driven the gravity center eastward. After 2018, the direction shifted from southeast to northeast. Combined with the change in azimuth, this may indicate that the development of the urban agglomeration in southern Sichuan Province has influenced the distribution of nighttime intensity across the entire region. Additionally, the decrease in the major axis length and the increase in the minor axis length suggest that cities have become more dispersed in the northwest-southeast direction while clustering in the northeast-southwest direction during the study period, leading to changes in the spatial distribution pattern.

4.3. Spatial Patterns of Urban Evolution

4.3.1. Speed and Intensity

a) General Characteristics

Table II presents the statistical results of the average annual growth area, expansion speed, and intensity of the built-up area in Sichuan Province over three periods from 2012 to 2021. Over this decade, Sichuan Province's built-up area expanded from 1,852.89 km^2 to 3,284.27 km^2, with an average annual growth of 143.14 km^2 per year. The expansion speed and intensity were 7.73% and 0.17%, respectively. The mid-study period saw the highest expansion speed (7.01%) and greatest expansion intensity (0.19%), with an average annual growth of 158.56 km^2 per year. The early-study period had a higher expansion speed of 5.52% compared to the last study period's 3.35%, although both periods exhibited the same expansion intensity. Urban development in Sichuan has shown rapid progress since 2012, however, the expansion speed slowed after 2018 compared to the previous two periods.

b) Changes in Spatio-Temporal Patterns

The spatio-temporal changes in the speed and intensity of urban expansion in Sichuan Province are illustrated in Figure 3. Cities with higher expansion speed and intensity are primarily concentrated in prefecture-level cities in east-central Sichuan.

During the first period, rapid development was predominantly observed in eastern and southern cities such as Bazhong, Guang'an, Neijiang, and Yibin, while county-level cities with medium development speed were mainly located around Chengdu. Langzhong and Huaying also exhibited medium expansion speed. Higher-intensity expansion cities were distributed along the Chengdu-Deyang-Mianyang-Meishan corridor, the southern Sichuan urban agglomeration, and the Bazhong-Dazhou-Guangan region in northeastern Sichuan. Notably, Guanghan was the only county-level city with high-intensity expansion.

By the middle period, four cities-including three prefecture-level cities (Chengdu, Bazhong, and Yibin) and one county-level city (Kangding)-exhibited high expansion speed. Six cities developed at a medium speed, including two county-level cities (Wanyuan and Langzhong). Cities such as Guanghan, Guangyuan, Huaying, Shifang, Jianyang, Neijiang, and Meishan, which had previously shown high or medium development speed, experienced a decrease in speed. In terms of expansion intensity, Chengdu and Guang'an maintained their development levels, while Deyang and Luzhou reached relatively high levels. Prefecture-level cities with relatively low expansion levels were mainly distributed in the eastern region, while all county-level cities exhibited low expansion levels. By the end of the study time, most cities experienced a decrease in expansion speed, with only a few cities maintaining medium expansion. Chengdu continued to have high-intensity expansion, while Nanchong and Dazhou developed into relatively high-intensity areas. Cities with relatively low expansion intensity were mainly concentrated in the southern region of Sichuan Province and around the capital city.

Due to the allocation of policies and resources, prefecture-level cities exhibit higher overall development speed and intensity compared to county-level cities. Prefecture-level cities have transitioned from high and relatively high expansion speed and intensity to lower levels, while county-level cities have developed more slowly, consistently maintaining low speed and intensity. The more developed cities are concentrated along the Chengdu-Deyang-Mianyang and Chengdu-Ziyang corridors, the South Sichuan City Cluster, and the four eastern cities of Bazhong, Dazhou, Nanchong, and Guang'an.

Table 1. Direction of Urban Spatial Pattern Evolution in Sichuan Province

Year	**Center Gravity Coordinates**		**Gravity Center Moving**			**Ellipse Distance (km)**		**Ellipse Azimuth**
	X	***Y***	***Direction***	***Distance(km)***	***Speed(km/a)***	***Long axis***	***Short axis***	
2012	832828.17	87560.13	Start Point	—	—	201.97	97.32	26.48°
2015	842524.98	93118.25	North-East	11.77	3.92	178.65	105.57	27.28°
2018	846147.81	95648.27	North-East	4.42	1.47	169.09	107.13	29.34°
2021	847777.92	89353.70	South-East	6.50	2.17	172.90	107.49	28.00°

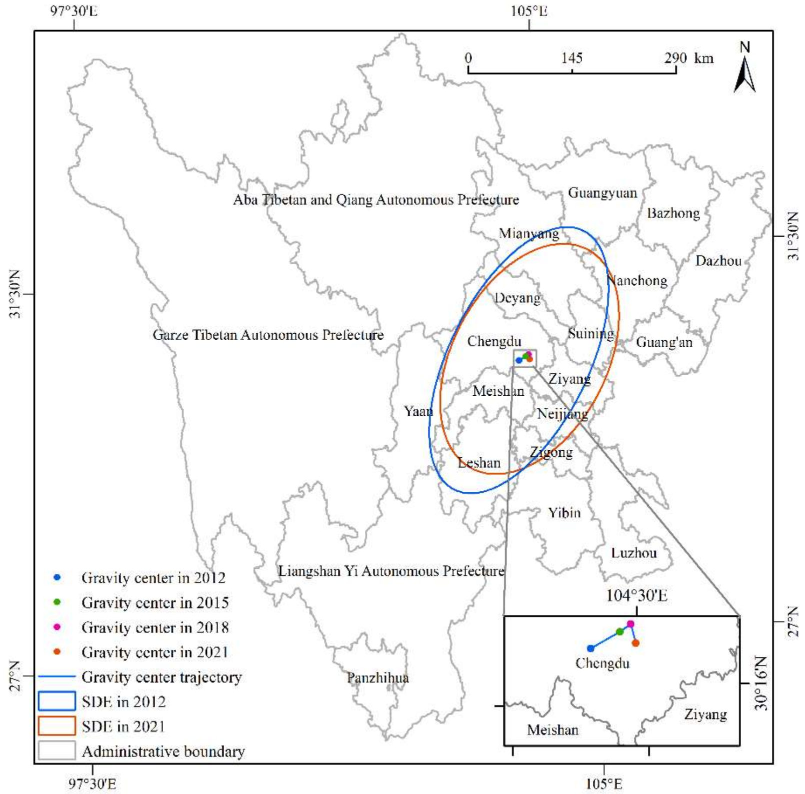
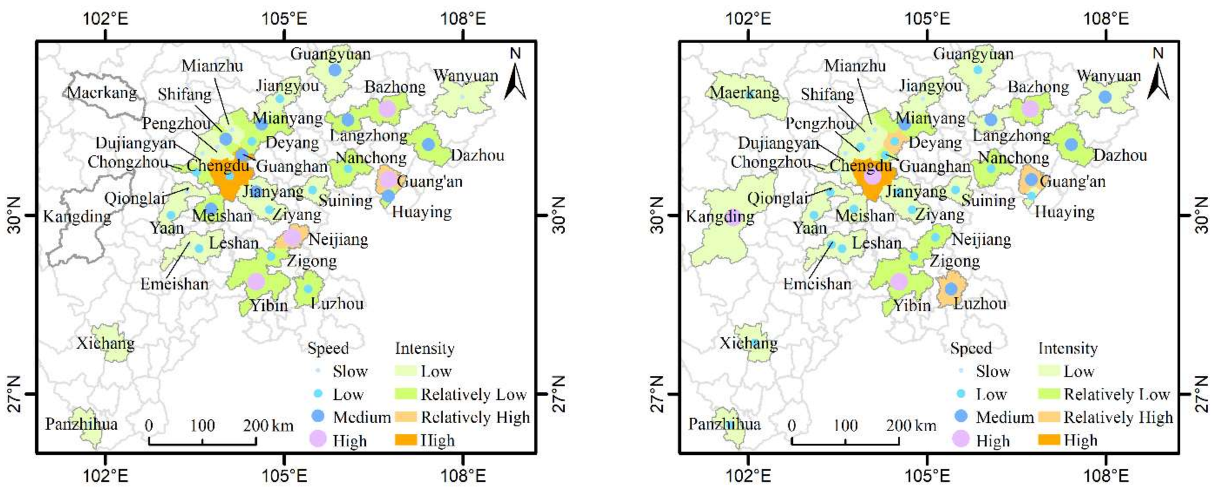


Figure 2. Direction of urban spatial pattern evolution in Sichuan Province from 2012 to 2021

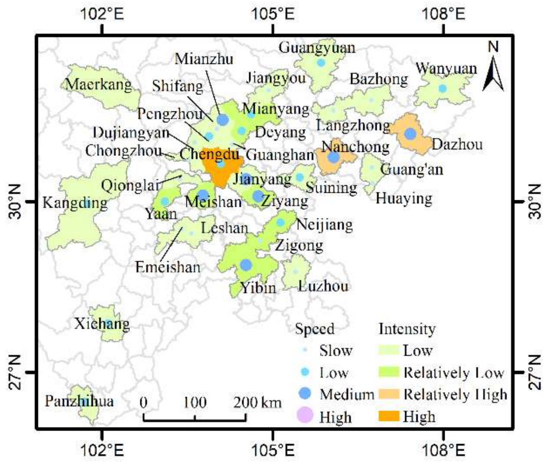
Table 2. Statistics on UBAs in Sichuan Province

Index	2012	2015	2018	2021	2012-2021
Total area (km²)	1852.89	2261.74	2895.97	3284.27	—
Increase area (km²)	—	408.85	634.23	388.31	1431.38
Average annual growth area (km²)	—	102.21	158.56	97.08	143.14
Expansion Speed (%)	—	5.52	7.01	3.35	7.73
Expansion Intensity (%)	—	0.12	0.19	0.12	0.17



(a) 2012-2015

(b) 2015-2018



(c) 2018-2021

Figure 3. Spatial and temporal changes in the speed and intensity of urban expansion in Sichuan province from 2012 to 2021

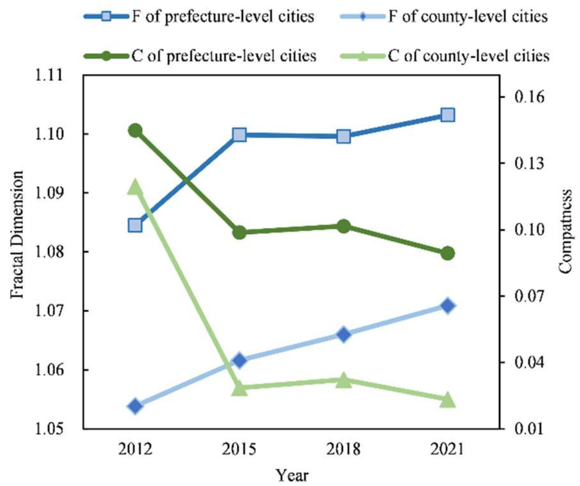


Figure 4. Mean values of fractal dimension and compactness in different types of cities

4.3.2. Patterns of Urban Evolution

a) Fractal Dimension and Compactness

During the study period, the mean fractal dimension of prefecture-level cities ranged from 1.08 to 1.10 (as shown in Figure 4). A significant change occurred between 2012 and 2015, with the mean value increasing from 1.08 to 1.10, followed by a stable trend. In contrast, the mean fractal dimension of county-level cities continuously increased from 1.05 in 2012 to 1.07 in 2021. Correspondingly, the compactness of these cities showed a decline: the mean compactness of prefecture-level cities decreased from 0.14 to 0.09, while that of county-level cities dropped from 0.12 to 0.02, indicating a more drastic change. The mean fractal dimension of prefecture-level cities was consistently higher than that of county-level cities throughout the study period, while compactness exhibited the opposite trend.

The more dispersed a city's built-up area, the less compact it becomes, resulting in a higher fractal dimension. These two indicators are negatively correlated. Over the 10-year study period, the complexity of city shapes in both prefecture-level and county-level cities in Sichuan Province increased, whereas their compactness decreased. Additionally, high fractal dimensions in prefecture-level cities were concentrated in the Chengdu-Deyang-Mianyang urban agglomeration and the southern Sichuan City Cluster, while high fractal dimensions in county-level cities were mainly distributed around Chengdu.

b) Urban Spatial Expansion Pattern

The spatial expansion pattern of cities in Sichuan Province from 2012 to 2021 is illustrated in Figure 5. Initially, outlying expansion was the dominant pattern. Six cities (two prefecture-level cities and four county-level cities) showed edge expansion development and three cities (Chengdu, Luzhou, and Mianzhu) with infilling type. However, significant changes occurred mid-period, with nine cities transitioning from outlying expansion to infilling and eight cities shifting to edge expansion, thereby diversifying the development patterns. Cities with outlying expansion were primarily concentrated in the Chengdu-Mianyang Plain urban agglomeration, with sporadic distribution in northeast Sichuan. Kangding also presented an outlying expansion. In contrast, cities undergoing infilling development were mainly located in the South Sichuan urban agglomeration and county-level cities around Chengdu, along with three prefecture-level cities: Bazhong, Nanchong, and Guang'an. By the end of the study period, eighteen cities, including ten prefecture-level cities, exhibited outlying expansion. The number of cities with infilling expansion decreased to five (including two prefecture-level cities), while eleven cities (including six prefecture-level cities) demonstrated edge expansion. Outlying expansion cities were mostly concentrated in central Sichuan. Additionally, cities in western Panxi and eastern Sichuan were dominated by edge expansion, with infilling observed in Dazhou, Leshan, Kangding, and two cities around Chengdu.

Figure 6 presents the urban expansion map of Sichuan Province, illustrating that most cities are undergoing transformation, with only four cities-Mianyang, Guanghan, Suining, and Panzhihua-remaining stable. Cities that initially experienced change before stabilizing were predominantly located along the western edge of the Sichuan Basin, while areas that stabilized and then underwent change exhibited a relatively fragmented distribution. Overall, most cities in Sichuan Province were characterized by outlying expansion and displayed distinct spatial evolution patterns at different developmental stages.

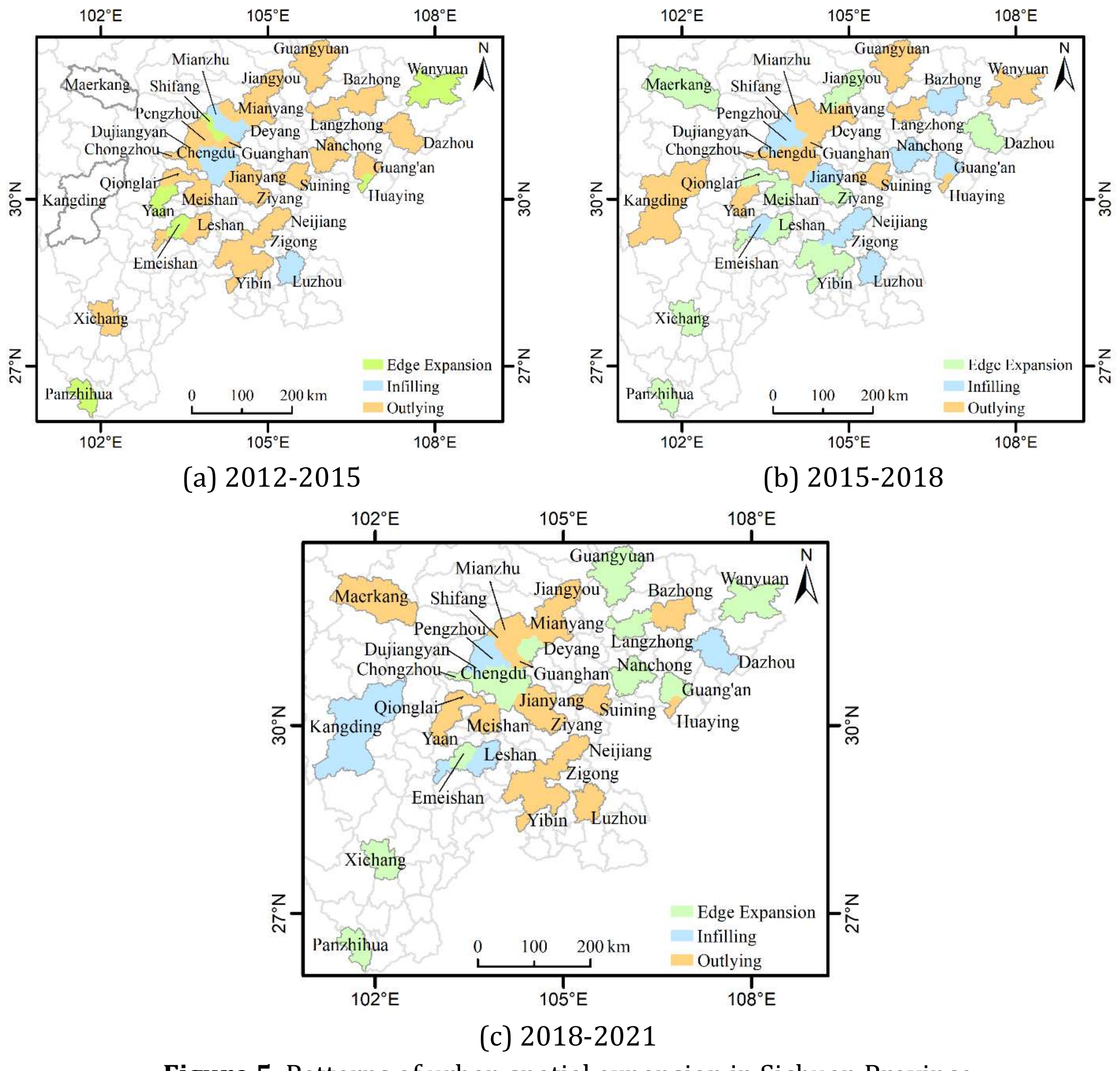
4.4. Results Analysis

As the capital city of Sichuan Province and a central hub within the Chengdu-Chongqing City Cluster, Chengdu has undergone considerable expansion over the past decade. However, its rate of development has been relatively modest, and its spatial evolution pattern has been inconsistent. Following substantial outlying expansion, Chengdu, like many large cities, has shifted towards developing its internal and edge areas, exhibiting edge expansion and a deceleration in development speed. A similar trend is observed in Panzhihua, which, owing to the mature state of its industrial and mining economy, did not experience significant expansion in rate or intensity during the study period, maintaining an edge expansion development pattern.

The development status of prefecture-level cities is notably superior to that of county-level cities, primarily due to the allocation of policy resources favoring the former. As the development pace of prefecture-level cities slows, the impetus for growth shifts to county-level cities, which become increasingly prominent in urban development. Notably, the expansion speed and intensity of many county-level cities surged in the middle of the study period compared to other phases. This shift is a key factor contributing to the higher overall development speed of Sichuan Province during this period relative to others.

Variations in the economic foundations of cities during the early period resulted in greater volatility in urban expansion patterns. Most cities exhibited outlying expansion, with those in eastern Sichuan demonstrating higher fractal dimensions and more advanced economic development. Conversely, cities in the Panxi region, the western Sichuan plateau, and other highland and mountainous areas experienced slower development due to constraints imposed by topography and natural conditions. Consequently, the urban economy in these regions lags behind that of cities located in plains and hilly areas.

In addition to geographic factors, external policies and planning significantly influence urban development. During the third period of the study, the pace and intensity of urban development in most cities decreased, likely due to the economic downturn and policies implemented after 2020 to curb the increase in built-up areas, a response to the impact of the epidemic. Changes in administrative divisions and city development also play a crucial role. For instance, Shuangliu and Pi County were reclassified as districts of Chengdu in 2015 and 2016, respectively, while Yibin County in Yibin City was incorporated into a new district (Xuzhou) in 2018. These administrative changes, coupled with policy adjustments, have significantly impacted urban development. We could see better development speed and intensity in the corresponding period. Additionally, in 2016, Jianyang became part of Chengdu, leading to substantial development driven by the establishment of Tianfu Airport and the optimization of related transportation routes. The development of Chengdu has notably influenced surrounding areas, affecting both the speed and intensity of urban expansion, particularly in county-level cities. The effects of policy adjustments and transportation improvements on urban development are highly significant [34].



(a) 2012-2015

(b) 2015-2018

(c) 2018-2021

Figure 5. Patterns of urban spatial expansion in Sichuan Province

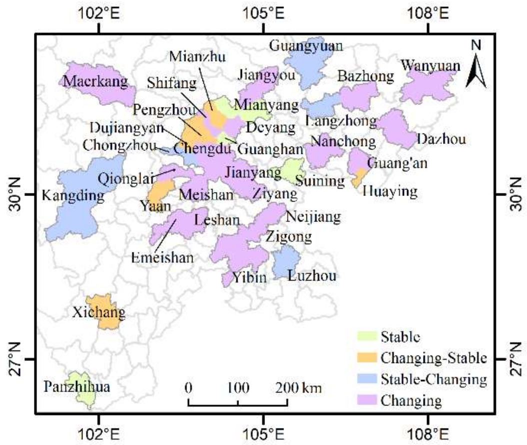


Figure 6. Urban expansion mapping in Sichuan Province

5. Conclusion and Discussion

The study extracted 34 UBAs of prefectural and county-level cities in Sichuan Province and explored their temporospatial pattern characteristics, using NPP/VIIRS NTL data from 2012 to 2021. The analysis revealed the following key findings: (a) The center of gravity of cities in Sichuan Province shifted in a “northeast-northeast-southeast” direction within the administrative boundaries of Chengdu over the study period. Cities displayed dispersal in the northwest-southeast direction and clustering in the northeast-southwest direction. (b) Over the ten years, the built-up area of cities in Sichuan Province expanded at an average rate of 7.73%, with the fastest expansion occurring between 2015 and 2018. Prefecture-level cities exhibited high and medium-speed to low-speed development, evolving towards lower-intensity expansion, while county-level cities developed more slowly, primarily at a low intensity. The development speed and intensity of prefecture-level cities surpassed those of county-level cities, with faster-growing cities concentrated along the Chengdu-Deyang-Mianyang corridor, the South Sichuan City Cluster, and in the eastern cities of Bazhong, Dazhou, Nanchong, and Guang'an. (c) The shape of the UBAs in the study area became increasingly complex, with rising fractal dimensions and decreasing compactness. The cities mainly exhibited outlying expansion and demonstrated distinct spatial evolution patterns at different stages of development.

This research relied solely on nighttime light remote sensing data to extract the built-up area, which may introduce errors and affect the result analysis. Future studies should consider incorporating additional auxiliary data, such as land use data and point-of-interest (POI) data, to enhance the accuracy of built-up area extraction. While this paper examined the spatial and temporal evolution patterns of major cities in Sichuan Province from 2012 to 2021, it offered a limited qualitative analysis of the factors influencing these pattern changes. To gain a deeper understanding of urban spatiotemporal evolution over a longer period, future research could integrate DMSP nighttime light remote sensing imagery, population data, and other datasets to quantitatively investigate changes in the spatial patterns of cities in Sichuan Province and the underlying driving forces.

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