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Spatio-Temporal Characteristics and Driving Mechanisms of Urban Expansion in the Central Yunnan Urban Agglomeration

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Abstract: Accurately identifying the expansion characteristics and driving mechanisms at different development stages of urban agglomerations is crucial for their coordinated development. Using the Central Yunnan Urban Agglomeration as a case study, we employ a data fusion approach to fuse nighttime light data with LandScan data and utilize the U-net neural network to systematically analyze the expansion characteristics and driving mechanisms of the urban agglomeration. The results indicate that, from 2008 to 2013, the Central Yunnan Urban Agglomeration was in an initial expansion stage, primarily driven by economic development levels and population size. From 2013 to 2018, the agglomeration entered an accelerated expansion stage, driven mainly by industrial structure transformation and the population agglomeration effect. From 2018 to 2023, the agglomeration experienced a steady expansion stage, with industrial structure upgrading and government support as the primary driving forces. Furthermore, we found that, over time, the influence of economic development levels and population size as driving forces gradually weakened, while the impact of industrial structure and government support significantly increased. Through the fusion of multi-source data and analysis of driving mechanisms at different developmental stages, we comprehensively revealed the development trajectory of the Central Yunnan Urban Agglomeration and provided valuable insights for future urban agglomeration development planning and policymaking.

Keywords: urban agglomeration expansion; built-up areas; data fusion; spatiotemporal characteristics; driving mechanisms

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1. Introduction

Urban agglomerations are regions composed of multiple geographically adjacent cities with close economic and social ties, serving as the core engines of regional economy, culture, and innovation, playing a crucial role in promoting the overall development of both the nation and its regions [1,2]. At present, due to the unbalanced distribution of economy and population, the development stages of different urban agglomerations in China differ from each other, which is reflected in the spatial expansion pattern, land use efficiency, resource allocation, and other aspects [3]. To better guide the scientific development of urban agglomerations, it is necessary to analyze the spatiotemporal characteristics of the spatial expansion of urban agglomerations at different stages of development and the driving mechanism, which not only helps to explain the diversity of urban agglomerations' development but also assists them in adopting targeted planning and management measures and promotes the sustainable development of urban agglomerations [4].

The development of cities progresses from an initial formation stage to gradual maturity, and similarly, urban agglomerations undergo comparable stages of development [5]. At different stages of city development, the characteristics and priorities of urban agglomerations vary, implying that planning and development strategies for these regions must be adjusted accordingly at each stage [6]. Therefore, accurately identifying the development stage of urban agglomerations is crucial to the formulation of scientific and reasonable development planning. Currently, scholars, drawing on theories of urban development and regional economics, categorize the development of urban agglomerations into stages such as the embryonic period, growth period, maturity period, and decline period [7,8]. Additionally, some studies, from the perspective of regional economic growth and spatial structure evolution, have constructed life cycle models for urban agglomerations, and these models typically encompass the stages of initial formation, accelerated development, integration, and maturity, as well as potential transformation or decline [9,10]. The identification of urban agglomeration development stages is primarily conducted through the analysis of quantitative indicators, and researchers often use multidimensional indicators such as population density, economic output, industrial structure, infrastructure construction, and transportation network density [11–13]. Through methods such as statistical analysis, cluster analysis, and principal component analysis, these indicators are employed to delineate the stages of urban agglomerations, thereby reflecting the relative position and characteristics of different urban agglomerations in their developmental processes [14–16].

In recent years, studies on the spatial expansion of urban agglomerations have gradually increased, and they have shown that the spatial expansion of urban agglomerations is often characterized by non-equilibrium and complexity [17], which is not only related to the level of economic development, population growth, and other factors but also affected by geographic conditions, policy orientations, and historical and cultural factors [18,19], and in this process, the expansion of built-up areas of urban agglomerations tends to show certain spatiotemporal regularity. Therefore, analyzing the characteristics of built-up area expansion provides an effective means to understand the processes and trends of spatial expansion in urban agglomerations [20]. Studies on urban land expansion can be classified into several major categories. The model simulation approach based on socioeconomic data and the spatial data analysis method using remote sensing images are currently well-developed areas of study. Additionally, mechanical statistical models hold a significant position in this field. Scholars such as Batty, Arcaute, and Barthelemy employ network theory, statistical mechanics, and complex systems analysis to investigate the dynamic mechanisms of urban growth. These methods often focus on the self-organizing characteristics of urban systems, analyzing how cities expand through self-organization processes and how urban morphology evolves over time [21–24]. Model simulation based on socioeconomic data explores the potential driving factors behind the spatial expansion of urban agglomerations by simulating the impacts of variables such as population, economic activities, and transportation networks on built-up area expansion [25]. This type of research usually relies on urban expansion models, such as the CLUE-S model, SLEUTH model, and Agent-based model, to predict the future expansion trend of built-up areas by simulating the urban development process under different scenarios [26–28]. Remote sensing image analysis, on the other hand, through multitemporal remote sensing data, can effectively monitor the dynamic changes of urban built-up areas and analyze the speed, direction, and pattern of their expansion. With the advancement of remote sensing technology, researchers are capable of obtaining higher-resolution image data, which makes the extraction and analysis of built-up areas more accurate [29–31]. Data from sources such as Landsat, MODIS, and high-resolution satellite imagery are widely used in the study of built-up area expansion [32]. Based on these data, researchers commonly employ techniques such as maximum likelihood classification and support vector machines to delineate built-up areas and use time series analysis methods to explore their patterns of change.

With the advancement of technology and the increasing availability of data resources, researchers studying urban built-up area expansion are gradually shifting from relying on single data sources to integrating multi-source big data for analysis [33]. Although remote sensing imagery has seen continuous improvements in spatial and temporal resolution, relying on a single data source for extracting urban built-up areas still presents certain limitations. For instance, remote sensing imagery may experience reduced classification accuracy under conditions such as cloud cover, image noise, and complex surface features. Additionally, a single data source is often insufficient to comprehensively capture the socioeconomic activities of a city [34–36]. Remote sensing data, such as Landsat, MODIS, and nighttime light (NTL) data, can provide spatial information on urban expansion [37,38], while socioeconomic data, including Points of Interest (POI) data, population density data, and transportation data, offer insights into urban functions and population distribution [39,40]. There have been studies to achieve the effect of improving the accuracy of built-up area extraction by fusing these two types of data [41]. For example, researchers can use NTL light data to identify active urban areas and then verify the specific functional types of these areas in combination with POI data to further determine the actual extent of built-up areas [42,43]. In the process of integrating remote sensing imagery with other data sources, image processing and classification algorithms play a crucial role. Commonly used methods include maximum likelihood classification, support vector machines (SVMs), random forests (RFs), and convolutional neural networks (CNNs) [44–46]. These algorithms are capable of processing the complexity of multi-source data and applying it to the extraction and analysis of urban built-up areas [47]. Although data fusion shows great potential in the study of urban built-up area expansion, it faces a number of challenges; firstly, the spatial and temporal resolution of different data sources may be inconsistent, making effective alignment and integration a difficult task; secondly, the heterogeneity of the data increases the complexity of the processing, presenting an additional challenge in effectively managing these differences during the integration process.

The spatiotemporal expansion characteristics of urban agglomerations are only a prerequisite for understanding the development of urban agglomerations, and the driving mechanisms behind them must be analyzed in depth to truly understand why urban agglomerations expand in a particular way [48]. These driving mechanisms may include a variety of factors such as economic, social, policy, technology, natural environment, etc., which collectively contribute to the expansion of urban space [19,49,50]. Current research generally identifies economic factors as the primary drivers of urban agglomeration expansion, particularly in regions experiencing rapid economic growth, where the pace of urban expansion is notably accelerated [51]. Additionally, population growth and migration is another significant driving force, especially in developing countries where there is a pronounced trend of population concentration in urban agglomerations [52]. Government policies and planning also play a crucial role in guiding and regulating the spatial expansion of urban agglomerations [53]. From the analysis of the driving mechanisms of spatial expansion of these urban agglomerations, quantitative analysis is still the most commonly used method in the study of driving mechanisms. Through quantitative tools such as statistical analysis, regression analysis, and structural equation modeling (SEM), researchers can reveal the independent effects and interactions of different drivers [54,55]. For example, spatial analysis methods, which often integrate GIS tools with spatial econometric models, are particularly focused on the geographical distribution and patterns of urban agglomeration expansion, exploring the spatial heterogeneity of these driving mechanisms [56,57]. Additionally, modeling approaches, including urban expansion models such as the CLUE-S model and the SLEUTH model, as well as system dynamics models, are widely used to simulate and predict the expansion trends of urban agglomerations. These models typically test the effects of various driving factors under different scenarios [58,59].

In existing studies, although extensive analyses have been conducted on the characteristics and driving mechanisms of urban agglomeration spatial expansion, it is important to recognize the significant differences in these aspects across urban agglomerations at different stages of development. Particularly, the driving mechanisms of spatial expansion in urban agglomerations can vary according to changes in the economic, social, and policy factors at different stages of development [60]. From this perspective, we take the Central Yunnan Urban Agglomeration in China as a case study to analyze the developmental stages of the urban agglomeration, as well as the spatiotemporal expansion characteristics and driving mechanisms at different stages, through the lens of multi-source data fusion. This study is conducted in the following steps: First, NTL light data, representing economic development, is fused with LandScan population data. Second, the developmental stages of the cities are identified. Third, deep learning techniques are employed to extract built-up areas in the Central Yunnan Urban Agglomeration, enabling the analysis of spatiotemporal expansion characteristics at different stages of development. Finally, the driving mechanisms behind the spatiotemporal expansion at different stages are analyzed and their differences compared. This study advances the application of multi-source data in urban spatial study by fusing two key dimensions: economy and population. Simultaneously, it reveals the differences in spatial expansion characteristics and driving mechanisms across various developmental stages of urban agglomerations, providing a scientific basis for formulating more precise regional development policies to promote coordinated and sustainable regional development.

2. Materials and Methods

2.1. Study Area

The Central Yunnan Urban Agglomeration (Figure 1) is located in the central region of Yunnan Province, China, and comprises Kunming, Qujing, Yuxi, Chuxiong Yi Autonomous Prefecture, and Honghe Hani and Yi Autonomous Prefecture. As the most economically developed area in Yunnan Province, this urban agglomeration covers 29% of the province's total area and is home to 44.02% of its population. In recent years, the Central Yunnan Urban Agglomeration, as a key region in Southwest China, has been experiencing rapid urbanization and economic growth [61]. However, due to differences in geographical location, economic development levels, and policy environments, the expansion of built-up areas in the Central Yunnan Urban Agglomeration exhibits unique spatiotemporal characteristics in terms of speed, scale, and spatial patterns. By studying the spatiotemporal characteristics of urban expansion in the Central Yunnan Urban Agglomeration, it is possible to uncover the expansion patterns and spatial structure changes during different periods, providing a scientific basis for the rational planning of urban development. Moreover, an in-depth studying of these characteristics and mechanisms can support the government in formulating more reasonable and effective regional development policies, thereby promoting the coordinated and sustainable development of the Central Yunnan Urban Agglomeration.

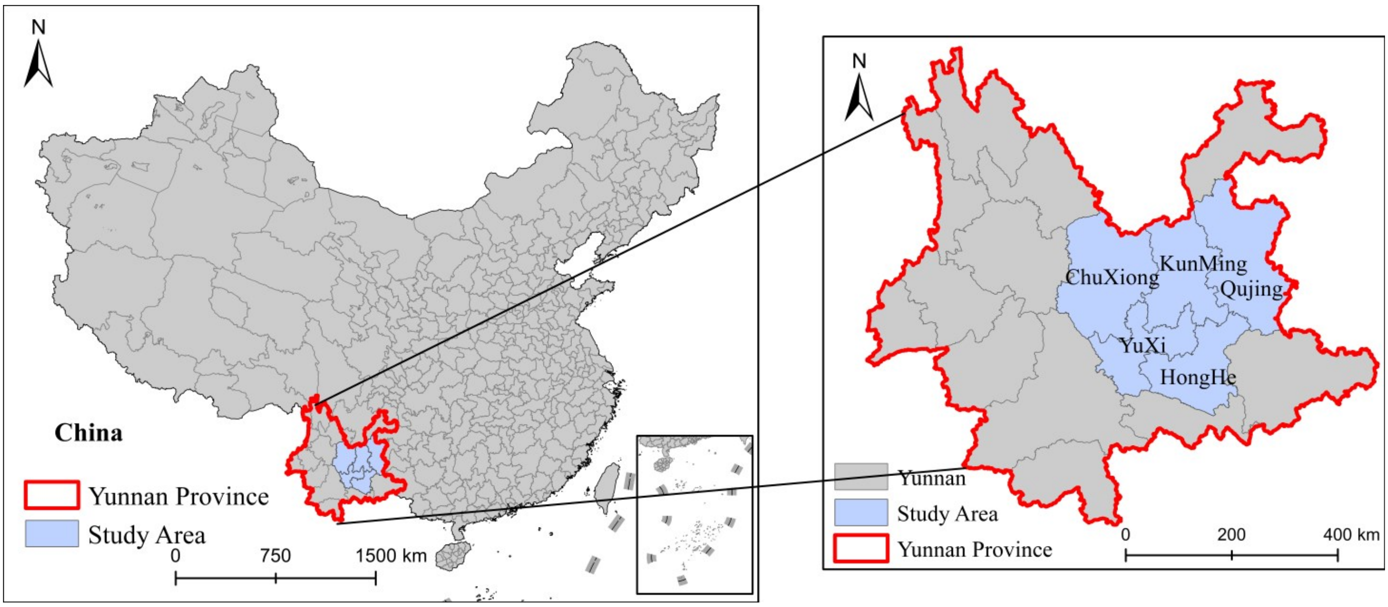

Figure 1. Study area.

2.2. Data Source

The data utilized in this study primarily include NTL data and LandScan data for four time periods: 2008, 2013, 2018, and 2023. The specific processing methods and workflows for these different datasets are outlined as follows.

2.2.1. NTL Data

NPP/VIIRS (Suomi National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite) NTL data are collected by the VIIRS sensors on Suomi NPP satellites, which record the brightness of the Earth's lights at night, including city lights, road lights, fishing boat lights, etc. [62]. The NPP/VIIRS NTL light data are an important tool for analyzing the expansion of urban agglomerations and their driving mechanisms because of its high resolution (500 m), wide dynamic range, regular updates, and global coverage. In addition to providing detailed and timely NTL light information, NPP/VIIRS NTL data can be combined with other geographic data to help uncover subtle changes and driving factors behind urban expansion. This makes it a valuable resource for urban planning, policymaking, and regional development by providing a scientific basis for decision-making. In this study, NPP/VIIRS NTL data for the Central Yunnan Urban Agglomeration for the years 2008, 2013, 2018, and 2023 are obtained from NASA's Earth Observing System Data and Information System (EOSDIS) website. After preprocessing the acquired data, including radiometric calibration and monthly averaging, the preprocessed NTL data for the Central Yunnan Urban Agglomeration is obtained, as shown in Figure 2.

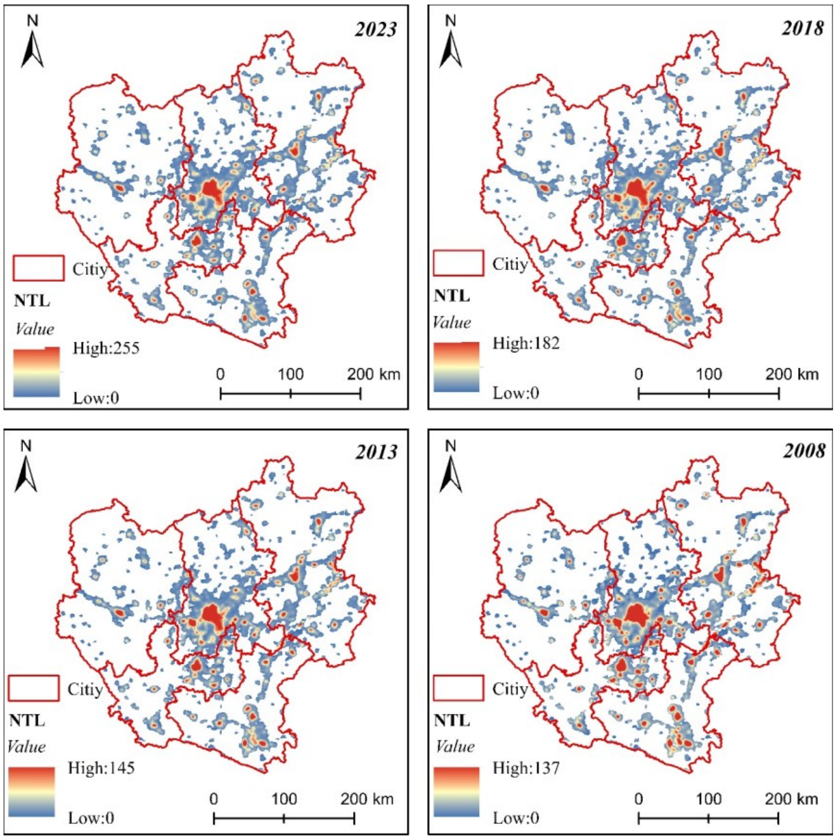

Figure 2. Preprocessing results of NTL data of the Central Yunnan Urban Agglomeration in 2008, 2013, 2018, and 2023.

2.2.2. LandScan Data

LandScan data are a global population distribution dataset developed and maintained by the Oak Ridge National Laboratory (ORNL) in the United States. This dataset leverages multi-source information, including satellite imagery, geographic information systems

(GIS) data, census data, and remote sensing technology, to generate high-resolution global population distribution maps. Due to its high resolution, global coverage, dynamic updates, and multi-source integration, LandScan data have become an essential tool for analyzing urban agglomeration expansion and its driving mechanisms [24]. It not only provides detailed population distribution information but also, when combined with other geographic data, helps to reveal subtle changes and driving factors behind urban expansion, offering a scientific basis for urban planning, policymaking, and regional development. In this study, LandScan population data for the Central Yunnan Urban Agglomeration for the years 2008, 2013, 2018, and 2023 are obtained from the official website (https://landscan.ornl.gov/ accessed on 1 March 2023). After preprocessing the data, the spatial population distribution map for the Central Yunnan Urban Agglomeration is generated, as shown in Figure 3.

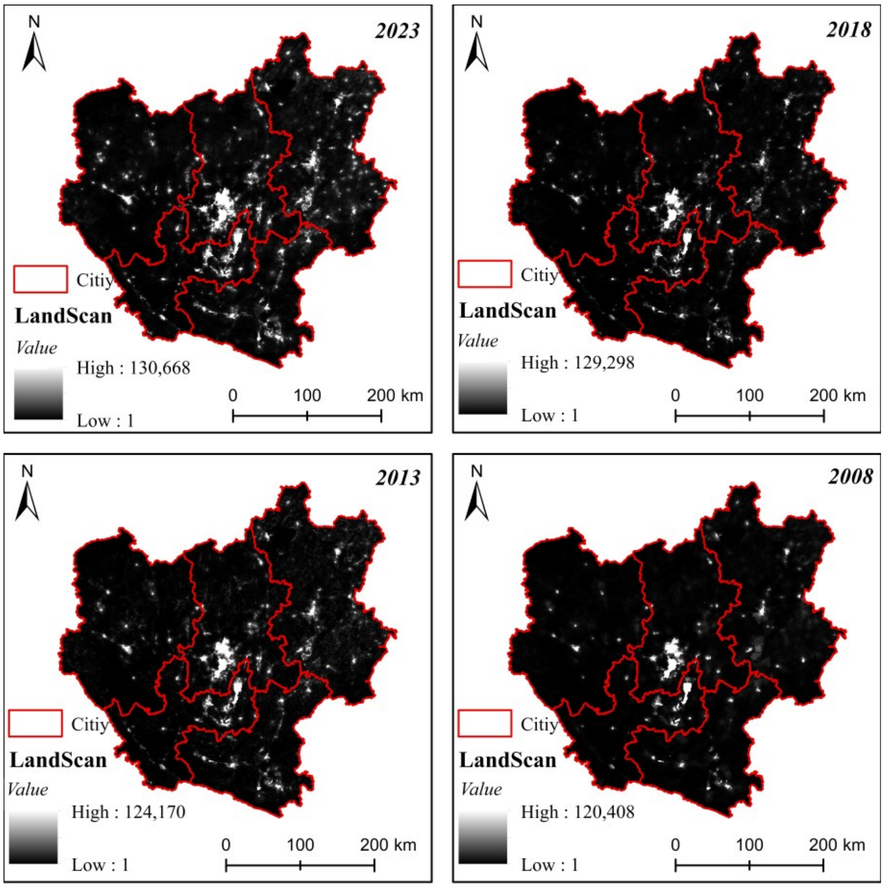

Figure 3. Preprocessing result of the LandScan Data of Central Yunnan Urban Agglomeration in 2008, 2013, 2018, and 2023.

2.3. Methods

2.3.1. Rank Size Rule

In the historical process of urban development, peripheral expansion has been the primary method of urban growth, where cities expand the scale of construction land into surrounding areas to promote economic and population growth. This model emphasizes the close connection between the spatial expansion rate of land development and urban economic growth, particularly in rapidly developing urban agglomerations. In this context, central cities expand their construction scale by occupying surrounding land resources, while peripheral cities gradually grow by absorbing spillover resources. This spatial expansion allows for the measurement of the degree of development coordination and scale differences between cities within an urban agglomeration through the spatial distribution characteristics of construction areas [63,64]. Furthermore, the development of urban agglomerations progresses from an initial to an advanced stage through a gradual process of integration. In the early stage, the central city expands rapidly due to its scale advantages, while peripheral cities develop more slowly, relying primarily on the economic spillover effects of the central city. At this stage, the central city's resource aggregation effect is highly pronounced. As the urban agglomeration evolves, peripheral cities gradually assume some functions of the central city, marking the onset of the accelerated agglomeration phase. With more balanced resource allocation, peripheral cities gain a greater capacity for independent development, and the urban agglomeration gradually evolves into a polycentric structure with more refined functional divisions. This leads to the phase of agglomeration decay and a tendency toward decentralization. Ultimately, cities within the agglomeration form a highly coordinated division of labor, with stronger linkages between central and peripheral cities, achieving overall functional integration [65,66].

Overall, the scale advantage of central cities and the level of coordination between central and peripheral cities are important criteria for evaluating the developmental stages of urban agglomerations. The rank–size rule can reflect the scale distribution and development imbalance among different cities, which is crucial for analyzing the relationship between central and peripheral cities within an agglomeration. Therefore, we aim to use the Zipf index (q value) of the rank–size rule to reveal the scale differences and distribution patterns among cities within the urban agglomeration. This analysis will further allow us to identify the coordination between central and peripheral cities and, subsequently, determine the developmental stage of the urban agglomeration [67,68].

$$lnY_i = lnY_1 - qlnr \tag{1}$$

where lnY_i represents the size of city i, Y_1 is the theoretical maximum NTL_LS value for the central city, and r is the rank of city i. The parameter q is the Zipf index, which reflects the degree of balance in the city size distribution. The specific calculation process involves sorting the city sizes of the Central Yunnan Urban Agglomeration in descending order based on NTL_LS data fusion. The rank r of each city is then obtained, and a linear regression analysis is performed based on the equation $lnY_i = lnY_1 - qlnr$. Through this regression analysis, the slope q is determined.

Specially, when q equals 1, it indicates an optimal distribution, which generally suggests that the resource allocation or size differences within the system are relatively balanced. When q is greater than 1, it indicates that the distribution of urban elements is concentrated, with the central city having a significant size advantage and smaller elements being relatively scarce. When q is less than 1, it indicates the distribution of urban elements is more balanced, with the central city having a weaker size advantage and small- to medium-sized cities being more developed. As the value of q increases, the spatial expansion coordination between the central city and peripheral cities gradually decreases, while a decrease in q enhances the spatial expansion coordination between the central and peripheral cities [66,69]. In the calculation of the Zipf index from 2008 to 2023, the q values for 2008, 2013, 2018, and 2023 are found to be 0.72, 1.13, 1.36, and 1.22, respectively. From 2008 to 2013, the increasing q value, with a value greater than 1 in 2013, indicates a high concentration of resources in the central city, with peripheral cities lagging in development. The central city was significantly larger than the other cities. From 2013 to 2018, the q value continued to rise, suggesting that the agglomeration effect of the central city further intensified, attracting more resources and population. The development of peripheral cities remained slow, widening the gap between central and peripheral cities. However, from 2018 to 2023, the q value decreased, indicating that, as peripheral cities developed, the distribution of resources and population within the urban agglomeration became more balanced, and the expansion rate of the central city slowed. Peripheral cities gradually began to assume regional functions, enhancing the coordination between cities within the agglomeration. Based on these findings, the development of the urban agglomeration can be divided into four stages: initial tendency toward agglomeration, accelerated agglomeration, agglomeration decay, and dispersal tendency.

2.3.2. Data Fusion

Data fusion refers to the integration and processing of data from different sources or sensors to obtain more comprehensive, accurate, and consistent results. By fusing multi-source data, the limitations of single data sources can be overcome, thereby enhancing the accuracy and quality of data analysis and decision-making. Wavelet transform, a commonly used signal processing tool, has been widely applied in the field of data fusion. Utilizing wavelet transform for data fusion effectively preserves the characteristic information of each data source and improves the quality of the fusion results [70,71].

The primary distinction between wavelet transform and Fourier transform lies in its ability to provide a time–frequency analysis of signals. Fourier transform only analyzes the frequency components of a signal, whereas wavelet transform not only captures frequency information but also detects local variations in the time or spatial domain. By decomposing a signal into wavelet functions at different scales and frequencies, wavelet transform enables multi-scale and multi-resolution analysis, allowing for the detection of subtle changes in the signal. This characteristic makes it an ideal tool for data fusion. The formula for wavelet transform is as follows:

$$WT(\alpha,\tau) = f(t)\varphi(t) = \frac{1}{\sqrt{\alpha}} f(t) \int_{-\infty}^{+\infty} \varphi(\frac{t-b}{\alpha}) dt \tag{2}$$

where $f(t)$ is the image signal vector, $\varphi(t)$ is the wavelet transform function, α is the wavelet transform scale, τ is the translation parameter of the image signal, and b is the parameter.

The basic process of wavelet transform includes multi-scale decomposition, the application of fusion rules, and inverse wavelet transform. First, data from different sources undergo wavelet transform, decomposing into detail and approximation components at multiple scales. This process allows for the extraction of key information at various scales. Second, at each scale, the detail and approximation components are processed based on predefined fusion rules, selecting or synthesizing critical features. These fusion rules can be tailored to the specific requirements of the application, such as selecting the maximum absolute value or calculating the mean. Finally, inverse wavelet transform is applied to reconstruct the multi-scale features into a single data result that contains more comprehensive and enriched information.

2.3.3. U-Net Neural Network

U-Net is a convolutional neural network (CNN) architecture composed of a down-sampling path (encoder) and an up-sampling path (decoder), with skip connections that fuse features across different scales, making it highly effective for pixel-level image segmentation tasks [72]. When extracting urban built-up areas, U-Net can classify each pixel in a remote sensing image as either "built-up" or "non-built-up", thereby accurately delineating the boundaries of urban regions. Its advantages include high-precision segmentation, multi-scale feature fusion, and the ability to learn effectively even with a small amount of training data [73]. These qualities make U-Net an ideal tool for remote sensing image analysis in urban planning and geographic information systems (GIS), providing precise technical support for the extraction of urban built-up areas.

Equations of the component layers of U-Net.

Layer Convolution:

$$C_{out\,j} = bias(C_{out}) + \sum_{k=0}^{C_{in}-1} weight(C_{out\,j}, k) * input(k) \tag{3}$$

Layer Max-pooling:

$$out(C_j,h,w) = max_{m=0,\ldots\ldots,kH-1} max_{n=0,\ldots\ldots,kW-1} input(C_j, stride[0] \times h + m, stride[1] \times w + n) \tag{4}$$

Layer ReLU:

$$ReLU(x) = max(0,x) \tag{5}$$

Layer Softmax:

$$Softmax(x_i) = \frac{exp(x_i)}{\sum_{j=1}^{k} exp(x_i)} \tag{6}$$

Layer Cross-entropy:

$$loss(x, y) = -log(\frac{exp(x[y])}{\sum_{j=1}^{k} exp(x[y])}) \tag{7}$$

In the Layer Convolution Formula (3), the input feature map has dimensions (C_{in}, H, W), and the output feature map has dimensions (C_{out}t, H_{out}, W_{out}). The output channel $C_{out\,j}$ is obtained by performing a weighted summation over all input channels C_{in} and adding a *bias* term. Here, the convolution kernel weight, $weight(C_{out\,j}, k)$, represents the convolution kernel between the *j*-th output channel and the *k*-th input channel. The convolution kernel slides over the input feature map (performing valid convolution), executing pointwise convolution operations. Through this weighted summation, the convolution layer can extract feature information at different scales and levels. The bias term is a trainable parameter for each output channel, used to adjust the convolution result, allowing the network to flexibly express different patterns. In the Layer Max-Pooling Formula (4), the max-pooling layer reduces the spatial dimensions of the feature map by selecting the maximum value within local regions of size (kH, kW). This operation retains the most important information within each local region while reducing the spatial dimensions of the feature map. The pooling operation reduces the height and width of the original input feature map, with the stride controlling the sliding step of the pooling operation. Max-pooling is primarily used for down-sampling, preserving the most significant features while reducing the spatial dimensions, which helps decrease the computational complexity and enhances the network's ability to handle invariance. In the Layer ReLU Formula (5), ReLU is a commonly used nonlinear activation function that truncates the negative values of the input to 0 while keeping the positive values unchanged. ReLU introduces nonlinearity, enabling the network to learn complex patterns and features. Additionally, by eliminating negative values, it helps mitigate the vanishing gradient problem and accelerates network training. In the Layer Softmax Formula (6), Softmax is used to convert the network's output into a probability distribution. The input x_i represents the raw classification score for a particular pixel, and Softmax transforms these scores into probabilities, ensuring that the sum of probabilities across all categories equals 1. Softmax is a commonly used activation function in multi-class classification tasks, producing the probability that each pixel belongs to different categories. In image segmentation tasks, it is employed for pixel-level classification to determine the category to which each pixel belongs. In the Layer Cross-Entropy Formula (7), Cross-Entropy is used to measure the difference between the model's predicted probability distribution and the true class labels. In the formula, $x[y]$ represents the score of the correctly predicted class by the model, and the loss value for the pixel is computed through the logarithm and negative sign operations. Cross-Entropy loss guides the network in optimizing the model parameters by minimizing the difference between predicted probabilities and the true classes, thereby improving the model's classification accuracy.

2.3.4. Geographical Detector (Geo-Detector)

The Geo-detector is a statistical method for detecting and analyzing spatial heterogeneity and its causes, which is mainly used for spatial data analysis in the fields of geography, environmental science, and public health. It aims to quantitatively assess the influence of various factors on spatial distribution characteristics and their interactions, thereby investigating and uncovering the driving forces behind geographical phenomena and their impact [74,75]. By quantitatively analyzing the influence of different geographical factors (such as the natural environment, socioeconomic conditions, etc.) on the spatial distribution of specific phenomenon (such as urban expansion), the Geo-detector can quantify the spatial heterogeneity of the phenomenon and identify the key influencing factors and their contributions. The formula for the Geo-detector model is as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{m=1}^{L} N_m \sigma_m^2 \tag{8}$$

where q is the explanatory power of regional geographical environmental factors; $m = 1, 2, \ldots$; L is the number of categories; N_{m} and N are the number of units in category m and the total number of units in the entire area, respectively; and σ^2 is the variance of the indicator. The q value ranges from 0 to 1, with higher q values indicating a stronger explanatory power for spatial heterogeneity.

The technical workflow of this study is as follows (Figure 4):

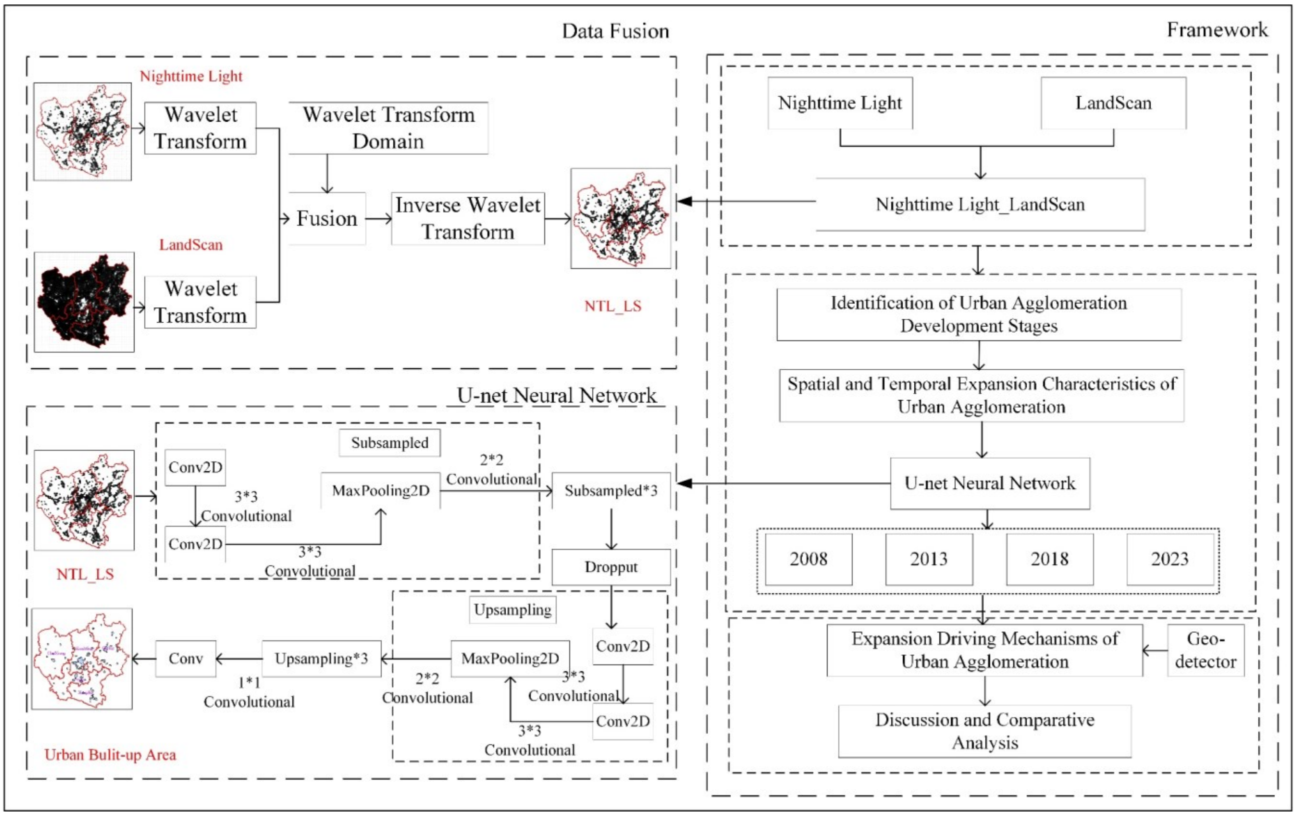

Figure 4. Data processing and analysis workflow.

3. Results

3.1. Multi-Source Big Data Fusion

As the complexity of urban systems continues to increase, a single data source often proves inadequate in fully capturing the intricate spatial structures and dynamic changes within cities. This is because urban spatial distribution encompasses multidimensional characteristics, such as land use, building density, population distribution, transportation networks, and the ecological environment, which exhibit significant heterogeneity and dynamism. Therefore, a single data source—such as relying solely on demographic data, remote sensing imagery, or traffic flow data—tends to capture only one aspect, making it difficult to provide a comprehensive perspective of the entire urban system. Data fusion refers to the integration of data from different sources, times, or spatial scales to generate information that is more comprehensive, accurate, and consistent than what a single data source can provide. By leveraging the strengths of multiple data sources, data fusion not only overcomes the limitations of a single data source in terms of space, time, and dimension but also reduces prediction errors in the analysis and enhances the reliability of data interpretation. For example, by fusing remote sensing imagery, socioeconomic data, and transportation network data, one can simultaneously capture changes in urban land use, population movement trends, and traffic pressure distribution, thereby providing a more comprehensive depiction of urban spatial distribution and dynamic changes.

In urban studies, spatial distribution refers to the pattern of how various elements, such as population, buildings, land use, and infrastructure, are arranged within a geographical space. The relationships between these elements are complex and influenced by multiple factors. A single data source may not effectively capture the interactions and spatial heterogeneity among different elements. Therefore, through multi-source data fusion, a deeper understanding of the complex spatial structure within a city can be revealed.

In urban spaces, NTL data and LandScan data exhibit significant spatial correlation, characterized by a gradual decrease in light intensity and population density from the urban center to the periphery. Based on this spatial correlation, we attempt to fuse NTL data with the LandScan data, as shown in Figure 5, which demonstrates the data before and after the fusion. Specifically, we use wavelet transform to fuse NTL data with LandScan data, utilizing the multi-scale analysis properties of wavelet transform to decompose the data into frequency bands of different scales.

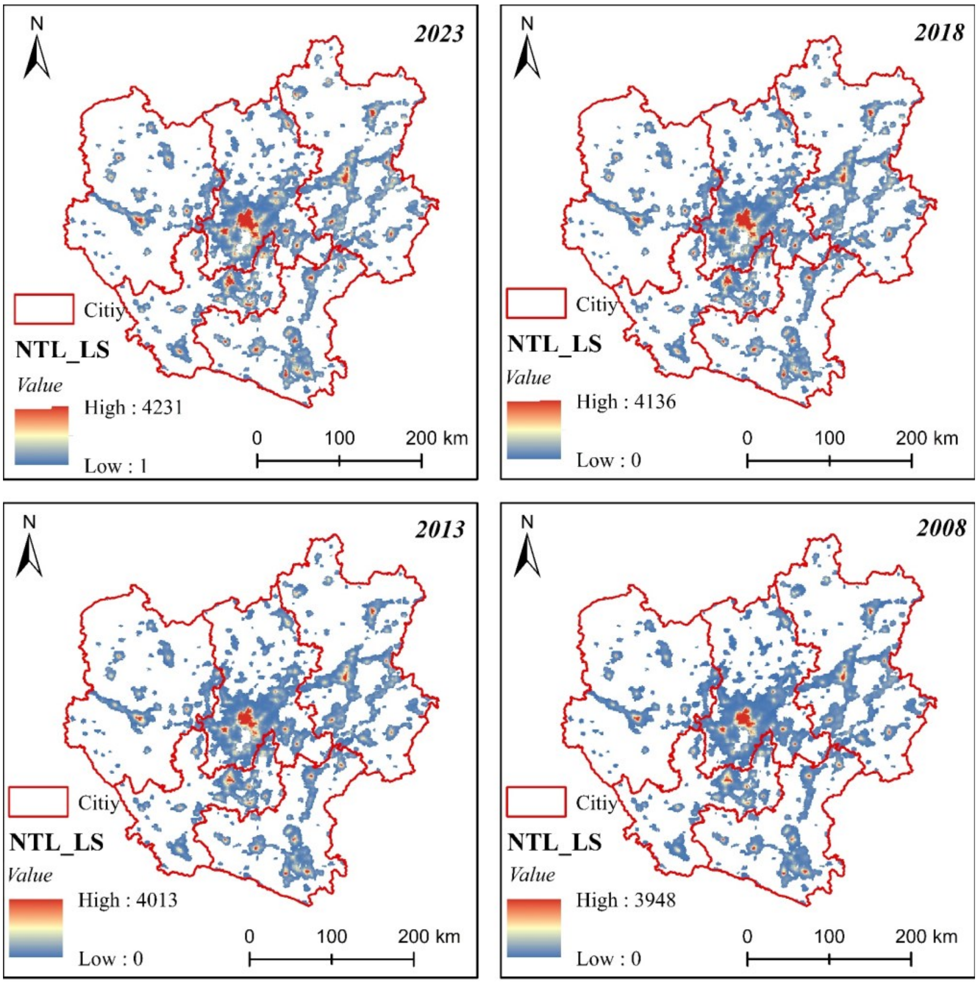

Figure 5. Fusion results of the NTL data and LandScan data.

Wavelet transform effectively separates low-frequency and high-frequency information by decomposing data into different frequency components. In the fusion of NTL data with LandScan data, wavelet transform helps distinguish the overall trend (low-frequency components) from local details (high-frequency components), allowing the fused data to preserve both macro-level information and detailed features [76]. In the low-frequency component, the global trend information dominates the data. To fuse the overall trends of NTL data and LandScan data, we use a weighted averaging method. By assigning appropriate weights to each data source, we ensure that both are adequately represented in the fused result [77]. The high-frequency component contains local detail information, such as city edges and subtle variations in population distribution. To preserve the most significant detail features, we employ a maximum value selection fusion strategy for the high-frequency component. By selecting the maximum value from the two data sources, the fused result retains the most representative details from both the NTL data and the LandScan data [78]. Overall, wavelet transform provides us with the ability to separate low-frequency and high-frequency information. The low-frequency component is fused using weighted averaging, ensuring that the global trend is included in the fused result, while the high-frequency component is fused using maximum value selection, preserving the local detail features in the data. This fusion strategy effectively enhances the expressiveness of the data while retaining significant features from different data sources.

By comparing the data before and after fusion, visual analysis shows that the pre-fusion data exhibits blurred city boundaries and unclear details, making it difficult to accurately describe the urban spatial structure. After fusion, the detail of spatial distribution is significantly clearer, and city boundaries become more distinct. This improvement is particularly notable in areas with complex terrain and densely populated regions, where the fused data show marked enhancements in spatial consistency and feature preservation. Additionally, we conduct a detailed analysis of the signal-to-noise ratio (SNR) before and after fusion, revealing that, before the fusion, the SNR was 15 dB, while, after the fusion, the SNR increased to 25 dB. Overall, the use of wavelet transform effectively separates and suppresses noise, enhances signal strength, and significantly improves data quality. This improvement supports the next step in analyzing the spatiotemporal expansion of the Central Yunnan Urban Agglomeration.

3.2. Urban Agglomeration Development Stages

By calculating the q values for the Central Yunnan Urban Agglomeration at four time points between 2008 and 2023 using the rank–size rule, we find the values to be 0.72, 1.13, 1.36, and 1.22, respectively. This indicates that the Central Yunnan Urban Agglomeration has transitioned from a tendency towards agglomeration and accelerated agglomeration phases since 2008 and is currently in a phase of agglomeration deceleration. From 2008 to 2013, the Central Yunnan Urban Agglomeration is in the initial stage of agglomeration. In 2008, the q value for the urban agglomeration is relatively low, indicating that the differences in city sizes within the agglomeration are minimal and that the spatial distribution of cities is relatively dispersed. During this period, the urban agglomeration has not yet developed a significant agglomeration effect, and the urbanization process is progressing at a relatively moderate pace. By 2013, the q value has increased significantly, indicating that the scale differences between cities begin to widen, and the major cities within the urban agglomeration gradually assert their dominant positions. This period may have been driven by economic policies and the development of transportation infrastructure (such as high-speed rail and airports), leading to the concentration of resources and population in the core cities of the Central Yunnan Urban Agglomeration, thereby initiating the formation of agglomeration effects. From 2013 to 2018, the Central Yunnan Urban Agglomeration enters a phase of accelerated agglomeration. During this period, the q value of the urban agglomeration continues to rise, indicating a further widening of the scale differences among cities within the region and a rapid intensification of the agglomeration effect. The radiating and driving influence of the core cities become increasingly prominent, with a significant concentration of resources, population, and economic activities in these core cities. With the acceleration of the agglomeration effect, there is an obvious imbalance in the development of cities within the urban development, with core cities experiencing rapid growth while peripheral cities grow at a relatively slower pace. The Central Yunnan Urban Agglomeration exhibits a pronounced siphoning trend during this stage, leading to a more centralized spatial structure within the region, and from 2018 to 2023, the Central Yunnan Urban Agglomeration entered a phase of agglomeration decay. After 2018, the decrease in the q value indicates that the agglomeration effect within the Central Yunnan Urban Agglomeration began to weaken. Although the core cities still maintain their dominance, the scale difference between them and the peripheral cities no longer expands significantly, and some cities begin to show a relatively balanced development trend. This shift can be attributed to policy interventions, industrial decentralization, and the advancement of transportation and communication technologies, which facilitates a more even distribution of resources and opportunities across the urban agglomeration. While the agglomeration effect is weakening, there is a trend of polycentric development in the Central Yunnan Urban Agglomeration. That is, numbers of sub-cities have formed several regional centers, alleviating the pressure on the core city of Kunming and promoting broader regional development within the urban agglomeration.

While the Zipf index is a useful tool for measuring the degree of imbalance in the size distribution of urban agglomerations, it is not sufficient on its own to explain agglomeration phenomena. The formation and evolution of agglomeration effects are influenced by multiple factors, including economic development, transportation infrastructure construction, policy regulation, and technological advancements, with the Zipf index representing only one aspect of this complex process. From 2008 to 2013, the rising q value reflected an increasing disparity in city sizes, driven by accelerated economic growth in the Central Yunnan Urban Agglomeration, particularly in core cities like Kunming, which attracted substantial investment and infrastructure development (e.g., high-speed rail and airports). These economic stimulus policies promoted the concentration of resources, population, and capital in core cities, exacerbating size differences within the agglomeration. However, after 2018, with the adjustment of industrial structures, some emerging industries and services began to diffuse into secondary cities, reducing the agglomeration effect in core cities and fostering a trend toward polycentric development. Thus, the weakening of the agglomeration effect does not indicate the decline of the urban agglomeration but rather the redistribution of resources and opportunities within it. As resources and opportunities spread to secondary cities, the agglomeration effect diminishes, and the q value starts to decline. However, this does not signify the decline of the urban agglomeration but instead indicates a transition from single-core concentration to more coordinated polycentric development.

3.3. Spatiotemporal Characteristics of Urban Agglomeration Expansion

To more accurately extract the built-up areas of the Central Yunnan Urban Agglomeration, we first divide the fused dataset into 512×512 tiles to generate training samples and labels. The label data are derived from the built-up area vector data published by the Central Yunnan Urban Agglomeration in 2020, which we cross-reference and calibrate with high-resolution satellite imagery to ensure a certain level of accuracy. After preprocessing, we generate binary images with the same resolution as the input data. The built-up areas of the Central Yunnan Urban Agglomeration at four time points from 2008 to 2023 are obtained using the U-net neural network, as shown in Figure 6.

From 2008 to 2023, the total built-up area of the Central Yunnan Urban Agglomeration increases from 1798.19 square kilometers to 4057.70 square kilometers, representing a growth of approximately 2.26-fold. The expansion of the built-up area of the Central Yunnan Urban Agglomeration shows a trend of gradual acceleration from 2008 to 2023, especially from 2018 to 2023, and the expansion speed is obviously accelerated, which is closely related to the advancement of regional economic integration, the improvement of transportation infrastructure, and the optimization of industrial distribution within the Central Yunnan Urban Agglomeration. Spatially, Kunming, as the core city of the Central Yunnan Urban Agglomeration, exhibits the fastest expansion and the largest growth area, demonstrating a significant polarization effect. Other cities, such as Qujing and Yuxi, also show notable expansion trends, indicating the gradual development of secondary center cities. The expansion in Chuxiong and Honghe is relatively slower but still demonstrates steady growth. With the progression of urbanization, the Central Yunnan Urban Agglomeration has gradually developed a polycentric spatial structure, with Kunming as the core, Qujing and Yuxi as secondary centers, and Chuxiong and Honghe as supporting cities.

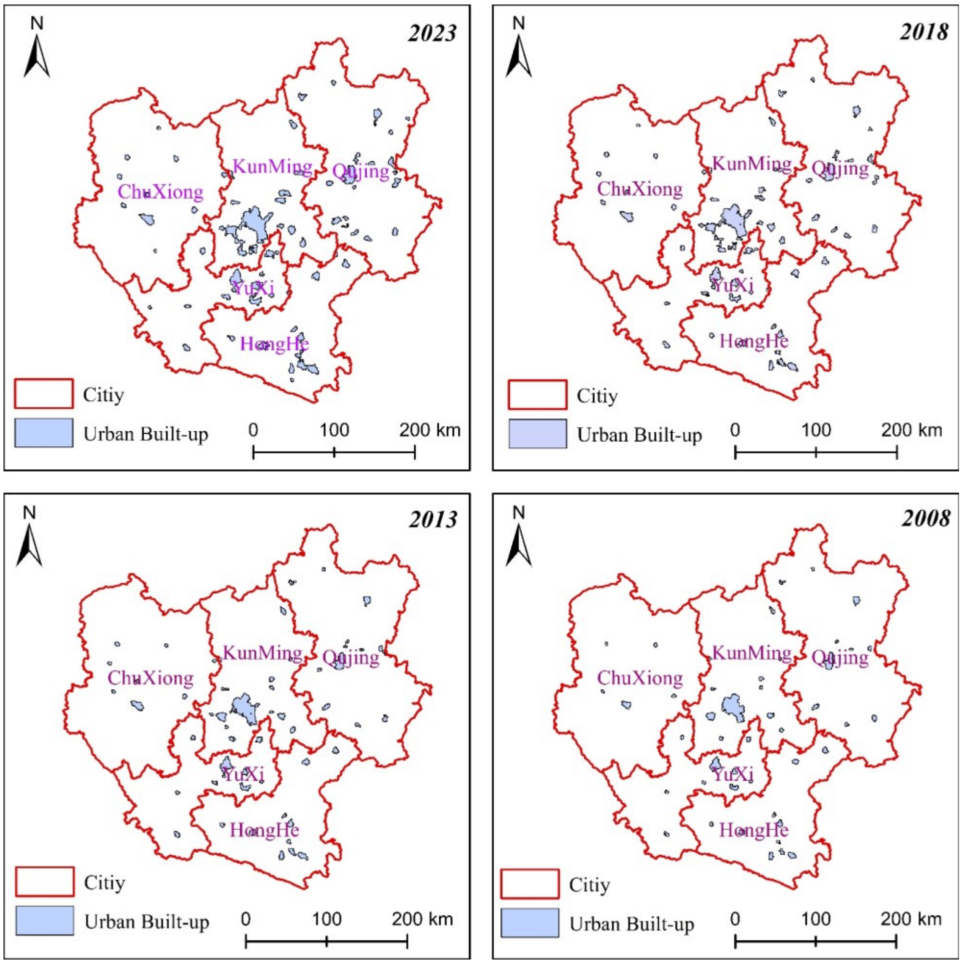

Figure 6. Distribution characteristics of built-up areas in the Central Yunnan Urban Agglomeration.

Specifically, in terms of the spatiotemporal characteristics of built-up area expansion, Kunming, as the core city of the Central Yunnan Urban Agglomeration, consistently maintains a dominant position in spatial expansion. The built-up area of Kunming expands most rapidly and with the greatest magnitude, and this polarization effect reflects the agglomeration effect of Kunming as the political, economic, and cultural center of Yunnan Province, which attracts a large amount of resources, population, and investment. This expansion pattern reinforces Kunming's regional core status but also exacerbates developmental imbalances among other cities in the region. Secondary center cities such as Yuxi and Qujing exhibit rapid growth in their built-up areas, particularly between 2018 and 2023, when their expansion rates accelerated significantly. This trend indicates that the urban system of the Central Yunnan Urban Agglomeration is gradually transitioning from a single-center to a more polycentric development model, forming a multi-tiered urban network with Kunming as the core and secondary cities as key supports. This polycentric expansion pattern helps alleviate urban pressure on Kunming and promotes a more balanced regional development. The growth of these secondary center cities benefits, to some extent, from regional policy support and improvements in the transportation network, gradually integrating them into the overall development framework of the Central Yunnan Urban Agglomeration. However, the expansion of these cities tends to be characterized by steady linear growth rather than explosive expansion, indicating that their roles in regional development remain primarily supportive.

As for the expansion focus of the urban agglomeration across different periods, from 2008 to 2013, the expansion of the Central Yunnan Urban Agglomeration primarily concentrated on the core city of Kunming and its surrounding areas. This period is characterized by a distinct core-to-periphery radiating pattern, where Kunming, as the regional core city, drives rapid expansion in the surrounding regions. From 2013 to 2018, the agglomeration's expansion shows the characteristics of multi-direction and multi-node. The expansion of the core city of Kunming is further accelerated, and the neighboring Yuxi and Qujing begin to show strong expansion momentum. From 2018 to 2023, the expansion of the Central Yunnan Urban Agglomeration entered a stage of full acceleration, with urban development advancing in all directions both within and beyond the agglomeration, reflecting a trend towards regional integration. Urban expansion is not only concentrated in the core area but also extends to the periphery of the agglomeration. Overall, from 2008 to 2023, the expansion of the Central Yunnan Urban Agglomeration transitioned from a single-center radiating expansion to multi-nodal, multi-directional growth, and, finally, to a stage of comprehensive integrated development.

3.4. Expansion Driving Mechanisms of Urban Agglomeration

From the results of the spatial expansion of the Central Yunnan Urban Agglomeration from 2008 to 2023, it is evident that the agglomeration has undergone significant growth over the past fifteen years. To accurately assess the driving processes at different stages of this development, we employ the Geo-detector to conduct an objective analysis of the potential driving mechanisms involved during various periods.

From the previous spatial expansion of urban agglomerations, there are many factors affecting the spatial expansion of cities, and the influencing factors vary from one city to another. However, from the comprehensive view of existing studies, there are several influencing factors that are generally recognized by researchers, including the level of economic development, the size of the resident population, the industrial structure, and the condition of transportation infrastructure, as these aspects inevitably affect the development of all cities. In addition, considering the actual development of the Central Yunnan Urban Agglomeration and existing literature, we select the economic development level, population size, industrial structure, elevation, slope, government support, transportation infrastructure, and openness as the driving factors. The descriptions and data sources for these driving factors are as follows [76,79–82]:

The level of economic development is one of the core driving factors of urban expansion. Higher levels of economic development are typically associated with increased investment, infrastructure development, and demand for land, which collectively drive urban growth. Within the Central Yunnan Urban Agglomeration, economically developed areas are often hotspots of urban expansion, with wealth accumulation and industrial development serving as key forces behind the agglomeration's growth. In this study, we measure the level of economic development using per capita GDP, calculated as the sum of the gross output of the secondary and tertiary sectors divided by the total urban population.

The population size has a direct impact on the development needs of cities. As the population increases, so does the demand for housing, infrastructure, public services, etc., thus contributing to urban expansion. In the Central Yunnan Urban Agglomeration, core cities like Kunming, with a high population density and rapid population growth, experience swift urban expansion. Population size not only determines the physical expansion needs of a city but also reflects its attractiveness and competitiveness. In this study, we use the resident population size to represent this factor.

Changes and upgrading in an industrial structure have an important impact on urban expansion. High value-added industries, such as high-tech and financial services, typically concentrate in economically developed areas, attracting a substantial labor force and resources, thereby driving urban growth. The Central Yunnan Urban Agglomeration has undergone industrial restructuring and upgrading in recent years, particularly in cities like Kunming and Yuxi, where industrial concentration and upgrading have markedly accelerated urban spatial expansion. This study examines the impact of industrial structure on the spatial evolution of urban agglomeration by analyzing the ratios of the secondary and tertiary sectors.

Elevation is one of the key natural geographic factors influencing urban spatial layout. The Central Yunnan Urban Agglomeration is located in a mountainous region with complex terrain, where high-altitude areas often limit the direction and scale of urban expansion. Urban expansion usually tends to occur in flatter and lower elevation areas; thus, elevation has a direct impact on the feasibility and cost of urban expansion. This study uses DEM to extract elevation.

Slope is another key topographic factor that affects the difficulty and cost of urban development. Steeper slopes increase the challenges of constructing buildings and infrastructure and impact the accessibility and convenience of transportation within the city. Therefore, in the expansion of the Central Yunnan Urban Agglomeration, areas with gentler slopes are more likely to be chosen for urban growth, while steeper areas may constrain expansion. In this study, we extract land slope data using DEM.

Government policies and support play a crucial role in urban expansion. The government directly influences the speed and direction of urban expansion through planning policies, investment guidance, and infrastructure construction. In the Central Yunnan Urban Agglomeration, government-led development plans, industrial policies, and investments in infrastructure, such as transportation and public services, are key drivers of urban expansion. Government support is also reflected in policies aimed at assisting underdeveloped areas and in preferential policies for new towns and economic development zones. In this study, we use the share of fiscal expenditure of the upper-level government in the GDP of the urban agglomeration to indicate the degree of support from the local government.

Transportation infrastructures directly affect a city's accessibility and external connectivity, which, in turn, affects urban expansion. A well-developed transportation network facilitates intercity connections and resource flows and reduces the marginal cost of urban expansion. In the Central Yunnan Urban Agglomeration, the construction of transportation infrastructure, such as highways and high-speed railways, significantly drives spatial expansion both within and beyond the urban agglomeration. The improvement of transportation not only promotes urban expansion but also strengthens interaction and cooperation between cities.

Openness refers to the degree to which a city is open to external exchanges, trade, and investment. A higher degree of openness is usually accompanied by a greater inflow of foreign capital, technological exchanges, and personnel exchanges, further promoting the economic development and spatial expansion of the city. As an important gateway connecting Southeast Asia, the Central Yunnan Urban Agglomeration, especially Kunming, has a high degree of openness and has attracted a number of foreign-funded enterprises and international projects, a factor that has significantly contributed to the city's expansion. This study examines the impact of economic globalization on the spatial structure of the urban agglomeration by using the proportion of actual utilized foreign capital to GDP as an indicator.

The results of the driving factors for the expansion of the Central Yunnan Urban Agglomeration at different periods, obtained through Geo-detector analysis, are presented in Figure 7. From the analysis of these driving factors, it is evident that, during the period of aggregation from 2008 to 2023, the expansion of the Central Yunnan Urban Agglomeration underwent significant phase changes, displaying an evolutionary process driven progressively by economic development, population size, industrial structure, and government support. During the period of accelerated agglomeration from 2008 to 2013, the urban expansion is mainly driven by the level of economic development and population size, and the economic growth brought by the infrastructure development and employment opportunities significantly contributed to the expansion of urban land, accompanied by rapid population growth, especially in core cities such as Kunming, where urban space expanded dramatically to meet the growing demand for housing and services. During the period of decelerating aggregation from 2013 to 2018, although the level of economic development remains an important driving force for urban expansion, its relative influence has weakened, and the transformation and upgrading of the industrial structure begins to play a more critical role, particularly with the rise of the tertiary sector and high-tech industries. This shift diversified the modes of urban expansion, leading to the optimization of urban functions and adjustments in spatial layout. From 2018 to 2023, industrial structure and government support became the main driving forces, with the rapid development of tertiary and innovative industries giving rise to new urban growth poles, while governments at all levels have further promoted the coordinated development of urban agglomerations and regional integration through policy guidance and infrastructure investment, especially in the development of key regions and the construction of new districts, where the government's leading role has been particularly prominent, prompting urban expansion towards functionality and integration. Additionally, during the period from 2018 to 2023, the expansion of the Central Yunnan Urban Agglomeration was inevitably impacted and adjusted by the COVID-19 pandemic. Following the outbreak, the pace of economic development in the urban agglomeration slowed down, particularly in the early stages of 2020 and beyond, as economic uncertainty delayed infrastructure investments and urban expansion projects. The pandemic's impact on traditional industries (such as manufacturing and retail) weakened the economic growth momentum, thereby affecting the process of urban expansion. During the initial lockdowns and restrictions of the pandemic, cross-regional mobility decreased, which slowed the pace of urban expansion within the Central Yunnan Urban Agglomeration to some extent. With population growth in Kunming tending to slow, other cities experienced a decline or stagnation in population inflows, temporarily easing the spatial pressure of urban expansion. The COVID-19 pandemic had a profound impact on the industrial structure of the Central Yunnan Urban Agglomeration, accelerating the process of industrial transformation and upgrading. These emerging industries stimulated new employment opportunities and demands for urban expansion, particularly in the formation of high-tech industrial parks and innovation clusters, driving the functional upgrading and spatial reorganization of cities. During this period, the development of innovative industries and digital economy infrastructure became key drivers of urban expansion in the Central Yunnan Urban Agglomeration. For example, the growth of e-commerce and logistics industries created new demands for industrial land, particularly evident in the construction of logistics hubs in Kunming and its surrounding areas.

We also found significant changes in the driving process over time. Specifically, the level of economic development and the size of the population gradually weakened as drivers of urban expansion over the period from 2008 to 2023. Although these factors played a critical role in the early stages, their direct impact on urban expansion diminishes as economic growth and population increase slow down. The driving force of the industrial structure strengthens continuously during this period, particularly in the later stages, where industrial upgrading and structural adjustment become key drivers of urban expansion. Additionally, the spatial expansion of the Central Yunnan Urban Agglomeration gradually shifts towards a focus on industrial development, driving the transformation of urban functions and layout. As the strategic importance of the Central Yunnan Urban Agglomeration increases, the roles of government support and openness as driving forces significantly intensify in the later stages. Government intervention through policy guidance and planning facilitates the coordinated development and external openness of the urban agglomeration, serving as a crucial force in ensuring urban expansion. However, natural geographic factors such as elevation and slope exhibit little change over time but continue to impose constraints on urban expansion. Especially in a region with complex topography like Central Yunnan, elevation and slope have an important influence on the spatial selection and development cost of urban expansion. These factors determine the feasibility of urban expansion, especially in terms of site selection and spatial layout, and thus influence the direction and pattern of urban expansion.

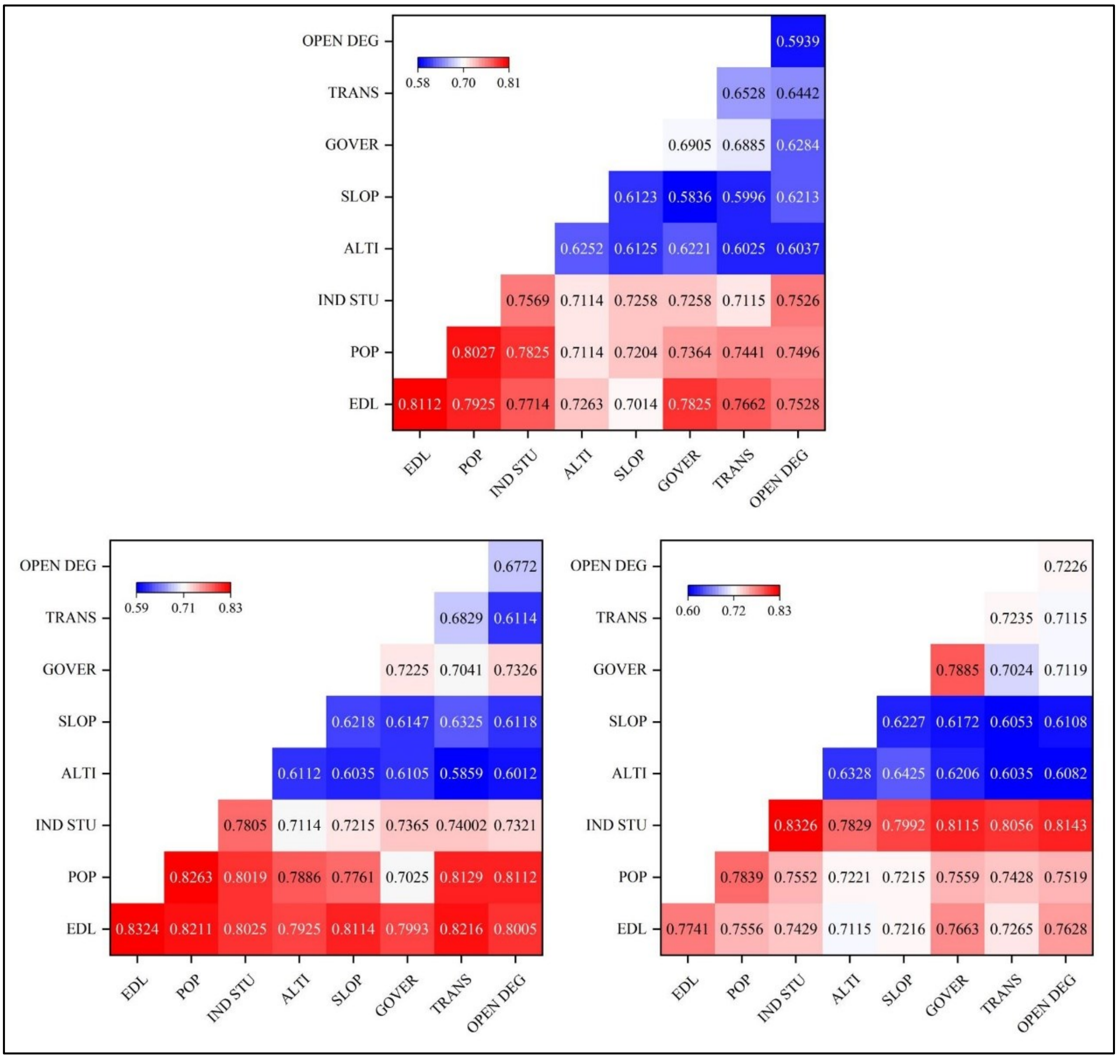

Figure 7. Analysis of the driving factors in the Central Yunnan Urban Agglomeration.

Overall, the urban expansion of the Central Yunnan Urban Agglomeration between 2008 and 2023 exhibited a clear shift in the driving mechanisms across different phases. Economic development and population size are the primary driving forces in the early stages, but their influence gradually diminish over time. In contrast, the roles of industrial structure and government support increasingly strengthen, becoming the key drivers of urban expansion in the later stages. The enhancement of openness also promotes outward-oriented urban development, while natural geographic factors such as elevation and slope continuously impact the spatial choices for urban expansion throughout the entire period.

4. Discussion

Traditional studies on urban agglomeration spatial expansion primarily rely on land use data and statistical data. While these conventional data sources provide a foundational basis for analyzing urban spatial expansion, they generally suffer from the problems of untimely updating, low resolution, and high influence of external conditions, which make it challenging to comprehensively and in real-time capture the dynamic processes of urban expansion [83]. As urbanization accelerates, the speed and complexity of urban expansion continue to increase, making it increasingly difficult for a single data source to accurately reflect the rapid changes occurring within urban spaces. Based on the spatial characteristics of NTL data and LandScan data, this study analyzes the spatiotemporal characteristics and driving mechanism of the spatial expansion of Central Yunnan Urban Agglomeration using data fusion methods. A simple and reliable approach for identifying urban agglomeration spatial expansion through multi-source data fusion is developed, and the driving mechanisms are systematically analyzed across different development stages. This approach allows for an in-depth understanding of the dynamic changes and spatial layout of urban agglomerations, helping to reveal the characteristics at various stages of development, thereby providing a scientific basis for understanding the overall development trends of urban agglomerations.

This study, through the analysis of spatial expansion in the Central Yunnan Urban Agglomeration between 2008 and 2023, reveals the phased characteristics and key driving factors of urban expansion in this region. Our findings align with some of the existing literature but also highlight unique regional characteristics and offer new insights [84]. Consistent with other studies on the development of urban agglomerations in China, we find that the early expansion of the Central Yunnan Urban Agglomeration is primarily driven by economic development and population size. This is similar to the phenomenon observed by Liu et al. (2016) in their study of the Yangtze River Delta Urban Agglomeration, indicating that economic growth and population concentration serve as the initial drivers of urban expansion [85]. However, our study further demonstrates that the relative influence of economic development and population size gradually diminishes over time. This contrasts with the findings of Zhou et al. (2020) in the Pearl River Delta region, where economic and population drivers remain strong over a longer time span [86]. This difference may stem from the relatively low economic starting point and greater topographical constraints of the Central Yunnan Urban Agglomeration, which makes other factors such as industrial structure and government support more important at later stages.

As time progresses, the transformation of the industrial structure in the Central Yunnan Urban Agglomeration plays an increasingly important role in urban expansion. This finding aligns with the perspective proposed by Yang et al. (2018) in their study of the Bohai Rim Urban Agglomeration, which suggests that the optimization and upgrading of industrial structures have become significant forces driving urban expansion [87]. However, our study further reveals that, during the period from 2018 to 2023, the rapid development of the tertiary industry and high-tech industry in the Central Yunnan Urban Agglomeration is particularly notable, contributing to the enhancement of urban functions and the optimization of the spatial structure. This contrasts with the view of Wang and Zhang (2019) in their study of the Chengdu-Chongqing Urban Agglomeration, where they suggest that the expansion in that region is more reliant on the development of traditional manufacturing and heavy industries [88]. This suggests that the path of industrial structure transformation in different regions may be significantly influenced by their historical development background and resource endowment. Additionally, our study also shows that government support emerges as a key driver for the expansion of the Central Yunnan Urban Agglomeration, especially during the period from 2018 to 2023. This finding is consistent with Xu et al. (2017) in their study of the Beijing-Tianjin-Hebei region, which also emphasizes the crucial role of government in regional coordinated development and urban agglomeration planning [89]. However, a notable difference is that the openness of the Central Yunnan Urban Agglomeration gradually becomes another important factor promoting urban expansion, especially in terms of strengthening connections with Southeast Asian countries. In contrast, Li et al. (2018), in their study of the Guangdong-Hong Kong-Macao Greater Bay Area, highlight that the impact of openness is more globalized, with a focus on attracting international capital and technology. This difference may reflect how the Central Yunnan Urban Agglomeration, as an inland region of China, leverages regional openness to enhance its position in national and international divisions of labor [90].

Overall, although the spatiotemporal characteristics and driving mechanism of urban expansion in urban agglomeration is not a brand new topic, and many studies have conducted various analyses of urban expansion in various urban agglomerations in China and even in the world, this study builds on this foundation by fusing NTL data with LandScan data to systematically analyze the expansion patterns and driving mechanisms of the Central Yunnan Urban Agglomeration across different development stages, revealing the region's unique urban development trajectory. Through the fusion of multi-source data and the application of the U-Net model, we not only accurately extracted the built-up areas of the Central Yunnan Urban Agglomeration to analyze the spatiotemporal characteristics of its expansion but also conducted an in-depth exploration of the impact of various factors such as economy, population, industry, and government support on urban expansion. This study deepens the understanding of the driving mechanisms of urban expansion and offers the potential for a comprehensive analysis of the multidimensional driving factors, thereby providing a possible timely feedback mechanism for urban agglomerations.

This study analyzes the spatiotemporal mechanisms of urban expansion in the Central Yunnan Urban Agglomeration and the driving mechanisms that influenced this expansion during different periods. However, there are some limitations in this study. First, at the data level, the spatial resolution limitation and the effect of light pollution of NTL data, and the timeliness and population estimation error of LandScan data, can all affect the accuracy of the analysis [91]. Second, the time span of this study is from 2008 to 2023, and future studies could further extend the time span to capture the expanding trend over a longer period. Additionally, although we discussed the role of industrial structure and government support, other potential drivers, such as environmental policies and sociocultural factors, have not been fully explored, which provides direction for future research.

5. Conclusions

Through an in-depth analysis of the spatial expansion characteristics and driving mechanisms of the Central Yunnan Urban Agglomeration from 2008 to 2023, we revealed the complexity and phased characteristics of urban agglomeration development in the region. By integrating multi-source data fusion techniques with the U-Net model, we successfully extracted changes in the built-up areas of the Central Yunnan Urban Agglomeration during different periods, allowing us to analyze the spatiotemporal characteristics of urban expansion and identify the primary driving factors at various stages. The study finds that the early spatial expansion of the Central Yunnan Urban Agglomeration is primarily driven by economic development and population growth. However, over time, the upgrading of the industrial structure and the strengthening of government support gradually become the core drivers of urban expansion. This is particularly evident during the period from 2018 to 2023, when industrial transformation and policy guidance play a significant role in optimizing urban functions and adjusting the spatial structure. Additionally, the study also highlights that, although natural geographic factors such as elevation and slope remain relatively unchanged throughout the period, their restrictive impact on the location choices and development costs of spatial expansion in the Central Yunnan Urban Agglomeration cannot be overlooked. By analyzing the driving mechanism of the Central Yunnan Urban Agglomeration, this study provides a new perspective for understanding the spatial expansion of inland urban agglomerations in China and offers a reference for related urban planning practices and policy formulation. Future studies can further extend the time span and consider additional environmental and social factors for a more comprehensive understanding of the complex dynamics of urban expansion.

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References

1. Alonso-Villar, O. Urban agglomeration: Knowledge spillovers and product diversity. *Ann. Reg. Sci.* **2002**, *36*, 551–573. [CrossRef]
2. Billings, S.B.; Johnson, E.B. Agglomeration within an urban area. *J. Urban Econ.* **2016**, *91*, 13–25. [CrossRef]
3. Wang, S.; Fang, C.; Sun, L.; Su, Y.; Chen, X.; Zhou, C.; Feng, K.; Hubacek, K. Decarbonizing China's urban agglomerations. *Ann. Am. Assoc. Geogr.* **2019**, *109*, 266–285. [CrossRef]
4. Li, W.; Yi, P.; Yu, H.; Lin, W.; Wu, X. Assessment on sustainable development of three major urban agglomerations in China based on sustainability-differentiation-combined weighting method. *Sustain. Dev.* **2023**, *31*, 2678–2693. [CrossRef]
5. Ma, S.; Cai, Y.; Xie, D.; Zhang, X.; Zhao, Y. Towards balanced development stage: Regulating the spatial pattern of agglomeration with collaborative optimal allocation of urban land. *Cities* **2022**, *126*, 103645. [CrossRef]
6. Tan, F.; Gong, C.; Niu, Z. How does regional integration development affect green innovation? Evidence from China's major urban agglomerations. *J. Clean. Prod.* **2022**, *379*, 134613. [CrossRef]
7. Yankovich, E.P.; Yankovich, K.S.; Baranovskiy, N.V. Dynamics of forest vegetation in an urban agglomeration based on Landsat remote sensing data for the period 1990–2022: A case study. *Remote Sens.* **2023**, *15*, 1935. [CrossRef]
8. Broes, T.; Dehaene, M. Mastering the urbanization process. The urban questions of engineer August Mennes in the Antwerp agglomeration. *Plan. Perspect.* **2017**, *32*, 503–531. [CrossRef]
9. Qu, L.; Zhang, T.; Liang, S. Waste management of urban agglomeration on a life cycle basis. *Resour. Conserv. Recycl.* **2013**, *78*, 47–53. [CrossRef]
10. Liu, X.; Guo, P.; Yue, X.; Qi, X.; Guo, S.; Zhou, X. Measuring metabolic efficiency of the Beijing–Tianjin–Hebei urban agglomeration: A slacks-based measures method. *Resour. Policy* **2021**, *70*, 101928. [CrossRef]
11. Xiong, W.; Qin, J.; Luo, W.; Cheng, Q. The Influence of the Spatial Structure of Urban Agglomeration on the Digital Economy and Its Impact Mechanism: Evidence from China. *Int. Reg. Sci. Rev.* **2024**, 01600176241253289. [CrossRef]
12. Huang, Q.; Liu, Y. The coupling between urban expansion and population growth: An analysis of urban agglomerations in China (2005–2020). *Sustainability* **2021**, *13*, 7250. [CrossRef]
13. Lu, Q.; Lv, T.; Wang, S.; Wei, L. Spatiotemporal Variation and Development Stage of CO2 Emissions of Urban Agglomerations in the Yangtze River Economic Belt, China. *Land* **2023**, *12*, 1678. [CrossRef]
14. Cao, R.; Huang, G.H.; Chen, J.P.; Li, Y.P. A fractional multi-stage simulation-optimization energy model for carbon emission management of urban agglomeration. *Sci. Total Environ.* **2021**, *774*, 144963. [CrossRef]
15. Zhang, N.; Sun, F.; Hu, Y. Carbon emission efficiency of land use in urban agglomerations of Yangtze River Economic Belt, China: Based on three-stage SBM-DEA model. *Ecol. Indic.* **2024**, *160*, 111922. [CrossRef]
16. Cui, Z.; Ren, F.R.; Wei, Q.; Xi, Z. What drives the spatio-temporal distribution and spillover of air quality in China's three urban agglomerations? Evidence from a two-stage approach. *Front. Ecol. Evol.* **2022**, *10*, 977598. [CrossRef]
17. Fang, C. The basic law of the formation and expansion in urban agglomerations. *J. Geogr. Sci.* **2019**, *29*, 1699–1712. [CrossRef]
18. Ma, S.; Li, L.; Zuo, J.; Gao, F.; Ma, X.; Shen, X.; Zheng, Y. Regional integration policies and urban green innovation: Fresh evidence from urban agglomeration expansion. *J. Environ. Manag.* **2024**, *354*, 120485. [CrossRef]
19. Liu, D.; Chen, N. Satellite monitoring of urban land change in the middle Yangtze River Basin urban agglomeration, China between 2000 and 2016. *Remote Sens.* **2017**, *9*, 1086. [CrossRef]
20. He, X.; Zhou, C.; Zhang, J.; Yuan, X. Using wavelet transforms to fuse nighttime light data and POI big data to extract urban built-up areas. *Remote Sens.* **2020**, *12*, 3887. [CrossRef]
21. Batty, M. The size, scale, and shape of cities. *Science* **2008**, *319*, 769–771. [CrossRef] [PubMed]
22. Batty, M. *The New Science of Cities*; MIT Press: Cambridge, MA, USA, 2013.
23. Bettencourt, L.M.A.; Lobo, J.; Helbing, D.; Kühnert, C.; West, G.B. Growth, innovation, scaling, and the pace of life in cities. *Proc. Natl. Acad. Sci. USA* **2007**, *104*, 7301–7306. [CrossRef] [PubMed]
24. Arcaute, E.; Hatna, E.; Ferguson, P.; Youn, H.; Johansson, A.; Batty, M. Constructing cities, deconstructing scaling laws. *J. R. Soc. Interface* **2015**, *12*, 20140745. [CrossRef] [PubMed]
25. Fu, Y.; Zhang, X. Mega urban agglomeration in the transformation era: Evolving theories, research typologies and governance. *Cities* **2020**, *105*, 102813. [CrossRef]
26. Peng, K.; Jiang, W.; Deng, Y.; Liu, Y.; Wu, Z.; Chen, Z. Simulating wetland changes under different scenarios based on integrating the random forest and CLUE-S models: A case study of Wuhan Urban Agglomeration. *Ecol. Indic.* **2020**, *117*, 106671. [CrossRef]
27. Liu, X.; Sun, R.; Yang, Q.; Su, G.; Qi, W. Simulating urban expansion using an improved SLEUTH model. *J. Appl. Remote Sens.* **2012**, *6*, 061709. [CrossRef]
28. Liang, X.; Liu, X.; Li, D.; Zhao, H.; Chen, G. Urban growth simulation by incorporating planning policies into a CA-based future land-use simulation model. *Int. J. Geogr. Inf. Sci.* **2018**, *32*, 2294–2316. [CrossRef]
29. Zhang, Z.; Liu, F.; Zhao, X.; Wang, X.; Shi, L.; Xu, J.; Yu, S.; Wen, Q.; Zuo, L.; Yi, L.; et al. Urban expansion in China based on remote sensing technology: A review. *Chin. Geogr. Sci.* **2018**, *28*, 727–743. [CrossRef]
30. Hawash, E.; El-Hassanin, A.; Amer, W.; El-Nahry, A.; Effat, H. Change detection and urban expansion of Port Sudan, Red Sea, using remote sensing and GIS. *Environ. Monit. Assess.* **2021**, *193*, 723. [CrossRef]
31. Shahtahmassebi, A.R.; Song, J.; Zheng, Q.; Blackburn, G.A.; Wang, K.; Huang, L.Y.; Pan, Y.; Moore, N.; Shahtahmassebi, G.; Haghighi, R.S.; et al. Remote sensing of impervious surface growth: A framework for quantifying urban expansion and re-densification mechanisms. *Int. J. Appl. Earth Obs. Geoinf.* **2016**, *46*, 94–112. [CrossRef]

32. Khanal, N.; Uddin, K.; Matin, M.A.; Tenneson, K. Automatic detection of spatiotemporal urban expansion patterns by fusing OSM and landsat data in Kathmandu. *Remote Sens.* **2019**, *11*, 2296. [CrossRef]
33. He, X.; Zhang, Z.; Yang, Z. Extraction of urban built-up area based on the fusion of night-time light data and point of interest data. *R. Soc. Open Sci.* **2021**, *8*, 210838. [CrossRef] [PubMed]
34. He, X.; Yuan, X.; Zhang, D.; Zhang, R.; Li, M.; Zhou, C. Delineation of urban agglomeration boundary based on multisource big data fusion—A case study of Guangdong–Hong Kong–Macao Greater Bay Area (GBA). *Remote Sens.* **2021**, *13*, 1801. [CrossRef]
35. Chen, Y.; Deng, A. Using POI data and Baidu migration big data to modify nighttime light data to identify urban and rural area. *IEEE Access* **2022**, *10*, 93513–93524. [CrossRef]
36. Zhang, S.; Wei, H. Identification of Urban Agglomeration Spatial Range Based on Social and Remote-Sensing Data—For Evaluating Development Level of Urban Agglomeration. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 456. [CrossRef]
37. Zeng, C.; Song, Y.; Cai, D.; Hu, P.; Cui, H.; Yang, J.; Zhang, H. Exploration on the spatial spillover effect of infrastructure network on urbanization: A case study in Wuhan urban agglomeration. *Sustain. Cities Soc.* **2019**, *47*, 101476. [CrossRef]
38. Peng, J.; Lin, H.; Chen, Y.; Blaschke, T.; Luo, L.; Xu, Z.; Hu, Y.N.; Zhao, M.; Wu, J. Spatiotemporal evolution of urban agglomerations in China during 2000–2012: A nighttime light approach. *Landsc. Ecol.* **2020**, *35*, 421–434. [CrossRef]
39. Ruan, L.; He, T.; Xiao, W.; Chen, W.; Lu, D.; Liu, S. Measuring the coupling of built-up land intensity and use efficiency: An example of the Yangtze River Delta urban agglomeration. *Sustain. Cities Soc.* **2022**, *87*, 104224. [CrossRef]
40. Su, Y.; Lu, C.; Su, Y.; Wang, Z.; Huang, Y.; Yang, N. Spatio-temporal evolution of urban expansion based on a novel adjusted index and GEE: A case study of central plains urban agglomeration, China. *Chin. Geogr. Sci.* **2023**, *33*, 736–750. [CrossRef]
41. He, X.; Zhou, Y. Urban spatial growth and driving mechanisms under different urban morphologies: An empirical analysis of 287 Chinese cities. *Landsc. Urban Plan.* **2024**, *248*, 105096. [CrossRef]
42. Zhang, J.; Yuan, X.; Tan, X.; Zhang, X. Delineation of the urban-rural boundary through data fusion: Applications to improve urban and rural environments and promote intensive and healthy urban development. *Int. J. Environ. Res. Public Health* **2021**, *18*, 7180. [CrossRef] [PubMed]
43. Chen, Y.; Zhang, J. Extraction of urban built-up areas based on data fusion: A case study of Zhengzhou, China. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 521. [CrossRef]
44. Huang, X.; Hu, T.; Li, J.; Wang, Q.; Benediktsson, J.A. Mapping urban areas in China using multisource data with a novel ensemble SVM method. *IEEE Trans. Geosci. Remote Sens.* **2018**, *56*, 4258–4273. [CrossRef]
45. Yu, M.; Xu, H.; Zhou, F.; Xu, S.; Yin, H. A Deep-Learning-Based Multimodal Data Fusion Framework for Urban Region Function Recognition. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 468. [CrossRef]
46. Hänsch, R.; Hellwich, O. Fusion of multispectral LiDAR, hyperspectral, and RGB data for urban land cover classification. *IEEE Geosci. Remote Sens. Lett.* **2020**, *18*, 366–370. [CrossRef]
47. Xing, J.; Wu, W.; Cheng, Q.; Liu, R. Traffic state estimation of urban road networks by multi-source data fusion: Review and new insights. *Phys. A Stat. Mech. Its Appl.* **2022**, *595*, 127079. [CrossRef]
48. Wei, G.; He, B.J.; Liu, Y.; Li, R. How does rapid urban construction land expansion affect the spatial inequalities of ecosystem health in China? Evidence from the country, economic regions and urban agglomerations. *Environ. Impact Assess. Rev.* **2024**, *106*, 107533. [CrossRef]
49. Zheng, Y.; Xu, W.; Dai, L. Urban growth in a post-2000 central Chinese urban agglomeration: Case study of the Changzhutan region. *Growth Change* **2020**, *51*, 464–487. [CrossRef]
50. Wang, H.; Wu, Y.; Deng, Y.; Xu, S. Model construction of urban agglomeration expansion simulation considering urban flow and hierarchical characteristics. *J. Geogr. Sci.* **2022**, *32*, 499–516. [CrossRef]
51. Poelmans, L.; Rompaey, A.V.; Ntegeka, V.; Willems, P. The relative impact of climate change and urban expansion on peak flows: A case study in central Belgium. *Hydrol. Process.* **2011**, *25*, 2846–2858. [CrossRef]
52. Terfa, B.K.; Chen, N.; Liu, D.; Zhang, X.; Niyogi, D. Urban expansion in Ethiopia from 1987 to 2017: Characteristics, spatial patterns, and driving forces. *Sustainability* **2019**, *11*, 2973. [CrossRef]
53. Rijal, S.; Rimal, B.; Stork, N.; Sharma, H.P. Quantifying the drivers of urban expansion in Nepal. *Environ. Monit. Assess.* **2020**, *192*, 633. [CrossRef] [PubMed]
54. Zhu, X.; Zhang, P.; Wei, Y.; Li, Y.; Zhao, H. Measuring the efficiency and driving factors of urban land use based on the DEA method and the PLS-SEM model—A case study of 35 large and medium-sized cities in China. *Sustain. Cities Soc.* **2019**, *50*, 101646. [CrossRef]
55. Azhdari, A.; Sasani, M.A.; Soltani, A. Exploring the relationship between spatial driving forces of urban expansion and socioeconomic segregation: The case of Shiraz. *Habitat Int.* **2018**, *81*, 33–44. [CrossRef]
56. Wu, C.; Huang, X.; Chen, B. Telecoupling mechanism of urban land expansion based on transportation accessibility: A case study of transitional Yangtze River economic Belt, China. *Land Use Policy* **2020**, *96*, 104687. [CrossRef]
57. Chioda, L.; De Mello, J.M.; Soares, R.R. Spillovers from conditional cash transfer programs: Bolsa Família and crime in urban Brazil. *Econ. Educ. Rev.* **2016**, *54*, 306–320. [CrossRef]
58. Batisani, N.; Yarnal, B. Urban expansion in Centre County, Pennsylvania: Spatial dynamics and landscape transformations. *Appl. Geogr.* **2009**, *29*, 235–249. [CrossRef]

59. Sakieh, Y.; Amiri, B.J.; Danekar, A.; Feghhi, J.; Dezhkam, S. Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of Karaj City, Iran. *J. Hous. Built Environ.* **2015**, *30*, 591–611. [CrossRef]
60. Li, G.; Sun, S.; Fang, C. The varying driving forces of urban expansion in China: Insights from a spatial-temporal analysis. *Landsc. Urban Plan.* **2018**, *174*, 63–77. [CrossRef]
61. Zhang, Z.; Wang, B.; Buyantuev, A.; He, X.; Gao, W.; Wang, Y.; Dawazhaxi; Yang, Z. Urban agglomeration of Kunming and Yuxi cities in Yunnan, China: The relative importance of government policy drivers and environmental constraints. *Landsc. Ecol.* **2019**, *34*, 663–679. [CrossRef]
62. Hillger, D.; Seaman, C.; Liang, C.; Miller, S.; Lindsey, D.; Kopp, T. Suomi NPP VIIRS imagery evaluation. *J. Geophys. Res. Atmos.* **2014**, *119*, 6440–6455. [CrossRef]
63. Antrop, M. Landscape change and the urbanization process in Europe. *Landsc. Urban Plan.* **2004**, *67*, 9–26. [CrossRef]
64. Fujita, M.; Krugman, P.; Venables, A.J. *The Spatial Economy: Cities, Regions, and International Trade*; MIT Press: Cambridge, MA, USA, 1999.
65. Dobson, J.E.; Bright, E.A.; Coleman, P.R.; Durfee, R.C.; Worley, B.A. LandScan: A global population database for estimating populations at risk. *Photogramm. Eng. Remote Sens.* **2000**, *66*, 849–857.
66. Gabaix, X. Zipf's law for cities: An explanation. *Q. J. Econ.* **1999**, *114*, 739–767. [CrossRef]
67. Krugman, P. Confronting the mystery of urban hierarchy. *J. Jpn. Int. Econ.* **1996**, *10*, 399–418. [CrossRef]
68. Konishi, Y.; Nishiyama, Y. Hypothesis testing in rank-size rule regression. *Math. Comput. Simul.* **2009**, *79*, 2869–2878. [CrossRef]
69. Zipf, G.K. *Human Behavior and the Principle of Least Effort*; Addison-Wesley: Cambridge, MA, USA, 1949.
70. Peng, J.; Liu, Y.; Ma, J.; Zhao, S. A new approach for urban-rural fringe identification: Integrating impervious surface area and spatial continuous wavelet transform. *Landsc. Urban Plan.* **2018**, *175*, 72–79. [CrossRef]
71. Myint, S.W.; Zhu, T.; Zheng, B. A novel image classification algorithm using overcomplete wavelet transforms. *IEEE Geosci. Remote Sens. Lett.* **2015**, *12*, 1232–1236. [CrossRef]
72. Delibasoglu, I.; Cetin, M. Improved U-Nets with inception blocks for building detection. *J. Appl. Remote Sens.* **2020**, *14*, 044512. [CrossRef]
73. Sultonov, F.; Park, J.H.; Yun, S.; Lim, D.W.; Kang, J.M. Mixer U-Net: An improved automatic road extraction from UAV imagery. *Appl. Sci.* **2022**, *12*, 1953. [CrossRef]
74. Zhang, X.; Gong, Z. Spatiotemporal characteristics of urban air quality in China and geographic detection of their determinants. *J. Geogr. Sci.* **2018**, *28*, 563–578. [CrossRef]
75. Li, J.; Sun, Z. Urban function orientation based on spatiotemporal differences and driving factors of urban construction land. *J. Urban Plan. Dev.* **2020**, *146*, 05020011. [CrossRef]
76. Mallat, S. A theory for multiresolution signal decomposition: The wavelet representation. *IEEE Trans. Pattern Anal. Mach. Intell.* **1989**, *11*, 674–693. [CrossRef]
77. Li, S.; Kwok, J.T.; Wang, Y. Combination of images with diverse focuses using the spatial frequency. *Inf. Fusion* **2002**, *2*, 169–176. [CrossRef]
78. Burt, P.J.; Adelson, E.H. The Laplacian pyramid as a compact image code. *IEEE Trans. Commun.* **1983**, *31*, 532–540. [CrossRef]
79. He, X.; Zhou, Y.; Yuan, X.; Zhu, M. The coordination relationship between urban development and urban life satisfaction in Chinese cities-An empirical analysis based on multi-source data. *Cities* **2024**, *150*, 105016. [CrossRef]
80. Ding, R.; Fu, J.; Zhang, Y.; Zhang, T.; Yin, J.; Du, Y.; Zhou, T.; Du, L. Research on the evolution of the economic spatial pattern of urban agglomeration and its influencing factors, evidence from the Chengdu-Chongqing urban agglomeration of China. *Sustainability* **2022**, *14*, 10969. [CrossRef]
81. He, X.; Zhang, R.; Yuan, X.; Cao, Y.; Zhou, C. The role of planning policy in the evolution of the spatial structure of the Guangzhou metropolitan area in China. *Cities* **2023**, *137*, 104284. [CrossRef]
82. Zhang, J.; Zhang, R.; Zhang, X.; Yuan, X. Polycentric Spatial Structure Evolution and Influencing Factors of the Kunming–Yuxi Urban Agglomeration: Based on Multisource Big Data Fusion. *Land* **2023**, *12*, 1340. [CrossRef]
83. Zhang, J.; Zhang, R.; Li, Q.; Zhang, X.; He, X. Spatial Sifferentiation and Differentiated Development Paths of Traditional Villages in Yunnan Province. *Land* **2023**, *12*, 1663. [CrossRef]
84. Zhou, K.; Liang, Y.; Zhong, C.; Zeng, J.; Zhou, Z. Spatial features of urban expansion in Vietnam based on long-term nighttime lights data. *Land* **2022**, *11*, 601. [CrossRef]
85. Liu, X.; Li, X.; Chen, Y.; Tan, Z.; Li, S.; Ai, B. A new landscape index for quantifying urban expansion using multi-temporal remote sensing data. *Landsc. Ecol.* **2016**, *31*, 2035–2049.
86. Zhou, Y.; Li, X.; Asrar, G.R.; Smith, S.J.; Imhoff, M. A global record of annual urban dynamics (1992–2013) from nighttime lights. *Remote Sens. Environ.* **2020**, *232*, 111273. [CrossRef]
87. Yang, X.; Chen, L. The spatiotemporal pattern of urban land use efficiency and its influencing factors: A case study of the Bohai Rim Region. *Land Use Policy* **2018**, *74*, 245–255.
88. Wang, J.; Zhang, W. Industrial structure optimization and economic resilience in China's resource-based cities. *Resour. Policy* **2019**, *64*, 101515.
89. Xu, W.; Li, J.; Wang, Q.; Liu, X. Government policies and urban growth dynamics in China: A spatial econometric approach. *Urban Stud.* **2017**, *54*, 2330–2349.

90. Li, Y.; Yang, Z.; Song, W. Evaluating the effects of urban expansion on a metro-centric agricultural region using integrated environmental models: A case study of the Pearl River Delta. *J. Clean. Prod.* **2018**, *171*, 1524–1536.
91. Alahmadi, M.; Mansour, S.; Martin, D.; Atkinson, P.M. An improved index for urban population distribution mapping based on nighttime lights (DMSP-OLS) data: An experiment in Riyadh Province, Saudi Arabia. *Remote Sens.* **2021**, *13*, 1171. [CrossRef]