IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 18 September 2023, accepted 21 November 2023, date of publication 24 November 2023, date of current version 30 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3336735

RESEARCH ARTICLE

Evolution and Influencing Factors of Urban Built-Up Areas in the Yangtze River Delta Urban Agglomeration

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ABSTRACT The scale of urban built-up areas is one of the important indicators for measuring urban development, understanding the evolution and underlying mechanisms of urban built-up areas is of significant value for the development and planning of urban agglomerations. Based on Nighttime Light (NTL) data, Point of Interest (POI) data and LnadScan data, this study constructs a new index to extract the built-up area through multi-source big data fusion, automatically extracts the built-up area of urban agglomerations in a long time series based on U-net neural network, and finally analyzes the dominant factors driving the evolution of built-up area of urban agglomerations in different periods. The results indicate that the fusion of multi-source big data can accurately extract urban built-up areas and analyze their evolution process. The dominant factors driving the evolution of built-up areas vary across different periods, with a weakening influence of the per GDP factors and population dynamics, while the driving force of urban planning for the evolution of built-up areas is strengthened. This study, through the analysis of the evolution process and influencing factors of urban built-up areas in the Yangtze River Delta (YRD) urban agglomeration, contributes to the accurate identification of the internal urban development within the YRD urban agglomeration, assisting in the formulation of subsequent development plans. Furthermore, it provides relevant references for the development of urban areas in other regions.

INDEX TERMS Urban built-up areas, evolution, differentiated influencing factors, data fusion, geographical detector.

I. INTRODUCTION

The urban built-up area refers to a region within the urban administrative area where significant development, municipal and public facilities have been established [1]. It is an important indicator of urban development, reflecting the degree of urbanization of a city, and the growth rate of the built-up area side by side reflects the speed of urban development, and provides basic data for further research on urban geography, urban planning, and urban ecology [2]. With the acceleration of urbanization in recent years, China's urban built-up areas show an explosive growth trend. In 2021, China's built-up areas reach 62,420.53 square kilometers, an increase of 259% compared with 24,026.63 square kilometers in 1981 [3]. In the process of urban built-up area expansion, problems such as intensified land use contradiction and unbalanced regional development are often accompanied, and the prominent urban problems caused by urban built-up area expansion in different periods are also different [4], [5]. Therefore, it becomes increasingly important to monitor the evolution of urban built-up areas and judge the factors influencing their evolution [6].

In the past, the identification, extraction and monitoring of urban built-up areas mainly relied on statistical survey data, such as urban statistical yearbooks and urban built-up area statistics [7]. This kind of statistical survey data is not only slow in updating and large in volume, but also difficult to be generalized to other cities and regions [8]. Additionally, the

The associate editor coordinating the review of this manuscript and approving it for publication was Wenming Cao.

development characteristics of built-up areas are different in different periods, and the evolution process of built-up areas is also different in different periods, and the influencing factors that drive their evolution are also different [9], [10], which requires us to develop a new method to monitor the evolution process of built-up areas and determine the dominant factors that drive the evolution of built-up areas in different periods.

Remote sensing image data, as one of the important sources of urban spatial information, can not only reflect the spatial characteristics of urban landscape and infrastructure [11], but also realize large-scale and high-frequency urban spatial dynamics study due to its fast-updating speed and wide coverage, which has led to the wide application of remote sensing images in the study of internal evolution of the city and other related studies [12], [13]. As one of the remote sensing data, Nighttime Light (NTL) data reflects the distribution trend of urban infrastructure and the strength of urban population spatial activities by capturing the brightness of urban lights at night [14], [15]. With the advantages of high accuracy, objectivity and wide coverage, NTL data have been widely used in urban studies, and have been well applied in the identification and evolution of urban built-up areas, the delineation of urban agglomeration boundaries and the identification of urban agglomeration centers [16], [17], [18]. However, in the actual process of extracting built-up areas from NTL data, the spillover effect of the data itself may cause certain errors in the extraction of built-up areas.

In recent years, with the rise of the application of big data in urban research, researchers have found that big data is highly compatible with urban space and can be used to make up for the shortcomings of traditional study data in urban-related research [19]. Therefore, more and more big data are applied to urban-related research, including social software data, cell phone signaling data, Global Positioning Systems (GPS) data, Point of Interest (POI) data, and LandScan population data [20], [21]. Among them, POI data, as a kind of urban big data, is point-type geographic entity data in Internet e-maps, which generally consists of four basic attributes: name, category, address, and coordinates, and is used to express the spatial location and attribute information of geographic entities [22]. Compared with the previous traditional urban data, POI data not only has the advantages of wide sampling range and fast collection speed, but also can reflect the urban function through the aggregation of POI itself [23]. Additionally, researchers also found that POI data has a strong correlation with NTL data in urban space. NTL data reflects the characteristics of urban development through the brightness of urban night lighting, while POI data reflects different functional attributes of the city through the aggregation of different types of POI points, so the two have a strong spatial correlation within the city [24], [25]. Since POI data can reflect the urban functional agglomeration which is difficult to be reflected by NTL data, more and more researches have started to fuse NTL data and POI data, in order to make up for the shortcomings of NTL data, and then make a better observation effect on the built-up area [26], [27], [28]. However, in the inner space of the urban area, the information exchange is getting more and more complicated, and both NTL data and POI data reflect the static information of the city space, which cannot meet the needs of dynamic information exchange in the inner space of the city [29].

As the distribution and flow of population is an important part of information exchange within the city, more and more researchers are trying to reflect the dynamic process of the city through population data [30]. LandScan data is one of the global population dynamics statistical analysis data with the best resolution based on geographic location. Its advantages of wide coverage, high spatial resolution, and short update cycle make it quickly become an important data source for urban space and population related research [31]. Since the spatial distribution of urban built-up areas is highly correlated with the distribution of population, that is, the population density of urban built-up areas is much higher than that of non-urban built-up areas, which means that LandScan data can be used as one of the data to study urban built-up areas [32], and there are also studies that analyze urban built-up areas by means of LandScan data, and the results also illustrate that LandScan in urban built-up areas have high suitability for extraction [33]. Due to the fragmentation of information from a single data source, more and more scholars begin to pay attention to the fusion of information from different data sources to reflect the evolution of urban built-up areas and its influencing factors. Data fusion refers to combining and transforming information from single or multiple sources obtained from different channels [34], and the fused information not only provides more accurate estimation and judgment than information from a single source, but also greatly improves data and information validity and reliability [35]. As a key direction of data fusion, image fusion has been widely used in remote sensing, vision, urban observation and other fields [36]. Image fusion is divided into three levels, pixel fusion, feature fusion, and decision fusion, and the goal of feature fusion is to improve the results of image processing and analysis by fusing the feature information of different images to extract a more comprehensive, rich, and accurate feature representation [37]. Among them, the U-net image feature fusion mode can connect the underlying features with the higher-level features through stitching operations, which allows us to utilize both global and situational feature information, thus effectively capturing the detail information of the target and accurately segmenting at the pixel level [38], [39]. Therefore, this study tries to further fuse LandScan population data on the basis of NTL and POI data to obtain a new kind of data for dynamically analyzing the characteristics of the evolution pattern of urban built-up areas and their influencing factors, so as to further improve the accuracy of grasping the evolution pattern of urban built-up areas.

In recent years, the study on multi-source big data fusion analysis of cities mainly focuses on a single time cross-section. For example, by fusing big data, it is possible to

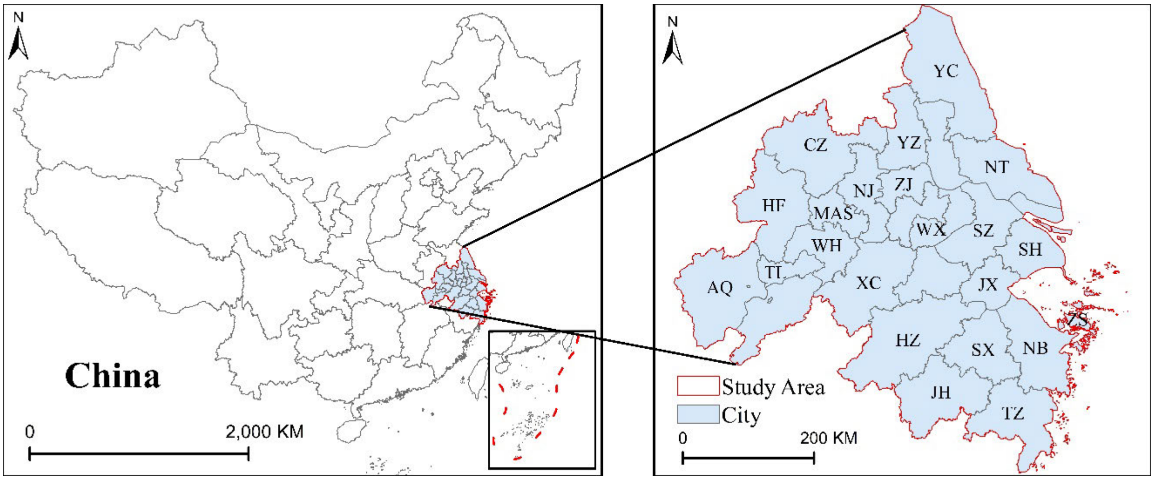

FIGURE 1. Study area.

extract the built-up area of the urban as well as to identify the spatial structure of the urban area [40]. However, due to the difficulty of collecting long time series of big data and the fact that the research on big data in urban spatial applications has not been long, there are certain difficulties in the acquisition of big data and the timeliness of data storage in urban spatial applications resulting in the research on the use of multi-source big data to extract the urban built-up area often stays only in a single time cross-section [41], and there is less analysis of the evolution of the built-up area. However, in the process of urban development, the evolution of urban built-up areas and the driving mechanism behind them are of great significance in determining urban development [42], including the formulation of future urban development plans. Based on the advantages of the use of multi-source big data fusion in urban space, we believe that the next relevant research focus should be on the analysis of the evolution of urban built-up areas using long time series big data.

In the process of urban development, the evolution speed and degree of built-up areas in different periods are different, and the evolution of built-up areas in different cities is obviously different due to the differences in social, economic and natural conditions [43]. Although the influencing factors and driving mechanisms of urban built-up area evolution have been well and comprehensively studied, the impacts of different influencing factors on urban built-up area evolution over long time series (e.g., ten or twenty years) can be judged and valuable conclusions have been drawn, providing feasible references for urban development [44], [45]. While for Chinese cities, the evolution of built-up areas is very rapid, especially for urban agglomerations, which have different development priorities at different stages. This leads to differences in the influencing factors driving the evolution of built-up areas within urban agglomerations at different stages [42], [46]. However, current research on the influencing factors and driving mechanisms of urban built-up areas rarely takes this into account.

In this study, we hope to analyze the evolution process of built-up areas in urban agglomerations under U-net neural network based on NTL data, POI data and LandScan data over a long period of time, and to determine the differences and similarities between the main factors driving the evolution of built-up areas in urban agglomerations in different periods, which makes it possible to, on the one hand, to analyze and understand in detail the evolution of built-up areas in the Yangtze River Delta (YRD) urban agglomerations and to judge their evolutionary mechanisms to provide certain references for the development of the cities in YRD urban agglomeration, and on the other hand, it can also provide feasible references for the studies of other urban agglomerations.

II. METHODS AND MATERIALS

A. STUDY AREA

The Yangtze River Delta (YRD) urban agglomeration includes Shanghai, Jiangsu Province, Zhejiang Province, and Anhui Province, with a total of 27 prefecture-level cities under its jurisdiction (Figure 1). The YRD urban agglomeration is located in the lower reaches of China's Yangtze River, bordering the Yellow Sea and the East China Sea, and is situated in the place where the river and the sea meet, with a large number of coastal harbors along the river. By the end of 2020, the permanent population of the YRD urban agglomeration is 237 million, with an area of 358,000 square kilometers and an urbanization rate of more than 70% of the permanent residents, it is one of the urban agglomerations with the most active economic development, the highest degree of openness and the strongest innovation capability in mainland China [47]. The YRD urban agglomeration, as an urban agglomeration with a complex internal city structure and a significant rate of urbanization in recent years, has a built-up area evolution that is also more typical of other urban agglomerations in China. Therefore, we extract the built-up area of the YRD urban agglomerations and analyze the evolution of the built-up area of the cities and its

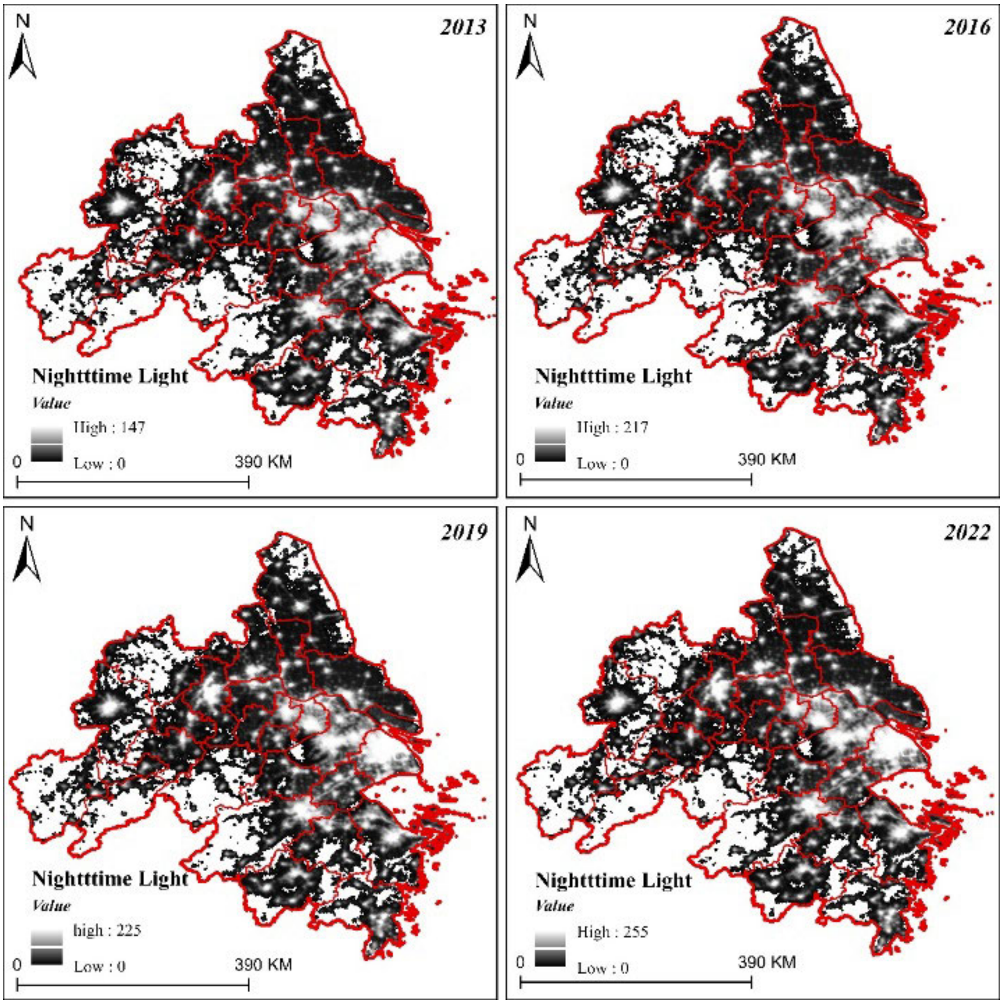

FIGURE 2. Pre-processing result of NTL data.

influencing factors which are of great value for the sustainable and healthy development of the YRD urban agglomerations.

B. STUDY DATA

The study data mainly include NPP/VIIRS NTL data, POI data, and LandScan data.

Commonly used NTL data include DMSP NTL data, NPP/VIIRS NTL data, and Luojia-01 NTL data. Among them, NPP/VIIRS NTL data has significant advantages in spatial resolution and temporal consistency compared to other NTL dataset [48]. It is also more suitable for long-term observational studies. Furthermore, NPP/VIIRS NTL data has a observation time of 12 hours and a wavelength range of 505 to 890μm. It allows for fast data acquisition and is conducive to monthly averaging calculations. In this study, the NTL data for the YRD urban agglomeration at four time points, namely 2013, 2016, 2019, and 2022, are obtained by accessing https://www.ngdc.noaa.gov/eog/viirs/download_dnb _composites.html. After radiometric correction and monthly averaging, the preprocessed NTL data results for the YRD urban agglomeration are shown in Figure 2.

With the introduction and development of early Geographic Information Systems (GIS) and Global Positioning Systems (GPS) technologies, the sharing and updating of POI data has been facilitated. Currently, map companies such as Baidu Maps, Tencent Maps, and Amap all provide API (Application Programming Interface) access services for developers to access their various types of open data [49]. In this study, the POI data for the YRD urban agglomeration at four time points, namely 2013, 2016, 2019, and 2022, are obtained by accessing the Amap API (https://www.amap.com). After screening, deduplication, filtering, and cleaning of the obtained POI data, the spatial distribution results of the POI data in the YRD urban agglomeration are shown in Figure 3.

LandScan data is a global population distribution dataset developed by Oak Ridge National Laboratory, USA. It uses population census data, Geographic Information System (GIS) data, satellite remote sensing data, and other data

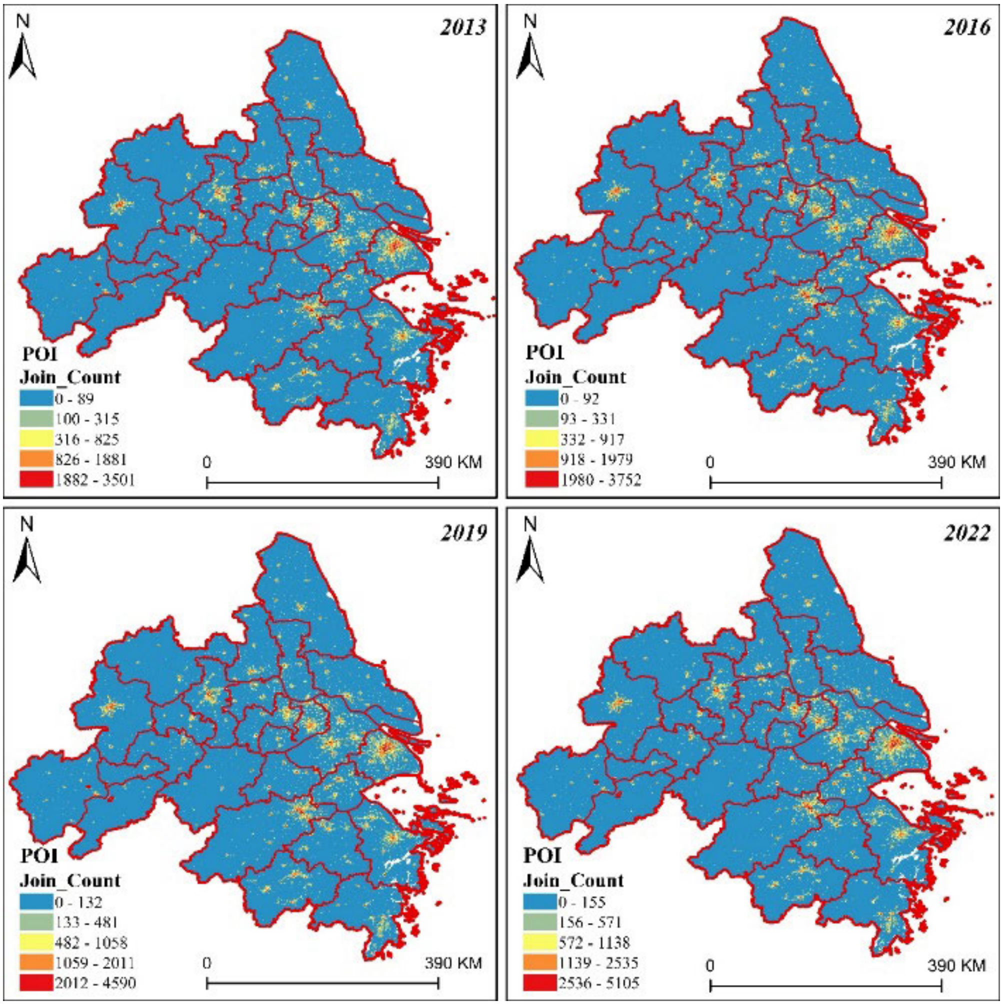

FIGURE 3. Spatial distribution of POI data in the YRD urban agglomeration.

sources, as well as geographic modeling algorithms, to simulate and estimate the distribution of population across the globe. Compared to other types of population data, LandScan data not only allows for updates and improvements based on available data sources and technological advances but also provides high-resolution population data, making it widely applied in studies related to urban planning, environmental assessment, disaster management, and energy planning [50], [51]. In this study, LandScan data for the YRD urban agglomeration at four time points, namely 2013, 2016, 2019, and 2022, are obtained. After processing the data, the spatial distribution results of LandScan population data are shown in Figure 4.

C. METHODS

1) WAVELET TRANSFORM (WT)

Wavelet transform (WT) is an image transformation analysis method. Compared with other fusion algorithms, wavelet transform has good localization ability in both time and frequency domains by providing a "time-frequency" window that changes with frequency [52], [53]. In the process of transforming the image, the wavelet transform can not only fully highlight the characteristics of certain aspects of the problem, but also localize the analysis of time (spatial) frequency, and also gradually carry out multi-scale refinement of the signal (function) through the telescopic translation operation, which further makes the wavelet transform automatically adapt to the requirements of the time-frequency analysis at the same time, but also focus on any details of the image, making the image fused to achieve the best observation results [54]. The formula for the wavelet transform is:

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

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

2) IMAGE FEATURE EXTRACTION

The extraction of urban built-up areas essentially involves extracting pixel regions with built-up area characteristics

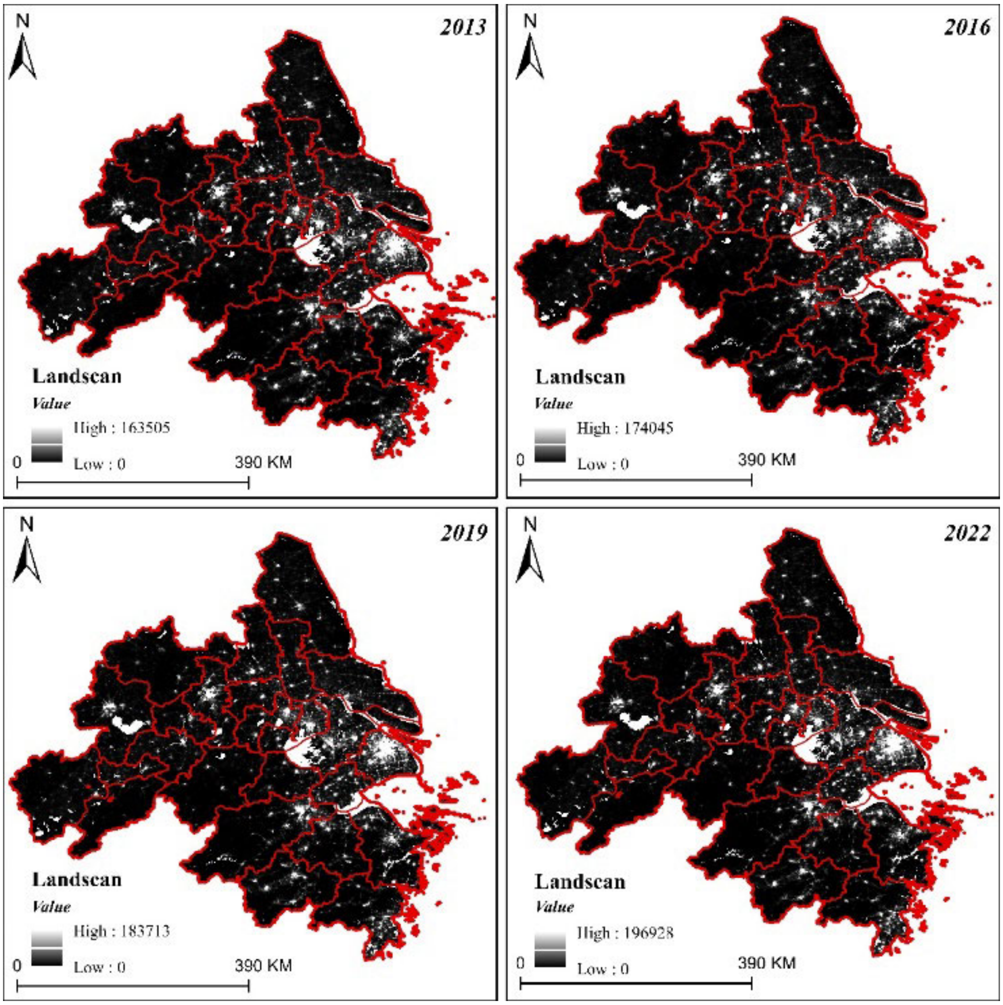

FIGURE 4. Spatial distribution of LandScan data of the YRD urban agglomeration.

from the fused images of NTL data, POI data, and LandScan data. In the field of image feature extraction, methods such as machine learning can be utilized for hierarchical learning and extraction of different features. Currently, convolutional neural networks (CNNs) and fully convolutional neural networks (FCNs) are commonly applied for image feature extraction. However, CNNs can only handle fixed-sized image inputs, which may lead to the loss of some image information, and the training time for the samples is relatively long. Therefore, in this study, the aim is to extract the features of built-up areas using the U-net neural network. U-net is an improvement on the FCN, as it comprehensively considers both the global and local details of the image. Additionally, U-net concatenates the results of each layer from the encoder to the decoder to achieve better segmentation results, thereby improving the accuracy of image feature extraction.

The U-Net neural network mainly contains an encoder (downsampler) and a decoder (upsampler), and combines the features of the encoder with those of the decoder through skip connections [55]. This architecture allows the U-Net neural network to have both high-resolution detail information and global context information, which is particularly effective for image segmentation tasks [56].

Equations of the component layers of U-Net.

Layer Convolution:

$$C_{out\ j} = bias(C_{out}) + \sum\nolimits_{k=0}^{C_{in}-1} weight\left(C_{out\ j}, k\right) * input(k) \tag{2}$$

Layer Max-pooling:

$$\begin{aligned} out(C_j, h, w) = {} & max_{m=0,\ldots\ldots,kH-1} max_{n=0,\ldots\ldots,kW-1} \\ & input(C_j, stride\,[0] \times h + m, stride[1] \times w + n) \end{aligned} \tag{3}$$

Layer ReLU:

$$ReLU(x) = max(0, x) \tag{4}$$

Layer softmax:

$$Softmax(x_i) = \frac{exp(x_i)}{\sum_{j=1}^{k} exp(x_i)} \tag{5}$$

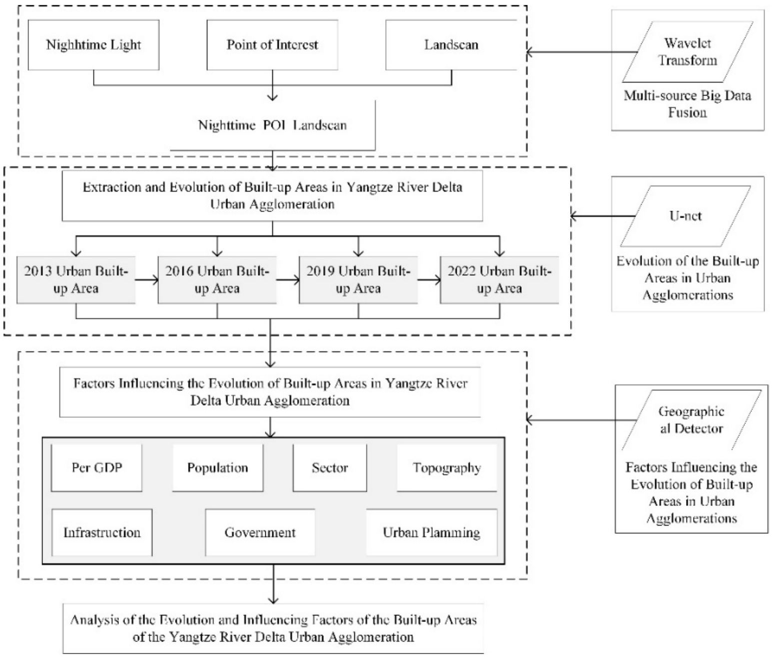

FIGURE 5. Work flow.

Layer Cross-entropy:

$$loss(x, y) = -log(\frac{exp(x[y])}{\sum_{j=1}^{k} exp(x[y])}) \tag{6}$$

In eq. (2), the sizes of the input and output images are (C_{in}, H, W) and $(C_{out}t, H_{out}, W_{out})$, C denotes the number of channels, H is the height of the input planes in pixels, W is the width in pixels, * is the valid cross-correlation operator, and j is the j -th channel of the output feature map. In eq. (3), (kH, kW) denotes the kernel size of the pooling, h and w refer to the height and width of the output image, respectively. In eq. (4), x denotes the pixel values of the input feature map. In eq. (5), x_i is the i-th pixel value of the input feature map and K is the number of classes. In eq. (6), x and y refer to the predicted and reference pixel values, respectively, and K is the number of classes.

In this study, U-net neural network is used to extract the urban built-up area, but the accuracy of the extraction needs to be verified, so the accuracy of the research results obtained in this study is verified with reference to other studies of the same type [57], [58].

3) GEOGRAPHICAL DETECTOR

Geographical detectors can explore the geographical correlations between different geographical phenomena, allowing researchers to explore the spatial heterogeneity of influencing factors by leveraging their advantages in spatial regression. This study uses geographical detector model to explore the spatial stratification heterogeneity characteristics that affect the evolution of urban built-up areas in urban agglomerations [59]. The formula for the geographic detector model is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum\nolimits_{m=1}^{L} N_m \sigma_m^2 \tag{7}$$

where, q is the explanatory power of regional geographic environmental factors, $M = 1, 2, \ldots, L$ is the number of categories, N_m and N is the number of layers q and the number of units in the whole region, respectively, and σ^2 is the variance of the indicator, q value ranges from 0 to 1, and the larger the q value is, the stronger the explanatory power of the spatial differentiation heterogeneity it has.

The technical process and study framework of this study are shown in Figure 5.

III. RESULTS

A. MULTI-SOURCE BIG DATA FUSION

The purpose of multi-source big data fusion is to obtain more comprehensive, accurate and insightful data by fusing information from multiple data sources, in order to provide a more global perspective to support decision making, problem solving and insight discovery. Faced with increasingly complex urban systems, single data gradually cannot fully reflect the true state of urban internal space. Therefore, we hope that by fusing multi-source data, not only can we compensate for the errors caused by a single data source in observing cities to enhance data integrity, but also cross validation between different data sources can help eliminate errors and noise in a single data source, thus improve data quality and accuracy.

NTL data, POI data, and LandScan population data express different attribute information in urban space, and this attribute information have high spatial correlation. Studies have shown that fusing these three types of data can reduce

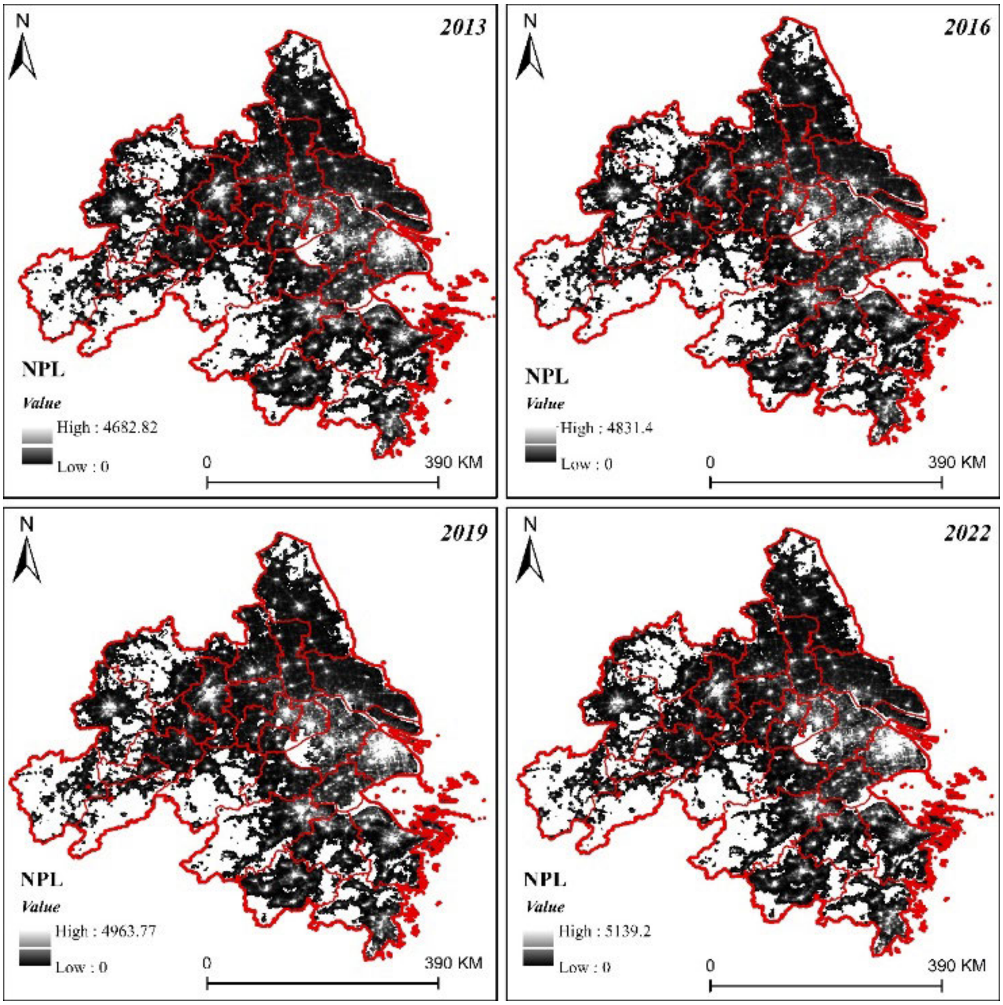

FIGURE 6. Data fusion results.

the noise in the data itself, thus achieving a more accurate characterization of urban built-up areas, which is conducive to our analysis of the evolution of urban agglomerations. The data fusion results obtained from the fusion study of NTL data, POI data and LandScan population data are shown in Figure 6.

B. EVOLUTION OF URBAN BUILT-UP AREAS IN THE YRD URBAN AGGLOMERATION

In the process of using the U-net neural network to extract urban built-up areas, the first step is to establish training samples based on the fused data. The labels of the samples are derived from the built-up area data released by the Chinese government, which has a certain level of accuracy. The next step is to annotate the training samples, dividing them into test set, training set, and validation set. Finally, the results of the urban built-up areas in the YRD urban agglomeration from 2013 to 2022 are obtained. The evolution of urban built-up areas in the YRD urban agglomeration from 2013 to 2022 is shown in Figure 7. In 2013, 2016, 2019, and 2022, the area and proportion of urban built-up areas in YRD urban agglomeration are 16244.72 square kilometers, 27717.19 square kilometers, 31549.32 square kilometers, and 33993.66 square kilometers, respectively, accounting for 4.54%, 7.74%, 8.8%, and 9.49% of the total administrative area (358000 square kilometers), indicating that, the urban built-up area of YRD urban agglomeration is gradually increasing.

Before 2013, urban built-up areas showed a trend of rapid urbanization, with an expansion of urban area, an increase in population inflow, and a rapid growth in urban scale. However, during this period, traditional manufacturing remained the dominant industry, with a large number of factories and production facilities clustered in urban built-up areas, leading to further population aggregation in the urban built-up areas. Therefore, as shown in Figure 6, the identified urban built-up areas in 2013 are mainly concentrated in Shanghai, central and southern Suzhou, southeastern Wuxi, northern and central regions of Nanjing, the capital city of Jiangsu Province, central regions of Hefei, the capital city of Anhui Province, and northeastern regions of Hangzhou, the capital city of Zhejiang Province. In general, the urban built-up areas

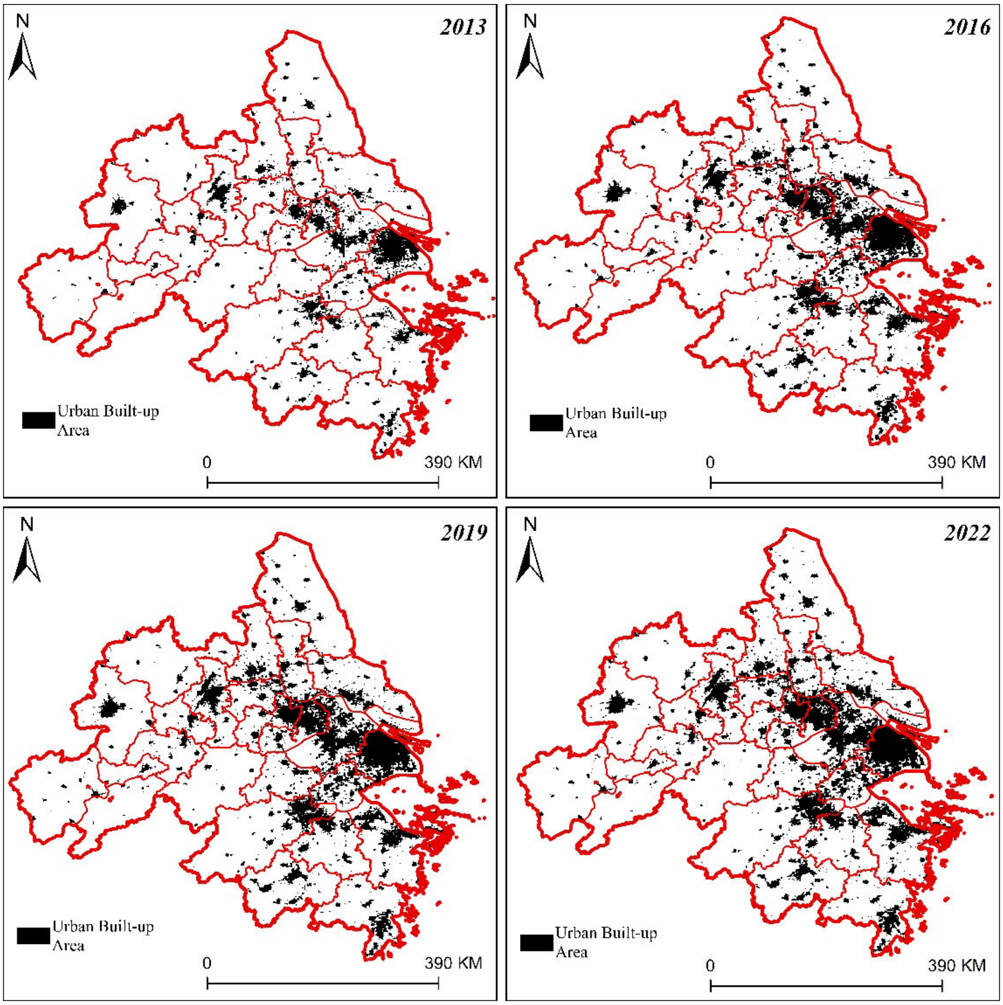

FIGURE 7. Evolution of built-up areas in the YRD urban agglomeration.

identified at this time present a state of micro-aggregation within a certain area of the city, while macro-dispersion within the urban agglomeration.

From 2013 to 2016, the built-up areas of the YRD urban agglomeration were in a process of high-speed urbanization, with the scale of the major cities expanding, the built-up area of the cities increasing, the inflow of population accelerating, and the infrastructure continuously improving. During this period, the YRD urban agglomeration began to undergo economic restructuring, manifested as a gradual decrease in traditional manufacturing industries, while the development of emerging industries such as high-tech and service industries was relatively fast. The structure of the urban economy began to upgrade towards high-end manufacturing and service industries. In addition, major cities have strengthened cooperation during this period, forming closer regional cooperation. Therefore, the identified urban built-up areas in 2016 were not only concentrated in Shanghai, Suzhou, Wuxi, Nanjing, Hefei, and Hangzhou, but also new urban built-up areas were identified in the surrounding cities of these cities, such as Ningbo, Shaoxing, Jinhua, and Taizhou. This is mainly due to the fact that as the population and internal costs of the major cities increase, the major cities face high congestion costs and low agglomeration economies, causing the population and employment opportunities to spread outward. Overall, compared to the urban built-up areas in 2013, the identified urban built-up areas showed a form of explosive expansion and a central diffusion within the urban agglomeration.

From 2016 to 2019, the YRD urban agglomeration began to focus on innovation-driven development, with high-tech industries and innovative enterprises supported and developed, innovation resources and entrepreneurial environments gradually upgraded, and high-tech industries becoming an important economic growth point. During this period, the YRD urban agglomeration advocated high-quality development, focusing on enhancing high value-added industries such as urban service industry, cultural tourism industry, and technological innovation. Therefore, the built-up area of 2019 identified at this time compared with the built-up area of 2016, although showing a continuous expansion, overall presents a state of further improvement in the previous urban built-up area.

From 2019 to 2022, the YRD urban agglomeration began to promote urban-rural integration development, implement the rural revitalization strategy, and further deepen cooperation among major cities. By promoting interconnectivity between cities, strengthening regional transportation and exchanges, the overall development of YRD urban agglomeration has also been further promoted. Therefore, the identified urban built-up areas in 2022 have further improved and developed, forming two development zones centered around Shanghai. One is the Shanghai Suzhou Wuxi Zhenjiang urban built-up area zone, and the other is the Shanghai Jiaxing Hangzhou built-up area development zone.

In general, the characteristics of these four stages show the continuity and evolution of urban built-up area development in the YRD urban agglomeration.

C. ANALYSIS OF FACTORS INFLUENCING THE EVOLUTION OF URBAN BUILT-UP AREAS IN THE YRD URBAN AGGLOMERATION

As one of the major urban agglomerations in China, the YRD urban agglomeration has developed rapidly in recent years, and the evolution of built-up areas is also very obvious when viewed in conjunction with Figure 6. In order to accurately assess the dominant influencing factors on the evolution of built-up areas in the urban agglomeration of YRD urban agglomeration in different periods within the study area, we utilize geo-detectors to carry out objective analyses of the influencing factors that may have been involved in different periods.

From the development of urban built-up areas in previous urban agglomerations, there are many factors that affect their development and evolution, and the influencing factors of different urban built-up areas vary, and even the influencing factors of the same city at different periods have different focuses [60]. However, in combination with the existing studies, there are several influencing factors that are generally recognized, including the per GDP, population, sector, infrastructure, government, urban planning, topography and urban planning [61], [62]. Therefore, we choose the above factors as the main influencing indicators for the urban built-up area evolution of YRD urban agglomeration. The specific explanations of different factor indicators are as follows:

The per GDP: the per GDP is an important driving force for early urban expansion. Firstly, rapid economic growth can bring more employment opportunities, attracting a large influx of foreign population into the city and contributing to urban expansion. Secondly, economic development can lead to the construction and improvement of urban infrastructure, providing the necessary support for urban expansion. In highly economically developed cities, the demand for housing, commercial and service facilities will continue to increase, thus further triggering urban expansion and spatial reorganization. Therefore, in this study, the sum of the gross domestic product (GDP) of the secondary and tertiary industries in the YRD urban agglomeration is divided by the total urban population to obtain the GDP per capita as a measure of the level of economic development of the built-up area of the city.

1) POPULATION

The growth of urban built-up areas is driven by accelerated urbanization, the continued concentration of population in cities, and rapidly growing demand for land. With the development of urban agglomerations, the population in the central urban and suburban areas continues to expand, presenting a monocentric pattern of high density in the center and decreasing towards the outer circle. The more rapid pattern of population urbanization in the central city and the decentralized development of the suburbs have in turn further bring about a rapidly growing demand for land. Therefore, this study uses the distribution of permanent urban population in the YRD urban agglomeration as an indicator to measure its regional population size.

2) SECTOR

The industrial structure of a city directly determines its economic function, affects its spatial structure, and subsequently leads to the expansion of urban land use. Industrialization is the main driving factor of urbanization development in the first place, and with the adjustment of industrial structure, traditional industries are expanding to the suburbs, and industrialization has become a new driving force for suburban urbanization. The YRD urban agglomeration now proposes to accelerate the development of suburban manufacturing industry and service industry in the central city, which makes the suburbanization of the manufacturing agglomeration area obvious, while the production and commercial service agglomeration area is mainly concentrated in the central city. This adjustment of industrial layout forms the agglomeration of service industry in the central city, and the dual urban spatial structure of scattered peripheral manufacturing industry causes a large number of new employment population from outside to flow to the suburban rural-urban fringe. At the same time, the redistribution trend of the resident population in the central city gradually transfers to the suburbs promotes the process of urban expansion. In this study, the impact of industrial restructuring on the evolution of the spatial structure of the urban built-up areas in the YRD urban agglomeration is examined by adopting the ratio of the output of the second and third industries.

3) INFRASTRUCTURE

The development of urban transportation infrastructure has a significant impact on urban scale and land use. Firstly, transportation infrastructure increases spatial accessibility, and changes in spatial accessibility affect changes in urban spatial structure. Secondly, the planning and layout of major urban roads affect the scale and direction of urban spatial expansion. Additionally, at different stages of urban expansion, the impact of transportation on urban land expansion changes varies. On the one hand, the development of transportation provides opportunities for land use expansion along and around the route. On the other hand, with the development and perfection of public transportation, people are prompted to migrate to the outskirts of the city for the sake of economic, comfortable living conditions and beautiful environment, and at the same time, functional departments and service industries are also driven to move out, which leads to the expansion of urban built-up areas. The increase in accessibility brought about by the development of transportation infrastructure attracts some residents to relocate from the central area to the outer areas of the city with lower housing prices and better living conditions, thus enabling the expansion of built-up areas. In this study, the traffic road area and total infrastructure in the YRD urban agglomeration are divided by the urban permanent population as the variables influencing the level of transportation infrastructure on the evolution of built-up areas.

4) GOVERNMENT

The government plays an important role in the development of urban agglomerations. Its preference for a specific city or region in urban development will affect the allocation of various economic factors, thus affecting the development trend of urban built-up areas. As China's most economically developed and densely populated urban agglomeration, the YRD urban agglomeration is characterized by distinct city levels and differences, and government intervention has a very significant role to play. In this study, it is expressed as the share of the fiscal expenditure of the upper-level government in the GDP of the urban agglomeration.

5) TOPOGRAPHY

Different topography can affect the expansion of urban built-up areas, such as water systems, mountains, gradients, and so on. Different topographic features will also affect the price of land use, thus affecting the development of urban built-up areas. In this study, DEM is used to extract land slope as a variable of topographic factors.

6) URBAN PLANNING

Urban planning and related policies play an important guiding role in urban development, including urban spatial layout, infrastructure development and urban expansion direction. In this study, the change of urban spatial organization before the implementation of urban planning policy is used to represent the impact of planning intervention.

In order to analyze the influencing factors on the evolution of urban built-up areas in the YRD urban agglomeration, we use geographical detectors to realize this process. Firstly, we conduct a Person correlation analysis on different influencing factors, and the results show a positive correlation between the per GDP, population, sector, infrastructure, government, urban planning, topography, and urban planning, all of which pass the significance test of 0.01. Then, using the differentiation and factor detection of geographical detectors, we obtain the spatial differentiation explanatory power and significance P-values of each influencing factor on the evolution of urban agglomeration built-up areas. The results show that the significance P-values are all less than 0.100, indicating that these influencing factors have significant spatial differentiation and have a significant impact on the evolution of urban built-up areas in the YRD urban agglomeration. However, the dominant influencing factors in different periods varied, as shown in Figure 8.

From the results of geographical detectors, although the dominant factors affecting the spatial structure evolution of urban built-up areas in the YRD urban agglomeration vary in different periods, in general, the main factors affecting the spatial structure evolution of urban built-up areas are the per GDP, population, and government. Among them, from 2013 to 2016, the main factors affecting the evolution of urban built-up areas are the per GDP, population, and government, from 2016 to 2019, the main influencing factors are the per GDP, population, and from 2016 to 2019, the main influencing factor become the government.

In the light of the actual development process of the YRD urban agglomeration, the early economic growth of the urban agglomeration brought more employment opportunities, commercial activities, and investment opportunities to the built-up areas, promoting continuous population growth. The increasing population implies higher demands for housing, transportation, infrastructure, and public services, thereby driving the planning, construction, and expansion of the built-up areas. With the continuous optimization, development, and transformation of the industrial structure within the YRD urban agglomeration, more high-tech and innovative enterprises are introduced into the built-up areas, enhancing the competitiveness of the industry chain and the level of urban economic development. At this stage, a more convenient transportation network and improved traffic systems facilitate the flow of people and goods, promoting the development of the built-up areas and improving connectivity with surrounding regions, further expanding the built-up areas. Additionally, the increasing planning interventions within the YRD urban agglomeration provide guidance for the development of the built-up areas. Government investment is utilized for infrastructure construction and the enhancement of public services, providing better education, healthcare, transportation, and other public facilities in the built-up areas, further driving their expansion. Overall, the evolution of the built-up areas within the YRD urban agglomeration is a result of rapid economic development guided by the government and influenced by multiple factors. The built-up areas have transitioned from a concentration of economy and population to a regionally coordinated development led by the government within the YRD urban agglomeration.

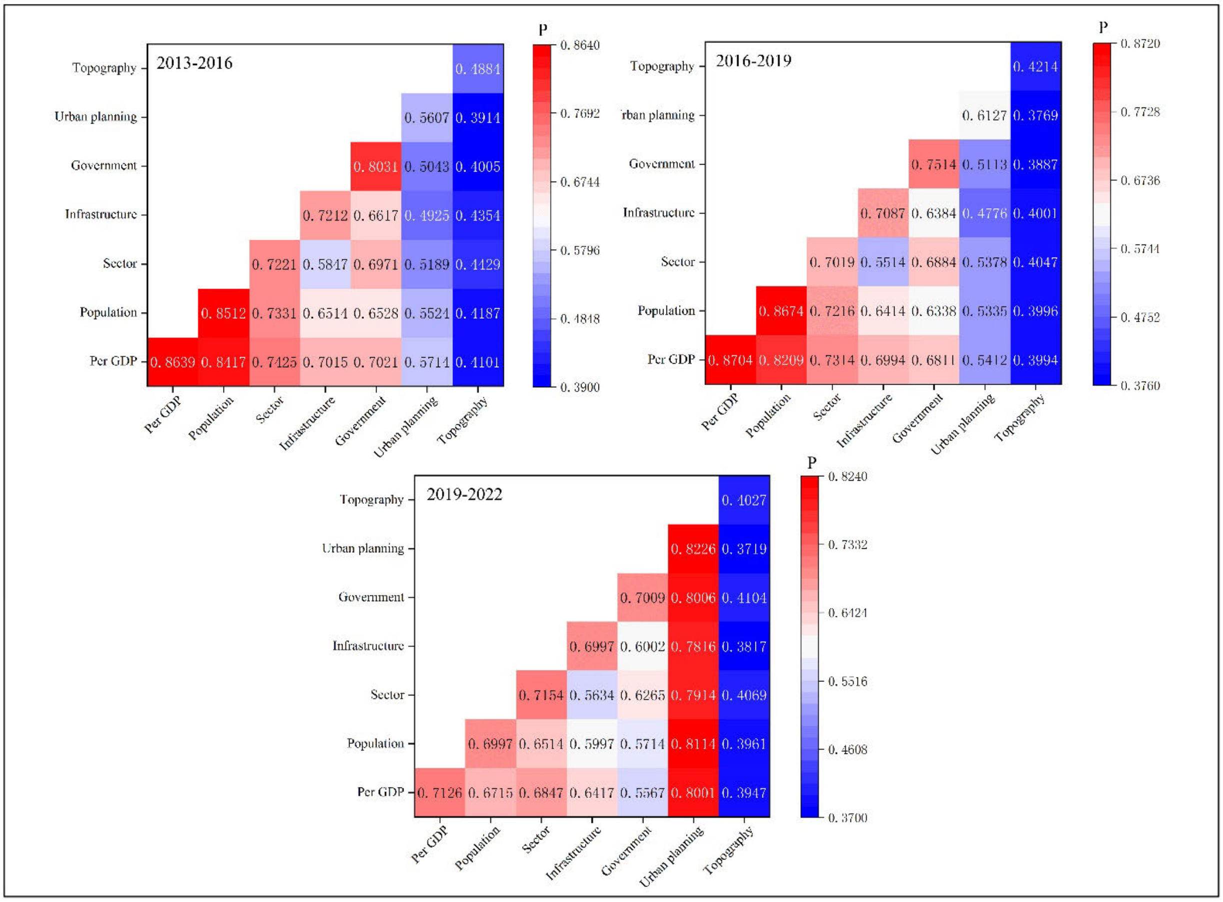

FIGURE 8. Geographical detector results in different periods.

IV. DISCUSSION

Traditional research on urban built-up areas mainly relies on local statistical and remote sensing data. However, local statistical survey data have long update cycles, and local governments often intentionally expand the built-up areas to attract more investment and support from higher authorities, thereby increasing the urbanization rate [63]. Remote sensing image data, including nighttime lights, is also subject to the influence of the data itself in the extraction of urban built-up areas. Therefore, there is a lack of accurate and easily generalizable methods for studying urban built-up areas, especially large-scale areas [64]. This study fuses NTL data, POI data, and LandScan data to analyze the evolution of urban built-up areas in the Yangtze River Delta urban agglomeration and their influencing factors. This study proposes a simple and reliable method for extracting urban built-up areas, allowing for a more comprehensive analysis of urban built-up areas and a more objective understanding of the current urban development status.

In previous studies on urban built-up areas, more emphasis has been placed on exploring the role of different methods and data in analyzing urban built-up areas. Even the research on data fusion for urban built-up areas has remained limited to a single time snapshot [65], [66]. However, for the study of large-scale urban agglomerations, identifying and extracting their built-up areas is only one aspect. More importantly, it is crucial to explore the patterns of their evolution and understand the driving mechanisms behind it, which is vital for the subsequent development of urban agglomerations. During the expansion process of urban built-up areas, urban areas generally experience a rapid expansion followed by a slower expansion until ultimately reaching a stable state. This process is closely linked to the development trajectory of cities [67], [68]. Currently, Chinese cities have gone through a period of rapid expansion, and future urban expansion will no longer be driven solely by economic and population growth, which means that the inherent expansion factors will also become more complex [69]. In the current expansion of built-up areas within urban agglomerations, factors such as local policies and industrial structure can directly influence the expansion patterns of urban built-up areas. For example, previous studies have shown that macro policies regarding the development of built-up areas in the western Chinese urban agglomerations have played a positive role [70]. Therefore, analyzing the dominant influencing factors affecting the evolution of built-up areas within urban agglomerations in different periods is crucial for the healthy development of urban agglomerations [71]. In the development of YRD urban agglomeration, we analyze the dominant driving factors affecting the evolution of built-up areas in urban agglomerations in different periods, which is rare in other studies. The results are highly consistent with the development of the YRD urban agglomeration, further highlighting the practical value of this study.

Although the study of urban built-up area evolution and its influencing factors is not a new topic, with many studies on the evolution of urban built-up areas in different urban agglomerations in China and its influencing factors have been comprehensively analyzed. On the basis of previous studies, this study analyzes the evolution of the built-up area of the YRD urban agglomeration and discusses various factors affecting its evolution. Based on the fusion of three kinds of data, NTL data, POI data and LandScan data, a new index is obtained to evaluate the evolution of the built-up area of the urban agglomeration. In addition, this study comprehensively analyzes the main influencing factors that dominate the spatial evolution of built-up urban areas in different periods of the YRD urban agglomerations, which has an important guiding role for the future spatial planning and high-quality collaborative development of the YRD urban agglomeration. Taking the YRD urban agglomeration as the study area can provide important references for understanding the development mode, economic characteristics, urban collaborative development, planning and environment of China's urban agglomerations. As a typical urban agglomeration with early urbanization development in China, the experience and practice of the YRD urban agglomeration can serve as a model and inspiration for other urban agglomerations in China in terms of their development and sustainable development.

Based on the method of multi-source big data fusion, this study comprehensively analyzes the evolution of urban built-up areas and the influencing factors at different periods in the YRD urban agglomeration, yielding valuable results. However, this study still has certain limitations. Firstly, from the perspective of the study data, LandScan data is based on the estimation of population distribution in space using population data, which may have some differences from the actual distribution of the population. While, POI data may suffer from missing, erroneous, or outdated information, especially in rapidly changing cities or regions. On the other hand, although we consider the potential positive effects of policies and planning in the analysis of influencing factors, it is challenging to quantitatively measure the effectiveness of government policies and planning. Therefore, this study is more of a foundation based on mathematical analysis, and further consideration is needed when applying it to specific studies in urban agglomerations. In the future, we will on the one hand attempt to expand the spatial scale of the research and consider the intrinsic mechanisms of built-up area evolution in a larger spatial scope, and our future research will explore in detail on how to further improve the U-net neural network model to more accurately extract built-up areas from the following aspects. First, try using different types of convolutional layers to extract more feature information. Second, attempt to use data augmentation technology to expand the training dataset to increase the diversity of training samples and improve the performance of the model. Third, perform various preprocessing before inputting images to improve the distinguishability of the built-up area. Additionally, our future research will also focus more on the discussion on how these study findings can be practically applied in urban planning and policy-making, which will provide better reference value for urbanization studies in China and other regions.

V. CONCLUSION

We analyze the evolution of urban built-up areas in the YRD urban agglomeration and the factors influencing it through the multi-source big data fusion. The identified evolution of urban built-up areas in the YRD urban agglomeration corresponds well with the actual development of urban built-up areas in the agglomeration, further highlighting the importance of fusing different data sources. Moreover, we find that the factors driving the evolution of urban built-up areas in the YRD urban agglomeration vary across different periods. Specifically, the influence of the population on the evolution of urban built-up areas is decreasing, while the impact of urban planning and the per GDP are increasing, which suggests that the future development of the YRD urban agglomeration would no longer focus solely on attracting a large population, but will instead promote coordinated development within the region guided by government urban planning policies. The development and evolution of urban built-up areas are crucial aspects of urban research, and this study demonstrates the vital role of multi-source data fusion in understanding their evolution and influencing factors, which provides a valuable reference for future urban research. Additionally, based on the development of urban built-up area, this study puts forward a conclusion that the leading factors in different periods are different, offering important insights for the high-quality and fine-grained development of urban agglomerations and holding positive implications for the development and planning of other similar urban agglomerations.

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