

RESEARCH ARTICLE

Using POI Data and Baidu Migration Big Data to Modify Nighttime Light Data to Identify Urban and Rural Area

YAPING CHEN¹ AND AKOT DENG^{1,2} ¹School of CML Engineering Architecture, Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang, Zhejiang 322100, China²Architecture and Planning, Sudan University of Science & Technology, Khartoum 999129, Sudan

Corresponding author: Akot Deng (1813487135@qq.com)

This work was supported by the Colonel-Level Project-Establishment of Zhejiang Guangsha Vocational and Technical University of Construction in 2022: Study on Extraction of Built-Up Areas in Zhejiang City Group Based on the Fusion of Multi-Source Remote-Sensing Big Data under Grant 2022QNPY007.

ABSTRACT The spatial difference between urban and rural areas is the direct result of urban-rural relations. Accurate identification of urban-rural area is helpful to judge the urban-rural mechanism and promote the integration development of urban-rural area. Previous studies only used single nighttime light (NTL) data to identify urban and rural areas, which is likely to have an impact on the identification results due to the large brightness difference of lights. Therefore, based on NTL data and combine with data level fusion algorithm, this study separately fuses point of interest (POI) data that representing the quantity distribution of urban infrastructure and Baidu migration big (BM) data that representing the change relationship of regional population mobility to identify urban and rural areas by using deep learning method. The results show that the highest accuracy of urban-rural spatial identification with single NTL data is 84.32% and kappa is 0.6952, while the highest accuracy identified by data fusion is 95.02% and kappa is 0.8259. It can be seen that the differences caused by light brightness are effectively corrected after data fusion, which greatly improves the accuracy of urban and rural spatial identification. By comparing the results of NTL data modified by different big data, this study analyzes and identifies the accuracy of urban and rural area by using deep learning method, which not only enriches the study of data fusion in urban area, but also provides a basis for analyzing regional urban-rural relations and urban-rural development. Therefore, this study is believed to have important practical value for the coordinated development of urban and rural areas.

INDEX TERMS Urban-rural difference, POI, night light, BM data, Zhengzhou.

I. INTRODUCTION

With the acceleration of urbanization, more and more population, especially rural population swarm into urban area, resulting in the disordered expansion of cities [1], then traditional urban-rural boundary is becoming too vague to express the regional differences between urban and rural areas [2], [3], [4]. On the other hand, rural area has many important functions that cannot be replaced by urban area [5], including but not limited to agricultural production and environmental protection [6], [7]. The blind expansion of urban area means the massive encroachment and impaired function of rural area, which could undoubtedly affect the sustainable development of urban area [8], [9]. With the

proposal and intensively promotion of strategy for rural revitalization and strategy for urban finer governance, the importance of rural area is becoming more and more obvious. While the accurate identification of urban-rural area is the chief precise to achieve the finer governance of urban area [10], [11].

The accurate identification of urban-rural area means the accurate distinguishment of urban-rural differences, which would greatly contribute to the formulation of demand-oriented policy of different areas [12], so that to limit the disordered expansion of urban area and protect the rural area and finally achieve the harmonious development of both urban and rural area [13], [14]. However, current studies on the identification of urban-rural area mainly use indicators including the area of urban built-up area, the population size of urban and rural population, and the industrial

The associate editor coordinating the review of this manuscript and approving it for publication was Manuel Rosa-Zurera.

distribution to distinguish the urban-rural area [15], [16], [17], which resulting in the identified area pays more attention to entity form without considering the development difference between urban rural area. Additionally, with the promotion of urban-rural integration strategy and coordinated development between regions strategy, more and more rural area is sharing same spatial characteristics with urban area, which makes the urban-rural boundary even more vague [18], [19]. Therefore, the accurate identification of urban-rural spatial difference is of great practical significance to the harmonious development of both urban area and rural area.

As one kind of remote-sensing data. Nighttime light (NTL) data could express the spatial distribution of population and development status of infrastructures by capturing the nighttime light brightness generated by human activity and infrastructures [20], [21]. Therefore, NTL data is widely used in studies on the analysis of human activities and on the estimation of socio-economic indicators [22], [23]. Using NTL data, scholars has successfully identified urban built-up area and observed human activities among different cities in years [24], [25], which all benefits to the obtaining of the difference of human activities in different period [26]. Besides, scholars have also analyzed the internal spatial structure within urban area [27], including the identification of urban center and delineation of urban boundary by using NTL data [28], [29]. Additionally, the development status of different cities in different period has also been successfully comparative analyzed by using NTL data [30], [31]. However, on the other hand, there is an oversaturation problem in the practical application of NTL data in urban space [32], [33]. Therefore, in order to improve the heterogeneity of urban interior space, researchers often use normalized difference vegetation index (NDVI) to correct the oversaturation of nighttime light [34], [35]. However, in some cities with rapid urbanization process, vegetation in the saturated area generally does not change significantly in a short period of time [36], and such methods rarely take the interference of human activity intensity and other factors into account [37], [38]. Therefore, this study uses the composite index of vegetation and human activity to modify NTL data, taking into account the impact of human activity intensity while improving the spatial heterogeneity within the city.

In October 2018, Wuhan University launched the Luojia-01 experimental satellite, which began to provide high-resolution nighttime light data with a spatial resolution of 130 meters. The great improvement in spatial resolution of the Luojia-01 data makes it possible to evaluate the urban internal spatial structure in a fine way [39]. Additionally, the higher spatial resolution makes the urban internal spatial structure reflected by the Luojia-01 more complete. Therefore, it can be concluded that Luojia-01 data have changed the study emphasis of NTL data from focusing on urban agglomerations and metropolitan areas to focusing on a single city [40], [41]. However, although NTL data could relatively represent the urban internal structure, there is a light spill

phenomenon [42], [43], which means that the areas with nighttime light are larger than actual urban areas [44], [45]. Therefore, studies that aim to improve the extraction accuracy of NTL data have been conducted [46].

Compared with traditional data, big data not only has the advantages of wider sampling range and faster collection speed [47], but it has also been found that there is a strong perceived fit between big data and the urban internal structure [48], [49]. At present, there are three kinds of spatial location big data that are widely used in studies related to urban space, including POI data [50], cellular signaling data and population migration data [51], [52]. Among which, POI data are a dataset where different urban entities are extracted in virtual geographical space, with which urban functions with different attributes can be represented by the construction of POI data [53], [54]. POI data is used to delineate urban boundary and to identify urban centers with different functions [55]. As for BM data, it can reflect the population flow in different regions by reflecting the degree of population agglomeration in specific period on the map [56]. Additionally, this study analyzes the spatial vitality of different regions through the population heat provided by BM data [57]. Therefore, it can be concluded that there is a strong relevance between POI data and NTL data in urban-related studies. Therefore, POI data and NTL data have been fused by researchers in the hope of obtaining a better observation effect on urban space after data fusion [58].

Although there is a significant difference among information provided by different data, it is becoming increasingly harder for single-source data to accurately represent the complex information within urban cities, so it has become increasingly popular to use different source data to modify NTL data to perform studies related to urban cities [59]. Data fusion refers to the fusion of multiband information from the same sensor and refers to the fusion of different types of sensors to remove the redundancy and contradiction that might exist among different sensors, hoping to perfect the timeliness and reliability of remote sensing information extraction to obtain a more defined, more secure, and more reliable estimation and judgment than single-source data [60], [61]. In order to identify urban and rural area more accurately, this study attempts to fuse POI data, BM data and NTL data through deep learning method, to make up for the deficiency of single-source data. Then the results of different data compensating for NTL data are verified. Finally, feasible methods and paths for urban and rural spatial identification are proposed. By accurately identifying urban and rural space, this study enriched the theoretical study on urban and rural differences on the one hand. On the other hand, it is also believed that the accurate identification of urban and rural space area would undoubtedly contribute to the accurate judgment of urban-rural differences, thus providing a theoretical foundation for regional governance and policy-making regarding the harmonious urban-rural development.

II. MATERIALS AND METHODS

A. STUDY AREA

The study area is located in the main urban area of Zhengzhou City, Henan Province, China, including Jinshui District, Zhongyuan District, Guancheng District, Erqi District, Huiji District, Shangjie District and Xingyang City. As the core area of Zhengzhou, the urbanization process of the main urban area of Zhengzhou has accelerated significantly in recent years. By the end of 2020, the urbanization rate of the main urban area of Zhengzhou is 78.40%, ranking first in Central China. The rapid urban modernization has intensified the expansion of urban space in the main urban area of Zhengzhou, constantly occupying rural space, and highlighted the contradiction between urban and rural areas, which makes the case study of Zhengzhou representative [62]. This study identifies the urban-rural spatial area of the main urban area of Zhengzhou, helps to understand the current situation of urban-rural development, and provides feasible suggestions for the healthy development of urban-rural integration in Zhengzhou.

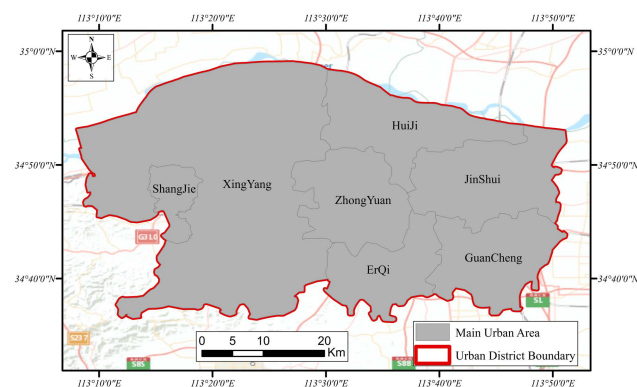


FIGURE 1. Study area.

B. STUDY DATA

The study data used in this study are mainly NDVI data, Luojia-01 NTL data, POI data and BM data.

The NDVI data are obtained from MODIS with a spatial resolution of 250m and a temporal resolution of 16d. The average NDVI data of 2020 can be obtained by averaging the acquired images. Luojia-01 data, provided by the Luojia-01 experimental satellite, can be downloaded for free at <http://59.175.109.173:8888/Index.html>. Compared with DMSP/OLS and NPP/VIIRS NTL data, Luojia-01 NTL data have a resolution of 130 m and a width of 20 km, which enable Luojia-01 NTL data to be more perfect in spatial scale analysis. Additionally, the finer numeric features of NTL data greatly improve its extraction accuracy within urban space. The NTL data of Zhengzhou from October 2018 to October 2021 were obtained for this study after accessing the website mentioned above, and the preprocessing figure of Zhengzhou NTL data (Figure 2) was obtained after conducting radiation correction and monthly average processing on all the obtained NTL data.

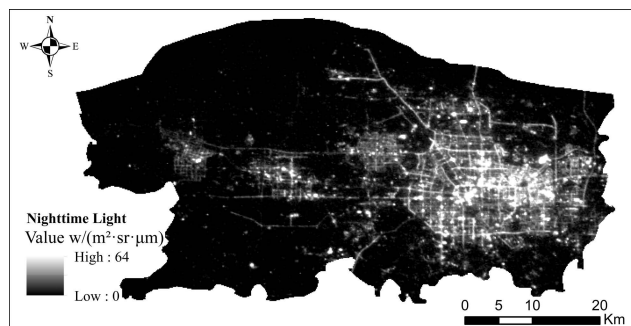


FIGURE 2. Preprocessing result of NTL data in Zhengzhou main urban area.

POI data refer to the point dataset in a networking electronic map, which consists of four attributes: name, address, coordinate and category [31]. At present, numerous maps, such as Baidu Maps, Amap and QQ Maps, have provided developers with API (application programming interface) access services, which allow users to sense all kinds of reasonable data. By accessing the API provided by Baidu maps (www.baidumap.com), this study sourced POI data from Zhengzhou in December 2021, and the category and quantity of POI data were 22 and 623,354, respectively. After screening, duplicate checking, filtering and cleaning all the obtained POI data, the category and quantity were 16 and 385,632, respectively. The quantity and spatial distribution of POI data in Zhengzhou are shown in Figure 3.

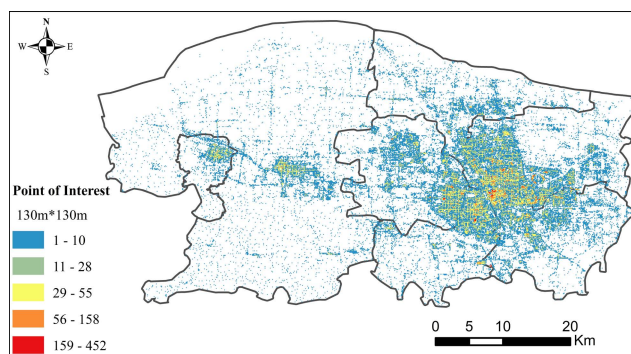


FIGURE 3. The quantity and spatial distribution of POI data in Zhengzhou main urban area.

BM data can directly represent the spatial distribution, density, and variation trend of regional population by representing the color depth and brightness of the data, so as to reflect the important data source of regional population change. Since BM data correspond to different spatial resolutions according to different levels, the 130m spatial resolutions of POI data and NTL data are considered in this study. The migration data from January to December 2020 were obtained by accessing Baidu Map API. After average processing of the obtained data, the population heat distribution in the main urban area of Zhengzhou is obtained, as shown in Figure 4.

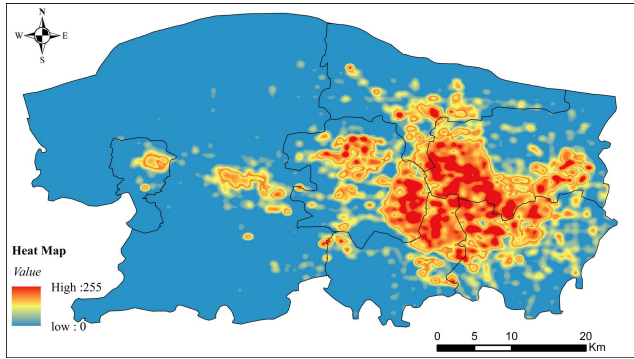


FIGURE 4. BM data of the main urban area in Zhengzhou.

C. STUDY METHODS

1) COMPOUND EXPONENTIAL MODEL ADJUSTED NIGHTTIME LIGHTS INDEX

As a spatial domain weighted fusion algorithm, the image fusion technology of PCA is to remove the redundant information in the source image by the principal component decomposition method to obtain the principal component components and the corresponding eigenvalues of each source image, and then determine the corresponding weighting coefficients, and finally obtain the fused image [56], [57], [58]. This method outperforms other non-multiscale fusion methods. As the NTL data value gradually decreases from the urban center to the suburbs, while the vegetation coverage gradually increases from the urban center to the suburbs [63], after normalization, the difference between nighttime light intensity and vegetation coverage shows a trend of gradually decreasing from the urban center to the suburbs [64]. The VANUI index of nighttime light data modified by NDVI is as follows:

$$VANUI = (1 - NVDI) * NTL \quad (1)$$

Although the light index NTL gradually decreased from the urban center to the suburbs, while the vegetation index NDVI gradually increased from the urban center to the suburbs, $1-NDVI$ changes the trend of NDVI to be the same as that of NTL and improves the spatial heterogeneity within urban area. Therefore, VANUI index could increase the DN value within urban area. Additionally, the DN value gradually decreases to the suburbs, which enhances the heterogeneity of inner urban space [65].

It has been shown by related studies that from rural areas to urban centers, with the increase of distance, the increase of population density is not a single linear growth, but a nearly reverse change based on light intensity and vegetation index [66]. Therefore, considering the change of population density, this study proposes a composite index model CEANI to modify NTL index, whose formula is:

$$CEANI = e^{k * \frac{2+(NTL-NDVI)}{2-(NTL-NDVI)}} * NTL \quad (2)$$

Among them, NTL and NDVI are normalized data, and the value of $NTL-NDVI$ ranges from -1 to 1 , showing a

gradual increasing trend from suburbs to urban centers. When the value of $NTL-NDVI$ is zero, this area is mostly the transition zone between urban centers and suburbs. Taking this transition zone as the critical point, the closer it is to the urban center, the greater its saturation degree would be. Therefore, it can be concluded that the distribution trend of composite urban population density has higher modification value for NTL data on the premise of reflecting urban spatial heterogeneity.

2) MULTI-SCALE TRANSFORM DOMAIN FUSION ALGORITHM

Image fusion algorithms include data level image fusion, feature level image fusion and decision level image fusion [67], [68]. Among which, data level image fusion has become one of the key directions of current image fusion study since data level image fusion can not only retain as much original data as possible but can provide subtle information that other fusion methods cannot provide [69]. Data-level fusion includes space domain algorithm and transform domain algorithm, and wavelet transform is the most important method in spatial domain transformation algorithm [70].

Wavelet transform can achieve image fusion by scaling and shrinking different images at different scales, so as to extract the feature information of the image. The unique time-frequency scaling window of wavelet transform can not only retain the feature part of the image, but also reflect the multiple features of different source data after fusion. Thus, wavelet transform has more significant advantages in data fusion [71]. The formula of wavelet transform is:

$$WT(\alpha, \tau) = f(t)\varphi(t) = \frac{1}{\sqrt{\alpha}}f(t) \int_{-\infty}^{+\infty} \varphi\left(\frac{t-b}{\alpha}\right)dt \quad (3)$$

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

The main idea of Formula 3 is to perform translation τ in the wavelet function firstly, and then do inner product with the analysis signal $f(t)$ at different scales α to achieve multi-scale image fusion. In the actual fusion process, the original images such as NTL data, POI data and BM data are decomposed by wavelet to obtain a series of sub-images of different high and low frequency bands, which can reflect the local features of the image. Then, different high and low frequency components are processed by different fusion rules. Finally, the fused images can be obtained by inverse wavelet transform.

3) IMAGE FEATURE EXTRACTION BASED ON U-NET

The identification of urban and rural spatial scope is essentially the classification and extraction of urban and rural spatial characteristics. On the other hand, deep learning has obvious advantages in image feature extraction, firstly, the main feature and advantage of deep learning is that it can greatly improve the interpretation of data by learning the inherent laws and representation levels of

sample data so as to achieve accurate extraction of image features [72]. Additionally, the high-efficiency algorithm replaces the previous manual calculation, which makes the extraction of image feature information simpler and more efficient [73], [74].

As a method of deep learning, U-net is a segmentation network based on feature extraction evolved from the fully convolutional network (FCN). Compared with other neural networks, such as convolutional neural network (CNN) and FCN, U-net can solve the problems of less fuzzy segmentation results and longer training time in jumping layer structure by transforming the input size of the image [75], [76]. Additionally, U-net can not only reflect the global information of the image, but also reflect the details of the image, which makes it possible to greatly improve the accuracy of image features [77].

The main idea of U-net extracting image features is to learn and train the sample data with urban and rural spatial characteristics respectively by using the officially published urban and rural spatial range data, then the index of each item can be obtained and the final training weights need to be saved, and finally the test data need to be read into the network for verification, so as to identify different images with the set network, and the urban and rural space of different images could be finally obtained.

The main process of urban and rural spatial identification is shown in Figure 5.

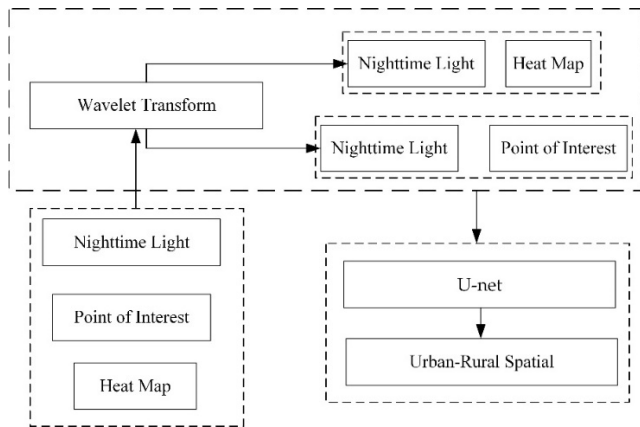


FIGURE 5. Framework of study methods.

The study ideas of this study are as follows : (1) perform desaturation on NTL data to obtain desaturated NTL data, and then identify urban and rural areas through U-net. (2) The desaturated NTL data and POI data are fused at the data level by wavelet transform, and then the urban and rural areas are identified by U-net. (3) The desaturated NTL data, POI data and BM data are fused by wavelet transform, and then the urban and rural areas are identified by U-net. (4) The different urban and rural area identified by different data fusion are verified and compared, and the conclusion of this study could be got.

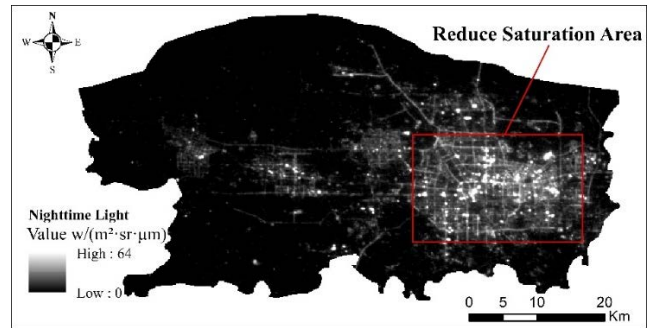


FIGURE 6. NTL data modified by CEANI index.

III. STUDY RESULTS

A. URBAN-RURAL AREA OF ZHENGZHOU IDENTIFIED BY DIFFERENT DATA

1) MODIFICATION OF NTL DATA

The NTL data modified by the CEANI index is shown in Figure 6. From the comparison between Figure 6 and Figure 2, it can be found that the oversaturation of NTL data has been modified to a certain extent, and the internal contour and spatial heterogeneity of the urban area have been highlighted, especially in the main areas of population activities with high nighttime light values such as in Jinshui District, high-speed railway stations and university town.

2) URBAN-RURAL AREA OF ZHENGZHOU IDENTIFIED BY NTL DATA

NTL data distinguish urban and rural space by light brightness, that is, the areas with high light brightness are urban areas, and the areas with low light brightness are rural areas, which is also the main manifestation of urban-rural development difference. By analyzing desaturated NTL data, it can be found that the high NTL values are mainly concentrated in Jinshui District, Zhengzhou railway station of Erqi District, the college town of Zhongyuan District and the Zijingshan trading area of Guancheng District, while the NTL values in other districts are relatively lower such as Shangjie District and Xingyang District. Therefore, it can be seen from the distribution of high and low NTL values that there is a significant spatial difference in the spatial development of Zhengzhou urban-rural area.

In this study, U-net is used to extract image features and the urban-rural area identified is shown in Figure 7. Figure 7 shows that the area identified by NTL data mainly has the following features. First, the area of urban-rural space identified by NTL data is 512.69 and 1514.51 km², respectively, accounting for 25.29% and 74.71% of the whole urban-rural area of Zhengzhou, we can find that the urban space identified by NTL data is smaller than the rural area, accounting for 66.33% of the whole urban-rural area of Zhengzhou. Second, the identified urban area is mainly concentrated in Erqi District, Guancheng District, Zhongyuan District and Jinshui District, while the identified rural area is mainly concentrated

in Xingyang city and Xinzheng District, so we can see that the identified spatial distribution is similar with the spatial distribution of NTL high and low values. Third, from the perspective of identified urban areas, the uneven distribution of light brightness leads to the fragmentation of urban cluster patches to a certain extent, and some rural patches are also identified in urban areas. Additionally, the identification of urban-rural boundary is too complicated due to the irregular edge of nighttime lights and the excessive brightness of some roads. Generally, although the urban and rural area identified by NTL data is obvious, the urban cluster is scattered, the fragmentation of urban patches is more serious and the urban-rural boundary is too complex, which all call for subsequent studies to perfect the identification results.

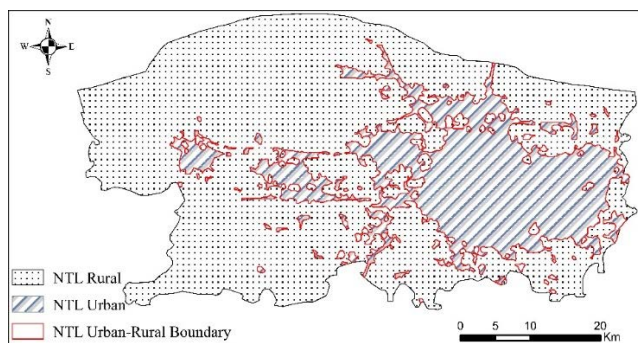


FIGURE 7. Urban-rural area of Zhengzhou identified by NTL data.

3) IDENTIFIED URBAN AREA OF ZHENGZHOU AFTER MODIFYING NTL DATA WITH POI DATA

There is a deep connection between the distribution of POI data and development level of urban city; that is, the more concentrated the POI data are, the higher the development level will be. The number and spatial distribution of POI data in Zhengzhou are shown in Figure 3. Figure 3 shows that POI is mainly distributed in the most areas of Erqi District, Zhongyuan District, Guancheng District and Jinshui District, as well as a small amount area of Shangjie District and some areas of Xingyang City. Compared with NTL data, the quantity and spatial distribution of POI data more directly reflects the difference between urban and rural areas.

Wavelet transform is firstly used in this study to fuse POI data and NTL data and the fused image is shown in 8.a, then this study uses U-net to extract the features of fused images and the identified urban-rural area is shown in Figure 8.b. Figure 8.b shows that the area identified after the fusion of POI data with NTL data mainly has the following features. First, the area of urban-rural space identified by NTL-POI data is 544.32 and 1482.97 km², respectively, accounting for 26.85% and 73.15% of the whole urban-rural area of Zhengzhou, we can find that the urban space identified by NTL_POI data is bigger than that identified by NTL data, accounting for 70.41% of the whole urban-rural area of Zhengzhou. Second, although the urban area identified by NTL_POI data is mainly concentrated in Erqi District,

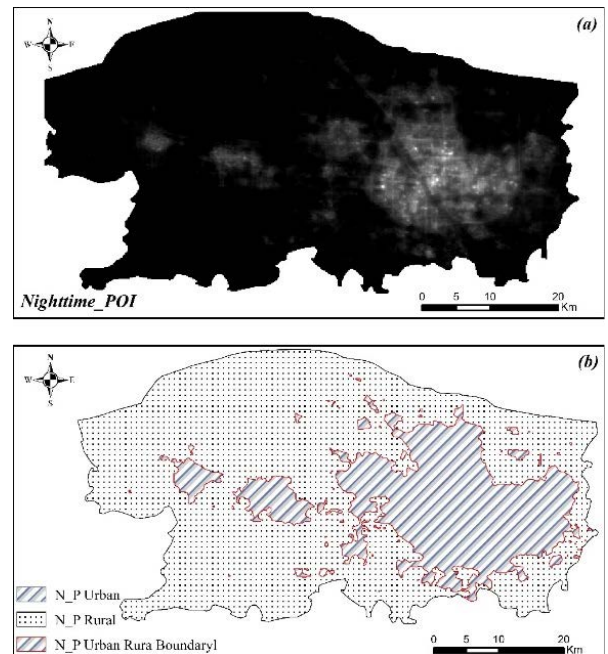


FIGURE 8. Identified urban area of Zhengzhou after modifying NTL data with POI data.

Guancheng District, Zhongyuan District and Jinshui District, there are only single urban area clusters in both Xingyang city and Xinzheng District. Third, from the perspective of identified urban areas, not only did the number of rural clusters identified within urban clusters significantly decrease, but also the degree of patch fragmentation and the complexity of urban-rural boundaries also decreased. In general, the results of urban-rural area identified by NTL_POI data are significantly improved.

4) IDENTIFIED URBAN AREA OF ZHENGZHOU AFTER MODIFYING NTL DATA WITH BM DATA

NTL data and POI data mainly use static factors to identify urban and rural area, which cannot reflect the dynamic changes within urban and rural area. While, on the other hand, BM data reflects the population change in a certain period, which is more obvious in urban areas than in rural areas. It can be seen from Figure 4 that the thermal high values are concentrated in Erqi District, Zhongyuan District and Jinshui District, while the thermal values are not obvious in other regions.

In this study, BM data and NTL data are firstly fused by wavelet transform and the fused image is shown in 9.a, then the features of fused images are extracted by U-net, and the identified urban and rural area is obtained as shown in Figure 9.b. Figure 9.b shows that the area identified after the fusion of POI data with BM data mainly has two features. First, the area of urban-rural space identified by fused BM_NTL data is 561.37 and 1465.83 km², respectively, accounting for 27.69% and 72.31% of the whole urban-rural area of Zhengzhou, we can find that the urban space identified by BM_NTL data is bigger than that identified by POI_NTL

TABLE 1. Comparison of urban areas identified by different data.

	Urban Area	Urban Area/Municipal Area	Urban Built-up Area	Urban Area/Urban Built-up Area
NTL	512.60	25.29%	772.97	66.33%
POI_NTL Data	544.23	26.85%	772.97	70.41%
BM_NTL Data	561.37	27.69%	772.97	72.63%

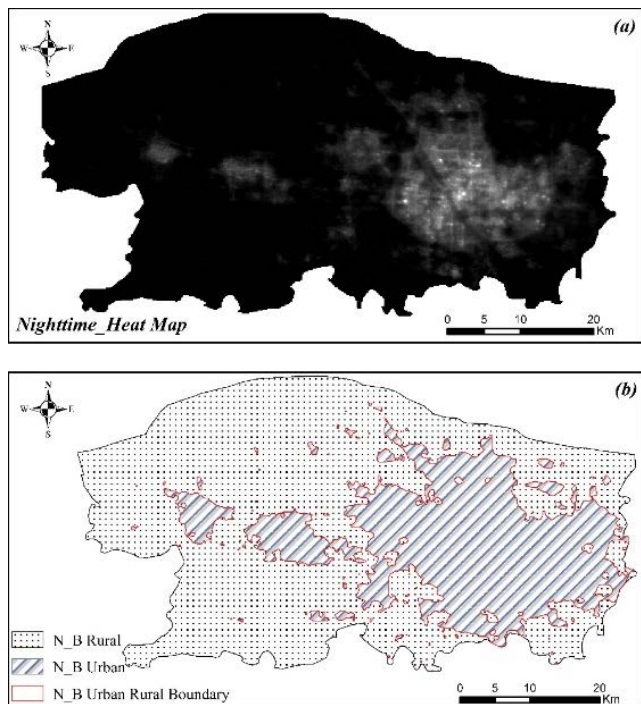


FIGURE 9. Identified urban area of Zhengzhou after modifying NTL data with BM data.

data., accounting for 70.41% of the whole urban-rural area of Zhengzhou. Second, although the patches and boundaries of urban and rural areas identified by BM_NTL data are similar to those identified by POI_NTL data, patches of urban space identified by BM_NTL is obviously correlated with each other.

B. COMPARATIVE VERIFICATION OF THE IDENTIFICATION RESULTS

1) COMPARATIVE ANALYSIS OF THE IDENTIFICATION RESULTS

It can be seen from Table 1 that the area of urban space identified by NTL data is 512.69 km², accounting for 25.29% of the whole urban area of Zhengzhou and for 66.33% of Zhengzhou’s whole urban built-up area; while the area of urban space identified by the fused POI_NTL data is 544.23 km², accounting for 26.85% of the whole urban area of Zhengzhou and for 70.41% of Zhengzhou’s whole urban built-up area; and the area of urban space identified by the fused BM_NTL data is 561.37 km², accounting for 27.69% of the whole urban area of Zhengzhou and for 72.63% of

Zhengzhou’s whole urban built-up area. Therefore, it can be concluded that from the area of the identified urban space, although the area identified by the fused BM_NTL data is the largest, the improvement of BM_NTL data on urban area identification results is not as obvious as POI_NTL data.

From the identification results of NTL data, POI data and BM data, there is a high degree of similarity in macro geographical space among these three data, they also directly reflect the urban internal spatial structure, which helps to distinguish urban and rural space more obvious., Secondly, from the urban center to the edge of the city and even to the rural areas, the values of the three kinds of data all show a declining trend. Additionally, the results of the urban and rural area identified by POI_NTL data is similar to that identified by BM_NTL data. In general, different data can accurately identify the urban internal spatial structure.

By comparing the urban and rural areas identified by different data (Figure 10), it can be found that since the NTL data only has the unique attribute of nighttime light brightness, the NTL data identifies the area with high light value as urban area, identifies the area with low light value or no light as rural area, which will cause errors in the identification results to a certain extent. Specifically, on the one hand, only a small amount of light is generated in residential and commercial areas inside the city at night, resulting in obvious light holes in urban space. While these light holes are often identified as rural space by NTL data. On the other hand, as NTL data often show discontinuity in areas with rapid decline in light value, that is, there is a great difference in light value change at the urban-rural edge, which makes the urban-rural boundary identified by NTL data more complicated and inconsistent with the actual situation of urban-rural spatial development. Additionally, in the process of identifying urban and rural area, the level of NTL value cannot reflect the possible connection between urban and rural areas, especially the mutual flow of population.

After the fusion of POI data, the fused POI_NTL data further comprehensively analyzes the concentration of POI number in the process of identifying urban-rural area rather than only considering the nighttime light brightness. Figure 10 shows that the fused POI_NTL data has the following two characteristics: First, the number of interlacing rural patches is decreasing, that is, the overall patch fragmentation is improving. The reason is that POI data are also widely distributed in some areas with weak light at night, which weakens the impact caused by light holes. Secondly, near the main road connecting urban and rural area, due to the needs

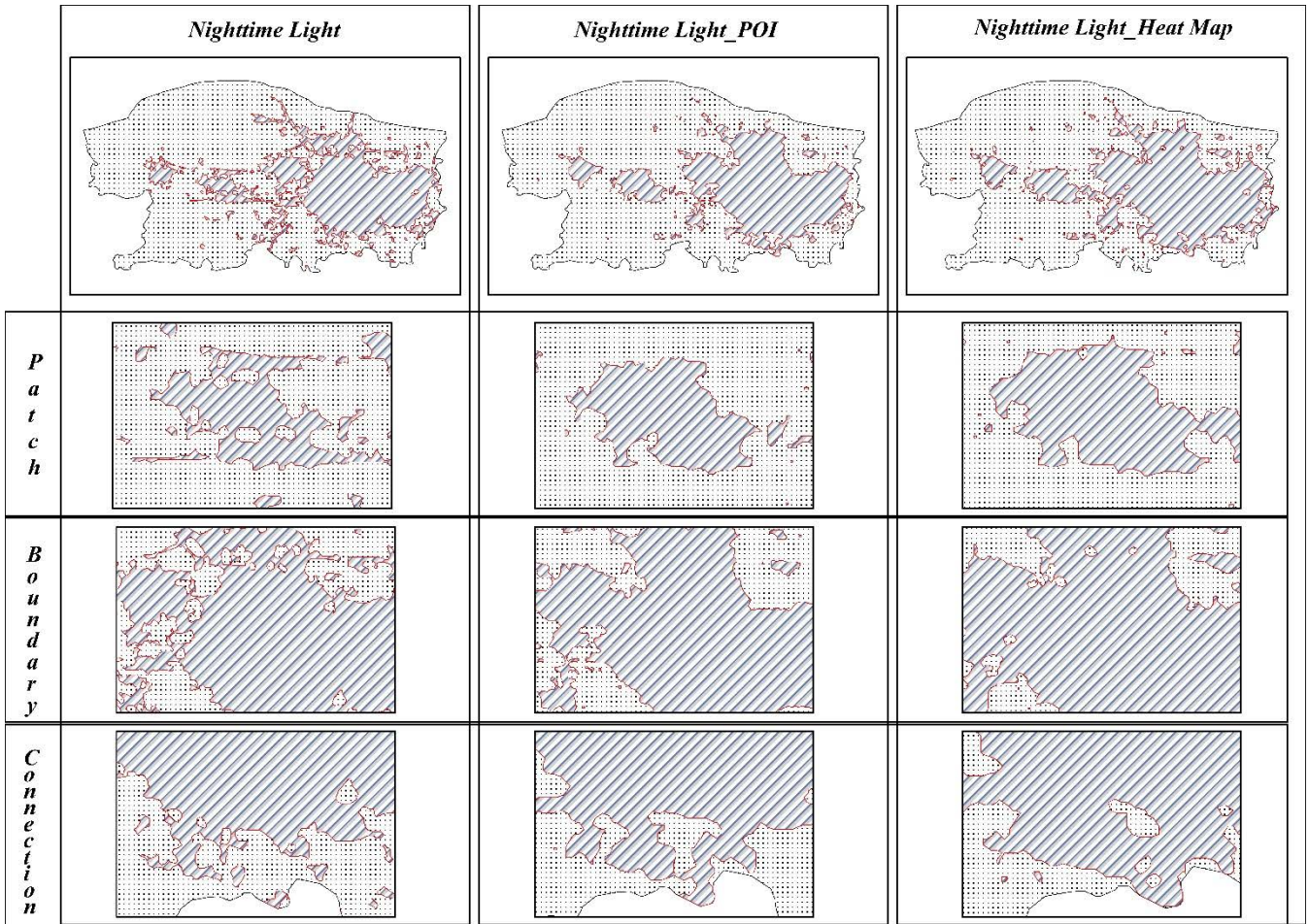


FIGURE 10. Comparative analysis before and after data fusion.

of urban development, although these places will generate strong light brightness at night, which will form a high concentration of NTL value around the road, there is almost no distribution of POI data next to the road, which reduces the complexity of the identified urban-rural boundary. In short, essentially speaking, the fused POI_NTL data is still a static element, which needs to supplement the mutual flow of dynamic elements within urban-rural area.

While the fused BM_NTL data combines the population change with the original light attribute of NTL data, which makes the identified urban area take light intensity and area population change into account at the same time. For example, although there is high light intensity in industrial and business office areas, the population flow is relatively small. From the identified urban spatial patches and urban-rural boundaries, there is no significant difference in the identification results between the fused POI_NTL data and the fused BM_NTL data. The reason is that both data correct the misjudgment of single NTL data to a certain extent. Although POI data is through the quantitative difference of urban and rural infrastructure, BM data is through the population mobility in urban and rural areas. By further analysis of urban and

rural patches identified by different data, it can be found that the number of urban spatial clusters identified by NTL data is the largest, and the existence of each cluster is relatively isolated, although the number of urban patches identified by the fused POI_NTL data is significantly reduced, there is no connection between each patch. While the urban patches identified by the fused BM_NTL data are obviously connected by a linear space. The reason is that the population flow in the regional area is often connected, and such virtual connection in geographical space is identified as urban area.

In general, although NTL data, POI data and BM data all can represent urban spatial structure, different data play different roles. The advantage of NTL data is to distinguish urban and rural areas through the difference of light brightness, but the difference of light brightness will have an impact in turn on the identification results. While the fused POI_NTL data and the fused BM_NTL data not only consider the level of urban development but also take into account the actual conditions of different cities including infrastructure distribution and population flow, which greatly modify NTL data and make the urban and rural areas better identified.

TABLE 2. Verification results of confusion matrix.

Data Source	Verification Data				Spatial Distribution of Population		
	Random Pixel Verification Points			Accuracy	Kappa	Accuracy	Kappa
		Urban	Rural				
NTL	Urban	821	179	83.95%	0.6952	84.32%	0.6014
	Rural	142	858				
POI_NTL	Urban	933	67	94.20%	0.8013	95.02%	0.8003
	Rural	49	951				
BM_NTL	Urban	944	56	93.45%	0.8059	93.47%	0.7893
	Rural	75	925				

2) PRECISION VERIFICATION OF IDENTIFICATION RESULTS

Since the changing state of urban and rural area, it is very complicated to verify the identification results, traditional verification methods such as urban built-up areas cannot accurately verify urban-rural area. Therefore, this study using two kinds of data to verify the identification results. The first data is population spatial distribution data, since there is a significant difference between urban and rural population density, this data can be used to verify the identification result. The population spatial distribution data used in this study are derived from the spatial grid distribution of China's resident population at the end of 2020. Second data is random pixels. A total of 2000 random pixels in Zhengzhou are selected to verify the urban-rural area identified in this study, of which 1000 pixels are training data and 1000 pixels are verification data. After conducting field visits with the help of Google Earth high-resolution image data, all 2000 pixels are verified to be located within the urban-rural area of Zhengzhou. The confusion matrix obtained according to the verification results is shown in Table 2. The precision in Table 2 is the proportion of all the pixels that have been successfully verified. While the kappa coefficient is used to verify classification precision to further track consistency, the possible values of the kappa coefficient range from -1 to 1 ; the closer the value is to 1 , the better the extraction will be.

As can be seen from Table 2, the results of random pixel verification points and population spatial distribution data test are roughly similar, indicating that this study has high credibility. Additionally, as seen from Table 2, the precision of the urban-rural area identified by NTL data, POI_NTL data and BM_NTL data are 84.32%, 95.02% and 93.47%, with kappa coefficients of 0.6952, 0.8013 and 0.8259, respectively. It can be concluded that although the identification precision obtained by the fused POI_NTL data and BM_NTL data have an edge over that obtained by the single-source NTL data, the accuracy difference is not obvious.

IV. DISCUSSION

In this study, the characteristics of NTL data, POI data and BM data within urban-rural area are analyzed first, and then

the advantages and disadvantages of identifying urban-rural areas by NTL data are used for reference to fuse POI data and BM data to improve identification accuracy after data fusion by using deep learning method. After competitive analysis of the urban-rural area identified by NTL data with that identified by the fused POI_NTL data as well as by the fused BM_NTL data, it can be concluded that compared with identifying the urban-rural area by single-source data, the result identified by data fusion is superior.

Although NTL data are one of the commonly used types of data in urban-related studies, the deficiency of NTL data leads to large errors in the study results of urban-rural identification [78]. Moreover, there is light overflow and oversaturation in NTL data. Therefore, researchers began to try to fuse urban big data to improve the accuracy of NTL data in urban space on the basis of considering the strong spatial correlation between big data and NTL data in urban space [79]. Among which, it is more common to fuse POI data with NTL data to extract urban built-up areas and to delineate urban agglomeration boundaries, etc. The accuracy of some studies even reaches more than 95%, indicating the high accuracy of data fusion in urban-related studies and making a great contribution to the study of data fusion [80], [81]. On the basis of referring to relevant studies, this study verifies the previous conclusions through case analysis. Although the highest accuracy achieved in this study is 95.02%, which is close with the highest accuracy of other studies [82], then this study further compares and analyzes the fusion of different big data with NTL data. The results show that unlike other results obtained by other studies (the more data used, the higher the accuracy of the results will be), there is no significant difference in big data's modification on NTL data in this study, which indicates that while big data modifies NTL data, NTL data also modifies the two kinds of big data, so the final difference is not obvious.

The traditional identification and extraction of urban-rural areas mainly depends on the subjective will of the government or the use of socioeconomic and statistical data [83]. The extensive application of remote sensing data represented by NTL has made the identification of urban-rural area gradually

move toward quantitative analysis. However, NTL data can only judge whether a certain area is an urban area simply by capturing the nighttime light brightness generated by urban infrastructure, which ignores the actual social development of urban space. This study fuses POI data that can represent the development of urban functions with NTL data and fuses BM data that can represent the population flow within urban area by using wavelet transform algorithm, and the rural and urban areas are identified by U-net of deep learning, which comprehensively considers the relationship between urban infrastructure and population flow, making the related studies of data fusion and deep learning play a greater advantage in the application of urban and rural spatial identification.

However, there is no doubt that there are some limitations in this study, which are mainly reflected in the fact that the development and change of urban areas are dynamic, and the scope of urban-rural areas will change dramatically with the development of the city. Therefore, to better identify urban-rural area and better serve urban planning and construction, it is necessary to identify the scope of urban-rural area in different periods of time to analyze the relationship between the spatial changes and urban development and further propose better strategies and plans conducive to urban development. Additionally, although this study fuses different big data and analyzes the differences of the identified urban and rural areas after data fusion, big data itself also has certain shortcomings, so the shortcomings of different data should be considered in the next study to minimize the error of data fusion.

V. CONCLUSION

Accurate identification of urban and rural area is an important prerequisite for judging the urbanization process and analyzing the relationship between urban and rural areas. Combining with the spatial characteristics of NTL data, POI data and BM data, this study fuses POI data and BM data respectively with NTL data on the identification of urban-rural area by using wavelet transform, then the characteristic of urban and rural areas are identified by using deep learning method. The highest identification accuracy obtained by NTL data is 84.32%, and the kappa coefficient is 0.6952. The highest identification accuracy of POI_NTL data is 95.02%, the Kappa coefficient is 0.8013, and that of BM_NTL data is 93.47%. Kappa coefficient is 0.8059. It can be concluded that after data fusion, urban infrastructure distribution and population flow are taken into comprehensive consideration, which effectively eliminates the error caused by single light brightness to the results and significantly improves the identification results. However, there is little difference between the results identified by the fused POI_NTL data and the BM_NTL data, which is mainly caused by the noise of big data itself.

In general, this study effectively modifies NTL data with urban big data, and explores a feasible method for identifying urban and rural area. The accurate Identification of urban and rural area is conducive to judging the differences between

urban and rural development, putting forward differentiated development strategies for urban and rural development, and promoting harmonious development between urban and rural areas.

REFERENCES

- [1] L. Han, W. Zhou, W. Li, and Y. Qian, "Urbanization strategy and environmental changes: An insight with relationship between population change and fine particulate pollution," *Sci. Total Environ.*, vol. 642, pp. 789–799, Nov. 2018.
- [2] R. Wang, Y. Feng, X. Tong, J. Zhao, and S. Zhai, "Impacts of spatial scale on the delineation of spatiotemporal urban expansion," *Ecol. Indicators*, vol. 129, Oct. 2021, Art. no. 107896.
- [3] P. Tian, J. Li, L. Cao, R. Pu, Z. Wang, H. Zhang, H. Chen, and H. Gong, "Assessing spatiotemporal characteristics of urban heat islands from the perspective of an urban expansion and green infrastructure," *Sustain. Cities Soc.*, vol. 74, Nov. 2021, Art. no. 103208.
- [4] L. Jiao, T. Dong, G. Xu, Z. Zhou, J. Liu, and Y. Liu, "Geographic micro-process model: Understanding global urban expansion from a process-oriented view," *Comput., Environ. Urban Syst.*, vol. 87, May 2021, Art. no. 101603.
- [5] L. Tian and J. Chen, "Urban expansion inferred by ecosystem production on the Qinghai-Tibet plateau," *Environ. Res. Lett.*, vol. 17, no. 3, Mar. 2022, Art. no. 035001.
- [6] Å. Gren and E. Andersson, "Being efficient and green by rethinking the urban-rural divide—Combining urban expansion and food production by integrating an ecosystem service perspective into urban planning," *Sustain. Cities Soc.*, vol. 40, pp. 75–82, Jul. 2018.
- [7] M. Chen, Y. Zhou, M. Hu, and Y. Zhou, "Influence of urban scale and urban expansion on the urban heat island effect in metropolitan areas: Case study of Beijing–Tianjin–Hebei urban agglomeration," *Remote Sens.*, vol. 12, no. 21, p. 3491, 2020.
- [8] H. M. Imran, J. Kala, A. W. M. Ng, and S. Muthukumar, "Impacts of future urban expansion on urban heat island effects during heatwave events in the city of Melbourne in southeast Australia," *Quart. J. Roy. Meteorol. Soc.*, vol. 145, no. 723, pp. 2586–2602, Jul. 2019.
- [9] N. Shatnawi, U. Weidner, and S. Hinz, "Monitoring urban expansion as a result of refugee fluxes in north Jordan using remote sensing techniques," *J. Urban Planning Develop.*, vol. 146, no. 3, Sep. 2020, Art. no. 04020026.
- [10] G. Li, Y. Cao, Z. He, J. He, Y. Cao, J. Wang, and X. Fang, "Understanding the diversity of urban–rural fringe development in a fast urbanizing region of China," *Remote Sens.*, vol. 13, no. 12, p. 2373, 2021.
- [11] S. Lee, D. Shin, C. Han, K.-S. Choi, S. D. Hur, J. Lee, D.-S. Byun, Y.-T. Kim, and S. Hong, "Characteristic concentrations and isotopic composition of airborne lead at urban, rural and remote sites in Western Korea," *Environ. Pollut.*, vol. 254, Nov. 2019, Art. no. 113050.
- [12] R. Silva, A. C. Carvalho, D. Carvalho, and A. Rocha, "Study of urban heat islands using different urban canopy models and identification methods," *Atmosphere*, vol. 12, no. 4, p. 521, Apr. 2021.
- [13] E. Cai, Y. Liu, J. Li, and W. Chen, "Spatiotemporal characteristics of urban–rural construction land transition and rural–urban migrants in rapid-urbanization areas of central China," *J. Urban Planning Develop.*, vol. 146, no. 1, 2020, Art. no. 05019023.
- [14] X. Ji, J. Ren, and S. Ulgiati, "Towards urban-rural sustainable cooperation: Models and policy implication," *J. Cleaner Prod.*, vol. 213, pp. 892–898, Mar. 2019.
- [15] J. Van Vliet, P. H. Verburg, S. R. Grădinaru, and A. M. Hersperger, "Beyond the urban-rural dichotomy: Towards a more nuanced analysis of changes in built-up land," *Comput., Environ. Urban Syst.*, vol. 74, pp. 41–49, Mar. 2019.
- [16] M. Li, "Rural-urban migration, urban-rural migration and urbanization in China," in *Proc. 12th Int. Conf. E-Bus., Manag. Econ.*, Jul. 2021, pp. 480–486.
- [17] Z. Junyi, S. Weici, and W. Lachun, "Rural revitalization path under urban-rural integration economic development in Karst region of southwest China," *Trans. Chin. Soc. Agricult. Eng. (Trans. CSAE)*, vol. 35, no. 22, pp. 1–8, 2019.
- [18] K. B. Moffett, Y. Makido, and V. Shandas, "Urban-rural surface temperature deviation and intra-urban variations contained by an urban growth boundary," *Remote Sens.*, vol. 11, no. 22, p. 2683, Nov. 2019.

- [19] J. Peng, S. Zhao, Y. Liu, and L. Tian, "Identifying the urban-rural fringe using wavelet transform and kernel density estimation: A case study in Beijing city, China," *Environ. Model. Softw.*, vol. 83, pp. 286–302, Sep. 2016.
- [20] N. Zhao, E. L. Samson, and Y. Liu, "Population bias in nighttime lights imagery," *Remote Sens. Lett.*, vol. 10, no. 9, pp. 913–921, Sep. 2019.
- [21] Y. Song, B. Chen, and M. P. Kwan, "How does urban expansion impact people's exposure to green environments? A comparative study of 290 Chinese cities," *J. Cleaner Prod.*, vol. 246, Feb. 2020, Art. no. 119018.
- [22] K. Shi, Z. Chen, Y. Cui, J. Wu, and B. Yu, "NPP-VIIRS nighttime light data have different correlated relationships with fossil fuel combustion carbon emissions from different sectors," *IEEE Geosci. Remote Sens. Lett.*, vol. 18, no. 12, pp. 2062–2066, Dec. 2021.
- [23] H. Fu, Z. Shao, P. Fu, and Q. Cheng, "The dynamic analysis between urban nighttime economy and urbanization using the DMSP/OLS nighttime light data in China from 1992 to 2012," *Remote Sens.*, vol. 9, no. 5, p. 416, Apr. 2017.
- [24] M. Kuffer, K. Pfeffer, R. Sliuzas, H. Taubenbock, I. Baud, and M. Van Maarseveen, "Capturing the urban divide in nighttime light images from the international space station," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 11, no. 8, pp. 2578–2586, Aug. 2018.
- [25] H. You, C. Jin, and W. Sun, "Spatiotemporal evolution of population in northeast China during 2012–2017: A nighttime light approach," *Complexity*, vol. 2020, 2020, Art. no. 3646145.
- [26] C. Liu, C. Wang, Y. Xu, C. Liu, M. Li, D. Zhang, G. Liu, W. Li, Q. Zhang, and Q. Li, "Correlation analysis between nighttime light data and socio-economic factors on fine scales," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022.
- [27] J. Li, F. Wang, Y. Fu, B. Guo, Y. Zhao, and H. Yu, "A novel SUHI referenced estimation method for multicenters urban agglomeration using DMSP/OLS nighttime light data," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 13, pp. 1416–1425, 2020.
- [28] Y. Sun, S. Zheng, Y. Wu, U. Schlink, and R. P. Singh, "Spatiotemporal variations of city-level carbon emissions in China during 2000–2017 using nighttime light data," *Remote Sens.*, vol. 12, no. 18, p. 2916, 2020.
- [29] Z. Yang, Y. Chen, G. Guo, Z. Zheng, and Z. Wu, "Using nighttime light data to identify the structure of polycentric cities and evaluate urban centers," *Sci. Total Environ.*, vol. 780, Aug. 2021, Art. no. 146586.
- [30] B. Wu, C. Yang, Z. Chen, Q. Wu, S. Yu, C. Wang, Q. Li, J. Wu, and B. Yu, "The relationship between urban 2-D/3-D landscape pattern and nighttime light intensity," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 15, pp. 478–489, 2022.
- [31] P. Tang, J. Huang, X. Zhang, X. Yang, and X. Shi, "Exploring the temporal and spatial evolution of the urbanization of 'Belt and Road' region based on nighttime light data," *Geoinform. Sustain. Ecosyst. Soc.* Singapore: Springer, 2019, pp. 221–233.
- [32] T. Ma, C. Zhou, T. Pei, S. Haynie, and J. Fan, "Quantitative estimation of urbanization dynamics using time series of DMSP/OLS nighttime light data: A comparative case study from China's cities," *Remote Sens. Environ.*, vol. 124, pp. 99–107, Sep. 2012.
- [33] S. J. Anderson, B. T. Tuttle, R. L. Powell, and P. C. Sutton, "Characterizing relationships between population density and nighttime imagery for Denver, Colorado: Issues of scale and representation," *Int. J. Remote Sens.*, vol. 31, no. 21, pp. 5733–5746, Nov. 2010.
- [34] R. Quiñonez-Piñón, A. Mendoza-Durán, and C. Valeo, "Design of an environmental monitoring program using NDVI and cumulative effects assessment," *Int. J. Remote Sens.*, vol. 28, no. 7, pp. 1643–1664, Apr. 2007.
- [35] Z. Jian and S. Hao, "Geo-spatial analysis and optimization strategy of park green space landscape pattern of Garden city—A case study of the central district of Mianyang city Sichuan province," *Eur. J. Remote Sens.*, vol. 53, no. 1, pp. 309–315, 2020.
- [36] K. Li and Y. Chen, "A genetic algorithm-based urban cluster automatic threshold method by combining VIIRS DNB, NDVI, and NDBI to monitor urbanization," *Remote Sens.*, vol. 10, no. 2, p. 277, Feb. 2018.
- [37] Y. O. Ouma, T. Tjitemisa, M. Segobye, K. Moreri, B. Nkwae, L. Maphale, and B. Manisa, "Urban land surface temperature variations with LULC, NDVI and NDBI in semi-arid urban environments: Case study of Gaborone city, Botswana (1989–2019)," *Proc. SPIE*, vol. 11864, pp. 28–40, Sep. 2021.
- [38] G. Y. Li, S. S. Chen, Y. Yan, and C. Yu, "Effects of urbanization on vegetation degradation in the Yangtze river delta of China: Assessment based on SPOT-VGT NDVI," *J. Urban Planning Develop.*, vol. 141, no. 4, Dec. 2015, 05014026.
- [39] Z. Jun, Y. Xiao-Die, and L. Han, "The extraction of urban built-up areas by integrating night-time light and POI data—A case study of Kunming, China," *IEEE Access*, vol. 9, pp. 22417–22429, 2021.
- [40] B. Arellano and J. R. Cladera, "Delimitation of urban systems by Luojia 1–01 nighttime light imagery," in *Proc. SPIE*, vol. 11157, Oct. 2019, Art. no. 111570H.
- [41] W. Jiang, G. He, T. Long, H. Guo, R. Yin, W. Leng, H. Liu, and G. Wang, "Potentiality of using Luojia 1-01 nighttime light imagery to investigate artificial light pollution," *Sensors*, vol. 18, no. 9, p. 2900, Sep. 2018, 2019.
- [42] W. Zhai, B. Han, and C. Cheng, "Evaluation of Luojia 1–01 nighttime light imagery for built-up urban area extraction: A case study of 16 cities in China," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 10, pp. 1802–1806, Dec. 2019.
- [43] Y. Wang and Z. Shen, "Comparing Luojia 1–01 and VIIRS nighttime light data in detecting urban spatial structure using a threshold-based kernel density estimation," *Remote Sens.*, vol. 13, no. 8, p. 1574, Apr. 2021.
- [44] G. Fang, Z. Gao, L. Tian, and M. Fu, "What drives urban carbon emission efficiency?—Spatial analysis based on nighttime light data," *Appl. Energy*, vol. 312, Apr. 2022, Art. no. 118772.
- [45] M. Yu, S. Guo, Y. Guan, D. Cai, C. Zhang, K. Fraedrich, Z. Liao, X. Zhang, and Z. Tian, "Spatiotemporal heterogeneity analysis of Yangtze river delta urban agglomeration: Evidence from nighttime light data (2001–2019)," *Remote Sens.*, vol. 13, no. 7, p. 1235, 2021.
- [46] J. Fang, C. Zhang, J. Fang, M. Liu, and Y. Luan, "Increasing exposure to floods in China revealed by nighttime light data and flood susceptibility mapping," *Environ. Res. Lett.*, vol. 16, no. 10, Oct. 2021, Art. no. 104044.
- [47] S. Panichpapiboon and K. Khunsri, "A big data analysis on urban mobility: Case of Bangkok," *IEEE Access*, vol. 10, pp. 44400–44412, 2022.
- [48] B. Chen, Y. Tu, Y. Song, D. M. Theobald, T. Zhang, Z. Ren, X. Li, J. Yang, J. Wang, X. Wang, P. Gong, Y. Bai, and B. Xu, "Mapping essential urban land use categories with open big data: Results for five metropolitan areas in the united states of America," *ISPRS J. Photogramm. Remote Sens.*, vol. 178, pp. 203–218, Aug. 2021.
- [49] M. M. Madbouly, S. M. Darwish, N. A. Bagi, and M. A. Osman, "Clustering big data based on distributed fuzzy K-medoids: An application to geospatial informatics," *IEEE Access*, vol. 10, pp. 20926–20936, 2022.
- [50] A. Yassine, S. Singh, and A. Alamri, "Mining human activity patterns from smart home big data for health care applications," *IEEE Access*, vol. 5, pp. 13131–13141, 2017.
- [51] X. He, C. Zhou, Y. Wang, and X. Yuan, "Risk assessment and prediction of COVID-19 based on epidemiological data from spatiotemporal geography," *Frontiers Environ. Sci.*, vol. 9, Jul. 2021, Art. no. 634156.
- [52] F. Li, F. Li, S. Li, and Y. Long, "Deciphering the recreational use of urban parks: Experiments using multi-source big data for all Chinese cities," *Sci. Total Environ.*, vol. 701, Jan. 2020, Art. no. 134896.
- [53] W. Wu, Z. Ding, K. Huang, Y. Song, and H. Dong, "Spatial distribution of enterprise communities and its implications based on POI data: Case of Xi'an, China," *J. Urban Planning Develop.*, vol. 147, no. 3, 2021, Art. no. 05021028.
- [54] K. Gao, X. Yang, C. Wu, T. Qiao, X. Chen, M. Yang, and L. Chen, "Exploiting location-based context for POI recommendation when traveling to a new region," *IEEE Access*, vol. 8, pp. 52404–52412, 2020.
- [55] J. Bao, X. Shi, and H. Zhang, "Spatial analysis of bikeshare ridership with smart card and POI data using geographically weighted regression method," *IEEE Access*, vol. 6, pp. 76049–76059, 2018.
- [56] X. Xin, S. H. I. Kai-Fang, and Y. A. N. G. Qing-yuan, "Analysis of urban network structure in China based on Baidu migration data—take the data of spring festival in 2015 and 2019 for example," *J. Southwest China Normal Univ. (Natural Sci. Ed.)*, vol. 46, no. 4, pp. 79–88, 2021.
- [57] W. Liu and E. Shi, "Spatial pattern of population daily flow among cities based on ICT: A case study of 'Baidu migration,'" *Acta Geographica Sinica*, vol. 71, no. 10, pp. 1667–1679, 2016.
- [58] T. Ye, N. Zhao, X. Yang, Z. Ouyang, X. Liu, Q. Chen, K. Hu, W. Yue, J. Qi, Z. Li, and P. Jia, "Improved population mapping for China using remotely sensed and points-of-interest data within a random forests model," *Sci. Total Environ.*, vol. 658, pp. 936–946, Mar. 2019.
- [59] Z. Chen, Y. Wei, K. Shi, Z. Zhao, C. Wang, B. Wu, B. Qiu, and B. Yu, "The potential of nighttime light remote sensing data to evaluate the development of digital economy: A case study of China at the city level," *Comput., Environ. Urban Syst.*, vol. 92, Mar. 2022, Art. no. 101749.
- [60] L. Cheng, L. Wang, R. Feng, and J. Yan, "Remote sensing and social sensing data fusion for fine-resolution population mapping with a multimodel neural network," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 14, pp. 5973–5987, 2021.

- [61] S.-J. Park, S.-G. Jeong, Y. Park, S.-H. Kim, D.-K. Lee, Y.-W. Mo, D.-S. Jang, and K.-M. Park, "Phenological analysis of sub-alpine forest on Jeju island, South Korea, using data fusion of landsat and MODIS products," *Forests*, vol. 12, no. 3, p. 286, Mar. 2021.
- [62] C. Xi, Y. Guo, R. He, B. Mu, P. Zhang, and Y. Li, "The use of remote sensing to quantitatively assess the visual effect of urban landscape—A case study of zhengzhou, China," *Remote Sens.*, vol. 14, no. 1, p. 203, 2022.
- [63] Y. Zheng, Q. Zhou, Y. He, C. Wang, X. Wang, and H. Wang, "An optimized approach for extracting urban land based on log-transformed DMSP-OLS nighttime light, NDVI, and NDWI," *Remote Sens.*, vol. 13, no. 4, p. 766, Feb. 2021.
- [64] S. Karateke, M. Zontul, N. E. Bozkurt, and Z. Aslan, "Wavelet-ANFIS hybrid model for MODIS NDVI prediction," *J. Appl. Remote Sens.*, vol. 15, no. 2, Jun. 2021, Art. no. 024519.
- [65] D. Kováč, A. Ač, L. Šigut, J. Peñuelas, J. Grace, and O. Urban, "Combining NDVI, PRI and the quantum yield of solar-induced fluorescence improves estimations of carbon fluxes in deciduous and evergreen forests," *Sci. Total Environ.*, vol. 829, Jul. 2022, Art. no. 154681.
- [66] X. Zhang, K. Liu, X. Li, S. Wang, and J. Wang, "Vulnerability assessment and its driving forces in terms of NDVI and GPP over the loess plateau, China," *Phys. Chem. Earth, A/B/C*, vol. 125, Feb. 2022, Art. no. 103106.
- [67] Y. Zhang, J. Cheng, H. Bai, Q. Wang, and X. Liang, "Multilevel feature fusion and attention network for high-resolution remote sensing image semantic labeling," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022.
- [68] S. Dong and Z. Chen, "A multi-level feature fusion network for remote sensing image segmentation," *Sensors*, vol. 21, no. 4, p. 1267, Feb. 2021.
- [69] D. Liu, F. Yang, H. Wei, and P. Hu, "Remote sensing image fusion method based on discrete wavelet and multiscale morphological transform in the IHS color space," *J. Appl. Remote Sens.*, vol. 14, no. 1, p. 1, Mar. 2020.
- [70] S. Wu and H. Chen, "Smart city oriented remote sensing image fusion methods based on convolution sampling and spatial transformation," *Comput. Commun.*, vol. 157, pp. 444–450, May 2020.
- [71] Z.-X. Huang and C.-W. Jing, "Super-resolution reconstruction method of remote sensing image based on multi-feature fusion," *IEEE Access*, vol. 8, pp. 18764–18771, 2020.
- [72] H. Jiang, M. Peng, Y. Zhong, H. Xie, Z. Hao, J. Lin, X. Ma, and X. Hu, "A survey on deep learning-based change detection from high-resolution remote sensing images," *Remote Sens.*, vol. 14, no. 7, p. 1552, Mar. 2022.
- [73] D. Li, B. Lin, X. Wang, and Z. Guo, "High-performance polarization remote sensing with the modified U-Net based deep-learning network," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–10, 2022.
- [74] T. Davydzhenka, P. Tahmasebi, and M. Carroll, "Improving remote sensing classification: A deep-learning-assisted model," *Comput. Geosci.*, vol. 164, Jul. 2022, Art. no. 105123.
- [75] N. Ruiwen, M. Ye, L. Ji, Z. Tong, L. Tianye, F. Ruilong, G. He, H. Tianli, S. Yu, G. Ying, L. Shijun, and T. Louis Tyasi, "Segmentation of remote sensing images based on U-Net multi-task learning," *Comput., Mater. Continua*, vol. 73, no. 2, pp. 3263–3274, 2022.
- [76] X. Xie, L. Ye, X. Kang, L. Yan, and L. Zeng, "Land use classification using improved U-Net in remote sensing images of urban and rural planning monitoring," *Scientific Program.*, vol. 2022, pp. 1–9, Apr. 2022.
- [77] J. Zhang, X. Zhang, X. Tan, and X. Yuan, "Extraction of urban built-up area based on deep learning and multi-sources data fusion—The application of an emerging technology in urban planning," *Land*, vol. 11, no. 8, p. 1212, 2022.
- [78] M. Ma, Q. Lang, H. Yang, K. Shi, and W. Ge, "Identification of polycentric cities in China based on NPP-VIIRS nighttime light data," *Remote Sens.*, vol. 12, no. 19, p. 3248, Oct. 2020.
- [79] Y. Zheng, Y. He, Q. Zhou, and H. Wang, "Quantitative evaluation of urban expansion using NPP-VIIRS nighttime light and landsat spectral data," *Sustain. Cities Soc.*, vol. 76, Jan. 2022, Art. no. 103338.
- [80] G. Lou, Q. Chen, K. He, Y. Zhou, and Z. Shi, "Using nighttime light data and POI big data to detect the urban centers of Hangzhou," *Remote Sens.*, vol. 11, no. 15, p. 1821, Aug. 2019.
- [81] L. Wang, H. Fan, and Y. Wang, "Improving population mapping using luojia 1-01 nighttime light image and location-based social media data," *Sci. Total Environ.*, vol. 730, Aug. 2020, Art. no. 139148.
- [82] X. He, Y. Zhu, P. Chang, and C. Zhou, "Using tencent user location data to modify night-time light data for delineating urban agglomeration boundaries," *Frontiers Environ. Sci.*, vol. 10, Mar. 2022.
- [83] C. Zhou, X. He, R. Wu, and G. Zhang, "Using food delivery data to identify urban-rural areas: A case study of Guangzhou, China," *Frontiers Earth Sci.*, vol. 10, 2022, Art. no. 860361.



YAPING CHEN was born in 1993. Since July 2020, she has been a University Teacher working with the Zhejiang Guangsha Vocational and Technical University of Construction, Dongyang, Zhejiang. Her research interests include urban planning, urban, and rural security.



AKOT DENG was born in 1992. He received the bachelor's and master's degrees from the Sudan University of Science & Technology, in 2015 and 2019, respectively. He is currently a Teacher at Sudan University. His research interests include urban planning and sustainable development.