land

MDPI

Article

Identification of the Spatial Structure of Urban Polycentres Based on the Dual Perspective of Population Distribution and Population Mobility

Rongrong Zhang [1], Ming Li [2], Xiao Zhang [2], Yuanyuan Guo [1], Yonghe Li [3], Qi Gao [4,*] and Song Liu [5,*]

[1] School of Political Science and Law, Zhengzhou University of Light Industry, Zhengzhou 450000, China; zhangrr94@zzuli.edu.cn (R.Z.); xinyongyuan@zzuli.edu.cn (Y.G.)
[2] Land Consolidation and Rehabilitation Center, MNR (Land Science and Technology Innovation Center, MNR), Beijing 100035, China; liming@lcrc.org.cn (M.L.); zhangxiao@lcrc.org.cn (X.Z.)
[3] Henan Urban Planning Institute & Co., Ltd., Zhengzhou 450044, China; liyonghe0708@163.com
[4] School of Economics and Trade, School of Marxism, Guangdong University of Foreign Studies, Guangzhou 510006, China
[5] Guangzhou Academy of Social Sciences, Guangzhou 510410, China
* Correspondence: 201910067@oamail.gdufs.edu.cn (Q.G.); liusong6@mail2.sysu.edu.cn (S.L.)

Abstract: The accelerated growth of urban areas has resulted in substantial alterations to the spatial structure of these settlements. The accurate identification of the multi-centre spatial structure is a fundamental prerequisite for the assessment of urban spatial development and the optimisation of urban space. Accordingly, this study aimed to identify the multi-centre spatial structure of cities through a novel approach of data fusion based on night-time lighting data, LandScan data, and population heat data. Furthermore, this study compared the differential effects of population distribution and population mobility in identifying urban spatial structures. The empirical research results for Zhengzhou City demonstrate that the accuracy of using LandScan data fusion to identify multi-centre spatial structures was 0.7463, while the accuracy of using night-time light data fusion to identify urban spatial structures through population mobility reached 0.8235. This suggests that, in the context of increasing population mobility and economic activity, the integration of population mobility data may have a significant impact on the accuracy of urban spatial research. Moreover, this study places a dual focus on population distribution and population mobility and a new method of data integration for urban spatial research. These are of considerable practical value in facilitating spatial optimisation and the coordinated development of cities.

Keywords: population distribution; population mobility; urban polycentres; spatial structure; Zhengzhou

check for updates

Citation: Zhang, R.; Li, M.; Zhang, X.; Guo, Y.; Li, Y.; Gao, Q.; Liu, S. Identification of the Spatial Structure of Urban Polycentres Based on the Dual Perspective of Population Distribution and Population Mobility. *Land* **2024**, *13*, 1159. https://doi.org/10.3390/land13081159

Academic Editor: Thomas W. Sanchez

Received: 13 June 2024
Revised: 21 July 2024
Accepted: 26 July 2024
Published: 29 July 2024

1. Introduction

The term "urban spatial structure" refers to the configuration and organisation of various functional areas within a city. This reflects the distribution of land use types in each area of the city and the layout of urban functional areas [1]. The accurate identification of a city's spatial structure enables an understanding of the layout and development trend of each functional area. This, in turn, facilitates the promotion of spatial optimisation, thereby enabling the formulation of reasonable urban development planning and construction programmes. These programmes are designed to ensure the efficient operation of the city [2,3].

In the context of rapid urbanisation, the spatial structure of cities typically evolves from a monocentric to a polycentric configuration [4]. The spatial structure of urban monocentricity is characterised by a centralised core and a radial distribution of different functional areas. This spatial structure is more prevalent in cities with smaller scale, convenient traffic patterns, and a more concentrated population distribution [5,6]. However, as urban areas expand, populations grow, and lifestyles change, single-centre areas frequently encounter challenges related to traffic congestion, land resource scarcity, and rising living costs. These challenges make it increasingly challenging to meet the demands of urban development in the present era [7]. In this context, the multi-centre spatial structure has emerged as a novel trend in urban development. The urban structure of polycentricity refers to the development and layout of a city comprising multiple centres or nodes, which are geographically independent of each other but functionally interconnected and coordinated [8]. In contrast to a monocentric spatial structure, within the same spatial scope, a polycentric urban spatial structure not only optimises the utilisation of resources within the city but also improves the accessibility and equality of services within the city. This is conducive to the promotion of balanced development between urban areas. Consequently, it is of paramount importance to accurately identify the urban spatial structure [1].

Since the 1960s, researchers have extensively explored the urban spatial structure from different perspectives. The emergence of the concept of urban polycentricity can be traced back to this time when the traditional single-centre urban structure began to change due to the growing popularity of automobiles and urban expansion. Researchers have noticed that the development of suburban areas means not only the expansion of residential areas but also the spillover of commercial and service functions. For example, although Burgess and Hoyt do not explicitly propose the concept of polycentricity in their concentric circle and fan-shaped models, respectively, they already imply a trend of outward diffusion of urban functions [9,10]. Multicentric research made significant progress in the late 1980s and early 1990s. During this period, scholars in the field of urban studies began to systematically study the formation mechanism and spatial characteristics of multi-centre structures in cities. Garreau's "Edge City" theory is one of the important contributions of this period, as he pointed out the formation of secondary centres with significant economic vitality on the edge of large cities [11]. In addition, McDonald and McMillen's research further validated the existence and economic impact of multi-centre structures in major cities in the United States through empirical analysis [12]. In the 21st century, with the rapid development of globalisation and information technology, research on urban polycentricity has further deepened. Researchers have begun to pay attention to polycentricity on a global scale and its impact on urban planning and policies. For example, Hall and Pain's theory of polycentric network cities proposes that globalisation promotes the formation of intercity networks, and a polycentric structure within cities is an important component of this network [13]. Meanwhile, studies by scholars such as Batten and Davoudi also emphasise the role of polycentricity in enhancing urban competitiveness and sustainable development [14,15].

Previous methods for identifying the urban spatial structure have included spatial statistical analysis [16], network analysis [17], the gravity model [18], primacy [19], the Pareto distribution [20], the Gini index [21], White's coefficient [22], the relative dispersion coefficient [23], and least-squares estimation [24], among others. The research data primarily comprise census data, economic data, and traffic data [25,26]. These datasets are employed to identify the urban spatial structure by elucidating the spatial patterns of economic agglomeration and population distribution within cities through the application of quantitative methods. For instance, in 2001, McMillen defined an urban sub-centre as an area with a high population density situated at a certain distance from the city's main centre, as determined by employing census data [27]. In 2009, Adolphson proposed a method for measuring the number of urban cores, the distribution of the size of urban cores, the spatial distribution of urban cores, and the degree of polycentricity. This involved measuring the polycentric urban structure and the connectivity between urban resources in the region [28]. The application of urban remote sensing and big data in recent years has also provided a new way of identifying the urban spatial structure [29]. However, the identification of urban centres is still primarily focused on single economic or demographic data sources. Yet, both the economy and the population play dominant roles in the process of the evolution of the urban spatial structure. The distribution of economic activities and the pattern of development determines the formation of and change in a city's functional areas, while the population size and mobility further promote and adjust these spatial layouts [30,31].

Economic growth, as the primary driving force behind urban development, can frequently result in the transformation of urban spatial structure and the formation of new centres [32]. Concurrently, economic growth increases the cost of living in specific areas, which may result in the migration of the population away from these areas. This can include migration from the main centre to a sub-centre, as well as from the centre to the periphery [33,34]. In other words, despite the fact that the overall economy exhibits growth, population mobility also contributes to a more complex and diverse urban spatial structure [35]. In contrast to economic growth, population data offer a more nuanced understanding of the urban spatial structure, encompassing resident, employed, and mobile populations, among others. In this context, studying the employed population is more likely to reveal professional centres, while studying the resident population tends to reveal urban centres through the concentration of population density and the demand for public service facilities. As the urbanisation process accelerates and population mobility increases, the distribution of mobile populations (including commuter and tourist populations, among others) within cities and their mobility characteristics become increasingly important for the identification of urban centres [36,37]. Existing studies indicate that the mobile population can serve as a proxy for the vitality and attractiveness of a city. This allows for the identification of commercial centres and cultural and entertainment centres and reveals the dynamic characteristics of the urban space. Additionally, it reflects the connection between different centres of the city through the need for transportation and infrastructure planning [38,39]. Consequently, the spatial structure of urban centres can be identified through an analysis of the mobile population.

When studying the urban spatial structure, multi-source data fusion has emerged as a significant research methodology. This approach is primarily concerned with a comprehensive analysis and understanding of the urban space from multiple perspectives and at different levels, achieved through the integration of diverse data sources [40]. Data sources commonly used to identify the spatial structure of cities include population data, land use data, traffic data, remote sensing images, socioeconomic data and Internet data [41,42]. The methods of multi-source data fusion include data integration, spatial analysis techniques, statistical analysis and machine learning, and spatiotemporal analysis [43–45]. The specific applications of multi-source data fusion in urban spatial structural research include the identification of urban centres, the division of functional areas, the analysis of traffic flows, the assessment of environmental quality, and the planning of emergency management and security measures. For instance, the fusion of population data, traffic data, and land use data enables the identification of the core and sub-centre areas of a city [46]. Similarly, the combination of land use data, socioeconomic data, and remote sensing imagery facilitates the classification of functional areas of the city [47]. By combining traffic and population mobility data, the spatial and temporal distribution of traffic flows can be analysed and transport planning and management can be optimised [48]. Similarly, by combining environmental data and population distribution data, the environmental quality of different areas of the city can be assessed and environmental protection measures formulated [49]. The existing research indicates that data fusion can effectively improve observation accuracy for urban spaces.

The study of urban development is informed by two key factors: the economy and the population. The current methods for identifying urban centres through data fusion typically combine these two types of data. Economic data frequently employ night-time lighting data as a proxy variable, while demographic data commonly utilise LandScan data—that is, a high-resolution population distribution dataset that primarily reflects the spatial distribution of the resident population and is effective for identifying densely populated areas and residential areas [50]. However, as urbanisation and population growth slow, many cities have begun to experience population contraction. Resident population data are insufficient to fully reflect the dynamic changes in cities [51]. For instance, some regions may have a relatively small resident population, yet may have a high urban centre status due to a dense mobile population for business, tourism, or other reasons. Consequently, relying solely on resident population data may no longer fully reflect the dynamic changes of the city [52]. In this context, more accurate observations can be achieved by using the mobile population distribution. However, there are relatively few studies of this kind, and further exploration is urgently needed.

This study uses night-time lighting data, LandScan data, heat-map data, and Weibo check-in data. Night-time lighting data are used to reflect the level of economic development, LandScan data are used to reflect the spatial distribution of the population within the city, heat-map data are used to reflect the movement of the population within the city, and Weibo check-in data are used to validate the accuracy of the identified city centre. Specifically, this study encompasses two main areas of investigation. The first is the analysis and integration of data pertaining to the city's economic development, as reflected by night-time lighting, with data on population density, as reflected by LandScan data, and the flow of people, as reflected by heat-map data. The second area of focus was the identification of the polycentric spatial structure of Zhengzhou City, based on the fusion of night-time lighting data and LandScan data and of night-time lighting data and heat-map data. The third aspect of this study was a comparison of the results and verification using Weibo and microblog check-in data, to identify the spatial structure of the Zhengzhou urban polycentre. By using night-time lighting data, LandScan data, heat-map data, and social media data, this study aims to explore a more accurate and popular method for identifying urban centres by integrating data from different sources. By accurately identifying the multi-centre spatial structure of a city, it can provide an effective policy basis for urban planning and resource allocation.

2. Materials and Methods

2.1. Research Area

Zhengzhou City, the capital of Henan Province, has undergone significant urbanisation in recent years. By 2020, the city's resident population had reached approximately 12.6 million, with an urbanisation rate of 78.4%. Zhengzhou City is representative of a city where population mobility has driven the transition from a monocentric to a polycentric urban spatial structure, contributing to a more differentiated urban functional area [53]. Zhengzhou City has seen the formation of three distinct districts, each with a specific role within the urban landscape. Zhongyuan District is home to a multitude of commercial and administrative activities, Xinzheng District serves as a gateway for international exchanges, and Zhengdong New District is a hub for high-tech enterprises and financial institutions. This study accurately identified the urban polycentric spatial structure of Zhengzhou City, thereby facilitating the spatial optimisation and layout of the city by providing a reference for the development planning of the city. The study area comprised the eight major administrative districts of Zhengzhou (Table 1): Jinshui District, Zhongyuan District, Guancheng District, Erqi District, Huiji District, Shangjie District, Xinzheng City, and Xingyang City.

Table 1. Relevant information on the eight major administrative districts of Zhengzhou.

District	GDP (Ten Thousand RMB)	Population (Ten Thousand People)	Land Area (km^2)	Built-Up Area (km^2)
Jinshui	19,320,380	162.4	243	85.79
Zhongyuan	7,653,319	96.9	198	66.81
Guancheng	6,782,355	82.5	199	78.59
Erqi	7,856,087	106.5	155	71.98
Huiji	3,062,251	56.1	222	73.6
Shangjie	1,654,160	20.1	61	34.39
Xinzheng	8,198,484	120.4	885	134.37
Xingyang	5,587,621	73.4	943	83.11

2.2. Research Data

The data employed in this study were primarily NPP-VIIRS night-time light data, LandScan data, heat-map data, and microblog check-in data. The specific treatment and processing flow of each dataset are outlined below (Table 2).

Table 2. Relevant information about the dataset used.

Dataset	Format	Resolution	Date	Source Link
Night-time light data	Tiff	500 m × 500 m	January 2022–December 2022	https://eogdata.mines.edu/nighttime_light/monthly/v10/ (accessed on 1 March 2024)
LandScan data	Tiff	1 km × 1 km	January 2022–December 2022	https://landscan.ornl.gov/ (accessed on 10 January 2024)
Population heat distribution	Tiff	30 m × 30 m	January 2022–December 2022	https://huiyan.baidu.com/ (accessed on 5 February 2023)
Weibo check-in data	Point	—	January 2022–December 2022	https://github.com/WanZixin/SinaWeibo-LocationSignIn-spider (accessed on 20 December 2023)

2.2.1. Night-Time Light Data

The NPP/VIIRS (Suomi National Polar-orbiting Partnership/Visible Infrared Imaging Radiometer Suite) dataset is a high-resolution night-time light dataset compiled by NASA and NOAA. Its 500-metre spatial resolution allows for the provision of fine night-time light information, which has led to the widespread use of NPP NTL data in the analysis and monitoring of night-time light changes in specific areas. In this study, the 2022 NPP/VIIRS NTL data for Zhengzhou City were obtained from the NASA Earth Observation Data Centre website. We pre-processed the acquired data, which included radiometric correction and monthly averaging. The results of this pre-processing are presented in Figure 1.

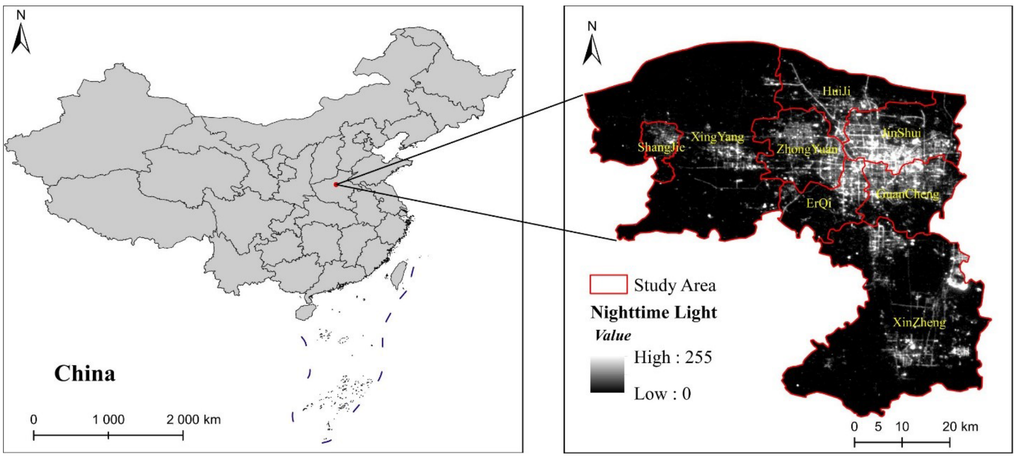

Figure 1. The pre-processing results of the study area, derived from night-time light data.

2.2.2. LandScan Data

LandScan is a high-resolution global population distribution dataset developed and maintained by Oak Ridge National Laboratory (ORNL), Oak Ridge, TN, USA. LandScan data are generated by integrating multiple data sources, including satellite imagery, remote sensing data, geographic information system (GIS) data, census data, and other statistical data. It uses a multi-scale approach, including land use/land cover, night-time light data, road networks, slopes, terrain, and other factors, to accurately model population data and allocate them to high-resolution grid cells. The spatial resolution of LandScan data is 1 km, and the temporal resolution is continuous. This study was conducted by visiting official websites, including https://landscan.ornl.gov/, in order to obtain the LandScan population data for Zhengzhou City in 2022. The data were then pre-processed in order to obtain a spatial distribution map of Zhengzhou City's population, as shown in Figure 2.

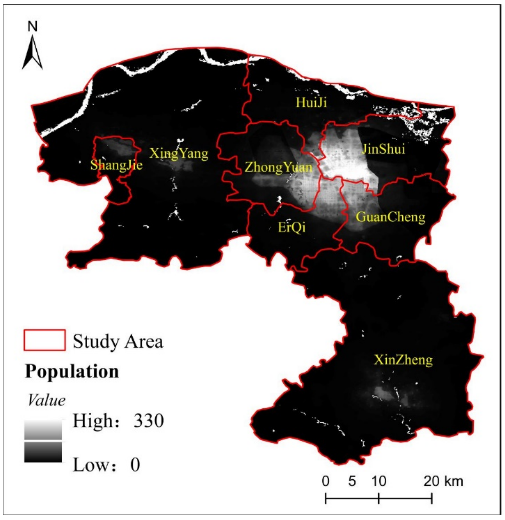

Figure 2. The pre-processing results of LandScan data.

2.2.3. Population Heat Distribution

The Baidu heat map is a big data service provided by Baidu Maps. It utilises user location data to generate city heat maps, reflecting the population densities, flows, and activities in different areas. These heat-map data can be represented visually, such as the spatial distribution of population, traffic flows, or commercial activities, through the use of colour. Additionally, visuals can be employed to display dynamic changes in time-series data. The Baidu heat-map data for 2022 were obtained via the Baidu Map Open Platform API interface. In order to eliminate discrepancies in population mobility between dates, the heat data were averaged for the entire year of 2022. This process yielded the heat distribution of the population, as illustrated in Figure 3. Red indicates areas with a high population density, while green and blue indicate areas with a low population density.

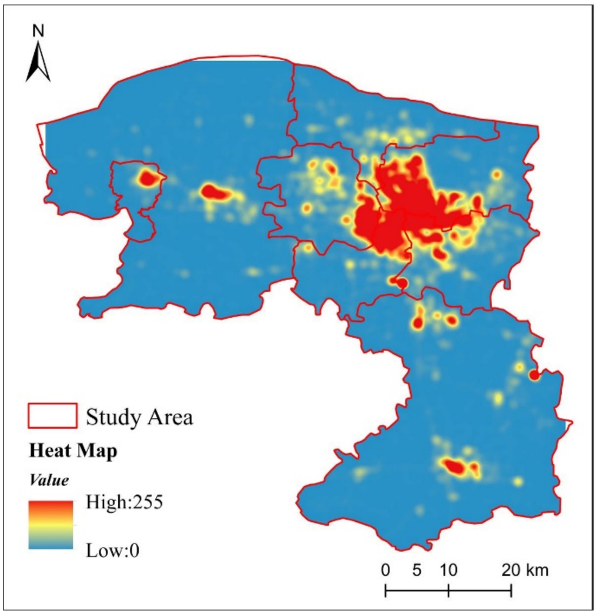

Figure 3. The pre-processing results of population heat distribution data.

2.2.4. Weibo Check-in Data

Weibo check-in data were derived from the Sina Weibo platform. As the Internet continues to evolve, individuals are engaging in an increasing number of online social activities on Sina Weibo, Zhihu, Xiaohongshu, and other social media platforms. With regards to Sina Weibo, the platform's active user base reached approximately 300 million during the 2023 Spring Festival Gala, thus ranking first among mainstream social media in China. Weibo check-in data are geographic data that include latitude and longitude, location information, and text content. Weibo offers a significant quantity of data, a wealth of information, and real-time performance at a low cost. In this study, we obtained Weibo check-in data for Zhengzhou City in 2022 by accessing the open platform of Sina Weibo, with a total of 198,753 entries. Following the pre-processing of the obtained data, which included deduplication, format conversion, handling of missing values, outlier detection, and verification of data quality, the final results were obtained and are presented in Figure 4. Finally, the Weibo check-in data were compiled into a 0.1-kilometre grid.

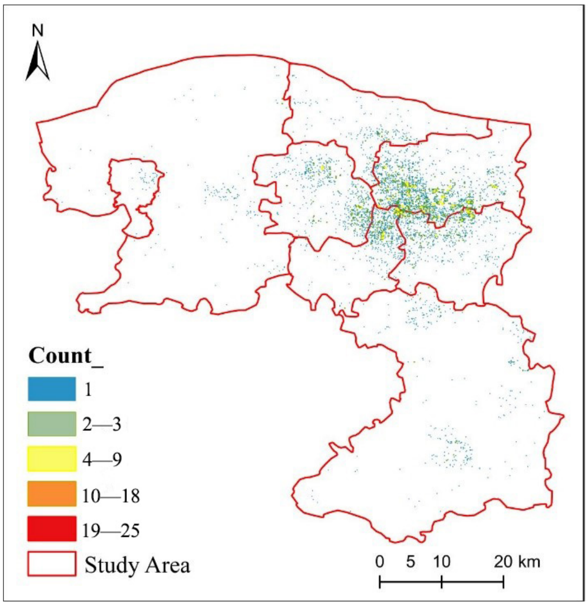

Figure 4. The pre-processing results of Weibo check-in data.

2.3. Research Methodology

In order to unify the spatial resolution of the data, we performed resampling operations on different TIFF data. The spatial resolution was uniformly resampled to 500 m for subsequent calculations.

2.3.1. Data Fusion

The wavelet transform is an exemplary algorithm for data fusion, which operates by decomposing data from different sources at multiple scales, extracting the details and approximate information at each scale, and then selecting or generating key features according to specific fusion rules. Finally, the fused features are reconstructed into a new, more information-rich image through inverse wavelet change. In comparison to other algorithms, the multi-resolution analysis capability and signal localisation features of the wavelet transform permit the efficient processing and analysis of data at both global and local levels [54]. The formula for the wavelet change is as follows:

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

In Equation (1), f(t) is the image signal vector, φ(t) is the wavelet transform function, α represents the wavelet transform scale, τ represents the image signal translation amount, and b is a parameter.

2.3.2. Local Autocorrelation

Local autocorrelation is a statistical method for measuring the similarity between data points in geospatial space, which is particularly useful for identifying urban centres. This method is predicated on the analysis of data within a region in comparison to its neighbours, with the objective of determining whether spatial aggregation exists. The most common local autocorrelation indices include the local Moran's I index, Geary's C index, and the Getis–Ord G* index, which reveal spatial dependence or aggregation trends among geographic units [55,56]. The Moran index is capable of sensitively capturing the global autocorrelation of spatial data for a wide range of data types. Furthermore, it provides statistical significance tests (e.g., Z-scores and p-values) to ensure the reliability of the results. Furthermore, the results of the Moran index are straightforward to interpret and visualise, which facilitates the generation of intuitive spatial clustering maps indicating areas of high and low concentration within a city. Consequently, the Moran index was selected in this study to identify the principal urban centre of Zhengzhou City. The formula for the Moran index is as follows:

$$I_i = \frac{x_i - \overline{x}}{S_2^i} \sum\nolimits_{j=1, j \neq i}^{n} w_{ij}(x_i - \overline{x}) \tag{2}$$

In the equation above, I_i is the statistical count of LMI for point i, w_{ij} is the spatial weight matrix, x_i is the attribute value of point i, $\overline{x}$ is the mean value of all attribute values, and S_i^2 is the total sample variance.

$$S_i^2 = \frac{\sum\nolimits_{j=1, j \neq i}^{n} (x_i - \overline{x})2}{n-1} \tag{3}$$

The spatial weight matrix w_{ij} is normalised as follows:

$$\sum\nolimits_{i=1}^{n} \sum\nolimits_{j \neq i}^{n} w_{ij} = n \tag{4}$$

The Z score is introduced to represent the statistical values with similar values of I_i:

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{Var(I_i)}} \tag{5}$$

where $E(I_i)$ is

$$E(I_i) = -\frac{\sum\nolimits_{j=1, j \neq i}^{n} w_{ij}}{n-1} \tag{6}$$

$$Var(I_i) = E\left(I_2^i\right) - E(I_i)^2 \tag{7}$$

A high positive Z score (greater than 1.96) indicates that a statistically significant (0.05 level) cluster has been obtained, and an aggregation of these high scores is denoted as a high–high region, i.e., there is a strong correlation. When all the high-score spatial units cluster together, it is referred to as an HH area.

2.3.3. Geographically Weighted Regression

Geographically weighted regression (GWR) is a local spatial analysis technique that reveals the local characteristics of geographic processes by introducing location weights into the regression model so that the model parameters vary with geographic location. GWR is particularly suitable for dealing with spatial heterogeneity, where data from different locations exhibit different statistical characteristics [57]. Due to the fact that GWR allows regression coefficients to vary with spatial location, it can capture the differences in features within different regions of the city. By considering spatial heterogeneity, GWR provides a detailed spatial analysis capability that traditional regression analysis cannot achieve. By analysing the changes in local relationships between data from different areas, GWR can identify specific areas that have an impact on urban functions, thus effectively identifying the sub-centres of a city. The formula for GWR is

$$y_i = \beta_0(\mu_i, v_i) + \sum_{j=1}^{k} \beta_j(\mu_i, v_i)x_{ij} + \varepsilon_i \tag{8}$$

In the equation above, y_i represents the density of urban activity, which is the dependent variable; μ_i,v_i represents geographic location of the spatial centre; β_0 (μ_i,v_i) is the intercept, which represents the basic regression value at the geographical location $(\mu_i,\ v_i)$, where the intercept varies with the geographical location; β_j (μ_i, v_i) represents the local estimation coefficient, which reflects the local influence of the explanatory variable on the dependent variable and captures spatial heterogeneity; x_{ij} represents the *j*th explanatory variable for the *i*th observation; and ε_i is the residual value, representing the randomness that the model cannot fully explain.

The identification of urban sub-centres is contingent upon the significance of the regression coefficients and the goodness of the model fit. An area can be identified as an urban sub-centre when the effect of the explanatory variables on the dependent variable is significantly higher than that of the surrounding areas and when the model fit is good. GWR reveals the complexity of local differences in urban development and provides more accurate decision support for urban planning.

2.3.4. Accuracy Verification

In order to assess the accuracy of urban polycentric spatial structural recognition, the F_1 per unit pixel was calculated based on the population activity centre reflected in the microblog check-in data. Here, F_1 was the reconciled average of the check-full rate (recall) and check-accuracy rate (precision), with a value range from 0 to 1, where a larger value is associated with higher accuracy. The check-full rate, the check-accuracy rate, and the F_1 are as follows:

$$precision = \frac{a_{overlap}}{a_{computed}} \tag{9}$$

$$recall = \frac{a_{overlap}}{a_{comparative}} \tag{10}$$

$$F_1 = \left(\frac{2}{recall^{-1} + precision^{-1}}\right) = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{11}$$

Here, $a_{overlap}$ represents the total area of overlap between the identified city centre and the urban population's activity centre reflected in the Weibo check-in data, $a_{computed}$ represents the identified city centre, and $a_{comparative}$ represents the urban population's activity centre reflected in the Weibo check-in data.

3. Results

3.1. Multi-Source Big Data Fusion

Data fusion is the integration of data from the same area obtained through different methods. The resulting fused data can better reflect the characteristics of the phenomena, thus improving the efficiency and effectiveness of data use and facilitating a more comprehensive and accurate judgement of the target area. In this case, the spatial connection between night-time lighting data and LandScan and heat-map data in urban areas was strong. The former reflected the economic activities and residential density of the city, while the latter provided detailed information on the population distribution and mobility. In this study, the wavelet transform was employed to extract features from multiple data sources and perform prediction and analysis. Due to the different spatial resolutions of the data, we resampled the data during the data processing. During the resampling process, it was found that the 1 km spatial resolution lost too much spatial information, while the 100 m spatial resolution had complex redundant information. Therefore, we chose 500 m spatial resolution as the resampling result.

By fusing the night-time lighting data with the LandScan data, a new dataset, designated NTL-LandScan, was generated. This is illustrated in Figure 5, showing high-value areas of the NTL-LandScan data concentrated in the western region of Jingshui District, the southeastern part of Zhongyuan District, the northeastern region of Erqi District, the northwestern region of Guancheng District, and the southern region of Huiji District. These areas exhibit high night-time lighting brightness, indicating intense economic activity and a dense population. This concentration of values forms a high-value concentration circle, which is recognised as the primary central area of Zhengzhou City. In addition, other areas, including Xingyang City, the majority of Xinzheng City, all of Shangjie District, and the majority of Huiji District are classified as address clusters. These areas exhibit significantly lower brightness and population densities, indicating a transition zone between the city and the surrounding rural or natural areas.

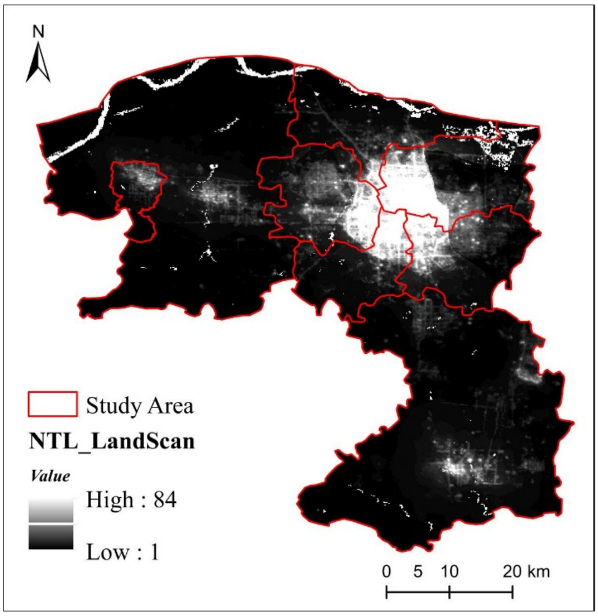

Figure 5. The integration of night-time light data with LandScan data.

The night-time lighting data were integrated with the heatmap data to generate novel NTL-Heatmap data, as illustrated in Figure 6. The high-value areas in the figure are concentrated in Jinshui District, the northern and eastern parts of Zhongyuan District, the northern part of Erqi District, and most of the northern part of Guancheng District. These areas not only exhibit high economic activity at night but also serve as principal gathering points for population mobility. In the Xingyang and Xinzheng Districts, for instance, the brightness of these areas is low, and several areas of high values on the map form clear clusters, particularly in and around the city centre. Areas such as the Jinshui, Zhongyuan, and Erqi Districts exhibit a notable concentration of high values, which suggests that these areas serve as major commercial and residential hubs. The high-value areas are connected by corridors with high brightness, indicating the presence of major transport networks and economic links within the city. Conversely, areas such as Xingyang and Xinzheng exhibit markedly lower brightness, reflecting the divergence in economic activities and population mobility between these regions and the city centre.

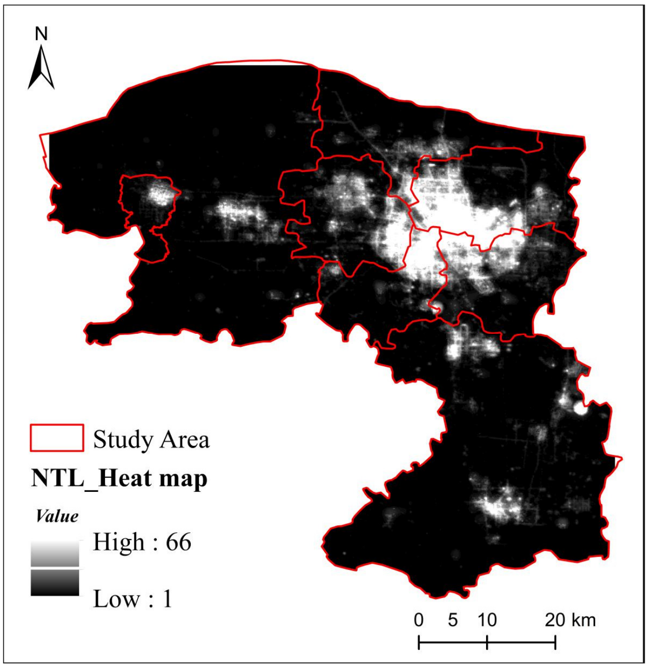

Figure 6. The integration of night-time light data with population thermal data.

A comparison of the data before and after fusion revealed that the distribution of high and low values of the NTL-LandScan and NTL-Heatmap data in Zhengzhou City was similar to that of night-time lights. High values were mainly concentrated in the Jingshui, Zhongyuan, Erqi, and Guancheng Districts, indicating that both NTL-LandScan and NTL-Heatmap data can reflect the spatial structure of a city centre accurately. Nevertheless, the accuracy of the night-time lighting data fused with the LandScan and heat-map data required further verification.

3.2. Spatial Structure of Urban Polycentres Identified by Night-Time Lighting Data Fusion with LandScan Data

The city centre of Zhengzhou, as identified by the NTL-LandScan data, is illustrated in Figure 7. This figure demonstrates that five urban centres in Zhengzhou were identified, with a total area of 384.03 km^2. The main centre is concentrated in the core area of urban development, while the sub-centres are distributed in the peripheral areas of the city, forming a relatively clear urban polycentre pattern. The NTL-LandScan data revealed a single main centre located in the Zhongyuan, Jinshui, and Erqi Districts. These districts serve as both the administrative and commercial centres of Zhengzhou and are characterised by a high concentration of economic activities, the highest luminance at night, and the highest density of resident population. The area of these districts is 316.90 km^2. Sub-centres are located in Shangjie District, Xinzheng City, and Xingyang City, with centre areas of 27.17 km^2, 17.68 km^2, 15.23 km^2, and 4.97 km^2, respectively. Although the night-time light luminance and the resident population density of these areas are not as high as in the main centre, they still demonstrate significant economic and population densities and a high level of economic and demographic vitality.

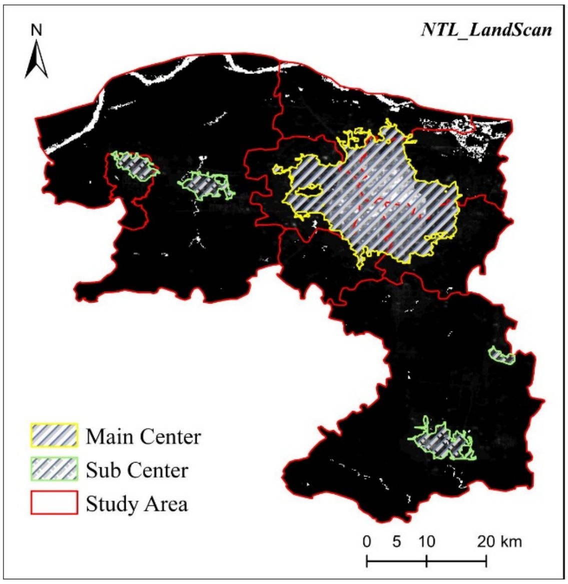

Figure 7. Night-time light illumination data fusion with LandScan data to identify the spatial structure of urban polycentres.

3.3. Spatial Structure of Urban Polycentres Identified by Fusing Heatmap Data with Night-Time Lighting Data

The eight centres of Zhengzhou city, as identified by NTL-Heatmap data, are depicted in Figure 8. Of these is the main centre, while the remaining seven are sub-centres. The main centre area is primarily situated within the boundaries of the Zhongyuan, Jinshui, and Erqi Districts, which collectively represent the primary economic and population concentration areas within the city. The total area of this zone is 230.97 km^2, representing a reduction of 153.06 km^2 in comparison to the main centre area identified by the NTL-LandScan data. The NTL-Heatmap data identified seven sub-centres, located in Shangjie District, Xingyang City, Zhongyuan District, Huiji District, and three in Xinzheng City. The areas of the various sub-centres were as follows: 21.28 km^2, 16.46 km^2, 15.97 km^2, 6.71 km^2, 15.38 km^2, 1.49 km^2, and 8.21 km^2.

From the centres identified by NTL LandScan and NTL Heatmap, in addition to the main centre of Zhengzhou, the sub-centres of Zhengzhou can be roughly divided into the following types: administrative sub-centre, commercial sub-centre, industrial sub-centre, and residential sub-centre. For example, the sub-centre in Shangjie District is the industrial sub-centre, the sub-centre in Xingyang is the industrial and residential sub-centre, the sub-centre in Xinzheng City is the comprehensive sub-centre, and the sub-centre in Huiji District is the residential and commercial sub-centre. The main and sub-centres of Zhengzhou have complementary and synergistic effects in the overall urban development. Each sub-centre has a clear division of labour in terms of functional positioning. For example, Shangjie District focuses on industry, Xingyang and Xinzheng have both industrial and residential functions, while Zhongyuan District and Huiji District focus on commerce and residence. This division of labour and collaboration helps to balance the distribution of urban functions and alleviate the pressure on the main centre. The sub-centre and the main centre support each other economically and functionally, forming a positive, interactive relationship. The main centre focuses on high-end service industries and administrative functions, while the sub-centre ensures the overall efficiency of the city's operation by providing support functions such as residential, industrial, and logistical. Although there may be competition among sub-centres in certain areas, this is more about attracting resources and optimizing services, with the ultimate goal of promoting the prosperity of the entire city.

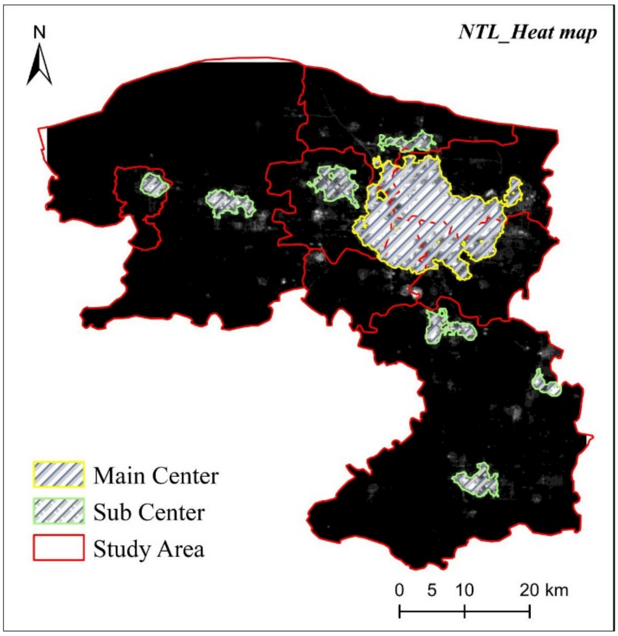

Figure 8. Night-time light data fused with population thermal data to identify polycentric spatial structure.

A comparison of the spatial structures of urban polycentres identified by NTL-LandScan and NTL-Heatmap revealed that the two fused datasets differed in the concentrations of the main centres. The main centres identified by NTL-LandScan were more concentrated and larger in area, indicating that the main centre areas it identified had higher economic and population concentrations. In contrast, the main centres identified by NTL-Heatmap were smaller, suggesting that the core areas identified were more dispersed, with reduced economic and population density. Furthermore, the distribution of sub-centres differed between the two datasets. NTL-LandScan had fewer and larger sub-centres, indicating that each had relatively greater economic and population dynamism. In contrast, NTL-Heatmap had a relatively large number of sub-centres, each with a smaller area, indicating that they had a relatively low economic and population concentration. Finally, there was also a difference in the coordination of spatial distribution. NTL-LandScan demonstrated a more concentrated and clearer polycentric pattern, where the distribution of main centres and sub-centres was conducive to the formation of a balanced urban structure. In contrast, NTL-Heatmap illustrated a more dispersed polycentric pattern, characterised by a greater number of sub-centres. This may indicate more vibrant economic and demographic activity in the peripheral parts of the city, contributing to the expansion and diversification of the city.

3.4. Comparative Analysis

A comparison of the spatial structures of the Zhengzhou City polycentre identified by NTL-LandScan (economic integration of resident population data) and NTL-Heatmap (economic integration of population mobility data) revealed a significant difference between the two (Figure 9). The area of the city centre identified by NTL-LandScan was larger, with the main centre covering 316.90 km^2, and four sub-centres were identified, also with a larger area. This indicated a high concentration of the city centre area and a limited expansion of the peripheral area. The NTL-Heatmap identified smaller urban centres, with the main centre covering 230.97 km^2 and a larger number of sub-centres (seven) covering a smaller area, indicating a more decentralised polycentric structure of the city, with economic and demographic activities distributed over a wider area. The NTL-LandScan data are mainly based on the resident population, reflecting a more static pattern of urban centres. Today, the increased mobility of the urban population and the dispersion of economic activities make it challenging to accurately capture the actual urban polycentric structure with the traditional resident-population-based urban centre identification method. NTL-Heatmap data, however, combine population mobility and can more dynamically reflect the economically and demographically active areas within a city.

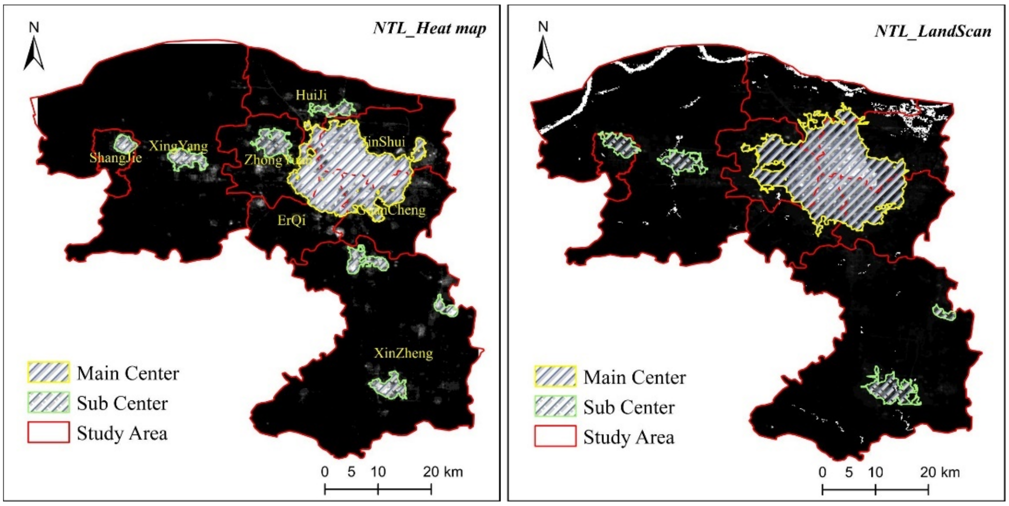

Figure 9. Comparison of the results identifying the spatial structure of urban polycentres.

In particular, NTL-Heatmap data incorporate information on population movements and thus can dynamically capture the actual movements of people within a city. In contemporary urban environments, populations are no longer constrained to their fixed residences. Instead, individuals frequently traverse diverse spatial domains at disparate temporal intervals. By analysing these mobility data, it is possible to identify with greater accuracy which areas are densely populated and economically active at particular times. Economic activity is concentrated in high-traffic areas, such as business centres, work zones, and entertainment districts. By capturing population movement data, NTL-Heatmap is able to identify these hot zones of economic activity, rather than simply identifying areas with a large population distribution. The advent of the sharing economy and the rise in popularity of telecommuting have rendered traditional resident population data inadequate for reflecting the distribution of economic vitality in cities. Modern cities are also becoming more polycentric, with the emergence of sub-centres and new business districts. The identification of multiple sub-centres by NTL-Heatmap indicates that economic and demographic activities have been expanding over a wider area. Conversely, NTL-LandScan, which is based on resident population data, may fail to identify these emerging areas and may not fully reflect the diverse development pattern of the city. Finally, in the context of population contraction, resident population data may underestimate the actual density of the population and economic activities. In the context of population contraction, population movement and redistribution are often observed. NTL-Heatmap can capture these changes, thereby providing a more flexible identification of urban centres in real time. This enables urban planners to gain a deeper understanding of the impacts of population contraction and to respond accordingly.

3.5. Validation of Recognition Results

The real-time and dynamic nature of Weibo check-in data means that they can reflect the population distributions at different times and locations in a timely manner. The populations of urban centres are in constant flux, and Weibo check-in data can be employed to capture such changes, accurately reflecting the level of activity in urban centres. Moreover, Weibo check-in data reflect the social behaviours of users, with social activities often concentrated in areas of the city that are particularly busy, such as business centres and cultural and entertainment districts. Consequently, Weibo check-in data can be employed to infer the concentrated areas of population movement, which align with the locations of urban centres.

The results of fusing LandScan and heat-map data with the city centre and night-time lighting data were validated by the microblog check-in data (Table 3). The F_1 of NTL-LandScan was found to be 0.7463, while that of NTL-Heatmap was 0.8235. The recognition results indicated that NTL-Heatmap had higher accuracy, as it incorporated real-time population mobility data and was thus better able to capture the dynamic changes in population and economic activities within the city. In contrast, NTL-LandScan was based on population distribution data, which reflected more static, long-term residential conditions; therefore, they were unable to account for instantaneous changes in population and economic activities in a timely manner. Furthermore, economic activities are usually concentrated in places with high human flows, not just in areas with high population distribution. NTL-Heatmap can identify actual economic hotspots and active areas through population mobility data, while NTL-LandScan may underestimate these dynamic economic centres. As modern urban development is becoming more polycentric, business districts and sub-centres continue to emerge. NTL-Heatmap can capture these emerging areas more sensitively, whereas NTL-LandScan may overlook such changes. Finally, in the context of increasing population mobility and population contraction, NTL-Heatmap can provide more flexible and real-time identification of urban centres by capturing mobile population data; conversely, NTL-LandScan cannot accurately reflect these dynamic changes due to its reliance on resident population data.

Table 3. Verification of the identification results.

	Recall	**Precision**	**F_1**
NTL-LandScan	0.6705	0.8416	0.7463
NTL-Heatmap	0.7710	0.8837	0.8235

4. Discussion

In recent years, urbanisation has been rapidly advancing, the urban structure has become increasingly complex, and the traditional monocentric structure has become insufficient for the needs of modern urban development [58]. The multi-centre spatial structure has emerged as a significant development mode, alleviating pressure on the central region and facilitating balanced development across all regions by dispersing urban functions [59]. This study has provided a detailed analysis of the polycentric spatial structure of Zhengzhou City based on the dual perspectives of mobile and resident populations. The population distribution data usually come from the population census, registered residence or regular population sampling survey. These data reflect the population distribution of fixed residents in Zhengzhou, which can reveal long-term stable population distribution characteristics and population density in the central area of the city. Floating population data can reveal the population distribution and concentration areas within the city during different time periods, reflecting daily activity hotspots and temporary population agglomeration of the city. Fusing resident population and mobile population data with night-time lighting data provides a method for accurately identifying the spatial structure of urban polycentres, which enables an in-depth analysis of the relationship between urban population activities and spatial distribution, as well as an understanding of the density of population activities and their changing law in each centre area. This not only facilitates comprehension of the spatial configuration and functional disposition of a city but also provides a robust scientific foundation for urban planning and administration, which has considerable practical significance and application value.

In previous studies, the identification of the spatial structure of urban polycentres has typically been based on a single data source, such as the distribution of the resident population or night-time lighting data [60]. These traditional methods can provide some information on the urban structure, but they have obvious limitations. The use of population distribution data is limited by their static nature, which precludes the capture of instantaneous population movement and dynamic economic activities [61,62]. Furthermore, although night-time lighting data can reflect the brightness distribution of a city, they are unable to accurately distinguish the specific population and economic activities in different areas [29]. This study has addressed the limitations of traditional methods by proposing a novel approach to identify the spatial structure of urban polycentres. The proposed method integrates night-time lighting data, population distribution data, and population mobility data. In particular, NTL-LandScan data integrate the distribution of economic activities and resident populations, while NTL-Heatmap data incorporate the dynamic characteristics of economic activities and population mobility. We can display the dynamic characteristics of population mobility at different time periods through heat-map data. Combining them with night-time lighting data can more comprehensively reflect the economic activities and population mobility in different areas of the city. The introduction of dynamic features compensates for the shortcomings of static data, making the identification of urban multi-centre structures more in line with practical operational mechanisms. While breaking through the limitations of traditional methods, it provides a more comprehensive and accurate means of identification.

This study employed a novel approach to investigate the potential of population mobility data in reflecting real-time demographic and economic activity changes within cities. Conversely, traditional methodologies that depend on resident population data are unable to capture these changes [63]. By utilising night-time lighting data, this study was able to identify the most economically active areas within the city. The initial distribution of economic activities was identified through the use of night-time lighting data, which was then refined through the incorporation of population movement data, thereby enhancing the precision of the results. Furthermore, the development of modern cities is often characterised by a polycentric structure, which means that a single data source may not be sufficient to identify emerging business districts and sub-centres [64–66]. The integration of multiple data sources can facilitate the identification of these emerging areas, reflecting the diverse development patterns observed in a city.

This study validated the enhancement provided by population mobility data fusion in terms of the precision of urban polycentric spatial structural identification through a comparative analysis. The recognition accuracy of NTL-LandScan was 0.7463, while that of NTL-Heatmap was 0.8235. These values indicated that the fusion of population mobility data enhanced the accuracy of urban polycentric structural recognition. NTL-Heatmap is most effective at reflecting the actual situation within the city, particularly in response to an increase in population mobility and the decentralisation of economic activities [67]. This study enhanced the precision of identifying the spatial configuration of urban polycentric areas by integrating multiple data sources. This accurate means of identification is of great importance for urban planning and management, as it enables city managers to gain a more comprehensive understanding of the distribution of economic activities and the population within the city. This, in turn, facilitates the formulation of more appropriate urban development strategies and resource allocation schemes, as well as the promotion of coordinated urban development [68]. Furthermore, by fusing night-time lighting and population movement data, the changes at play can be captured in a more timely and accurate manner, thereby providing an effective tool for assessing rapidly evolving urban dynamics.

In sum, this study proposed a novel method for identifying the spatial structure of urban polycentres. This method integrates night-time lighting data, resident population distribution data, and population movement data. This method overcomes the limitations of traditional single data sources and can reflect the actual distribution of population and economic activities within a city more comprehensively and dynamically.

Note, however, that although this study analysed the urban polycentric spatial structure from the perspective of data fusion, it did so using Zhengzhou City as a case study. We achieved satisfactory results in Zhengzhou City, but the availability and accuracy of data sources may vary in different cities and regions. Consequently, further validation of the applicability and effectiveness of this method in other cities is required. Furthermore, although this study incorporated night-time lighting, resident population, and population movement data; there are other important data sources that were not included (e.g., traffic flows, mobile communication data, and social media data) [69]. The incorporation of additional data sources may enhance the precision of identification and the intricacy of data processing. Future research should continue to explore the optimisation and extension of multiple-data-source fusion methods in order to further improve their recognition accuracy and applicability.

5. Conclusions

As polycentrism is an inevitable trend in urban spatial development, the accurate identification of polycentric spatial structures is crucial. Accordingly, this study proposed a method for identifying the polycentric spatial structures of cities. This method integrates night-time lighting data, population distribution data, and population mobility data to present a comprehensive and dynamic reflection of the actual distribution of the population and economic activities within a city. This investigation was conducted in Zhengzhou City; the results demonstrated that using the method proposed in this study led to a notable enhancement in identification accuracy in comparison to previous studies. Specifically, the spatial structure of urban polycentricity was identified with an accuracy of 0.8235, verifying the effectiveness of integrating population mobility data to improve the identification accuracy. Compared to other data fusion studies on urban spaces, the results of this study, especially in terms of accuracy, are a significant improvement [70]. Furthermore, in this study, the previous finding of a polycentric development trend in Zhengzhou City was validated, offering a valuable reference for urban planning and management in Zhengzhou. The findings of this research not only contribute to the advancement of urban research theory and methodology but also provide more scientific and intelligent decision-making support for urban management.

Author Contributions: Conceptualization, R.Z. and S.L.; data curation, M.L. and X.Z.; formal analysis, Y.G. and Y.L.; investigation, X.Z.; methodology, R.Z. and M.L.; software, R.Z. and M.L.; validation, S.L.; writing—original draft, R.Z.; writing—review and editing, R.Z., M.L., X.Z., Y.G., Y.L., S.L., and Q.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (42101206); the Doctoral Research Fund of Zhengzhou University of Light Industry (0187/13501050037); the General Project of Humanities and Social Sciences Research in Henan Province's Universities (2025-ZDJH-592); the Municipal Social Science Foundation of Guangzhou (2023GZGJ27); and the Henan Province University Science and Technology Innovation Talent Support Program (Humanities and Social Sciences 2021-CX-052).

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Conflicts of Interest: Author Yonghe Li was employed by the company Henan Urban Planning Institute & Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. He, X.; Zhang, R.; Yuan, X.; Cao, Y.; Zhou, C. The role of planning policy in the evolution of the spatial structure of the Guangzhou metropolitan area in China. *Cities* **2023**, *137*, 104284. [CrossRef]
2. Wang, Y.; Fan, J. Multi-scale analysis of the spatial structure of China's major function zoning. *J. Geogr. Sci.* **2020**, *30*, 197–211. [CrossRef]
3. Vanderhaegen, S.; Canters, F. Mapping urban form and function at city block level using spatial metrics. *Landsc. Urban Plan.* **2017**, *167*, 399–409. [CrossRef]
4. He, X.; Zhou, Y. Urban spatial growth and driving mechanisms under different urban morphologies: An empirical analysis of 287 Chinese cities. *Landsc. Urban Plan.* **2024**, *248*, 105096. [CrossRef]

5. Schmidt, S.; Krehl, A.; Fina, S.; Siedentop, S. Does the monocentric model work in a polycentric urban system? An examination of German metropolitan regions. *Urban Stud.* **2020**, *58*, 1674–1690. [CrossRef]
6. Agyemang, F.S.K.; Silva, E.; Poku-Boansi, M. Understanding the urban spatial structure of Sub-Saharan African cities using the case of urban development patterns of a Ghanaian city-region. *Habitat Int.* **2019**, *85*, 21–33. [CrossRef]
7. He, X.; Zhou, Y.; Yuan, X.; Zhu, M. The coordination relationship between urban development and urban life satisfaction in Chinese cities—An empirical analysis based on multi-source data. *Cities* **2024**, *150*, 105016. [CrossRef]
8. Xiao, W.; Liu, W.; Li, C. Can the urban spatial structure accelerate urban employment growth? Evidence from China. *Growth Change* **2022**, *53*, 1668–1693. [CrossRef]
9. Anas, A.; Arnott, R.; Small, K. Urban Spatial Structure. *J. Econ. Lit.* **1998**, *36*, 1426–1464.
10. Cervero, R.; Kockelman, K. Travel demand and the 3Ds: Density, diversity, and design. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [CrossRef]
11. Garreau, J. *Edge City: Life on the New Frontier*; Knopf Doubleday Publishing Group: Broadway, NY, USA, 1991.
12. McMillen, D.P.; McDonald, J.F. Suburban Subcenters and Employment Density in Metropolitan Chicago. *J. Urban Econ.* **1998**, *43*, 157–180. [CrossRef]
13. Timberlake, M. The Polycentric Metropolis: Learning from Mega-City Regions in Europe. *J. Am. Plan. Assoc.* **2008**, *74*, 384–385. [CrossRef]
14. Batten, D.F. Network Cities: Creative Urban Agglomerations for the 21st Century. *Urban Stud.* **1995**, *32*, 313–327. [CrossRef]
15. Davoudi, S. EUROPEAN BRIEFING: Polycentricity in European spatial planning: From an analytical tool to a normative agenda. *Eur. Plan. Stud.* **2003**, *11*, 979–999. [CrossRef]
16. Li, W.; Sun, B.; Zhao, J.; Zhang, T. Economic performance of spatial structure in Chinese prefecture regions: Evidence from night-time satellite imagery. *Habitat Int.* **2018**, *76*, 29–39. [CrossRef]
17. Liu, X.; Derudder, B.; Wu, K. Measuring Polycentric Urban Development in China: An Intercity Transportation Network Perspective. *Reg. Stud.* **2016**, *50*, 1302–1315. [CrossRef]
18. Wu, C.; Smith, D.; Wang, M. Simulating the urban spatial structure with spatial interaction: A case study of urban polycentricity under different scenarios. *Comput. Environ. Urban Syst.* **2021**, *89*, 101677. [CrossRef]
19. Dadashpoor, H.; Alidadi, M. Towards decentralization: Spatial changes of employment and population in Tehran Metropolitan Region, Iran. *Appl. Geogr.* **2017**, *85*, 51–61. [CrossRef]
20. Alidadi, M.; Dadashpoor, H. Beyond monocentricity: Examining the spatial distribution of employment in Tehran metropolitan region, Iran. *Int. J. Urban Sci.* **2018**, *22*, 38–58. [CrossRef]
21. Sohn, S.-H.; Kim, T.-H.; Lee, J.-S.; Kim, H.-K. Spatial Analysis of Urban Structure Changes in Korean Mega-Cities. *J. Asian Archit. Build. Eng.* **2010**, *9*, 201–206. [CrossRef]
22. Connors, J.P.; Galletti, C.S.; Chow, W.T.L. Landscape configuration and urban heat island effects: Assessing the relationship between landscape characteristics and land surface temperature in Phoenix, Arizona. *Landsc. Ecol.* **2013**, *28*, 271–283. [CrossRef]
23. Wang, N.; Du, Y.; Liang, F.; Yi, J.; Qian, J.; Tu, W.; Huang, S.; Luo, P. Disentangling relations between dynamic urban structure and its efficiency in 287 cities across China. *Sustain. Cities Soc.* **2023**, *99*, 104879. [CrossRef]
24. Klopfer, F. The thermal performance of urban form—An analysis on urban structure types in Berlin. *Appl. Geogr.* **2023**, *152*, 102890. [CrossRef]
25. Lobsang, T.; Zhen, F.; Zhang, S.; Xi, G.; Yang, Y. Methodological Framework for Understanding Urban People Flow from a Complex Network Perspective. *J. Urban Plan. Dev.* **2021**, *147*, 04021020. [CrossRef]
26. Liu, P.; Qin, Y.; Luo, Y.; Wang, X.; Guo, X. Structure of low-carbon economy spatial correlation network in urban agglomeration. *J. Clean. Prod.* **2023**, *394*, 136359. [CrossRef]
27. McMillen, D.P. Identifying Sub-centres Using Contiguity Matrices. *Urban Stud.* **2003**, *40*, 57–69. [CrossRef]
28. Adolphson, M. Estimating a Polycentric Urban Structure. Case Study: Urban Changes in the Stockholm Region 1991–2004. *J. Urban Plan. Dev.* **2009**, *135*, 19–30. [CrossRef]
29. Xie, Z.; Yuan, M.; Zhang, F.; Chen, M.; Shan, J.; Sun, L.; Liu, X. Using Remote Sensing Data and Graph Theory to Identify Polycentric Urban Structure. *IEEE Geosci. Remote Sens. Lett.* **2023**, *20*, 1–5. [CrossRef]
30. Yang, X.; Zou, X.; Li, M.; Wang, Z. The Decarbonization Effect of the Urban Polycentric Structure: Empirical Evidence from China. *Land* **2024**, *13*, 173. [CrossRef]
31. Huang, Y.; Liao, R. Polycentric or monocentric, which kind of spatial structure is better for promoting the green economy? Evidence from Chinese urban agglomerations. *Environ. Sci. Pollut. Res.* **2021**, *28*, 57706–57722. [CrossRef]
32. Patala, S.; Albareda, L.; Halme, M. Polycentric Governance of Privately Owned Resources in Circular Economy Systems. *J. Manag. Stud.* **2022**, *59*, 1563–1596. [CrossRef]
33. Meijers, E.; Hoogerbrugge, M.; Cardoso, R. Beyond Polycentricity: Does Stronger Integration Between Cities in Polycentric Urban Regions Improve Performance? *Tijdschr. Voor Econ. En Soc. Geogr.* **2018**, *109*, 1–21. [CrossRef]
34. Bentlage, M.; Müller, C.; Thierstein, A. Becoming more polycentric: Public transport and location choices in the Munich Metropolitan Area. *Urban Geogr.* **2021**, *42*, 79–102. [CrossRef]
35. López-Gay, A.; Salvati, L. Polycentric development and local fertility in metropolitan regions: An empirical analysis for Barcelona, Spain. *Popul. Space Place* **2021**, *27*, e2402. [CrossRef]

36. Xie, X.; Hou, W.; Herold, H. Ex Post Impact Assessment of Master Plans—The Case of Shenzhen in Shaping a Polycentric Urban Structure. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 252. [CrossRef]
37. Han, H.; Yang, C.; Wang, E.; Song, J.; Zhang, M. Evolution of jobs-housing spatial relationship in Beijing Metropolitan Area: A job accessibility perspective. *Chin. Geogr. Sci.* **2015**, *25*, 375–388. [CrossRef]
38. Zhang, P.; Liu, Y.; Miao, L. Impacts of social networks on floating population wages under different marketization levels: Empirical analysis of China's 2016 national floating population dynamic monitoring data. *Appl. Econ.* **2021**, *53*, 2567–2583. [CrossRef]
39. Zhang, C.; Li, M.; Ma, D.; Guo, R. How Different Are Population Movements between Weekdays and Weekends: A Complex-Network-Based Analysis on 36 Major Chinese Cities. *Land* **2021**, *10*, 1160. [CrossRef]
40. He, X.; Cao, Y.; Zhou, C. Evaluation of Polycentric Spatial Structure in the Urban Agglomeration of the Pearl River Delta (PRD) Based on Multi-Source Big Data Fusion. *Remote Sens.* **2021**, *13*, 3639. [CrossRef]
41. He, X.; Zhou, C.; Zhang, J.; Yuan, X. Using Wavelet Transforms to Fuse Nighttime Light Data and POI Big Data to Extract Urban Built-Up Areas. *Remote Sens.* **2020**, *12*, 3887. [CrossRef]
42. Zhang, J.; Zhang, X.; Tan, X.; Yuan, X. 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* **2022**, *11*, 1212. [CrossRef]
43. Zhou, Y.; He, X.; Zhu, Y. Identification and Evaluation of the Polycentric Urban Structure: An Empirical Analysis Based on Multi-Source Big Data Fusion. *Remote Sens.* **2022**, *14*, 2705. [CrossRef]
44. Xie, L.; Feng, X.; Zhang, C.; Dong, Y.; Huang, J.; Liu, K. Identification of Urban Functional Areas Based on the Multimodal Deep Learning Fusion of High-Resolution Remote Sensing Images and Social Perception Data. *Buildings* **2022**, *12*, 556. [CrossRef]
45. Priyashani, N.; Kankanamge, N.; Yigitcanlar, T. Multisource Open Geospatial Big Data Fusion: Application of the Method to Demarcate Urban Agglomeration Footprints. *Land* **2023**, *12*, 407. [CrossRef]
46. Poudyal, N.C.; Hodges, D.G.; Merrett, C.D. A hedonic analysis of the demand for and benefits of urban recreation parks. *Land Use Policy* **2009**, *26*, 975–983. [CrossRef]
47. Jim, C.Y. Spatial differentiation and landscape-ecological assessment of heritage trees in urban Guangzhou (China). *Landsc. Urban Plan.* **2004**, *69*, 51–68. [CrossRef]
48. Xu, J. From walking buffers to active places: An activity-based approach to measure human-scale urban form. *Landsc. Urban Plan.* **2019**, *191*, 103452. [CrossRef]
49. Kaiser, R.A.; Polk, J.S.; Datta, T.; Keely, S.P.; Brinkman, N.E.; Parekh, R.R.; Agga, G.E. Occurrence and prevalence of antimicrobial resistance in urban karst groundwater systems based on targeted resistome analysis. *Sci. Total Environ.* **2023**, *874*, 162571. [CrossRef]
50. Li, Y. Towards concentration and decentralization: The evolution of urban spatial structure of Chinese cities, 2001–2016. *Comput. Environ. Urban Syst.* **2020**, *80*, 101425. [CrossRef]
51. Lan, F.; Gong, X.; Da, H.; Wen, H. How do population inflow and social infrastructure affect urban vitality? Evidence from 35 large- and medium-sized cities in China. *Cities* **2020**, *100*, 102454. [CrossRef]
52. Wu, C.; Zhao, M.; Ye, Y. Measuring urban nighttime vitality and its relationship with urban spatial structure: A data-driven approach. *Environ. Plan. B Urban Anal. City Sci.* **2022**, *50*, 130–145. [CrossRef]
53. Mu, B.; Liu, C.; Tian, G.; Xu, Y.; Zhang, Y.; Mayer, A.L.; Lv, R.; He, R.; Kim, G. Conceptual Planning of Urban–Rural Green Space from a Multidimensional Perspective: A Case Study of Zhengzhou, China. *Sustainability* **2020**, *12*, 2863. [CrossRef]
54. Peng, J.; Hu, Y.n.; Liu, Y.; Ma, J.; Zhao, S. A new approach for urban-rural fringe identification: Integrating impervious surface area and spatial continuous wavelet transform. *Landsc. Urban Plan.* **2018**, *175*, 72–79. [CrossRef]
55. Pino, C.; Torrecillas, C.; Cáceres-Sánchez, N.; Pino-Mejías, J.-L. Using Getis-Ord Gi* Maps To Understand Bicycle Mobility During The Winter Season In Valencia, Spain. *Dyna* **2022**, *97*, 436–444. [CrossRef]
56. Laffan, S.W. Using process models to improve spatial analysis. *Int. J. Geogr. Inf. Sci.* **2002**, *16*, 245–257. [CrossRef]
57. Xie, Z.; Ye, X.; Zheng, Z.; Li, D.; Sun, L.; Li, R.; Benya, S. Modeling Polycentric Urbanization Using Multisource Big Geospatial Data. *Remote Sens.* **2019**, *11*, 310. [CrossRef]
58. Huang, D.; Liu, Z.; Zhao, X. Monocentric or Polycentric? The Urban Spatial Structure of Employment in Beijing. *Sustainability* **2015**, *7*, 11632–11656. [CrossRef]
59. Ming, Y.; Liu, Y.; Liu, X. Spatial pattern of anthropogenic heat flux in monocentric and polycentric cities: The case of Chengdu and Chongqing. *Sustain. Cities Soc.* **2022**, *78*, 103628. [CrossRef]
60. Yang, Z.; Chen, Y.; Guo, G.; Zheng, Z.; Wu, Z. Using nighttime light data to identify the structure of polycentric cities and evaluate urban centers. *Sci. Total Environ.* **2021**, *780*, 146586. [CrossRef]
61. Ma, M.; Lang, Q.; Yang, H.; Shi, K.; Ge, W. Identification of Polycentric Cities in China Based on NPP-VIIRS Nighttime Light Data. *Remote Sens.* **2020**, *12*, 3248. [CrossRef]
62. Lou, G.; Chen, Q.; He, K.; Zhou, Y.; Shi, Z. Using Nighttime Light Data and POI Big Data to Detect the Urban Centers of Hangzhou. *Remote Sens.* **2019**, *11*, 1821. [CrossRef]
63. Ma, Q.; Gong, Z.; Kang, J.; Tao, R.; Dang, A. Measuring Functional Urban Shrinkage with Multi-Source Geospatial Big Data: A Case Study of the Beijing-Tianjin-Hebei Megaregion. *Remote Sens.* **2020**, *12*, 2513. [CrossRef]
64. Li, D.; Lan, G.Z. The dynamics between urban planning and public policy: Lessons and experiences from the city of Beijing, China. *Int. Rev. Adm. Sci.* **2020**, *88*, 721–738. [CrossRef]

65. Baffoe, G.; Roy, S. Colonial legacies and contemporary urban planning practices in Dhaka, Bangladesh. *Plan. Perspect.* **2023**, *38*, 173–196. [CrossRef]
66. Lyles, W. Using social network analysis to examine planner involvement in environmentally oriented planning processes led by non-planning professions. *J. Environ. Plan. Manag.* **2015**, *58*, 1961–1987. [CrossRef]
67. Wang, F.; Ren, J.; Liu, J.; Dong, M.; Yan, B.; Zhao, H. Spatial correlation network and population mobility effect of regional haze pollution: Empirical evidence from Pearl River Delta urban agglomeration in China. *Environ. Dev. Sustain.* **2021**, *23*, 15881–15896. [CrossRef]
68. Ma, D.; Liu, B.; Huang, Q.; Zhang, Q. Evolution Characteristics and Causes—An Analysis of Urban Catering Cluster Spatial Structure. *ISPRS Int. J. Geo-Inf.* **2023**, *12*, 302. [CrossRef]
69. Yi, C.; Nam, J.; Kim, J.; Lee, J.-S. Comparison of the distributions of centrality indices: Using spatial big data to understand urban spatial structure. *Cities* **2024**, *150*, 105046. [CrossRef]
70. He, X.; Yuan, X.; Zhang, D.; Zhang, R.; Li, M.; Zhou, C. Delineation of Urban Agglomeration Boundary Based on Multisource Big Data Fusion—A Case Study of Guangdong–Hong Kong–Macao Greater Bay Area (GBA). *Remote Sens.* **2021**, *13*, 1801. [CrossRef]