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Township Development and Transport Hub Level: Analysis by Remote Sensing of Nighttime Light

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Abstract: The coordinated development of township and city transportation is expected to reach new heights in the global sustainable transport plans of emerging economies. However, few studies have focused on the transport hub features considering marginal administrative division. This study examines the correlation between township development and hub level by using remote sensing of nightlight imagery. Systematically corrected satellite images of Global NPP-VIIRS Nighttime lights were selected as experimental data. Furthermore, the township hub level model and nighttime light indices were established to demonstrate the correlation characteristics of 6671 townships. Results show that the development level of road transport for a considerable number of townships is positively correlated with the hub level. The positively correlated townships show a spatial clustering distribution. In contrast, several negative correlations and random townships are related to the radiation of adjacent city growth poles and township special industrial characteristics. Nighttime light data can compensate for the difficulty in obtaining socioeconomic data below the prefecture level from a multiscale micro perspective and statistical caliber differences. These findings can be proven to be valuable to planners and designers of township development and regional transport.

Keywords: township; hub level; road transport; correlation analysis; NPP-VIIRS; nighttime light indices

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1. Introduction

The urbanization pattern of harmony between man and nature and the co-prosperity of urban and rural areas is a necessary and interesting topic for exploration [1]. In the past 30 years, urban space in China has expanded by almost three times and the urbanization rate has reached 52.6%. However, spatial urbanization does not completely lead to population urbanization. Approximately 64% of the total population in China still live in townships [2,3]. At present, new-type urbanization is proposed to build a system that consists of multi-level metropolitan circles, regional central cities, medium/small cities, and small towns. The first two are highly valued and developed while township development has gained less focus and lacks vitality.

Transportation is an important support to increase the competitiveness of townships, thereby enhancing the agglomeration and radiation effect of pivot areas [4,5]. Simultaneously, the siphoning effect from important transportation channels passing through or gathering in one area can have a strong attraction to talents, commodities, materials, information, and other production factors [6]. Therefore, an important economic functional area [7] gradually evolves. From 14 to 16 October 2021, the Second United Nations Global Sustainable Transport Conference released the China Sustainable Transport Development Report [8], according to which, by 2035, China is to basically become a "transportation power" with a developed fast network, a sound trunk network, and an extensive basic network. One of the highlights is that coordinated development of rural and urban transportation can reach new heights. As such, the premise of the township hub economy is the formation of a pivot area, where the location advantage is based on the importance and convenience of transportation.

As the smallest administrative division in China, townships [9] are highly dependent on road transport rather than on railways and airlines because of the universality of road infrastructure. One fact to be aware of is that the rank and the positioning of the township in China dictate that it is hardly a center or has a distinct hierarchical structure at a level. To deeply understand the transportation hub economic sustainability of township, we find it worthy to study the characteristics of township road networks and the correlation of township development and transportation junctions. Findings can be used to assist in township development and regional transport planning.

The problem of marginal administrative units in emerging economies (e.g., township, village, rural area) is a highly pluralistic global phenomenon. In southern Sweden, a case study shows that the insufficiency of the transport network poses a threat to the possibilities of living in rural areas outside villages [10]. In China, land transport infrastructure contributes more to economic growth in locations with poor land transport means [11]. Thus, townships with a transportation hub function serve with irreplaceable value as a link and distribution for passengers and logistics flow. A township hub economy is thereby the network-wide effect outcome of road transportation on multiple geo-spatial scales. As marginal administrative units increase, the complexity of the system correlation also increases.

Therefore, this study examines the correlation between township development and hub level through a novel perspective. In particular, we investigate the transportation spatial–economic impact of township regional inequalities in China by using nighttime light remote sensing. Our contributions to the existing literature are threefold. First, to the best of our knowledge, few studies to date have attempted to examine the correlation between hub level and road transport while considering marginal administrative division. This study aims to fill this gap. Second, we observe the nature of transportation hubs in townships rather than travel convenience. The asymmetrical effect of the locational pattern of road accessibility on township regional inequalities thereby potentially provides policy implications for future transport policy design. Third, compared with traditional measurement of socioeconomic data, remote sensing imagery of nighttime lights provides more distinct technical support for the breadth and precision of data access (e.g., statistics and survey data). This method can make up for the difficulty in obtaining socioeconomic data below the prefecture level from the multiscale micro perspective and statistical caliber differences.

2. Literature Review

2.1. Relationship between Transportation and Regional Development

Previous literature has mainly focused on the effect of transportation infrastructure construction and investment on economic development in different countries [12,13]. In Spain, the direct, indirect, and total effects of roads, railways, ports, and airports are determined by examining the regional convergence of transport infrastructure for the period of 1980–2008 [14]. The results indicate that the equalization of infrastructure endowments among the different Spanish regions promotes transport investments. In Poland, the general productivity effects of major transport infrastructure investments from 2004 to 2014 show that accessibility improvement is weakly but positively correlated with growth in regional employment [15]. Across Chinese regions, analogously, the uneven distribution of transport infrastructure is an important reason behind economic disparities based on the panel data model from 1998 to 2007 [16]. Land and water transport infrastructures have stronger and more significant effects than air transport infrastructure. Moreover, transport investment and mobility have significant positive effects in both the short and long term [17]. In Shaanxi province, China, an improved super-efficiency slacks-based measure model with weighting preference is proposed to evaluate the regional transport sustainability efficiency during the period of 2000–2015 [7].

For the past few years, the effect of high-speed rail (HSR) and air transport services in the metropolitan economy has been widely discussed [18,19]. In general, air transport affects a larger area and a relatively smaller audience than HSR. In Canada, the effects of air–HSR competition and intermodal services are analyzed based on a survey [20]. Results show that HSR can have a traffic redistribution effect on airport traffic and the disparity tends to rise between cities with and without HSR.

Air passenger transport is a necessary part of, but not a sufficient condition for, generating regional development among European urban regions [21]. In regional Australia, low-cost international airline services contribute positively to market growth. However, policy on airport infrastructure investment must take caution because they do not always translate into employment income [22]. In Italy, the HSR project brings wide economic benefits, leading to an extra growth of per capita gross domestic product (GDP) of +2.6% in 10 years [23]. In China, the interdependence between the airline industry and provincial economies shows a spatial variation along the east–west axis [24]. The availability of HSR services also disperses the tourism economies among cities with the HSR network step by step [25]. Cities in the southeastern coastal provinces and middle reaches of the Yangtze River receive more services than those in West China [26].

In general, transportation-based regional inequality is highly apparent. At present, studies on regional transport focus on either metropolitan areas or emerging modes of transportation but exhibit limited application engagement with spatial–economic heterogeneity of marginal administrative units.

2.2. Application of Nighttime Light Series Data

In view of the increasingly complex urban problems, traditional remote sensing monitoring can extract land cover/use type data and analyze the dynamic changes of urban spatial structure in horizontal or vertical directions [27,28], but are weak in analyzing large-scale urban systems and their spatial structures. At the same time, traditional remote sensing data has no effective direct monitoring for urban social–economic characteristics. One glaring problem is that the estimation accuracy and the result resolution are low [29]. As an optical remote sensing technology, nighttime light remote sensing can detect the low light level in the evenings and obtain information that cannot be obtained by daytime remote sensing. The imagery has been proven to be more intuitive to reflect the differences of human activities at night [30].

At present, nighttime remote sensing series data have been widely used in multi-scale urban spatial structure analysis, social-economic index estimation, and public security. Remote sensing images of nighttime light can be used not only to analyze urban elements and internal spatial structures, urban regions, hierarchical structures of urban systems and agglomerations [31–33], but also to estimate multi-scale social and economic development indicators (e.g., population, GDP, electricity consumption, carbon emissions, urban housing vacancy rate [34–36]). In addition, few studies examine the application of night light remote sensing images in the comprehensive monitoring of urbanization and urban public security, including natural disasters, epidemics, festivals, wars, and environmental and health issues [37,38].

For instance, nighttime light remote sensing is used to evaluate highway traffic prosperity. Results show that the national general highway of Shanghai is the most prosperous at night, reaching 22.34% in 2015 [39]. For urban sprawl in China from 1990 to 2010, the annual growth rate was 2.45% greater than that of the urban population [40]. The analysis of daily electricity consumption and nighttime light intensity in India during the Coronavirus disease 2019 national lockdown period shows the significant decline of energy consumption [41], and higher infection rates at the district level are associated with larger declines in nighttime light intensity. Interestingly, nighttime light satellite imageries are also used to explore the intensity of urban heat island effect in a case study of London and Paris in 2011 [42]. In summary, nighttime light remote sensing series data present ideal accuracy in estimating various social and urban issues at the national, provincial, and district levels. Nighttime light remote sensing data is particularly effective in reflecting the level of comprehensive regional development [43–45]. Nighttime lighting indicators reflect both the level of development in the physical space and social space of the region.

In summary, these two sections show that nightlight remote sensing data are indeed an ingenious analytical tool that has not been fully developed in the field of transportation. This topic is well worth exploring to fill in the gaps in examining the correlation of road transport hub levels on marginal administrative division.

3. Study Area and Data Description

This study examines the township, a marginal unit in the administrative division of China, as the research object. Four provinces, namely, Shanxi Province in North China, Shaanxi Province in northwest China, and Henan and Hunan Provinces in central China, are selected as the sample areas according to the road transport network and socio-economic situation at the provincial scale. The sample areas include northern and southern provinces, as well as inland and coastal areas, which are representative to a certain extent. The total area of the sample region, which include 51 cities, 494 counties, and 6671 townships, is 676,000 km^2. Figure 1a shows the spatial distribution, in which townships are represented by black blocks. High-precision road network data are obtained to satisfy the need of calculating the hub index based on the roads between townships. In Figure 1b, all the roads are marked in black curves, hence appearing as wisps of smoke. Figure 1e shows a close-up of a typical plot. The road network that is marked in red accurately captures the rural roads among townships.

The administrative division areal data and administrative central point data adapted in this study were obtained from the National Geomatics Center of China. The road network source data were collected from OpenStreetMap and corrected according to the data provided by the China World Map online mapping service. Satellite images of Global NPP-VIIRS Nighttime lights [46] are selected as the experimental data to study township hub level. To improve data comparability and accuracy, the data of nighttime lights are adjusted to correct the effects of cloud polluted pixels. Furthermore, the effects of VIIR day/night band radiation on atmosphere, terrain, vegetation, snow, moonlight, and stray light are rectified [47]. Thankfully, these products have been calibrated over a long period and verified by ground measurements. Thus, the quality indicators have been greatly improved and can be effectively used for scientific and applied research. The average annual product of 2021 (V2) was selected as the dataset, in which stray light, lightning, biomass burning, gas flares, high energy particle detections, and background noise have been removed. In Figure 1c, the nighttime lighting data are fairly standard with spatial resolution of 500 m. This imagery consists of 30 arc-second grids, spanning 106–118° longitude and 28–41° latitude. For clarity, an enlarged nighttime light view of a typical small plot is cut out. Compared with the actual administrative division and road transport network, this plot has a better preliminary matching effect (Figure 1d).

China's administrative regions are divided into provincial-level, prefecture-level, county-level, and township administrative regions. Therefore, the city is a second-level administrative unit that includes a number of three-level county administrative units, which in turn contains four-level township administrative units. The essential object of transportation network analysis is the connectivity between nodes. Therefore, converting these three administrative units into network nodes is necessary when modeling transportation hubs. Our approach is to use the administrative centers of cities, counties, and townships as study nodes. In addition, the nighttime light distribution data are a set of areal data. Thus, they are more intuitive in analyzing the development level and transport hub with township based on an area.

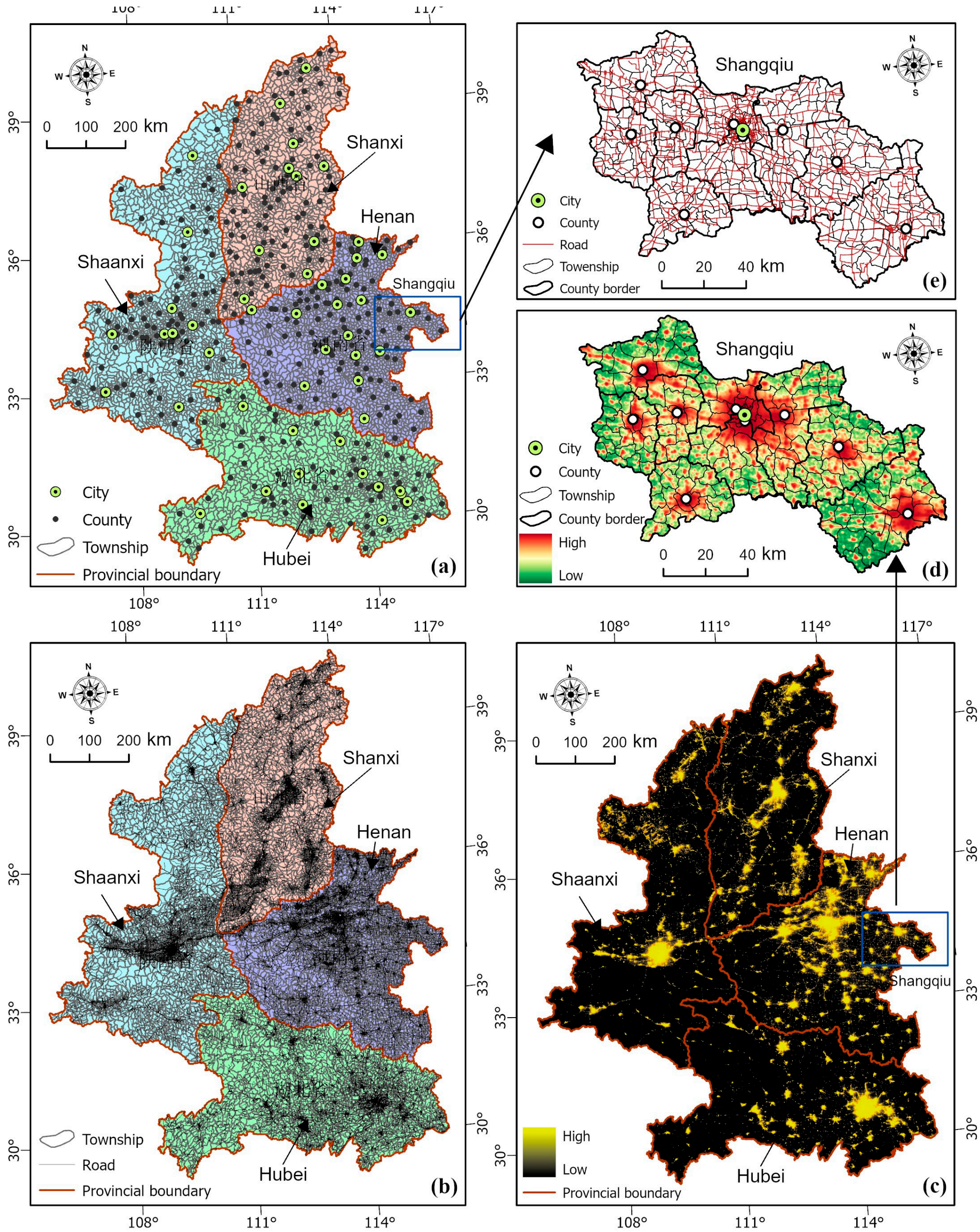

Figure 1. Study area and nightlight remote sensing imagery: (**a**) Townships in the provinces of Shanxi, Shaanxi, Henan, and Hubei in China; (**b**) Road transport network distribution in 2021; (**c**) Average nighttime light distribution in 2021; (**d**) Enlarged nighttime light view of a typical small plot; (**e**) Enlarged view of townships and roads in a typical small plot.

As a hub, a region can have multiple connotations, such as being an economic, cultural, or political hub [48–51]. For example, in China, Shanghai is an economic hub, whereas Beijing is a political and cultural hub. However, for townships, China's five-level administrative unit are generally not equipped to be economic, cultural, political, and other hubs. Due to the small size of township areas, small populations, sparse and uneven population density, and high-density populations are mainly distributed within the downtown areas of townships. Multiple factors led to the development of the township being highly dependent on the flow of people passing through it, and for the more peripheral lower-level administrative districts, whether or not they are transportation hubs is the main driving factor in determining the flow of people. In summary, the level of transportation hubs is likely to be a potential major influencing factor in the development of townships.

4. Methodology

4.1. Research Framework

The objective of this study is to analyze the spatial association characteristics of township development and transport hub level through the remote sensing of nighttime light. The research framework is shown in Figure 2. First, the zonal statistics of nighttime lights in each township administrative region were presented to reflect the development level of the township under three different perspectives. Second, a road–node network was established based on distance cost impedance and mode type weighting to calculate the township hub level. Finally, the Local Geary model for multivariate was adapted to analyze the corresponding spatial association characteristics.

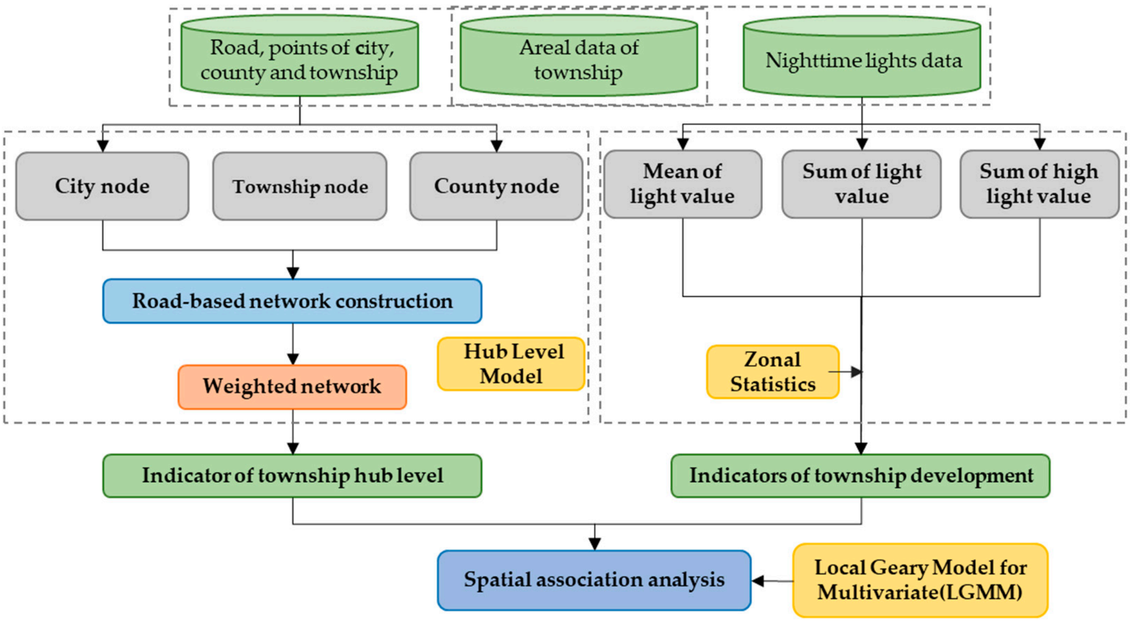

Figure 2. Research framework.

4.2. Nighttime Light Imagery and Measuring Indices

In this study, the brightness values statistics of nightlight remote sensing data are used to reflect the overall development level of the townships, rather than their specific inversion calculation of GDP and population indicators. Figure 3a shows a part nightlight map of 41.274 million townships in China. In all towns, the distribution patterns of high light brightness values can be classified into three basic categories, as shown in Figure 3b–d, respectively. In township A of Figure 3b, areas with high light brightness values are highly clustered and the whole township forms a single-core development center. In township B shown in Figure 3c, the areas with high light brightness value are discretized in different locations and the whole township forms a development trend of discrete clumps. Meanwhile, in township C shown in Figure 3d, most areas have high light brightness values. The ranking of the high and low nightlight values in the map was done using the natural intermittent method, thus achieving the goal of minimal variation within groups and maximum variation between groups as much as possible.

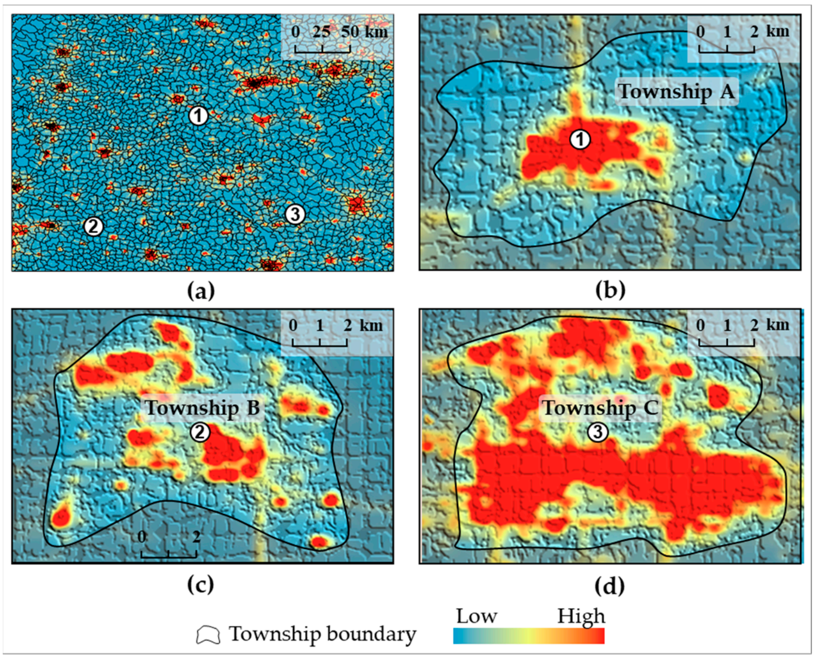

Figure 3. Spatial patterns of township nightlight distribution: (**a**) Close-up view of the nighttime light distribution of the townships; (**b**) Single-core nighttime light distribution; (**c**) Discrete clumps of nighttime light distribution; (**d**) Concentrated-bright nighttime light distribution.

To effectively measure the relationship between township development level and nightlight distribution pattern from multiple angles and directions, we constructed measuring indices of the total development level (TDL), the average development level (ADL), and high-light development level (HDL) of the township based on the total brightness, average brightness, and the total high brightness values. In this way, several problems can be avoided given the imbalanced sizes of the townships and the fact that distribution characteristics of regional lights within the township are not prominent enough. Measuring indices values of TDL, ADL, and HDL are extracted by ArcGIS Pro, and the formulas for calculating their i-th township can be expressed respectively as:

$$TDL_i = \sum_{j=0}^{j=K_i} C_{ij}, \tag{1}$$

$$ADL_i = \frac{1}{S_i} \sum_{j=0}^{j=K_i} C_{ij} = \frac{1}{S_i} TDL_i, \tag{2}$$

$$HDL_i = \sum_{j=0}^{j=L_i} C_{ij}, \tag{3}$$

where C_{ij} represents the brightness values of the j-th pixel of the nightlight remote sensing image of the i-th township, K_i represents the total number of pixels in town i, S_i represents the total area of the i-th township, and L_i represents the total area of the i-th township with a high brightness value meeting the given threshold. The threshold for a high-light night light is 0.8 in this study.

In this study, the overall development level of the township is reflected by the total light value, the average light value, and the total light value of the high light area in the statistical township area. The number of cells with high luminance values plays a decisive role in all three statistical approaches. The high light value area of the township is mainly distributed in the downtown area, which shows a clustering distribution. Given that the dominant factor is the high light value area (downtown area), the three township development indicators are mainly the development level of the downtown area of the township, which can also be regarded as the overall development level.

4.3. Hub Level Model Establishment of Townships

Given the development limitations of townships, road transport mode is more widely adopted than rail, air, and water transport services. Therefore, the road connectivity between townships is the main factor physically and in terms of image. In this study, the hub level of a town is defined as the weighted sum of the total number of times that any two other townships must pass through and the distance to the township by road. The greater the weighted value is, the higher the hub level of the township will be. Some of the cities in the higher classes form economic, cultural, or political centers. However, townships generally do not. We do not deny that some townships may still assume a central role in the local economy or even culture to a certain extent. However, this phenomenon is not evident for most townships.

To determine the connectivity among townships and facilitate the calculation of hub levels further, we transform the transport network problem into a spatial graph problem considering connectivity and distance (Figure 4). We assume a set of townships connected by roads, namely, TSet = {T1, T2, T3, . . . , T9}, as shown in Figure 4a. Apparently, several towns are connected by only one road, whereas others are connected by two or more roads. The calculation of the hub level considers not only the number of times each township is passed but also the actual distance of the road network between townships. Therefore, to facilitate interpretation, we use the thickness of edges to represent the actual path distance between township nodes in Figure 4b. For example, township nodes 1 and 9 have two paths but the actual path distances differ, and thus the thicknesses of the edges between nodes also vary.

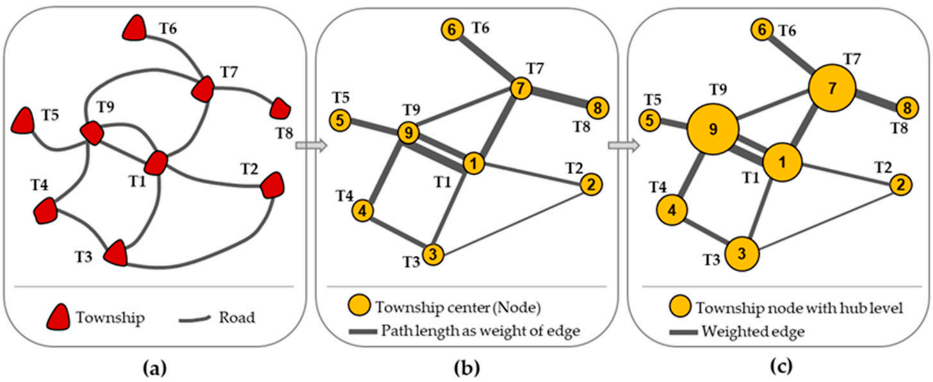

Figure 4. Transforming a transport network problem of the townships to a spatial graph problem considering connectivity and distance: (**a**) Townships connected by roads; (**b**) Road network with distance cost and number of paths as edge weight; (**c**) Size of township node indicates the hub level.

The following is a brief introduction to calculating the hub level of each township algorithm logic. First, we select and set a township as the focal node. Then, townships with direct road connectivity with the focal node are further set as its neighbors. Next, the number of times that the path between any two neighbors passes through the focal node is calculated while recording the actual path distance. Finally, the hub level of the focal township can be calculated by using the weighted method. Figure 4c shows the calculation results. Clearly, township nodes with the same number of passes may have different traffic hub levels due to variations in the actual path lengths.

The two neighboring nodes that drive a township to become a hub can be other townships, cities, or counties. The hub function formed by the city or county and the township is stronger compared with that formed between two townships. Therefore, this study also considers the influences of the nearest county seat and prefecture-level city on each township on the strength of its hub function. Figure 5a shows that the network structure not only contains multiple township nodes but also includes the adjacent county seat and prefecture-level city nodes. From each of these townships, the solid blue lines represent the nearest county, and the red dotted lines represent the nearest city.

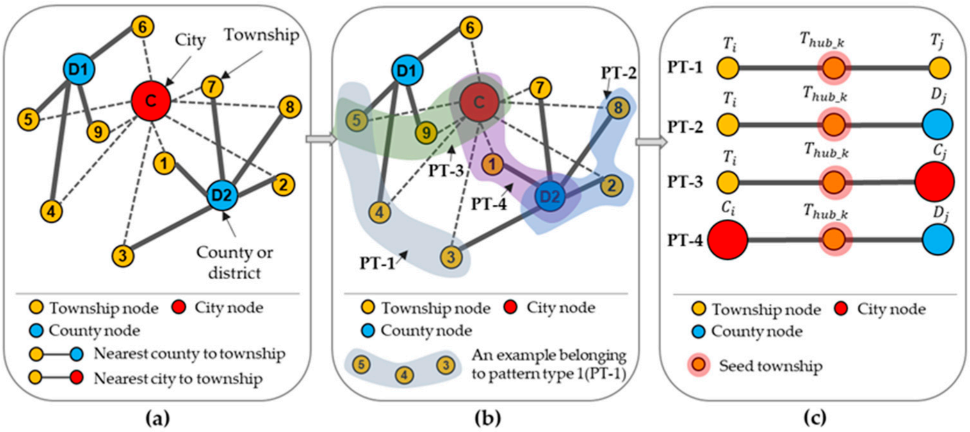

Figure 5. Four township hub level patterns with city and country nodes: (**a**) Form of proximity among townships, counties, and cities; (**b**) Township hub of PT1-PT4 marked by shadow paths; (**c**) Four patterns of focal township nodes as a hub of different townships, counties, or city nodes.

Township hub level with city and country nodes are divided in four patterns according to the origins and destinations of the paths, as shown in Figure 5b,c. Pattern Type 1 (PT-1) is identified as a township hub form with two township origins and destinations. For instance, node 4 is T_{hub}^{k} and the shadow path is with node 3-4-5. However, Pattern Type 2 (PT-2) is identified as a township hub form with a township as origin and a county as destination. By contrast, node 2 is T_{hub}^{k} and the shadow path is with node 8-2-D2. Pattern Type 3 (PT-3) is identified as a township hub form with a township as origin and a city as destination. Here, node 9 is T_{hub}^{k} and the shadow path is with node 5-9-C. Finally, Pattern Type 4 (PT-4) is identified as a township hub form with a city as origin and a county as destination. Similarly, node 1 is T_{hub}^{k} and the shadow path is with node C-1-D2.

Figure 6 illustrates the calculation logic model of township hub level with an example of township node 12. Assuming that T_i represents the focal township node ordered as I, D_i and C_i represent the counties and prefecture-level cities closest to T_i, respectively (Figure 6a). Therefore, the neighbor set (NSet) of T_{12} can be searched and calculated as $\{T_4, T_7, T_8, T_{10}, T_{11}, T_{13}\}$ in Figure 6b. For instance, two paths pass through T_{12} from T_4 to T_7.

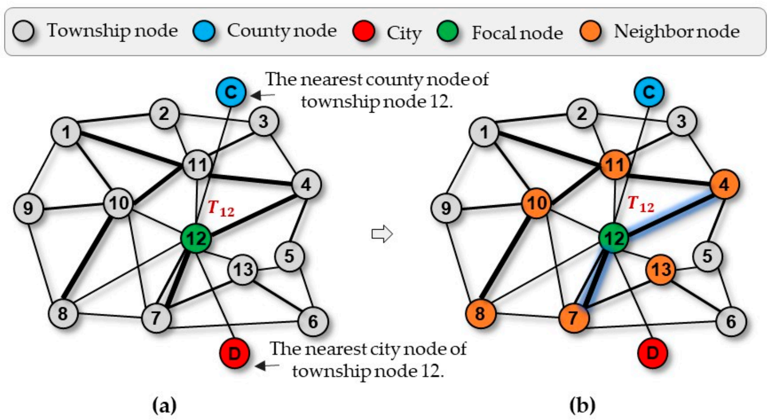

Figure 6. Calculation model of township hub level: (**a**) Road connectivity-based township network that contains cities and counties; (**b**) Focal township node and its neighbor nodes.

If $d_{j,i,k}^{n}$ represents the distance impedance of the l-th path from T_j to T_k by T_i, then the distance impedance factor $D_{j,i,k}$ can be calculated as:

$$D_{j,i,k} = \sum_{l=1}^{n} d_i^n, \tag{4}$$

where the larger $D_{j,i,k}$ is, the greater the contribution to the node T_i as a transport hub. This means a longer, more extensive path from j to k, covering more potential traffic flow.

If $w1$, $w2$, $w3$, and $w4$ are used to represent the weights of the four connectivity modes PT-1, PT-2, PT-3, and PT-4, respectively, as shown in Figure 4c, then the calculation formula of hub level H_i of focal town T_i is expressed as follows:

$$H_i = w1 \cdot \sum_i^{l1} \frac{n}{\sqrt{D_{j,i,k}}} + w2 \cdot \sum_i^{l2} \frac{n}{\sqrt{D_{j,i,d}}} + w3 \cdot \sum_i^{l3} \frac{n}{\sqrt{D_{j,i,c}}} + w4 \cdot \frac{n}{\sqrt{D_{d,i,c}}}, \quad (5)$$

where $l1$, $l2$, and $l3$ represent the total number of path nodes PT-1, PT-2, and PT-3 of T_i in the focal township, respectively. PT-4 has only one case for the same focal township and thus, counting is unnecessary.

4.4. Local Geary Model for Multivariate Spatial Association Analysis

Considering the effects of spatial proximity effect and local autocorrelation, we used the Local Geary model to explore the spatial correlation between township hub level and the three types of nighttime light statistics in township units. Anselin proposed the multivariate extension of Local Geary statistics [52,53], which measures the spatial autocorrelation of multiple variables at the same location to realize whether they have consistent spatial significance.

Essentially, multivariate Local Geary statistics calculate the extent to which the average distance between multiple variable values at one location and at adjacent locations is larger or smaller than the values under random conditions. Under the condition of statistical significance, a larger value represents positive spatial autocorrelation, whereas a smaller value represents negative spatial autocorrelation. In this study, c_i^M is defined as the multivariate Local Geary statistics index, which is assigned the value of the sum of a single local statistic (the difference between the observed value and the mean) for each variable. The corresponding expression for k variables is:

$$c_i^M = \sum_{h=0}^{k} \sum w_{ij} \left(x_{hi} - x_{hj} \right)^2, \quad (6)$$

where h is the variable index, k is the total number of variables, k = 2, x_{hi} represents the h-th variable of the i-th region, x_{hj} represents the h-th variable of the j-th neighbor of i, and w_{ij} is the weight between regions i and j. If the rule "two regions have common edges or common nodes" is adopted, then the w_{ij} between regions conforming to the above rule is 1; otherwise, w_{ij} = 0.

5. Results

5.1. Composite Development Indices of Township under Different Statistical Rules

Figure 7 shows the statistical results obtained by the mean, total, and total high brightness values, which describe the rank distribution of nighttime light brightness values for all townships. For the convenience of comparison, Figure 7a–c adopt the quintile clustering method for classification. Clearly, the three statistical results have very significant spatial differences.

As shown in Figure 7a, spatial differentiation is the most significant in the mean brightness distribution diagram and townships with high brightness values have significant spatial agglomeration characteristics. By contrast, the spatial heterogeneity of the sum of brightness is much weaker in Figure 7b. Notably, the township area is also one of the factors affecting the total brightness. Under the same development level, the larger the area of the township, the greater the total brightness value. Figure 7c illustrates that the spatial differentiation based on the sum of high brightness is between the mean value and the sum of brightness.

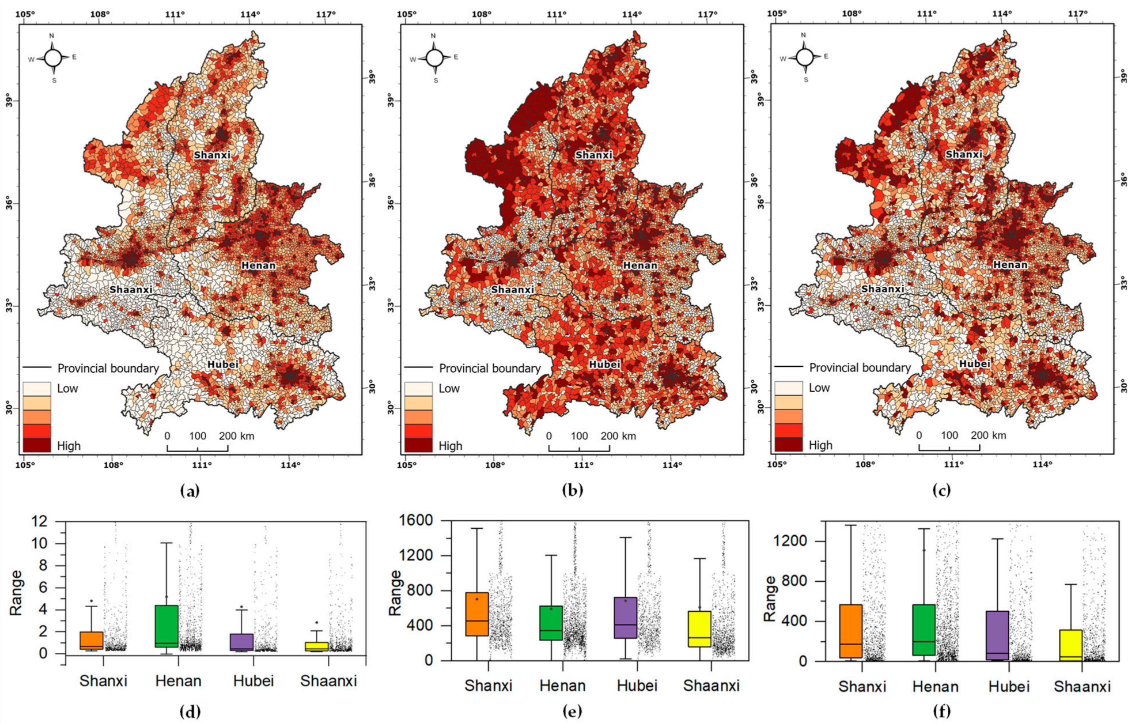

Figure 7. Spatial distribution of three nighttime light indices: (**a**) Mean value of nighttime light; (**b**) Sum value of nighttime light; (**c**) Sum value of nighttime high-lights; (**d**) Box diagram of mean light brightness value distribution for four provinces; (**e**) Box diagram of sum light brightness value distribution for four provinces; (**f**) Box diagram of sum high-light brightness value distribution for four provinces.

In the statistical representation of three kinds of nighttime light data, we found that the average value could not reflect the real development level for townships with high brightness values and large areas. The sum of brightness values reflects the overall development level of townships. However, this statistical method reduces the accuracy of the analysis results for townships with similar development levels and large area differences. The sum of high brightness values mainly focuses on only the high development area of the township and it is easy to ignore other local differences within the township. This method is helpful for comparing the differences in development levels between different townships. Nevertheless, townships with relatively balanced development without a high concentration of nighttime light distribution could not be taken into account. Therefore, this study adopts each of these three ways to explore the relationship between township hubs since each method has its pros and cons.

Figure 7d–f show the distribution results of nighttime light values in different provinces under different statistical methods. As shown in Figure 7d, it is illustrated that the four provinces have varying dispersion degrees of mean nighttime light distributions. The mean nighttime light distribution of Henan Province is the highest degree of dispersion, while that of Shaanxi Province is the largest degree of aggregation. Shanxi and Hubei provinces have similar mean distributions of nighttime lights, falling between these two provinces. By contrast, the sum value of nighttime light brightness has a similar distribution in the four provinces with relatively discrete characteristics, which is shown in Figure 7e. To a certain extent, the statistical method of the sum brightness reduces the differences in the statistical values of different townships, allowing for relatively stable statistical results. Figure 7f displays the statistical results of data distribution based on high-light brightness value, where the degree of dispersion is higher than the above two nighttime light statistical methods. As seen, the high brightness value is very low in most townships.

5.2. Spatial Distribution of Township Hub Level

Figure 8a illustrates the spatial distribution diagram of hub levels of each township. As seen, five hub levels are divided from low to high. The distribution of townships with high hub levels presents two modes, namely, clustered and banded. Similarly, townships with low hub levels also show a certain concentration distribution. On the whole, the townships with lower hub levels are mainly located in the northwest and southwest of the study area, while the townships with higher hub levels and concentrated distributions are mainly located in the central and southwest regions.

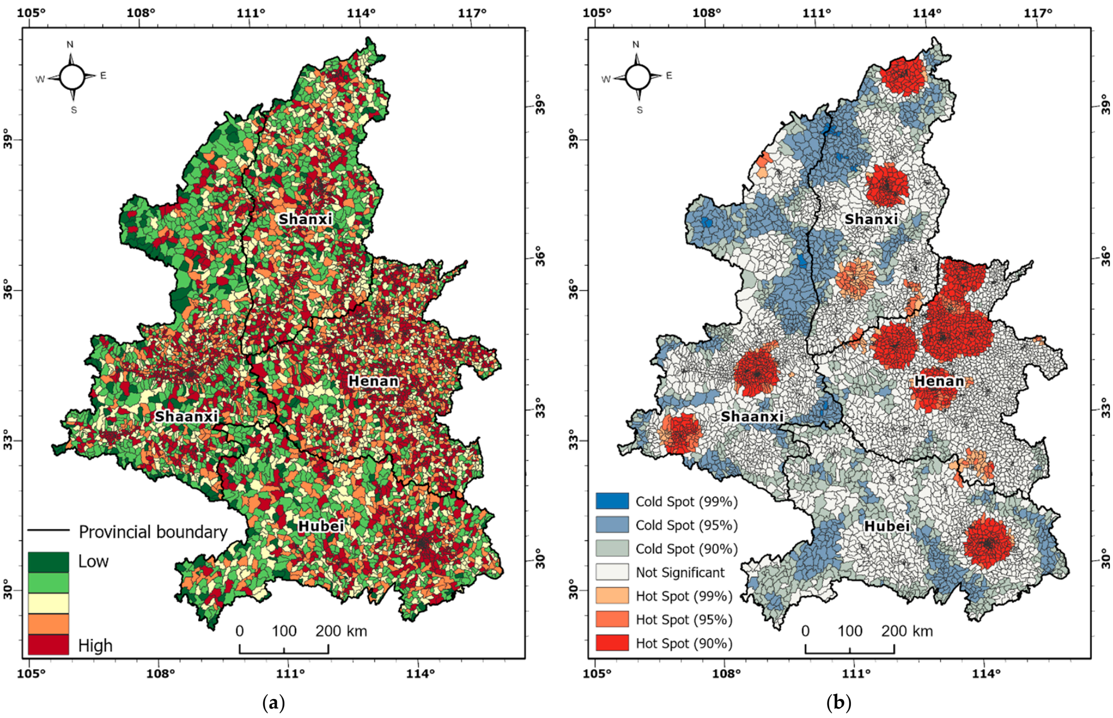

Figure 8. Characteristics of township hub level: (**a**) Spatial distribution of township hub level; (**b**) Spatial autocorrelation of township hub level.

To further understand the spatial distribution pattern of the hub index in each township, we adopt the local spatial autocorrelation method based on the G-Statistic for analysis. As seen from the spatial model diagram in Figure 8b, the township hub index has significant spatial autocorrelation. In the whole study area, Shanxi province has two hot spots of high significance (99%) and one hot spot of low significance (95% or 90%), while Shaanxi and Hubei provinces contain two and one hot spots of high significance level, respectively. The positive townships marked by hot spots in the Henan province are most concentrated in the north, while negatively correlated townships marked by cold spots are scattered throughout the study area. On the whole, most areas with high values are circular, which is because prefecture-level cities have a very large positive effect on the hub index of their neighboring townships. Most of the regions show a positive or negative correlation pattern of spatial agglomeration and only a small proportion of townships show randomness.

5.3. Spatial Association Mapping between Township Development and Hub Level

In this section, the multivariate Geary model is used to calculate the spatial association pattern between two types of variables under different nighttime light statistical methods for 6671 townships. Figure 9a–c respectively show the spatial correlation modes between the mean value of nighttime light brightness, the sum value of nighttime light brightness, and the sum value of high brightness at the township hub level. In this study, the spatial correlation modes include three types, namely, positive, negative, and random correlations. From the perspective of univariate spatial autocorrelation, positive correlation means that in the area with a high mean brightness aggregation value, the township hub level also shows a high aggregation value. By contrast, a negative correlation shows a high-value aggregation of night light brightness, but the township hub level presents a low-value aggregation. The performance of the random mode is that the light brightness value variable shows high-value aggregation, while the township hub level shows an insignificant correlation.

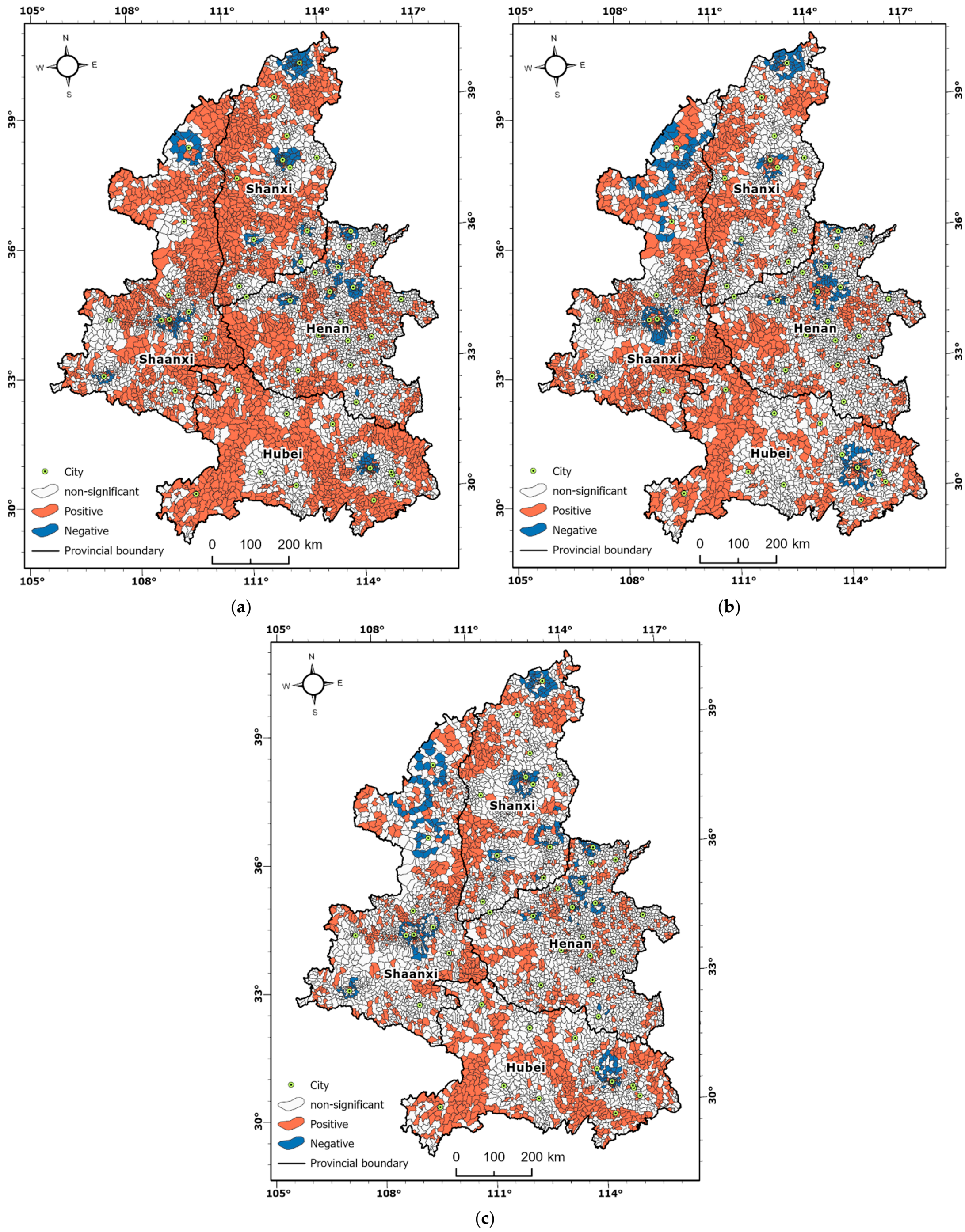

Figure 9. Spatial association mapping between the township development and hub level: (**a**) Correlation with the mean value of nighttime light; (**b**) Correlation with sum value of nighttime light; (**c**) Correlation with sum value of nighttime highlights.

Table 1 shows the statistics of the number and ratio of townships in different modes under each method of light value. Under the three statistical methods, the proportion of towns with positive correlation accounts for 44.98%, 31.18%, and 26.17%, respectively.

Meanwhile, the negative correlation is less than 10% and these correlated townships are distributed around large cities. The radiation effects of large cities weaken the hub levels of surrounding towns. One interesting finding is that the larger townships tend to show a positive correlation pattern, whereas the smaller towns tend to show a random relationship. If a statistical method for measuring the hub level of the township is selected, the average brightness of night lights is superior to the sum of night lights and high-lighted night lights.

Table 1. Number and rate of townships of various patterns under different statistical methods.

Statistical Type	Positive Correlation		Negative Correlation		No Significant	
	Total	**Rate**	**Total**	**Rate**	**Total**	**Rate**
Mean of light value	2978	44.98%	324	4.79%	3468	51.23%
Sum of light value	2111	31.18%	508	7.55%	4151	61.31%
Sum of high light value	1772	26.17%	504	7.44%	4494	66.38%

Based on the characteristics reflected by the nighttime light data, we also found the transport location characteristics of several marginal administrative units of townships. The closer the township is to the city and the township with high transport accessibility, the more apparent the characteristics of integration into the urban economy are shown in the aspects of production and circulation, thereby showing a positive correlation between the township development and the hub levels. The farther away from cities and townships with poor transportation conditions, the weaker the external economic ties and dependence, and even remote towns remain highly self-sufficient economically. The correlation between township development and hub level appears to be random or negative.

From the statistical results of the significance level of positive correlation for four provinces, almost all statistics show that the townships with high confidence levels are less than the townships with a low confidence level in the overall trend, as shown in Figure 10. According to the significant characteristics of the positive correlation between a single statistical indicator of nighttime light and hub levels, except for Shaanxi, the number of townships with a high significance level of mean statistics in other provinces is more than the number of townships with other significance levels.

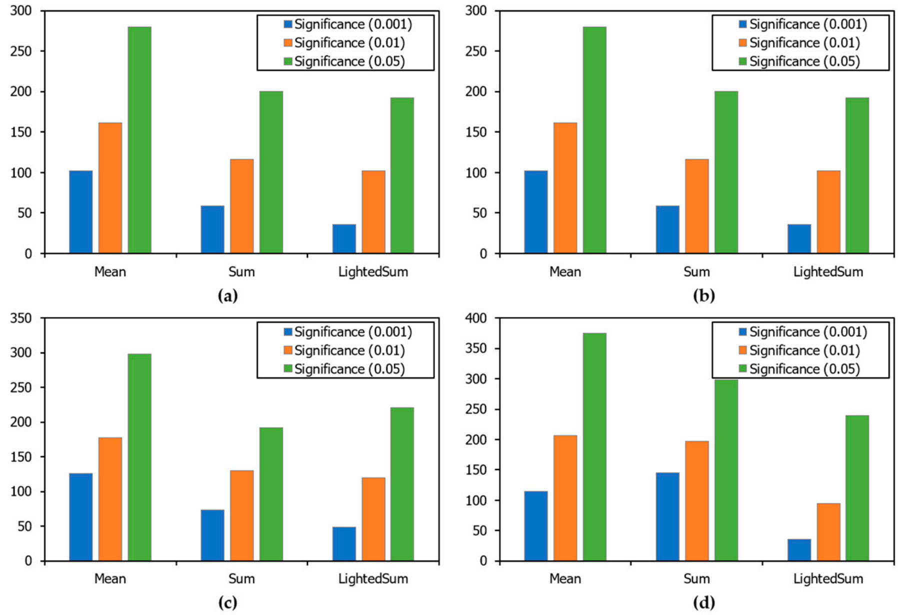

Figure 10. Confidence comparison of association analysis for township hub level and nighttime light indices: (**a**) Shanxi Province; (**b**)Henan Province; (**c**) Hubei Province; (**d**) Shaanxi Province.

At the high significance level of 0.001, Shaanxi Province has the largest number of townships with a positive correlation based on total brightness value, while in the confidence interval of 0.01, Shanxi Province has a similar number of townships with a positive correlation based on mean brightness value and total brightness value. In addition, in the statistics of Hubei Province, the number of townships with positive correlation based on the analysis of total light brightness is the least. Overall, in the townships with positive correlation between nighttime light brightness lighting statistics and hub levels in these four provinces, the quantitative relationship is similar in the overall trend at different significance levels, but the individual statistics of Hubei and Shaanxi provinces are different from the overall trend.

6. Discussion

6.1. Theoretical Contribution

The relationship and influence of transportation on regional economic development have always been important topics in economics and geography. The theoretical contribution of this study is to demonstrate and expand the transport location theory of township marginal administrative units. A mature theory, such as point axis diffusion, has been developed to drive the economic growth of urban and rural areas [54–56]. However, the quantification of the level of township hub function and the quantitative interlinking of economic development and transport function remain to be improved. This study provides an innovative method and analysis to explain the aforementioned problems.

The hierarchical role of the hub also shows the marginal character of the township. The townships have a clear regional feature, which is dominated by the production of primary products. Its economic activities and settlement forms are still dominated by natural conditions and resources. Thus, the absolute dominance of road transport on township development is not apparent. Townships that are closely related to transport locations mainly include industry-oriented and commercial-oriented townships, such as mineral processing, wood processing, agricultural and sideline food processing, warehousing and logistics, sightseeing and recreation, and professional markets. Their hub levels are higher than those of agriculture-oriented townships, such as traditional farming, forestry, and animal husbandry.

6.2. Potential Applications and Relevance

This study presents practical significance for the hub construction and transport planning of the marginal administrative unit of townships in China. For instance, several measures can be proposed accordingly as enhancements for the hub of townships. First, the construction of roads that extend to all townships must be accelerated, and standardized and sustainable management mechanisms must be established. Second, the transport modes in old revolutionary bases, ethnic minority areas, borders, poor areas, and reclaimed forests require vigorous development. Third, transportation construction projects in deeply impoverished areas can be tilted to townships and households as much as possible. Furthermore, the development of road transport in resource-rich and poverty-stricken areas with relatively dense populations must be promoted. Finally, the construction of transportation in advantageous areas of characteristic agricultural products and rich areas of tourism resources must be strengthened. Subsequent research can focus on the national scale effects of township hub level with high density in terms of the difficulty of presentation. With the development of the "transportation power" plan, more and more small railway stations can be developed in townships. Thus, the construction of township hub indicators can also consider the rail transit factor.

6.3. Shortcomings and Future Directions

In this study, we illustrate the rationality of using road transport factors to measure the hub levels of townships. The hub index of each township is calculated under three path modes, namely, township–township, township–county, and township–prefecture-level city. According to the analysis results, the highest positive correlation is 44.98%. In other words, road transport factors account for nearly half of the role of township hub rating. As known, the factors that affect the type of township development in many aspects include the following: natural factors, such as landform, climate, and natural resources; human factors, such as population size and folk culture; economic factors, such as location, transportation, and industrial structure; and political factors, such as policies and regulations [57]. Different influencing factors cause varying characteristics of township development. Therefore, undoubtedly, road transport plays an important role in the level of township development. However, not all townships depend on road transport. For instance, Enshi Tujia and Miao Autonomous Prefecture in Hubei Province has a mountainous terrain, rich resources, and self-sufficiency. The nighttime light brightness in this location is high, but its township hub level regarding road transport is relatively low. Therefore, future research can advance from univariate to multi-variable index township measurement.

Another key issue is the availability of diverse methods to characterize the development level of townships based on nightlight remote sensing data and how to perceive the relationship among different nightlight indicators and the development level of townships more correctly as the key to the reasonable construction of regional development indicators. The complete elimination of non-downtown areas from the nightlight data may also improve the accuracy of regional development indicators. This important topic will be worth exploring in the future. In addition, further comparative studies are needed to confirm whether this research framework and the results can be applied to the township regions of other countries. The aforementioned aspects will be one of our next major research efforts.

7. Conclusions

This study explores the spatial association between township development and the hub level in terms of road transport. First, the development level of the township is reflected from three aspects based on the average brightness, total brightness, and the total high brightness of nighttime light remote sensing data. These three indicators reflect the development level of the township from different perspectives. Second, the hub index of each township is calculated under the three path modes of the township–township, township–county, and township–prefecture-level city. The variability of transportation connectivity between cities, counties, and towns create differences in the level of transportation hubs in various towns. Finally, the correlation between different statistical methods of township development and its hub level is explored by using the multivariate spatial correlation model.

The results show that development is positively correlated with the hub level regarding road transport for a considerable number of townships. At the same time, several negative correlations and random townships are related to the radiation of adjacent city growth poles and township special industrial characteristics. The positively correlated townships show a spatial clustering distribution and a zonal distribution along the north–south direction. The correlation effects of nighttime average brightness are better than those of the sum of nighttime brightness and nighttime high brightness. The townships with positive correlation in the three patterns have similar spatial distribution positions. This study provides an effective analytical method for transportation hub-driven cities or regional hub hierarchy analysis and provides an analytical framework for the correlation analysis between marginal cities and transportation hub hierarchy. In addition, this paper provides an idea for introducing nightlight remote sensing data into the development-level assessment of marginal cities.

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