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Research Article

Evaluating the Spatial Deprivation of Public Transportation Resources in Areas of Rapid Urbanization: Accessibility and Social Equity

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To better understand the transportation situation in rapid urbanization areas and to improve social equity, this study constructed an approach to assess the spatial differentiation of public transportation resources based on deprivation theory and an accessibility analysis. Chenggong New District in Kunming, a typical rapid urbanization area in China, was analyzed as a case study. We introduced 6 indexes to establish a public transportation spatial deprivation evaluation system and applied SPSS to screen out two main factors that reflected the spatial deprivation associated with public transportation resources and services. Then, we adopted the accessibility model and spatial cluster model to embody residents' opportunities to obtain access to public transportation and to judge whether public transportation resource allocation is appropriate. In addition, we used ArcGIS technology to better understand the spatial deprivation characteristics of public transportation. We found that the pattern of public transportation spatial deprivation in Chenggong could be summarized as "multicore and local radiation": the spatial accessibility characteristics of public transportation take the form of a circular layer along with the metro lines and decline progressively toward the peripheral areas, where public transportation resource allocation is lacking. These findings show that the public transportation situation in rapid urbanization areas is consistent with the local land-use context and the suitability of established methods for extracting spatial public transportation characteristics.

1. Introduction

With economic success and social progress, rapid urbanization has become a common phenomenon in developing countries in which the scale of cities has expanded rapidly due to urban expansion. As one of the fastest-growing countries in the developing world, China has undergone a phenomenal urbanization process. The average urbanization growth rate ranges from 1% to 1.5% per year, and China's urbanization rate reached 54.77% in 2014 [1]. The urbanization process has been transformed since the early stage, which mainly occurs in the city center as a medium-term accelerated stage of attempts to expand a city [2]. Although urbanization has been associated with economic prosperity, it has also brought a series of problems, for example, local environmental changes caused by land-use transition [3–7]; increasing energy consumption [8]; and an increasing need for access to opportunities such as education, health care, and recreation. To meet the needs of urbanization areas, rural land around large and medium-sized cities has been expropriated, and the direct urbanization that has occurred in suburban and rural areas has led to problems when the residential spatial differentiation and commuting distance increased simultaneously. The formation of rapid urbanization can usually be

described as government-oriented and market-oriented due to the different forces driving urbanization. Government-oriented urbanization highlights the creation of a series of preferential policies or institutions through which the process of urban development is promoted under the influence of the government. In contrast, market-oriented urbanization is a spontaneous bottom-up process that appears to rely heavily on the market economy and fickle consumers. The rapid urbanization process involves three main aspects: (1) the rapid spread of an urban area to the periphery, which has strong social, economic, and cultural impacts on the entire area; (2) the inrush of a large number of rural residents from rural to nonrural areas; and (3) the transformation of rural areas into new towns or satellite towns through nonagricultural development. The government in China has increased its focus on development speed and demand, and the positive side of urbanization in terms of social development is continuously emerging. Therefore, a series of policies and institutions have been created to perform administrative interventions in urbanization and to promote and guide the urbanization process, making government-oriented urbanization the typical mode. However, even with high-level planning, the government cannot avoid differential development due to the different contexts of land use in rapid urbanization areas, which may lead to the nonuniform spatial distribution of the transportation infrastructure and services due to the broadening diffusion of the urban form [9]. Urbanization will continue to be a long-term general trend of urban development in developing countries.

Social equity is sometimes equated with the term "social stability," which means that until all people are in a relatively socially stable condition, inadequacies in transportation provision could undoubtedly exclude a number of people from fully participating in daily activities, for instance, obtaining access to education, employment, and various social and leisure pursuits [10, 11], which may foster social exclusion and therefore inequity. With the widening economic gap in rapid urbanization areas, the unequal spatial diffusion of social resources makes people, especially the poor, feel deprived. In addition, those who believe they will benefit but instead suffer a disadvantage may experience a psychological change and even increased social dissatisfaction [12], thus causing a negative effect on social stability. Urban transportation resources are among the most frequently used public services, and the allocation of these resources can embody social fairness [13–15] and enable researchers to examine the spatial mismatches between the home locations of vulnerable population groups and the availability of urban services to assess equity. One of the most powerful instruments is the accessibility analysis [16, 17], in which the accessibility measures comprise two main parts: the cost of travel (e.g., money or time) and the availability of opportunities (e.g., the distance to public transportation services). Depending on the perspective of the researcher or the location of origin, transportation mode accessibility can be measured differently, but few scholars have paid attention to the linkage between spatial and temporal issues in social activities. An analysis of this relationship may help government officials identify the appropriate land-use arrangements, especially in rapid urbanization areas where the high-level planning is imperfect. Currently, many countries enjoy automobile-dominated urban travel markets, which make it difficult to promote alternative modes of travel [18], but the detrimental effects of automobiles on both human physical health and the environment [19–21], such as traffic congestion and pollution, have exerted considerable pressure on transportation infrastructures. Therefore, access to public transportation is becoming increasingly important.

This paper aims to establish a relatively complete method to better understand transportation situations in rapid urbanization areas, thus improving the supply level of urban public transportation resources and effectively reducing the differences between different groups in the traffic environment. To build the evaluation index system of public transportation spatial deprivation, we attempted to determine the spatial deprivation characteristics by applying geographical information system (GIS) technique; then, using the minimum time as the travel cost, we constructed a public transportation accessibility evaluation model and obtained the time needed to access public transportation in each traffic analysis zone by calculating the average travel time from a public transportation station to all other public transportation stations. Finally, we introduced a spatial clustering model to evaluate the overall public transportation resource allocation.

2. Methodology

To explore the spatial differentiation characteristics of public transportation and evaluate whether the resource allocation is appropriate among different areas, the methodology was conducted in three steps as follows: first, we established an evaluation index system of the public transportation spatial deprivation; a factor analysis method was used in the evaluation model, and SPSS was used to analyze the factors in the evaluation index system. Then, we established a model to evaluate how public transportation resources are allocated, based on the accessibility evaluation method and spatial clustering analysis method, and to obtain the accessibility spatial pattern of public transportation.

2.1. Establishment of Evaluation Index System. Based on the actual accessibility of transportation resources in most rapid urbanization areas, this research constructed the evaluation index system of public transportation spatial deprivation with two aspects, considering both the transportation infrastructure and its services, shown in Table 1 as infrastructure indicators and service indicators. The former category embodies the distribution of public transportation infrastructure resources in different traffic analysis zones and in turn the convenience of residents in obtaining access to public transportation, which consists of public transportation network coverage, bus station occupancy, and the location quotient of public transportation network density. The latter category includes indexes related to transportation services, such as the availability of bus stations within a diameter of 300 and 500 meters, and the number of bus lines in traffic analysis zones, which can reflect the level of residents' opportunities to obtain access to public transportation and

Table 1: Evaluation index system of spatial deprivation of public transportation.

Category	Index	Definition
infrastructure indicators	public transportation network coverage	proportion of the road length traveled by a bus in relation to the total road length in a traffic analysis zone
	bus station occupancy	proportion of the number of bus stops in each traffic analysis zone in relation to the total number of bus stops in the area
	location quotient of public transportation network density	ratio of network density in each traffic analysis zone to public transportation network density in the overall area
service indicators	number of bus lines per traffic analysis zone	the total number of bus lines in each traffic analysis zone
	location quotient of bus station availability within a 300 meter diameter	ratio of bus station availability in each traffic analysis zone to bus station availability in the overall area within a 300 meter diameter
	location quotient of bus station availability in a 500 meter diameter	ratio of bus station availability in each traffic analysis zone to bus station availability in the overall area within a 500 meter diameter

the public transportation services scope of different traffic analysis zones. The established index system and the index definitions are shown in Table 1.

2.2. Main Factor Analysis Model. Factor analysis is a statistical analysis method based on multiple factors. After the dimension processing of the collected primitive variables is reduced, those that are relatively fewer and play a supporting role for the primitive variables are found to account for most of the information. This paper adopted factor analysis to extract the main deprivation factors from a spatial deprivation evaluation index system, which is given as follows:

$$F_z = \beta_{z1}x_1 + \beta_{z2}x_2 + \cdots + \beta_{zp}x_p \tag{1}$$

where F_z is the score obtained by the main factor z in a traffic analysis zone; β_{zp} is the coefficient of p-th standardization index; x_p represents p-th standardization index of this traffic analysis zone, which is obtained automatically by SPSS processing; and p is a parameter denoting the total number of indexes. Based on the calculated main factor scores, the spatial distribution of public transportation resources and services could be determined. The average score of the main factors was 0, and a negative score indicated deprivation in the aspect of that main factor; the lower the score, the more severe the deprivation.

Based on the scores and contribution rates of the main factors obtained above, we could calculate the composite index of public transportation in each traffic analysis zone. The computation formula is given as follows:

$$C_i = \sum_{z=1}^{m} F_{iz} \times r_{iz} \tag{2}$$

where C_i is the composite index of public transportation in traffic analysis zone i, F_{iz} represents the score obtained by main factor z in traffic analysis zone i, r_{iz} is the contribution rate of main factor z in traffic analysis zone i, and m is a parameter denoting the total number of factors. The average score of the composite index of each traffic analysis zone is 0, and a negative score indicates that it is below the average level. The lower the score, the more severe is the spatial deprivation of public transportation in that traffic analysis zone.

2.3. Accessibility Evaluation Model. Generally, accessibility refers to the degree of difficulty experienced by different residents in traveling through the urban spatial structure from their home to their destination by various transportation modes within the urban transportation network. As an important index that reflects the relationship between urban spatial structure and the transportation network, it can also measure the spatial distribution proportion of transportation resources in the urban spatial structure. To measure accessibility, there are three main methods: the spatial barrier model, the cumulative opportunity model and the spatial interactive model. To measure public transportation network accessibility in rapid urbanization areas, this paper considers the attraction of all public transportation stations to be equal; thus, a spatial barrier model was selected. With the minimum travel time as a spatial barrier, the time accessibility of each public transportation station can be characterized by calculating the shortest average travel time from a public transportation station to all other public transportation stations; the lower the accessibility value, the shorter the average travel time and the better the accessibility. The calculation formula is given as follows:

$$A_e = \frac{1}{n-1} \sum_{\substack{e=1 \\ e \neq f}}^{n} \left(d_{ef}\right) \tag{3}$$

where A_e is the time accessibility of public transportation station e, d_{ef} is the shortest travel time from station e to station f, and n is the total number of public transportation stations in a traffic analysis zone. To characterize the convenience of travelers in obtaining access to public transportation in an integrative manner and to reflect the spatial structure of the time accessibility of public transportation stations, we constructed a comprehensive transportation accessibility

evaluation model based on formula (4), which is given as follows:

$$X_i = \frac{\sum_{e=1}^{n} A_{ei}}{n} \tag{4}$$

where X_i means the public transportation accessibility of traffic analysis zone i, A_{ei} is the time accessibility of public transportation station e in traffic analysis zone i, and n is the total number of public transportation stations in traffic analysis zone i. When we calculated the average time accessibility of public transportation stations to reflect the public transportation accessibility of all traffic analysis zones, if there was no public transportation station in a traffic analysis zone, we used ArcGIS to search for the nearest stations. Therefore, the accessibility of such a traffic analysis zone was calculated by the time needed to walk to the nearest station.

2.4. Spatial Clustering Model. There are two main spatial clustering analysis methods: the global spatial autocorrelation model and the partial autocorrelation model. When a unit was verified, the particular attribute values in the study area were identified as related, alien, or independent of those in the neighboring regions; next, we determined whether the property value was spatial agglomeration or spatial proportionality. There are various indexes and calculation methods for the global spatial autocorrelation model, but the most commonly used Moran's I index, of which the range is $[-1, 1]$. Spatial agglomeration exists when the attribute value is positive, meaning each unit has a positive spatial correlation and good spatial proportionality. In contrast, a spatial differential exists when the attribute value is negative, indicating that each unit has a negative spatial correlation and the resource availability is spatially disproportionality. If the Moran's I index value is zero, it means that there is no spatial correlation, and the attribute values are independent. Usually, the standardized value $Z(I)$ calculated in Moran's I is used to check the statistical significance of the spatial correlation based on the spatial autocorrelation analysis rules in ArcGIS. When $Z(I)$ is greater than 1.65, it suggests a significant spatial relation and good spatial agglomeration; when it is in the range of (-1.65, 1.65), there is a close spatial correlation; and if it is less than -1.65, it indicates that there is significant spatial discreteness. The Moran's I equations are expressed as follows:

$$I = \frac{\sum_{i=1}^{q} \sum_{j=1}^{q} W_{ij} \left(x_i - \overline{x}\right) \left(x_j - \overline{x}\right)}{S^2 \sum_{i=1}^{q} \sum_{j=1}^{q} W_{ij}} \tag{5}$$

$$S^2 = \frac{1}{q} \sum_{i}^{q} \left(x_i - \overline{x}\right)^2 \tag{6}$$

$$\overline{x} = \frac{1}{q} \sum_{i=1}^{q} x_i \tag{7}$$

where S^2 is the variance of public transportation accessibility; x_i and x_j represent the public transportation accessibility of traffic analysis zones i and j, respectively; and W_{ij} is the weight of the spatial distance, which is equal to 1 only if traffic analysis zones i and j are public boundaries and otherwise is equal to 0. q is the total number of traffic analysis zones in the study area.

However, it is difficult to use the global autocorrelation to identify the spatial position when there is agglomeration within a regional space mode; if no statistical significance is embodied, then partial agglomeration may exist. Therefore, in this paper, we combined the global spatial autocorrelation and partial autocorrelation models to reveal the spatial association and agglomeration of the attribute values between the spatial units and their neighborhoods as follows:

$$L(I) = Z_j \sum W_{ij} Z_j \tag{8}$$

$$Z_i = \frac{\left(x_i - \overline{x}\right)}{\sqrt{(1/q) \sum_{i=1}^{q} \left(x_i - \overline{x}\right)^2}} \tag{9}$$

$$Z_j = \frac{\left(x_j - \overline{x}\right)}{\sqrt{(1/q) \sum_{j=1}^{q} \left(x_j - \overline{x}\right)^2}} \tag{10}$$

The analysis depends mainly on whether the value $L(I)$ is positive or negative. If the value is positive, it suggests that the public transportation accessibility of a traffic analysis zone and its surrounding zones are alike; that is, traffic analysis zones with high accessibility are surrounded by high-accessibility areas, and traffic analysis zones with low accessibility are surrounded by low-accessibility areas. In contrast, if the value is negative, traffic analysis zones with high accessibility are surrounded by low-accessibility areas, and traffic analysis zones with low accessibility are surrounded by high-accessibility areas. To consider and clarify the balance between service supply and demand diversity, we divided the traffic analysis zones into four categories: high-high superior, low-low trough, high-low outstanding, low-high backward. The first word in each category, high or low, represents the transportation resources in the traffic analysis zone, and the following words represent the resources in the surrounding areas.

3. Case Study

3.1. Background of Study Area and Traffic Analysis Zone Division. We chose Chenggong New District, which is located in the southeastern part of Kunming, the capital of Yunnan Province, as a case study because it is a microcosm representing many similar areas in China. The district is experiencing unbelievably rapid urbanization, and the infrastructure cannot support the increasing demand. Taking the lead in constructing a new modern version of Kunming, Chenggong is a typical rapid urbanization area. It was 160 km^2 in size with a population of 400 thousand in 2014 and consisted of several functional areas (e.g., the Dounan Flower Industry Area, Luoyang International Logistic Area, Dachong Industrial Area, Wulong Sports Area, Wujiaying Business District, Yuhuayuxiu Education Area, and Dayuxiang Recreational Area) (Figure 1). With the rapid development of the economy

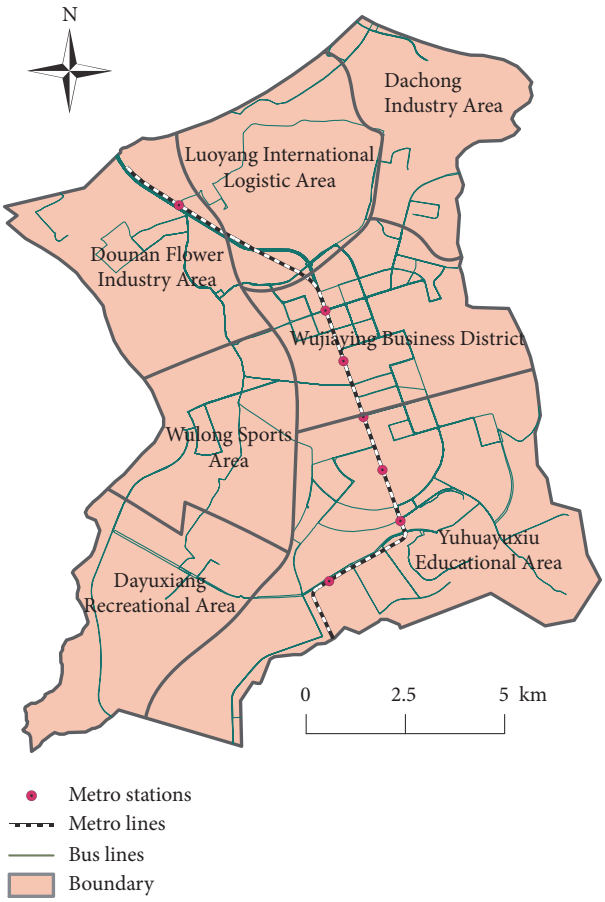

Figure 1: Distribution of the metro and bus line network in Chenggong New District.

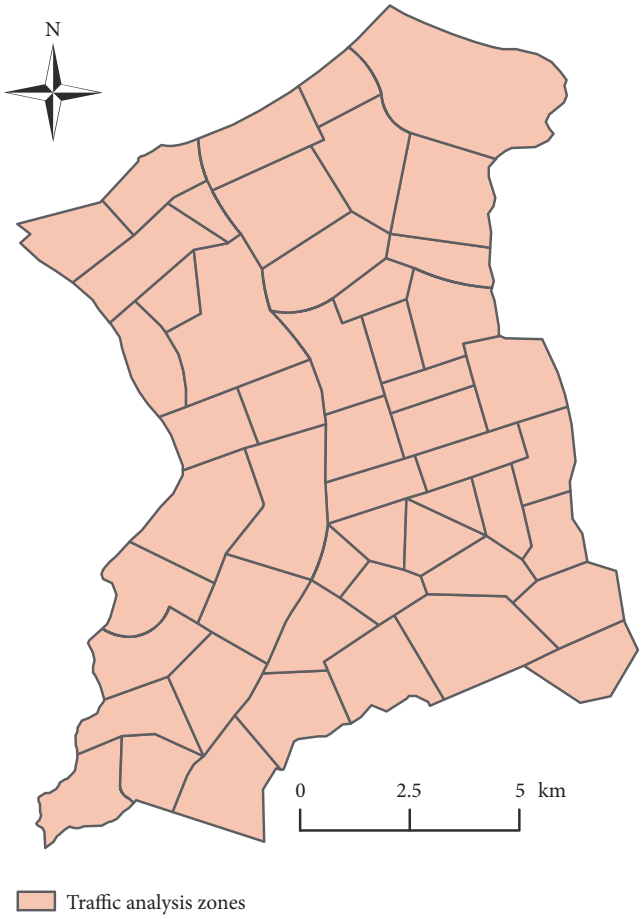

Figure 2: Division of Chenggong New District into traffic analysis zones.

and constant construction, the transportation infrastructure in Chenggong has been greatly improved. The total road length is approximately 285 kilometers, with a core backbone network of more than 100 kilometers. The coverage rate is 58.8%, and the rail transit network is nearly 14.5 km long and includes seven metro stations.

However, due to the phases and the specific nature of the rapid urbanization area under development, Chenggong will remain a diverse urban spatial structure of new central districts, relocated communities and rural areas for some time. Most of the residents of the new districts are farmers, college students, and migrant workers. Due to the limitations of their income, these people rely mainly on public transportation for their travel modes. For people who live in the more dispersed areas of Chenggong, where the public transportation options are bus or subway, different levels of public transportation services are significant differences in space that may produce public transportation spatial deprivation.

To investigate public transportation spatial deprivation and then identify spatial deprivation patterns, the study area was divided into 52 traffic analysis zones based on administrative regions and site characteristics. The traffic analysis zone division results of the Chenggong New District are presented in Figure 2.

3.2. Data Sources. The data adopted in this study were mainly extracted from ArcGIS, including the local public transportation and road transportation networks in Chenggong and roadway network data. To calculate the accessibility of the public transportation network, a network analysis method was used. First, a planning schematic diagram of the Chenggong New District was introduced into ArcGIS for geographic distribution and supplemented by Google Maps. The raster base maps needed in the study were obtained with the digital function of ArcGIS, in addition to the boundaries of the study area and the road transportation network area, and then vectorized in ArcGIS. Second, by querying the Baidu map to obtain bus line and bus station information, which was also vectorized in ArcGIS, a database of the transportation infrastructure in Chenggong was established. By analyzing the buffer zones of bus stations within a diameter of 300 meters and 500 meters in the study area, we clarified the availability of bus stations divided into different sections according to the boundaries of each traffic analysis zone. Finally, we searched the ArcGIS attribute table to obtain parameter values.

Because rail transit and bus transit are independent, they become synchronized only through metro stations. This

Table 2: Calculation results of main spatial deprivation factors.

Evaluation index	Main factor load	
	1	2
location quotient of public transportation network density	0.794	0.343
bus station occupancy	0.831	0.093
location quotient of bus station availability within a 300 meter diameter	0.905	0.172
location quotient of bus station availability within a 500 meter diameter	0.832	0.294
number of bus lines per traffic analysis zone	0.795	0.048
public transportation network coverage	0.162	0.972
Eigenvalue	3.435	1.191
Contribution value (%)	57.248	19.842
Contribution rate (%)	57.248	77.090

paper adopted methods based on a multimodal transportation network data set, meaning that we considered regular bus transit line and rail transit line networks to be connected only in metro stations. To establish a public transportation network and database, ArcCatalog was used to build a dataset of multiple patterns of public transportation networks. Stopping time was converted to time cost, and for the actual operations of public transportation in Kunming, we established two public transportation speeds: the bus was 20 km/h, and rail transit was 40 km/h. Finally, we calculated the shortest travel time from a bus/metro station to all other bus/metro stations and used the network analyst module in ArcMap to analyze the spatial structure of public transportation accessibility in Chenggong New District.

4. Results

4.1. Spatial Deprivation Characteristics of Public Transportation. By applying SPSS statistical analysis software for factor analysis and using orthogonal rotation to reduce the dimensions of the spatial deprivation evaluation index system of public transportation, we obtained results showing that the Kaiser-Meyer-Olkin (KMO) statistic was 0.778, meaning the partial correlation between the different variables was strong. The Bartlett spherical inspection probability was 0.00, less than 0.05 and therefore below the significance level. Therefore, we rejected the null hypothesis and found that the constructed evaluation index system of public transportation spatial deprivation was suitable for factor analysis. Furthermore, we screened out two main factors with eigenvalues exceeding one, and the cumulative explanatory variance reached 77.09%.

The calculation results of the factors are shown in Table 2. The eigenvalue of factor 1 is 3.435, and the contribution value is 57.248%, which is proportional to the density of the public transportation network. The occupation rate of the bus stations, the availability of bus stations within diameters of 300 and 500 meters, and the number of bus routes, as we mentioned before, are related to public transportation services. The eigenvalue of factor 2 is 1.191, with a contribution value of 19.842%, which is proportional to the public transportation line network coverage, indicating a relationship to the transportation infrastructure.

Figure 3 shows that two core regions have been formed based on the spatial distribution of the public transportation service factor scores: the Chenggong Downtown Area (including the Municipal Party Committee and the Longtan District) and the University Town Area. The main factor 1 scores are degressive from the core region to the outward areas, as are the public transportation services, while the spatial deprivation is the opposite (Figure 3(a)). The lower main factor 2 scores are mainly in the inner-city core areas, where the public transportation network has low coverage and where some road branches even have no public transportation lines. In contrast, most rural areas have higher scores with less road length than the core areas; the roads are used as connections to outer areas and thus have a higher coverage rate by the public transportation network (Figure 3(b)). Considering both service deprivation and infrastructure, it is apparent that the spatial deprivation pattern of public transportation in Chenggong is "multicore and local radiation" (Figure 3(c)), with the degree of public transportation spatial deprivation increasing gradually from the urban core to the periphery and the two core regions enjoying a lower level of deprivation. The spatial deprivation pattern of Chenggong is mainly due to inadequate funding to develop the overall area in a coordinated manner; thus, the government gives priority to developing areas with strong actual production demands and business opportunities. Therefore, spatial differentiation of public transportation resources exists.

4.2. Spatial Accessibility Characteristics of Public Transportation. Figure 4 shows that the public transportation accessibility pattern of Chenggong New District forms a circular layer along with the rail transit lines and declines progressively toward the peripheral areas (Figure 4(a)). The more peripheral an area is, the longer the time cost related to its accessibility. The time accessibility of each public transportation station was obtained by querying ArcGIS, and the public transportation accessibility level of each traffic analysis zone was then classified (Figure 4(b)), showing that the spatial diffusion outside the core region is similar to the distribution of public transportation accessibility. The areas with better transportation accessibility are mainly core regions; one of the best is Milan Garden, whose time accessibility is 15.72 minutes, while the lower-accessibility areas are focused on the

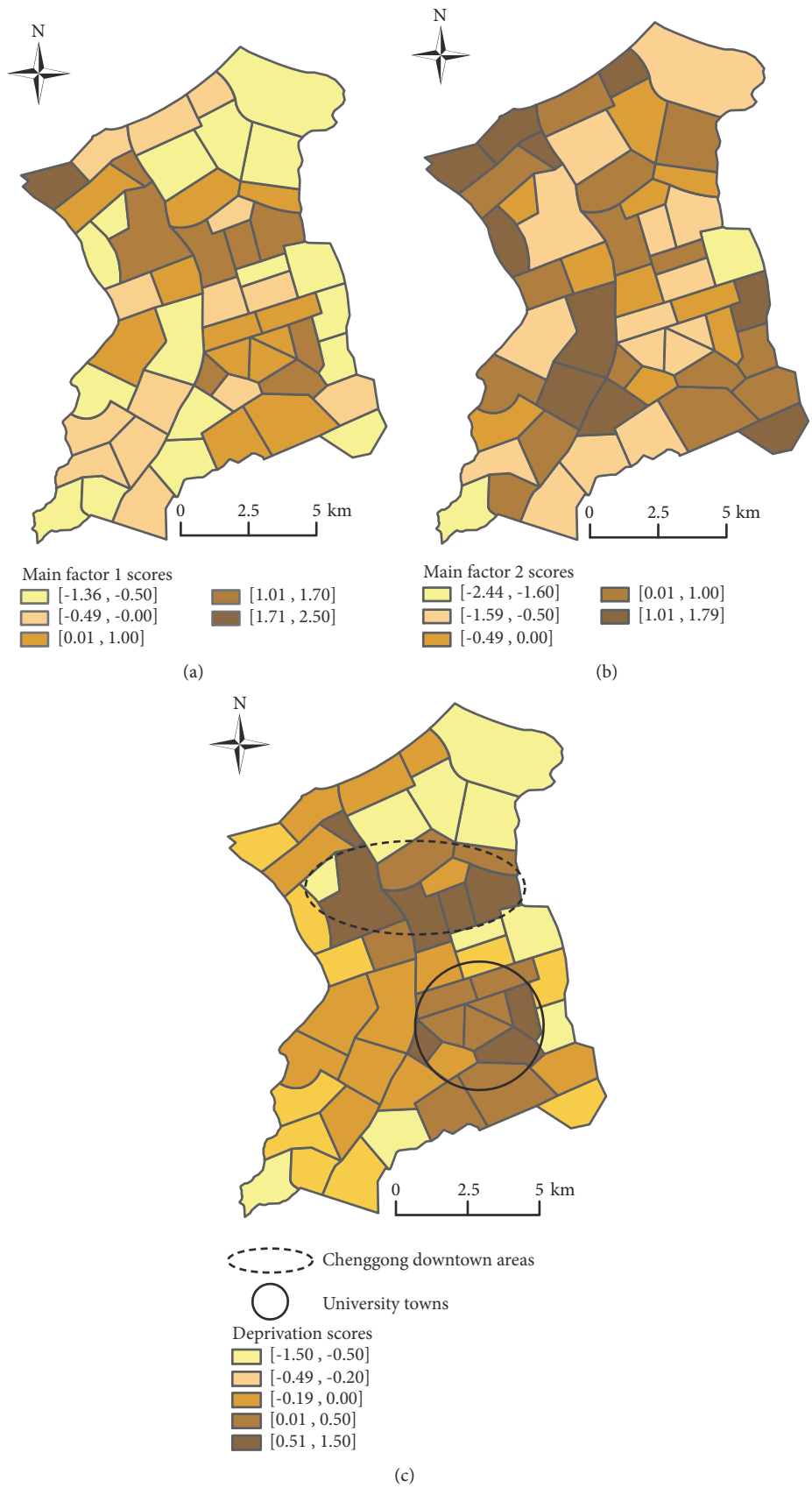

Figure 3: Spatial deprivation distribution of public transportation in Chenggong New District.

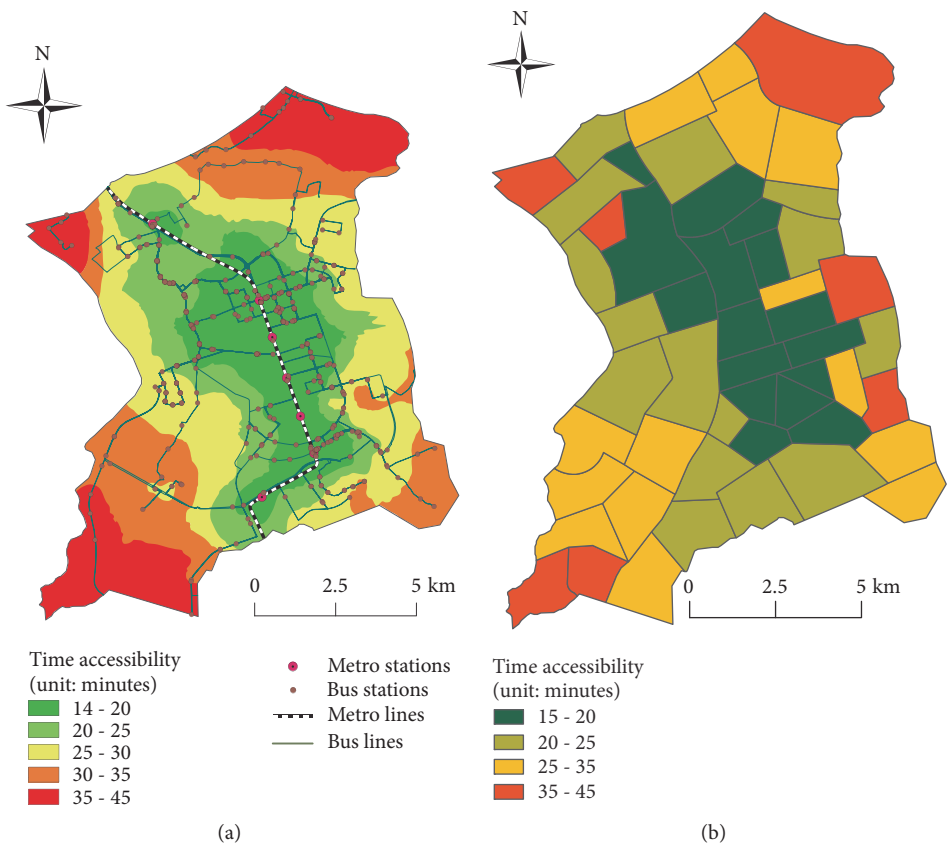

Figure 4: Spatial accessibility distribution of public transportation in Chenggong New District.

Table 3: Distribution frequency of time accessibility in traffic analysis zones.

Time (minutes)	Number of traffic analysis zones	Frequency (%)
15~20	17	32.69
20~25	15	28.85
25~33	13	25.00
35~45	7	13.46

peripheral northwestern, northeastern, southwestern, and southeastern areas. The area with the worst time accessibility is Dawan, at 43.93 minutes. There are certain special cases; for example, the time accessibility of the Plum community is 41.27 minutes, even though the area has a good accessibility atmosphere and is surrounded by areas with good time accessibility. After further investigation, we found that the poor accessibility of the Plum community is mainly due to its social organization, consisting of villages with no public transportation lines or with public transportation lines but no station.

The overall distribution frequency of time accessibility in all traffic analysis zones is presented in Table 3. Traffic analysis zones with good accessibility, meaning a time accessibility of less than 25 minutes, accounted for 61.54% of the zones, but since 38.46% of the traffic analysis zones have a time accessibility of more than 25 minutes, the overall accessibility of Chenggong New District remains low. Seven traffic analysis zones had a time accessibility that exceeded 35 minutes; the residents of those areas experience serious spatial deprivation.

4.3. Spatial Allocation Analysis of Public Transportation Resources. In terms of the results calculated by the spatial clustering model, the values of Moran's I and $Z(I)$ are 0.29 and 3.74, respectively; p is less than 0.01, which suggests that the test results are significant, and the public transportation accessibility of Chenggong is significantly positively correlated (Figure 5). According to the results, Chenggong New District can be divided into three categories as follows.

High-High Superior. In this type of area, traffic analysis zones and their neighborhoods have good transportation accessibility, and a positive spatial correlation is observed. Compared with other areas, the traffic analysis zones enjoy a complete infrastructure. These areas are mainly the core regions of the city.

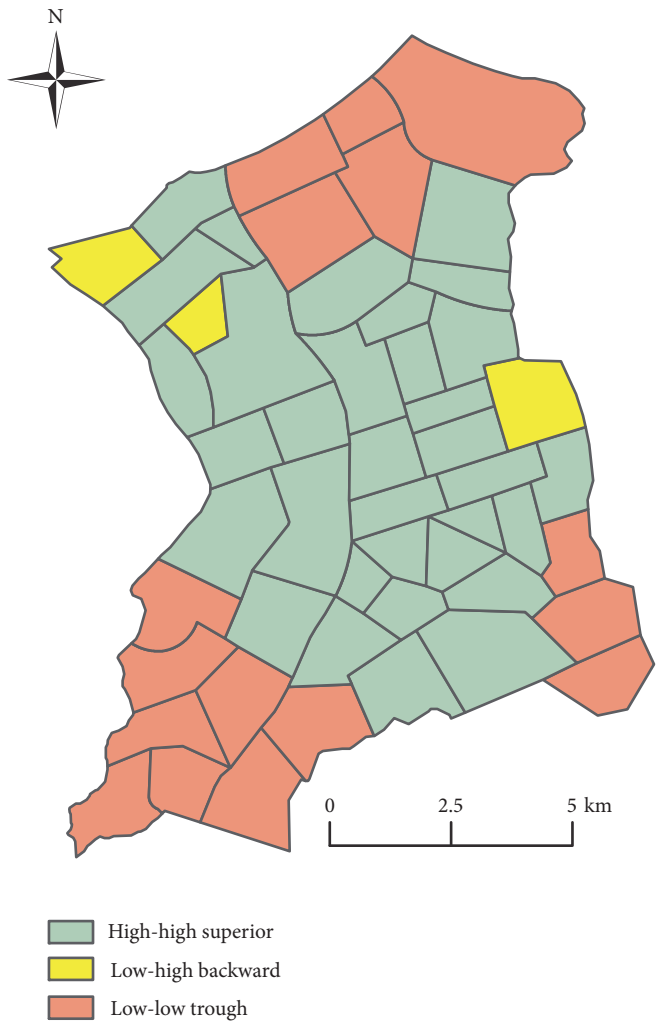

Figure 5: Spatial allocation pattern of public transportation resources in Chenggong New District.

Low-High Backward. In low-high backward areas, the traffic analysis zones have good transportation accessibility, while the neighborhoods have bad accessibility, meaning they are spatially negatively correlated. Three obvious trough areas in Chenggong New District, which also have poor transportation accessibility, are the Wangguan, Plum and White Longtan communities.

Low-Low Trough. Areas with poor transportation accessibility in both traffic analysis zones and neighborhoods and with a positive spatial correlation are low-low trough areas. In Chenggong, this type of area is mainly located in the northeastern, southwestern, and southeastern parts, accounting for 37%, which indicates that public transportation resource allocation in Chenggong remains obviously inequitable.

Compared with high-high superior regions, low-high backward and low-low trough areas are mainly located in the outer regions of Chenggong, which is consistent with the development pattern that usually expands outward in rapid urbanization areas.

5. Conclusion and Discussion

The assessment of transportation situations in rapid urbanization areas is critical to enable the creation of proactive policies for high-level planning, to reduce spatial deprivation and to improve social equity, which are urgent problems. However, few studies have focused on this issue. This study proposed a complete evaluation system based on the establishment of an index system, an assessment of transportation deprivation and an analysis of public transportation resource allocation to evaluate transportation situations in rapid urbanization areas on the basis of the actual data we could obtain. First, by considering the transportation infrastructure and transportation services that greatly influence residents' trips, an evaluation system was established that consisted of six indexes. Then, a main factor analysis was used to calculate the eigenvalues and contribution values of each evaluation index. Two main factors were chosen by SPSS to represent the public transportation network coverage and transport infrastructure services, and the spatial deprivation characteristics of public transportation in the case study

area were obtained. Second, by using the accessibility model and with the shortest time as the trip cost, ArcGIS was applied to determine the spatial structure of each traffic analysis zone. Third, global spatial autocorrelation and partial autocorrelation models were combined to analyze the spatial distribution of public transportation resources in the case study area. The results show that there are three types of resource allocation: high-high superior, low-high backward and low-low trough. These types appear most often in the outer regions of rapid urbanization areas, exhibiting obvious transportation inequity and spatial deprivation that should attract our attention.

This study proposed a useful method to evaluate the spatial deprivation of public transportation resources. This method will be beneficial for planners and managers seeking to better understand the spatial distribution of public transportation resources and develop appropriate strategies for equally allocating public transportation resource across regions to better meet residents' basic travel needs. However, the deprivation evaluation system constructed in this paper should be further discussed, as the number of indexes is relatively low. The limits of our capability to obtain more data indicate that a more comprehensive evaluation system can be created to take more deprivation factors into account, for example, the population of traffic analysis zones, average income level and/or public transportation service frequency. In addition, even though we take the transfer riding strategy between bus and rail transit into account for the transportation accessibility analysis, other factors, such as transfer fee affordability, that influence public transportation accessibility have been omitted. Thus, a certain gap with actual accessibility exists.

Data Availability

The transportation network data used to support the findings of this study were supplied by Kunming Traffic Transport Bureau under license and so cannot be made freely available. Requests for access to these data should be made to Kunming Traffic Transport Bureau.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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