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Numerical Simulation and Spatial Distribution of Transportation Accessibility in the Regions Involved in the Belt and Road Initiative

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Abstract: The Belt and Road Initiative (BRI) is a Chinese strategy, proposed to strengthen the connectivity and cooperation among BRI countries. Under this circumstance, many transportation projects are planned to be carried out, which means the transportation accessibility evaluation is of significance in providing valuable suggestions for transportation construction. This research established a global transportation accessibility index (GTAI) model in the BRI region using raster data. Based on its gridded outputs, we conducted classification evaluation, autocorrelation analysis, and a geographical weighted regression model to explore the spatial characteristics of the GTAI distribution and its correlation with population density. The results show that: (1) most countries in Europe and the Middle East, western Russia, and eastern China enjoy high accessibility, while central regions (e.g., Central Asia and western China) have poor access to destinations; (2) the GTAI values are distributed as a spindle, where about 60% areas belong to the middle transportation accessibility region, mapped as a non-significant type; and (3) there is a positive relationship between transportation accessibility and population distribution, but their connection tends to be weaker as socioeconomic development increases. Finally, several policy implementations are provided: (1) give a priority to road or railway construction between China and Central Asian countries; (2) establish an innovative transportation system and introduce advanced technologies to enhance the exchange and cooperation among the BRI countries; (3) improve public transport management in well-developed regions, and introduce talents and strengthen transportation infrastructure construction in developing regions.

Keywords: transportation accessibility; correlation analysis; spatial analysis; Belt and Road initiative

1. Introduction

The Belt and Road Initiative (BRI) is a Chinese strategy with the principle of "openness and inclusiveness" and "wide negotiation, joint development and sharing benefits," aiming to strengthen the connectivity and cooperation among BRI countries [1]. Since its inception in 2013, the BRI regions have made significant progress [2]. According to the World Bank statistics, the share of 65 BRI countries (more details are presented in Section 2.1) in world GDP increased by 3% and the GDP per capita of those countries has increased by 132% in the past five years, significantly outpacing the growth rate of global GDP per capita. It is this rapid development that catches the eyes of many scholars. Specifically, Suocheng et al. [3] put forward four modes of sustainable economic development for the Silk Road Economic Belt to show the distribution pattern of resources, ecological environment, society, and economy for the Silk Road Economic Belt. Li et al. [2] used nighttime light data to reflect the spatial and temporal city development of countries along the Belt and Road. In addition, the change of

population and urbanization in those counties has been studied by Liu et al. [4] based on a spatial auto-correlation analysis and hierarchical cluster analysis from 1950 to 2050.

Although there has been much research related to BRI countries' development, few of them focus on evaluating the transportation accessibility in those regions. However, under BRI, many roads, railways, ports, and airports are planned to be built to address the transport disadvantage and achieve transportation equality in BRI regions [5], so as to balance socioeconomic progress and integrate the principle of territorial cohesion [6]. Within this context, accessibility evaluation is of great significance, which could answer the question of where the transportation infrastructures need to be built.

Accessibility, meaning the ease of reaching destinations, consists of two parts: mobility and potential, reflecting the ability to move in the traffic network and the number or size of reachable opportunities, respectively [7]. Many scholars have focused on the measurements of transportation accessibility. In 1959, Hansen was the first to put forward a gravity measure for accessibility in view of land development [8]. After that, lots of new approaches have been developed. For example, Murray et al. [9] used buffer analysis to evaluate public transport accessibility in the Southeast Queensland region of Australia. Yigitcanlar et al. [10] and Liu and Zhu [11] proposed a general framework to conduct accessibility analysis based on geographic information systems. Mavoa et al. [12] and Saghapour et al. [13] focused on developing related indexes to illustrate levels of accessibility. Balsa-Barreiro et al. [14] took territorial cohesion into consideration and evaluated accessibility in a Spanish region by considering both public and private transport modes.

Based on the above discussion, we find that existing transport accessibility measures mainly focused on one or two transportation modes (such as roads and railways), often presented as vector data, which cannot fully reflect the regional transportation ability. Besides, many researchers focused on evaluating transportation accessibility in a city or subarea by calculating residents' travel time, cost, and distance [8–14], which is not suitable for determining the transportation condition level at the macro scale due to problems in data availability. In light of this, we developed a global transportation accessibility index (GTAI) model based on raster data, and took road, railway, waterway, airports, and ports into consideration. Then, classification evaluation and autocorrelation analysis were applied to figure out the distribution characteristics of accessibility in BRI regions. After that, a geographical weighted regression (GWR) model was conducted to explore the spatial relationship between accessibility and population density. Finally, several policy suggestions are provided based on our results.

This paper is organized into six sections. In Section 2, we expound the study area and data source. In Section 3, the GTAI model, weight assignment methods, and spatial analysis methods are presented. In Sections 4 and 5, we analyze the results and conduct a discussion of our work, respectively. The conclusions are drawn in Section 6.

2. Study Area and Data Sources

2.1. Study Area

There is no defined list of countries or regions in the Belt and Road initiative (BRI) because it is open to all interested countries. However, in academic research, there is a widely used group of 65 countries [15]. At present, the total length of main roads in those countries is around 517,400 km, while the total length of the railway networks is about 384,500 km, accounting for 28% of the world's total railways [16]. In addition, the socioeconomic conditions and infrastructure quality of those countries vary widely [17,18]. Considering their development inequity, we selected them as our study area, which could also provide valuable suggestions for a global accessibility evaluation. In this study, we divided those countries into six sub-regions based on their location (see Table 1). The spatial distribution of six economic corridors (Bangladesh–China–India–Myanmar Economic Corridor, BCIMEC; New Eurasian Continental Bridge, NECB; China–Pakistan Economic Corridor, CPEC; China–Indochina Peninsula Economic Corridor, CIPEC; China–Mongolia–Russia Economic Corridor, CMREC; China–Central

Asia–West Asia Economic Corridor, CCAWAEC) and population density in the BRI region are presented in Figure 1. Since the Maldives lacks related data, only 64 countries are included in the later discussion.

Table 1. Countries involved in the Belt and Road initiative.

Region	Countries	Number
China–Mongolia–Russia	China, Mongolia, Russia	3
Southeast Asia	Vietnam, Laos, Cambodia, Thailand, Malaysia, Singapore, Indonesia, Brunei, Philippines, Myanmar, Timor-Leste	11
South Asia	India, Pakistan, Bangladesh, Afghanistan, Nepal, Bhutan, Sri Lanka, Maldives	8
Central Asia	Kazakhstan, Kyrgyzstan, Tajikistan, Uzbekistan, Turkmenistan	5
Central and Eastern Europe	Poland, Czech Republic, Slovakia, Hungary, Slovenia, Croatia, Romania, Bulgaria, Serbia, Montenegro, Macedonia, Bosnia and Herzegovina, Albania, Estonia, Lithuania, Latvia, Ukraine, Belarus, Moldova	19
West Asia and Middle East	Turkey, Iran, Syria, Iraq, United Arab Emirates, Saudi Arabia, Qatar, Bahrain, Kuwait, Lebanon, Oman, Yemen, Jordan, Israel, Palestine, Armenia, Georgia, Azerbaijan, Egypt	19

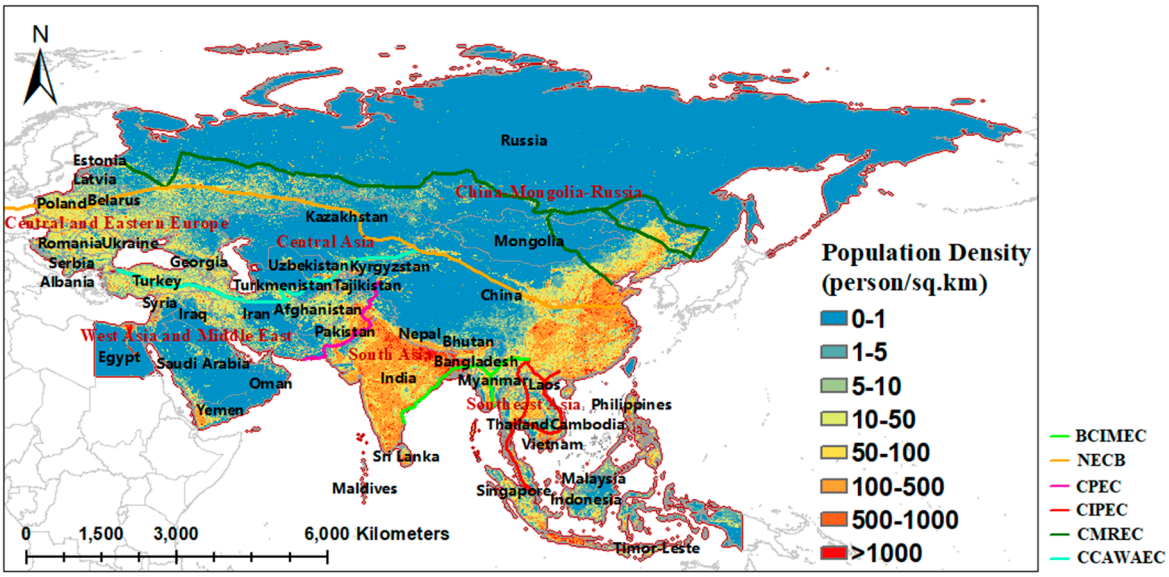


Figure 1. Map of population density and six economic corridors in the Belt and Road Initiative (BRI) region. BCIMEC, Bangladesh–China–India–Myanmar Economic Corridor; NECB, New Eurasian Continental Bridge; CPEC, China–Pakistan Economic Corridor; CIPEC, China–Indochina Peninsula Economic Corridor; CMREC, China–Mongolia–Russia Economic Corridor; CCAWAEC, China–Central Asia–West Asia Economic Corridor.

2.2. Data Sources

The point layers (airports and ports data) were downloaded from OurAirports [19] and the Food and Agriculture Organization of the United Nations (FAO) GeoNetwork [20], respectively. The line layers, such as road and railway data, were obtained from DIVA-GIS [21], while river data were acquired from Natural Earth [22]. In order to determine the road, railway, and waterway density data, we calculated the sum of the road, railway, and river lengths in each grid cell (10 km × 10 km), and then divided the length by the area of the grid cell. Considering that this is a large-scale study, we only selected primary and secondary roads, operational railways, and rivers with moderate detail

(under a 50 m level). The shortest distances in each grid cell to four kinds of transport facilities were calculated using ArcPy. The distance is the length of the straight line from the center point of each cell to a nearest road, railway, airport, or port in the same country. If a facility is not present in a country, for example, many landlocked countries do not have ports, the shortest distance is automatically assigned as the maximum distance from other cells to this type of facility. Also, to some extent, transportation evaluation needs to take population density into account [23]. Many studies have been conducted on this topic [24,25]. In light of this, LandScan population data in 2015 were used in this study to adjust transportation indices [26] (see Figure 1).

3. Method

3.1. Global Transportation Accessibility Index Model

Referring to Feng et al.'s study [27], two main sub-indices, namely the transportation density index (TDI) and transportation convenience index (TCI), were assigned the same weights to calculate the GTAI. The TDI is the aggregation of the normalized road density (RDI), railway density (RWDI), and waterway density (WDI) based on correlation analysis. The TCI is the combined normalized shortest distances from each grid cell to roads (SDRI), railways (SDRWI), airports (SDAI), and ports (SDPI) based on a pairwise comparison. Min-max normalization was used in this study, which is defined as follow:

$$x_i^* = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{1}$$

$$x_i^* = \frac{\max(X) - x_i}{\max(X) - \min(X)} \tag{2}$$

where x_i^* is the normalized value of x in grid cell i, and X is the set of variable x. In this study, SDRI, SDRWI, SDAI, and SDPI were normalized using Equation (2), while other variables used Equation (1). As such, all indices ranged from 0 to 1, and high values indicated a high transportation ability. The detailed process of the GTAI model is presented in Figure 2.

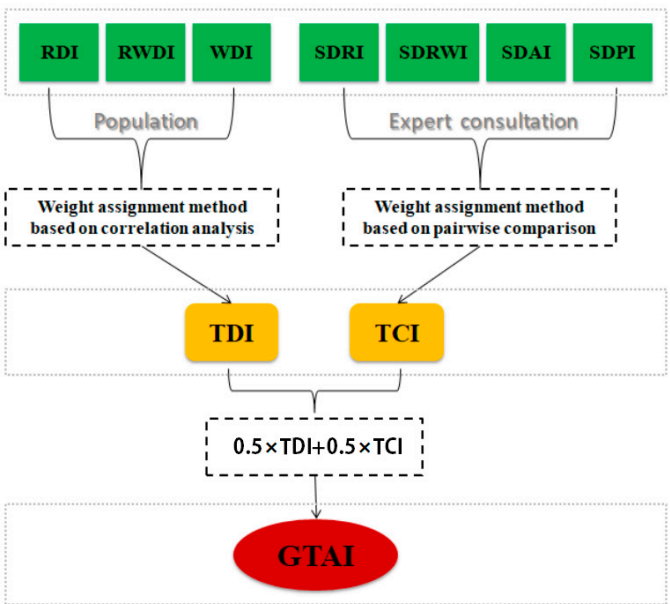


Figure 2. Schematic of GTAI model. RDI, road density index; RWDI, railway density index; WDI, waterway density index; SDRI, shortest distance to road index; SDRWI, shortest distance to railway index; SDAI, shortest distance to airport index; SDPI, shortest distance to port index; TDI, transportation density index; TCI, transportation convenience index; GTAI, global transportation accessibility index.

3.2. Weight Assignment Method Based on Correlation Analysis

There are two general types of relationships between things, a functional relationship and statistical relationship. Because of the uniqueness of the functional relationship, it is easier to analyze and measure [28]. However, relationships often appear in non-unique and indirect forms, which cannot be described using a functional formula. Within this context, correlation analysis was introduced to reveal, analyze, and explain the connection between things. Considering that different transport modes may contribute differently in each country, correlation analysis was used to explore the relationship between the population and three normalized traffic density factors (RDI, RWDI, and WDI) for each country in this study. This was done to determine the appropriate weights, and the degree of correlation was shown using Pearson's correlation coefficient, which is the covariance of the two variables divided by the product of their standard deviations [29]. Assuming that there are two variables, x and y, we can calculate their Pearson correlation coefficient based on Equation (3):

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})\left(y_i - \overline{y}\right)}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(x_i - \overline{y})^2}} \tag{3}$$

where r represents the Pearson correlation coefficient, $\left(x_i, y_i\right)$(i = 1, 2, ..., n) is the n-pair observed values of two variables (population density and RDI/ RWDI/ WDI), and $\overline{x}$ and $\overline{y}$ are the mean values of the n-pair observed values. The range of the r value is from −1 to 1, where a positive value indicates a positive correlation, while a negative value indicates a negative correlation. Moreover, the greater the absolute value of r, the closer the connection between x and y. Because of this, the absolute values of the correlation coefficients between the population and three kinds transportation density were conducted as a reference for the weight assignment to calculate TDI. Its equation can be expressed as:

$$TDI_i = \frac{r_1 RDI_i + r_2 RWDI_i + r_3 WDI_i}{r_1 + r_2 + r_3} \tag{4}$$

where r_1, r_2, and r_3 refer to the correlation coefficient between road density, railway density, waterway density and population in a country, respectively; and RDI_i, $RWDI_i$, and WDI_i are the grid cell i's normalized road density, railway density, and waterway density, respectively. The weights of the RDI (W_1), RWDI (W_2), and WDI (W_3) of each country are presented in Appendix A.

3.3. Weight Assignment Method Based on A Pairwise Comparison

Since airports are less likely to be located in a densely populated area and most large transportation ports are by the sea, it is not reasonable to use correlation coefficients between them and the population to determine their contributions. Given this, pairwise comparison was applied to the assignment weights for those four shortest distance indices. This is in line with the analytical hierarchy process, widely used in complex decision-making models [30,31]. The detailed processes used to calculate weights for each shortest distance index is described as follows.

First, a pairwise comparison matrix was constructed. In this study, SDRI, SDRWI, SDAI, and SDPI were assumed as factors affecting transportation convenience. After consulting experts and performing investigations, we determined a matrix of pairwise comparisons of those four factors (see Table 2), and then its eigenvector, maximum eigenvalue, and consistency ratio (CR) were calculated. If CR was less than 0.1, the normalized eigenvector was the weight vector. If not, the pairwise comparison matrix needed to be reconstructed. For the following matrix, its maximum eigenvalue and CR were 4.02 and 0.07, respectively; therefore, the normalized eigenvector was regarded as a weight vector (see Table 2).

Table 2. Pairwise comparisons of factors affecting transportation convenience.

	SDRI	SDRWI	SDAI	SDPI	Weight
SDRI	1	3	3	6	0.53
SDRWI	1/3	1	1	3	0.20
SDAI	1/3	1	1	3	0.20
SDPI	1/6	1/3	1/3	1	0.07

3.4. Autocorrelation Analysis

3.4.1. Global Moran's I

Moran's I has been frequently introduced to demonstrate the spatial autocorrelation characteristics of geographical features [32,33], which can be calculated as follows:

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})\left(x_j - \overline{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \tag{5}$$

where W_{ij} represents the weight; X_i and X_j are the values of X in the corresponding spatial units i and j, respectively; $\overline{X}$ denotes the average of the X value; n is the total number of spatial units; and i represents the ith unit. Moran's I value is between −1 and 1. A value close to 1 implies a positive autocorrelation, while a value close to −1 refers to a negative autocorrelation. If its value is close to 0, it suggests a random spatial distribution. Moreover, Moran's I can be tested using the z-value and *p*-value, and their relationship with confidence levels is shown in Table 3.

Table 3. The criteria of z-score, *p*-value and confidence level.

Z-Score	*p*-Value	Confidence Level
<−1.65 or >1.65	<0.10	90%
<−1.96 or >1.96	<0.05	95%
<−2.58 or >2.58	<0.01	99%

3.4.2. Local Moran's I

To deeply analyze the spatial correlation of accessibility, this paper applied local Moran's I to analyze the spatial cluster and outlier of accessibility in GeoDa (developed by Anselin et al., Chicago, IL, USA), which is also known as the local indicators of spatial association (LISA) [34]. It can be measured using:

$$\text{LISA}_i = \frac{X_i - \overline{X}}{\sigma^2}\sum_{j=1}^{n} w_{ij}\left(X_j - \overline{X}\right)(i \neq j) \tag{6}$$

where LISA_i is the local Moran's I for sample i, σ^2 is the overall variance of all samples, while other variables are the same as Equation (5). There are four kinds of distribution characters: cluster of high values (HH), cluster of low values (LL), high values surrounded by low ones (HL), and low values surrounded by high values (LH).

3.5. Geographical-Weighted Regression Model

Unlike traditional linear regression, which assumes that the relationship is spatially constant, GWR uses the local statistics, using local parameters to represent the non-stationarity of geographical variables [33,35]. It can be expressed as the following:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{7}$$

where (u_i, v_i) denotes the coordinates of location i in space, $\beta_0(u_i, v_i)$ represents the intercept value, x_{ik} is the kth independent variable at location i, and $\beta_k(u_i, v_i)$ represents the parameter for the kth independent variable at location i. In this study, about 10,000 points randomly located in the BRI region were selected as samples to conduct the GWR, reflecting the spatial relationship of GTAI and the population.

4. Results

4.1. Classification Evaluation of Transportation Accessibility

For a better discussion, we divided the BRI region into five classes based on GTAI values using natural breaks in ArcGIS 10.2. The GTAI of the low transportation accessibility region was defined as being less than 0.35. As presented in Figure 3 and Table 4, only a small area suffered low accessibility, accounting for 1.21% of the whole BRI territory, with a population density close to 0, mainly in the eastern parts of Russia. The GTAI of the middle–low transportation accessibility region was defined as being between 0.35 and 0.46, mainly concentrated in northern and eastern Russia, western and eastern Mongolia, western China, western Indonesia, Afghanistan, Yemen, Oman, and Laos. Although those areas covered an area of 7.42 million km^2, which was twice as the large as high accessibility regions, only 1.09% people were living in there. This was possibly due to their poor conditions, high elevation, adverse climate, or low economic capabilities, which restricted local transportation development. About 60% of the BRI regions belonged to the middle transportation accessibility regions, defined as a GTAI from 0.46 to 0.53, which was more likely distributed in Central Russia, northwestern China, most areas in Central Asia and Belarus, parts of Southeast Asia, western Indonesia, and Egypt, with a population density of 35 people/km^2. As for the middle–high transportation accessibility region (defined as a GTAI between 0.53 and 0.59) and the high transportation accessibility region (defined as a GTAI larger than 0.59), their distribution characteristics were similar, mostly located in European regions, western Russia, India, eastern China (especially in the Beijing–Tianjin–Hebei region, Yangtze River Delta, and Pearl River Delta), with population density of 187 people/km^2 and 437 people/km^2, respectively. It suggests that a high accessibility level was more likely to attract more residents [36]. The detailed spatial relationship between the population density and accessibility is discussed in Section 4.3.

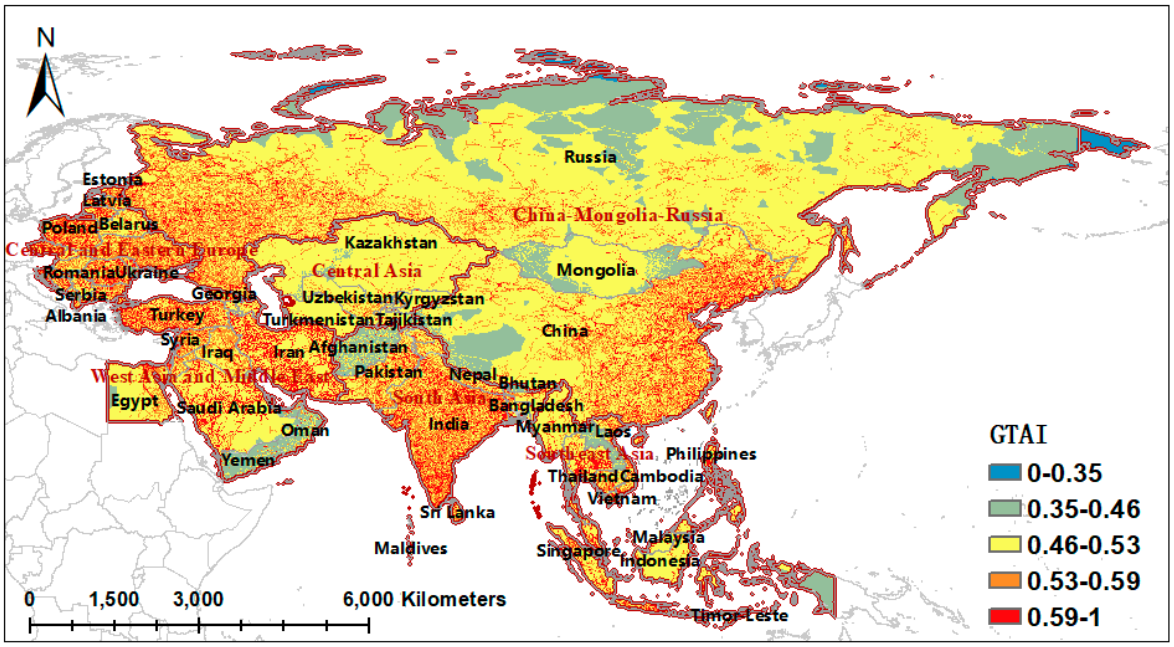


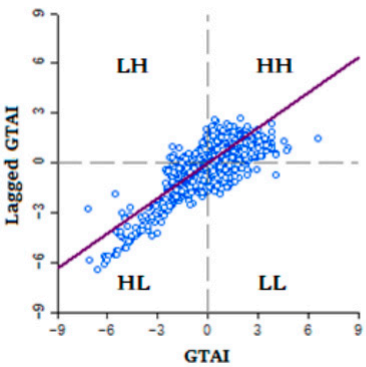
Figure 3. Spatial distribution of GTAI in the BRI region.

Table 4. Statistics of land in different transportation accessibility regions.

Class	Land		Main Regions
	Area (million km^2)	Proportion (%)	
Low transportation accessibility region	0.61	1.21	Eastern Russia
Middle–low transportation accessibility region	7.42	14.69	Northern and eastern Russia, western and eastern Mongolia, western China, western Indonesia, Afghanistan, Yemen, Oman, and Laos
Middle transportation accessibility region	29.74	58.84	Central Russia, northwestern China, most areas in Central Asia and Belarus, parts of Southeast Asia, western Indonesia, and Egypt
Middle–high transportation accessibility region	9.06	17.92	Most European regions, eastern Egypt, western Russia, central and eastern China, India
High transportation accessibility region	3.71	7.34	Most European regions, western Russia, eastern China, India

4.2. Autocorrelation Analysis of GTAI

Considering that a simple classification evaluation cannot reflect spatial distribution characteristics, we selected 10,000 random points in ArcGIS for spatial analysis. After removing invalid records, only 9950 sample points were used in the analysis discussed below. The result suggests that there is less than a 1% possibility that this clustered pattern could be the result of random chance, with a global Moran's I of 0.48, z-score of 287.42, and *p*-value less than 0.001. Under this circumstance, LISA was conducted to map its spatial cluster effects. Figure 4 shows the Moran scatter plot of GTAI and the number of samples for each cluster type. It shows that more than 60% of points belonged to a non-significant (NS) type, while about 21.33% of samples were regarded as HH clusters, 15.21% samples were classified into LL regions, and only 85 samples experienced different accessibility with their surroundings. These ratios imply the aggregation of the GTAI distribution, consistent with the results of the global Moran's I and previous classification evaluations. For example, about 60% of the BRI regions belonged to middle transportation accessibility regions, which was close to the sample proportion of the NS type.



Cluster types		Number	Proportion (%)
Significant	HH	2123	21.34
	HL	33	0.33
	LL	1513	15.21
	LH	52	0.52
	Total	3721	37.40
Not Significant	NS	6229	62.60

Figure 4. Moran scatter plot of the GTAI. HH, cluster of high values; LL, cluster of low values; HL, high values surround by low values; LH, low values surrounded by high values; NS, not significant.

In order to more intuitively express the clusters and outliers, we mapped the LISA clusters (see Figure 5). Each cluster has its own characteristics: (1) HH clusters: those areas that had high accessibility and were surrounded by points with high accessibility. The specific characteristics were that the accessibility in this type of region was relatively high, but with weak spatial heterogeneity. Most of them were distributed in Central and Eastern Europe, northern parts of West Asia and Middle East, India, and eastern China. Those regions tended to enjoy high socioeconomic levels. (2) LL clusters: those areas that had low accessibility, as well as their neighbors. Similar to HH clusters, a small spatial

difference was observed. They mainly concentrated in less-developed regions, depopulated zones, or natural reserves, with few people, like northern and eastern Russia, western and eastern Mongolia, western China, Afghanistan, Yemen, Oman, and eastern Indonesia. Those areas were more likely to be dominated by mountainous terrain with large slopes covered by vegetation. (3) HL regions: those areas that had high accessibility but surrounded by points with low accessibility, with a strong spatial heterogeneity. Compared with the HH and LL samples, their distribution was relatively discrete. (4) LH regions: those areas that suffered from low accessibility but were surrounded by points with high accessibility, and experience strong spatial heterogeneity. Most of them were located in the national border region.

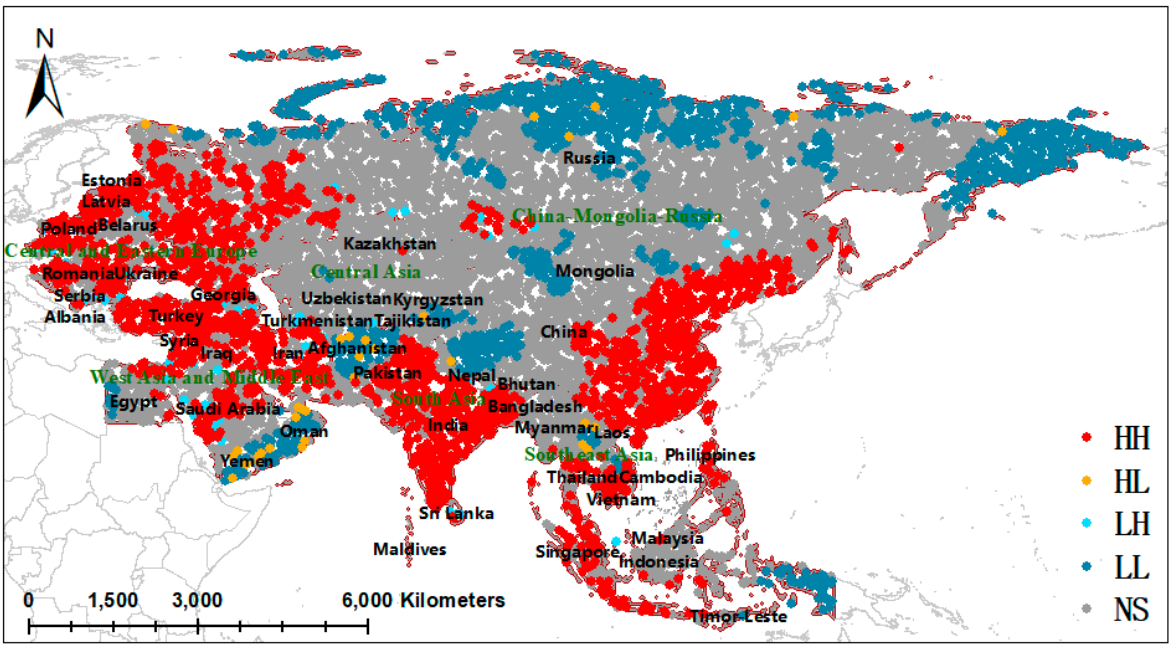


Figure 5. Spatial clusters and outliers of GTAI.

4.3. Spatial Relationship between GTAI and Population Density

Considering the spatial heterogeneity of the GTAI distribution, we established a GWR model between the normalized population density and the GTAI using selected sample points, which could explore their local relationship to provide key references for transportation planning. Since most road construction is due to population gathering, in this study, GTAI was regarded as the dependent variable, and population density was deemed to be the explanatory variable. For a better discussion, the results were interpolated using inverse distance weighting, which are presented in Figure 6.

The population density had a positive impact on transportation accessibility, with an overall R^2 of 0.69, which is in line with previous classification evaluations and existing studies [37]. However, a negative relationship was found in some areas, like some parts of Russia, western Saudi Arabia, and Yemen, where the corresponding R^2 values in these places were relatively low (see the black circles in Figure 6). This indicates that population density was not the main factor contributing to accessibility differences in these regions. In fact, using the GWR, we found that a low R^2 was observed in most BRI regions (see the second picture in Figure 6). This was chiefly due to the following reasons: (1) The population was much larger than the carrying capacity of transportation facilities. Those places normally belonged to developed areas (e.g., Beijing, Shanghai, New Delhi, Mumbai, Moscow), and had many infrastructures with high accessibility, but due to a large number of residents and limited traffic land, there was no strong connection between population density and accessibility. (2) The population was much smaller than the carrying capacity of transportation facilities. Regions in this situation could be divided into two groups. The regions in the first group mostly had a middle population density but

with high accessibility, like most Central and Eastern European countries. The second group contained the areas with a low population density but had middle or high accessibility. Those regions were generally traffic nodes, although they were located in remote areas.

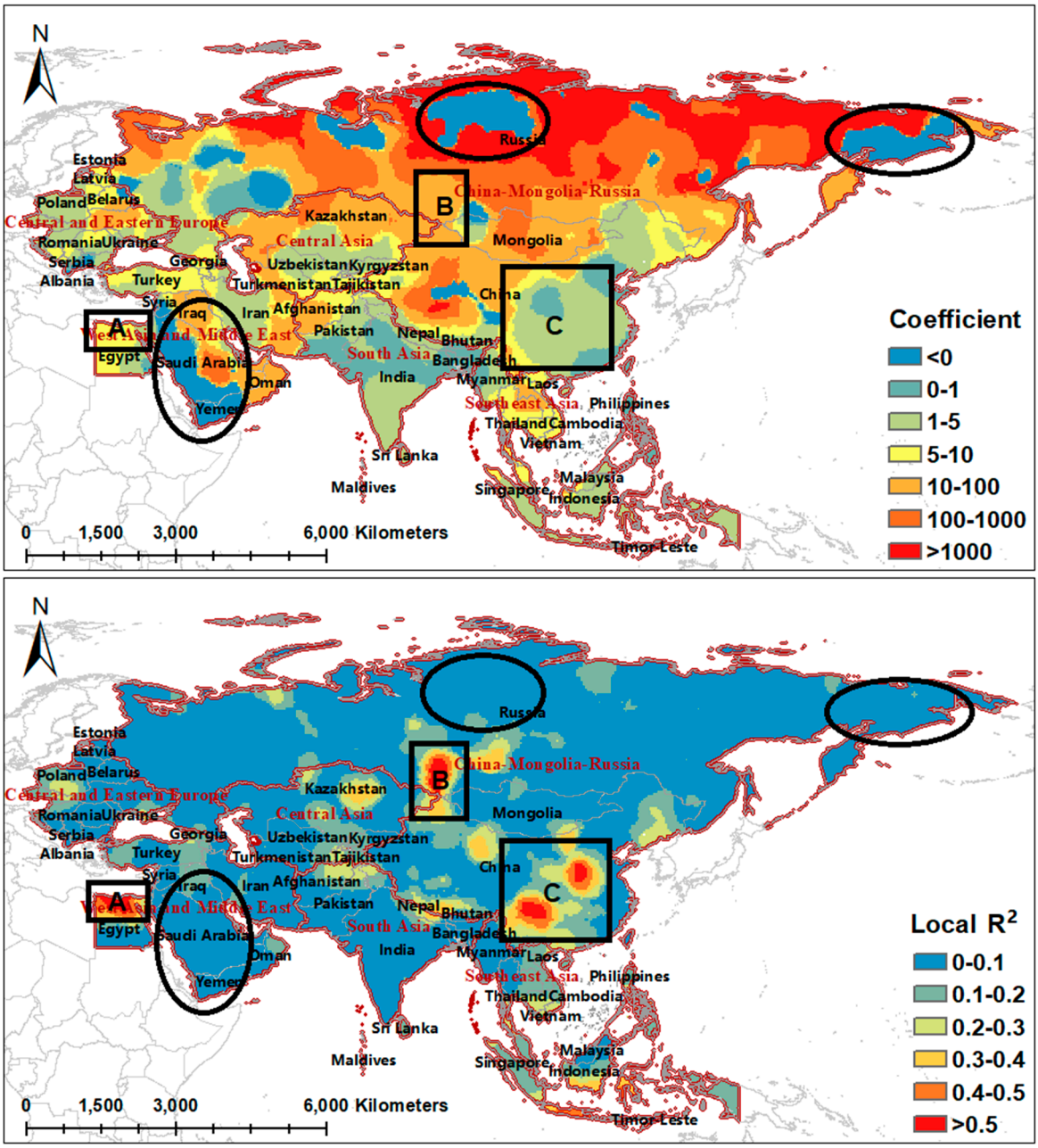


Figure 6. Interpolated results of GWR in the BRI region.

In addition, as marked by the black box in Figure 6, a strong positive relationship between population density and GTAI was more likely to occur in developing regions. Box A corresponds to the northern parts of Egypt, mainly including Cairo, Alexandria, Matruh, Giza, Ismailia, and Fayoum. Those areas had relatively developed tourism and strong industrial development potential. Regions with a high R^2 in box B were mostly distributed in Kemerovo and Gorno-Altaysk. Due to limited natural resources and uncomfortable climatic conditions there, the development has been relatively slow. In comparison, the two red clusters in box C enjoyed relatively higher socioeconomic development. The southwestern red cluster was largely located in Sichuan province, while the northeastern cluster

was situated in southern parts of Shanxi province and northern parts of Henan province. All of them have made some achievements in socioeconomic development. On the basis of the above analysis and coefficient map in Figure 6, we conclude that the positive relationship between population concentration and accessibility tended to be stronger in the areas with relatively low development levels, and became weak as the local development level increased. This was partly because more factors restricted transport construction in the regions with a better socioeconomic situation, such as limited land, environmental protection, and so on.

5. Discussion and Suggestion

According to the spatial distribution of the GTAI, we can suggest that there are three apparent clusters with a fairly high accessibility. The first cluster was in Central and Eastern Europe regions and western Russia; the second cluster mainly included countries in West Asia, the Middle East, and South Asia; and the last cluster was in eastern China. These regions were more likely to be well-developed and the terrain was level. However, the central regions (e.g., Central Asia) were experiencing relatively accessibility. In this case, the road or railway construction between China and Central Asian countries should be given priority, which has significant and long-term implications for the economic development in both Central Asian regions and western China.

Besides, the cluster type statistics of sample points shows that about 80% of BRI regions were not classified into HH or HL types. This was mainly due to their sparse transportation networks, weak transportation management, and closed society, which also largely restricted local socioeconomic development. In this context, in addition to strengthening the transportation construction, new transportation cooperation mechanisms can be developed in two parts: (1) establishing an innovative transportation system, like adjusting or configuring the function and responsibility of the transportation cooperative organization; and (2) proposing feasible transportation regulations. Furthermore, governments could replace traditional customs with electronic customs, which will simplify the exit and entry procedures, thereby improving customs efficiency, promoting exchanges and cooperation. Finally, some international logistics information networks could be constructed, which can integrate logistics data along the BRI regions and improve the efficiency of transnational logistics.

Moreover, results of the GWR indicate that there was a positive relationship between the accessibility degree and population density. As the development level increased, partly due to land restriction, their relationship became weak. Based on their spatial correlation, we suggest that: (1) For the regions with extremely high population density and high accessibility (e.g., Beijing, Shanghai, New Delhi, Mumbai, Moscow), governments could implement some transportation policies, like vehicle restrictions, to encourage citizens using public transportation, and enhance public transportation management and traffic education, which will not only improve commuting efficiency but also reduce the air pollution. (2) For the regions with a relatively low population density but relatively high accessibility (e.g., northwestern China), governments could invest funds to develop these places and carry out preferential policies to attract talent. For example, improving salary and housing allowance. (3) For the regions with a relatively high population density but a relatively low accessibility, these areas were generally less developed, like Yemen, Bhutan, Laos, and western China, due to natural conditions, and road and railway construction is necessary. Countries with a low overall transport levels may need outside help, and places with good natural conditions (e.g., low elevation) and relatively high population density should be prioritized. The governments with a rich experience in transportation development could give valuable suggestions and technical and financial support to less-developed areas. (4) For the regions with a coordinated population density and accessibility, such as northern parts of Egypt; Kemerovo and Gorno-Altaysk of Russia; and Sichuan, Shanxi, and Henan province of China; they were developing areas and still had strong potential, especially for places with a relatively low socioeconomic level. Under these circumstances, governments could invest in roads and railways, and some policy and welfare for talent introduction could be made. However, if the regions suffer low population density as well as low accessibility, they were more likely to be nature

reserves or depopulated areas, which are normally regarded as ecological barriers. In this case, no human intervention should be given.

6. Conclusions

This study proposed a global model to visualize transportation accessibility and took the BRI region as the study case. On the basis of the gridded output, we conducted a simple classification evaluation of accessibility based on natural breaks and used Moran's I to explore the spatial characteristics of the GTAI distribution. Then, a GWR model was applied to study the relationship between population density and accessibility. Finally, some feasible policies were provided. Our findings and policy suggestions are as follows.

Overall, the spatial distribution of the GTAI looked like an oblique U shape. The two ends of the NECB were economically prosperous regions, with high accessibility, but there was an accessibility depression in the middle region that consisted of western China and Central Asia. In view of this, we recommend strengthening the connection between China and Central Asian countries using road and railway construction. In addition, considering only about 20% land was recognized as HH type, we think it would be helpful to improve the BRI regions' transportation condition by establishing an innovative transportation system, introducing advanced technologies to enhance the exchange, and developing cooperation among the BRI countries.

More importantly, we found that the relationship between population density and accessibility varied in different regions. A weaker connection between them was more readily observed in well-developed regions than in developing areas, which was chiefly due to the accessibility being already saturated in metropolises and will not changes with the increasing of population density. In those regions, government ought to improve public transport management and promote public transportation. However, for developing or less-developed regions, transportation construction should be given a priority in regions with good natural conditions and relatively high population density, and preferential policies could be put forward for talent introduction. Of course, all development must be carried out with regard to the ecological carrying capacity. In future study, we could involve natural indexes (e.g., temperature, terrain, vegetation) to conduct a comprehensive assessment of sustainable development in the BRI regions.

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Appendix A

Table A1. Weights of the three transport density indices of the Belt and Road countries [a].

Country	W_1	W_2	W_3	Country	W_1	W_2	W_3
Afghanistan	0.90	0.01	0.10	Macedonia	0.55	0.45	0.00
Albania	0.35	0.65	0.00	Malaysia	0.56	0.43	0.01
Armenia	0.23	0.77	0.00	Maldives	-	-	-
Azerbaijan	0.33	0.67	0.00	Moldova	0.62	0.26	0.11
Bahrain	1.00	0.00	0.00	Mongolia	0.17	0.83	0.00
Bangladesh	0.31	0.67	0.02	Montenegro	0.33	0.67	0.00
Belarus	0.35	0.43	0.22	Myanmar	0.27	0.52	0.21
Bhutan	1.00	0.00	0.00	Nepal	0.58	0.42	0.00
Bosnia and Herzegovina	0.50	0.50	0.00	Oman	1.00	0.00	0.00

Table A1. *Cont.*

Country	W_1	W_2	W_3	Country	W_1	W_2	W_3
Brunei	0.91	0.09	0.00	Pakistan	0.43	0.53	0.04
Bulgaria	0.49	0.36	0.15	Palestine	0.22	0.55	0.23
Cambodia	0.34	0.35	0.31	Philippines	0.63	0.37	0.00
China	0.45	0.48	0.07	Poland	0.33	0.38	0.30
Croatia	0.46	0.48	0.07	Qatar	1.00	0.00	0.00
Czech Republic	0.58	0.24	0.18	Romania	0.35	0.62	0.03
Egypt	0.26	0.37	0.37	Russia	0.34	0.48	0.18
Estonia	0.39	0.61	0.00	Saudi Arabia	0.79	0.21	0.00
Georgia	0.44	0.56	0.00	Serbia	0.33	0.52	0.15
Hungary	0.22	0.35	0.42	Singapore	0.36	0.64	0.00
India	0.41	0.48	0.11	Slovakia	0.32	0.40	0.28
Indonesia	0.50	0.48	0.03	Slovenia	0.18	0.77	0.05
Iran	0.74	0.25	0.01	Sri Lanka	0.45	0.55	0.00
Iraq	0.23	0.38	0.39	Syria	0.37	0.50	0.13
Israel	0.58	0.35	0.06	Tajikistan	0.25	0.65	0.10
Jordan	0.35	0.64	0.01	Thailand	0.61	0.37	0.01
Kazakhstan	0.23	0.49	0.28	Timor-Leste	1.00	0.00	0.00
Kuwait	1.00	0.00	0.00	Turkey	0.49	0.49	0.02
Kyrgyzstan	0.18	0.81	0.01	Turkmenistan	0.19	0.62	0.19
Laos	0.57	0.00	0.43	Ukraine	0.25	0.44	0.30
Latvia	0.17	0.36	0.48	United Arab Emirates	1.00	0.00	0.00
Lebanon	0.71	0.11	0.19	Uzbekistan	0.41	0.47	0.12
Lithuania	0.54	0.46	0.00	Vietnam	0.42	0.34	0.24

Note: "-" indicates no data.

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