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Road Centrality and Landscape Spatial Patterns in Wuhan Metropolitan Area, China

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Abstract: Road network is a corridor system that interacts with surrounding landscapes, and understanding their interaction helps to develop an optimal plan for sustainable transportation and land use. This study investigates the relationships between road centrality and landscape patterns in the Wuhan Metropolitan Area, China. The densities of centrality measures, including closeness, betweenness, and straightness, are calculated by kernel density estimation (KDE). The landscape patterns are characterized by four landscape metrics, including percentage of landscape (PLAND), Shannon′s diversity index (SHDI), mean patch size (MPS), and mean shape index (MSI). Spearman rank correlation analysis is then used to quantify their relationships at both landscape and class levels. The results show that the centrality measures can reflect the hierarchy of road network as they associate with road grade. Further analysis exhibit that as centrality densities increase, the whole landscape becomes more fragmented and regular. At the class level, the forest gradually decreases and becomes fragmented, while the construction land increases and turns to more compact. Therefore, these findings indicate that the ability and potential applications of centrality densities estimated by KDE in quantifying the relationships between roads and landscapes, can provide detailed information and valuable guidance for transportation and land-use planning as well as a new insight into ecological effects of roads.

Keywords: road centrality; landscape patterns; kernel density estimation (KDE); landscape metrics; Wuhan Metropolitan Area; China

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1 Introduction

Roads are well known as a corridor network that is designed and built for regional development. In addition to the social and economic benefits, road network also has significant impacts on the landscape pattern, such as habitat fragmentation and urbanization (Forman and Alexander, 1998; Mitsuda and Ito, 2011). These impacts are mainly resulting from two aspects. One is the transformation of existing land cover to roads, leading to the loss and separation of habitat (Carr *et al*., 2002; Coffin, 2007). On the other hand, the accessibility provided by road network can induce the landscape change, such as reducing habitat quality by fragmentation and loss of connectivity (Castella *et al*., 2005; Patarasuk and Binford, 2012). Therefore, understanding the relationships between road network and landscape pattern will provide in-depth information for land-use and transport planning.

A number of studies have used diverse measures to evaluate the road impacts on the landscape, including road density (Saunders *et al*., 2002), road grade (Liang *et al*., 2014), road accessibility (Salonen *et al*., 2012), *etc*. These measures are rarely investigated from a spatial network perspective. The hierarchical structure of roads, however, indicates the linking role of each road in

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road network. Therefore, the association of the hierarchical structure of roads in the network with landscape patterns can provide an important direction to reveal the impacts of road network on landscape (Barthélemy, 2011; Ying *et al*., 2014). To quantify the hierarchy of road network, the multiple centrality assessment (MCA) model derived from structural sociology, has been proposed in geographical space (Porta *et al*., 2006). Integrating space and topology, this model systematically comprises the closeness, betweenness, straightness centrality, and information centrality. Therefore, these measures are able to assess the functional importance of road network comprehensively. For example, several studies using MCA in Bologna (Porta *et al*., 2009), East Baton Rouge Parish of Louisiana (Wang *et al*., 2011), and Barcelona (Porta *et al*., 2012), have shown that the centrality can capture the hierarchy of street network and thus reflect land-use intensity and economic activity density in urban space. These studies only focus on the intra-urban context, however, applying centrality in a region and further characterizing its relationship with landscape patterns at the regional scale were poorly studied.

The Wuhan Metropolitan Area, located in the east of Hubei Province, has half the population and more than 60 percent of total GDP but with a less than one-third area in the whole region. In 2007, it was approved as a comprehensive reform test area, concentrating on resource efficiency and environmental protection. With rapid social and economic development, the road network has also been extensively developed in this area. With an average annual growth rate of 4%, the total road length has reached 76 637.15 km by 2009. Since the rapid extension of road network introduces increasing pressures to the landscape, the Wuhan Metropolitan Area can be exemplary to promote our understanding of ecological effects of roads and thus offer useful reference for road management.

In this study, we attempt to apply centrality measures at a regional scale and use kernel density estimation (KDE) method to measure the centrality densities, which represent the centrality patterns over the region. In addition, as a statistical methodology used to link pattern to process, landscape metrics have been widely applied to quantify landscape patterns (Nagendra *et al*., 2004; De Clercq *et al*., 2007). Therefore, we selected four landscape metrics combining with MCA model and KDE to investigate the relationship between road centrality and landscape patterns in the Wuhan Metropolitan Area. The following questions were addressed: 1) How do the centrality measures distribute in the study area? 2) Whether the centrality densities correlate with landscape patterns at different bandwidths in the whole region? 3) How does the correlation of centrality densities change with the different land-use types at different bandwidths?

2 Materials and Methods

2.1 Study area and data preparation

The study area was the Wuhan Metropolitan Area, located in Hubei Province in the center of China, between latitudes 28°59′ and 31°51′N and longitudes 112°29′and 116°10′E. The Wuhan Metropolitan Area has a total terrestrial area of 5.78×10^4 km^2, with the topography being higher in the northern, southern, and eastern areas, and lower in the western and central parts. Farmland and forest are the primary land-use types in the Wuhan Metropolitan Area. It is known as the ′1+8′ metropolitan area, which contains one provicial capital city (Wuhan), five prefecture-level cities (Huangshi, Xianning, Huanggang, Xiaogan and Ezhou) and other three county-level cities (Xiantao, Tianmen and Qianjiang).

The road network map was obtained from the database of the Chinese country-wide land-use investigations (2009), supplemented with a digitized version of the Hubei and surrounding provinces highway mileage atlas (2009) (Fig. 1). The roads were checked and modified to eliminate topology errors in the ArcGIS 10.1 network analysis and topology tools. The road data set was then grouped into four functional grades, including county and rural roads (grade 1), provincial roads (grade 2), national roads (grade 3), and expressways (grade 4), where larger magnitude means higher road grade. The whole road network contained 951 junction elements and 2782 edge elements.

The land-use map was obtained from the generalized database of the Chinese country-wide land-use investigations (2009) (Fig. 2). We reclassified the land-use data into seven land-use categories: cultivated land, orchards, forest, grassland, water (water bodies and related facilities), construction land (cities, towns, villages, isolated industry districts, and transportation land use), as well as other land-use types. To eliminate the impact of land

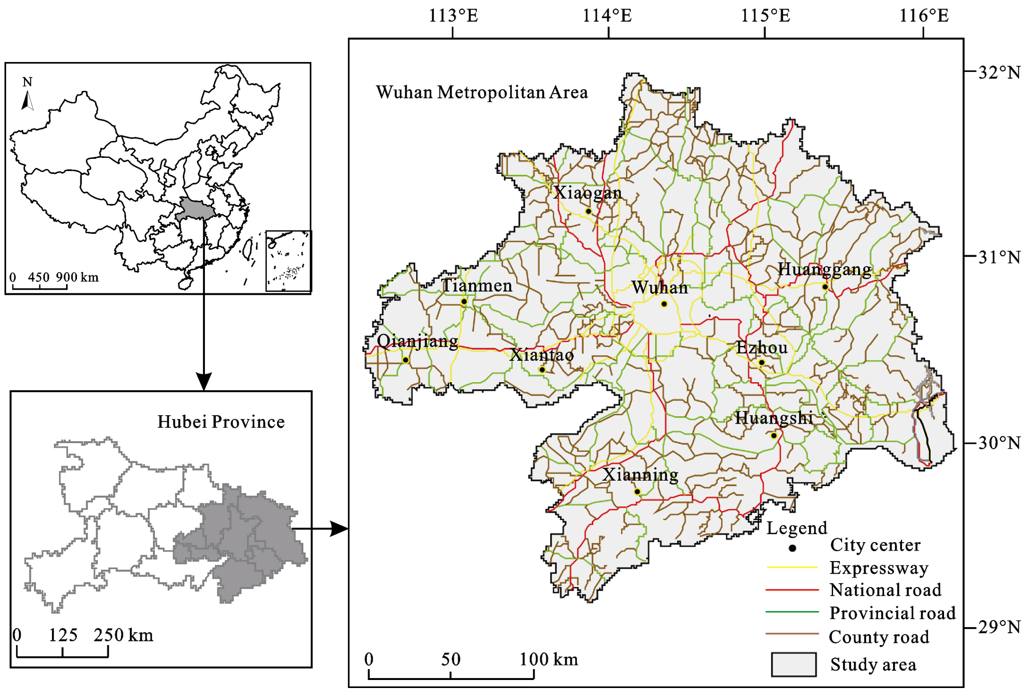

Fig. 1 Location and road network of Wuhan Metropolitan Area in 2009

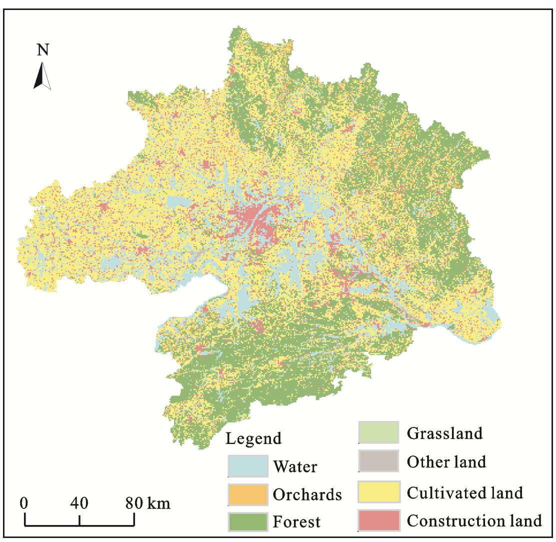

Fig. 2 Land-use map of Wuhan Metropolitan Area in 2009

patch ownership, the land-use data were dissolved by ArcGIS. In total, the vector land-use data consisted of 328 126 land patchs.

Finally, the road network and land-use map were transformed into the same coordinate system (Xian_1980_3_Degree_GK_Zone_38, Gauss Kruger projection), and adjusted in corresponding spatial locations.

2.2 Methodology

2.2.1 Centrality measures of road network

A primal graph approach was used to construct geographic networks that represent roads as links and intersections as nodes (Fig. 3). In MCA model, the centrality measures consist of closeness, betweenness, straightness, and information. Among these measures, closeness, betweenness, and straightness were selected to apply at a regional scale. As each road has its own grade and driving speed (Table 1), we used time instead of length as the impedance attribute to realistically characterize the network structure.

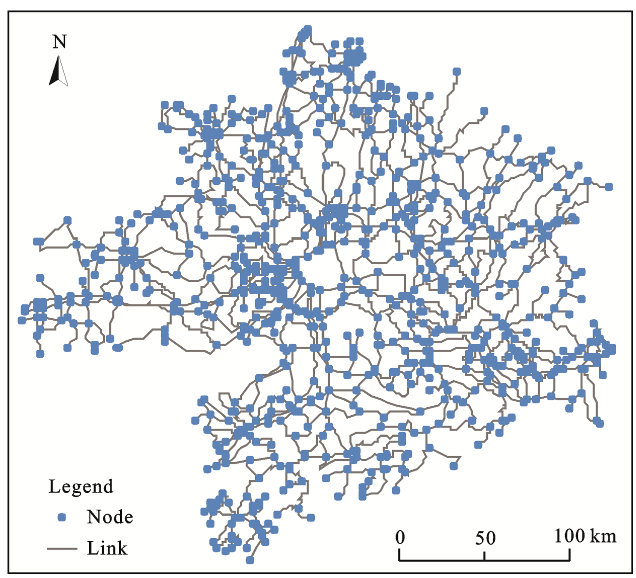

Fig. 3 Primal graph of roadwork in 2009: roads as links and intersections as nodes

Table 1 Speed for each road type

	County and rural road	Provincial road	National road	Expressway
Speed (km/h)	40	60	80	120

Closeness C^C is a measure of accessibility, revealing the proximity of a node to other nodes in the network (Sabidussi, 1966). The node with the highest closeness value will always be near to the geometrical center of a network (Erath *et al.*, 2009). C^C for a node i is defined as Equation (1):

$$C_i^C = \frac{N-1}{\sum_{j=1;j\neq i}^{N} t_{ij}} \tag{1}$$

where C_i^C is the closeness value of node i; N is the total number of nodes in the network, and t_{ij} is the time from node i to node j by the shortest route.

Betweenness C^B is a useful index to predict traffic flow. It is defined as the fraction of the shortest paths between pairs of other nodes in the network that pass by node i (Freeman, 1979) as Equation (2):

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum_{j=1;k=1;j\neq k\neq i}^{N} \frac{n_{jk}(i)}{n_{jk}} \tag{2}$$

where C_i^B is the betweenness value of node i; $n_{jk}(i)$ is the number of shortest paths from node j to node k that pass by node i, and n_{jk} is the total number of shortest paths from node j to node k. The shortest path here means the route with the shortest travelling time.

Straightness C^S measures the circuity or directness by comparing the length of the shortest paths between nodes with crow-fly distance from a node of interest to all the other nodes in the network (Latora and Marchiori, 2007). A higher C^S reflects a node or place that can go to all the other places more directly. It is defined as Equation (3):

$$C_i^S = \frac{1}{N-1} \sum_{j=1;j\neq i}^{N} \frac{d_{ij}^{Eucl}}{d_{ij}} \tag{3}$$

where C_i^S is the straightness value of node i; d_{ij}^{Eucl} is the Euclidean distance between nodes i and j, and d_{ij} is the shortest distance between nodes i and j.

Centrality values of each node were calculated in the Urban Network Analysis toolbox by ArcGIS 10.0/10.1 as previously described (Sevtsuk and Mekonnen, 2012). Then, the centrality values of each road segment were assigned as the average value of its two end nodes using the spatial join tool of ArcGIS 10.1.

We further examined the statistic law of Centrality measures, which is defined as Equation (4):

$$F_X(x) = P(X \leq x) \tag{4}$$

where x is the normalized centrality value of the road segments; X represents the centrality value of a randomly selected link; and F_x is the cumulative distribution function value.

2.2.2 Kernel density estimation

To explore the relationships between road centrality and landscape patterns, it is necessary to extend centrality measures in the whole region. As a spatial smoothing method, KDE calculates a magnitude per unit area from point or polyline features. It is consistent with Tobler′s first law of geography, distance decay. Its results are continuous and unconfined by artificial boundaries (Cai *et al.*, 2013). Meanwhile, it is more effective to estimate the ecological effects of roads than grid computing method. Therefore, we used KDE method to present centrality patterns so that they can be associated with landscape patterns.

The bandwidth (h) and cell size are the two parameters which affect the outcome of the KDE (Anderson, 2009). Firstly, as the average distance from each town centroids to its nearest neighboring town centroids is about 5 km in the Wuhan Metropolitan Area, we set three bandwidths of 1 km, 5 km and 10 km, which reflect the effect range of road centrality and allow a comprehensive investigation of the relationships. Then, the cell size was set at 200 m × 200 m. After determining the above parameters, the weights (′population′ field) were set as the values of closeness, betweenness, and straightness, respectively. All the above procedures were performed in the KDE tool by ArcGIS to obtain three measures of centrality density. In addition, the road density was also calculated by the KDE tool using the same parameters, whereas the weight was selected as none.

2.2.3 Landscape metrics

Four landscape metrics, including the percentage of land-use type (PLAND), Shannon′s diversity index (SHDI), the mean patch size (MPS), and mean shape index (MSI), were chosen to quantify the landscape pattern. PLAND and SHDI were used to reveal the landscape composition, whereas MPS and MSI were applied to describe the specific spatial form of each class. Among these metrics, SHDI is suited for the landscape level, PLAND is employed at the class level, while the other two metrics can be utilized at both landscape and class levels. In equation definition, land-use type corresponds to landscape class (Liu *et al.*, 2011).

PLAND describes the proportion of total area occupied by a particular land-use type i, represented as PL_i in Equation (5):

$$PLAND = PL_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} \times 100 \tag{5}$$

where A is the total area of land use; n is the patch number of land-use type i; and a_{ij} is the area of patch j belonging to land use i. It is applied at the class level.

SHDI measures landscape diversity, which is suited to the landscape level. This index will be equal to zero when there is only one land-use type in the whole area, and increases as the number of land-use types and/or the proportional distribution of the area among the land-use types becomes more equitable (McGarigal *et al.*, 2002). It is defined as Equation (6):

$$SHDI = -\sum_{i=1}^{m} (PL_i \times \ln PL_i) \tag{6}$$

where m is the number of land-use types.

MPS represents the average patch size of land-use type i, expressed as P_i in Equation (7). It also characterizes the degree of clustering of land-use type i, which is the inverse of the land-use fragmentation extent.

$$MPS = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{n} \tag{7}$$

where n is the patch number of land-use type i, and a_{ij} is the area of patch j belonging to land use i.

MSI measures the average patch shape complexity of land-use type i, compared with a circular standard. High values correspond to irregular patch shapes. It is expressed as S_i in Equation (8):

$$MSI = S_i = \frac{\sum_{j=1}^{n} \frac{l_{ij}}{2\sqrt{(\pi \times a_{ij})}}}{n} \tag{8}$$

where n is the patch number of land-use type i; l_{ij} is the perimeter of patch j belonging to land use i.

2.2.4 Quantification of relationships between centrality densities and landscape patterns

As the centrality densities generated by KDE are continuous values, raster reclassification was applied to divide the whole region into several landscape subsets and investigate the relationships between the centrality pattern and the landscape structure within each subset. Concretely, we reclassified the KDE results of centrality into 10 classes using natural breaks as a base framework, where high centrality value means a high central grade. Each class corresponds to a landscape subset. Then, at the landscape level, the corresponding pattern metrics were calculated in each landscape subset and matched with the grade of centrality densities for correlation analysis. While at the class level, we calculated the pattern metrics of different land-use types. Since Spearman rank correlation is a non-parametric statistical test for a rank variable, we used it to quantify the relationships between centrality densities and landscape patterns via the SPSS 17.0 statistical package. In general, the flow diagram of this study is shown in Fig. 4.

3 Results

3.1 Distribution and statistics of centrality measures

Since the distribution of centrality measures can reveal the hierarchical structure of road network, we analyzed it using MCA model. As shown in Fig. 5, the closeness measure distributes in a concentric ring and declines with distance from the geometric center of Wuhan. The betweenness measure shows a strongly polarized structure, and the road segments with high betweenness values appear to locate at important intersections and constitute the skeleton of the whole region. The straightness measure, however, shows a more dispersed pattern among the measures, as high straightness values associate with the road segments that have a straight line shape and better surrounding connectivity. Based on these results, we examined the statistic law of these measures. As shown in Fig. 6, the distribution of betweenness measure shows a noticeable 80/20 pattern, which means 80% of betweenness values are less than or equal to 0.2, while 20% possess a value more than 0.2. Conversely, the closeness and straightness measures show a more even distribution.

Road grade is a traditionally used index to assess the road function. To ask whether centrality measures are

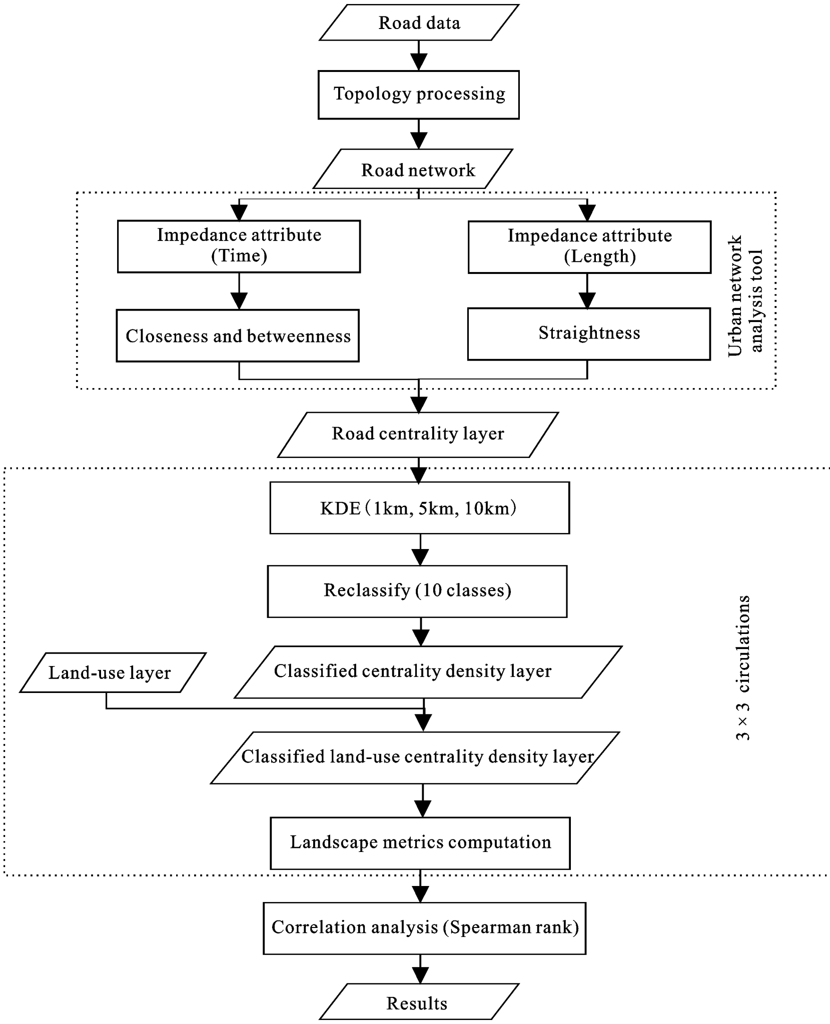

Fig. 4 Flow diagram of this study

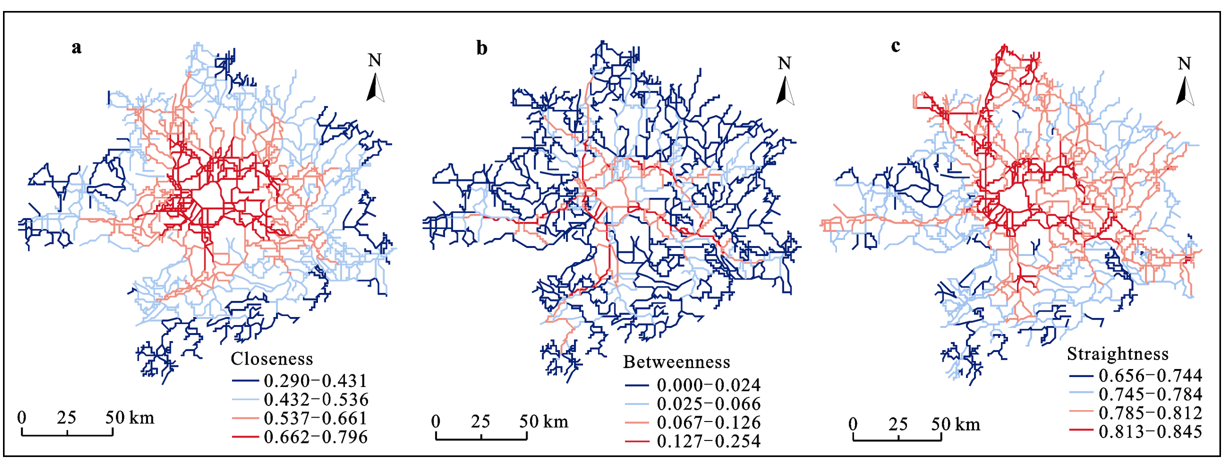

Fig. 5 Maps of three centrality measures: a) closeness; b) betweenness; c) straightness

affected by different road types, we next explored their relationships with road grade. The result show that centrality measures are positively associated with the road grade (Table 2), suggesting that the road segments with a high grade may be functionally important in road network.

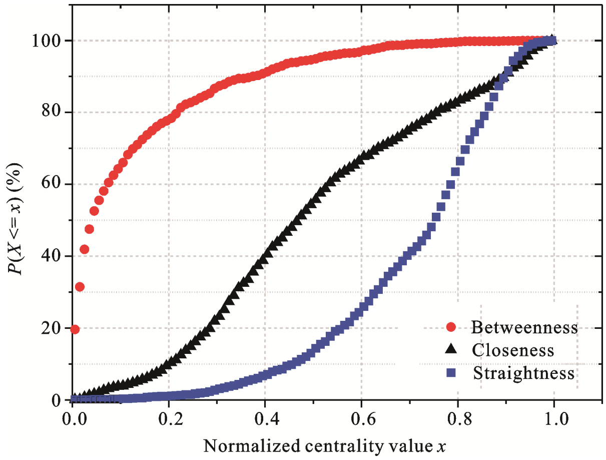

Fig. 6 Cumulative distribution of three centrality measures

Table 2 Spearman rank correlation between road grade and centrality measures

	Straightness	Betweenness	Closeness
Road grade	0.254**	0.532**	0.384**

Note: ** means significant at $P < 0.01$

3.2 KDE patterns of centrality measures

To show the centrality patterns over the study region, we used KDE method to calculate the centrality densities. In addition, since road density is another widely used index that can measure the dispersion of roads, we thus also investigated its correlation with centrality densities. As shown in Fig. 7 and Fig. 8, the centrality densities and road density both become more homogeneous as the bandwidth increases, suggesting the similar effect of bandwidth on these densities. Moreover, the KDE patterns of closeness and straightness are seemed to be similar to the road density at the bandwidths of 5 km and 10 km. To confirm the relationship between the centrality densities and road density, we used Pearson correlation coefficients to analysis their correlation. As shown in Table 3, all three centrality densities positively associate with the road density at three bandwidths. Among the centrality densities, the closeness density and straightness density are more significantly correlated with the road density ($R > 0.9$), demonstrating further the robust relationship between them. These results indicate that as the local roads aggregate, the location advantage becomes more evident, especially for the accessibility and directness of a place to others. Although

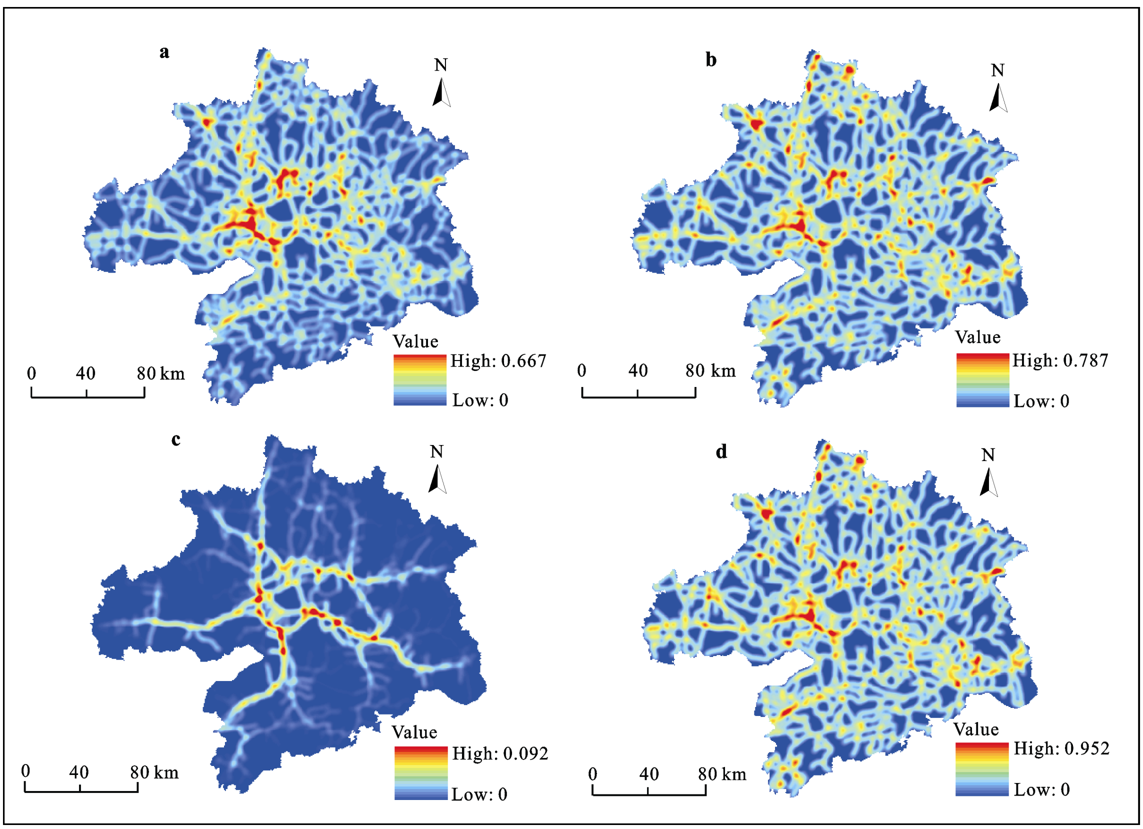

Fig. 7 Classified kernel density estimation: a) closeness density by KDE; b) straightness density by KDE; c) betweenness density by KDE; d) road density by KDE. Bandwidth $h = 5$ km

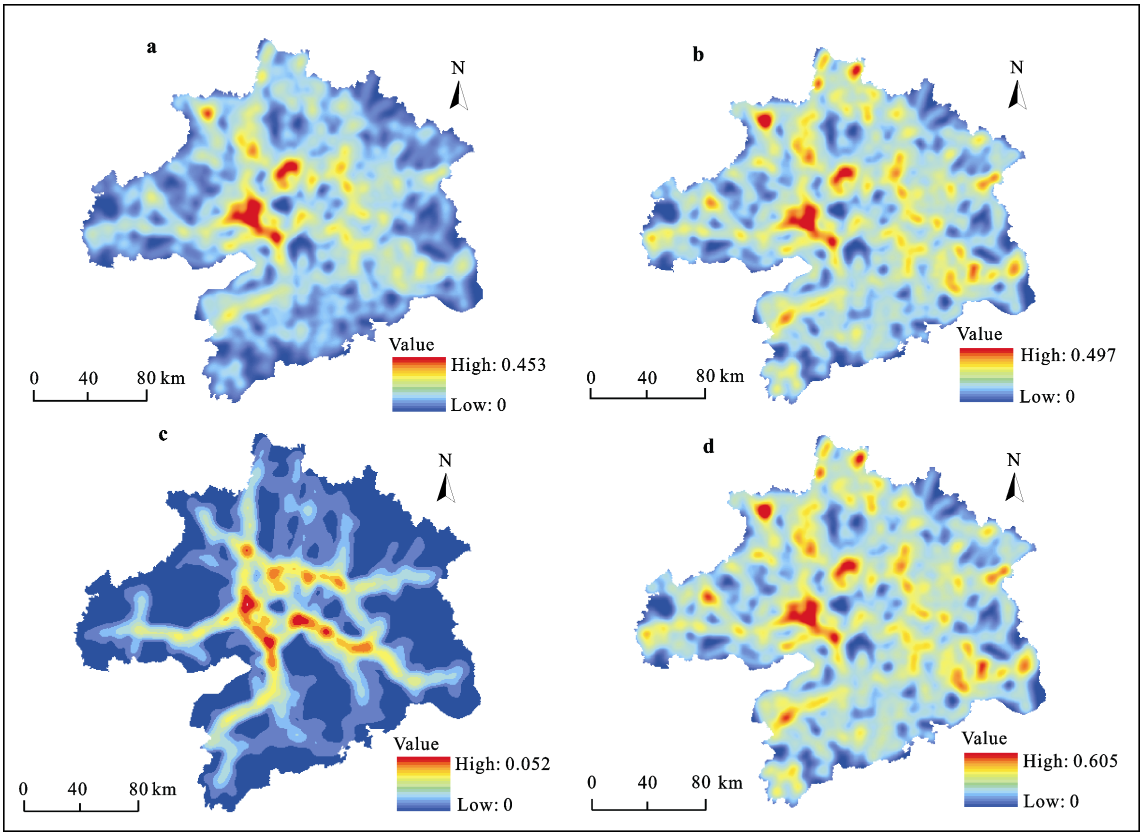

Fig. 8 Classified kernel density estimation: a) closeness density by KDE; b) straightness density by KDE; c) betweenness density by KDE; d) road density by KDE. Bandwidth h = 10 km

Table 3 A correlation analysis between centrality densities and road density

Measures	Bandwidth	Closeness Density	Betweenness density	Straightness density
Road density	1	0.978**	0.556**	0.994**
	5	0.942**	0.535**	0.998**
	10	0.922**	0.565**	0.997**

Note: ** means significant at $P < 0.01$

the betweenness density exhibits a weaker association with the road density, it can offer more details about the pass-through traffic volume of a place that may be not provided by road density.

3.3 Correlation analysis

3.3.1 Relationships between centrality density and landscape patterns at landscape level

To investigate whether the centrality densities correlate with landscape patterns, we firstly used Spearman rank correlation method to analyze their relationship at the landscape level. As Table 4 shows, the centrality densities generally have a negative correlation with MSI at larger bandwidths, suggesting land-use patches tend to be more regular when the location enjoys central advantages. For MPS of the landscape, straightness density negatively associates with it at all bandwidths, while closeness density and betweenness density are almost irrelevant with it, indicating the degree of landscape fragmentation is more sensitive to straightness. Unlike the other landscape metrics, SHDI is almost uncorrelated with centrality densities, suggesting that road centrality may not be the dominant factor to affect the landscape diversity. In general, the landscape shape becomes more fragmented and regular as the centrality densities increase.

Since the road density plays an important role in landscape fragmentation, we used it as a reference to verify the relationship between the centrality densities with landscape patterns. As shown in Table 4, road density is negatively correlated with MSI and MPS instead of SHDI at 5 km and 10 km, which is similar with the action of some centrality densities such as straightness density, demonstrating their ability to influence landscape patterns. In addition, the densities of closeness and betweenness exhibit a distinct correlation with MPS

Table 4 Spearman rank correlations between density measures and MSI, MPS, and SHDI at landscape level

Measure	Bandwidth (km)	MSI	MPS	SHDI
Closeness density	1	−0.479	−0.261	−0.479
	5	−0.927**	−0.503	−0.188
	10	−0.915**	−0.539	0.018
Betweenness density	1	−0.939**	−0.709*	−0.176
	5	−0.867**	−0.273	−0.515
	10	−0.879**	−0.212	−0.770**
Straightness density	1	−0.467	−0.733*	0.091
	5	−0.964**	−0.818**	0.067
	10	−0.988**	−0.770**	0.212
Road density	1	−0.212	−0.564	−0.370
	5	−0.964**	−0.818**	0.018
	10	−0.988**	−0.758*	0.333

Notes: * means significant at $P < 0.05$; ** means significant at $P < 0.01$; PLAND means percentage of land-use type; MSI means mean shape index; MPS means mean patch size

compared to road density. Therefore, the results suggest that these density measures can be used to describe specific landscape character, and the centrality densities may provide more detailed information.

3.3.2 Relationships between centrality density and landscape patterns at class level

Since different land-use types have their own characters and may associate diversely with road centrality, we firstly analyzed the typical land-use types in the Wuhan Metropolitan Area. As shown in Table 5, the cultivated land is dominant with a covering proportion of 40.71%. The forest, water, and construction land account for 29.29%, 15.67%, and 9.63%, respectively. In all, these four land-use types comprise over 95% of the total area. As the distribution of water bodies and related facilities is mainly influenced by natural conditions, we chose cultivated land, forest land, and construction land for the correlation analysis. Among the three types, the forest and cultivated land constitute the landscape matrix with a higher MPS and MSI, suggesting that their patterns are more continuous and irregular. The pattern of construction land, however, is more scattered but regular in the whole region.

Based on the above results, we then examined the relationships between centrality densities and landscape patterns with a reference of road density at the class level. As shown in Table 6, although the centrality densities and road density associate with cultivated land

Table 5 Statistics of overall land-use patterns.

Land-use type	PLAND (%)	MSI	MPS (ha)
Cultivated land	40.71	2.41	51.74
Orchards	2.48	1.81	5.79
Forest	29.29	2.16	49.00
Grassland	1.73	1.98	9.88
Water	15.67	1.52	9.46
Construction land	9.63	1.59	4.71
Other land	0.49	1.75	13.72

Notes: PLAND means percentage of land-use type; MSI means mean shape index; MPS means mean patch size

patterns at certain bandwidths, their correlations generally seem to be discontinuous and ruleless. However, for the forest patterns, the landscape metrics are almost negatively associated with all density measures at three bandwidths, suggesting that roads exert stronger effects on forest than cultivated land. With regard to construction land, the densities of closeness and straightness correlate positively with PLAND and MPS, which is the same as the manner of road density. The relationship between betweenness density and construction land patterns, however, is more complex. The result indicates that the area proportion and aggregation degree may be more sensitive to the accessibility and directness in construction land. Taken together, our data show that the closeness density and straightness density correlate with the patterns of forest and construction land similar to road density, which is consistent with the previous analysis (Table 3).

4 Discussion

The impact of road network on landscape patterns has been a hotspot in road ecology, transportation and land-use planning (Geurs and van Wee, 2004; Chen and Roberts, 2008; Tyrväinen *et al*., 2014). Actually, most attention rarely focuses on the role of hierarchical structure of road network. However, the hierarchy, represented as road centrality in the network, reveals the rank of functional importance of road segments. Therefore, it can provide in-deep information about the impacts of road network on landscape patterns. For example, the roads with high centrality, which tend to attract more traffic and human activities, are able to accelerate the transformation of natural landscape into artificial landscape (Rui and Ban, 2014).

Table 6 Spearman rank correlations between density measures and landscape metrics at class level

Measure	Bandwidth (km)	Cultivated land			Forest			Construction land		
		PLAND	MSI	MPS	PLAND	MSI	MPS	PLAND	MSI	MPS
Closeness density	1	0.212	−0.527	0.115	$\mathbf{-0.879}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{-0.794}^{**}$	$\mathbf{0.867}^{**}$	$\mathbf{0.976}^{**}$	$\mathbf{0.952}^{**}$
	5	0.261	−0.236	$\mathbf{0.685}^{*}$	$\mathbf{-0.964}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{0.964}^{**}$	−0.079	$\mathbf{0.976}^{**}$
	10	$\mathbf{0.806}^{**}$	0.188	$\mathbf{0.952}^{**}$	$\mathbf{-0.915}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{-0.891}^{**}$	$\mathbf{0.915}^{**}$	−0.333	$\mathbf{0.952}^{**}$
Betweenness density	1	−0.285	$\mathbf{-0.927}^{**}$	−0.467	0.139	$\mathbf{-0.733}^{*}$	−0.612	$\mathbf{0.721}^{*}$	$\mathbf{-0.733}^{*}$	0.176
	5	0.418	−0.515	0.297	$\mathbf{-0.782}^{**}$	$\mathbf{-0.988}^{**}$	$\mathbf{-0.952}^{**}$	0.467	−0.576	0.455
	10	0.467	$\mathbf{-0.648}^{*}$	0.515	$\mathbf{-0.842}^{**}$	$\mathbf{-0.976}^{**}$	$\mathbf{-0.939}^{**}$	$\mathbf{0.685}^{*}$	−0.345	$\mathbf{0.648}^{*}$
Straightness density	1	−0.018	−0.600	−0.358	$\mathbf{-0.939}^{**}$	$\mathbf{-0.891}^{**}$	$\mathbf{-0.818}^{**}$	$\mathbf{0.903}^{**}$	$\mathbf{0.988}^{**}$	$\mathbf{0.915}^{**}$
	5	0.297	0.103	0.382	$\mathbf{-0.939}^{**}$	$\mathbf{-0.988}^{**}$	$\mathbf{-0.964}^{**}$	$\mathbf{0.988}^{**}$	−0.091	$\mathbf{0.939}^{**}$
	10	0.539	$\mathbf{0.661}^{*}$	$\mathbf{0.842}^{**}$	$\mathbf{-0.939}^{**}$	$\mathbf{-0.903}^{**}$	$\mathbf{-0.976}^{**}$	$\mathbf{0.939}^{**}$	−0.588	$\mathbf{0.927}^{**}$
Road density	1	0.103	−0.588	−0.370	$\mathbf{-0.891}^{**}$	$\mathbf{-0.770}^{**}$	$\mathbf{-0.915}^{**}$	$\mathbf{0.939}^{**}$	$\mathbf{0.988}^{**}$	$\mathbf{0.891}^{**}$
	5	$\mathbf{0.842}^{**}$	0.515	0.406	$\mathbf{-0.915}^{**}$	$\mathbf{-0.939}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{0.976}^{**}$	0.152	$\mathbf{0.915}^{**}$
	10	0.467	0.564	$\mathbf{0.855}^{**}$	$\mathbf{-0.927}^{**}$	$\mathbf{-0.976}^{**}$	$\mathbf{-0.952}^{**}$	$\mathbf{0.952}^{**}$	−0.467	$\mathbf{0.830}^{**}$

Notes: * means significant at $P < 0.05$; **means significant at $P < 0.01$. PLAND means percentage of land-use type; MSI means mean shape index; MPS means mean patch size

Recent studies have applied MCA model to analysis the urban structure (Gao *et al.*, 2013; Sheikh and Rajabi, 2013; Wang *et al.*, 2014). We here used the same centrality measures to investigate their correlations with landscape patterns, however, at a regional instead of intra-urban scale. Our results show that high closeness and betweenness tend to cluster in the geometric center, while straightness exerts a relatively dispersed pattern in Wuhan Metropolitan Area (Fig. 5), indicating that the nature of closeness and betweenness may be more vulnerable to the interference of edge effect. Similar to previous studies in urban space (Porta *et al.*, 2012), these findings suggest that the centrality measures are determined by road network but not the area. To ask whether the centrality measures could reflect the hierarchy of road network, we then tested their relationship with road grade and found that road centrality associates positively with road grade (Table 2). This is because the roads with high grade, which usually have high driving speed and large traffic volume, play an important role in the network (Su *et al.*, 2014; Ying *et al.*, 2014).

As KDE analysis exhibits the distribution of centrality measures (Wang *et al.*, 2014), it can reveal the location advantages determined by road network in the region. Our data have shown that the centrality densities have a positive relationship with road density, while the relationship of betweenness density is relatively weak. This is intriguing because, the centrality density of intersections will increase as streets converge in one place (Porta *et al.*, 2012), however, betweenness density emphasizes the bridge effect linking two places in the whole area, which means local road aggregation does not significantly improve the mediator effect of a place.

A number of studies have revealed that centrality measures are associated with land-use patterns in urban area (Wang *et al.*, 2011; Rui and Ban, 2014). Same in the Wuhan Metropolitan Area, centrality densities were also found to have certain relationships with landscape patterns. In detail, at the landscape level, as the places with local advantages can save transportation costs and connect easily with others, they will increase human activity and economic activity, such as converting natural landscape into cultivated land or buildings. As a result, the landscape shape turns to be regular (Fu *et al.*, 2006; Saura *et al.*, 2008). With regard to landscape fragmentation, it is more sensitive to straightness density. This is because the geometric center in the Wuhan Metropolitan Area, dominated by well-connected construction lands, can disturb the fragmentation degree, while straightness density is more dispersed in this area and thus unlimited by the center. A similar result is road density (Table 4), which has been reported to correlate with landscape fragmentation (Hawbaker *et al.*, 2005; Laurance and Balmford, 2013). However, the landscape diversity may be affected by natural factors, such as soil and slop, and thus exhibit an insignificant relationship with centrality densities. Therefore, these findings may be beneficial for the overall land-use policies from the perspective of landscape ecology.

In addition to the landscape level, studies at the class level can offer direct information about how different land-use types associate with centrality densities. Specifically, the construction land increases and becomes more compact with rising centrality densities, while the forest gradually diminishes and turns to be fragmented. These results are consistent with previous studies that the increased accessibility can promote human settlement and accelerate the exploitation of forest resources (De Clercq *et al*., 2007; Perz *et al*., 2008; Gao and Li, 2011). But for cultivated land, its location is primarily constrained by government policies and natural conditions. Hence, its correlation with centrality densities generally seems insignificant. Together, these relationships can provide important references for land-use and transport planning, such as the site choice of construction land expansion and the decision of forest conservation priority.

Besides applied in the cities, centrality measures can also be adopted at a regional scale. Although centrality densities associate with road density, they exhibit differential relationships with landscape patterns (Tables 4 and 6), suggesting that compared with single measure, multiple centrality densities can provide a richer characterization of road impacts on landscapes. However, there are still improvements for further study. For instance, as expressways have specific entrances and exits, their intersections with surrounding links are not always connected. It is more reasonable to improve the model of road network by supplementation with expressway-related data. Moreover, the heterogeneity of the local environment, as well as government policies, could be another promising direction for further analysis of road impacts on landscapes.

5 Conclusions

In this study, we investigated the relationship between road centrality and landscape patterns at both landscape and class levels in the Wuhan Metropolitan Area. The centrality measures exhibit correlations with road grade, suggesting that it is reasonable to apply them at a regional scale. Further analysis show that there are significant relationships between centrality densities and landscape patterns. Specifically, at the landscape level, the landscape shape is more fragmented and regular when the centrality densities increase. At the class level, high centrality densities lead to a large and contiguous construction land, while forest exhibits an opposite trend. These findings suggest that centrality densities can serve as a useful reference in regional land-use and transport planning.

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