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Impacts of road network expansion on landscape ecological risk in a megacity, China: A case study of Beijing

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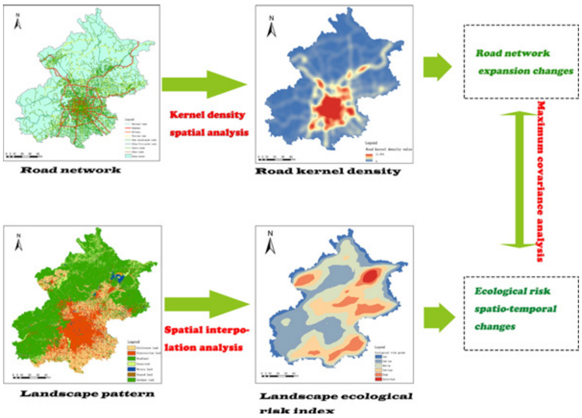
HIGHLIGHT

- The kernel density estimation based on GIS characterized the expansion of road network effectively.
- Constructing the landscape ecological risk index with landscape indices.
- Both the road network expansion and the ecological risk changes had close relations to expressways in space.
- The maximum covariance analysis was used to explore the affecting laws of road network on regional ecological risk.

GRAPHICAL ABSTRACT



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ABSTRACT

Road networks affect the spatial structure of urban landscapes, and with continuous expansion, it will also exert more widespread influences on the regional ecological environment. With the support of geographic information system (GIS) technology, based on the application of various spatial analysis methods, this study analyzed the spatiotemporal changes of road networks and landscape ecological risk in the research area of Beijing to explore the impacts of road network expansion on ecological risk in the urban landscape. The results showed the following: 1) In the dynamic processes of change in the overall landscape pattern, the changing differences in landscape indices of various landscape types were obvious and were primarily related to land-use type. 2) For the changes in a time series, the expansion of the road kernel area was consistent with the extension of the sub-low-risk area in the urban center, but some differences were observed during different stages of development. 3) For the spatial position, the expanding changes in the road kernel area were consistent with the grade changes of the urban central ecological risk, primarily because both had a certain spatial correlation with the expressways. 4) The influence of road network expansion on the ecological risk in the study area had obvious spatial differences, which may be closely associated with the distribution of ecosystem types.

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1. Introduction

The road network is a product of urban development processes, and it plays a role in urban economic development. Additionally, a road network has many influences on ecological processes within the urban landscape. On one hand, a road network affects material cycles, energy and information communication in human societies and in addition to reducing the cost of transportation, a road network also expands the scope of human activities (Forman and Alexander, 1998). On the other hand, road networks also cause various adverse effects, including division, interference, damage, and pollution (Forman and Alexander, 1998; Karlson et al., 2014), which directly or indirectly affect ecological processes and accelerate habitat destruction and ecosystem degradation, eventually leading to an increase in regional ecological risk. Landscape ecological risk is an important branch of ecological risk at the regional scale and primarily depends on the coupling of landscape patterns and ecological processes to achieve integrated characterization of multi-source risks from natural or human activities (Simmons et al., 2007; Li and Zhou, 2015). Because of the complexity of human activities and their effects on ecological processes, the influences of road network expansion on regional ecological risk are also diverse. These influences include changes in regional biodiversity and in the transfer of energy and materials among ecological systems (Barandica et al., 2014; Staab et al., 2015), in addition to changes in land-use and the evolution of landscape patterns (Patarasuk et al., 2012; Xie et al., 2016). The evolution of forest landscapes over time and the spatial separation of water areas are also affected (Freitas et al., 2012; Du et al., 2010). By studying these processes, researchers have made progress in their research and have constantly deepened the understanding of the mutual relations between road network expansion and ecological risk. For example, the studies on road network structure include either a single main road or a complex road network (Fan et al., 2011; Redon et al., 2015), and study areas include small regions with little interference from human activities, such as forests, and areas that are greatly affected by human activities, such as cities and large basins (Narayanaraj et al., 2012; Xie et al., 2016; Barber and Cochrane, 2014). Additionally, research contexts include the influence of road networks on regional landscape ecological risk (Liu et al., 2008), using ecological risk assessment for guidance in the construction and planning of the road networks (Cao et al., 2010), and some other aspects (Staab et al., 2015). However, because of the complexity of the study areas and the diversity of ecological research methods, most studies focus on landscape ecological risk assessment (Huang et al., 2016; Bian et al., 2015; Liu et al., 2016), and studies of changes in the spatial characteristics of road networks are rare.

A road network is a complex network system with certain spatial features that is gradually formed by a few roads in a region through long-term planning and development. It also stands for the urban development level, especially Beijing—a city with extra high urbanization level. In the process of urbanization, the road network expansion exerts extensive and profound influences on regional ecological systems (Tian et al., 2016). On one hand, the ecological effects of road networks will continually increase over time. With the continuous concentration of the population, the natural environment surrounding roads has been severely damaged, resulting in a weakened ability of regional ecosystems to resist external risks and increases in ecological risks (Liu et al., 2008). On the other hand, the scope of influence of road networks will further enlarge in the process of expansion (Coffin, 2007). With improvements in road systems, the range of human activities also expands, which increases the human impact on the natural ecology (Forman and Alexander, 1998; Karlson et al., 2015). According to some research, approximately 15–20% of the U.S. total geography is land affected by road networks (Forman, 2000) and about 16% of the Netherlands is covered by road effect zones (Reijnen et al., 1997).And In China, the affected area reached 18.37% (Li et al., 2004). However, the development of the regional economy cannot leave the extension of the road network, but the ecological effects caused by the road network expansion cannot be ignored. Facing the increasingly prominent contradiction between economic development and ecological protection, people urgently need to find a scientific way to solve the problem. Therefore, studying the road network expansion and its impacts on the ecological risk in Beijing as the study area, this study can provide important references for city in road network planning and ecological management. Meanwhile, the study also has important value to further understand the effects of road networks on landscape ecological risk (Liu et al., 2008; Eigenbrod et al., 2009; Karlson et al., 2014).

It's worth noticed that, in recent years, with the rapid development of spatial information technology, the research methods of geography have been used in a wide range of applications in various fields, particularly in the development of the geographic information system (GIS). GIS is used to solve many questions about transportation and the environment with various methods of spatial analysis (Guo et al., 2014; Chang et al., 2015; Hu et al., 2016). Among these methods, the kernel density estimation, an important spatial analysis tool based on geographic information systems, offers a powerful method of analysis to study the effects of road network expansion on landscape ecological risk by addressing the limitations of classical road density at different scales effectively. Kernel density spatial analysis is an important spatial analysis tool based on the combination of the nonparametric estimation of kernel density and geographic information systems (Liu et al., 2011; Cai et al., 2012; Anderson, 2009). To reflect the spatial differences of the road network density in the study process, according to the values of kernel density, we defined the values within a certain range as a "kernel" in space. According to the size of the kernel area or the sequence of the kernel generation, the kernels were classified as main kernels, subkernels, old kernels, or new kernels, which intuitively characterized the expansion processes of the regional road network (Liu et al., 2011; Xie and & Yan, 2008).

The aim of this study was to explore the road network expansion changes in Beijing and its impact on landscape ecological risk. For the purpose, with the support of geographic information technology (GIS), by applying the kernel density estimation tool, the road network density in Beijing was derived and an ecological risk index was constructed based on the landscape indices. Then, we analyzed changes in the road network and the landscape ecological risk by time–space evolution analysis to reveal the effects of road network expansion on regional landscape ecological risk.

2. Materials and methods

2.1. Study area

Beijing is located on the eastern coast of China (115.7°–117.4° E, 39.4°–41.6° N) and has 14 districts and 2 counties for a total area of 16,410.54 km^2. Since 2005, the government has led the establishment of the city's development model, and all of the districts and counties were classified into four large functional districts to support sustainable development: the capital core district (Inner city), the urban functional extension district, the new urban development district, and the ecological conservation district (Fig. 1). The capital core district and the urban functional extension district were primarily based on an artificial greenland ecosystem; most of the farmland ecosystems were located in the new urban development district and these areas were seen as the urban outskirts; and the woodland and grassland ecosystems were primarily distributed in the mountains of the ecological conservation district, which were took as the urban suburban. The entire city is surrounded by mountains in the west, north and northeast and to the southeast, is the Beijing plain. Depended on the flat terrain, the road network system in the middle of city is extremely developed. The urban road network uses the loop line as the backbone, with successively built urban expressways from two-ring to six-ring. The other primary trunk roads form a spatial pattern that radiates outward from the urban center, and they connect the internal and external branches of the loop

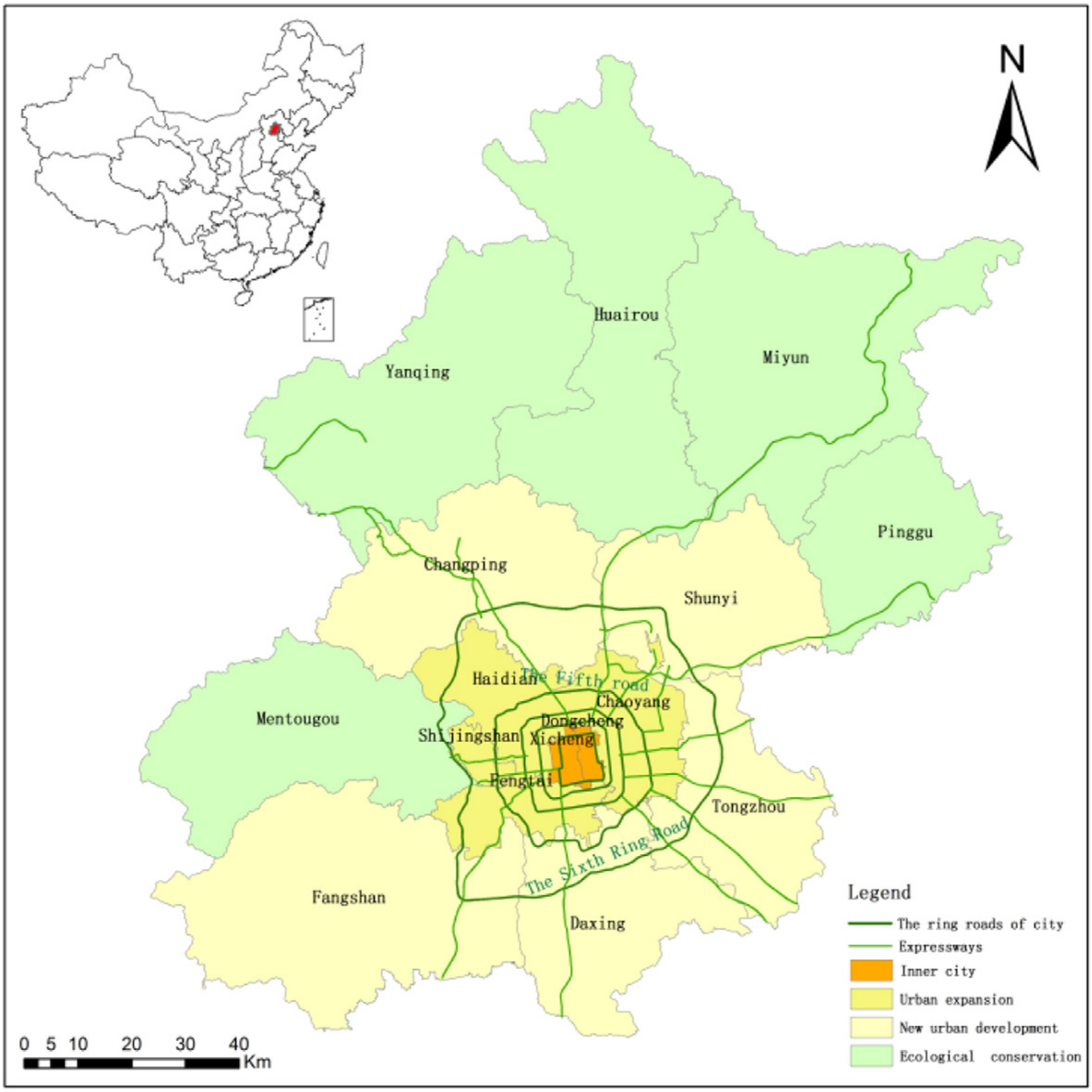


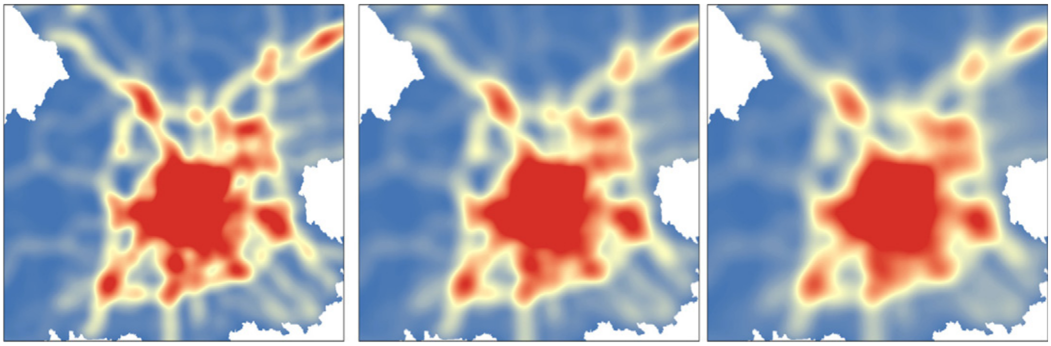
Fig. 1. The functional area development plan map of Beijing.

line. By 2010, the total mileage of domestic roads in Beijing reached 279 million km; the total mileage increased by 471 km in the last year.

Beijing is a developed city and the capital of China and therefore, is the national center of politics, culture, science, technology, and international exchange. The planning of the road network and the protection of the ecological environment in Beijing are very important and require significant planning. Therefore, studying the processes by which the road network affects regional ecological risk can provide a theoretical basis and technical support for future ecological construction and road planning. Additionally, the study also can be instructive for the development of other cities in China.

2.2. Data sources

The data used in the study primarily included administrative districts and road vector data for Beijing, land use/land cover data, and remote sensing image data. 1) The remote sensing image data were primarily obtained from the NASA data-sharing site (http://earthexplorer.hsgs.gov). We obtained Landsat TM images with 30-m resolution that covered the overall scope of Beijing in 2000, 2005 and 2010 and used them as the basic data source for the study after orthorectifying treatment and other preprocessing. 2) The administrative district data and road vector data for Beijing and the land use/land cover data were provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The administrative district data were primarily administrative border data recorded in Beijing in 2000 and 2005, which included the administrative boundaries and administrative centers of the districts. The road network vector data were obtained for Beijing in 2000, 2005, and 2010 and included data for expressways, ring expressways, national highways, provincial roads, first-grade urban roads, county roads and other roads. Land use/land cover data were primarily from the three periods of 2000, 2005, and 2010. These data were divided into two levels. In the first level, land cover was classified into 6 classes, including woodland, grassland, wetland, farmland, and construction land. In the second level, according to the definition of Food and Agriculture Organization Land Cover Classification System (FAO LCCS), the land cover was classified into 38 classes (Wang et al.,



(a)Bandwidth =5000m **(b) Bandwidth =6000m** **(c) Bandwidth =7000m**

Fig. 2. Density of road network with bandwidth 5000 m (a), 6000 m (b), 7000 m(c) in Beijing in 2010. (a) Bandwidth = 5000 m (b) Bandwidth = 6000 m (c) Bandwidth = 7000 m.

2015). The data have been widely used in related studies on land use/land cover, with a total accuracy of 95% and a Kappa coefficient above 0.81 (Liu et al., 2005, 2010; Wang et al., 2015).

2.3. Research methods

2.3.1. The kernel density analysis based on GIS

Kernel density estimation based on GIS primarily calculates the point density or linear density of a moving window (Ying et al., 2014). We assumed that $x_1,\ldots\ldots,x_n$ are independent and identically distributed samples, which are extracted from the population with probability density function f. Then, the value of f at point x is estimated as$f(x)$, which is usually calculated with Rosenblatt-Parzen's KDE (Rosenblatt, 1956; Parzen, 1962):

$$f_n(x) = \frac{1}{nh}\sum_{i=1}^{n} k\left(\frac{x-x_i}{h}\right) \tag{1}$$

In this Formula (1), $k(x)$is the kernel function; h is the bandwidth; $(x-x_i)$ is the distance between x and x_i, and n is the total number of samples.

Among these parameters, the identification and choice of h has the greatest effect on the calculated results. At large values of h, the kernel density is small and the curves of the density values are smooth. By contrast, when values of h are small, the curves of density values are more abrupt. In this study, we used the road data in 2010 as an example, and selected bandwidths of 500 0 m, 6000 m and 7000 m for comparison. As is shown in Fig. 2, we could clearly distinguish the density center of the road network and the kernel borders in the bandwidth at 6000 m, which effectively reflected the grade difference. Therefore, we selected 6000 m as the bandwidth length in this study. Additionally, the specific steps in solving the KDE are presented in other papers (Ying et al., 2014). For the purpose of this study, and referring to related study results, we set the weight of expressways at 5, the weight of national roads and ring expressways at 4, the weight of provincial roads at 3, the weight of urban first-grade roads at 2, and the weight of county roads and other roads at 1 (Ji et al., 2014). Lastly, we calculated the kernel values of the road network by using the spatial analysis tools of Arcgis10.1 to characterize regional road network density.

Table 1
The calculation method for landscape indices.

Landscape index	Formula	References
Landscape fragmentation index (C_i)	$C_i = n_i/A_i$	Xie et al., 2016
Landscape splitting index(S_i)	$S_i = D_i \cdot A/A_i$, $D_i = (1/2) \cdot \sqrt{n_i}/\sqrt{A}$	Zhang et al., 2013
Landscape dominance index(D_i)	$D_i = (R+F)/4 + L/2, R = n_i/N$, $F = B_i/B$, $L = S_i/S$	Gong et al., 2015
Landscape disturbance index (E_i)	$E_i = aC_i + bS_i + cD_i$	Liu et al., 2012
Landscape vulnerability index (F_i)	Obtained by normalization	Wu et al., 2015

2.3.2. Construction of the ecological risk index

n_i: patch number of landscape type i; A_i: total area of landscape type i; D_i: distance index of landscape type i; A: total area of the landscape; N: total number of patches; B_i: sample number of patch i; B: total number of samples; S_i: area of patch type i; S: total area of all samples. a, b, and c are weights of indices C_i, S_i and D_i, respectively.

Ecological risk is a reflection of the possibility that an ecosystem maintains itself into a low-energy equilibrium with relatively simple structures and functions in response to external disturbance (Gong et al., 2015). In this study, the ecological risk was characterized by landscape ecological risk which is associated with the degree of the external disturbance and its vulnerability. The ecological risk is primarily built by two landscape-level indices: landscape disturbance index (external) and landscape vulnerability index (internal) (Shi et al., 2015). Landscape disturbance index measures the magnitude of the disturbance from natural and human drivers. The landscape disturbance index (E_i) is used to measure the resistance of the landscape pattern to external interference, usually with landscape fragmentation (C_i), landscape splitting (S_i) and landscape dominance (D_i) indices weighted and summed for quantitative characterization. The landscape fragility index (F_i) primarily evaluates the internal capability of a landscape type to maintain its stability, generally by artificial assignment (Xie et al., 2013). The relevant parameters calculation showed in Table 1.

2.3.2.1. Landscape disturbance index. For the landscape disturbance index (E_i), $+b+c=1$. Because of the high urbanization of Beijing, the expansion of the road network would most likely first lead to a greater degree of landscape fragmentation (C_i) and then second, would more likely change the degree of landscape splitting (S_i), which would result in the dominant production of some landscape types. According to previous studies and the opinions of experts, we expected that the fragmentation index would be the most important index, followed by the splitting degree index and the dominance index. Therefore, the weights were assigned as 0.5, 0.3 and 0.2, respectively (Liu et al., 2012; Gong et al., 2015; Zhang et al., 2013; Di et al., 2014). Thus, the landscape disturbance index (E_i) was obtained.

2.3.2.2. Frangibility degree index. According to the first-level classification standard of China, the overall landscape of Beijing is divided into seven landscape types. According to the characteristics of the research area and referring to previous study results (Zhang et al., 2013; Di et al., 2014), we divided the grade of fragility degree of the landscape types into seven levels; the unused land was the weakest, followed by cultivated land, and the construction areas were considered the most stable. Therefore, the grade of fragility degree for each landscape type was as follows: unused land 7, wetland 6, cultivated land 5, garden land 4,

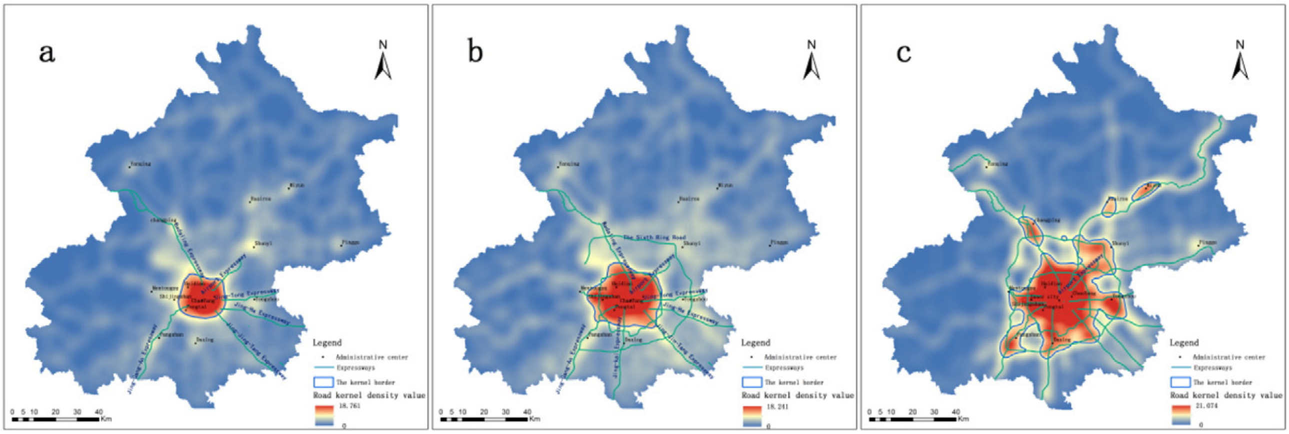


Fig. 3. Road kernel density distribution maps for Beijing in 2000(a), 2005(b) and 2010(c).

grassland 3, forested land 2, and construction land 1, then normalized to obtain their own vulnerability index (*Fi*) (Shi et al., 2015; Wu et al., 2015).

2.3.2.3. Landscape ecological risk index. Based on the above-mentioned landscape disturbance index and vulnerability index, we constructed the landscape ecological risk index. This index is used to describe the relative sizes of integrated ecological losses in a type of sample and can fully reflect the changes in ecological risks caused by changes in landscape pattern. Moreover, the index can change landscape spatial structure into spatialized ecological risk variables by sampling. The formula is as follows (Zhang et al., 2013):

$$ERI = \sum_{i=1}^{N} \frac{S_{ki}}{S_k} \sqrt{E_i \cdot F_i} \tag{2}$$

In this Formula (2), *ERI* represents the landscape ecological risk index; *N* represents the number of landscape types in the sample areas; S_{ki} represents the area of landscape type *i* in sample area *k*; S_k is the total area of sample area *k*; E_i represents the disturbance index of landscape type *i*; and F_i is the frangibility degree index of landscape type *i*. Referring to a previous study (O'neill et al., 1996) and according to local conditions of the landscape patches in the study area, this study used an 8 km × 8 km square grid to spatialize the ecological risk index, and we sampled a total of 319 sample areas with an equal interval method. Then, we calculated the landscape ecological risk index for each sample area as the ecological risk value of the sample area center.

2.3.3. Correlation analysis

The Spearman rank correlation coefficient is a type of statistical analysis that is calculated based on the rank of each type of element sample to replace the actual data. And this analysis method was primarily used to discuss the impacts of road network expansion on landscape pattern. The formula is as follows (Zhang et al., 2016):

$$r = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n^3 - n} \tag{3}$$

In this Formula (3), *r* is the rank correlation coefficient between *x* and *y*; $d_i^2 = x_i - y_i, i = (1, 2, 3, \ldots.., n)$; *n* is the total number of samples; x_i is the rank of sample value for element *x*; and y_i is the rank of sample value for element *y*.

2.3.4. Maximum covariance analysis

To analyze the impacts of road expansion on the regional ecological risk index, this study used maximum covariance analysis (MCA) to analyze road density and ecological risk index. Maximum covariance analysis, also known as the singular value decomposition (SVD) (Mardia et al., 1979), is used more generally in climatological science. The analysis can distinguish the best coupling relationship and the corresponding time between the two physical fields. In the MCA analysis, the covariance contribution (SCF) represents the importance of modal, and the cumulative covariance contribution (CSCF) reflects the interpretation degree of the first few modes in the two physical fields and reduces the dimension of variables. The modal correlation coefficient presents the relevant degree of the left and right fields in each modality. Modal space distributions use the homogeneous and heterogeneous correlation coefficients between time series in MCA analysis results and the original physical field for characterization. Based on the research objective, only the distribution of the heterogeneous correlation coefficient was analyzed in this study, and for all processes in the analyses and the significance of the parameters, refer to Bretherton 1992.

3. Results and analyses

3.1. Evolution of road kernel density

To facilitate comparisons, according to the actual distribution of the road network in each year, we defined the "kernel" or "kernel area" as areas in which the road network density value was greater than or equal to 6 km/km^2 (Fig. 3). Of these areas, the urban area within the six-ring was defined as the "urban center". The largest kernel area was located in the urban center and was defined as the "main kernel", and another small kernel was defined as a "sub kernel". As shown in Table 2, the overall road network of Beijing increased greatly from 2000 to 2010. The number of road network kernels increased from 1 to 5; the maximum kernel density increased from 18.761 km/km^2 to 21.074 km/km^2; and the total area of the kernel increased from 355.89 km^2 to 1949.07 km^2, a 4.5-fold increase compared with 2000.

The road network kernels are observed to expand not smoothly with time, which varied slowly during 2000–2005 and rapidly thereafter. The period of 2000–2005 was one of slow expansion. In this stage, only the main kernel was present and the number of kernels did not increase. The area of the main kernel increased to 752.72 km^2, which was twice

Table 2
The road network kernel of Beijing in 2000, 2005 and 2010.

Year	Number of kernels	Total area (km^2)	Growth (km^2)
2000	1	355.89	0
2005	1	752.72	396.83
2010	5	1949.07	1196.35

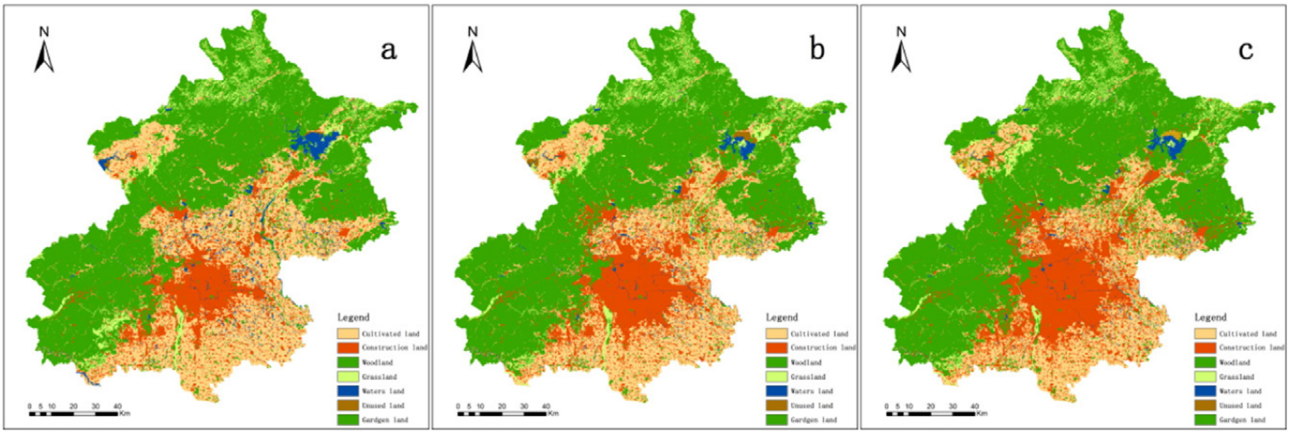


Fig. 4. Land type maps of Beijing in 2000(a), 2005(b) and 2010(c).

the area in 2000 (Table 2). During this expansion, the main kernel gradually formed five directions of expansion to the southeast, northeast, southwest, northwest and east (Fig. 3b). Rapid development of road kernels occurred in the period of 2005–2010. The main kernel continued to expand outward, and the total area of road kernels increased by 1196.35 km^2, which was a threefold increase compared with the area in 2000. Simultaneously, four sub-kernels were generated, and the average kernel area reached 389.814 km^2, which was very similar to the kernel area in 2000. Thus, the growth speed was rapider.

Using spatial comparison analysis (Fig. 3), we found that the space expansion model of the road kernel area was consistent with the development planning of the regional functional orientation in Beijing. In 2000–2005, the road network kernels expanded slowly because the population growth was relatively slow, and large area of tourist attractions of Inner city limited the road network expansion to a certain extent. To satisfy the increasing demands of traffic, urban construction and road expansion extended outward based only on the main kernel; thus, the highest value of the main kernel in 2005 was slightly less than that in 2000 (Figs. 3a and b). Simultaneously, the area of the main kernel covered the districts that were in the urban functional extension district, namely, Shijingshan, Fengtai, Chaoyang, and Haidian, and the expanding direction of the main kernel corresponded to the five primary directions of the Jing-Gang-Ao Expressway (southwest), the Jing-Jin-Tang Expressway (southeast), the Airport Expressway (northeast), the Badaling Expressway (northwest), and the Jing-Tong Expressway (east). By 2010, the main kernel had expanded rapidly to cover the districts of Shunyi, Tongzhou, Changping, and Fangshan, and two sub-kernels were in Daxing (Fig. 3c), which represented future satellite areas of urban economic development. These were the districts covered by the new urban development area. The new urban development area was the primary area that developed manufacturing and modern agriculture in Beijing and will be the center of economic development in the future. Thus, the expansion of road kernels was tightly correlated with urban development planning.

Further analysis showed that the expansion of the road network kernel was in a certain space relevant to the expressways. In contrast to the expanding direction of the main kernel in 2000 and 2005 and the sub-kernel in 2010 (Fig. 3), the extension of the road main kernel in 2000–2005 clearly corresponded to the beltway and expressways leading out of the city (five directions). From 2005 to 2010, the sub-kernels were distributed generally around the expressways and were primarily associated with the properties of expressways. Expressways are the arteries and backbone of a regional integrated transport system, and with high traffic volume and large traffic capacity, they are fundamental to the spatial layout of satellite cities. Therefore, the road network also gradually expanded with the advent of satellite cities.

3.2. Analysis of landscape pattern change

To comprehensively analyze the overall landscape pattern of Beijing based on land-use status in the study area and Chinese land classification standards, the overall landscape was classified into seven categories: grassland, woodland, cultivated land, wetland, unused land, garden land, and construction land.

Cultivated land, forested land and construction land were the primary types of land-use, which were closely associated with the terrain (Fig. 4). The urban center and southeast were suitable for living and social production, with flat terrain and a developed traffic network, and therefore, the construction land and cultivated land were primarily found in these areas. The west, north and northeast were mountainous, rugged and less affected by human activities; these areas were primarily composed of woodland and grassland.

Due to distribution differences of land-use types, the corresponding landscape types changed significantly over time and large changes were concentrated in the cultivated land and construction land, as shown in Fig. 5. In three years, forested land was the most abundant landscape type; however, changes were small in the two year periods, whereas in these periods, great changes occurred in cultivated land and construction land. The largest changes were in cultivated land; cultivated land decreased by 4.31% from 2000 to 2005 and by 3.94% from 2005 to 2010. Opposite changes were observed for construction land; construction land increased by 6.31% in ten years, which was one of the largest increases of all landscape types. These changes in the two landscape types were highly correlated with urban development and construction. Urban economic development promoted the change from traditional agriculture to the second and third industries. Thus, the reduction in cultivated land provided sufficient space for the formation of new industries, and the expansion of construction land offered the

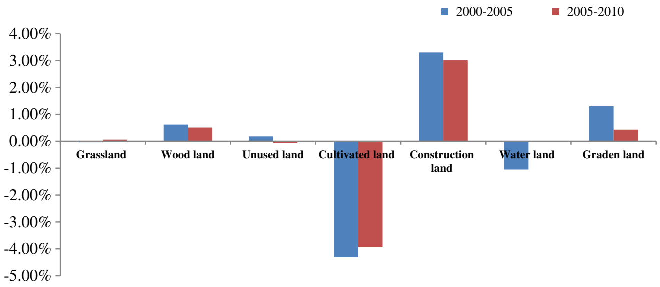


Fig. 5. . The changes of each landscape type in 2000–2005 and 2005–2010.

Table 3
The landscape index of the main landscape types in Beijing from 2000 to 2010.

Landscape index	Year	Grassland	Wood land	Unused land	Cultivated land	Construction land	Water land	Garden land
Landscape fragmentation index	2000	0.0314	0.0017	0.0777	0.0073	0.0226	0.0585	0.0318
	2005	0.0320	0.0015	0.0522	0.0086	0.0190	0.0850	0.0232
	2010	0.0295	0.0016	0.0536	0.0089	0.0176	0.0840	0.0219
Landscape splitting index	2000	0.4057	0.0296	2.2040	0.0825	0.2044	0.7529	0.4584
	2005	0.4120	0.0282	1.4996	0.0973	0.1678	1.1777	0.3376
	2010	0.3929	0.0289	1.6042	0.1089	0.1490	1.1765	0.3153
Landscape dominance index	2000	0.2370	0.4482	0.1306	0.3925	0.3576	0.2013	0.2088
	2005	0.2458	0.4490	0.1336	0.3704	0.3756	0.1956	0.2123
	2010	0.2326	0.4571	0.1336	0.3391	0.3984	0.1941	0.2101
Area proportion (%Land)	2000	4.76%	48.03%	0.40%	26.92%	13.52%	2.58%	3.78%
	2005	4.72%	48.65%	0.58%	22.61%	16.82%	1.53%	5.08%
	2010	4.78%	49.16%	0.52%	18.67%	19.83%	1.53%	5.51%

necessary resources and transportation advantages for the development of new industries.

To study the changes of landscape pattern, we used Fragstats3.3 to calculate the landscape indices (Table 3). Obvious changes in the landscape indices of the different landscape types were observed. In three years, the unused land and wetland were highly fragmented and showed high degrees of separation, which were primarily related to the nature of land-use in the landscape types. Unused land was scarce and covered <1% of the study area, and therefore, the landscape fragmentation and degree of splitting were relatively high. The patches of wetland were generally distributed as clumps or strip-types, and the area of the wetland was relatively small and easily divided by roads and other linear structures. In 2000–2005, the wetland area decreased by 1.05%, a decrease by half compared with that in 2000; thus, the degree of fragmentation of wetland exceeded that of unused land and became the landscape with the highest degree of fragmentation. Of all the landscape types, the dominance index of the woodland was the highest as a result of human activity and nature. In recent years, with the promotion of coordinated development of the economy and ecological environment in the capital of China, the government has protected the natural forests with high environmental standards. The urban ecological conservation area in which woodland was the primary landscape type was not conducive to road construction and economic development because the area was basically mountainous. Thus, woodland was more dominant.

3.3. Analysis of landscape ecological risk

To analyze the ecological risk of the entire area, we used the formula for landscape ecological risk and the spatial grid method to calculate the risk value for each grid center (Fig. 7c). Then, after performing ordinary kriging interpolation with the data layer of the central point, we divided the ecological risk index into six grades using the Natural Breaks method of Arcgis10.1 (Zhou et al., 2014; Zhang et al., 2013): low risk, sub-low risk, medium risk, sub-high risk, high risk and extra-high risk (Fig. 6). The results showed that the distribution of overall ecological risk was uneven in Beijing, with an obvious east–west polarization. The high ecological risk values were in the east, south and water-adjacent areas in the northeast, and the low ecological risk values were in the urban center and the west.

Through specific analysis, we found that the sub-low risk area of the urban center showed obvious outward expansion, which was consistent with that of the road network kernel, but there were differences during different stages of development. In 2000–2005, the extension process was relatively slow in the sub-low risk area, which increased from 163.241 km^2 to 458.456 km^2, an increase of almost 1.8-fold (Table 4). The growth speeds of the kernel areas were generally the same. The risk area surrounded the center of the main kernel and gradually expanded from the capital core district to the urban function extension district. By 2005, the risk area covered most of the urban function extension district with a clumped distribution (Figs. 6a and b). In 2005–2010, the risk area began to expand rapidly. The sub-low risk area increased from 458.456 km^2 to 866.23 km^2, a 2.5-fold increase compared with the area in 2000, but this increase was slower than that of the growth rate of the kernel area. The risk area continued to surround the center of the main kernel with a block distribution of which most covered the urban function extension district. Simultaneously, few areas stretched to the new urban development district, which highlighted the trend of outward expansion along the beltways (Figs. 6b and c). Unlike the expansion changes of the risk area, in the expansion processes of the road kernel area, other sub-kernels were generated in addition to the extension of the main kernel.

To further explore the changes in ecological risk, we conducted spatial analysis with Arcgis10.1 to perform raster computing on the

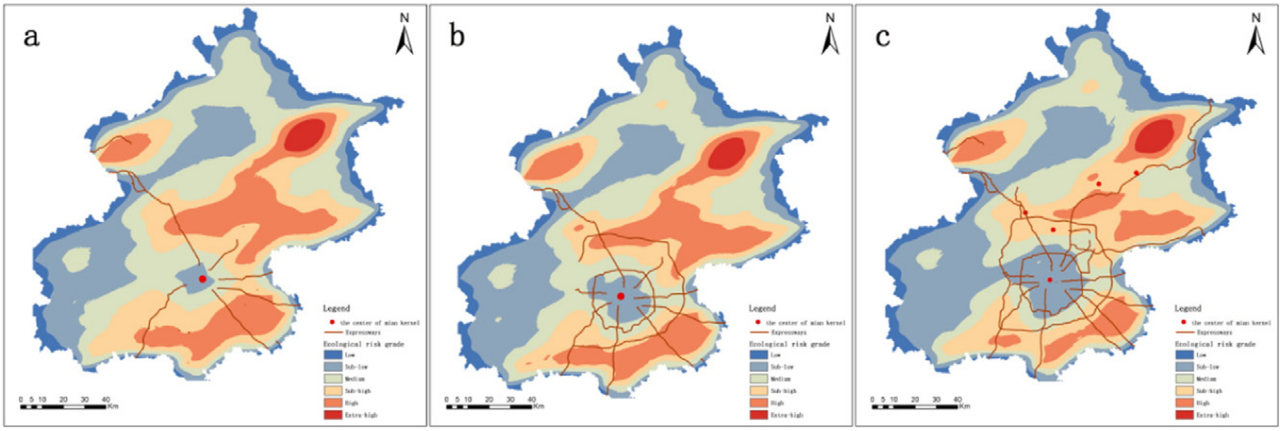


Fig. 6. Maps of the ecological risk level in 2000 (a), 2005 (b) and 2010 (c).

Table 4
The area changes of the sub-low risk area in the middle of the city.

Year	Area (km^2)	Growth(km^2)
2000	163.241	0
2005	458.456	295.215
2010	866.23	407.774

Table 5
Changes in the ecological risk grade areas in Beijing from 2000 to 2010.

	2000	2005	2010	2000–2005	2010–2005
Risk grade	Area (km^2)	Area(km^2)	Area(km^2)	Change proportion	Change Proportion
Low	1405.15	1418.72	1402.89	0.08%	−0.09%
Sub-low	4902.73	5288.55	5114.11	2.36%	−1.06%
Medium	3769.5	3673.23	4047.43	−0.59%	2.30%
Sub-high	3072.23	2894.34	2967.81	−1.09%	0.45%
High	2965.57	2841.29	2573.89	−0.76%	−1.63%
Extra-high	213.85	212.9	218.92	−0.01%	0.04%

distribution of ecological risk changes (Fig. 7). We found that the changes in ecological risk level in the central city were closely associated with expressways, which were consistent with the expansion of the road kernel. In 2000–2005, the changes in low-risk areas were the largest, with an increase of 2.36%. The sub-high risk areas decreased the most and were reduced by 1.09% (Table 5). In 2005–2010, the medium-risk areas increased the most, by 2.3%, and the high-risk areas decreased the most, by 1.63%. These changes were closely related to human disturbances. Because of the influence of human activity, some of the ecological environments with high-risk indices, such as cultivated lands, water and other ecological systems, had some abilities to resist interference, which led to declines in their risk levels. Simultaneously, the low-risk areas continually expanded, and their level of risk began to increase due to land exploitation, such as that of woodlands and grasslands. This pattern was more obvious in the areas of road network expansion (Fig. 7a). In 2000–2005, the areas of sub-low risk expansion and sub-high risk reduction were distributed around the beltway and expressways, which indicated that, in the process of urban expansion, parts of the cultivated land were gradually replaced by land for housing and transport. Correspondingly, the ecosystem changed into an urban green space ecological system that was strongly affected by human protection, and therefore, the risk level declined with the strengthening of *anti*-interference measures. In 2005–2010, a large-scale expansion of the medium-risk areas and a reduction of high-risk areas were also concentrated around the beltway and the expanding position of the main kernel (Fig. 7b). Additionally, the low-risk area decreased, with an increase in the level of risk, which caused growth of the medium-risk and sub-high risk areas. Based on the above analysis, we could know that the road network expansion had a certain spatial association with the changes of regional ecological risk.

3.4. Maximum covariance analysis

To explore the action relationship of the road network on ecological risk, maximum covariance analysis (MCA) was performed with the ecological risk index in 2000–2010 as the left field and the road kernel density value for the same time period as the right field. Table 6 shows the two singular vector covariance contributions (SCF), the cumulative covariance contributions (CSCF) and the modal correlation coefficients obtained by the singular value decomposition (SVD).

As shown in Table 6, the cumulative covariance contribution rate in the first two spatial distribution patterns reached 99% in which the cumulative covariance contribution in the first pair of singular vectors reached 98%, with the largest contribution for the covariance of the two fields; the modal correlation coefficient reached 0.92 and passed the 95% significance test, indicating that the left field and the right field had good synergistic change characteristics. Therefore, analyzing the first space distribution type (SVD 1) fully reflected the coupling characteristics of road density and ecological risk index.

Further analyzing the heterogeneous correlation coefficient distribution of the two fields, we found that the influence of road network density on the ecological risk had obvious spatial differences. The heterogeneous correlation pattern distribution structure of the first mode in ecological risk is shown in Fig. 8(a): the negative correlation area was obviously less than the positive correlation area and was primarily distributed in the urban center and eastern and northern regions; the significant negative correlation areas were relatively large, primarily located in Miyun, Pinggu and suburban areas with a high degree of correlation (|R|≥0.8). By contrast, the heterogeneous correlation pattern distribution difference of the first mode in road density was obvious (Fig. 8 b), with the urban, southeastern edge a positive correlation area, the west and north negative correlation areas, and the overall correlation strong. Areas of significant correlation were primarily located in Tongzhou, Shunyi and other suburban areas. From the overall MCA results, in the urban center, road density and ecological risk index were negatively correlated, i.e., the ecological risk index was smaller with greater regional road density. For the outskirts of the urban southeast, road density and ecological risk index were strongly positively correlated, i.e., the ecological risk index was greater with a more complex regional road network. Finally, in the northern mountains, the two were also positively correlated. This difference might be closely related to the distributions of urban ecosystem types. First, the artificial green ecosystem was the general ecosystem of the urban center, which was

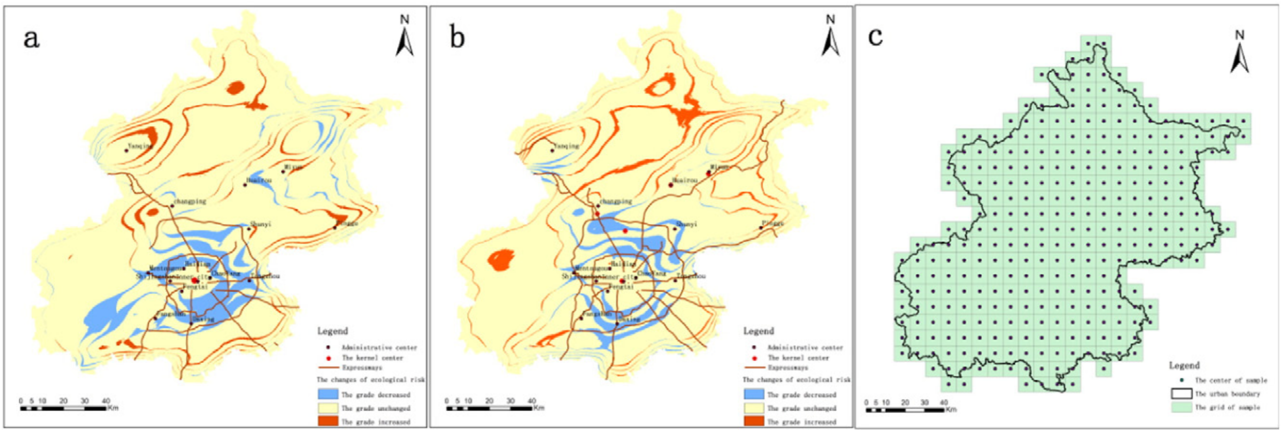


Fig. 7. Ecological risk areas (c) and changes of risk levels in 2000–2005 (a) and 2005–2010 (b).

Table 6
The results of MCA analysis for ecological risk index and road kernel density.

Mode	Modal correlation coefficient	Covariance contribution	Cumulative covariance contribution
SVD1	0.92**	0.98	0.98
SVD2	0.97**	0.01	0.99

** Passing the 95% significance test.

Table 7
Correlation of road kernel density and landscape index.

Year	Landscape fragmentation	Landscape splitting	Landscape dominance
2000	−0.360**	0.019	−0.560**
2005	−0.457**	0.020	−0.576**
2010	−0.370**	0.230**	−0.276**

** If p < 0.01, Significant correlation.

strongly influenced by human protections, and therefore, because people focused and emphasized ecological protection in the course of road construction, such as including ecological corridors, regional road network expansion reduced ecological risk to a certain extent. Second, most of cultivated land was distributed in the suburban plain area, which was an area in which land use change was obvious and that was easily occupied by urban traffic or commercial land; therefore, the ecological risk was largely influenced by road networks. Last, in the northern part of the city, the ecological systems were primarily woodlands and grasslands, and because of the mountainous terrain, extending the road network was limited. Although these systems continued to operate under the ecological process of natural succession, the increasing road network density still influenced their ability to resist external interference, causing an increase in the ecological risk. Of note, as shown in Fig. 8 (a), a significant negative correlation area was in the northeast of the city in the region primarily near the Miyun reservoir, which is the primary drinking water supply in Beijing, in which the surrounding natural environment was protected by special government policies and roads were constructed with outstanding attention to ecological effects. Thus, as the number of roads increased, the regional ecological risk was actually reduced.

4. Discussion

With the support of geographic information technology, this study used kernel density estimation and an ecological risk index to perform space–time dynamic analysis for the road network and urban ecological risk in Beijing. The results revealed the influence of road network expansion on regional ecological risk. Most traditional research has focused on the impacts of land-use changes around roads on the regional ecological environment (Liu et al., 2010; Liu et al., 2008; Patarasuk, 2012), and the analysis of changes caused by road networks has been limited to numerical expressions of various measured indices, which cannot accurately reflect the variations in local road networks. In this study, kernel density estimation was used to calculate the urban road network density, which effectively overcame the limitations of traditional road network density analysis at a big scale and revealed the impacts of road network expansion on landscape ecological risk more intuitively.

4.1. Influence of road network expansion

The landscape ecological risk index based on landscape indices quantifies the regional ecological risk well, but this index cannot directly reflect the affecting process of road network expansion on the ecological environment. How the road network changes landscape patterns to affect regional ecological risk requires further study.

4.1.1. Correlation of road kernel density with landscape indices

To eliminate the influences of the study area boundaries and to improve the accuracy of the analysis, we excluded some samples in the study area boundary and analyzed the correlations between landscape fragmentation index, splitting index, and dominance index and road kernel density in the remaining regions (Table 7). We found that road network expansion influenced the changes in regional ecological risk primarily through landscape fragmentation and dominance. 1) In the three years, the road kernel density was significantly negatively correlated with landscape fragmentation and dominance indices and was also significantly positively correlated with the landscape splitting index in 2010, but the correlation was weak. 2) In 2000 and 2005, the correlations between road kernel density and landscape dominance were relatively high, which illustrated that the influence of road

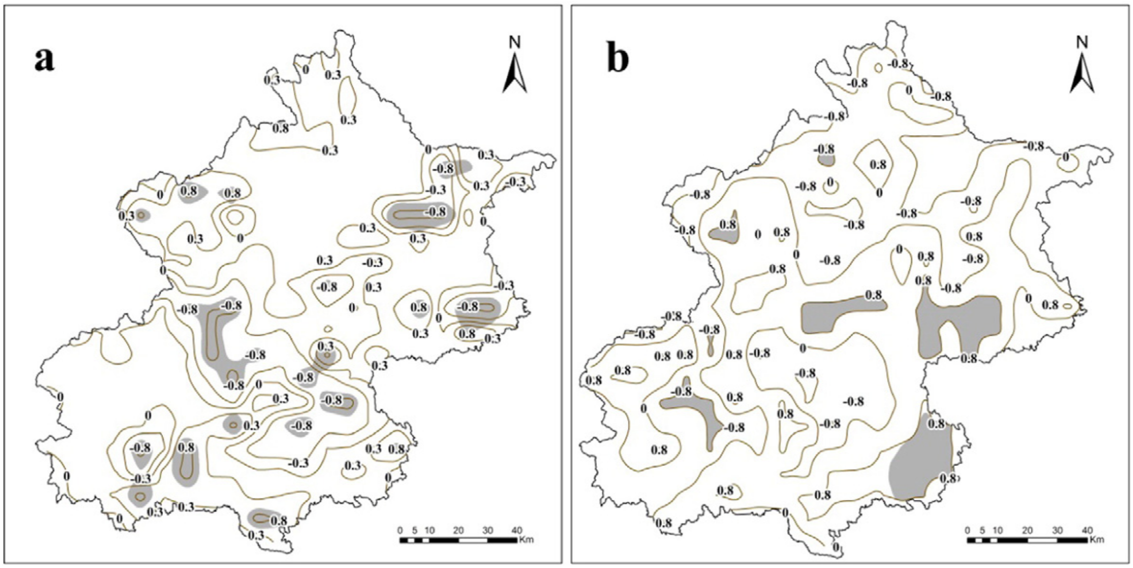


Fig. 8. Heterogeneous correlation patterns for the first mode of ecological risk index (a)、road density(b). The shaded areas showed that the significance correlation passed the 95% of significance test.

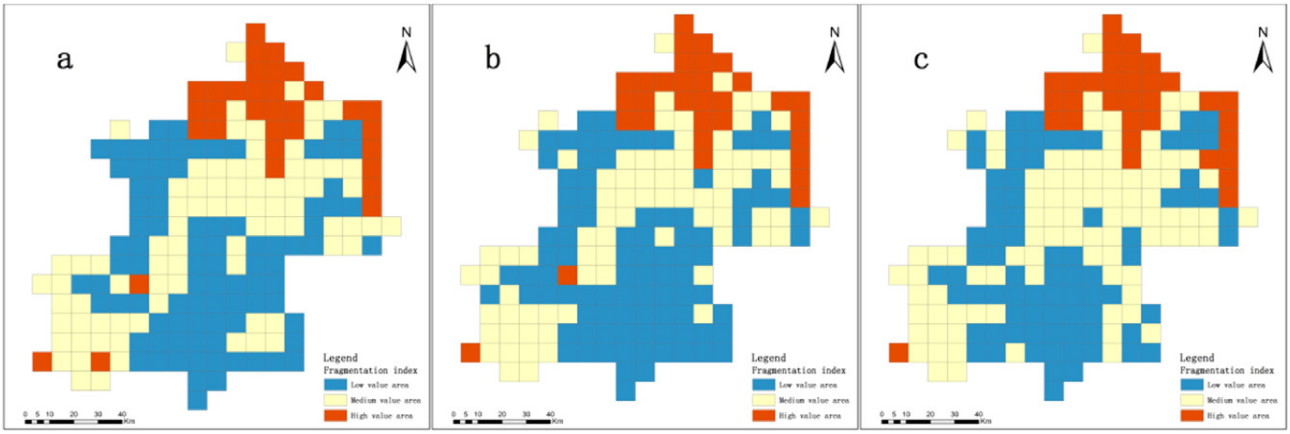


Fig. 9. Spatial analysis of landscape fragmentation in 2000 (a), 2005 (b) and 2010 (c).

network expansion on changes of ecological risk was mainly determined by the landscape dominance. In 2010, a weak correlation showed that the impacts of the road network on landscape dominance were not stable. 3) For the three years, the road kernel density and landscape fragmentation index maintained a stable relationship, and the correlation was significant, which illustrated that the impacts of the road network on landscape fragmentation were relatively stable. The significant negative correlation was consistent with previous research results (Liu et al., 2014).

4.1.2. Landscape index spatial relationships

For further discussing the influence laws of the road network, we used the Nature breaking method of Arcgis10.1 to divide landscape fragmentation, landscape dominance and ecological risk into three levels (Figs. 9, 10 and 11). As described above, road kernel density and landscape fragmentation were significantly negatively correlated, and with a denser road network, the landscape fragmentation was lower. This result was opposite to the positive correlation found in other research areas (Liu et al., 2008; Cai et al., 2012). For the urban center in Beijing, the original natural landscape and ecological system were previously replaced and the original ecological environment was completely lost because of the land-use changes caused by the expansion of the road network. Therefore, the degree of fragmentation was low because there were fewer patches and the more effective patches were protected by artificial ecosystems such as construction land (Fig. 9). By contrast, grasslands were far from the urban area and were easily affected by the terrain; therefore, the fragmentation degree of grasslands was higher because patches were more abundant and scattered. Moreover, due to the time scale dependence of the affecting processes, the correlations between road density and landscape fragmentation were not strong (Table 7). Landscape dominance was negatively correlated with road kernel density, and therefore, the landscape dominance of the urban center was also relatively low (Fig. 10). In 2000 and 2005, the landscape dominance of the urban central area was low and that of the mountain woodlands was high, which was the complete opposite to the spatial layout of the road network. In 2010, the urban central area had a large high-dominance area (Fig. 10c), which corresponded to the weak correlation of road kernel density and landscape dominance (Table 7). The direct effect of the road network expansion was a decrease in landscape dominance, but with enhancement of human disturbance, the ecosystem types surrounding the road were controlled by people completely and changed in a positive direction for urban construction. Thus, the landscape dominance of the urban central area increased.

In conclusion, although the expansion of roads increased landscape fragmentation (Cai et al., 2012), the road network often caused patches of regional construction land to continually expand and more strongly affect the changing of the regional landscape. Due to influence of human activities, patches of construction land were large and fewer, and therefore, landscape fragmentation was reduced. By the decrease in landscape dominance, the ecological diversity of the landscape increased and there was closer contact among ecological systems, which finally lowered the ecological risk of the urban central area. For woodlands and grasslands, the landscape fragmentation and dominance were higher, but fragility indices were lower; thus, they were less affected by the road network and were primarily distributed in the

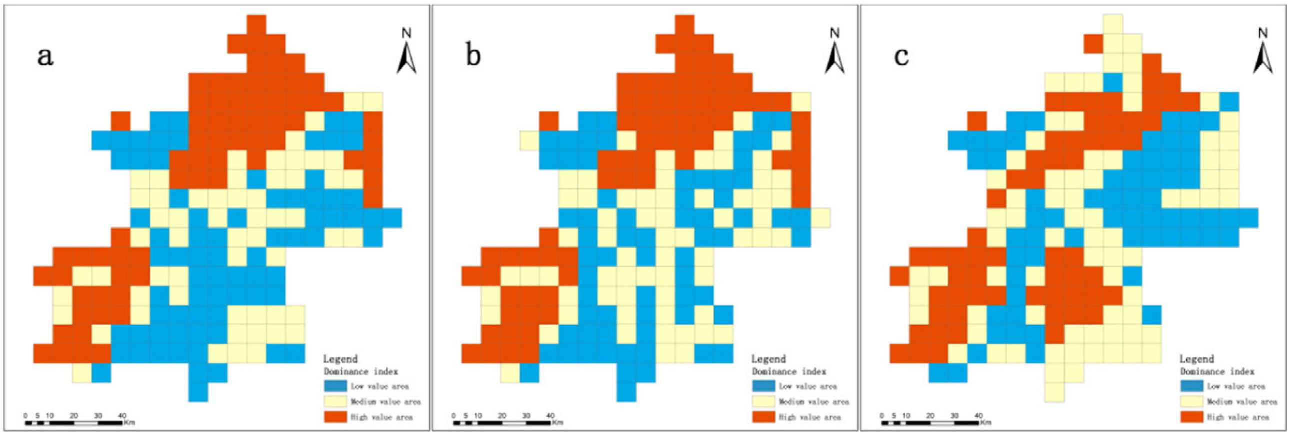


Fig. 10. Spatial analysis of landscape dominance in 2000 (a), 2005 (b) and 2010 (c).

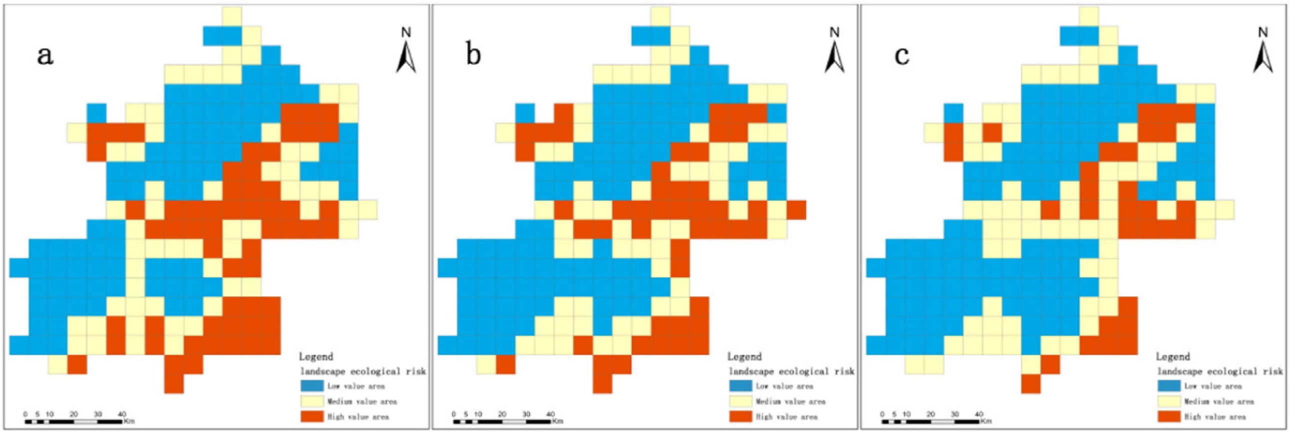


Fig. 11. Spatial analysis of the ecological risk level in 2000 (a), 2005 (b) and 2010 (c).

mountains. By contrast, the landscape fragmentation and dominance of cultivated land and wetland were relatively low, but the fragility indices were relatively high; thus, they were greatly affected by the road network and human activity. Moreover, the ecological high-risk areas were primarily distributed in the northeast and southeast (Fig. 11) in which wetland and cultivated land were the primary landscape types. Based on the above discussion, the road network caused changes in ecological risk primarily by influencing landscape fragmentation and dominance to a certain extent.

5. Conclusions

With the support of geographic information system (GIS) technology, we used the kernel density estimation to calculate urban road density and analyzed the temporal and spatial changes in the road kernel areas. With this approach, we conducted comparative research on an ecological risk index through spatial interpolation to explore the influence of road network expansion on regional landscape ecological risk.

(1) In the dynamics of the overall landscape pattern, changes in landscape indices of various landscape types were obvious and were primarily related to the type of land-use. Under the influence of urbanization, patches of cultivated land changed the most, and with little unused land, the degree of fragmentation and splitting was high. Wetland was easily divided by linear structures such as roads, and therefore, the fragmentation of this land type increased rapidly. The landscape dominance of woodland was consistently high due to the combined effects of humans and nature.

(2) In the time series, the expansion of the road kernel area was consistent with the changes in the sub-low risk area in the urban center, but there were differences during different stages of development. Specifically, two periods of expansion were observed, one slow and the other rapid. The period of 2000–2005 was the slow expansion stage, and both areas rapidly expanded in the urban function expansion district based on the capital core district. The growth speed of the two areas was basically the same. The period of 2005–2010 was the stage of rapid development, and the two areas extended from the urban function expansion district to the new urban development district, in which the growth speed of the road kernel areas was relatively rapid and the overall road kernel did not remain unified with the generation of sub-kernels.

(3) In the spatial pattern, expanding changes of the road kernel area were consistent with the grade changes of the urban central ecological risk, which both had a certain spatial correlation with expressways. The positions of the road network expansion along the expressways corresponded to the changing areas of the ecological risk grade in the urban center.

(4) The effects of road networks on the ecological risk in the study area had obvious spatial differences, which might be closely related to the distribution of urban ecosystem types. In the urban center and the vicinity of Miyun reservoir, road density and ecological risk index were primarily negatively correlated. These areas were basically in the artificial ecosystem in which, because of the effect of human protection, the ecological risk index was smaller when the road network density was higher. In the southeast plain area of the urban outskirts, road density and ecological risk index were positively correlated. Most of this area was cultivated land in which the land-use changed significantly due to the influence of the road network. Because of the lack of sufficient time samples, studying the impacts of road network expansion on the regional ecological risk based on the spatial correlation had a limitation; therefore, the authors will further explore the action mechanism in more time series.

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References

Anderson, T.K., 2009. Kernel density estimation and K-means clustering to profile road accident hotspots. Accid. Anal. Prev. 41 (3), 359–364.

Barandica, J.M., Delgado, J.A., Berzosa, Á., et al., 2014. Estimation of CO2 emissions in the life cycle of roads through the disruption and restoration of environmental systems. Ecol. Eng. 71, 154–164.

Barber, C.P., Cochrane, M.A., 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. Biol. Conserv. 177, 203–209.

Bian, B., Lin, C., Wu, H.S., 2015. Contamination and risk assessment of metals in road-deposited sediments in a medium-sized city of China. Ecotoxicol. Environ. Saf. 112, 87–95.

Bretherton, C.S., 1992. An Intercomparison of methods for finding coupled patterns in climate data. J.Climate. 5 (6), 541–560.

Cai, X.J., Wu, Z.F., Cheng, J., 2012. Analysis of road network pattern and landscape fragmentation based on kernel density estimation. Chin. J. Ecol. 31 (1), 158–164 (In Chinese).

Cao, S.X., Ye, H.H., Zhan, Y., 2010. Cliff roads: an ecological conservation technique for road construction in mountainous regions of China. Landscape. Urban. Plan. 94 (3–4), 228–233.

Chang, S.Y., Vizuete, W., Valencia, A., et al., 2015. A modeling framework for characterizing near-road air pollutant concentration at community scales. Sci. Total Environ. 538, 905–921.

Coffin, A.W., 2007. From roadkill to road ecology: A review of the ecological effects of roads. J. Tr. Geogr. 15 (5), 396–406.

Di, X.H., Wang, Y.D., Hou, X.Y., 2014. Ecological risk caused by land use change in the coastal zone: a case study in the Yellow River Delta High-Efficiency Ecological Economic Zone. IOP Conference Series: Earth and Environmental Science (17), 682–691.

Du, N.R., Ottensb, H., Sliuzas, R., 2010. Spatial impact of urban expansion on surface water bodies—A case study of Wuhan. China. Landscape. Urban. Plan. 94, 175–185.

Eigenbrod, F., Hecnar, S.J., Fahrig, L., 2009. Quantifying the Road-Effect Zone: Threshold Effects of a Motorway on Anuran Populations in Ontario. Canada. Ecol. Soci. 14 (1), 24–28.

Fan, J.T., Li, J.S., Quan, Z.J., 2011. Impact of road construction on giant panda's habitat and its carrying capacity in Qinling Mountains. Acta Ecol. Sin. 31 (3), 145–149.

Forman, R.T.T., 2000. Estimate of the area affected ecologically by the road system in the United States. Conserv. Biol. 14, 31–35.

Forman, R.T.T., Alexander, L.E., 1998. Roads and their major ecological effects. Annu. Rev. Ecol. Evol. Syst. 29, 207–231.

Freitas, S.R., Alexandrino, M.M., Pardini, R., et al., 2012. A model of road effect using line integrals and a test of the performance of two new road indices using the distribution of small mammals in an Atlantic Forest landscape. Ecol. Model. 247, 64–70.

Gong, J., Yang, J., Tang, W., 2015. Spatially explicit landscape-level ecological risks induced by land use and land cover change in a National Ecologically Representative Region in China. Inter.J. Environ. Res. Public. Health. 12 (11), 14192–14215.

Guo, Z., Hu, D., Zhang, F.H., et al., 2014. An integrated material metabolism model for stocks of urban road system in Beijing. China. Sci. Total. Environ. 470-471, 883–894.

Hu, X.S., Wu, Z.L., Wu, C.Z., et al., 2016. Effects of road network on diversiform forest cover changes in the highest coverage region in China: an analysis of sampling strategies. Sci. Total Environ. 565, 28–39.

Huang, J.H., Li, F., Zeng, G.M., 2016. Integrating hierarchical bioavailability and population distribution into potential eco-risk assessment of heavy metals in road dust: A case study in Xiandao District, Changsha city. China. Sci. Total. Environ. 541, 969–976.

Ji, W., Wang, Y., Zhuang, D.F., 2014. Spatial and temporal distribution of expressway and its relationships to land cover and population: A case study of Beijing. China. Transport. Res. D-Tr. E. 32, 86–96.

Karlson, M., Mörtberg, U., 2015. A spatial ecological assessment of fragmentation and disturbance effects of the Swedish road network. Landscape.Urban. Plan. 134, 53–65.

Karlson, M., Ulla, M., Berit, B., 2014. Road ecology in environmental impact assessment. Environ. Impact Assess. Rev. 48, 10–19.

Li, J., Zhou, Z.X., 2015. Coupled analysis on landscape pattern and hydrological processes in Yanhe watershed of China. Sci. Total Environ. 505, 927–938.

Li, S.C., Xu, Y.Q., Zhou, Q.F., et al., 2004. Statistical analysis on the relationship between road network and ecosystem fragmentation in China. Prog. Geogr. 23 (5), 78–85 (In Chinese).

Liu, C., Yang, H.J., Wang, Z.Q., 2014. Spatial network of road and its impact on fragmentation of rural settlement in Qinling Mountain area. J. Shandong. Agricul. Uni. 45 (2), 252–256 (Natural Science Edition).

Liu, D., Qu, R., Zhao, C., et al., 2012. Landscape ecological risk assessment in Yellow River Delta. J. Food. Agricul. Environ. 10 (2), 970–972.

Liu, J.Y., Liu, M.L., Tian, H.Q., et al., 2005. Spatial and temporal patterns of China's cropland during 1990–2000: an analysis based on Landsat TM data. Remote Sens. Environ. 98 (4), 442–456.

Liu, J.Y., Zhang, Z.X., Xu, X.L., et al., 2010. Spatial patterns and driving forces of land use change in China during the early 21st century. J. Geogr. Sci. 20 (4), 483–494.

Liu, R., Hu, W.P., Wang, H.L., 2011. The road network evolution of Guangzhou-Foshan metropolitan area based on kernel density estimation. Sci. Geogr. Sin. 31 (1), 83–86 In Chinese.

Liu, S.L., Cui, B.S., Dong, S.K., et al., 2008. Evaluating the influence of road networks on landscape and regional ecological risk—a case study in Lancang River valley of Southwest China. Ecol. Eng. 34 (2), 91–99.

Liu, Y.X., Peng, J., Zhang, T., Zhao, M.Y., 2016. Assessing landscape eco-risk associated with hilly construction land exploitation in the southwest of China: trade-off and adaptation. Ecol. Indic. 62, 289–297.

Mardia, K.V., Kent, J.T., Bibby, J.M., 1979. Multivariate Analysis. Academic Press, New York.

Narayanaraj, G., Wimberly, M.C., 2012. Influences of forest roads on the spatial patterns of human- and lightning-caused wildfire ignitions. Appl. Geogr. 32 (2), 878–888.

O'Neill, R.V., Hunsaker, C.T., Timmins, S.P., et al., 1996. Scale problems in reporting landscape pattern at the regional scale. Landsc. Ecol. 11 (3), 169–180.

Parzen, E., 1962. On estimation of a probability density function and mode. Ann. Math. Stat. 33, 1065–1076.

Patarasuk, R., Binford, M.W., 2012. Longitudinal analysis of the road network development and land-cover change in Lop Buri province, Thailand, 1989–2006. Appl. Geogr. 32 (2), 228–239.

Redon, (d.) L., Viol, I.L., Jiguet, F., et al., 2015. Road network in an agrarian landscape: potential habitat, corridor or barrier for small mammals? Acta Oecol. 62, 58–65.

Reijnen, R., Foppen, R., Veenbaas, G., 1997. Disturbance by traffic of breeding birds: evaluation of the effect and considerations in planning and managing road corridors. Biodivers. Conserv. 6 (4), 567–581.

Rosenblatt, M., 1956. Remarks on some nonparametric estimates of a density function. Ann. Math. Stat. 27, 832–837.

Shi, H., Yang, Z.P., Han, F., Shi, T.G., Li, D., 2015. Assessing landscape ecological risk for a world natural heritage site: a case study of Bayanbulak in China. J. Environ. Stud. 24, 269–283.

Simmons, M.T., Venhaus, H.C., Windhager, S., 2007. Exploiting the attributes of regional ecosystems for landscape design: the role of ecological restoration in ecological engineering. Ecol. Eng. 30 (3), 201–205.

Staab, K., Yannelli, F.A., Lang, M., Kollmann, J., 2015. Bioengineering effectiveness of seed mixtures for road verges: functional composition as a predictor of grassland diversity and invasion resistance. Ecol. Eng. 84, 104–112.

Tian, Z., Jia, L.M., Dong, H.H., et al., 2016. Analysis of urban road traffic network based on complex network. Protein Eng. 137, 537–546.

Wang, Y., Yu, X.F., Zhuang, D.F., 2015. Temporal and spatial characteristics of Beijing golf courses over the past 30 years. Acta Pratacul. Sinorama 24 (8), 188–198 In Chinese.

Wu, J., Peng, J., Liu, Y., et al., 2015. Assessing landscape ecological risk in a Mining City: a case study in Liaoyuan City, China. Sustain. For. 7 (7), 8312–8334.

Xie, H.L., Wang, P., Huang, H.S., 2013. Ecological risk assessment of land use change in the Poyang Lake eco-economic zone. China. Inter.J. Environ. Res. Public. Health. 10 (1), 328–346.

Xie, Y.C., Gong, J., Sun, P., et al., 2016. Impacts of major vehicular roads on urban landscape and urban growth in an arid region: a case study of Jiuquan city in Gansu Province. China. J. Arid Environ. 127, 235–244.

Xie, Z.X., Yan, J., 2008. Kernel density estimation of traffic accidents in a network space. Comput. Environ. Urban. Syst. 32 (5), 396–406.

Ying, L.X., Shen, Z.H., Chen, J.D., Fang, R., Chen, X.P., Jiang, R., 2014. Spatiotemporal patterns of road network and road development priority in three parallel rivers region in Yunnan, China: an evaluation based on modified kernel distance estimate. Chin.Geogra.Sci. 24, 39–49.

Zhang, W.Y., Wei, Z.W., Wang, B.H., et al., 2016. Measuring mixing patterns in complex networks by spearman rank correlation coefficient. Physica. A. Stati. Mech. Appli. 451, 440–450.

Zhang, X.B., Shi, P.J., Luo, J., 2013. Landscape ecological risk assessment of the Shiyang River basin. Geo-informatics in resource management and sustainable ecosystem.(GRMSE). Part II, CCIS 399, 98–106.

Zhou, D., Shi, P., Wu, X., et al., 2014. Effects of urbanization expansion on landscape pattern and region ecological risk in Chinese Coastal City: a case study of Yantai City. TheScientificWorldJOURNAL 2014 (10), 821781.