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# Spatial variations in the relationships between road network and landscape ecological risks in the highest forest coverage region of China

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ABSTRACT

The road network is one of the most ubiquitous and significant long-term legacies of all types of human disturbances on the landscape. Taking the upper reaches of the Minjiang River in Fujian Province of southeast China as a case, the spatiotemporal dynamics of the landscape patterns and landscape ecological risk (LER) were explored, and based on the geographically weighted regression (GWR) model, the geographical heterogeneity in the correlations between the road network and the LER were identified. Our results showed that: (1) The distribution of the LER had a gradually decreasing trend from the middle to the periphery in 2007, with the high-risk area expanding to the western part of the study area in 2012 and 2016. The LER close to the road network was generally higher than those far from the road network. (2) The GWR model fit our case better than the ordinary least square (OLS) model, with both of the measurements of the road network (i.e., distance to the nearest road, DNR; and kernel density estimation, KDE) being significantly correlated with the LER at the 1% level. (3) According to the quantified coefficients estimated by the GWR model, we found that there were spatial variations in the associations between the two regressors and different level effects of roads on the LER. (4) The GWR analysis also indicated that the high-level roads mainly affected areas where human activities were more intensive, whereas the low-level roads infiltrated every corner of the region, mainly affecting areas that were far from the city. (5) The significant cumulative impacts of the road network on the LER were also observed in this study. Benefitting from the quantification and visualization of the spatial paradigm in regard to their trade-off and the synergistic associations between the LER and the road network at the grid level, our study provides suggestions for implementing more appropriate policies that will alleviate the impact of road construction on the landscape. This study also sheds light on further applications of the GWR model in future research on road ecology.

## 1. Introduction

Ecological risks reflect the possibility that an ecosystem will be confronted with a degrading response to external disturbances (Gong et al., 2015). One of its major branches is landscape ecological risk (LER). The magnitude of LER is affected by multi-source threats from both natural and human interferences, such as agricultural and forestry practices and road network extension, which can be observed by the integrated trait of both landscape patterns and ecological processes at the regional scale (Li and Zhou, 2015; Simmons et al., 2007). The road network is among the most prevalent of all the types of human disturbances (Forman et al., 2002; Valipour, 2015), and its increasing influence on natural ecosystems has been observed over the past two decades (Coffin, 2007; Karlson and Mortberg, 2015; Selva et al., 2011). According to previous studies, nearly 15–20% of the total land is covered by the road effect zone in the USA (Forman, 2000), approximately 16% in the Netherlands (Reijnen et al., 1997), and this number is approximately 18.37% in China (Li et al., 2004). The road network will directly or indirectly accelerate the fragmentation and degradation of a habitat, eventually resulting in an increase of LER (Freitas et al., 2012; Barandica et al., 2014; Staab et al., 2015). With a sharp increase in the contradiction between the road network and ecological resources protection, it is important to better understand their relationships to find scientific methods to pursue sustainable development.

In recent years, evaluations of LER have drawn wide attention around the world (Ayre and Landis, 2012; Li et al., 2017; Peng et al.,

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2015). These studies provide an important contribution to the understanding of the effects of human disturbances on the ecosystem (Li and Huang, 2015; Xu and Kang, 2017; Zhou et al., 2014). Meanwhile, the effects of road construction on landscape sustainability have also been extensively investigated at various levels, including a single road, a certain level of roads or even a complicated road network (Barber et al., 2014; Hu et al., 2016; Narayanaraj and Wimberly, 2012). However, most of these studies concerning the effect of roads tend to focus on analysing the patterns of landscapes (Liu et al., 2014; Redon et al., 2015); few studies have performed a LER assessment associated with the road network; in particular, spatial variations in the relationships between the road network and LER across locations have not yet been reported (Mo et al., 2017).

The road network, which enhances the attraction and radiation of the manmade landscape, has become a focus of landscape research over the past two decades (Hawbaker et al., 2006). Along with long-term planning and the development of roads in a region, a complex network system with certain spatial characteristics has gradually formed. To observe the ecological effects of a road network, the spatial pattern of the road network should be quantified first (Cai et al., 2013; Mo et al., 2017). Road density (RD) is one of the most commonly used indices that can effectively characterize the features of a road network. Due to the rapid development of geographic information systems (GIS), its spatial analysis tools have been used extensively in various fields, including road ecology studies (Hu et al., 2014; Karlson et al., 2014; Vu et al., 2013). Among these spatial analysis tools based on ArcGIS, kernel density estimation (KDE) (Parzen, 1962), which is a spatial analysis method that measures the density of the road network, offers a powerful tool for quantifying the spatial features of a road network. KDE has been employed to observe the ecological impacts of the road network and has proven to be an effective measurement in its joint consideration of both the spatial configuration and the function of a road network (Anderson, 2009; Cai et al., 2013; Hu et al., 2017). Buffer analysis (BA) and distance to the nearest road (DNR) are also effective methods employed in many road impact analyses; for example, researchers have used the DNR index to analyse the impacts of the road network on the changes in forest cover (Hu et al., 2014; Chaudhuri and Clarke, 2015; Hu et al., 2016) and have used the BA index to explore the impacts of road network extensions on landscape patterns (Liu et al., 2014; Liang et al., 2014).

As mentioned above, the spatial distribution of a road network characterized by the indicators of RD, KDE, and DNR constrains the rates and pathways of LER changes. However, how much these variables are able to explain the patterns of LER is still uncertain. The OLS technique has been used to explore the effects of human interference factors on the landscape in many of previous studies; for example, the linear regression model was used to study urban landscape changes (Seto and Kaufmann, 2003), the multinomial logistic model was applied to explore the forces of forest landscape change (Poudyal et al., 2008), and the maximum covariance analysis was applied to analyse the impact of the road network on LER (Mo et al., 2017). However, the OLS may ignore the spatial non-stationarity of geographical factors (i.e., LER) and lead to biased outcomes or inefficient estimations (Austin, 2007; Valipour, 2015) because the relationships between road indicators and LER may vary greatly across a study area. In this context, the geographically weighted regression (GWR) model was proposed (Fotheringham et al., 2002) to identify the geographical variation in the relationship between two regressors at the pixel level. The GWR model has been extensively used to explore the driving patterns in land use and cover changes (Buyantuyev and Wu, 2010; Giri and Qiu, 2016; Tu, 2011), forest landscape dynamics (Hou et al., 2015; Pineda Jaimes et al., 2010), and other ecological and environmental process (Hu et al., 2015; Mulley et al., 2016; Zhang et al., 2016). The GWR model has been proven to be an effective solution to evaluate the spatial non-stationarity and thus overcome the problem produced by OLS models. Therefore, in this study, the GWR model was employed to explore the impact of different dimensions of road networks on LER.

Fujian Province, which is located on the southeast coast of China, has the highest forest coverage rate in the country (Ren et al., 2011). Sanming City possesses the highest vegetation coverage in the province and is one of the major areas in China in terms of the forest production industry. However, the region is experiencing active transformations among landscape types caused by the combination of nature and human activities (Zhang et al., 2010). Furthermore, the road network of Sanming City has expanded rapidly over the past 30 years (Hu et al., 2017). The significant alteration of the forest landscape by the extension of the road network has potentially negative effects on biodiversity conservation and habitat loss, thus leading to an increase of the LER. Therefore, identification and quantification of LER associated with road network development are of great value for this region. Meanwhile, this study will provide an important theoretical basis and methodology for road network planning in other regions to alleviate its impact on the ecosystem.

Taking Sanming City as a case, the aim of this study was to fill in the knowledge gap of spatial variation in the association between the road network and LER. For this purpose, we initially introduced the GWR model to analyse the spatial paradigm in their associations. Specifically, the objectives were to: (1) quantify and visualize the spatio-temporal distributions of the landscape pattern and LER in different periods; (2) identify the spatial variation of the effects (both sign and size) of the road network on the LER by applying GWR models at the grid level, with the LER index as a dependent variable and the KDE and DNR of different level roads as well as topography indicators (i.e., slope and elevation) as independent variables.

## 2. Materials and methods

### 2.1. Study area

Sanming City (116°22′–118°39′E, 25°30′–27°07′N), including the Sanyuan District and Meilie District, is located in the western part of Fujian Province in China. Sanming City is in the upper reaches of the Minjiang River, which has the seventh highest annual runoff in China. The study area has a total area of 115 815 $hm^2$, and most of its lands are mountainous areas with steep slopes. The climate is generally mild and moist, with an annual average relative humidity of 78.3% and an average temperature of 19.55 °C. The annual average precipitation is 1665.3 mm, most of which occurred during the period of March to August (Yang et al., 2007). In the study area, the forest is the predominant landscape, constituting of more than 80% of the land use. Thus, it was labelled as the most "green" city in the most "green" province of China.

Sanming City was chosen as the case study here for two reasons. First, Sanming City is located in the middle subtropical zone, where the North-South subtropical flora meets, with complex terrain, rich wildlife and lush vegetation. At the same time, it was also one of the refuges for plants during the Quaternary glacial period in China, thus preserving many valuable prehistoric "relic plants"; e.g., there are near 700 $hm^2$ secondary forest of *Castanopsis kawakamii* in the study area, which is among the largest in the world. It has been reported that the forest has experienced increasing artificial interference in recent decades (Hu et al., 2014). Second, the study area has vigorously developed transportation in recent years and will in the future to promote the development of eco-tourism and other related industries. The significant alteration of the forest landscape by the extension of the road network has potentially negative effects for biodiversity conservation and habitat loss, thus leading to the increase of LER. How to deal with the harmonious relationship between the road network extension and ecological protection is a key scientific issue for the study area and elsewhere in the world. Thus, our results will have a good policy implication for biodiversity and habitat protection, and the method applied here (i.e., the LER index and the local model) have a good reference for other places in the world.

### 2.2. Data source

The data used in the study mainly included the Forest Resources Inventory Database (FRID), the road network dataset, and a city centre distribution map. (1) The FRID of the study area in 2007, 2012, and 2016 was obtained from the local forestry bureau. The FRID database is a shapefile that records forest traits (e.g., tree species, age, breast diameter, tree height, etc.) and corresponding ecological factors (e.g., land type, slope, altitude, soil type, etc.) at the forest patch level (Guan et al., 2015; Piao et al., 2005). The forest vegetation inventory is investigated every 5 years at the county level and is constantly updated at the end of each year (State Forest Administration, 2003; Xie et al., 2011; You et al., 2017). (2) The road network dataset was based on the transportation maps of the study region in 2016 and was obtained from the National Fundamental Geographical Information Centre, and the road network was digitized as vector data (rectified by 1:10,000). The road network primarily included the expressway, national roads, provincial roads, county roads, country roads, rail roads, and other main roads. (3) The centres of the city were defined as the locations where the administrative building of the Sanyuan district, Melie district, and Sanming City were located, respectively.

### 2.3. Classification of landscape

To comprehensively describe the landscape structure of the study area, the overall landscape was classified into ten categories (Table 1): (1) nature forest, (2) artificial mixed forest, (3) artificial pure forest, (4) bamboo forest, (5) economic forest, (6) other forest, (7) construction land, (8) cultivated land, (9) unused land, and (10) water land. To avoid deviation arising from differences in resolution, we transformed the forest landscape type map into a uniform spatial resolution (5 × 5 m) for the study years of 2007, 2012 and 2016.

### 2.4. Establishment of the landscape ecological risk index

#### 2.4.1. Definition of the landscape ecological risk index

Ecological risk assessment is the method for evaluating the degree of risk of an ecosystem that has been exposed to one or more stressors, such as land change, road construction, climate change or natural disturbance (Gong et al., 2015). Ecological risk assessment is now applied more broadly to assess the potential impact of multiple 'threats' against measured present impacts on ecosystem structure and function. One of the important branches of ecological risk is LER, which explores the effects of a variety of hazards for large-scale units and is the complement to and expansion of a general ecological risk assessment. Specifically, the LER assessment refers to the landscape composition, structure and function of a specific area by analysing the landscape element mosaic, landscape pattern and landscape ecological process to respond to intrinsic risk sources and external disturbances (Mo et al., 2017). The LER assessment is a method for determining or predicting how a process is affected by human activities or natural disasters. An LER assessment not only pays attention to the extent of damage to specific risk receptors but also considers the impact of ecological risks on the fragmentation and diversity of the overall landscape pattern. Therefore, in the related research of LER assessments, the landscape index that measures the regional landscape pattern is often included in the framework of LER (Simmons et al., 2007; Li and Zhou, 2015). The LER is primarily constructed of two landscape-level indices: the Landscape Disturbance Index (LDI) (external) and the Landscape Vulnerability Index (LFI) (internal) (Shi et al., 2015). It is significant to make a reasonable assessment of LER to optimize the landscape structure, establish the risk alarm mechanisms, and maintain the ecological function in upstream of the basin because the provision of ecosystem services (e.g., soil and water conservation) is vital to its downstream.

#### 2.4.2. Calculation of the landscape ecological risk index

In reference to previous studies (Gong et al., 2015; Mo et al., 2017), LER is quantified by the combination of two landscape-level indices, LDI and LFI, which can not only measure the degree of internal vulnerability but also the external disturbance of certain ecosystems. The LDI reflects the extent to which ecosystems that are represented by different landscapes are impacted by external disturbances (e.g., road construction), while the LFI primarily measures the stability or anti-interference ability of a landscape component itself (Xie et al., 2013). The detailed formula and descriptions are shown in Table 2.

(1) LDI is employed to observe the intensity of an ecosystem impacted by natural and human dimensions, which is derived from a combination of three landscape metrics, including the fragmentation index ($C_i$), the splitting degree index ($S_i$) and the dominance index ($D_i$). In the context of rapid urbanization in the southeast coastal areas of China, the expansion of the road network is the key driving force that is most likely to cause forest fragmentation by splitting the forest into pieces and creating some advantageous landscapes (i.e., plantations in the study area). The dominance index indicates the extent to which a certain landscape dominates. The higher the dominance of a landscape, the lower the landscape diversity and the weaker the resistance to external disturbances should be, or the greater the ecological loss associated with adverse impacts on it (Peng et al., 2015). According to previous studies, the weights for the fragmentation index, the splitting degree index and the dominance index were assigned as 0.5, 0.3 and 0.2, respectively (Gong et al., 2015; Mo et al., 2017; Liu et al., 2012).

(2) LFI. Different landscape types themselves, with different sensitivity and resilience, may have different abilities to recover them from human interference (Peng et al, 2015); therefore, the fragility index of is a function of the certain landscape types. According to the first-level classification standard of China and the difference in the

**Table 1**
Classification of landscape.

| Land use types | Landscape classes | Description |
|---|---|---|
| Forest land | Nature forest | Forests that have re-grown after a timber harvest for a long enough period without human disturbance. |
| | Artificial mixed forest | Mixed forest with coniferous and species |
| | Artificial pure forest | The standing volume of a single tree species is more than 90% |
| | Bamboo forest | *P. pubescens* |
| | Economic forest | Forests with the main purpose of producing forest products, such as fruits, edible oils, industrial raw materials and herbs, other than wood, such as *Camellia oleifera*, *Citrus reticulata* and *C. mollissima* |
| | Other forest | Including shrubwood land, sparse forest land, unforested land |
| Non-forest land | Construction land | Including industrial and mining, urban and rural residential, and transportation land |
| | Cultivated land | Including rice, wheat, and vegetable land |
| | Unused land | Including burned area and barren land |
| | Water land | Rivers |

**Table 2**
The calculation formulas for landscape ecological risk index.

| Landscape index | Formula | Descriptions |
|---|---|---|
| Landscape fragmentation index | $C_i = n_i/A_i$ | To describe the degree of patches fragmentation for a certain landscape type |
| Landscape splitting index | $S_i = L_i A/A_i$, $L_i = (1/2)\cdot\sqrt{n_i}/\sqrt{A}$ | To indicate the degree of patches separation for a certain landscape type |
| Landscape dominance index | $D_i = (Q_i + M_i)/4 + G_i/2$, $Q_i = n_i/N$, $M_i = B_i/B$, $G_i = A_i/A$ | To describe the degree of patches importance for a certain landscape type |
| Landscape disturbance index | $LDI_i = aC_i + bS_i + cD_i$ | To quantify the intensity of a landscape subjecting to external interference |
| Landscape fragility index | $LFI_i$, obtained by artificial assignment and normalization | To evaluate the internal capability to maintain stability for a certain landscape type |
| Landscape Ecological Risk Index | $LER_k = \sum_{i=1}^{J} \frac{A_{ki}}{A_k}\sqrt{LDI_{ki}Â\cdot LFI_{ki}}$ | To reflect the relative magnitudes of integrated ecological pressures caused by external interference and internal vulnerability for a certain study area |

*Note:* $C_i$: landscape fragmentation index of landscape type *i*; $n_i$: patch number of landscape type *i*; $A_i$: total area of landscape type i; $S_i$: landscape splitting index (LSI) of landscape type *i*; $L_i$: patch density of landscape type *i*; *A*: total area of the entire landscape; $D_i$: landscape dominance index of landscape type *i*; $Q_i$: the frequency of landscape type *i*; *N*: total number of all type of patches; $M_i$: the density of landscape type *i*; $G_i$: the ratio of landscape type *i*; $B_i$: number of samples appearing landscape type *i*; *B*: total sample number; $LDI_i$: the disturbance index of landscape type *i*; *a*, *b*, and *c* are weights of indices $C_i$, $S_i$ and $D_i$, respectively; $LFI_i$: the degree of vulnerability in landscape type *i*; $LER_k$: the Landscape Ecological Risk Index of sample *k*; *J*: the number of landscape categories in the sample k; $A_{ki}$: the area of landscape type *i* in sample *k*; $A_k$: the area of sample *k*.

resilience of different forests (Shi et al., 2015; Mo et al., 2017), the fragility degree of landscape was classified into ten grades, with nature forest considered to be the most stable ecosystem, while construction land is considered to be the most vulnerable ecosystem. Therefore, the grade of the fragility degree for the ten landscapes were as follows: construction land = 10, unused land = 9, water area = 8, cultivated land = 7, other forest = 6, economic forest = 5, bamboo forest = 4, artificial pure forest = 3, artificial mixed forest = 2, and nature forest = 1, then normalized and finally multiplied by the area ratio of each landscape type to obtain the fragility index ($F_i$) of each landscape type.

(3) LER. The study area was first divided into 164 sample units with a grid of 3 × 3 km. Then, the LER was calculated with the formulas in Table 2 for each sample. Hereafter, the LER of the entire area was interpolated into 1148 grids of 1 × 1 km using the reverse distance method in ArcGIS 10.2. Finally, we divided the LER into five grades using the method of natural breaks, including low risk, sub-low risk, medium risk, sub-high risk, and high risk.

## 2.5. Regression models

### 2.5.1. OLS and GWR regression

Both the global regression model (i.e., OLS) and the local regression model (i.e., GWR) were employed to analyse the driving patterns of the LER.

First, we adopted the OLS model to examine the linear relationship between the LER and its factors. The regression model was specified as Eq. (1):

$$y_i = \beta_0 + \sum \beta_j x_i + e_i \tag{1}$$

where $y_i$ is the value of LER for the *i*th grid and $x_i$ is the selected factors of LER (e.g., KDE, DNR, and topography indicators) of the *i*th grid. $\beta_0$ and $\beta_j$ are the coefficients of the constant and the explanatory variables, and $e_i$ is the stochastic error term.

Second, the GWR model was employed, which is shown as Eq. (2):

$$y_i(u_i, v_i) = \beta_0(u_i, v_i) + \sum \beta_j(u_i, v_i)x_i + e_i(u_i, v_i) \tag{2}$$

here $(u_i, v_i)$ represents the geographic coordinates of the *i*th grid.

GWR allocates a unique parameter for each grid. The estimation of the coefficients are specified as Eq. (3):

$$\hat{\beta}(u_i, v_i) = (X'w(u_i, v_i)X)^{-1}X'w(u_i, v_i)Y \tag{3}$$

where $w(u_i, v_i)$ is the spatial weight matrix (Hu et al., 2017; Poudyal et al., 2008) that is unique for each grid.

In this study, both the OLS model and GWR model were processed in SAM v 3.1 (Hu et al., 2015; Rangel et al., 2010). During processing, the Gaussian function was selected, and the cross-validation and the Golden Section Search (searching from 10 to 15% of neighbours) were adopted to optimize bandwidth and to reduce the Akaike Information Criterion (AICc) to a minimum.

### 2.5.2. Variables

The dependent variables were the LER at the 1 × 1 km grid level in 2016. Two sets of independent variables (i.e., accessibility factors and topography factors) were considered in the models (Table 3).

The first group of independent variables is the accessibility factors, including distance to the nearest road of different levels (i.e., DNR-WH, DNR-E, DNR-H, and DNR-L), the road density of different levels (i.e., KDE-WH, KDE-E, KDE-H, and KDE-L), and the distance to the nearest city centre (DIST-CTY). (1) The road network was reclassified into three levels: (i) expressway; (ii) high-level roads (including national and provincial level roads); and (iii) low-level roads (including county level roads and country level roads) (Hu et al., 2016; Liu et al., 2014). (2) The distance to the nearest road of each level for each grid was calculated using the neighbour analysis tool in the ArcGIS 10.2 program. (3) KDE was calculated using a moving window by ArcGIS (Mo et al., 2017; Ying et al., 2014). A default bandwidth generated automatically was applied to optimize the outcome in the ArcGIS 10.2 program. Therefore, the KDEs of different level roads were obtained. (4) The distances from each grid location to the nearest city centre (i.e., Sanyuan district, Melie district, and Sanming city) were measured with the neighbour analysis tool in the ArcGIS 10.2 program.

The second group of independent variables is the topography factors, including slope (SLOPE) and elevation (ELEV), which imply the costs of the conversions among landscapes because they have a strong influence on the level of mechanization or accessibility on foot.

Before processing the GWR program, we first changed the original values of the independent variables into the logarithm values to reduce the impact of abnormal value and minimize the residual values; then, to avoid the multicollinearity problem between the factors, SPSS17 was used to carry out a step-wise regression analysis; finally, six factors (i.e., KDE, DNR-WH, DNR-H, DIST-CTY, ELEV, and SLOPE) were selected as explanatory variables for the LER in the simulation of the GWR models. Table 4 exhibited the description of the dependent variables and the six filtered independent variables.

**Table 3**
Independent variables used in the regression models.

| Variables | Abbreviation | Unit | Proxy for | Source and spatial resolution |
|---|---|---|---|---|
| *Accessibility factors* | | | | |
| Distance to the nearest road (whole road network) | DNR-WH | m | The accessibility and opportunity costs of farm labour and the access to output and input markets, and the potential effects of human settlement or agricultural or industrial activity on land use and forest management | Obtained from the National Fundamental Geographical Information Center (1:10000) |
| Distance to the nearest road (expressway) | DNR-E | m | | |
| Distance to the nearest road (high-level roads) | DNR-H | m | | |
| Distance to the nearest road (low-level roads) | DNR-L | m | | |
| Distance to the nearest city centre | DIST-CTY | m | | |
| Kernel density estimation of (whole road network) | KDE-WH | km/km$^2$ | | |
| Kernel density estimation of (expressway) | KDE-E | km/km$^2$ | | |
| Kernel density estimation of (high-level roads) | KDE-H | km/km$^2$ | | |
| Kernel density estimation of (low-level roads) | KDE-L | km/km$^2$ | | |
| *Topography factors* | | | | |
| Slope | SLOPE | degree | The costs of conversions among landscapes because they influence the degree of mechanization and on-foot accessibility | The data set is provided by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn) (1000 m) |
| Elevation | ELEV | m | | |

**Table 4**
Description of the variables used in the regression models.

| Variables | | Maximum | Minimum | Mean | Std. Dev. | P-value in step-wise regression |
|---|---|---|---|---|---|---|
| Dependent | LER in 2016 | 0.377 | 0.185 | 0.293 | 0.039 | – |
| Independent | KDE | 7.019 | 0.000 | 0.430 | 0.779 | 0.000** |
| | DNR-WH | 3.913 | 0.000 | 2.939 | 0.632 | 0.000** |
| | DNR-H | 4.185 | 0.000 | 3.487 | 0.534 | 0.000** |
| | DIST-CTY | 4.500 | 2.562 | 4.031 | 0.291 | 0.000** |
| | ELEV | 3.147 | 0.000 | 2.247 | 0.850 | 0.000** |
| | SLOPE | 1.690 | 0.000 | 1.235 | 0.471 | 0.000** |

** Indicates statistical significance at 0.01 level.

## 3. Results

### 3.1. Dynamic of landscape composition

In the study years, the primary landscape of the study area was the forest land, which accounted for nearly 80% of the entire landscape (Figs. 1 and 2). Among the forests, the dominant landscapes were the artificial pure forest and the bamboo forest, which accounted for more than 23.0% and 21.0% of the total area, respectively. Nature forests were also widely distributed in the study area, occupying more than 16.0% of the study area. Non-forest landscapes, such as construction land, cultivated land, unused land, and water areas, only composed a relatively low proportion of the entire landscape.

Fig. 3 indicated that the forest cover changes varied among the landscapes over time. In both of the two periods (i.e., 2007–2012 and 2012–2016), great changes occurred in the economic forest, the other forest, construction land and unused land, while minor changes happened in the artificial pure forest, the artificial mix forest, the water area, and the bamboo forest. Among these, construction land was one of the largest increasing landscape types, which was observed to increase by 42.5% and 16.5% in the two periods, respectively; the bamboo forest increased 4.2% and 3.8% in the two periods, respectively; and the artificial pure forest increased 3.6% and 1.4% in the two periods, respectively. However, the opposite changes were observed for the economic forest, the unused land, and the artificial mixed forest, with the economic forest decreasing 40.5%and 49.7% in the two study periods, respectively; the unused land decreasing 63.3%and 36.7% in the two study periods, respectively; and the artificial mixed forest decreasing 3.4% and 4.0% in the two study periods. Additionally, the other forest reduced significantly (51.5%) in the early stage and stayed unchanged (0.2%) during the later period; the nature forest increased 9.5% during 2007–2012, and then remained stable during 2012–2016, while the cultivated land increased 11.3% in the early stage and then remained stable (0.4%) in the later period.

### 3.2. Dynamic of landscape metrics

Figs. 4 through 6 revealed that there were obvious changes in the landscape indices over time. In terms of fragmentation (Fig. 4), the economic forest, other forest, construction land, cultivated land and unused land had high values according to the landscape fragmentation index, which implied high degrees of patch separation for these types of landscapes. During the two studied periods, the landscape fragmentation index of the economic forest, other forest and unused land all increased, cultivated land decreased, and construction land decreased first from 2007 to 2012 and then increased from 2012 to 2016.

In terms of separation (Fig. 5), the values of the LSI for the economic forest and other forest showed an increasing trend, and that of cultivated and construction land decreased during the two periods, while

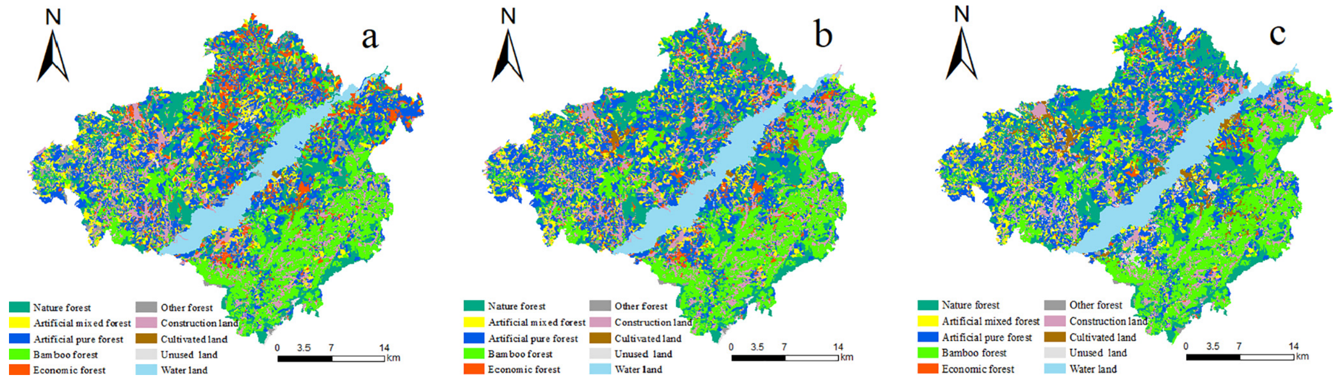


**Fig. 1.** Spatial distribution of the landscapes in 2007, 2012 and 2016.

the splitting index of the unused land decreased first and then increased during the two periods.

In terms of the dominance (Fig. 6), its index of the artificial pure forest was among the highest, followed by bamboo forest and nature forest, which was in line with the size of the area of each landscape (Fig. 2). During the two studied periods, the landscape dominance indices of the economic forest showed a decreasing trend, the construction land decreased first from 2007 to 2012 and then increased from 2012 to 2016, while the unused land increased first from 2007 to 2012 and then decreased from 2012 to 2016. The value changes in the other forest and the cultivated land were small.

Additionally, the values of fragmentation, separation and the dominance of the other landscapes, such as the nature forest, the artificial mixed forest, the artificial pure forest, the bamboo forest, and the water land, were relatively low and stable during both of the two periods.

### 3.3. Dynamic of landscape ecological risk

Fig. 7 depicted the distribution of the LER for the years of 2007, 2012, and 2016. The figure indicated that the overall distribution of the LER was uneven and varied over time and space.

In 2007, the high-risk areas were mainly distributed in the middle of the study area, with a small part located in the west corner, and the low-risk areas were mainly located in the southeast parts of the study region. In 2012, the distribution of the LER showed an obvious structure of south-north polarization, with high-risk distributing in the south area and low-risk distributing mainly in the north part. The distribution of LER in 2016 was similar to that of 2012.

Summarily, the LER showed a gradually decreasing tendency from the middle to the periphery in 2007, and then the high-risk area expanded to the western section of the study area in 2012 and 2016. It is worth noting that the higher-risk areas generally were distributed around the high level of roads and city centres. Moreover, the degree of the risk had an obvious gradient parallel to the road, with the risk decreasing as the distance from the high-level road increased.

Table 5 showed the area of different LER grades and their changes during the studied periods. Overall, the medium-risk and the sub-high-risk regions accounted for the highest proportion. The medium-risk accounted for more than 22% of the total area, and the sub-high-risk accounted for more than 24%. The proportion of the high-risk areas was the lowest, accounting for 9.815%, 7.236%, and 14.821% of the total study area in 2007, 2012, and 2016, respectively.

From 2007 to 2016, the medium-risk region had an increasing tendency, with growth rates of 2.184% and 2.283% for the two time periods, respectively, and the high-risk area decreased first and then increased, with growth rates of −2.578% and 7.585% for the two time periods, respectively. The low-risk area and the sub-high-risk area exhibited a decreasing pattern, and the sub-low risk area increased first and then decreased.

### 3.4. Driving pattern of landscape ecological risk

The geographical variations in the correlations between the LER and the independent variables (i.e., DNR-WH, DNR-H, DIST-CTY, KDE-WH, elevation, and slope) were examined by both the OLS and the GWR regression. Because the regression results of the three years were relatively similar, only the outcomes of the year 2016 were elaborated here.

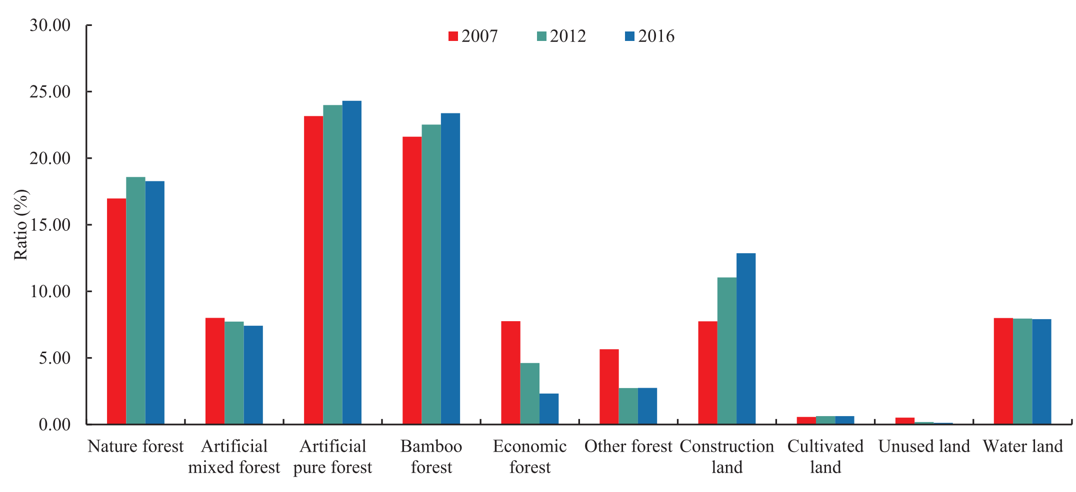


**Fig. 2.** Proportion of each landscape in 2007, 2012 and 2016.

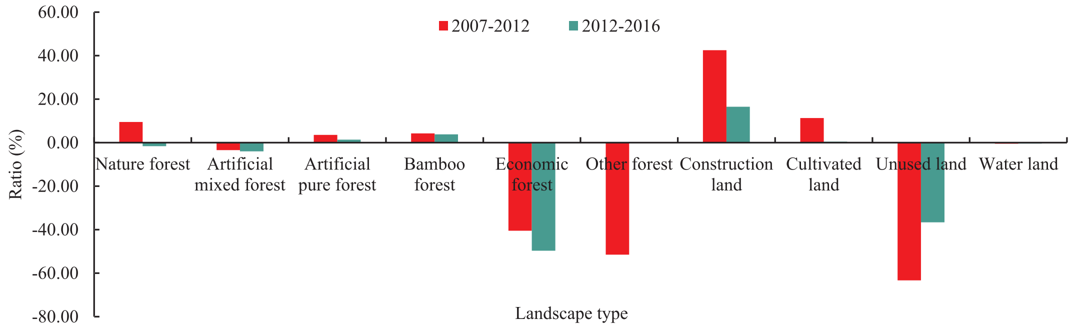


**Fig. 3.** Changes in each landscape during periods of 2007–2012 and 2012–2016.

The adjusted R-squared of the GWR model was 0.697, which is higher than that of the OLS models (0.134); the AICc of the GWR model was -5519.219, which was less than that for the OLS models (−4375.427). All of these outcomes indicate that the GWR model is superior to the OLS model in this case. Therefore, the results of the GWR regression can be applied to analyse the correlations between the road network and the LER. The six variables were all statistically significantly related to the LER at the 1% level.

Table 6 presented the parameter statistics of the GWR model. These statistics showed how great the coefficient of each variable varied within the study area, with minimum, lower quartile, median, upper quartile, and maximum values being summarized here. The comparison of the magnitude of the coefficients among all the variables can help to explain the geographical heterogeneity in the associations between the LER and its impact factors.

Fig. 8 visualized the spatial distribution of the statistically significant associations between the LER and the independent variables, respectively, at the grid level. Considering that the main purpose of this study was to identify the impact of the road network on the LER, and the few areas of the significant clusters being observed for the variables of DIST-CITY, elevation and slope, then only the spatial variations in the effects of the significantly related road measurements (i.e., KDE-WH, DNR-WH, and DNR-H) were discussed in Fig. 8. In the figures, the colorized clusters (red indicating a positive relationship, and blue indicating a negative relationship; the deeper the colour, the greater the correlation) indicated that the statistical significance level was less than 5%, implying that the independent variable had a great impact on the dependent variable, while the grey clusters indicated that the statistical significance level was greater than 5% and revealed that there were no obvious relationships between the two regressors.

Fig. 8a indicated that the right part of the study area showed a significantly positive association between the LER and the KDE-WH. The figure also indicates an obvious trend, with the degree of the positive correlation increasing gradually from the northwest to the southeast of the study region, that was exactly parallel with the high-level road across the city centres.

Fig. 8b showed that there was only a small part of the grids that revealed a significant correlation between the LER and the DNR-WH. A red cluster distributed on the northern section of the study area, which was located to the west of the high-level road. At the same time, only a few portions of blue grids occurred in the southern part of the study area. In terms of the red cluster, the farther away from the city centre, the greater the value of the coefficient was.

Fig. 8c indicated that most of the study area showed significantly negative associations between the LER and the DNR-H. The distribution in the coefficient of the DNR-H had an obviously downward trend from the city centre to the surrounding.

## 4. Discussions

### *4.1. Spatio-temporal pattern of landscape ecological risk*

The LER assessment explores the impacts of a variety of hazards on ecosystem at the large-scale units by assessing potential and cumulative ecological effects. However, most previous studies on the LER were based on satellite imagery (Ayre and Landis, 2012; Li et al., 2017; Zhang et al., 2016), and the landscape is generally divided into forested and non-forested land type due to image resolution limitations. In this study, LER was constructed based on two landscape-level metrics (i.e., LDI and LFI) to comprehensively analyse the overall ecological risk. LDI is based on the synthesis of three landscape indices: the fragmentation index, the splitting index, and the dominance index. More importantly,

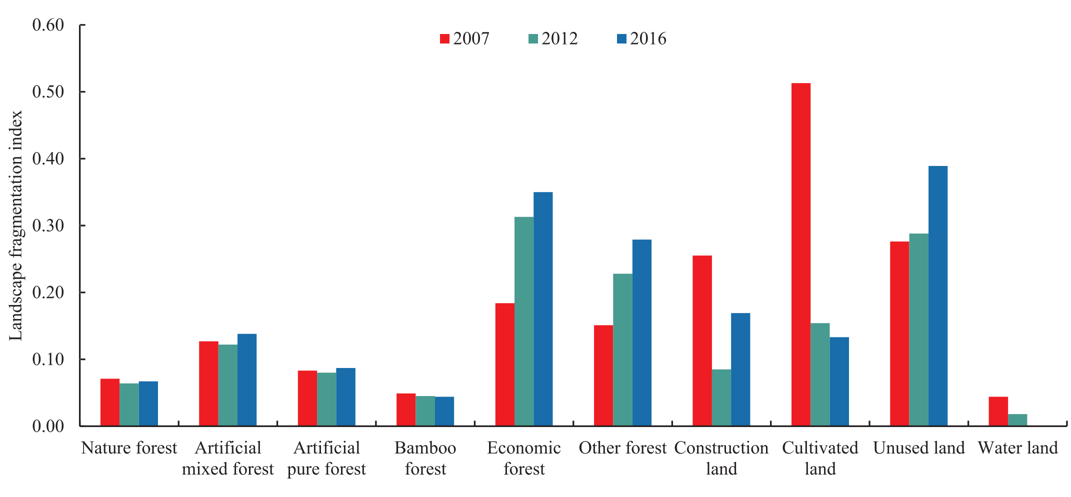


**Fig. 4.** Landscape fragmentation index of each landscape in 2007, 2012 and 2016.

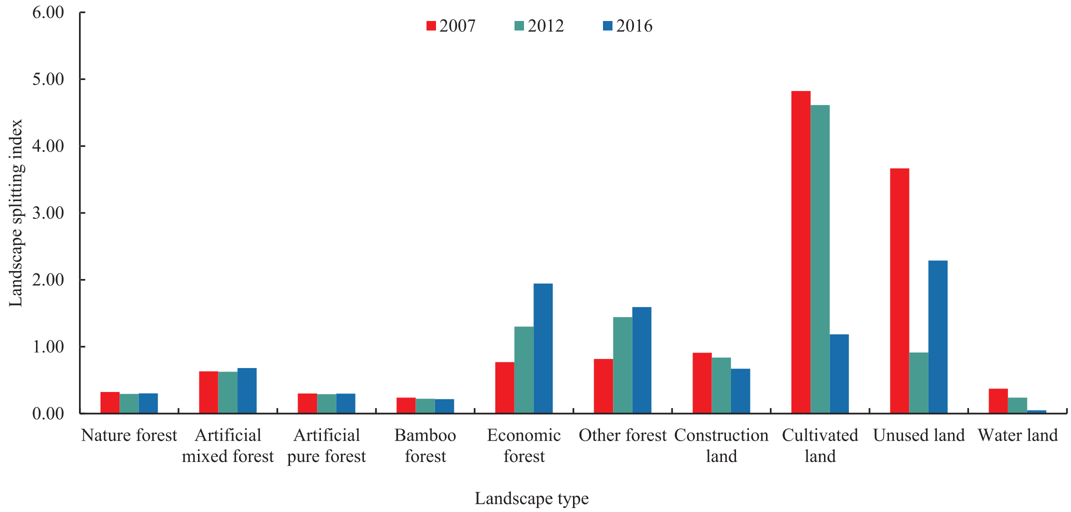


**Fig. 5.** Landscape splitting index of each landscape in 2007, 2012 and 2016.

the landscape was classified into ten categories and different weights were assigned to the three indices to calculate the LFI. Specifically, our study considered the significant heterogeneity among different forest types or tree species compositions in a certain forest landscape, owing to the availability of the FRID. As a result, the forested land was finely divided into six forest landscapes (i.e., nature forest, artificial mixed forest, artificial pure forest, bamboo forest, economic forest, and other forest). Thus, our information collection and classification of the landscape using FRID provides a more precise analysis of the regional ecological risk at a finer level. The results revealed that the LER based on landscape metrics quantified the LER well and could perform a space–time dynamic analysis on the ecological risk for the study area.

In terms of the time dynamic in the LER, we witnessed that its changes varied in different grades of the risk. It is worth noting that there were upward trends in the areas of medium-risk and high-risk from 2007 to 2016 (Table 5). The reason is that the LER consists of landscape indices (Table 2); as a result, the value of the LER is affected by the combination of landscape type and landscape pattern (Xie et al., 2013; Xu and Kang, 2017). In the study periods, the rapid urbanization process had promoted land use and cover changes from traditional agriculture to the secondary or tertiary industries (Mo et al., 2017). Thus, the geographic atrophy in the economic forest, the other forest, and the unused land offered sufficient space for construction (Fig. 3), such as the expansion of the build-up area, the development of new industries or the road network. As a consequence, these changes also cause the economic forest, the other forest, and the unused land to become more fragile and separated (Figs. 4 and 5), which resulted in exerting more pressure on the LER and led to an increase in the proportion of medium-risk and high-risk areas in the study region (Gong et al., 2015). Our results are in line with the previous findings, which have revealed that the road network extension contributes significantly to the increase in the quantity and fragmentation of the landscape patches; moreover, habitat loss occurs more often in areas near the city and road network (Liu et al., 2014; Karlson and Mortberg, 2015).

In terms of the spatial dynamic in the LER (Fig. 7), we found that the overall distribution of the LER was uneven across the study area. It is worth mentioning the obvious structure of south-north polarization in the LER in 2012 and 2016. Moreover, when overlaying the map of the risk with the high-level road network, we found that the values of the LER near the road network were generally higher than those far away from the road network (Fig. 7), which might be due to areas near the road having been mainly invaded by the high fragile land use/covers (e.g., construction land, cultivated land, or unused land) and having higher values of LDI and LFI. Our results are consistent with the previous results (Freitas et al., 2012; Hawbaker et al., 2005; Hosseini Vardei et al., 2014) that indicated that the road network is one of the most important biophysical factors driving changes in the landscape patterns by introducing various other human disturbances to the road

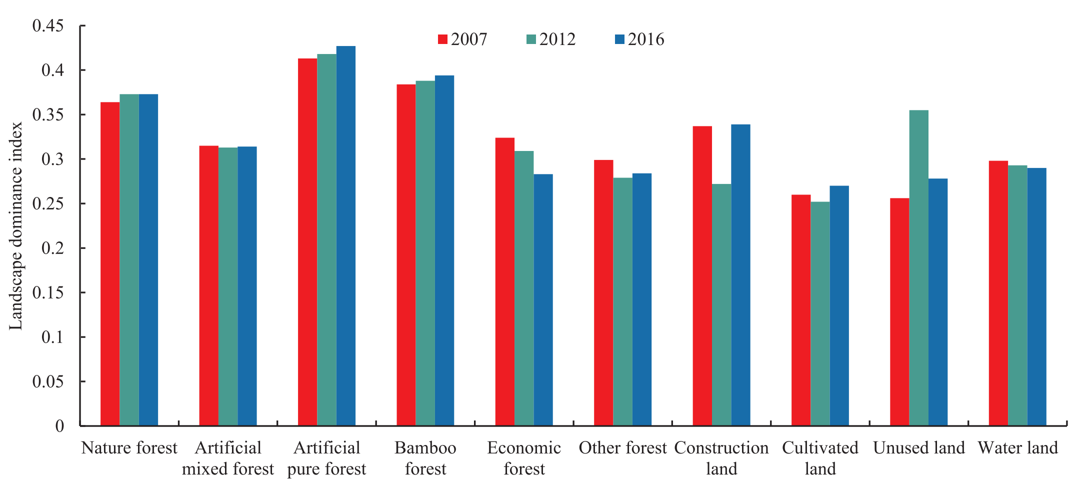


**Fig. 6.** Landscape dominance index of each landscape in 2007, 2012 and 2016.

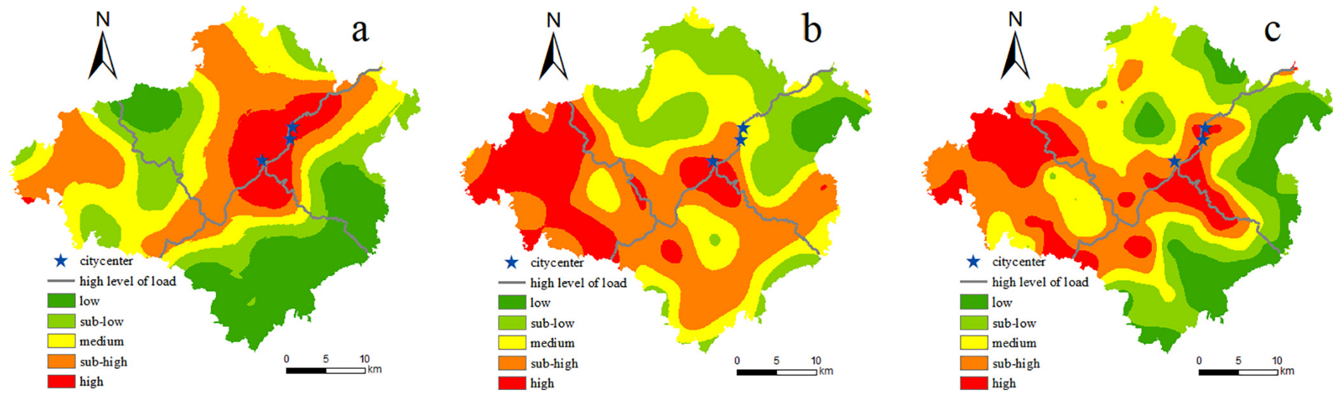


**Fig. 7.** Spatial distribution of the landscape ecological risk in 2007, 2012 and 2016.

effect zone.

### 4.2. Spatial paradigm in the impact of road network on landscape ecological risk

The change of land use and land cover related to the road network has been widely investigated in previous studies (Cai et al., 2013; Hu et al., 2016; Liang et al., 2014; Ying et al., 2014). These quantitative findings make up for the lack of understanding of the road impacts on landscape stability to a large extent. However, these studies have several limitations. First, some of these previous studies only considered a single indicator, e.g., RD or DNR. Second, some of them did not take the grade effects of roads into account. Third, most of these studies are based on global models (i.e., OLS), which ignore the spatial variation in the correlations between the two regressors across the study region (Cieszewski et al., 2004; Fotheringham et al., 2002; Hu et al., 2015).

To overcome these limitations, two dimensions of the road network (i.e., both DNR and KDE) and different grades of roads (i.e., the entire road network, expressways, high-level roads and low-level roads) were employed to explore spatial variation in their effects on the LER using a local model (i.e., GWR) in this study. Our regression outcomes verify past studies, which have indicated that the variable of RD, KDE, and DNR are significantly related to many ecological processes. We also found that the variables of KDE and DNR were statistically significantly correlated with the LER. Comparing this study to previous studies on road impacts (Cai et al., 2013; Hu et al., 2017), a major distinction is found: the grades of roads were taken into account. This is a very good response to previous works (Hu et al., 2017; Liang et al., 2014), which have noted the need for comparative studies on the grade impacts of the road network on the landscape ecology. Among the indices of different grades in terms of the road network, we found that the KDE-WH, DNR-WH, and DNR-H were statistically significantly correlated with the LER in the regressions, while the other road network measurements were not significantly related with the LER. The modelling results not only verified the importance of the road network as a key driver of the LER but also revealed the different effects on the LER caused by the different levels of roads. Moreover, the spatial heterogeneity in the effects of these roads was observed and visualized. Thus, to some extent, this study fills the gap for the study of road ecology.

**Table 6**
Parameter descriptive statistics from the GWR regression (Local model).

| Variables | Minimum | Lower quartile | Median | Upper quartile | Maximum |
|---|---|---|---|---|---|
| DNR-WH | −0.010 | −0.003 | 0.003 | 0.008 | 0.016 |
| DNR-H | −0.049 | −0.032 | −0.026 | −0.019 | −0.009 |
| DIST-CTY | −0.080 | −0.053 | −0.017 | 0.031 | 0.109 |
| KDE | −0.007 | 0.001 | 0.006 | 0.016 | 0.035 |
| Elevation | −0.020 | −0.011 | −0.006 | 0.002 | 0.014 |
| Slope | −0.029 | −0.003 | 0.010 | 0.017 | 0.043 |

The KDE-WH was among the most significant index of the road density measurement indices. This finding corroborated the previous study, which proved that the index of KDE can effectively quantify the effect of the road network on landscape (Anderson, 2009; Cai et al., 2013; Mo et al., 2017). The GWR result showed that it was significantly positively associated with the LER in the eastern part of the study area, while its impact was insignificant in the western part (Fig. 8a). When we looked closely at Fig. 1, we found that there was a larger proportion of the bamboo forest and other forest in the southeastern part of the study area, while the proportion of the natural forest and the artificial mixed forest in the northwest part was relatively high. The landscape fragmentation index of the other forest increased dramatically from 2007 to 2016, while landscape fragmentation was relatively stable for the nature forest and artificial mixed forest during the studied periods. The landscape splitting index had the same tendency as the fragmentation index (Figs. 4 and 5). Moreover, it is well known that bamboo forest is one of main timber species in southern China (Zhang et al., 2010), which indicates that the planting practices are more active in the eastern part of the study area. Following this logic, it is necessary that the road network have more impact on the forest landscape in such areas. However, the natural forest and the artificial mixed forest are well protected, according to local policies (Hu et al., 2014), which implies less human disturbance in such regions. All these results are consistent with the significant cluster of GWR analysis, which indicated that the road network has a greater impact in the southeast part of the

**Table 5**
Changes in the proportion of the LER from 2007 to 2016.

| Grade | 2007 | | 2012 | | 2016 | | 2007–2012 | 2012–2016 |
|---|---|---|---|---|---|---|---|---|
| | Area ($km^2$) | % | Area ($km^2$) | % | Area ($km^2$) | % | % | % |
| Low | 275.270 | 23.899 | 238.844 | 20.736 | 184.140 | 15.987 | −3.162 | −4.749 |
| Sub-low | 212.868 | 18.481 | 257.498 | 22.356 | 205.226 | 17.818 | 3.875 | −4.538 |
| Medium | 254.974 | 22.137 | 280.128 | 24.321 | 306.426 | 26.604 | 2.184 | 2.283 |
| Sub-high | 295.655 | 25.669 | 291.996 | 25.351 | 285.308 | 24.770 | −0.318 | −0.581 |
| High | 113.048 | 9.815 | 83.349 | 7.236 | 170.715 | 14.821 | -2.578 | 7.585 |

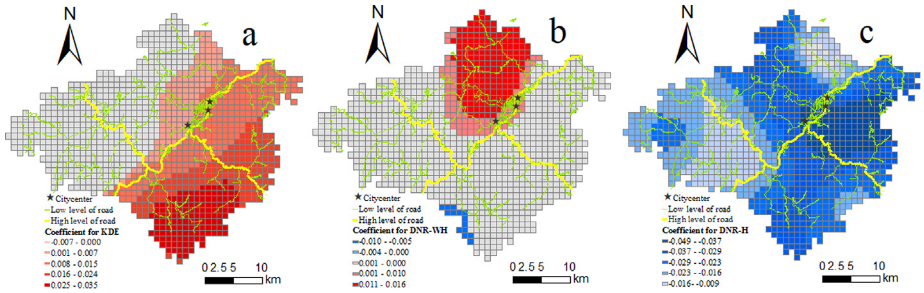

**Fig. 8.** Significant clusters of GWR coefficients for KDE-WH, DNR-WH, and DNR-H.

study area than in the northwest part (Fig. 8). Therefore, our findings are quite consistent with the objective reality (Ren et al., 2011).

Moreover, the relationship between the LER and KDE-WH showed an obvious gradient variation, with the coefficients of the KDE-WH being smaller closer to the city centre, mainly due to the higher density of the road network in the city centre than that in other areas, resulting in much higher values of KDE-WH in the city centre than that in the areas farther away from the city centre. Thus, we assume that the range of the dependent variable (i.e., LER) is relatively small and the higher the value of the independent variable (i.e., KDE-WH), the lower the GWR coefficient should be, which implies that the independent variable is less sensitive, with a marginal increase of KDE-WH in the city centre area than in locations that are relatively far away from the centre.

The DNR-WH and the DNR-H were also significant indicators of the LER. The GWR outcome showed that the significant effect of the DNR-WH on the LER was concentrated in the area near the city centres (Fig. 8.b), where the road network is more developed; as a consequence, the histogram of the indicator of DNR-WH is normally distributed. However, in other regions, where the road network is relatively underdeveloped and even sparse, the histogram of the DNR-WH is randomly distributed, leading to the distribution of the significant cluster shown in Fig. 8.b.

It is unexpected that the DNR-WH is positively correlated with the LER; that is, a marginal decease of the DNR-WH may result in a decrease of the LER. However, most previous works have found negative effects of the road network on the landscape, such as an alteration, isolation, fragmentation, or degradation (And and Alexander, 1998; Forman et al., 2002). Furthermore, we found that DNR-H was significantly and negatively correlated with the LER in most of the study area (Fig. 8.c). Therefore, it is interesting to explain this anomaly. According to the previous stepwise regression, the variables of DNR-WH and DNR-L were both positively correlated with the LER (Tables 4 and 6). It is well known that high-level roads have a limited range of distribution, whereas low-level roads infiltrate everywhere; as a result, the nearest road to each sampling grid is most likely a low-level roads. Following this logic, to some extent, the variable of the DNR-WH is similar to the variable of the DNR-L, so the DNR-L was excluded by step-wise regression to avoid a multicollinearity problem. Thus, we can assume that the positive effect of DNR-WH on the LER is mainly caused by the low-level roads. Our finding is in accordance with previous works, which revealed that low-level roads provide human beings with more feasible access to the forest landscape, which will make the landscape more separation, thus enhancing the fragmentation of the landscape and putting the landscape at risk. As a result, low-level roads are much more sensitive to nature habitats (Hu et al., 2016; Liang et al., 2014; Liu et al., 2008).

The transit-oriented development mode not only prevails in the developed countries but also becomes a developing mode of emerging cities in China (Cervero et al., 2005), which is also true for our study region. The significant GWR clusters for the coefficient of the DNR-WH are urban areas, with large built-up areas that are highly concentrated near roads because of the transit-oriented development mode, resulting in a lower degree of fragmentation and a splitting of the matrix (i.e., construction land). However, a variety of land-use types are mixed in places far away from roads in the urban area, resulting in a higher degree of fragmentation and splitting of the patches (i.e., construction land, forested lands). As a consequence, the LER in places closer to the roads is relatively lower than that in places farther away from the roads.

Additionally, the negative correlations between the LER and the DNR-H varied across locations, with higher values of the coefficient in the areas closer to the city centre and lower values in the regions farther away from the city centre. The gradient patterns and causes are similar to the relationship between the LER and the KDE-WH (Fig. 8.a). In summary, we can infer that high-level roads went through the city centre (Fig. 8.c), thus mainly affecting areas where human activities are more intensive, while low-level roads mainly affected remote regions (Fig. 8.b). Our analysis further confirms the previous studies (Hu et al., 2017; Liu et al., 2008; Liu et al., 2014) that have indicated that the effect of roads on landscape ecology is hierarchical among different levels of roads.

### 4.3. Limitations of landscape ecological risk index

A landscape consists of mosaic patches, and its stability and resilience capability from disturbance are closely related to its diversity. The highly heterogeneous landscape, its overall structural changes and dynamic processes are relatively slow. Thus, the landscape not only has the key elements of a risk receptor but also the key reflections of a hazard status; simultaneously, the landscape dynamic process is often built in a static pattern (Forbes and Calow, 2013). Therefore, in the process of the LER assessment, it is essential to embody the landscape pattern or land mosaic pattern in the LER index. Currently, the most commonly used LER index based on the landscape pattern is synthesized by the two types of landscape-level metrics: the landscape disturbance index (external) and the landscape vulnerability index (internal) (Gaines et al., 2004). External interferences of the ecological risk are relatively discrete events that alter the landscape structure, such as the patch, corridor and matrix, thus altering the landscape heterogeneity and connectivity. The frangibility reflects not only the natural attributes of the landscape but also the conjoint effect of human activity on the land (Deal and Pallathucheril, 2009; Scott et al., 2013).

Although the LER index can quantitatively characterize the safety status and degree of forcedness to indirectly represent the complexity, stability and diversity of the landscape, the index itself cannot reflect the formation mechanism of the nonlinear dynamics and evolution of the landscape and cannot explain the driving mechanism for the ecological consequences of the landscape pattern evolution from the perspective of complexity science. This inability has led to an unclear ecological connotation of the current LER assessment, and it is impossible to correspond the assessment results with specific ecological factors, thus causing risk management control to lose its directivity (Deal and Pallathucheril, 2009; Scott et al., 2013). In addition, the complex relationship between the landscape dominance index and ecosystem stability has not yet reached an agreement. Therefore, in further research, the process-based pattern analysis method should be developed and applied to the LER assessment (Liu et al., 2008;

Malekmohammadi and Blouchi, 2014); for example, while selecting and calculating the landscape disturbance index, the dynamic changes of the landscape pattern with time should be considered, such as incorporating road obstruction into the overall measure of landscape disturbance (Peng et al., 2015). In this way, the current patterns of disturbance and the probability of future human disturbance are combined simultaneously in the landscape disturbance index.

## 5. Conclusions

In this study, we first classified the landscape into ten categories based on FRID for the years 2007, 2012 and 2016 and then constructed a LER index using the landscape indices. DNR and KDE, two dimensions of the road network, were applied to quantitatively to estimate the road effects on the LER using the GWR model.

(1) The distribution of the LER was uneven across the study region, with an obvious structure with a south–north polarization. Specially, the areas of sub-high and high-risk levels of LER were mostly distributed in the vicinity of high-level roads, while the low-risk levels of LER were mainly located in the southeast parts of the study region.
(2) The results of the GWR analysis indicated that were existed spatial variations in the associations between the two regressors. According to the magnitude (both the sign and the size) of the estimated coefficients, we confirmed that the effects of the road network on the LER were obviously different among different levels of roads; even among the same level of roads, their impacts varied greatly across locations.
(3) The significant cumulative impacts of the road network on the LER were identified in this study. The highest values of the LER were distributed in the city centre areas, where the high-level roads pass; the KDE-WH had a significant impact in the eastern part of the study region, where the forest activities were more active, while the impacts were insignificant in the western part, where there was less human disturbance.
(4) The sensitivity of LER to road network changed with different distances from the city centre. The indicator of the DNR-H showed that the impact of the road network decreased with the increasing distance from the city centre. Moreover, the effects of both the DNR-WH and KDE-WH on the LER gradually increased with the distance from the city centre.
(5) Our results also indicate that high-level roads mainly affect areas where human activities are more intensive, whereas low-level roads infiltrate every corner of the region, mainly affecting areas far from the city.

Benefitting from the quantification and visualization of the spatial paradigm in their associations at the grid level, our study suggests more accurate policies to alleviate the negative impact of road construction on the LER. Our study will also inspire further applications of a local model in the research of road ecology.

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