RESEARCH

IMPACT OF ROAD GRID TEMPORAL AND SPATIAL CHANGES ON THE ECOSYSTEM IN THE HIGH-ALTITUDE PLATEAU AREA: AN EMPIRICAL STUDY

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ABSTRACT

This empirical research utilized geographic information system (GIS) data and involved kernel density estimation (WKDE), ecological footprint modeling, landscape index analysis, and spatial analysis methods. A plateau landscape ecological risk model is constructed, and the temporal and spatial changes in the road network pattern and the landscape ecological risk in the region in 2012 and 2020 are investigated. The study results identify that the expansion of the road network led to a rapid increase in construction land area and a decrease in cultivated land area. However, there is little impact on other landscape types. The study reveals that road network expansion leads to landscape ecological risk changes, primarily in low-altitude urban centers. The risk levels decrease with increasing ecological risk levels, with the proportion of road level lengths increasing and decreasing. Landscape ecological risk and road level is correlated. This study will interest practitioners engaged in ecosystem management, infrastructure planning, and transportation systems development, as well as researchers in these and related areas.

KEYWORDS

Road network; plateau area; weighted kernel density estimation; landscape pattern; ecological risk; ecological ecosystem; temporal and spatial road grid changes

1. INTRODUCTION

Roads closely connect the local area with the outside world, greatly reduce transportation costs between regions, and play an important role in regional economic development (Forman and

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Alexander 1998). However, the expansion of the road network inevitably occupies the surrounding land area, directly leading to the disappearance of the original habitat patches and the corresponding fragmentation of the ecological landscape. Thus, regional landscape patterns are affected differently (Geneletti 2004). Landscape patterns and changes can be viewed as a comprehensive reflection of the ecological environment system, which can be acted on by natural and synthetic factors or ecological processes on a certain scale (Hualin 2008). Indeed, previous studies show that direct occupation of land by road construction firstly impacts landscape patterns, such as reducing the area of the ecosystem (Forman 2000).

As an important way to penetrate the landscape, roads provide convenience for land development and utilization, greatly changing land use patterns (McGarrigle et al. 2001). Further, the research field mainly focuses on the impact of roads (i.e., road networks) on land use (Saunders et al. 2002), landscape patterns (Zhu et al. 2006), and ecosystems (Findlay and Kelly 2011). At the regional scale, the impact of roads on the ecological environment is extended through the road network, and these impacts are reflected in the change of land use patterns in the area affected. In some cases, the impact of roads on land use and landscape patterns is greater than that of topography (Saunders et al. 2002). Furthermore, the existence and expansion of the road network affects regional ecological security by impacting the surrounding land use patterns. Therefore, the quantitative expression of land use change within the road influence area is significant for ecosystem management. However, due to the complexity of study areas, and coupled with the impact range of roads being generally large, few studies consider the quantitative relationship between temporal and spatial changes in landscape ecological risk and road grid bureau (Bian et al. 2015, Huang et al. 2016).

It is worth noting that, with the rapid development of information technology (IT), GIS (geographic information system) technology and spatial analysis technology are now widely used in various fields to solve many problems related to road system development and associated ecological aspects (Chang et al. 2015, Hu et al. 2016). Of these, kernel density estimation, an important spatial analysis method, can be used to study the regional road network's density pattern quantitatively. At the landscape scale, road kernel density is also considered an important index for measuring the impact of road networks on landscape ecology. It has been widely used in species fragmentation and human activity agglomeration (Forman and Alexander 1998). Existing studies mostly harness qualitative methods to analyze the impact of road networks on the ecological environment (Bai et al. 2017, Yang et al. 2010, Ming and Jiang 2022).

Consequently, more recent studies turn to the quantitative examination of the response thresholds of road networks to the ecological environment (Lin et al. 2019b, Grundy et al. 2015, Cai et al. 2013b). This includes utilizing evaluation indicators of ecological risk mainly aimed at soil-heavy metal pollution (He et al. 2019, Dumitrel et al. 2013) and landscape pattern changes (Wang and Wang 2022, Liu et al. 2021). Landscape ecological risk assessment focuses more on the temporal and spatial heterogeneity and scale effects of risks, providing a decision-making basis for regional risk prevention and effectively guiding the optimization and management of regional landscape patterns (Peng et al. 2015).

The present study examines the high-altitude plateau area in China, a dense distribution of nature reserves and ecological security barrier, revealing a fragmented landscape pattern due to alpine environment fragility and external disturbance sensitivity. With the expansion of the road network in this region, such development has a substantial impact on the changes in the landscape pattern and ecological environment. However, current study sites are mainly concentrated in developed urban areas (Wolff and Wu 2004, Pan et al. 2015); lakes or river basins

(Paukert et al. 2011, Silva et al. 2021); and mostly in plains and basins with low topography, featuring flat topography, large populations, and ease of data acquisition. Due to the complex terrain and climatic conditions in the high-altitude plateau area and the difficulty of data acquisition and processing, research into the influence mechanism of road grid bureau and ecosystem in the high-altitude plateau area has hitherto lacked scale and complexity.

To meet this challenge, and with the support of GIS, the study takes the G City in China's high-altitude plateau area as an example. The spatial distribution of road network density in G City is obtained using the weighted kernel density estimation (WKDE) method, and an ecological risk index model is constructed based on the landscape pattern to analyze the temporal and spatial changes of the road grid layout and landscape ecological risk. The purpose of the study is to identify the characteristics and extent of the impact of road network expansion on landscape patterns and ecological risks in high-altitude plateau areas, and provide a scientific basis and technical support for ecological restoration along highways in high-altitude plateaus. The study uses the WKDE method to calculate the road density and compared it with general kernel density estimation. It is found that the WKDE method can better reflect the influence intensity of different grades of roads on the surrounding environment. In addition, there are few studies of the ecological risks of road networks on a large scale. Therefore, there is a need to address this gap in the knowledge base. Highways, national roads, provincial roads, and county and township roads are investigated and the correlation between landscape ecological risks and roads are examined at all levels.

The remainder of this paper is organized as follows: section 2 contains a literature review; section 3 describes the data and methods used; section 4 analyzes and discusses the results of the study; and section 5 presents the conclusions, limitations, and potential future work.

2. LITERATURE REVIEW

2.1 Landscape ecological risk assessment methods

Landscape ecological risk assessment uses landscape patterns and risk sources/sinks, but early assessment is less effective when regional ecological stress factors are unclear (Wu et al. 2013). The method based on landscape patterns evaluates ecological risk from regional spatial patterns, making changes in land use and cover a research hotspot (Wang et al. 2008). Both methods are essential for assessing landscape ecological risk.

Ecological risk assessment involves constructing landscape ecological risk indicators based on landscape patterns or land mosaics (Xie 2008). Risk levels can be measured by such external forces as rapid urbanization and internal stress capacity (Jinggang et al. 2008). Expert scoring and ranking normalization methods are used for evaluation, but subjective weight normalization affects the final evaluation of different indicators (Jie et al. 2020).

The multi-criteria decision-making (MCDM) approach, a systematic method, reduces subjective judgments in ecological risk assessment (Malekmohammadi and Blouchi 2014, Campos et al. 2020). Common methods include the analytic hierarchy process (AHP) and the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS). Peng et al. (2019) uses AHP to determine the weight of factors affecting wetland ecological risk and establish a risk assessment model. Zhang et al. (2020) and Luan et al. (2019) use a combined TOPSIS and improved AHP method to assess an expressway's ecological and environmental impact—the improved approach demonstrating good objectivity and reliability, with the TOPSIS method providing scientific guidance for regional environmental management and planning. Combining these methods has become essential for ecological risk assessment (Ramya and Devadas 2019, Koc et al. 2021).

Most landscape ecological risk assessment methods use multiple methods (Srinivas et al. 2022, Arianoutsou et al. 2011). However, selecting indicators is subjective, and there are no quantitative criteria for ecological risk. A comprehensive system is needed to determine standard methods and provide a theoretical basis for further management and risk prevention measures in the ecological environment.

2.2 Impact of the road network on landscape patterns

At the landscape scale, roads are connected to networks that penetrate various landscapes and present unique network structure characteristics and topologies, profoundly affecting the landscape pattern structure and biological activity process in the study area (Barber et al. 2014, Redon et al. 2015). As a source of interference under human factors, roads impact on the regional landscape during different construction and operation periods. In the construction phase, road construction can lead to landscape fragmentation. In addition, roads further influence the composition and migration of various species by influencing the material composition of the surrounding ground and space (Keken et al. 2016).

Previous studies examine the impact of roads on landscape scale, focusing on single and complex road networks (Liu et al. 2008), the research covering both low and high human activity areas. Current research focuses on landscape fragmentation (Cai et al. 2013a, Karlson and Mörtberg 2015). Studies have found that roads have a corridor and obstruction effect on small mammals in agricultural landscapes, highlighting the need for further research (Redon et al. 2015).

Wu et al. (2014) find that expressway construction in Puli Town, Taiwan, leads to land-use landscape fragmentation. Liu et al. (2014) find that road network expansion causes forest landscape fragmentation and loss of connectivity. In addition, Vardei et al. (2014) use the landscape index to analyze the cumulative effects of roads on landscape ecology.

Overall, the influence of road networks on landscape patterns is a multifaceted issue. Therefore, there is an urgent need to study the impact of different road grades on the ecological ecosystem in different areas.

2.3 Impact of road networks on ecological risk

The road network directly and indirectly impacts the ecological process by affecting surrounding landscape patterns. Landscape ecological risk concerns the degree of harm that the structure and function of the ecosystem will experience from external disturbances at the regional landscape scale (Li and Li 2008).

Various recent studies use indicators, methods, and models for different regions and evaluation purposes. For instance, Lin et al. (2019a) study the correlation between road network and landscape ecological risk based on the Geographically Weighted Regression (GWR) model, the research results providing a reference for the further application of the GWR model in road ecology. Mann et al. (2019) study the impact of road network construction on regional ecological risk by quantifying and visualizing the ecological risk index based on GIS and RS technology, exploring the relationship between road types and terrain using OLS regression analysis and the GWR model. Bian et al. (2015) assess the ecological risk in the surrounding area of the expressway by analyzing the heavy metal content and enrichment index, and further assess the health risks of residents. Finally, Igondova et al. (2016) investigate the ecological risk index and, through quantitative research, propose an ecological impact assessment of the proposed road.

There are many microscopic studies of the landscape ecological problems in the affected area of the highway, and quantitative research into the layout of the highway network and ecological risks is lacking. Moreover, there are few studies of the ecological risk of developing road networks on a large scale. At the same time, research into large-scale and ecologically complex areas still need to be undertaken in more depth.

3. MATERIALS AND METHODS

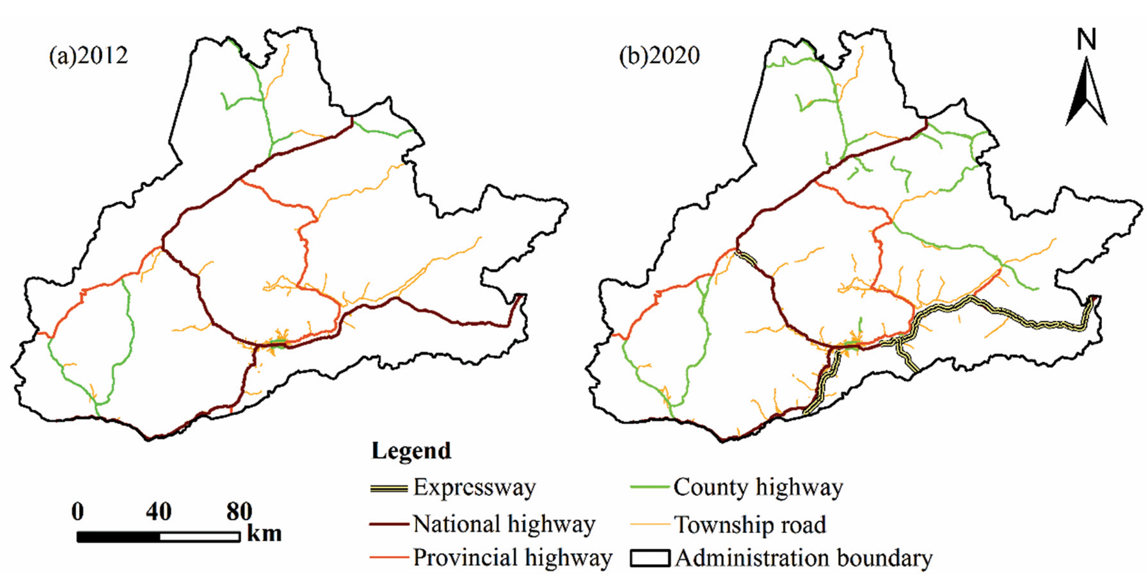
3.1 Study area

G City is in the southeastern part of the high-altitude plateau area north of a Brahmaputra tributary. In the city, the two original remote sensing images are preprocessed on the ENVI5.3 platform—including radiometric calibration, band combination, atmospheric correction, mosaicking, and cropping—and then imported into ArcGIS 10.2. The background scale of road vectorization is uniformly set to 1:100,000, and the main road network of the city in 2012 and 2020 is obtained by referring to the road traffic map of the study area and the historical image map of Google Earth, respectively (see Figure 1). The highways of all grades are mainly distributed at relatively low altitudes, the main growth area of county roads being in the city's northern part, while the increased township roads are mainly located in the south and extend in three directions to the west.

3.2 Data sources

The data include G City's administrative boundary data, main road vector data, and remote sensing image data in 2012 and 2020. The administrative boundary data and remote sensing

FIGURE 1. G City's main road network in 2012 and 2020.



images are from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/). The road vector data of each period is from the traffic map of the high-altitude plateau area released in the corresponding year and includes expressways, national highways, provincial highways, county highways, and township roads. The calculated data for the ecological footprint model are mainly derived from the statistical bulletins of the high-altitude plateau area and G City and FAO Output Statistical Yearbook. Combined with the actual land use and distribution in the study area, the land use types are divided into forest, grassland, cultivated land, construction land, water, and unused land. Landsat8 data with a spatial resolution of 30m × 30m are selected for the two phases of remote sensing images. The imaging time is between August and September, and the cloud coverage is lower than 0.1%.

Using the remote sensing image processing software ENVI5.3, the remote sensing images are firstly preprocessed through geometric correction and band fusion. Secondly, an interpretation sign is established, using field survey data and Google Earth images to select training and validation samples. Thirdly, the maximum likelihood classification method is used to classify the image data of the two phases, respectively. Finally, the classification results are post-processed to ensure a total accuracy of the classification results of more than 85%. After the above steps, the land use distribution map is obtained.

3.3 Research methods

3.3.1 Weighted Kernel Density Estimation (WKDE) Method

The kernel density estimation method can be used to calculate the KDE value of the road network linear density: that is, the linear density of each grid cell is calculated through a moving window in the ArcGIS software. Hence, there is a need to calculate and output the result (Wang and Wang 2019). It is generally defined by letting $x_1, \ldots, x_n$ be independent and identically distributed samples drawn from a population with the distribution density function f, and $f(x)$ is the value of point x in f, which usually has

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

where $k(x)$ is the kernel function, h is the bandwidth, $(x - x_i)$ represents the distance from the estimated point x to the sample point x_i, and n is the total number of samples.

In the KDE estimation process, the determination or selection of the bandwidth h influences the results. With the increase in h, the change of point density in space is smoother, but will cover the density structure; when h decreases, the estimated point density changes abruptly. The road network data in G City in 2020 is taken as an example. Comparing the kernel density distribution map of the road network under different bandwidths (see Figure 2) indicates that when the bandwidth is 8km, it can be considered a good reflection of the nuclear density grade distribution differences. Therefore, the 8km bandwidth is used to analyze the characteristics of G City's road grid.

Considering the different traffic capacity levels of roads of different grades and referring to relevant literature (Lin et al. 2021) as well as combining with the actual situation of the road network in the study area, the weight coefficients of different types of roads are determined as follows: Expressway 0.25, National road 0.3, Provincial road 0.2, County road 0.15, and Township road 0.1. The specific estimation method is

$$WD_i = \sum_{i_1}^{i_n} D_{in} W_{in} \tag{2}$$

where WD_i is the weighted road density of grid I, D_{in} is the density of the n-th grade road in grid I, W_{in} is the density of the n-th grade road in grid I, and W_{in} is the weight of the n-th grade road in grid i.

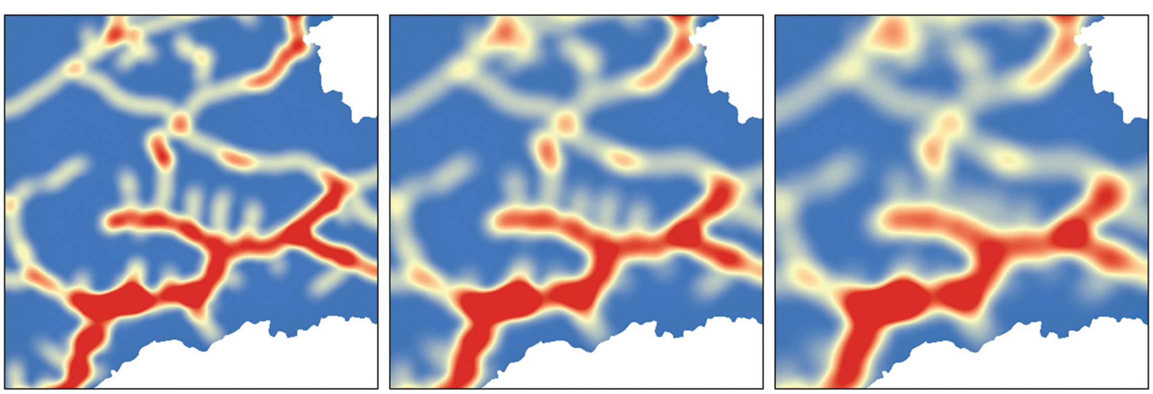
3.3.2 Construction of the ecological footprint model

The ecological footprint (EF) is proposed by economist William Wackernagel (1996) to evaluate the degree of sustainable development based on the measurement of biophysical quantities, and the EF index has become one of the most important theoretical indicators reflecting sustainable development (Wang et al. 2020). In this regard, the EF has become an important index and method to measure sustainable development. This study refers to the calculation process of Wang et al. (2020). It calculates the EF and ecological capacity of G City to calculate its ecological deficit or ecological surplus. When the EF is smaller than the ecological capacity, an ecological surplus will occur; while when the EF exceeds the ecological capacity, there will be an ecological deficit. The mathematical formula is

$$EF = \sum \frac{C_{N,i,j}}{Y_{W,i,j}} \times IYF_{W,i,j} \times EQF_{i,j} \tag{3}$$

(1) *Calculation of the ecological footprint.* EF refers to the bio-productive land area with a certain production capacity to produce resources and digest waste (Guo et al. 2017). The calculation of EF involves various resource and energy consumption items, which are converted into the six types of biologically productive land areas (cultivated land, forest land, grassland, water area, construction land, and unused land) and multiplied by a corresponding equilibrium factor to obtain the biological productivity and EF in the region. In Eq (3), i and j represent the product and year consumed; C_N represents

FIGURE 2. Comparison of different bandwidths and determination of optimal bandwidth.



(a)h=6km (b)h=8km (c)h=10km

the total resource consumption; and Y_w, IYF_w, and EQF represent the average yield, world average yield, and equilibrium factor, respectively.

$$BC = \sum A_{N,i,j} \times YF_{N,i,j} \times IYF_{W,i,j} \times EQF_{i,j} \tag{4}$$

(2) *Calculation of ecological capacity.* Bio-capacity (BC) refers to a region's actual biological productive area (Guo et al. 2017). To make a comparison between different types of landscape land area ecological capacity, yield factors are introduced to eliminate the difference between different land types in the calculation process. In Eq (4), i and j represent products consumed and years; YF_N, IYF_w, and EQF represent yield, world average, and equilibrium factors, respectively; and A_N represents the available productive land area.

$$ED = EF - BC \tag{5}$$

(3) *Calculation of ecological surplus and deficit.* Ecological deficit or surplus refers to the difference between EF and ecological capacity. In Eq (5), ED represents ecological deficit or surplus, and EF and BC have the same meanings as before.

3.3.3 Construction of Landscape Ecological Risk Index

The landscape ecological risk index construction is based on the landscape disturbance and vulnerability indices (Shi et al. 2015). The disturbance index (E_i) reflects the resistance of the landscape pattern to external disturbance. It is usually constructed by the landscape fragmentation (C_i), landscape separation (Q_i), and landscape dominance (DO_i) according to the corresponding weights (Mo et al. 2017); the fragility index (F_i) reflects the ability to maintain stability within the landscape (Xie et al. 2013). Table 1 shows the method used for calculating the correlation index.

TABLE 1. Landscape index calculation.

Landscape Index	Formulas
Landscape Fragmentation Index (C_i)	$C_i = n_i/A_i$
Landscape Separation Index (Q_i)	$Q_i = D_i \times A/A_i$, $D_i = (1/2) \times \sqrt{n_i}/\sqrt{A}$
Landscape Dominance Index (DO_i)	$DO_I = (R + F)/4 + L/2$ $R = n_i/N$, $F = B_i/B$, $L = S_i/S$
Landscape Disturbance Index (E_i)	$E_i = aC_i + bQ_i + cDO_i$

Note: n_i is the number of patches of landscape type i; N is the total number of patches of all landscape types; A_i represents the area of landscape type i; A is the landscape total area; B_i is the number of quadrants of patch i; B is the total number of squares; S_i is the area of patch i; S is the total area of the square; and a, b, and c are the weights of C_i, S_i, and DO_i, respectively.

(1) Landscape Interference Index (E_i)

The landscape disturbance index reflects the disturbance degree of different landscape types. The landscape fragmentation index, separation index, and dominance index are used to construct the landscape disturbance index, where $a + b + c = 1$. Road construction in G City has the greatest impact on landscape fragmentation, followed by landscape separation, and has the least impact on landscape dominance. Therefore, based on the relevant research results and the contribution of each landscape index to landscape ecological risk, the weights of fragmentation, separation, and dominance to 0.5, 0.3, and 0.2, respectively, are assigned (Su et al. 2020). Finally, the landscape disturbance index is obtained, which are 0.2857, 0.2381, 0.1905, 0.1429, 0.0952, and 0.0476, respectively.

(2) Landscape vulnerability index (F_i)

The landscape vulnerability index concerns the ability of regional ecosystems to resist external disturbances and represents the internal factors of ecological risks. This index is closely related to the landscape stage in the natural alternation process. Of the landscape types in the study area, unused land is the most vulnerable, followed by water area, and construction land is the most stable. Referring to previous studies (Xie et al. 2013), the vulnerability grades are assigned as follows: unused land 6, water area 5, cultivated land 4, grassland 3, forest land 2, and construction land 1, and normalized, thus obtaining the landscape vulnerability index.

(3) Landscape Ecological Risk Index (ERI_k)

Combined with the above-established landscape disturbance index and vulnerability index, a landscape ecological risk index model is constructed based on the area proportion of each landscape type. The index model can describe the relative loss degree of the comprehensive ecology of a certain sample area and fully reflect the ecological risk changes caused by changes in the landscape pattern. The model's construction is

$$ERI_K = \sum_{i=1}^{n} \frac{A_i}{A}\left(E_i \times F_i\right) \tag{6}$$

where ERI_k is the ecological risk index value of the k-th risk assessment unit; A_i is the area of land cover type i in the k-th risk assessment unit; A is the area of the k-th risk assessment unit; and E_i and F_i are the disturbance index value and vulnerability index value of the land cover type i of the k-th risk unit, respectively. According to the actual scope of the study area and the sampling workload, and based on ArcGIS software, the landscape ecological risk index is spatialized using the equidistant systematic sampling method, and a total of 935 sampling grids (the grid size is 6km × 6km) are generated. Each sampling area's landscape ecological risk index is calculated, and the value is taken as the attribute value of the center point of the sampling area. Furthermore, the Kriging interpolation method (Li et al. 2013) is used to obtain the entire study area's landscape ecological risk distribution map.

4. RESULTS AND ANALYSIS

4.1 Analysis of the road network's evolution characteristics

Table 2 shows the results obtained using the ArcGIS software to count the length of roads of different grades each year. This indicates that, during the period from 2012 to 2020, the total length of roads increases significantly; the total length of the road network increases by

1405.12km; and the total density increases from 0.0654km/km^2 to 0.1125km/km^2. Among the roads of all grades, national roads and provincial roads have only a small change. The expansion trend of township roads is the most significant, followed by county roads, whose length increases from 307.87km in 2012 to 723.03km in 2020, and density also increases from 0.0103km/km^2 to 0.0243km/km^2 accordingly. During the study period, expressways are built entirely anew and, as of 2020, 385.39km are built.

To more clearly and intuitively reflect the spatial patterns of the road network, the spatial distribution map of the road network density in G City in 2012 and 2020 is obtained based on KDE and WKDE (see Figure 3). Overall, the road density distribution has clear spatial differences, and the distribution of various regions is extremely uneven. The density cores are concentrated in the southern part of the study area and on both sides of high-grade highways such as expressways, national highways, and provincial highways. The largest core density is in the city center, and the overall attenuation being from the city center to the surrounding areas. This is due to the developed economy and transportation in the city's central area, with a relatively complete road network, and a road network density significantly higher than in other areas.

The weighted WKDE estimates road network density, revealing that high-value areas are enlarged and distributed on both sides of high-grade highways, indicating their large traffic capacity and influence. This analysis accurately reflects the road network's state and ecological impact, while the unweighted KDE attenuates its impact.

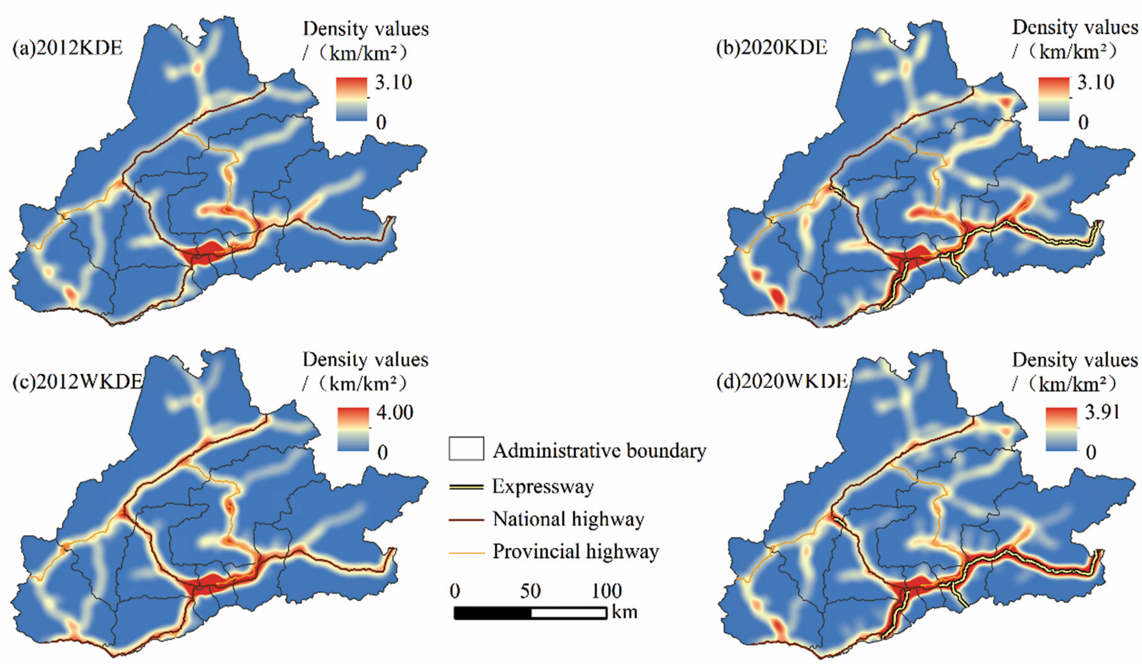
4.2 The relationship between the change trend of ecological deficit and the expansion of the road network

Table 3 shows the results of G City's EF, ecological capacity, and deficit in 2012 and 2020. This indicates that, from 2012 to 2020, the EF significantly increases by 1.15 ghm^2, while the

TABLE 2. Length and density of roads of different grades.

Years	Road grades	Length/km	Density/(km/km^2)
2012	Expressway	0	0
	National highway	515.19	0.0173
	Provincial highway	290.04	0.0097
	County highway	307.87	0.0103
	Township road	833.14	0.0280
	Total	1946.24	0.0654
2020	Expressway	385.39	0.0129
	National highway	513.46	0.0172
	Provincial highway	307.37	0.0103
	County highway	723.03	0.0243
	Township road	1422.12	0.0478
	Total	3351.36	0.1125

FIGURE 3. Spatial distribution of road network density.



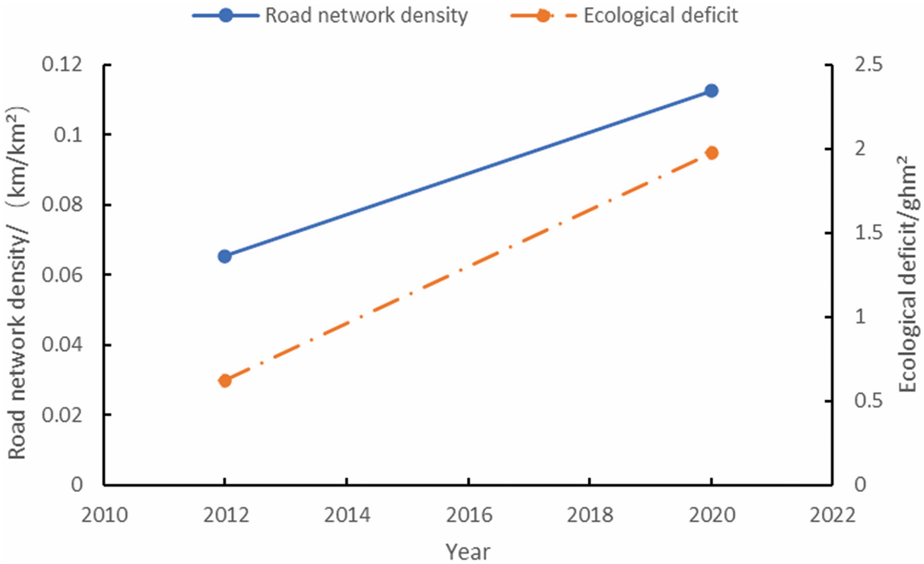
ecological capacity has a downward trend, decreasing by 0.2 ghm^2. Further, ecological surplus or deficit is formed by reducing EF and ecological capacity. Ecological deficit means that the EF exceeds the ecological capacity; that is, the environment is not strong enough to carry the consumption of resources and the output of waste, and ecological surplus means that the ecological capacity is higher than the EF. As a result of the increase in the EF and the decrease in the ecological capacity, the ecological deficit of G City in 2020 is 3.18 times that of 2012. The increase in EF indicates that the residents of G City increase their consumption of various products, which reflects the improvement of people's living standards. The decreased ecological capacity indicates that urban economic development gradually increases the pressure on the ecological environment, resulting in decreased ecological carrying capacity.

The ecological deficit is compared with the change in road network density, and the interaction between the two parameters is analyzed. Figure 4 shows the change trend and impact relationships, the road density and ecological deficit in G City showed a rising trend, with an increase in road density of 72.02% and an increase in ecological deficit of 217.74%. With the increase in road density, the ecological deficit becomes more serious, indicating a positive

TABLE 3. EF, ecological capacity, and ecological deficit.

Year	EF (ghm^2)	Ecological capacity (ghm^2)	Ecological deficit (ghm^2)
2012	1.11	0.49	0.62
2020	2.26	0.29	1.97

FIGURE 4. Trends in road network density and ecological deficit.

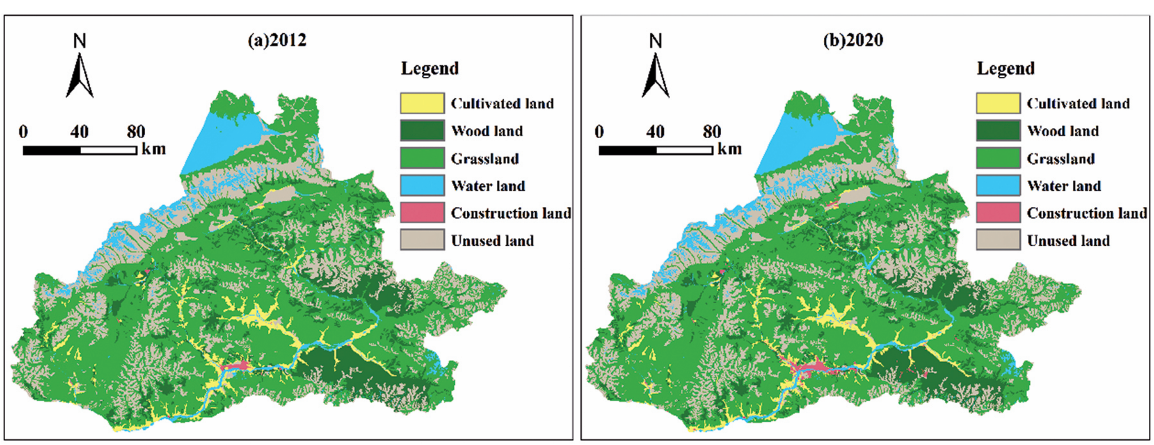


relationship between road network expansion and ecological deficit. On the one hand, constructing roads at all levels promotes the prosperity and development of G City's economy and society. However, on the other hand, it also brings pressure to the ecological ecosystem.

4.3 Landscape pattern changes analysis

G City's landscape pattern is divided into six categories: cultivated land, forest land, grassland, water area, construction land, and unused land. The main land use types are grassland, unused land, and forest (Figure 5). The topography of the area is closely related to land use distribution. The City Proper District is the main urban area, with low altitude and flat terrain. It is the nodal location for all grades of roads and a developed transportation network suitable for living and social production. Therefore, construction and cultivated land are primarily concentrated in these areas, with the north and west being mountainous with altitudes up to 7,000 meters. The terrain is complex and less affected by human activities.

FIGURE 5. Distribution map of land use types in 2012(a) and 2020(b).



Due to the distribution differences of land use types and increased road network density, the corresponding landscape types change accordingly. The landscape types with the greatest changes are construction land and cultivated land (see Figure 6). Grass is the most abundant landscape type in both years, but changes little. The landscape type with the largest area increase is construction land, which nearly triples from 2012 to 2020, and the landscape type with the largest area decrease is construction land, which decreases by 7.48% from 2012 to 2020. Changes are closely related to urban development and road construction. Expanding road networks offer abundant resources and convenient transportation, facilitating the development of emerging industries and transforming traditional agriculture into other sectors.

To study changes in landscape patterns, landscape indices are calculated using Fragstats4.2 software. As Table 4 shows, the fragmentation index of each landscape type is low, which indicates that the complexity of the landscape spatial structure in G City is low. The water area's highest separation index is due to its patchy shape, easily divided by linear structures such as roads, resulting in a relatively scattered geographical distribution of the water landscape. Forest land has the highest dominance index among all the landscapes, mainly due to human activities. During the study period, the local government formulated a series of ecological protection measures and established grassland-based ecological reserves.

4.4 Landscape ecological risk change analysis

Based on the landscape-type data and 935 sampling grids, the index is divided into normalized grades. The normalized risk index is divided into five grades at equal intervals: low-risk area ($0 \le ERI < 0.2$), lower-risk area ($0.2 \le ERI < 0.4$), medium-risk areas ($0.4 \le ERI < 0.6$), higher-risk areas ($0.6 \le ERI < 0.8$), and high-risk areas ($0.8 \le ERI \le 1.0$), finally forming the distribution map of ecological risk levels, as shown in Figure 7. This indicates that high ecological risk areas are mainly distributed in the west and north of the study area. The landscape types in this area are relatively simple, mainly water and unused, which are also landscape types with a high vulnerability index. Therefore, this results in a higher risk level in this area. The areas with the most obvious changes in risk level are mainly located in the city center, characterized by the transfer of medium-risk areas to lower-risk areas, increasing in lower-risk areas.

FIGURE 6. Changes in land use types.

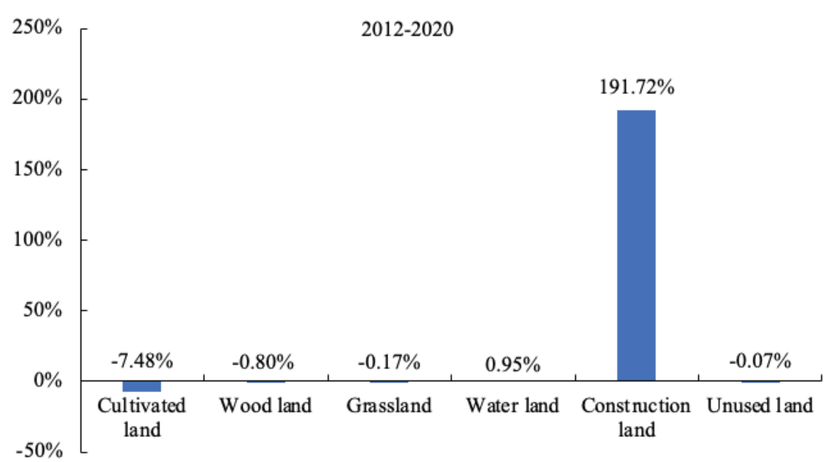


TABLE 4. Landscape indices.

Landscape index	Year	Cultivated land	Woodland	Grassland	Waterland	Construction land	Unused land
Landscape fragmentation index	2012	0.0021	0.0011	0.0001	0.0024	0.0059	0.0008
	2020	0.0023	0.0012	0.0001	0.0023	0.0084	0.0008
Landscape splitting index	2012	0.1191	0.0490	0.0076	0.0931	0.8292	0.0307
	2020	0.1313	0.0497	0.0077	0.0922	0.5777	0.0308
Landscape dominance index	2012	0.1073	0.2394	0.5350	0.2082	0.0151	0.3854
	2020	0.1051	0.2356	0.5335	0.2044	0.0479	0.3818
Area proportion (%)	2012	3.63%	11.90%	55.09%	6.83%	0.22%	22.34%
	2020	3.36%	11.81%	54.99%	6.89%	0.63%	22.33%

The road density within the influence area of the road domain often affects the landscape ecological risk index. Therefore, the road core density in 2012 and 2020 is normalized and divided it into eight roads according to the density segmentation method. Figure 8 shows the density grades, indicating that the variation characteristics of ecological risk with road density level are the same in the two years. When the road density grade is less than five, the ecological risk decreases with the increase of the density grade, and the downward trend is clear. The opposite trend is shown when the road density grade exceeds five, but the increase is not obvious. Therefore, human activities are intensifying their impact on the ecological landscape, with road construction dividing landscapes and increasing ecological diversity, thereby increasing the ecological risk index. The risk index remains consistent at density levels of less than five, as seen in 2012 and 2020.

FIGURE 7. Distribution map of landscape ecological risk levels.

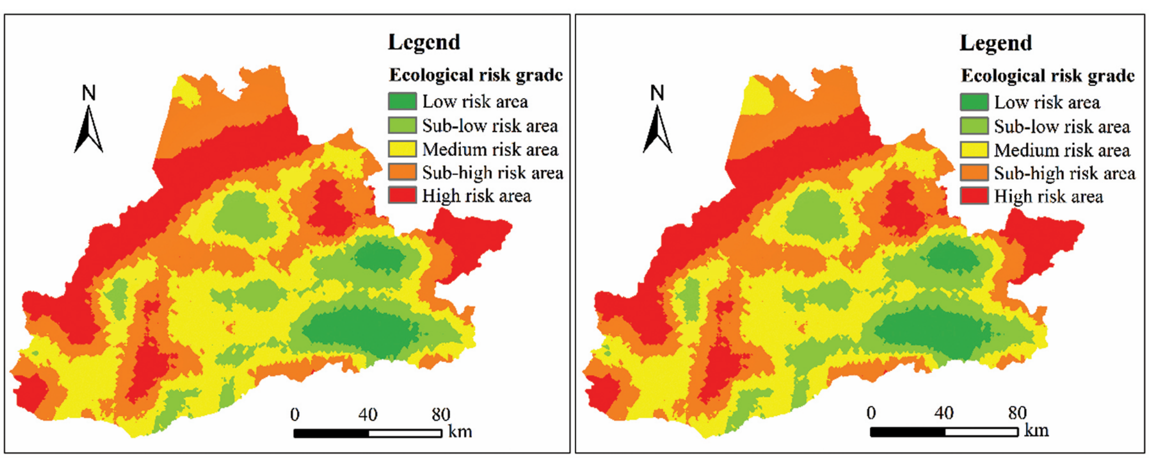
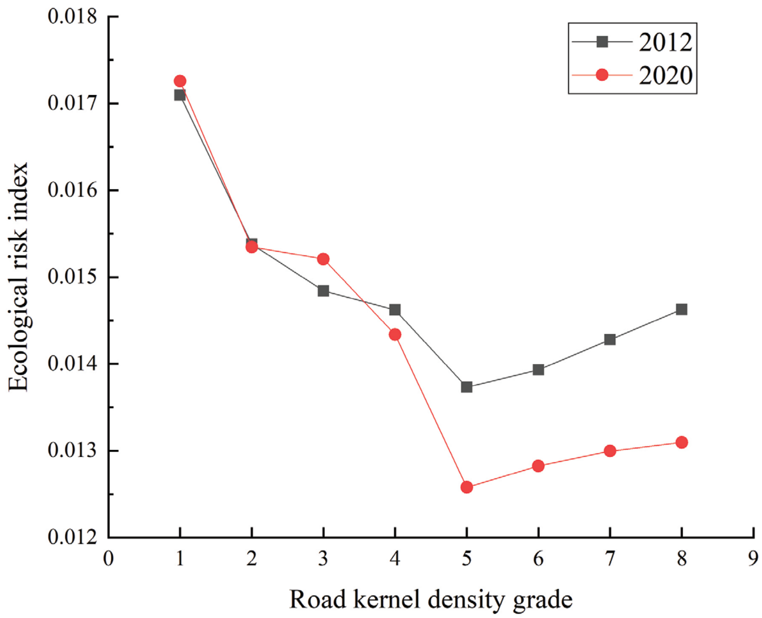
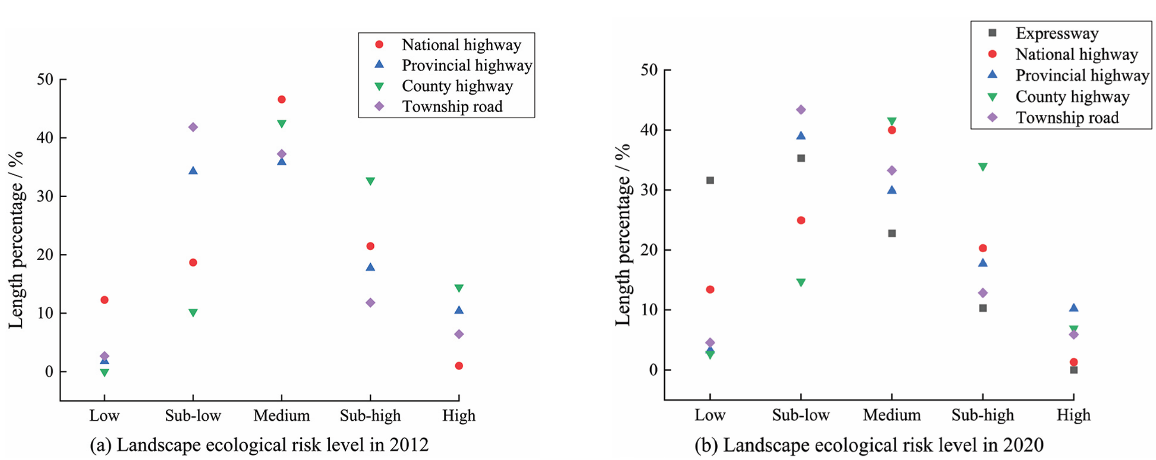


FIGURE 8. Ecological risk changes under different road densities.



Due to the difference in the total length of various types of roads and the proportion of ecological grades, in order to analyze the correlation between G City's landscape ecological risk and various types of roads, the percentage of lengths of different types of roads within each grade of landscape ecological risk is calculated (Figure 9). In 2012, when the ecological risk is at a low level, the proportion of roads at each level is very small; when the ecological risk is at the next lower level, the proportion of roads at each level varies significantly, and in the following order: township road > provincial road > national road > county. When the ecological risk is at the medium level, the length of each road grade has a higher proportion. When the ecological risk is at sub-high and high levels, the length of the county road accounts for the largest proportion. Except for expressways, the proportion of each road length in different ecological risk levels in 2020 is similar to 2012.

FIGURE 9. Proportion of road length in different ecological risk levels in 2012 and 2020.



5. DISCUSSION

The impact of highway construction on the ecological environment is mainly concentrated in developed cities with high population density. Based on the macro perspective of the landscape pattern, this study develops a landscape ecological risk model in the plateau area, analyzing the impact of road network construction on the ecological environment by comparing landscape patterns and ecological risk changes before and after the expansion. The results have a reference value for road network planning and ecological management in high-altitude areas of the plateau.

Previous studies conduct in-depth research on the impact assessment of road networks on landscape types. Indeed, Vardei et al. (2014) evaluate the cumulative effect of road networks on forest cover in Golestan province, Iran, showing that road network expansion increases the fragmentation of woodland landscape patches, and the distribution of vulnerable patches is related to the distance on both sides of the road. Liu et al. (2014) research the road network of Lantsang in Lincang, China, and obtain similar results, also showing that habitat loss is more likely to increase at lower elevations and in areas near urban road networks. Xie et al. (2016) take Jiuquan, a city in the arid region of China, as the research focus and analyze the temporal and spatial changes of the urban landscape on the cross-section of the road, showing that the road plays a positive role in urban expansion and increases the landscape complexity of the structure. The results of the above cases provide an important reference for planning the regional landscape pattern. However, the evaluation indicators focus on the changes in a single type of landscape, with no further research into regional ecological risks.

The present study establishes a landscape ecological risk assessment model to evaluate the quantitative relationship between the road grid and ecological risk. Furthermore, Mo et al. (2017) use Beijing as an example to study the impact of highway network expansion on landscape patterns and landscape ecological risks, showing that the increase in the density of the road network in the city center leads to a decrease in the ecological risk level. This is similar to the present study, except that the latter also includes national roads, provincial roads, county roads, and some township roads, and the correlation between landscape ecological risks and different road levels is also studied. In addition, and in terms of research methods, the present study also considers the traffic capacity of roads of different grades. It establishes a weighted kernel density estimation method suitable for plateau areas to study the relationship between landscape ecological risk and road density grades. The kernel density estimation method is utilized to study the temporal and spatial variation of landscape patterns and ecological risk (LER) in the upper reaches of the Minjiang River and the correlation between road network and landscape ecological risk (Lin et al. 2019a, Mann et al. 2019).

An ecological risk assessment model, influenced by social, historical, economic, and environmental factors, is crucial for establishing a scientific and practical ecological development model. Studying ecological risk changes from a landscape structure perspective helps toobjectively reflect ecological risk patterns along roads of various levels, potentially serving as a valuable research direction in the future.

6. CONCLUSION

Combining land use data and road vector data, this study uses weighted kernel density estimation, geographic information system, statistical analysis, and other methods to study the impact of road network expansion in high altitude areas on the landscape pattern and ecological risks. In summary, the main findings are as follows.

1. From 2012 to 2020, the road network density changes significantly, manifested in the rapid expansion of county and township roads. However, the overall road network density value is low, with obvious regional differences. Moreover, the weighted density analysis can more realistically reflect the actual condition of the road network and its ecological impact. In contrast, the road density estimated by the unweighted KDE weakens the impact of high-grade roads.
2. From 2012 to 2020, the development of EF and ecological deficit in G City has an upward trend and significant changes, which indicates that the economic development, on the one hand, increased the consumption of various products and, on the other hand, led to the decline of ecological environment carrying capacity. By comparing road network expansion with the ecological deficit development trend, road network expansion positively promotes the ecological environmental pressure index.
3. The changes in each landscape type are very different in the landscape pattern's temporal and spatial changes. Under the influence of urbanization, the area of construction land changes the most, followed by cultivated land. Affected by road segmentation, the degree of fragmentation of the waters increases significantly. Due to the joint action of humans and nature, the dominance of grassland is always high.
4. From 2012 to 2020, the change in the sub-low-risk area in the urban center is consistent with the expansion trend of the road network. As the road network's density increases, the sub-low-risk area's size increases accordingly. In non-urban central areas, the expansion of the road network does not cause significant changes in ecological risk levels.
5. The ecological risk first decreases rapidly with the change in road density level and then shows a slow upward trend when the density level is 5. Overall, under the same density level, the ecological risk in 2020 is lower than in 2012. This is because the artificial ecology gradually improves over the period, and the protective effect of human beings is reflected. Within the research scope of the road area, and with the increase of the ecological risk level, the proportion of the length of each road level has a trend of first increasing and then decreasing, and there is a correlation between the landscape ecological risk and the road level.

This study quantitatively analyzes urban road network evolution in high-altitude plateau areas and their ecological effects. However, it is limited by the relationship between buffer distances and landscape ecological risks not being addressed. Further study is needed to understand the impact of highway network construction on the ecological environment.

Author contributions

Jingxiao Zhang contributed to the conception of the study, Hui Li performed the experiment; Simon P. Philbin and Shuwen Cao contributed significantly to analysis and manuscript preparation; Hui Li performed the data analyses and wrote the manuscript together with Liyuan Cheng; Jingxiao Zhang, Shuwen Cao helped perform the analysis with constructive discussions; and Martin Skitmore helped with the manuscript publication.

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