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Exploration of roadway factors and habitat quality using InVEST

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ABSTRACT

Roadways vary in structural, geotechnical, locational, and operational properties, and synergies among these factors may present overwhelming challenges to understanding their full effects on the habitat quality (HQ). To explore the impact of dense roadway networks on an ecologically fragile region in the northwest of China, this study applied the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) to evaluate the HQ spatiotemporal distribution of the study area. Then, Generalised Estimating Equations (GEE) were formulated to examine the cumulative impact due to the operation of an increasing amount of roadways over the past two decades. According to the results, the influence of different road types on the HQ was apparent within the road-effect zone, and road grading reduction, road length and operation duration increase can harm the HQ within the road-effect zone. Overall, this study generates knowledge concerning the design and operation of environmentally-friendly roadways in ecologically fragile areas.

1. Introduction

Nowadays, many countries have suffered from severe environmental problems as a consequence of the development of infrastructure projects that have modified biophysical characteristics of the earth's terrestrial surface, including the distribution of vegetation, water and soil (Zhou et al., 2019). Changes in land use and land cover (LULCc) are important drivers of global environmental changes such as emissions of greenhouse gases, global climate change, loss of biodiversity, and loss of soil resources. In recent years, LULCc research has become an essential topic to climate and environmental change programs at a global scale, as rapid economic and infrastructure development that lead to LULCc can impair ecological environment and biological habitats. And the direct impact could be habitat loss, fragmentation, degradation of landscape connectivity, biodiversity disappearance, and so on (Bruschi et al., 2015; Mortelliti et al., 2011; Rubio and Saura, 2012). Numerous approaches have been formulated and applied for detecting and modelling the LULCc at different levels, which provides valuable lessons for infrastructure planning decision-making and achieving ecological balance. These approaches include remote sensing (Li et al., 2014), terrestrial scanning (Gruszczyński et al., 2017), species richness monitoring (Pedersen and Krogli, 2017), ecological dominance (Garcia-Vega and Newbold, 2020), endemism analysis (Ocampo Salinas et al., 2019), temporal analysis (Jiang et al., 2020), vegetation index differencing (Zhou et al., 2020), Landsat image analysis (Duan et al., 2020), principal components analysis (Fan and Zhao, 2019), and so forth. Besides, accurate georeferencing landmarks and chronological repetitive data can be acquired using satellite sensing and geographic information system (GIS). These types of applications have been widely used for identifying uncharacteristic changes between multiple environmental

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datasets which can accurately reflect the LULCc in large scale terrain (MohanRajan et al., 2020).

According to D'Amico et al. (2015) and Delgado et al. (2019), building linear roads adjacent to or inside a habitat would directly affect the life of the habitat wildlife, followed by behavioural responses such as flushing, fleeing, and avoiding frequently disturbed areas. In the long run, there will be other side effects such as alien species invasion to the local ecosystem, reduced food intake, and so on (Boarman and Sazaki, 2006; Clements et al., 2014; Ibisch et al., 2016). Vehicle noise and exhaust pollution can also deteriorate the biological environment. Using the traffic noise and avian vocal activity techniques, Halfwerk et al. (2011) measured the noise and species-specific acoustic behaviours of the roadside forest affected by the traffic. It was found that the traffic noise level varied substantially in space, time and frequency, which caused the significant negative impact on certain species. A viable solution of lowering the traffic noise volume was to levy the 'noise tax' or limit the vehicles within a certain time period during a day. Typically, a geographical region where significant environmental effects may present on its natural systems and be influenced by its road networks/traffic is defined as the road-effect zone (van der Ree et al., 2011). The zone of impact varies in types and degree of impact, based on distance from the roadway, environmental conditions, and traffic intensity (Wu et al., 2014a). Prime approaches for understanding road-effect zone biodiversity include statistical analysis (such as meta-analysis and regression modelling), observational simulation, field investigation, and use of information technology systems (such as GIS applications) (Wang et al., 2014). Eigenbrod et al., (2009) formulated a linear piecewise regression model to measure the extent and type of a heavy-truck traffic motorway's road-effect zone, which revealed that the zone width was as wide as up to 1 km to amphibians such as frogs and toads. It was also found that truck traffic at night was the second to none factor that significantly reduced the use of breeding habitat within the motorway effect-zone. Benitez-Lopez et al. (2010) collected the mean species abundance data and applied the meta-analysis and meta-regression technique to measure the road-effect size on mammals and birds. The results manifested the effect of infrastructure development could reach 1 km to small-sized mammals (such as bird populations) and 5 km to large-sized mammals. Otherwise, no significant relation between the species abundance and traffic intensity was found. D'Amico et al. (2015) used vertebrate animals causality data to examine the impact of road life-history and spatiotemporal factors. Other researchers also used species distribution models to explore the spatial distribution of biodiversity in large-scale terrain (Araujo et al., 2019; Di Febbraro et al., 2015). Despite ample, these studies present very similar methodologies which are animal pattern observation, data collection and processing. Unfortunately, the data could have over-fitting and under-fitting problems (Xu et al., 2015, 2016), let alone the tedious process of acquiring and processing this data.

To overcome the data problem, Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) models were later on formulated, and have provided viable solutions for evaluating habitat quality (HQ) (Moreira et al., 2018), hydrological services, carbon storage and sequestration, and nutrient and sediment delivery (Arunyawat and Shrestha, 2016; Trisurat et al., 2016). Wu et al. (2014a) used the InVEST model to assess the long-term effects of transportation infrastructure on habitats, which proved the conservation of agricultural and forested lands could improve the HQ and preserve the rare habitats. Terrado et al. (2016) modified the InVEST model for the assessment of terrestrial and aquatic HQ. It was found their modified model can precisely forecast the effects of land and freshwater habitat conservation. Shaffer et al. (2019) parameterised the InVEST model, quantified the grassland-bird habitat, and assessed the degradation status of the remaining grassland-bird habitat as influenced by crop and energy. Overall, InVEST models seem to offer a promising means for understanding the ecological impact caused by infrastructural projects, especially the roadways this study focused on, under the backdrop of China's massive road network construction that gives rise to growing environmental problems. Nevertheless, assessing a roadway's impact on the surrounding landscape is not an easy task as part of the impact can take years to manifest. Besides, roadways may vary in structural, geotechnical, location, and operational properties, and synergies among these factors may present overwhelming challenges to understanding the full effects of roads on the HQ. In view of this, this study attempts to examine as many aspects of the roadways and their interaction with the habitat surrounding environment, and to provide unique findings on the spatial scales at which the studied roads affected the HQ. A general hypothesis to underpin the following investigation is that within the road-effect zone, roadway-related factors (e.g. road type, operation duration, length, etc.) can affect the HQ to different extents.

2. Research methodology

2.1. Study areas

Qinghai Province (89°35′–103°04′E, 31°09′-39°19′N) is species-rich and ecologically sensitive. It is located in the Qinghai-Tibet Plateau with an average elevation of 4000 m (Li et al., 2018). According to the World Database of Key Biodiversity Areas (International Union for Conservation of Nature, 2019), the biodiversity area of Qinghai accounts for 28.29% of the total provincial area (Fig. 1). Qinghai belongs to a typical plateau continental climate, i.e. colossal day and night temperature difference, little and concentrated precipitation, etc. The average annual temperature is −5.7 to 8.5 °C, and the average yearly rainfall is 50–450 mm, mainly concentrated from July to September (Dong et al., 2013). East Qinghai is less mountainous than the west and is of rich species diversity. Due to climate change and human activity invasions, its regional ecosystem services and biodiversity are facing severe degradation problems (Li et al., 2018; Zhang et al., 2019). In recent years, Chinese governments at different levels have demarcated several nature reserves and promulgated ecology conservation and restoration programs to protect Qinghai's wildlife, wetlands, forests and desert ecosystems (Ministry of Ecology and Environment of the People's Republic of China, 2017). This study focused on the eastern Qilian Mountains (Zone 1) and the area between the Qinghai Lake and Amne Machin Range (Zone 2) (Fig. 1), as the habitats in these areas are more biodiverse yet vulnerable due to sustained drought and rapid development of infrastructure (partly because of China's Belt and Road initiative). There are various endangered species listed in the Red List of Threatened Species and the

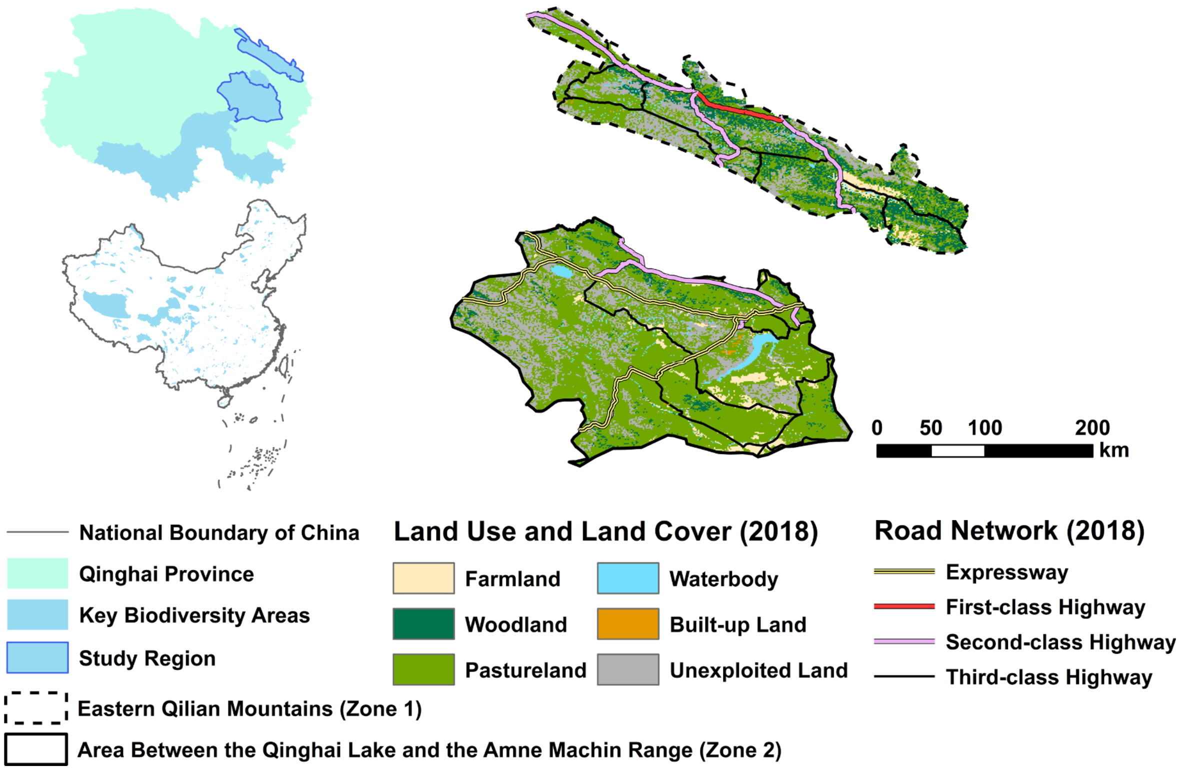

Fig. 1. Land overlays of the study areas (referred to from http://www.resdc.cn).

Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) (Table A.1). Since 2000, road projects in both Zone 1 and Zone 2 have increased dramatically. As of 2018, the total first-class, second-class and third-class highway mileages of Zone 1 had increased by 70.866 km, 254.558 km and 435.033 km; the total expressway, second-class and third-class highway mileages of Zone 2 had increased by 556.795 km, 555.895 km and 333.558 km (Table 1).

Table 1
Road project demographics in the study areas.

Study areas	Road ID	Level	Length of increase since 2000 (km)	Years of operation (as of 2018)
Zone 1	S304	First-class	70.866	2
	G227	Second-class	119.798	≥18
	S204	Second-class	254.558	6
	S105	Third-class	58.878	9
	S207	Third-class	109.373	≥18
	S302	Third-class	367.155	13
	X522	Third-class	171.026	≥18
	X566	Third-class	34.518	≥18
Zone 2	G6	Expressway	298.515	6
	G0613	Expressway	194.534	1
	S2013	Expressway	63.746	2
	G214	Second-class	233.769	12
	G109	Second-class	286.706	9
	S206	Second-class	35.420	9
	X310	Second-class	20.925	≥18
	S101	Third-class	138.160	9
	S201	Third-class	88.829	≥18
	S207	Third-class	266.110	≥18
	S301	Third-class	23.084	9
	S311	Third-class	172.314	9
	X303	Third-class	23.324	≥18

2.2. LULCc analysis

The land use and land cover (LULC) raster maps of 2000, 2010 and 2018 generated by the Landsat Thematic Mapper/Landsat Enhanced Thematic Mapper/Landsat 8 remote sensing images were retrieved from the data centre of the Resources and Environmental Science of Chinese Academy of Sciences. The resolution of the maps was 1 km. The study areas constituted both first-class land (i.e. farmland, woodland, pastureland, waterbody, built-up land and unexploited land) and second-class land (e.g. paddy field, dry land, shrub, sparse woodland, high coverage pastureland, river, lake, reservoir, swamp, rural settlement, wetland, etc.) (Liu et al., 2014). The Land-use Dynamic Degree (LDD) model adapted from Arunyawat and Shrestha (2018) and Wu et al. (2014b) was applied in this study to examine the first tier LULCc within a specified period, as represented in Equation (1).

$$K_{a-b} = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{1}$$

where K_{a-b} represents the LDD of a certain LULC throughout the study period, U_a represents the area of a certain LULC at the project outset, U_b represents the same area at the project completion, and T represents the period (measured in years). Then, the Markov transfer matrix was applied to quantitatively analyse the transfer area between the different LULC types, namely, spatiotemporal evolution, LULCc trend, and so on (Gurung et al., 2018). The Markov model was able to quantitatively describe the system state and transition and reflect the transition process of a meta-stable system from T to $T + 1$. The matrix can be expressed as Equation (2).

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \tag{2}$$

where the horizontal and vertical values represent the LULC status at the project outset and completion, P_{ij} represents the transformation of the ith area to the jth within the study period, and n represents the number of LULC types.

2.3. HQ evaluation

This study utilised the InVEST 3.5.0 × 86 HQ module to examine the HQ spatiotemporal characteristics and estimate the extent of habitat degradation. The advantage of this module is that it can generate the HQ maps based on LULC and threats information, regardless of the species distribution data adequacy (Sharp et al., 2018). This way, the habitat total threat level can be expressed as Equation (3).

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{w_r}{\sum_{r=1}^{R} w_r} \right) r_y i_{rxy} \beta_x S_{jr} \tag{3}$$

where D_{xj} represents the xth grid cell's threat level of the jth LULC type, y represents the grid cells entirety on threat r's raster map, w_r represents each threat's relative destructiveness (ranging from 0 to 1) to the habitats entirety, r_y represents the yth grid cell's threat intensity (ranging from 0 to 1), i_{rxy} represents the distance between the habitat and the threat source (its linear and exponential distance-decay functions can be expressed as Equation (4) and Equation (5)), β_x represents the xth grid cell's accessibility level (ranging from 0 to 1), and S_{jr} represents the jth LULC type's sensitivity (ranging from 0 to 1) on the threat.

$$i_{rxy} = 1 - \frac{d_{xy}}{d_{rmax}} \tag{4}$$

$$i_{rxy} = exp\left(-\frac{2.99}{d_{rmax}} d_{xy}\right) \tag{5}$$

where d_{xy} represents the linear distance between x and y, and $d_{r\ max}$ represents the maximum effective distance that r could reach. After the retrieval of D_{xj}, a half-saturation function expressed as Equation (6) was used to translate a grid cell's threat score into HQ.

$$Q_{xj} = H_j \left(1 - \frac{D_{xj}^Z}{D_{xj}^Z + k^Z}\right) \tag{6}$$

where Q_{xj} represents the quality of x in j, H_j represents the habitat suitability (ranging from 0 to 1) of j, and Z (i.e. a constant equaling to 2.5) and k (its default value is 0.5) are the scaling parameters. The farmland of Zone 2 and residential land (including roads) of Zone 1/Zone 2 were considered as the HQ threat sources. The parameters of each threat's relative impact weight, its maximum effective distance, and distance-decay function were determined according to the literature listed in Table 2. The habitat suitability of each LULC type and the relative sensitivity of each habitat type versus its threat were determined by the animal and plant information of the study areas (Table A.2). The accessibility levels of Zone 1 in 2010 and 2018 were identical (i.e. equaling to 0.8) because Zone 1 became a provincial nature reserve since 2005, and the remaining accessibility levels were all 1. A grid cell's threat source value was set to 1 if the threat was present or otherwise 0. The output results accuracy was improved using the resampling techniques (i.e. increasing the LULC raster maps resolution from 1 km to 30 m).

Table 2
Threats features.

Threats (distance-decay function: exponential)	Weight	Max effective distance (km)	References
Farmland	0.8	4	(Wu et al., 2014a; Terrado et al., 2016; Asadolahi et al., 2018; Shaffer et al., 2019)
Residential areas	1	5	
Expressways	0.9–1	4	(Wu et al., 2014a; Asadolahi et al., 2018; Hu et al., 2018; Li et al., 2019)
First-class highways	0.8–0.9	3	
Second-class highways	0.7–0.8	2	
Third-class highways	0.5–0.6	1	

2.4. Impact analysis techniques

Next, the retrieved road-effect zone HQ data (between 2000 and 2018) was fed into IBM SPSS Statistics 24 to establish Generalised Estimating Equations (GEE). Given the GEE were able to overcome the variable non-independence issue in repeated measurements (Önder, 2016), and they were used to analyse the relationship between the road-related variables and the HQ change (denoted as HQc) (these variables include, but are not limited to, road level (*G*), road operation duration (*Y*), road length (*L*), *LULC*c, and the distance between a data point and a road's centerline (*D*), and so on (Table 3)). During the process of GEE establishment, the Quasi-likelihood under Independence Model Criterion (QIC) and Corrected Quasi-likelihood under Independence Model Criterion (QICC) were collectively used to improve the data correlation (Kwon et al., 2017). As well, the establishment of optimal GEE was based on a series of steps, which included fixing the explanatory variables (i.e. *G*, *Y*, *L*, *D*, *LULC*c), using the QIC to determine the optimal working correlation structure (i.e. the correlation between datasets), changing the explanatory variables' values and forms, and applying the QICC for determining the optimal model. Lastly, the Binomial distribution type and Logit link function (Equations (7)–(10)) were formulated to determine the road-effect zone HQc:

$$Y = \begin{cases} 1 & if \quad HQ \quad decrease \\ 0 & \qquad else \end{cases} \tag{7}$$

$$\mu = E(Y) = P \tag{8}$$

$$g(\mu) = Logit(P) = log(P/(1-P)) \tag{9}$$

$$Logit(P) = \beta_0 + \beta_1 G + \beta_2 Y + \beta_3 L + \beta_4 LULCc + \beta_5 G * Y + \beta_6 LULCc * lnD \tag{10}$$

where *Y* represents the response variable which can also derive *HQ*c, μ represents the response variable expectation, *P* represents the probability when the response variable reaches 1, $g(\cdot)$ represents the link function, also known as the Logit function, and the parameter vector β comprises of (β_0, β_1, β_2, β_3, β_4, β_5, β_6).

3. Results analysis

3.1. LULCc

The LDD results indicated that the LULCc were minor in the study areas between 2000 and 2018 (Fig. 2). In Zone 1, the sizes of the farmland and the built-up land were increased by 0.5% and 0.7% per year between 2000 and 2018, and the size of the waterbody was reduced by 0.1% between 2000 and 2010 and 1% between 2010 and 2018. Meanwhile, apparent changes were not witnessed in other areas. In Zone 2, the sizes of the farmland, waterbody and pastureland kept increasing at a rate of 0.3% to 0.9% per annum since 2000, whereas the unexploited land and woodland downsized slightly. A noticeable increase in size at a rate of 10.1% per year

Table 3
Presentation of the non-collinear road-related variables.

Variable	Denotation	Value
Road level	*G*	0: expressway 1: first-class highway 2: second-class highway 3: third-class highway
Years of operation (as of 2018)	*Y*	integer
Road length (km)	*L*	decimal
The distance between a data point and a road's centerline	*D*	decimal
LULC changes (transforming into woodland or pastureland)	*LULC*c	1: observed 0: not observed
HQ reduction within the road-effect zone	*HQ*c	1: observed 0: not observed

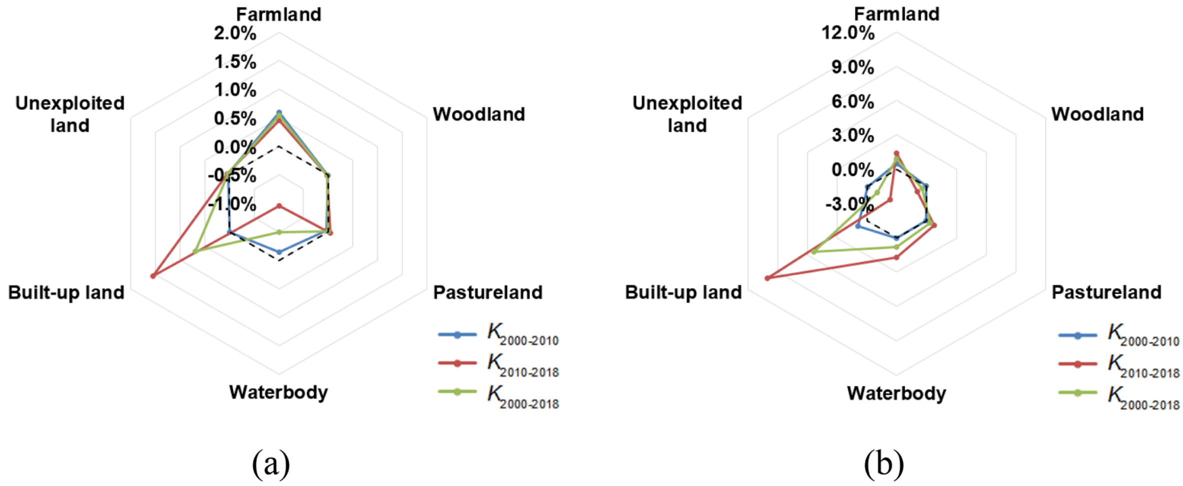

Fig. 2. Urban expansion LDD in Zone 1 (a) and Zone 2 (b).

was observed on the built-up land between 2010 and 2018.

The LULC area transfer matrix showed the original pastureland and woodland were exploited for infrastructural and agricultural purposes, and more and more unexploited land was used for recovering the pastureland and woodland (Fig. 3 and Table 4). In Zone 1, a total of 62 km^2 woodland and pastureland (equivalent to 83.78% of the increased farmland) was exploited for agricultural use, 11 km^2 pastureland (equivalent to 122.2% of the increased built-up land) for infrastructural use, and 60 km^2 unexploited land was turned into woodland; in Zone 2, 249 km^2 pastureland (equivalent to 91.89% of the increased farmland) was exploited for agricultural use, 69 km^2 pastureland (equivalent to 94.52% of the increased built-up land) for infrastructural use, and 1815 km^2 unexploited land was turned into pastureland.

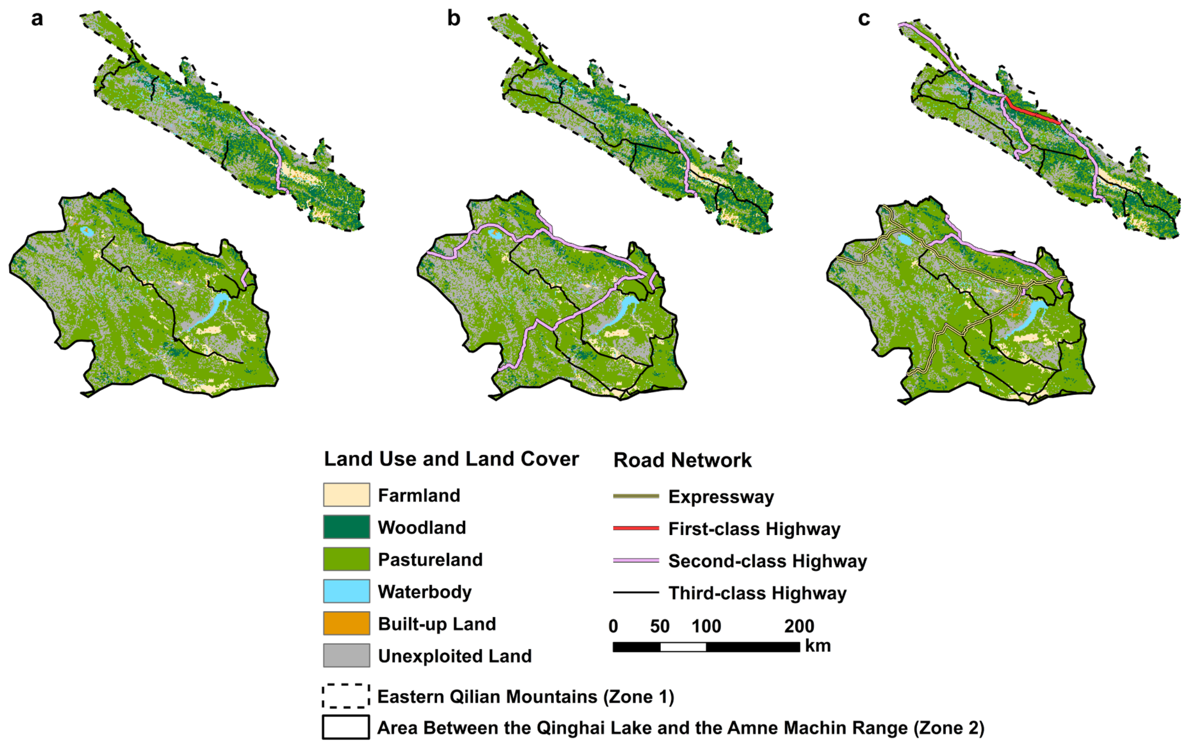

Fig. 3. Land overlays of the study areas in 2000 (a), 2010 (b), and 2018 (c).

Table 4
LULC transfer matrix from 2000 to 2018 (unit of measurement: km^2).

	LULC	Farmland	Woodland	Pastureland	Waterbody	Built-up land	Unexploited land	Total
Zone 1	Farmland	487	76	147	18	28	1	757
	Woodland	107	2660	1605	83	9	174	4638
	Pastureland	178	1554	6407	239	29	1449	9856
	Waterbody	15	91	277	130	2	118	633
	Built-up land	40	5	18	1	9	0	73
	Unexploited land	4	234	1390	105	5	2905	4643
	Total	831	4620	9844	576	82	4647	20,600
Zone 2	Farmland	1112	2	392	43	30	44	1623
	Woodland	3	687	709	9	0	143	1551
	Pastureland	641	589	21,547	290	82	2850	25,999
	Waterbody	25	6	265	460	4	60	820
	Built-up land	25	0	13	15	17	5	75
	Unexploited land	88	151	4665	120	15	5482	10,521
	Total	1894	1435	27,591	937	148	8584	40,589

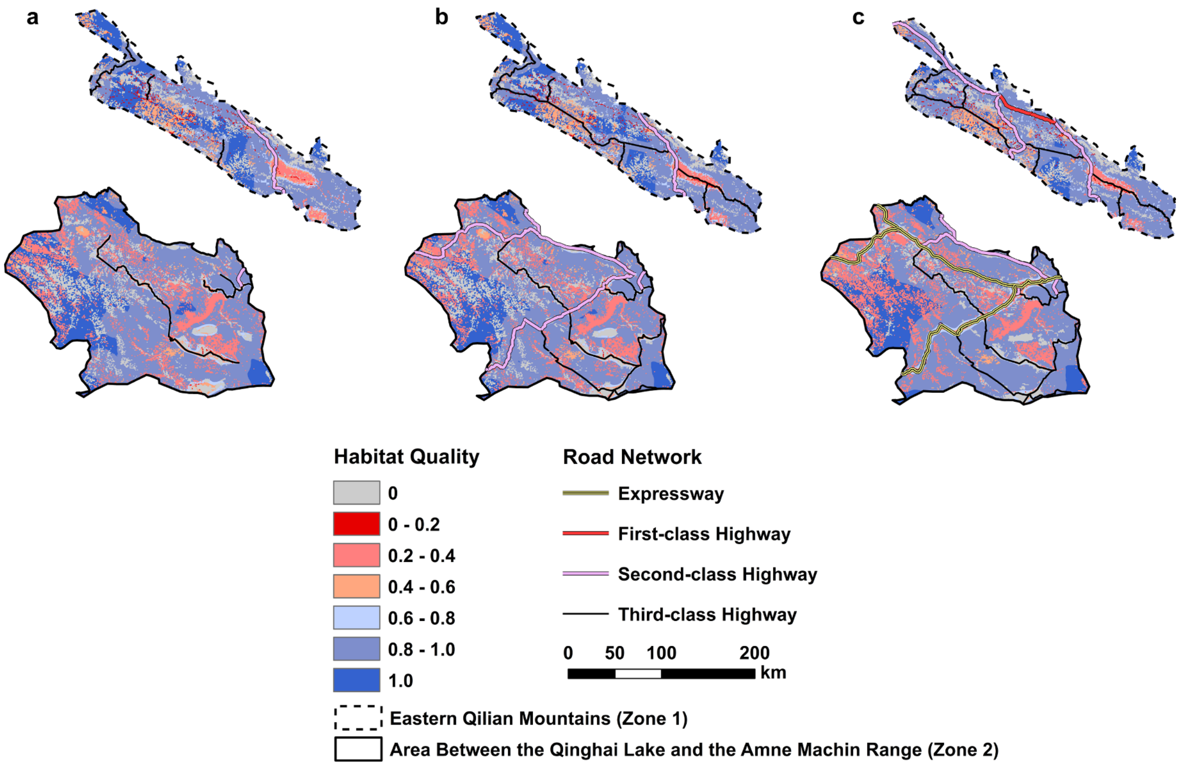

Fig. 4. HQ spatial distribution in 2000 (a), 2010 (b), and 2018 (c).

3.2. HQ spatiotemporal distribution

It can be seen from Fig. 4 and Fig. 5 that the HQ spatiotemporal distribution varied substantially in the study areas from 2000 to 2018. To the northwest Zone 1 and northwest Zone 2, the HQ went down significantly. An opposite trend was witnessed in the southeast areas of both zones.

The results also showed that the HQ within the road-effect zones reduced significantly (Table 5), which was much lower than the HQ of the entire study areas (the only exception occurred to the first-class highways of Zone 1 in 2018). The HQ improved when the

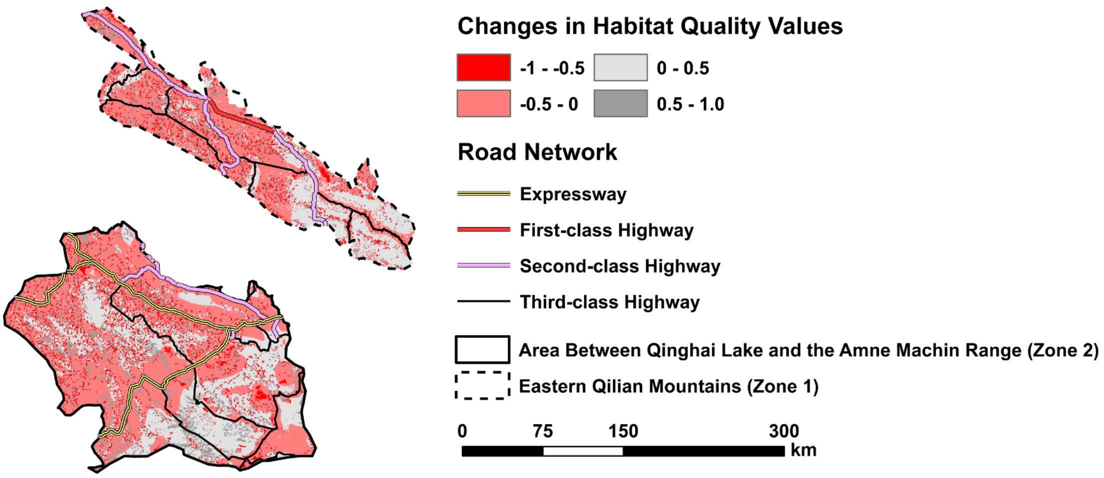

Fig. 5. HQc in the study areas.

Table 5
HQ and ANOVA scoring of different roadways.

	Year	Mean	Expressway	First-class highway	Second-class highway	Third-class highway	*P*-value
Zone 1	2000	0.715	Nil	Nil	0.512	0.583	< 0.001
	2010	0.717	Nil	Nil	0.587	0.572	< 0.001
	2018	0.709	Nil	0.769	0.653	0.568	< 0.001
Zone 2	2000	0.701	Nil	Nil	0.607	0.345	< 0.001
	2010	0.686	Nil	Nil	0.513	0.448	< 0.001
	2018	0.715	0.506	Nil	0.403	0.507	< 0.001

Table 6
Demonstration of *Y*, *G* and *HQ* reduction.

	Road	*Y*	*G*	*HQ* reduction after an operation
Zone 1	S304	2	First-class	0.131
	S204	6	Second-class	0.131
	S105	1	Third-class	0.263
	S302	5	Third-class	0.153
Zone 2	G6	6	Expressway	0.122
	G0613	1	Expressway	0.131
	S2013	3	Expressway	0.121
	G214	4	Second-class	0.242
	G109	1	Second-class	0.206
	S206	1	Second-class	0.264
	S101	1	Third-class	0.223
	S301	1	Third-class	0.029
	S311	1	Third-class	0.025

Table 7
QIC goodness of the fit values.

Working correlation structure	Covariates	QIC
Independent	*LULCc, G, Y, L, D*	8987.175
3-dependent		9038.375
5-dependent		9036.394
7-dependent		9032.873
9-dependent		9045.624
Autoregressive of Order 1		9037.237
Exchangeable		9120.492
Unstructured		11425.992

Table 8
QICC goodness of the fit values (only listing the top 10 models).

Working correlation structure	Covariates	QICC
Independent	*LULCc, G, Y, L,* (ln*D*)*, G*Y, LULCc** ln*D*	8762.647
Independent	*LULCc, G, Y, L,* ln*D, G*Y*	8775.663
Independent	*LULCc, G, Y, L, G*Y*L, LULCc** ln*D*	8790.380
Independent	*LULCc, G, Y, L,* (ln*D*)*, LULCc** ln*D*	8800.486
Independent	*LULCc, G, Y, L,* ln*D, G*Y*L*	8801.906
Independent	*LULCc, G, Y, L,* ln*D, Y *L*	8805.042
Independent	*LULCc, G, Y, L,* ln*D*	8810.969
Independent	*LULCc, G, Y, L,* ln*D, G*L*	8811.372
Independent	*LULCc, G, Y, L, D*	8811.381
Independent	*LULCc, G, L, G*Y, LULCc** ln*D*	8843.838

Table 9
Demonstration of the GEE results.

Parameter	Estimated coefficient (*B*)	95% Wald Confidence Interval		*Sig.*	Exp (*B*)
		Lower	*Upper*		
Intercept	1.838	0.591	3.086	0.004	6.286
G	0.446	0.097	0.795	0.012	1.562
Y	−0.124	−0.200	−0.048	0.001	0.883
L	0.003	0	0.006	0.041	1.003
LULCc = 1	−1.152	−2.524	0.220	0.100	0.316
[*LULCc* = 1] * ln*D*	0.059	0.010	0.108	0.018	1.060
[*LULCc* = 0] * ln*D*	−0.100	−0.218	0.018	0.097	0.905
G * *Y*	−0.036	−0.079	0.006	0.095	0.964

road grade increased, as illustrated from the comparison between the third-class highways and the second-class highways. In Zone 1, a continuous drop and increase of the HQ to the third-class highways and second-class highways were observed respectively. In Zone 2, this trend was completely opposite to Zone 1. To both zones, high-grade roadways compromised the HQ to the most (Table 6).

3.3. Analysis of the HQ reduction factors

Table 7 and Table 8 showed that the most optimal correlation structure is the one with the smallest QIC value, and the most optimal correlation model is the one with the smallest QICC value. According to the GEE results (Table 9), most of the significance values were lower than 0.05, meaning *G*, *Y*, *L*, *D*, *LULCc* were the most critical factors that affected the HQ. The estimated coefficient *B* values of 0.446 and 0.003 evidenced that within the road-effect zones, lowering the road grade and extending the road length is likely to reduce the HQ. The *B* value of −0.124 indicated that the longer a road was operated, the greater chance its HQ could be increased. This finding may be attributed to the establishment of environmental protection zones. The *B* value of 0.059 showed that some of the areas, despite far away from the road centerline, could still suffer from HQ drops even if the land was repurposed. Besides, there was not enough evidence from the GEE results that underpinned the functionality of land conversion into woodland and pastureland in HQ improvement.

4. Discussion and conclusions

This paper presents an innovative study that sheds light on transport engineering, environment ecology, ecological compensation, and LULC decision-making and management. It evidences that HQ within a road-effect zone can be significantly affected by roadway projects. Specifically, lowering the road grade, extending the road length, prolonging the operation duration, and increasing the traffic volume are the most influencing factors on the HQ, which may be because lower-grade roads are usually associated with higher density (i.e., length) and longer operation time (van Langevelde and Jaarsma, 2009). The study also showed that to certain higher-grade roads that possess complex structural properties and high volumes of traffic, the HQ drops were also apparent. Herein our hypothesis is verified. Interestingly, it is implied from the results that HQ drops caused by roadway networks may not be reversible, despite part of the woodland and pastureland studied was restored later on. Viable solutions of counterbalancing the HQ drops could be minimising and where possible avoiding the impacts of construction and maintenance activities on the environment (Santos et al., 2017), encouraging the use of sustainable materials such as recycled asphalt, concrete, glass fines and rubber (Duc et al., 2017), protecting and maintaining the flora, fauna and ecosystems that may be impacted by road operation and maintenance (Sitzia et al., 2016), and making the transport system more sustainable and environmentally conscious (Gössling et al., 2016). It is also recommended that road planning authorities should consider staggering infrastructure development times where possible.

As well, HQ is likely to be subject to the environmental protection zone level, size, time of establishment, and so on. To underpin, it was likely that the marginal improvement of HQ in Zone 1 between 2000 and 2010 was because its protection level was relatively low (i.e. provincial nature reserve) and the time of establishment was a bit late (i.e. since 2005), whereas in Zone 2, the HQ greatly improved since 2000 because the surrounding Qinghai Lake and Sanjiangyuan national nature reserves have been established over 30 years (Ministry of Ecology and Environment of the People's Republic of China, 2017).

This study took the LULC and threats information as the InVEST model inputs, and all threats were considered additive towards the evaluation of HQ, which were less than the collective impact of multiple threats (Sharp et al., 2018). We understand this could oversimplify the evaluation scenario. Therefore, we would like to address this shortfall in the future. As well, this study has not well rationalised the HQ change mechanism due to climate change, seasons, road properties, greenhouse gas emissions, human activities (e.g. grazing, mining, overhunting), and so on (Clements et al., 2014; Hu et al., 2018). Therefore, this will be a targeted area in our future work, along with other objectives such as formulating pragmatic road development methodologies for pursuing development and environmental sustainability.

Declaration of Competing Interest

None.

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Appendix

See Table A1-A2.

Table A1
The endemic species and their habitats and conservation status in the study areas.

Scientific name	Habitat	Distribution area	Conservation status		
			National	CITES	IUCN
Gazelle De Przewalski (*Procapra Przewalskii*)	Pastureland and sandy land	Zone 2	First-level	N/A	Endangered
Snow Leopard (*Panthera Uncia*)	Shrub, bare land and bare rock texture	Zone 2	First-level	Appendix I	Vulnerable
White-lipped Deer (*Cervus Albirostris*)	Pastureland and Shrub	Zone 1 & 2	First-level	N/A	Vulnerable
Wild Yak (*Bos Mutus*)	Pastureland	Zone 1 & 2	First-level	Appendix I	Vulnerable
Black-necked Crane (*Grus Nigricollis*)	Pastureland, lake, swamp and beach	Zone 1 & 2	First-level	Appendix I	Vulnerable
Band-tailed Fish-eagle (*Haliaeetus Leucoryphus*)	Pastureland, lake, river channel and reservoir pit	Zone 2	First-level	N/A	Endangered
Asian Imperial Eagle (*Aquila Heliaca*)	Pastureland, beach, woodland	Zone 2	First-level	Appendix I	Vulnerable
Black Stork (*Ciconia Nigra*)	Woodland, swamp, lake, river channel, reservoir pit, farmland and pastureland	Zone 1	First-level	Appendix II	N/A
Demoiselle Crane (*Anthropoides Virgo*)	Pastureland, swamp, lake, beach and farmland	Zone 1	Second-level	N/A	N/A
Qinghai Spruce (*Picea Crassifolia Kom.*)	Woodland	Zone 1	Provincial tree	N/A	N/A
Qilian Juniper (*Juniperus Przewalskii Kom.*)	Woodland	Zone 1	The dominant forest species	N/A	N/A

Table A2
Relative sensitivity of habitat type versus threat/habitat suitability of Zone 1 (left) and Zone 2 (right).

LULC	Habitat		Firs-class highways (Zone 1)	Expressways (Zone 2)	Second-class highways		Third-class highways		Residential areas		Farmland	
Dry land	0.3	0	0.85	0	0.75	0	0.65	0	0.95	0	0	0
Woodland	1	0.5	1	1	0.8	1	0.6	0.6	1	1	0.85	0.85
Shrub	1	1	1	1	0.8	1	0.6	0.6	1	1	0.85	0.85
Sparse woodland	0.8	0.5	1	1	0.8	1	0.6	0.6	1	1	0.75	0.75
High coverage pastureland	1	1	1	1	0.8	1	0.6	0.6	1	1	0.65	0.65
Medium coverage pastureland	1	1	1	1	0.8	1	0.6	0.6	0.8	0.8	0.65	0.65
Low coverage pastureland	1	1	1	1	0.8	1	0.6	0.6	0.75	0.75	0.65	0.65
River channel	0.5	0.4	0.6	0.6	0.5	0.6	0.4	0.4	0.65	0.65	0.3	0.3
Lake	0.5	0.5	0.4	0.4	0.3	0.4	0.2	0.2	0.65	0.65	0.3	0.3
Reservoir pit	0.45	0.4	0.45	0.45	0.35	0.45	0.25	0.25	0.65	0.65	0.3	0.3
Permanent glacier snow	0	0	0	0	0	0	0	0	0	0	0	0
Beach	0.1	0.3	0.75	0.75	0.65	0.75	0.55	0.55	0.85	0.85	0.75	0.75
Urban land	0	0	0	0	0	0	0	0	0	0	0	0
Rural settlement	0	0	0	0	0	0	0	0	0	0	0	0
Other construction land	0	0	0	0	0	0	0	0	0	0	0	0
Sandy land	0	0.35	0	0.5	0	0.5	0	0.3	0	0.65	0	0.4
Gobi	0	0	0	0	0	0	0	0	0	0	0	0
wetlands	0.45	0	0.75	0	0.65	0	0.55	0	0.85	0	0.75	0
Bare land	0	0.35	0	0.75	0	0.75	0	0.55	0	0.85	0	0.75
Bare rock texture	0	0.25	0	0.5	0	0.5	0	0.3	0	0.65	0	0.4
Other	0	0.25	0	0.5	0	0.5	0	0.3	0	0.65	0	0.4

References

Araujo, M.B., Anderson, R.P., Barbosa, A.M., Beale, C.M., Dormann, C.F., Early, R., Garcia, R.A., Guisan, A., Maiorano, L., Naimi, B., O'Hara, R.B., Zimmermann, N.E., Rahbek, C., 2019. Standards for distribution models in biodiversity assessments. Sci. Adv. 5. https://doi.org/10.1126/sciadv.aat4858.

Arunyawat, S., Shrestha, R.P., 2016. Assessing land use change and its impact on ecosystem services in Northern Thailand. Sustainability 8, 22. https://doi.org/10.3390/su8080768.

Arunyawat, S., Shrestha, R.P., 2018. Simulating future land use and ecosystem services in Northern Thailand. J. Land Use Sci. 13, 146–165. https://doi.org/10.1080/1747423x.2018.1496157.

Asadolahi, Z., Salmanmahiny, A., Sakieh, Y., Mirkarimi, S.H., Baral, H., Azimi, M., 2018. Dynamic trade-off analysis of multiple ecosystem services under land use change scenarios: Towards putting ecosystem services into planning in Iran. Ecol. Complex. 36, 250–260. https://doi.org/10.1016/j.ecocom.2018.09.003.

Benitez-Lopez, A., Alkemade, R., Verweij, P.A., 2010. The impacts of roads and other infrastructure on mammal and bird populations: A meta-analysis. Biol. Conserv. 143, 1307–1316. https://doi.org/10.1016/j.biocon.2010.02.009.

Boarman, W.I., Sazaki, M., 2006. A highway's road-effect zone for desert tortoises (Gopherus agassizii). J. Arid Environ. 65, 94–101. https://doi.org/10.1016/j.jaridenv.2005.06.020.

Bruschi, D., Garcia, D.A., Gugliermetti, F., Cumo, F., 2015. Characterizing the fragmentation level of Italian's National Parks due to transportation infrastructures. Transp. Res. PART D-TRANSPORT Environ. 36, 18–28. https://doi.org/10.1016/j.trd.2015.02.006.

Clements, G.R., Lynam, A.J., Gaveau, D., Yap, W.L., Lhota, S., Goosem, M., Laurance, S., Laurance, W.F., 2014. Where and how are roads endangering mammals in Southeast Asia's forests? PLoS ONE 9, 25. https://doi.org/10.1371/journal.pone.0115376.

D'Amico, M., Roman, J., de los Reyes, L., Revilla, E., 2015. Vertebrate road-kill patterns in Mediterranean habitats: Who, when and where. Biol. Conserv. 191, 234–242. 10.1016/j.biocon.2015.06.010.

Delgado, J.D., Duran Humia, J., Rodriguez Pereiras, A., Rosal, A., del Valle Palenzuela, M., Morelli, F., Arroyo Hernandez, N.L., Rodriguez Sanchez, J., 2019. The spatial distribution of animal casualties within a road corridor: Implications for roadkill monitoring in the southern Iberian rangelands. Transp. Res. PART D-Transport Environ. 67, 119–130. https://doi.org/10.1016/j.trd.2018.11.017.

Di Febbraro, M., Roscioni, F., Frate, L., Carranza, M.L., De Lisio, L., De Rosa, D., Marchetti, M., Loy, A., 2015. Long-term effects of traditional and conservation-oriented forest management on the distribution of vertebrates in Mediterranean forests: a hierarchical hybrid modelling approach. Divers. Distrib. 21, 1141–1154. https://doi.org/10.1111/ddi.12362.

Dong, Y., Hui, W., Junqi, C., Peipei, G., 2013. Climate change in Qinghai and its relationship with ENSO in the recent 50 years. Ecol. Environ. Sci. 22, 547–553. 10.16258/j.cnki.1674-5906.2013.04.009.

Duan, Y., Wang, X., Wei, Y., 2020. Land use change analysis of Daishan Island using multi-temporal remote sensing imagery. Arab. J. Geosci. 13. https://doi.org/10.1007/s12517-020-05513-5.

Duc, L.N., Vinh, L.H., Kim, T.N., Duy, T.N., 2017. Using rubber aggregate derived from discarded tires for producing cement concrete towards resource recovery and environmental protection in Vietnam. Int. J. Sustain. Energy Environ. Res. https://doi.org/10.18488/journal.13.2017.62.36.49.

Eigenbrod, F., Hecnar, S.J., Fahrig, L., 2009. Quantifying the road-effect zone: threshold effects of a motorway on anuran populations in Ontario, Canada. Ecol. Soc. 14.

Fan, X.C., Zhao, L.L., 2019. Land use changes and its driving factors: a case study in Nanping city, China. Appl. Ecol. Environ. Res. 17, 3709–3721. https://doi.org/10.15666/aeer/1702_37093721.

Garcia-Vega, D., Newbold, T., 2020. Assessing the effects of land use on biodiversity in the world's drylands and Mediterranean environments. Biodivers. Conserv. 29, 393–408. https://doi.org/10.1007/s10531-019-01888-4.

Gössling, S., Schröder, M., Späth, P., Freytag, T., 2016. Urban space distribution and sustainable Transport. Transp. Rev. https://doi.org/10.1080/01441647.2016.1147101.

Gruszczyński, W., Matwij, W., Ćwiąkała, P., 2017. Comparison of low-altitude UAV photogrammetry with terrestrial laser scanning as data-source methods for terrain covered in low vegetation. ISPRS J. Photogramm. Remote Sens. https://doi.org/10.1016/j.isprsjprs.2017.02.015.

Gurung, K., Yang, J., Fang, L., 2018. Assessing ecosystem services from the forestry-based reclamation of surface mined areas in the North Fork of the Kentucky River Watershed. Forests 9, 23. https://doi.org/10.3390/f9100652.

Halfwerk, W., Holleman, L.J.M., Lessells, C.M., Slabbekoorn, H., 2011. Negative impact of traffic noise on avian reproductive success. J. Appl. Ecol. 48, 210–219.

https://doi.org/10.1111/j.1365-2664.2010.01914.x.
Hu, T.H., Chang, J., Liu, X.X., Feng, S.S., 2018. Integrated methods for determining restoration priorities of coal mining subsidence areas based on green infrastructure: A case study in the Xuzhou urban area, of China. Ecol. Indic. 94, 164–174. https://doi.org/10.1016/j.ecolind.2017.11.006.
Ibisch, P.L., Hoffmann, M.T., Kreft, S., Pe'er, G., Kati, V., Biber-Freudenberger, L., DellaSala, D.A., Vale, M.M., Hobson, P.R., Selva, N., 2016. A global map of roadless areas and their conservation status. Science (80-.). 354, 1423–1427. 10.1126/science.aaf7166.
International Union for Conservation of Nature, 2019. World Database of Key Biodiversity Areas [WWW Document]. URL www.keybiodiversityareas.org (accessed 5. 15.19).
Jiang, S., Meng, J., Zhu, L., 2020. Spatial and temporal analyses of potential land use conflict under the constraints of water resources in the middle reaches of the Heihe River. Land Use Policy 97. https://doi.org/10.1016/j.landusepol.2020.104773.
Kwon, Y., Choi, Y.-G., Park, T., Ziegler, A., Paik, M.C., 2017. Generalized estimating equations with stabilized working correlation structure. Comput. Stat. Data Anal. 106, 1–11. https://doi.org/10.1016/j.csda.2016.08.016.
Li, J., Hou, L., Wang, X., Wang, J., Guo, J., Zhang, S., Jiao, Y., 2014. A project-based quantification of BIM benefits. Int. J. Adv. Robot. Syst. 10.5772/58448.
Li, R., Powers, R., Xu, M., Zheng, Y., Zhao, S., 2018. Proposed biodiversity conservation areas: gap analysis and spatial prioritization on the inadequately studied Qinghai Plateau, China. Nat. Conserv. 1–20. https://doi.org/10.3897/natureconservation.24.20942.
Li, X.W., Hou, X.Y., Song, Y., Shan, K., Zhu, S.Y., Yu, X.B., Mo, X.Q., 2019. Assessing changes of habitat quality for shorebirds in stopover sites: a case study in Yellow River Delta, China. Wetlands 39, 67–77. https://doi.org/10.1007/s13157-018-1075-9.
Liu, J., Kuang, W., Zhang, Z., Xu, X., Qin, Y., Ning, J., Zhou, W., Zhang, S., Li, R., Yan, C., Wu, S., Shi, X., Jiang, N., Yu, D., Pan, X., Chi, W., 2014. Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. J. Geogr. Sci. 24, 195–210. https://doi.org/10.1007/s11442-014-1082-6.
Ministry of Ecology and Environment of the People's Republic of China, 2017. List of nature reserves in China.
MohanRajan, S.N., Loganathan, A., Manoharan, P., 2020. Survey on Land Use/Land Cover (LU/LC) change analysis in remote sensing and GIS environment: Techniques and Challenges. Environ. Sci. Pollut. Res. 27, 29900–29926. https://doi.org/10.1007/s11356-020-09091-7.
Moreira, M., Fonseca, C., Vergilio, M., Calado, H., Gil, A., 2018. Spatial assessment assessment of habitat conservation status in a Macaronesian island based on the InVEST model: a case study of Pico Island (Azores, Portugal). Land Use Policy 78, 637–649. https://doi.org/10.1016/j.landusepol.2018.07.015.
Mortelliti, A., Amori, G., Capizzi, D., Cervone, C., Fagiani, S., Pollini, B., Boitani, L., 2011. Independent effects of habitat loss, habitat fragmentation and structural connectivity on the distribution of two arboreal rodents. J. Appl. Ecol. 48, 153–162. https://doi.org/10.1111/j.1365-2664.2010.01918.x.
Ocampo Salinas, J.M., Castillo-Ceron, J.M., Manriquez-Moran, N., Goyenechea, I., Dolores Casagranda, M., 2019. Endemism of lizards in the Chihuahuan Desert province: An approach based on endemicity analysis. J. Arid Environ. 163, 9–17. https://doi.org/10.1016/j.jaridenv.2019.01.005.
Önder, H., 2016. Comparative study of generalized estimating equations and logistic regressions on different sample sizes and correlation levels. Commun. Stat. Simul. Comput. 45, 3528–3533. https://doi.org/10.1080/03610918.2015.1010000.
Pedersen, C., Krogli, S.O., 2017. The effect of land type diversity and spatial heterogeneity on farmland birds in Norway. Ecol. Indic. 75, 155–163. https://doi.org/10.1016/j.ecolind.2016.12.030.
Rubio, L., Saura, S., 2012. Assessing the importance of individual habitat patches as irreplaceable connecting elements: An analysis of simulated and real landscape data. Ecol. Complex. 11, 28–37. https://doi.org/10.1016/j.ecocom.2012.01.003.
Santos, J., Flintsch, G., Ferreira, A., 2017. Environmental and economic assessment of pavement construction and management practices for enhancing pavement sustainability. Resour. Conserv. Recycl. https://doi.org/10.1016/j.resconrec.2016.08.025.
Shaffer, J.A., Roth, C.L., Mushet, D.M., 2019. Modeling effects of crop production, energy development and conservation-grassland loss on avian habitat. PLoS ONE 14. https://doi.org/10.1371/journal.pone.0198382.
Sharp, R., Tallis, H.T., Ricketts, T., Guerry, A.D., Wood, S.A., Chaplin-Kramer, R., Nelson, E., Ennaanay, D., Wolny, S., Olwero, N., Vigerstol, K., Pennington, D., Mendoza, G., Aukema, J., Foster, J., Forrest, J., Cameron, D., Arkema, K., Lonsdorf, E., Kennedy, C., Verutes, G., Kim, C.K., Guannel, G., Papenfus, M., Toft, J., Marsik, M., Bernhardt, J., Griffin, R., Glowinski, K., Chaumont, N., Perelman, A., Lacayo, M., Mandle, L., Hamel, P., Vogl, A.L., Rogers, L., Bierbower, W., Denu, D., Douglass, J., 2018. InVEST 3.5.0 User's Guide.
Sitzia, T., Campagnaro, T., Grigolato, S., 2016. Ecological risk and accessibility analysis to assess the impact of roads under Habitats Directive. J. Environ. Plan. Manag. https://doi.org/10.1080/09640568.2016.1140023.
Terrado, M., Sabater, S., Chaplin-Kramer, B., Mandle, L., Ziv, G., Acuna, V., 2016. Model development for the assessment of terrestrial and aquatic habitat quality in conservation planning. Sci. Total Environ. 540, 63–70. https://doi.org/10.1016/j.scitotenv.2015.03.064.
Trisurat, Y., Eawpanich, P., Kalliola, R., 2016. Integrating land use and climate change scenarios and models into assessment of forested watershed services in Southern Thailand. Environ. Res. 147, 611–620. https://doi.org/10.1016/j.envres.2016.02.019.
van der Ree, R., Jaeger, J.A.G., van der Grift, E.A., Clevenger, A.P., 2011. Effects of roads and traffic on wildlife populations and landscape function: road ecology is moving toward larger scales. Ecol. Soc. 16.
van Langevelde, F., Jaarsma, C.F., 2009. Modeling the effect of traffic calming on local animal population persistence. Ecol. Soc. 14. https://doi.org/10.5751/ES-03061-140239.
Wang, J., Hou, L., Chong, H., Liu, X., Wang, X., Guo, J., 2014. A cooperative system of GIS and BIM for traffic planning: a high-rise building case study. Lecture Notes in Computer Science. 8683, 143-150. Springer International Publishing. 10.1007/978-3-319-10831-5_20.
Wu, C.F., Lin, Y.P., Chiang, L.C., Huang, T., 2014a.. Assessing highway's impacts on landscape patterns and ecosystem services: A case study in Puli Township, Taiwan. Landsc. Urban Plan. 128, 60–71. https://doi.org/10.1016/j.landurbplan.2014.04.020.
Wu, L., Yang, S., Liu, X., Luo, Y., Zhou, X., Zhao, H., 2014b. Response analysis of land use change to the degree of human activities in Beiluo River basin since 1976. Acta Geogr. Sin. 69, 54–63. https://doi.org/10.11821/dlxb201401005.
Xu, C., Yang, Y., Jin, S., Qu, Z., Hou, L., 2016. Potential risk and its influencing factors for separated bicycle paths. Accid. Anal. Prev. 87, 59–67. https://doi.org/10.1016/j.aap.2015.11.014.
Xu, Z.L., Peng, H.H., Peng, S.H., 2015. The development and evaluation of species distribution models. Shengtai Xuebao/ Acta Ecol. Sin. 35, 557–567. https://doi.org/10.5846/stxb201304030600.
Zhang, C., Zhang, H., Zhao, F., Sun, J., 2019. Understanding thermal impact of roads on permafrost using normalized spectral entropy. Sustain. 11. https://doi.org/10.3390/SU11247177.
Zhou, Y., Hou, L., Yang, Y., Chong, H., Moon, S., 2019. A comparative review and framework development on public participation for decision-making in Chinese public projects. Environ. Impact Assess. Rev. 75, 79–87. https://doi.org/10.1016/j.eiar.2018.12.006.
Zhou, Z., Ding, Y., Shi, H., Cai, H., Fu, Q., Liu, S., Li, T., 2020. Analysis and prediction of vegetation dynamic changes in China: Past, present and future. Ecol. Indic. 117. https://doi.org/10.1016/j.ecolind.2020.106642.

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摘要: Roadways vary in structural, geotechnical, locational, and operational properties, and synergies among these factors may present overwhelming challenges to understanding their full effects on the habitat quality (HQ). To explore the impact of dense roadway networks on an ecologically fragile region in the northwest of China, this study applied the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) to evaluate the HQ spatiotemporal distribution of the study area. Then, Generalised Estimating Equations (GEE) were formulated to examine the cumulative impact due to the operation of an increasing amount of roadways over the past two decades. According to the results, the influence of different road types on the HQ was apparent within the road-effect zone, and road grading reduction, road length and operation duration increase can harm the HQ within the road-effect zone. Overall, this study generates knowledge concerning the design and operation of environmentally-friendly roadways in ecologically fragile areas.

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