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Anthropogenic effect on forest landscape pattern and Cervidae habitats in northeastern China

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Abstract: Species abundance and habitat distribution are two important aspects of species conservation studies and both are affected by similar environmental factors. Forest resource inventory data in 2010 were used to evaluate the patterns of habitat for target species of Cervidae in six typical forestry bureaus of the Yichun forest area in the Lesser Xing'an Mountains, northeastern China. A habitat suitability index (HSI) model was used based on elevation, slope, aspect, vegetation and age of tree. These five environmental factors were selected by boosted regression tree (BRT) analysis from 14 environmental variables collected during field surveys. Changes in habitat caused by anthropogenic activities mainly involving settlement and road factors were also considered. The results identified 1780.49 km^2 of most-suitable and 1770.70 km^2 of unsuitable habitat areas under natural conditions, covering 16.38% and 16.29% of the entire study area, respectively. The area of most-suitable habitat had been reduced by 4.86% when human interference was taken into account, whereas the unsuitable habitat area had increased by 11.3%, indicating that anthropogenic disturbance turned some potential habitats into unsuitable ones. Landscape metrics indicated that average patch area declined while patch density and edge density increased. This suggests that as habitat becomes fragmented and its quality becomes degraded by human activities, cervid populations will be threatened with extirpation. The study helped identify the spatial extent of habitat influenced by anthropogenic interference for the local cervid population. As cervid species clearly avoid human activities, more attention should be paid on considering the way and intensity of human activities for habitat management as fully as possible.

Keywords: Cervidae; boosted regression tree; habitat suitability assessment; landscape pattern; Lesser Xing'an Mountains

1 Introduction

Species conservation includes not only maintaining a sustainable population size, but also

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protecting the environment necessary for that population to survive, so assessment of habitat quality is considered a critical precondition and basis for protecting habitat (Wilson *et al.*, 2013). The assessment of habitat can identify the distribution characteristics of a target species, which is beneficial for the management of the population and its essential environment. In recent years, a habitat suitability index (HSI) has been developed to predict and evaluate the habitat quality of target species. HSI models are widely used in ecological assessment and species protection to estimate habitat quality using environmental factors (Piekielek and Hansen, 2012; Cao and Liu, 2008; Xie *et al.*, 2006), especially when species distribution data are lacking (Qin *et al.*, 2015).

Human activity is one of the important factors affecting wildlife habitat. Anthropogenic interference including an increase in the intensity of land use, forest harvesting, agricultural development and road construction are considered as the main reasons for habitat loss for wildlife, leading to decreases in abundance, habitat degradation and the division of large, continuous areas of natural habitat into fragmented patches (Rodriguez and Delibes, 2003; Smith and Litvaitis, 2000). Many studies have addressed habitat selection by deer because deer often come into close contact with people (Anwar·*et al.*, 2008; Bonnot *et al.*, 2013; Bowman and Robitaille, 2005; Hemami *et al.*, 2004; Jiang *et al.*, 2005; Shen and Jia, 2006). Increased levels of disturbance cause modifications in landscape patterns and affect Cervidae's habitats (Houle *et al.*, 2010; Larson *et al.*, 2004; Li *et al.*, 2013; Lofman, 2007; Rempel *et al.*, 1997). Consequently, population quantity and geographical distribution changed. Human activities are spreading in China and the deer habitat has changed under the influence of these activities. Habitat assessment is the basis of population protection and assessment of habitat affected by human activities is crucial.

The selection of evaluation factors is very important in the assessment of habitat suitability. Generally, those factors include terrain, land cover, habitat accessibility, vegetation features, roads and settlements affecting animals by visual disturbance, noise and pollutants. Several evaluation studies have focused on activity intensity factors and population density factors (Piekielek and Hansen, 2012), but few studies have looked at the spatial extent of interference. Numerous mammals are reported to suffer higher mortality close to roads and settlements (Li *et al.*, 2014). Large mammals have also been shown to move their home range and avoid areas within 100–500 m from roads and 500–1000 m from settlements (Forman and Alexander, 1998; Li *et al.*, 2014; Trombulak and Frissell, 2000; Zeng *et al.*, 2005), which reduces the area of suitable habitat. Human activities generally occur within a radius of 500 m of residential areas. In this study, we defined buffer zones using these criteria as part of the habitat suitability assessment.

Degradation of natural habitats resulted from landscape fragmentation is recognized as the main reason for the reduction of large mammal populations (Bonnot *et al.*, 2013; Couturier *et al.*, 2014; Jorge *et al.*, 2013; Menard *et al.*, 2014), especially for ungulates. The ungulates like red deer (*Cervus elaphus*) are often difficult to monitor in forested environments because of their vigilance and wide–ranging movement, particularly in northeastern China where the density of cervid population is low due to extensive hunting and decreased suitable habitat area caused by historical high levels of deforestation. The research literature documents a positive correlation between deer abundance and habitat suitability, linked to environmental factors, such as terrain, food abundance and human activity (Qin *et al.*, 2015;

Reimoser *et al*., 2009). Some researchers have found that roe deer (*Capreolus capreolus*) congregate in the local habitat with the best quality (Reimoser *et al*., 2009). It can be concluded that anthropogenic factors (e.g. roads, agriculture activity and population density) will influence habitat suitability and abundance for a range of deer species (Miranda and Porter, 2003; Qin *et al*., 2015). Human activities in China are intense and complex, so it is especially important to evaluate the habitat. In recent years, the habitat of the Lesser Xing'an Mountains in northeastern China has been fragmented and habitat quality has declined, resulting in a poor living environment and declining numbers of deer. To protect the local cervid population, it is necessary to evaluate their habitat. However, only a few small-scale studies of habitat selection have been undertaken and little habitat evaluation has been carried out at a large scale (Jiang *et al*., 2005).

Based on field investigations, we used boosted regression tree (BRT) analysis to choose the main predictor variables for Cervidae. We used these environmental variables to analyze habitat patterns by building a habitat suitability index (HSI) with GIS (Geographic Information System), and we modeled and analyzed the effects of human activity on spatial patterns. Finally, the percentage variation in various landscape metrics was calculated, including grading the different habitats. The main objectives of this study were to: (1) determine spatial patterns of suitable habitat for Cervidae in a human–dominated landscape in the Lesser Xing'an Mountains, China; (2) prioritize areas for further research and conservation action; and (3) provide a sound scientific basis for protecting and managing deer populations in this region.

2 Study area and methods

2.1 Study area

The six forestry bureaus (Youhao, Cuiluan, Wu Mahe, Tieli, Taoshan and Shuangfeng) (46°23′–48°34′N, 127°37′–129°13′E) are located in Yichun, with an area of 10,870 km^2. Lying on the southern slopes of the Lesser Xing'an Mountains, China (Figure 1), the landscape is composed of low mountains and hills, at an elevation of 300–700 m a.s.l. Abundant water sources in the study area meant that water was not a limiting factor. The region's mixed broad-leaved and coniferous forests support more than 100 species of wild animals such as red deer, black bear (*Ursus thibetanus*) and lynx (*Felis lynx*) (Wu *et al*., 2016b).

Two main Cervidae species of red deer and roe deer inhabit the study area. According to the *Report on Investigation Results of Terrestrial Wild Animal Resources* (Forest Industry Bureau of Heilongjiang Province, 2000), red deer populations decreased by more than 50% and 35%, respectively, in the Greater and the Lesser Xing'an Mountains from the 1970s to the 2000s (Jiang *et al*., 2005; Wu *et al*., 2016c). Excessive hunting, habitat modification and related human activities have negatively affected Cervidae populations in recent years (Piao *et al*., 2006). This study selected red deer and roe deer as representative target species, based on their similar diets and habits. We found that these two species both favored *Pinus koraiensis* mixed broad-leaved and coniferous forest, *Populus-Betula* broad-leaved mixed forest and *Corylus heterophylla* shrub land, and preferred to eat *Carex pilosa*, *Glycine max*, leaves of *Fraxinus mandshurica*, and *Glycine max*. In addition, the population abundance and habitat distribution of both species are threatened by human activities.

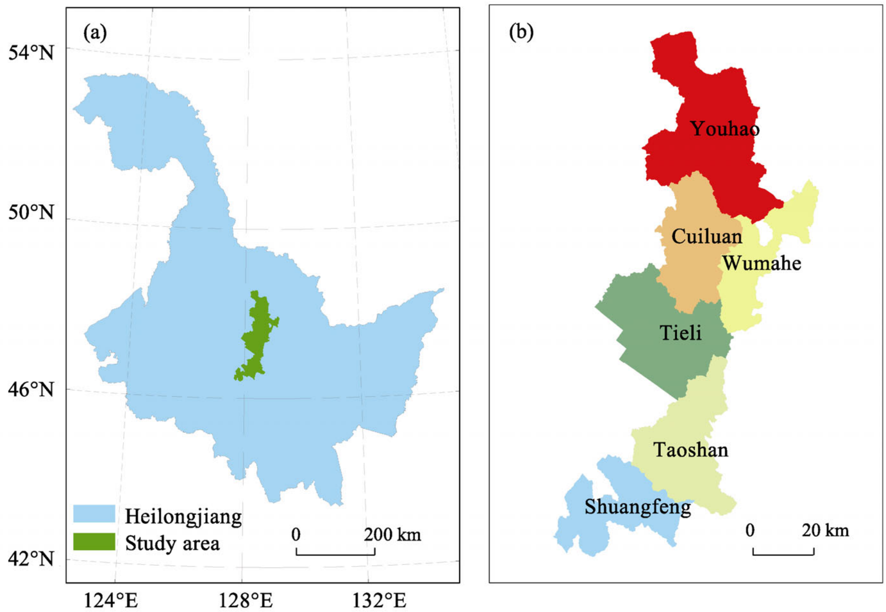

Figure 1 Study area in central Heilongjiang Province, China (a. Study area within Heilongjiang; b. Locations of the six forestry bureaus)

The Yichun state-owned forest region was the first national forest farm established in northeastern China and adopted a uniform quota of logging. Before that, there was no forest management. After 2006, the Yichun forest region initiated a state-owned forest tenure reform program. Based on this program, 80,000 ha of commercial forests was contracted by individuals to manage for their own benefit. Usually agaric (*Auricularia auricula*) and ginseng (*Panax ginseng*) were cultivated in these forest areas. The intensity and frequency of human activities associated with this industry disturbed the natural habitats of Cervidae (Jiang *et al*., 2005; Li *et al*., 2013; Li *et al*., 2014).

2.2 Methods

Habitat suitability evaluation was used to identify the distribution and characteristics of the habitat of Cervidae species, based on the results of BRT analysis and published literature related to behavioral ecology and habitat requirements (Jiang, 2007). Each factor was analyzed to build a comprehensive HSI model based on pre-established criteria. Finally, the data were processed through spatial analysis in ArcGIS 9.3 (ESRI Inc, 2008).

2.2.1 Data sources

Data sources included forest stand maps, Digital Elevation Models (DEM) and vegetation maps for the Lesser Xing'an Mountains, northeastern China. The 1:100,000-scale forest maps and vegetation maps were sourced from government sectors at the Forest Industry Bureau of Yichun. DEM (30 m spatial resolution) data were obtained from the USGS (United States Geological Survey) website (http://www.usgs.gov/).

2.2.2 Field investigations

Field investigations were conducted in the summer of 2013, summer and winter 2014, and winter 2015. To collect behavioral ecology information on target species, we used a distance sampling methodology (Thomas *et al*., 2010; Waltert *et al*., 2008) to design zigzag survey routes (about 2 km per line, total of 30 sample lines). The field observations included individual deer, footprints, repose imprints, feces, deer horn traces and foraging traces. A total of 154 data points of ecological trace information was recorded in the field. We estimated the number of signs of deer individuals suggested by all the signs in each 10 m × 10 m sample, and collected data on 14 environmental factors including elevation, aspect, slope, slope position, food, age of forest, density of trees, height of tree, shrub coverage, herb coverage, crown density, snow depth, generation time and visibility (Table 1).

Table 1 Environmental factors used for boosted regression tree analysis

Variables	Data range	Variable type	Measuring method
Elevation	278.33–648 m	Continuous/Float	GPS
Aspect	0–8	Classified/Integer	North arrow
Slope	0–18°	Continuous/Integer	Gradiometer
Slope position	0–3	Classified/Integer	Visual method
Food	0–5	Classified/Integer	Counting method
Age of forest	0–83 yr	Continuous/Integer	Expert appraisal approach
Density of trees	0–3000/ha	Continuous/Integer	Expert appraisal approach
Height of tree	0–20 m	Continuous/Integer	Altimeter/Expert appraisal approach
Shrub coverage	0–0.8	Continuous/Float	Counting method
Herb coverage	0–0.9	Continuous/Float	Counting method
Crown density	0–0.8	Continuous/Float	Expert appraisal approach
Snow depth	0–40 cm	Continuous/Integer	Ruler of measurement
Generation time	0–600 d	Continuous/Integer	Expert appraisal approach
Visibility	20–200 m	Continuous/Integer	Expert appraisal approach

Aspect was classified into nine types: 0-flat, 1-north, 2-northeast, 3-east, 4-southeast, 5-south, 6-southwest, 7-west and 8-northwest; Slope position was classified into four types: 0-no slope, 1-upper slope, 2-middle slope and 3-lower slope; Food was classified into five grades: 0, 1, 2, 3 and 4, from small to large abundance

2.2.3 Factor selection by boosted regression tree analysis

Boosted regression tree analysis is a machine–learning approach based on classification and regression trees (Elith *et al.*, 2008). In our study, the estimated number of signs left by deer individuals was selected as the response variable. None of the 14 predictor variables were highly correlated (R^2 > 0.7, Table 2). The gbm package in R was used to conduct BRT analysis (RDCT, 2011). Parameters including Bernoulli error distribution, a learning rate of 0.01, a bag fraction of 0.5, and fivefold cross–validation were set in BRT analysis. The most important predictor variables influencing response variables were chosen as natural environmental factors to build an HSI model.

2.2.4 Criteria establishment and the weight of factors

We established criteria for the habitat suitability assessment based on the response curves of important predictor variables in the BRT analysis and the habitat suitability requirements of

Table 2 Person correlation coefficients for all pairs of the environmental factors

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	–0.231	1													
3	–0.152	–0.015	1												
4	0.178	–0.121	–0.088	1											
5	–0.122	0.432	0.11	–0.248	1										
6	0.002	0.147	0.016	0.164	0.141	1									
7	–0.098	0.664	0.005	0	0.356	0.425	1								
8	–0.121	0.489	0.113	0.062	0.185	0.532	0.66	1							
9	–0.055	0.153	0.068	0.165	0.199	0.484	0.402	0.467	1						
10	–0.017	0.094	0.087	0.153	0.086	0.371	0.328	0.397	0.782	1					
11	–0.116	0.182	0.006	0.033	0.312	0.282	0.267	0.275	0.35	0.163	1				
12	0.145	–0.081	–0.064	0.329	0.086	0.283	0.117	0.141	0.288	0.185	0.447	1			
13	0.052	–0.153	–0.062	–0.097	–0.209	–0.448	–0.42	–0.483	–0.585	–0.421	–0.692	–0.514	1		
14	–0.01	0.183	0.055	0.242	0.288	0.552	0.357	0.441	0.81	0.575	0.54	0.524	–0.689	1	
15	–0.09	0.288	0.111	0.21	0.281	0.435	0.429	0.463	0.632	0.437	0.445	0.502	–0.621	0.704	1

1. Richness of deer; 2. Elevation; 3. Generation time; 4. Food; 5. Snow depth; 6. Aspect; 7. Slope; 8. Slope position; 9. Crown density; 10. Density of trees; 11. Shrub coverage; 12. Herb coverage; 13. Visibility; 14. Height of tree; 15. Age of forest

Cervidae species (Bowman and Robitaille, 2005; Li *et al.*, 2014; Zhang *et al.*, 2012). The selected variables can be grouped into three categories: topography, vegetation and interference factors (Shen and Jia, 2006; Zhang, 2001; Garcia-Aguirre *et al.*, 2007; Shifley *et al.*, 2006). The former two categories referred to the natural environment and the latter to anthropogenic activities. The main topographical factors considered in this study were elevation, slope and aspect. The vegetation factors affecting the habitat selection of Cervidae species were vegetation type and forest age. We developed a judgment matrix by combining an analytic hierarchy process and an expert scoring method (20 experts were invited for evaluation). The weights for environmental factors were estimated through a consistency check (Zhang and Zhang, 2010).

2.2.5 HSI model and spatial analysis

ArcGIS 9.3 was used to conduct spatial simulations and analysis based on the criteria. Topographical and vegetational factors related to deer habitat suitability were combined to determine the distribution of suitable habitat. In addition, a road layer and settlement layer were added to rebuild the HSI model taking account of human interference factors. Finally, based on the established criteria, habitats were classified into four types: most-suitable, moderately-suitable, inferior and unsuitable. The pre-processing of these data included the addition of different sizes of buffers in factor layers. The loss of habitat area and changes in landscape patterns were used to describe the effects of fragmentation. The characteristics of changes in landscape pattern were analyzed after computing habitat suitability. To analyze the characteristics of changes in landscape pattern, FRAGSTATS 4.1 was used to calculate landscape indexes at both landscape- and patch-level (Ko *et al.*, 2006; McGarigal and Cushman, 2002).

3 Results

3.1 Selection of habitat variables

In the BRT analysis (Figures 2 and 3), the three most important topographical factors influencing the number of signs of deer were elevation (25.6%), aspect (14.8%) and slope (6.3%). Deer signs at higher elevations showed a decrease in deer richness, indicating that areas with steep slopes were not suitable habitat. Most signs of deer individuals were in areas with gentle terrain, and on sunny or partially–sunny slopes. The three most important vegetation factors were food, age of forest and density of trees, with a relative contribution of 13.1%, 8.3% and 4.7%, respectively. Generally, an increase of food resulted in higher species abundance. The importance of shrub coverage (4.3%) and herb coverage (3.3%) was low (Figure 2). In Figure 3, each dependency point represents the marginal effect of a predictor variable on Cervidae species abundance. The BRT analysis indicated that the number of signs of deer was strongly correlated with topographical factors (elevation, aspect and slope) and vegetation factors (food and forest age). Quantitative data on food sources were not available at these spatiotemporal scales, so we had to substitute a vegetation factor for food. We recognize that this vegetation factor may partly reflect the food sources of deer habitat.

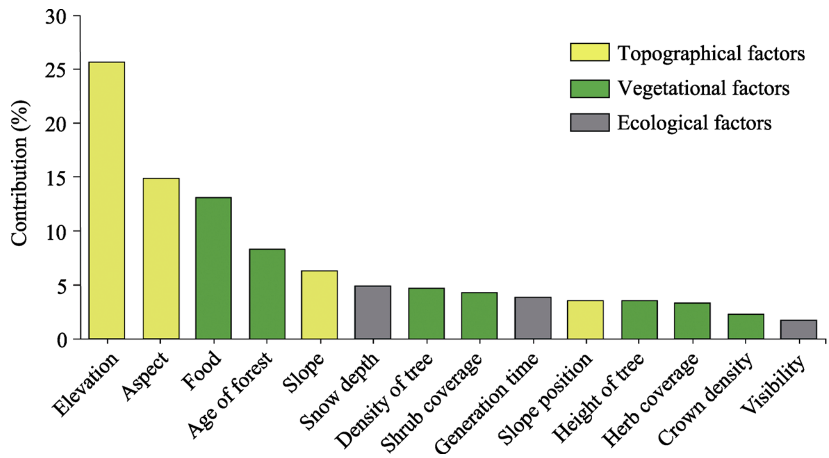

Figure 2 Relative influence on the richness of deer for the environmental factors in a boosted regression tree analysis

3.2 The weight of environmental factors

The above habitat variables were used to establish the criteria for habitat suitability assessment (Table 3). Five natural factor layers (elevation, slope, aspect, vegetation and age of forest) and two interference factor layers (distance to roads and distance to settlements) were overlaid to obtain the Cervidae habitat map. Vegetation types were divided into four classes: 1) Most-preferred (mixed broad-leaved and coniferous forest, shrub and grass); 2) Moderately–preferred (broad–leaved forest including *Betula platyphylla*, *Pinus koraiensis*, *Abies*

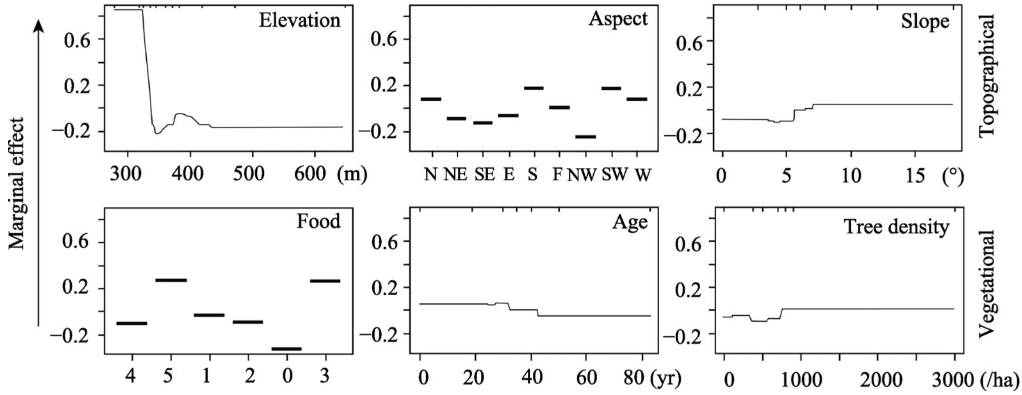

Figure 3 The influence of the main habitat factors on richness of species and dependency points for the first three most important predictor variables of topographical and vegetational factors, respectively, in the boosted regression tree analysis. Food was classified into six grades: 0, 1, 2, 3, 4 and 5, from none to abundant food resources. Age: age of forest

fabri, *Phellodendron amurense*, *Larix gmelinii*, *Acer mono*, *Picea asperata*, *Betula dahurica*, *Quercus mongolica*, *Pinus sylvestris*); 3) Preferred (coniferous forest, broad–leaved forest including *Populus cathayana*, *Fraxinus mandshurica*, *Tilia amurensis*, *Juglans mandshurica*, *Populus davidiana*); 4) Non–preferred. By combining an analytic hierarchy process and an expert scoring method, the weight of environmental factors for the comprehensive evaluation of the HSI model, in order of importance, were set at: vegetation type (0.3597), age of tree (0.1799), distance to roads (0.1458), distance to settlements (0.1458), aspect (0.0882), elevation (0.0485), and slope (0.0267).

Table 3 Criteria for suitability assessment of impact factors during the habitat assessment

Habitat factors		Most-suitable	Moderately-suitable	Inferior	Unsuitable
Geographical	Elevation (m a.s.l.)	215–300	300–500	500–700	700–1137
	Slope (°)	0–5	5–15	15–25	25–63
	Aspect	S/Flat	SE/SW	E/W/NE	NW/N
Biological	Vegetation	Most–preferred	Moderately-preferred	Preferred	Non-preferred
	Age (yr)	30–60	60–80	> 80	< 30
Interference	Distance to roads (m)	> 1000	500–1000	200–500	0–200
	Distance to settlements (m)	> 1500	1000–1500	500–1000	0–500

3.3 Suitable habitat distribution for Cervidae

The results of the HSI model for Cervidae showed that the most-suitable, moderately-suitable and inferior habitats covered 1780.49 km^2 (16.38%), 3216.40 km^2 (29.59%) and 4102.29 km^2 (37.74%) of the study area, respectively. Spatially, suitable habitats were mainly in regions far from urban settlements and were composed of three types of vegetation: mixed broad-leaved and coniferous forest, broad-leaved forest and shrubs. For example, suitable habitat was widely distributed in the more mature forests of the Tieli forestry bureau, while less suitable habitat was found in the Cuiluan and Wu Mahe forestry bureaus near Yichun (Figure 4).

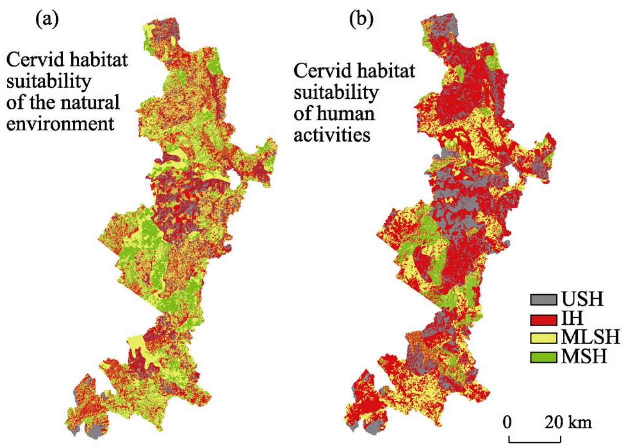

Figure 4 Habitat suitability for Cervidae in the study area (a. Cervid habitat suitability based on natural environmental conditions; b. cervid habitat suitability based on human activities. Acronyms: MSH, most-suitable habitat; MLSH, moderately-suitable habitat; IH, inferior habitat; USH, unsuitable habitat

When the influence of the distance to roads and the distance to settlement factors were considered, most-suitable habitat, moderately-suitable habitat and inferior habitat types covered 1252.21 km^2 (11.52%), 2297.89 km^2 (21.14%) and 4320.78 km^2 (39.75%), respectively (Table 4). Results indicated that human activities caused 1228.3 km^2 (11.3%) of the total area from other three habitat types to be converted into unsuitable habitats. There was a 4.86% reduction in the area of most-suitable habitat. Spatially, areas affected by human activities were mainly found in moderately-suitable and unsuitable habitats (Figure 4). The adverse effects of human activities were obvious, and they affected the quality and availability of nearly all habitat types.

Table 4 Habitat suitability for Cervidae in the study area

Habitat suitability	Natural environment, area (km^2)	Human influence, area (km^2)	Natural environment, percentage of area (%)	Human influence, percentage of area (%)
Most-suitable	1780.49	1252.21	16.38	11.52
Moderately-suitable	3216.40	2297.89	29.59	21.14
Inferior	4102.29	4320.78	37.74	39.75
Unsuitable	1770.70	2999.00	16.29	27.59

3.4 Habitat pattern analysis

The influence of human activities changed the spatial pattern of habitat at both landscape- and patch-level. At patch-level human interference decreased the proportions of the most-suitable and moderately-suitable habitat areas by 13.31%, while the areas of inferior and unsuitable habitat increased (Table 5). The average areas of the most-suitable, unsuitable and inferior habitat patches were all reduced from 4.12 km^2 to 2.56 km^2 for most-suitable habitat, from 6.51 km^2 to 1.30 km^2 for unsuitable habitat and from 4.75 km^2 to 3.75 km^2 for inferior habitat, although the average moderately-suitable patch area increased from 3.84 km^2 to 4.58 km^2. The two indicators of area (PLAND, percentage of landscape; and AREA_MN, mean patch area) showed that the habitat patches were fragmented. The analysis showed the patch density (PD) index tended to increase. The average patch shape index (SHAPE_MN) also increased, which indicated that the shape of patches was more complex. The PD index (which increased from 22.13 patches/km^2 in a natural environment to 40.91 patches/km^2 under anthropogenic influence) and the SHAPE_MN index (which decreased from 1.20 in a natural environment to 1.12 under anthropogenic influence) are expressions of habitat fragmentation. The patch density distributions showed the number of smaller patches increased. This pattern was characteristic of more fragmented landscapes within the most-suitable habitat (Table 5) and suggests that the quality of habitat declined under human disturbance.

Table 5 Spatial index of habitat pattern in the Lesser Xing'an Mountains, northeastern China

	Habitat	PLAND (%)	AREA_MN (km^2)	PD (Patches/km^2)	ED (m/km^2)	SHAPE_MN	AI
a	MSH	16.38	4.12	3.97	33.41	1.20	84.66
	MLSH	29.59	3.84	7.70	67.36	1.23	82.86
	IH	37.74	4.75	7.95	61.65	1.17	87.70
	USH	16.29	6.51	2.50	25.28	1.19	88.33
b	MSH	11.52	2.56	4.51	22.67	1.13	85.21
	MLSH	21.14	4.58	4.61	46.82	1.20	83.33
	IH	39.75	3.75	10.60	84.21	1.14	84.06
	USH	27.59	1.30	21.19	59.03	1.09	83.91
Landscape scale		a	4.52	22.13	93.85	1.20	85.87
		b	2.44	40.91	106.36	1.12	83.99

Acronyms: MSH, most-suitable habitat; MLSH, moderately-suitable habitat; IH, inferior habitat; USH, unsuitable habitat; ED, edge density; a, natural environment, b, anthropogenic influence

At landscape level, AREA_MN declined from 4.52 to 2.44 km^2 and the patch aggregation degree (AI) declined from 85.87 to 83.99 under the influence of human activities (Table 5). Results showed that the quality of habitat decreased under human disturbance, nevertheless, the effects of changes related to the degree of habitat fragmentation were not as obvious.

4 Discussion

4.1 Deer habitat changes

Our research showed human activities caused the conversion of some potential habitats into unsuitable habitats, indicated by a 1228.31 km^2 loss of habitat overall and a 4.86% reduction in the area of most-suitable habitat. When human disturbance factors were taken into consideration, the area of high-quality habitat was reduced in two locations, the northern portion of the Youhao and the entire Tieli forestry bureau areas (Figure 4). The negative effects of extensive forestry understory planting may explain this phenomenon. The woodland conditions of the Cuiluan and Wu Mahe forestry bureaus were not so good because the forest tenure reform program had disturbed forest conditions. Jin (2008) assessed *Sciurus vulgaris* habitat quality in the Lesser Xing'an Mountains using LANDIS and a landscape–level habitat suitability index (HSI) model in a GIS environment. The results showed that the increase of suitable habitat areas and the decrease of marginally suitable areas were the fastest under no cutting scenario and the slowest under clear cutting scenarios. Similar results were obtained in this study: in the absence of human interference, there was a large area of suitable habitat for deer.

4.2 The environmental factors of habitat suitability changes

Seven environmental factors were used to study the habitat suitability of deer, including elevation, slope, aspect, vegetation, age of forest, distance to roads and distance to settlements. In terms of factor selection, our study was similar to some other HSI models for deer. For example, Dettki *et al*. (2003) built an empirical model for moose (*Alces alces*), which included variables relating to the topographical properties of the landscape as well as distances to landscape features, and the species' preferences for habitat components related to food, cover and forest–stand characteristics. Ray and Burgman (2006) used sambar deer (*Cervus unicolor*) to illustrate the process within the spatial context of the alpine areas of Victoria in southern Australia. Four habitat variables (presence of forest, distance to forest edge, presence of gullies, and amount of solar radiation) were retained in habitat suitability maps. Reimoser *et al*. (2009) found that the HSI model for roe deer was most sensitive to vegetation factors, such as abundance of total ground vegetation without grass and abundance of woody ground vegetation.

Habitat degradation is the main cause of the loss of species, and human activity is leading to declines in forest biodiversity (Parks and Harcourt, 2002; Sanchez-Azofeifa *et al*., 2003). Daily human activities near roads and settlements, as measured by the proximity of these variables, affected habitat use by deer more directly than other factors (Bonnot *et al*., 2013; Brehme *et al*., 2013; Eigenbrod *et al*., 2008; Martin *et al*., 2012; Taylor and Goldingay, 2010). Studies revealed that the environmental variable of distance to settlement accounted for 9.2% of predicted potential habitat distribution for red deer and 21.4% for roe deer (Wu *et al*., 2016a). Distance to a forest management area was found to affect habitat suitability with a contribution probability ranging from 4% to 6% and, with an increase in the management area, suitable habitat for roe deer decreased. Habitat suitability for roe deer reached its peak about 1300 m from a forest management area (Wu *et al*., 2018). Bonnot *et al.* (2013) found that the average distance of a GPS location to the nearest human dwelling was 224 m (range: 1.8–995.8 m) and the average distance to the nearest road was 247 m (range: 0.2–818.1 m). With increasing distance to human dwellings and roads, roe deer showed an increase in the daytime use of open habitats (Bonnot *et al*., 2013). The results of this study also showed that distance to roads and distance to human dwellings factors had a great influence on habitat suitability for deer.

Human activities may have two main effects on deer habitat suitability in our study area. First, biodiversity loss (Mcshea, 2012) caused by deforestation raises ecological concerns. Logging, understory management and other human activities directly affect habitat quality and indirectly reduce the herbivor population density. It is necessary to protect the target species from the perspective of habitat protection. Second, the intensity and frequency of human interference is directly responsible for the lower population density of cervids according to our field investigation experience (Jiang *et al.*, 2005; Wu *et al.*, 2016a). This problem will become even more prominent with low deer population density in northeastern China. Many other factors also suggest that cervid populations in the Lesser Xing'an Mountains are probably low, such as habitat degradation (Wu *et al.*, 2016b), disease and vehicle collisions, and damage to agricultural crops providing highly nutritious food for Cervidae.

4.3 Advantages and limitations of HSI models

The HSI method is suitable for large-scale studies. Traditionally, survey data from sampling points or line transects are explored with appropriate statistical methods to study habitat quality assessment. However, the line transect method is only suitable for small–scale studies in regions with flat land and simple habitat, and there are problems such as difficulties in randomly setting line transects and large workloads for field surveys during large spatial and temporal studies in mountains or forests (Stehman and Salzer, 2000). Few large-scale studies on the habitat or population of deer have been conducted in the Lesser Xing’an Mountains, northeastern China (Wu *et al.*, 2016c), and investigations providing convincing examples of best practice at a larger scale are still lacking. The HSI approach breaks through the restrictions of traditional statistical methods on study scales, and provides a powerful tool for analyzing species habitat suitability and species protection.

The method used here for evaluating habitat suitability had some limitations. Although verification of HSI model has always been a difficult problem (Robel *et al.*, 1993; Van der Lee *et al.*, 2006), the model has been extensively used worldwide because the model itself is reasonable. Commonly, data from field investigations have been used to verify models (Ottaviani *et al.*, 2004; O’Hara and Ramage, 2013), but statistics related to Cervidae and their population in our large–scale study area are unavailable. There is no reference data for population sizes, therefore, lacking verification data, this study did not carry out model validation, although we believe that the results are still reasonable and reliable. In general, HSI models provide tools to solve a range of problems if they are based on reasonable assumptions. However, these assumptions may not always be correct, so HSI models may not accurately represent the real situation in the natural world.

4.4 Management implications

As cervid species clearly avoided roads, road use should be reasonable. We recommended people limit disruption to deer feeding or resting areas by choosing both the right time and the right path when working in forests, and by minimizing the overall level of disturbance, if possible. The size and spatial configuration of suitable habitats is critical for the long-term survival of wildlife. We suggest further studies on connectivity and patch occupancy. The absence of deer in many large areas of suitable habitat shows the need for the restoration of corridors between isolated habitats. It is important to conserve large patches of habitat and restore connectivity between core areas to ensure species survival. This will enable survival of not only the two target species but also other species dependent on these forest areas (Paudel *et al.*, 2015).

5 Conclusions

(1) Factors affecting potential suitable habitat for deer

In the BRT analysis, the important natural environmental factors influencing the richness of deer were elevation (25.6%), aspect (14.8%), food (13.1%), age of forest (8.3%) and slope (6.3%). The environmental factors that influenced the suitable habitat of deer, in order of importance, were: vegetation type (0.3597), age of tree (0.1799), distance to the road (0.1458), distance to the residence (0.1458), aspect (0.0882), elevation (0.0485), slope (0.0267). Two of the factors that reflected human activities were very important: distance to roads and distance to settlements. Our study also showed that human activities caused the conversion of some potential habitats into unsuitable habitats.

(2) The disturbance effect of human activities on deer habitat

Human activities have changed the size and patterns of suitable habitats for deer. On the one hand, the habitat area was reduced. These results helped identify the spatial extent of habitat influenced by anthropogenic interference for the local cervid population. The area of most-suitable habitat was reduced by 4.86% because of human interference, whereas the unsuitable habitat area increased by 11.3%. On the other hand, the habitat pattern was degraded from high quality into low quality habitat or into unsuitable habitat by human activities at various scales, suggesting more attention should be paid on considering the way and intensity of human activities for habitat management as fully as possible.

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