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Evaluating Spatiotemporal Patterns and Integrated Driving Forces of Habitat Quality in the Northern Sand-Prevention Belt of China

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Abstract: Understanding habitat quality patterns and their drivers in arid zones is of fundamental importance to the sustainability maintenance of terrestrial ecosystems, but remains elusive. Here, we applied the InVEST model to investigate the spatiotemporal patterns of habitat quality in the northern sand-prevention belt (NSPB) across five time periods (2000, 2005, 2010, 2015, 2018), coupled with the structural equation model (SEM) and boosted regression tree (BRT) model to identify their integrated driving forces. The results exhibited that habitat quality in high-level zones expanded gradually from 2000 to 2018, while the middle- and low-level zones shrank. Climate, soil, topography, and human activities were significantly correlated with habitat quality, with mean annual temperature (MAT) and human activities being key contributing factors in the high-level and low-level zones, respectively, whereas the contribution of factors varied considerably in the middle-level zones. The interactions among climate, soil, topography, and human activities jointly drive habitat quality changes. Climate intensified the positive effects of soil on habitat quality, while the topographic and human activities mainly affected habitat quality indirectly through climate and soil. Our findings offer a scientific guidance for the restoration and sustainable management of desertification ecosystems in northern China.

Keywords: habitat quality; sustainability maintenance; land use; driving forces; the northern sand-prevention belt; InVEST model

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1. Introduction

Habitat quality is generally defined as the potential of ecosystems to provide suitable conditions for biological conservation, which has fundamental importance to biodiversity maintenance and ecosystem service functions [1–3]. Over the decades, land use changes have dramatically affected habitat quality [4]. Field surveys, ecological index evaluation, and ecological models were widely applied to evaluate habitat quality and explore its dynamic change. Most early studies focused on exploring regional variations in habitat conditions and suitable habitats for species in specific regions through field surveys [5]. Various ecological indexes have been used to rapidly monitor biodiversity and ecological quality across different scales with the advancements of remote sensing technology [6–10]. Recently, ecological models (e.g., Integrated Valuation of Ecosystem Services and Tradeoffs, InVEST) were primarily employed to quantify, evaluate, and simulate habitat quality at larger scales [11–17]. Exploring the spatiotemporal evolution in habitat quality and driving forces has garnered growing attention in research [18,19].

Identifying the factors influencing habitat quality provides guidance on protecting the regional ecological environment [20,21]. Natural environment factors (e.g., climate, soil, and topography) and human activities are generally recognized as the major driving forces of variations in habitat quality [22]. Climatic conditions, such as temperature and precipitation, affect the land cover, vegetation growth, and water cycle in different environments, which causes significant differences in habitat quality [12]. Soil physical and chemical properties are profoundly affected by land use changes [23], with a corresponding regulation on the distribution characteristics of habitat quality to a certain extent [24]. Topographic conditions have not altered significantly in the short term but impact surface materials, energy transfer, and land use patterns, which in turn affect ecological environment quality [2,25]. In addition, as the primary sources of disturbance to the natural ecosystems, population pressure and human socio-economic activities are emerging as the most active factors affecting the evolution of ecosystem patterns. Anthropogenic intensity [26,27], grazing pressure [28], and urban expansion [29–31] significantly alter the spatiotemporal characteristics of habitat quality within diverse regions, leading to ecological degradation. Investigating the effects of various factors such as climate, soil, topography, and human activities on ecological environment quality is conducive to balancing regional construction and ecological development [20]. Therefore, examining the synergistic effects of multiple factors on habitat quality is crucial to fill gaps in the quantitative analysis.

As a national-level ecological barrier in northern China, the northern sand-prevention belt (NSPB) is highly significant in maintaining ecosystem services, economic development, and ecological security patterns [32–34]. In recent years, regional land desertification and vegetation degradation remained severe, especially under the dual pressures of climate change and human activities [35,36]. Extensive studies have focused on the regional ecological security, ecological vulnerability assessment, and ecosystem service function in the NSPB [34,37,38]. However, studies on the interrelationship between habitat quality and driving factors often adopt simple methods including geographical detectors [39,40], a correlation analysis [41], and a multiple regression analysis [42], and these studies only focus on examining the effect of a single factor or single natural element on the ecological environment, and fail to comprehensively explore the multifactorial influencing mechanisms and grasp the impact pathways of habitat quality from the perspective of ecological integrity. Therefore, spatiotemporal patterns and integrated driving forces of habitat quality within NSPB remain poorly understood.

In this study, we assembled a comprehensive database including environmental factors and human activities' index from 2000 to 2018. The InVEST model was then applied to quantify habitat quality of NSPB and grasp its temporal and spatial changes. Finally, the structural equation model (SEM) and boosted regression tree (BRT) model were introduced to investigate the influence of natural and anthropogenic factors on habitat quality across five time periods (2000, 2005, 2010, 2015, 2018). The specific objectives of this research were to (1) explore the habitat quality patterns in the NSPB; (2) identify the contribution of environmental and anthropogenic variables to habitat quality; (3) grasp the direct and indirect driving paths of habitat quality patterns. This study is essential for the ecological restoration and biodiversity conservation of ecological projects in northern China.

2. Materials and Methods

2.1. The Study Area

The NSPB is distributed in an elongated band across northern China (26°45′34″ N–43°53′25″ N, 71°34′23″ E–125°43′35″ E), which mainly includes three regions: the Inner Mongolia sand-prevention belt, the Tarim sand-prevention belt, and the Hexi Corridor sand-prevention belt (Figure 1). Among them, the Inner Mongolia sand-prevention belt is located in south-central Inner Mongolia, west of the Greater Khingan Mountains. The Tarim sand-prevention belt is situated between the Tianshan and Kunlun Mountains in southern Xinjiang, China. The Hexi Corridor sand-prevention belt is located in northwestern China, south of the Qilian Mountains, and includes parts of Gansu and Qinghai Provinces. The study area covers 8.1 × 10^5 km^2, with the mean annual temperature being −1.9–13.5 °C, the mean annual precipitation being 30–450 mm, and an arid and semi-arid temperate continental climate [38]. Soil types within our study area are diverse, including ordinary wind-sand mobile soil, brown desert soil, thin frozen soil, and ordinary brown soil. The biomes are mainly desert, grassland, and farmland, with typical characteristics of an agro-pastoral ecotone [38].

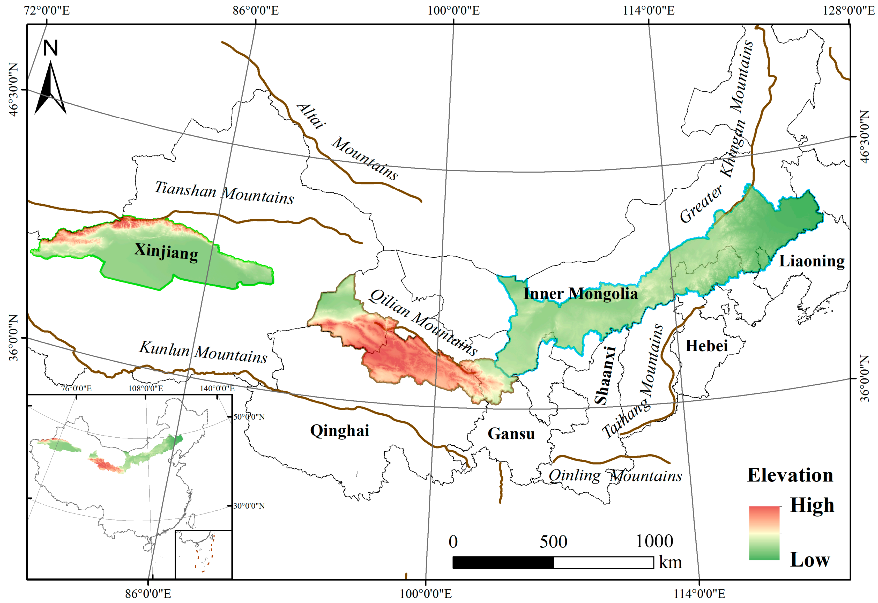

Figure 1. The location of the NSPB in China.

2.2. Data Collection and Processing

We assembled a comprehensive database by collecting datasets on land cover, climate, soil, topography, and human activities (Table 1), which are described as follows: (1) The NSPB of China boundary data were obtained from Global Change Research Data Publishing & Repository (http://www.geodoi.ac.cn, accessed on 20 June 2023). (2) The land use data with a 30 m resolution for five periods (2000, 2005, 2010, 2015, 2018) came from the CLCD database of Yang and Huang [43]. The first-level classification of land use data includes cropland, forest, shrub, grassland, water, snow, barren, impervious, and wetland. (3) Meteorological data with a 1 km resolution mainly contain mean annual temperature (MAT), mean annual precipitation (MAP), and potential evapotranspiration (PET), from the National Earth System Science Data Center (http://loess.geodata.cn, accessed on 22 June 2023). The average values of climate factors were calculated in the four continuous time series periods: 2001–2005, 2006–2010, 2011–2015, and 2016–2018. (4) Soil factors comprise total nitrogen (TN), total phosphorus (TP), soil organic carbon (SOC), soil pH, bulk density (BD), Clay, Silt, and Sand, which were obtained from the National Tibetan Plateau Science Data Center (https://data.tpdc.ac.cn, accessed on 26 June 2023) with a resolution of 1 km. (5) The 1 km resolution digital elevation model (DEM) data were derived from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn, accessed on 28 June 2023). The elevation data were processed by using the surface analysis tool of ArcGIS to obtain the Slope and Aspect. (6) The 1 km resolution human footprint index (HFI) data came from Mu et al. [44]. The average values of HFI were calculated in the continuous time series (2001–2005, 2006–2010, 2011–2015, 2016–2018) for the analysis of factors affecting habitat quality in five periods. To ensure data availability, the above data were uniformly converted into 1 km × 1 km raster data.

Table 1. Description of data source.

Category	Variable	Description	Resolution	Unit	Source
Climate factors	MAT	Mean annual temperature in study area	1 km	°C	National Earth System Science Data Center (http://loess.geodata.cn, accessed on 22 June 2023)
	MAP	Mean annual precipitation in study area	1 km	mm	
	PET	Mean potential evapotranspiration in study area	1 km	mm	
Soil chemical properties	TN	The total amount of all forms of nitrogen in the soil to assess soil fertility	1 km	g/kg	National Tibetan Plateau Science Data Center (https://data.tpdc.ac.cn, accessed on 26 June 2023)
	TP	The total amount of all forms of phosphorus in the soil to assess nutrient status	1 km	g/kg	
	SOC	The content of organic carbon in the soil	1 km	g/kg	
	pH	Soil acidity and alkalinity as a key index to evaluate soil environment	1 km	-	
Soil physical properties	BD	Soil texture density reflecting soil compactness	1 km	g/cm^3	
	Clay	The content of Clay particles in the soil	1 km	g/kg	
	Silt	The content of Silt particles in the soil	1 km	g/kg	
	Sand	The content of Sand particles in the soil	1 km	g/kg	
Topographic factors	DEM	Digital elevation model represents the topography of the area surface	1 km	m	Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn, accessed on 28 June 2023)
	Aspect	Aspect is extracted from DEM data for topography analysis	1 km	°	
	Slope	Slope is extracted from DEM data for topography analysis	1 km	°	
Human activities	HFI	Human footprint index systematically covers built environment, population density, night light, farmland, pasture, road, railway, navigable waterway	1 km	-	(Mu et al., 2022) [44]
Land use	Land use	The land use type includes cropland, forest, shrub, grassland, water, snow, barren, impervious, wetland	30 m	-	(Yang and Huang, 2021) [43]

2.3. Habitat Quality Assessment

The habitat quality module in the InVEST model can evaluate ecosystem suitability to support species survival and reproduction [45]. The module calculates the habitat quality index by integrating land use type sensitivity and external threat intensity. As the habitat quality index increases, the level of habitat quality improves accordingly [46]. Therefore, the InVEST model was employed to quantify habitat quality in the NSPB for five time periods. The input parameters of the model were confirmed according to the InVEST model manual and previous studies (Tables S1 and S2) [13,14,47]. On this basis, the habitat quality in the NSPB in 2000, 2005, 2010, 2015, and 2018 was calculated.

To precisely characterize the dynamic tendency of habitat quality, three levels were divided from the habitat quality in the NSPB through the natural breakpoint classification method, including low (0–0.4), medium (0.4–0.8), and high (0.8–1.0) [13].

2.4. Identify Drivers of Habitat Quality

The grid method was performed to sample in the study region at a 12 km × 12 km scale, so as to analyze the drivers of habitat quality and their contributions at a smaller unit scale. Finally, a total of 5632 sampling points in the NSPB were extracted. Data analysis tools were used to extract habitat quality of the corresponding grid and average value of environmental factors and human activities for each period. All sampling points were extracted in ArcGIS 10.8 software, and then the attribute tables were generated by removing missing values.

In order to screen out more variables by combining multicollinearity [48,49], 15 factors were analyzed with the Spearman correlation test. By combining relevant literature [40,50], we removed the variables that had a high correlation coefficient with the others ($|r| > 0.8$). PET, Sand, and SOC were therefore eliminated. After screening, 3 topographic factors (DEM, Aspect, Slope), 2 climatic factors (MAT, MAP), 6 soil factors (Clay, Silt, BD, pH, TN, TP), and 1 human activity (HFI) factor were included in the final modeling within the NSPB (Figure S1).

All statistical analyses in the research were performed in R (v4.3.0) [51]. To examine the correlation between habitat quality and variables, the linear mixed-effects model was conducted using the "lme4" package in R [52], habitat quality was regarded as the response variable, climate, soil, topography, and human activities were used as fixed effects, and land use types were included as a random effect. The relative importance of the screened variables on habitat quality was determined using the BRT algorithm [53] and ranked in order of importance. BRT can handle a nonlinear relationship and complicated interactions and is not constrained by covariance and missing data. The "XGBoost" package v.1.4.1.1 in R was utilized in the BRT analysis and visualization [54].

2.5. Quantify Driving Pathways of Habitat Quality

Piecewise SEM was introduced [55,56] to explore the direct and indirect effects (β represents the path coefficient) of these variables on the habitat quality in the NSPB. Piecewise SEM, as a commonly applied method for analyzing ecological data, can address non-independent observations and the non-multivariate normal distribution of residuals in response variables. The "piecewise SEM" [57], "nlme", and "lme4" packages in R were adopted to perform piecewise SEM. We employed Fisher's C test to evaluate the goodness of fit of the model ($0 \leq$ Fisher's $C/df \leq 2$, $0.05 < P \leq 1.00$), and the model was further refined based on significance ($p < 0.05$), and AIC values [55,58].

3. Results

3.1. Spatiotemporal Patterns of Habitat Quality

From 2000 to 2018, the high-level zones in the NSPB were primarily distributed in mountainous regions, including the Tianshan Mountain Area on the western edge of Xinjiang Province, the Qilian Mountain Area in the northeast of Qinghai Province, the edge of Greater Khingan Mountains, and other mountains areas in Inner Mongolia, covered by vegetation such as woodland, grassland, and scrubland (Figure 2). Medium-level zones were mainly dispersed in Inner Mongolia areas, where the land types mainly were cropland and grassland. Low-level zones were extensively distributed in areas spanning Xinjiang Province, a border area of Gansu Province and Inner Mongolia, as well as the northwest of Qinghai Province. These regions were mainly concentrated in large areas of desert and a small portion of grassland, while including areas strongly interfered with via human activities, such as construction land.

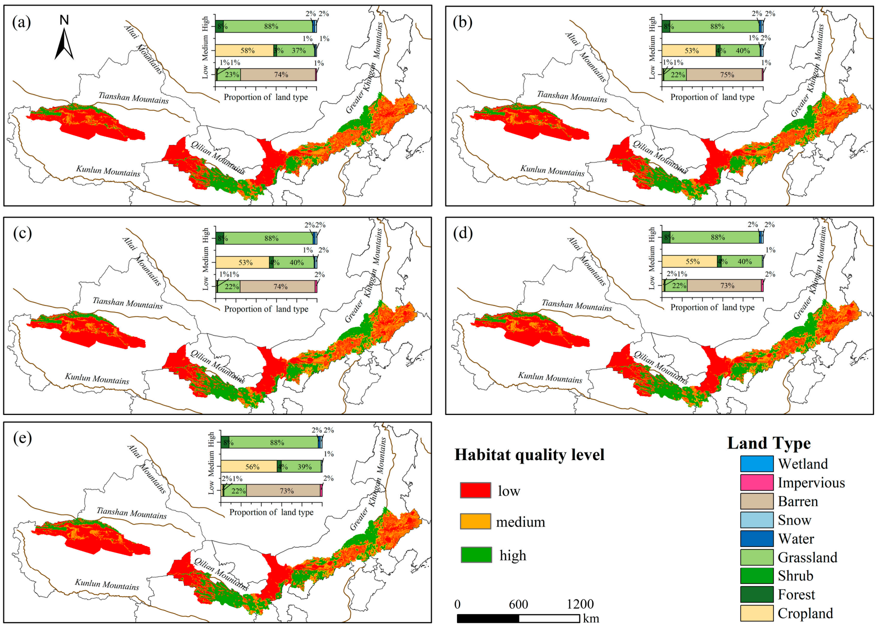

Figure 2. Habitat quality classification and the proportion of land type at three levels in (**a**) 2000, (**b**) 2005, (**c**) 2010, (**d**) 2015, and (**e**) 2018.

Across the five time periods, the area ratio of low-level zones was the highest, exceeding 50% (Table 2). The area of low-level zones exhibited a trend of "decreased-increased", decreasing from 54.10% in 2000 to 51.88% in 2010 and then increasing to 52.11% in 2018. Meanwhile, the area ratio of medium-level and high-level zones occupied over 20%, with the area of high-level zones showing a primarily increasing trend from 22.59% in 2000 to 25.24% in 2018.

Table 2. Habitat quality area and percentage statistic for the NSPB from 2000 to 2018.

Level	2000		2005		2010		2015		2018	
	Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%	Area/km^2	Percentage/%
Low	439,806	54.10	438,571	53.95	421,762	51.88	422,987	52.03	423,627	52.11
Medium	189,464	23.31	192,303	23.66	188,850	23.23	188,002	23.13	184,156	22.65
High	183,668	22.59	192,064	23.63	202,326	24.89	201,949	24.84	205,155	25.24

3.2. Drivers of Habitat Quality Patterns

The result of the linear mixed effect analysis showed that in the high-level zones, the habitat quality from 2000–2018 was positively correlated with DEM ($p < 0.001$), MAP ($p < 0.001$), TN ($p < 0.001$), TP ($p < 0.001$), and Silt ($p < 0.01$), and negatively correlated with MAT ($p < 0.001$), pH ($p < 0.01$), BD ($p < 0.001$), and Clay ($p < 0.01$), while no significant relationships were found with the Slope and Aspect (Figures S2–S5). The results of BRT showed that MAT (ranked as the top one) was the dominant factor shaping habitat quality in the high-level zones from 2000 to 2018, followed by MAP and HFI. The contribution of these factors showed significant differences among different periods. Climatic factors (MAT, MAP) ranked first in the cumulative importance ordering, accounting for more than 30% (Figure 3).

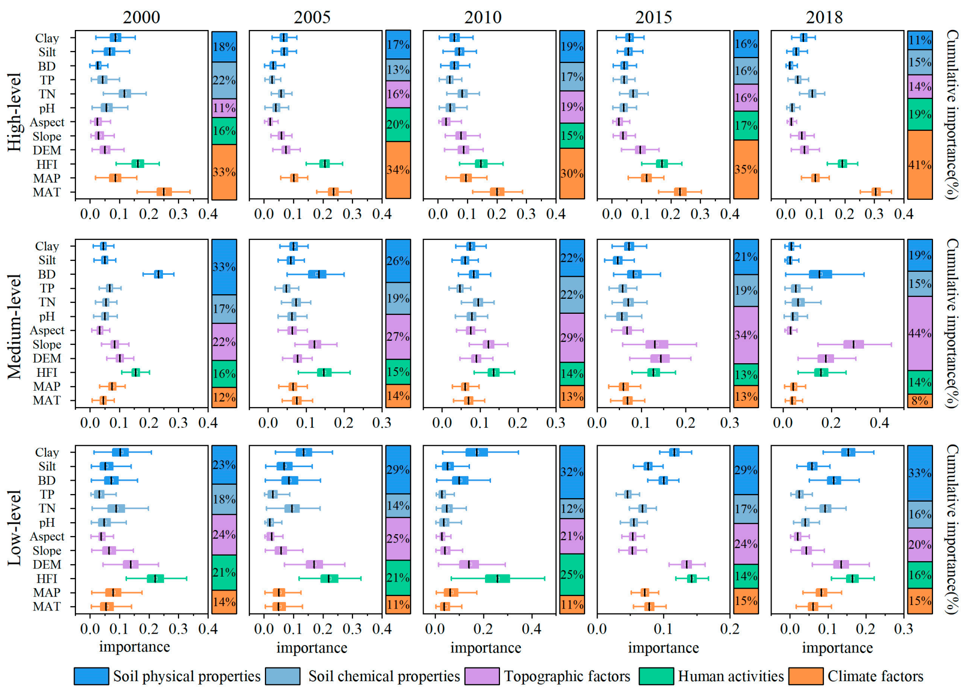

Figure 3. Ranking of the relative importance of different environmental variables.

In medium-level zones, the habitat quality showed a positive relationship with DEM ($p < 0.05$), Slope ($p < 0.001$), and TN ($p < 0.001$), a negative relationship with pH ($p < 0.01$) and BD ($p < 0.001$), and no significant relationship with Clay (Figures S2–S5). The BRT results showed a significant difference in the contribution rate of each environmental factor in the middle-level zones. The primary factors contributing to the habitat quality were DEM, Slope, BD, and HFI. The importance of soil physical properties in the cumulative importance ranking decreased by years, from 33% in 2000 to 19% in 2018. On the contrary, the importance of topographic factors in the cumulative importance ordering increased by years, from 22% in 2000 to 44% in 2018 (Figure 3).

In the low-level zones, habitat quality was positively correlated with DEM ($p < 0.001$) and Slope ($p < 0.001$), and negatively correlated with MAP ($p < 0.01$), MAT ($p < 0.05$), HFI ($p < 0.001$), pH ($p < 0.001$), BD ($p < 0.001$), Clay ($p < 0.001$), and Silt ($p < 0.001$), while the relationship with Aspect was not significant (Figures S2–S5). We identified HFI as the major driver of affecting habitat quality with BRT analyses, and the cumulative importance ranking of human activity was significantly higher than that in the medium-level zones (Figure 3).

3.3. The Driving Paths of Habitat Quality Patterns

In the high-level zones, the results showed that topographic factors had an indirect and positive effect on habitat quality through climatic factors and soil physical properties (Figure 4). The path coefficient of topographic factors on climatic factors was obviously greater than that of soil physical properties. The HFI contributed indirectly to habitat quality through its effects on climatic and soil factors. In 2015 and 2018, the HFI directly negatively affected habitat quality. Climatic factors exerted an indirect positive influence on habitat quality by regulating soil properties. Moreover, climate negatively affected habitat quality in 2000 (−0.0872), 2005 (−0.0835), 2010 (−0.0951), and 2015 (−0.0981). Soil chemistry properties always had positive effects on habitat quality, with path coefficients of 0.3298, 0.3127, 0.3347, 0.3231, and 0.3093 ($p < 0.001$) for each period (Figure 4). Notably, the impact coefficient of soil chemical properties on habitat quality was higher than that of soil physical properties.

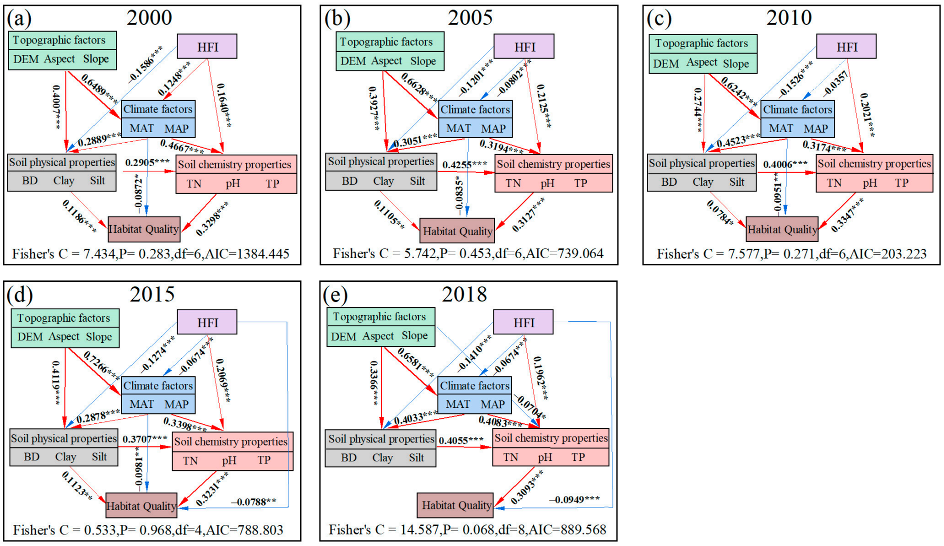

Figure 4. Structural equation modeling paths for relevant factors and habitat quality in high-level zones in (**a**) 2000, (**b**) 2005, (**c**) 2010, (**d**) 2015, and (**e**) 2018 (red and blue arrows indicate significant positive and negative paths between variables, respectively. Dashed lines indicate non-significant paths. Path widths are proportional to path coefficients, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

In the medium-level zones, the results demonstrated that topographic factors exerted two obvious influence paths on habitat quality from 2000 to 2018. One had a positive effect on habitat quality (β = 0.2759, 0.3065, 0.3353, 0.3105, and 0.2768, $p < 0.001$). Another had an indirect and positive effect through climate and soil (Figure 5). The HFI had direct negative impacts on habitat quality, with path coefficients of −0.2048, −0.2188, −0.2254, −0.1748, and −0.1509, respectively ($p < 0.001$), and indirectly inhibited habitat quality through adverse effects on climate and soil physical properties. In addition, climate had a direct and negative influence pathway from 2000 to 2018, with path coefficients of −0.1764 ($p < 0.05$), −0.2656 ($p < 0.001$), −0.2105 ($p < 0.001$), −0.2547 ($p < 0.001$), and −0.2925 ($p < 0.001$), respectively (Figure 5).

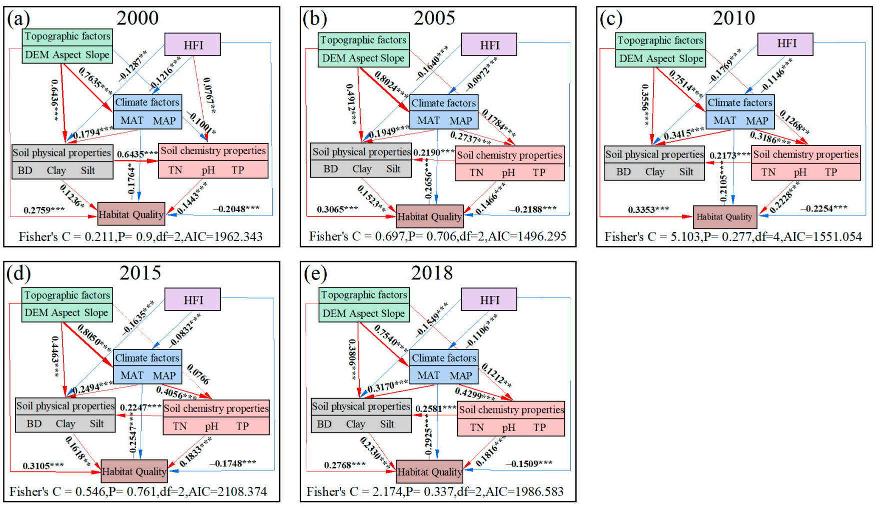

Figure 5. Structural equation modeling paths for relevant factors and habitat quality in medium-level zones in (**a**) 2000, (**b**) 2005, (**c**) 2010, (**d**) 2015, and (**e**) 2018 (red and blue arrows indicate significant positive and negative paths between variables, respectively. Dashed lines indicate non-significant paths. Path widths are proportional to path coefficients, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

In the low-level zones, topographic factors primarily had an indirect and positive effect on habitat quality through their effects on climatic factors and soil physical properties. In 2000 and 2018, topographic factors had a weak direct positive effect on habitat quality (Figure 6). Climatic factors in this region indirectly affected habitat quality by increasing soil physical properties and inhibiting soil chemical properties. In addition, we can observe that the influence of human activities in this range is more significant than other factors. There are two observable paths, one indirectly affected habitat quality by influencing climatic factors and soil physical properties, and another directly affected habitat quality, both of which displayed negative impacts and had significant impact coefficients (β = −0.2212, −0.3060, −0.1771, −0.1693, and −0.1778, $p < 0.001$) (Figure 6).

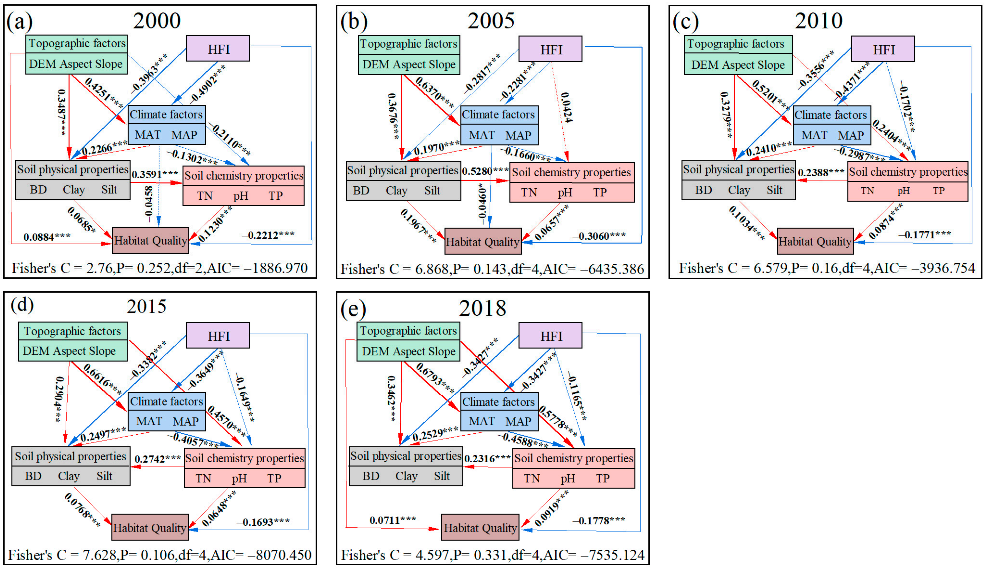

Figure 6. Structural equation modeling paths for relevant factors and habitat quality in low-level zones in (**a**) 2000, (**b**) 2005, (**c**) 2010, (**d**) 2015, and (**e**) 2018 (red and blue arrows indicate significant positive and negative paths between variables, respectively. Dashed lines indicate non-significant paths. Path widths are proportional to path coefficients, * $p < 0.05$, *** $p < 0.001$).

4. Discussion

4.1. Spatiotemporal Patterns of Habitat Quality

As a key means to understand ecological conditions, habitat quality assessment significantly contributes to sustainable development and ecological security. The exploration of habitat quality patterns provides valuable guidance for regional ecological planning and biodiversity conservation in the NSPB [59]. A previous study has suggested that threat factors to habitat quality incorporate construction land, desert, and cropland [45]. We demonstrated that habitat quality in NSPB was generally low (the proportion of low-level zones is 54.10%, 53.95%, 51.88%, 52.03%, and 52.11% in the five periods, respectively). The land type dominated by deserts was the most crucial factor that severely threatened environmental conditions in the NSPB. Habitat quality of the NSPB exhibited an escalating trend from 2000 to 2018, but the range remained as fluctuating (Table 2). This finding is consistent with existing research [7], which suggested that it is primarily related to the extreme ecological environment or periodic irrational human activities. In addition, there was a high degree of consistency in the distribution of habitat quality and land type (Figure 2) [60], which is in accordance with the findings obtained by Mu et al. [61] and Bi et al. [28]. Therefore, future ecological restoration efforts should place emphasis on the low-level zones and adopt more biological conservation and land restoration strategies.

4.2. Drivers of Habitat Quality Patterns

One of the motivators that promote the formation of and change in habitat quality patterns is the external environment [20]. In this study, we comprehensively consider the driving forces of multiple factors on habitat quality at a regional scale. Topographic factors can represent the geomorphic features of the NSPB, reflecting the accessibility of human activities to some extent. Habitat quality was positively correlated with the DEM and Slope (Figure S2) [2]. Soil properties can regulate habitat quality through feedback that affects plant composition and community structure [62,63]. Across three levels, soil pH and BD were found to be negatively related to habitat quality, while soil TN was positively correlated with habitat quality (Figure S4). Those sensitive soil quality indicators (e.g., soil pH, TN, and BD) adjusted plant nutrient absorption, soil element dissolution, and microbial community diversity, which jointly regulate ecosystem function and stability [64–67]. BRT models showed that MAT had the most considerable contribution to the habitat quality in high-level zones, which largely support previous findings [40]. Conversely, habitat quality in our study is significantly negatively correlated with MAT (Figure S3). The reason may be that temperature conditions in the NSPB exceed the optimum value for plant growth [11,68]. Temperature changes directly affect the metabolic processes and growth rates of plants, influencing the ecological environment quality by altering plant habitability [69]. In addition, it was demonstrated that human activities were negatively correlated with habitat quality (Figure S5) and their contributions were higher in the low-level zones (Figure 3), which is extremely similar to a previous study [26]. The above findings suggest that human activities are essential drivers of variations in regional habitat quality [27]. Irrational human behavior can destroy the original ecological conditions and accelerate the deterioration of regional habitat quality [11].

4.3. The Driving Paths of Habitat Quality Patterns

Except for exploring the drivers of habitat quality patterns, capturing the driving pathways is vital to understanding the complex ecological mechanisms. This study innovatively uses SEM models to explore the direct and indirect pathways of climate, soil, topography, and human activities on habitat quality. The findings indicate that these factors have not only direct influences on habitat quality distribution but also indirectly affect such distribution by impacting other factors. Our study found that topographic factors directly and positively influenced habitat quality in the medium-level zones across five periods (β = 0.2759, 0.3065, 0.3353, 0.3105, and 0.2768, respectively) (Figure 5), indicating that topography has a strong influence on medium habitats dominated by farmland [70,71]. Moreover, our SEMs revealed that topography indirectly affected the habitat quality through soil physical properties and climate factors, while soil chemical properties directly affected the habitat quality. The influence coefficient of soil chemical properties in the high-level zones was higher than other factors across five periods (β = 0.3298, 0.3127, 0.3347, 0.3231, and 0.3093, respectively) (Figure 4). Environmental conditions have critical long-term effects on soil, while both topography and climate are closely related to soil variations [72,73]. Soil chemical properties may vary greatly by different land use types [24,65,74]. Therefore, the significance of soil chemical properties for the habitat quality should not be ignored. In land use development activities, attention should be paid to the destruction of soil conditions and variation in soil chemical indicators to realize the sustainable development of ecological resources.

Furthermore, the responses of habitat quality to climate change should also be a focus in arid regions. We found that climate favorably mainly affected habitat quality by regulating the soil physical and chemical properties (Figures 4–6). Climate conditions influence landscape patterns, such as altering soil element concentration or moisture [64,75]. Notably, climate conditions had direct negative effects on habitat quality, and the influence pathway coefficients were higher in medium-level zones than in high-level zones across five periods (β = −0.1764, −0.2656, −0.2105, −0.2547, and −0.2925, respectively). Current climate conditions are increasingly unfavorable to habitat quality, attributed to global change and extreme weather (e.g., drought) [76,77].

Our SEMs exhibited that HFI had a direct negative influence on habitat quality, which was extremely similar to the linear mixed model results. Human activities not only directly affect the habitat quality but also indirectly impact through soil and climate (Figures 4–6). Mechanisms of anthropogenic impacts on habitat quality are incredibly complex, involving various dynamic processes [29,31,78]. Many studies have reported various ecological projects, such as the "Three-North Shelter Forest Program", "The Grain for Green Program", and "The Beijing-Tianjin Sand Source Control Project", which actively contribute to the environmental ecosystem in northern China [79–81]. Obviously, human activities can regulate the development of ecosystems in a benign direction under a strict ecological protection policy. In other words, economic development can be compatible with ecological protection.

4.4. Limitations and Outlooks

Achieving effective management of the ecological environment in the arid regions of northern China is a complicated and critical research topic. Prior studies mainly focused on how land use patterns affect variations in habitat quality, while the driving mechanism of natural and anthropogenic factors on habitat quality still needs to be clarified. This study extensively examined the spatiotemporal changes in habitat quality over the past 18 years in NSPB, and adopted multiple ecological factors to identify the drivers and influence pathways of variations in habitat quality by incorporating the natural environment and human activities into the comprehensive analysis framework, so as to better grasp the modulation of habitat quality in response to multiple factors and make up for the shortcomings of quantitative analyses in existing studies. This study has essential roles in promoting the sustainable and balanced advancement of the regional economy, society, and environment. The current database data used in this study may have accuracy limitations. In the future, more measured and observed data should be integrated to optimize the model.

Considering the complexity of the regional ecosystem, the evaluation indexes of ecological environment quality exhibit diversity. Future studies should explore how abiotic (e.g., wind, light, and nitrogen deposition) and biotic (e.g., species interactions, seed dispersal, and alien invasion) factors jointly affect habitat quality and analyze the intrinsic mechanisms of ecosystem responses to global changes. In addition, factors affecting habitat quality in different regions are often different. In the future, ecological assessment data with a regional dimension can be specifically selected, and the research framework can be extended to other regional studies with important ecological value.

5. Conclusions

This study puts forward an innovative research framework in investigating the effects of the natural environment, human activities, and their interactions on habitat quality. By assembling an integrated database including climate, soil, topography, human activities, and land use, the InVEST model, BRT model, and SEM model were applied to investigate habitat quality patterns and driving mechanisms in the NSPB. The conclusions are as follows:

(1) The habitat quality within NSPB was comparatively low, showing an upward trend from 2000 to 2018. During the study periods, the low-level and medium-level habitats tended to develop into high-level habitats, while the level of habitat quality remained as fluctuating. This result suggests that ecological conditions in the NSPB are gradually improved, but the potential risk of habitat degradation remains.

(2) Over most periods, habitat quality showed a significant correlation with the topography, climate, soil factors, and human activities, but was independent of Aspect. Across five periods, MAT and HFI were the most important for habitat quality in the high- and low-level zones, respectively, while there were period differences in the ordering of factor contributions in the middle-level zones.

(3) Focusing on the driving pathways of habitat quality variations, we found that soil chemical properties, topography, and human activities had the greatest direct influence on habitat quality of high-, medium-, and low-level zones, respectively. Habitat quality

was enhanced via the soil chemical properties and topography while it was decreased via human activities. The indirect pathways showed that climate enhanced the positive effects of soil factors on habitat quality, while topographic and human activities mainly influenced habitat quality indirectly through climate and soil factors.

In conclusion, our study further indicates that climate, topographic, and soil conditions are fundamental to maintaining ecosystem stability, while human activities are a significant threat to habitat quality within NSPB. In the background of accelerated global change and human activities, habitat quality within NSPB is still improved, which suggests that the implementation of ecological projects makes a positive contribution to habitat quality in northern China. Sustained ecological projects can effectively contribute to restoring natural ecosystems and curb the negative effects of global change.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16041508/s1, Table S1: Habitat threat factors. Table S2: Sensitivity of land use types to the threat factors. Figure S1: Variable correlations and interactions from 2000 to 2018 (* $p <= 0.05$). Figure S2: Relationship between topographic factors and habitat quality at three levels of habitat quality (blue, yellow, and green respectively indicate different levels of habitat quality: high, medium, and low. The solid line indicates the significance of the fitted regression line, dashed line indicates non-significance. Gray shading indicates 95% confidence intervals. The sample size is N). Figure S3: Relationship between climate factors and habitat quality at three levels of habitat quality (blue, yellow, and green respectively indicate different levels of habitat quality: high, medium, and low. The solid line indicates the significance of the fitted regression line, dashed line indicates non-significance. Gray shading indicates 95% confidence intervals. The sample size is N). Figure S4: Relationship between soil factors and habitat quality at three levels of habitat quality (blue, yellow, and green respectively indicate different levels of habitat quality: high, medium, and low. The solid line indicates the significance of the fitted regression line, dashed line indicates non-significance. Gray shading indicates 95% confidence intervals. The sample size is N). Figure S5: Relationship between human activities and habitat quality at three levels of habitat quality (blue, yellow, and green respectively indicate different levels of habitat quality: high, medium, and low. The solid line indicates the significance of the fitted regression line, dashed line indicates non-significance. Gray shading indicates 95% confidence intervals. The sample size is N).

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