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Unveiling the Secrets: How Landscape Patterns Shape Habitat Quality in Northeast China Tiger and Leopard National Park

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Abstract: The Northeast China Tiger and Leopard National Park (NCTLNP) is a critical habitat for the endangered Amur tiger and Amur leopard, making it a global biodiversity hotspot. This study explores how changes in landscape patterns have influenced habitat quality in the park, aiming to develop strategies for enhancing biodiversity conservation and ensuring the park's long-term sustainability. From 2012 to 2017, habitat quality in the NCTLNP experienced a significant decline; however, the launch of the national park pilot program in 2017 resulted in improvements, particularly in core protected areas, where habitat quality increased and landscape fragmentation decreased. These findings indicate that the national park initiative reduced the degradation of habitat quality. Key landscape metrics, especially the Shannon Diversity Index (SHDI), were found to significantly affect habitat quality. Additionally, the interaction between SHDI and landscape contagion (CONTAG) played a pivotal role in shaping habitat quality over time. Areas with high SHDI and low CONTAG showed declines in habitat quality, pointing to the need for focused conservation efforts. This study offers valuable insights for policymakers seeking to improve habitat quality through targeted landscape management practices.

Keywords: landscape patterns; habitat quality; Northeast China Tiger and Leopard National Park; GeoDetector

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1. Introduction

Human activities pose a significant threat to global biodiversity and land health [1–3]. Landscape fragmentation, caused by human-induced changes to land use patterns, is a major culprit in biodiversity loss [4,5]. It disrupts habitats, leading to ecological degradation and declining habitat quality. High-quality habitats are crucial for maintaining biodiversity and supporting ecosystem services [6,7]. By improving habitat quality, we can increase resources available to organisms, ultimately promoting ecological balance.

Protected areas are vital for biodiversity conservation. They offer concentrated areas to preserve the integrity of critical natural ecosystems [8,9]. China's ambitious effort to create the world's largest national park system highlights its commitment to conservation. In the first phase, nearly 30% of the country's key terrestrial wildlife species are being protected [10]. Among these is the Northeast China Tiger and Leopard National Park (NCTLNP), a globally recognized biodiversity hotspot crucial for safeguarding endangered species like the Amur tiger and Amur leopard. It provides critical habitat for the Amur tiger and Amur leopard, classified as endangered and critically endangered by the IUCN Red List, respectively [11,12]. However, human pressures such as agricultural land conversion, deforestation, forest fires, mining operations, and road traffic have altered the park's landscape in recent decades, consequently impacting its landscape structure and function [13]. These changes have negatively impacted habitat quality, raising concerns among researchers and management departments. To facilitate NCTLNP's restoration and promote sustainable development, evaluating changes in habitat quality within the park is crucial. Assessing habitat quality is essential for effective conservation within national parks, as it reflects the physical environment, ecosystem processes, and overall ecological health of a region [14]. The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is a GIS-based tool that enables rapid assessments of the impacts of various threats and land use changes on biodiversity [15]. It quantifies, maps, and values multiple ecosystem services (ESs) simultaneously and is widely used to evaluate ecosystem health. This model is particularly useful for habitat conservation planning and landscape management [16]. Globally, the InVEST biodiversity model is employed to assess habitat quality and monitor changes over time.

High-quality habitats serve as a crucial buffer against the adverse effects of climate change on diverse organisms, including ground beetles [17] and mammals of varying sizes [18]. These habitats are critical for wildlife protection, providing the necessary resources for species survival and reproduction. Fragmentation, often caused by human activities, has been shown to degrade habitat quality, reducing biodiversity and increasing species vulnerability [19]. Establishing protected areas like national parks helps mitigate these negative effects by preserving key habitats and supporting biodiversity conservation [20,21]. For example, Gibe Sheleko National Park in Ethiopia has played a vital role in improving habitat quality in the Omo-Gibe Basin, demonstrating the positive impact of protected areas on biodiversity. Importantly, habitat connectivity is crucial for enabling wildlife movement and gene flow, both of which are necessary for sustaining healthy populations [22,23]. Adaptive management strategies, such as temporary road closures, have also been effective in enhancing habitat quality by minimizing human disturbances during critical wildlife periods [24].

It is clear that habitat quality is fundamentally influenced by landscape patterns, which refer to the spatial composition, configuration, and arrangement of landscape elements [25]. These patterns can be measured using landscape indices, enabling researchers to track changes in habitat quality over time. Studies have shown that land use changes significantly impact habitat quality by reducing landscape connectivity and increasing fragmentation, which in turn negatively affects wildlife populations and biodiversity [26,27]. As such, ongoing research is vital to understand the dynamics of landscape patterns and their implications for habitat quality. By enhancing our understanding of these dynamics, we can develop more-effective conservation strategies that promote the sustainability of ecosystems and protect biodiversity [28]. Therefore, the relationship between landscape patterns and habitat quality has been a focal point in ecological research, with traditional methodologies predominantly relying on linear associations [29]. While correlation analysis [30], principal component analysis [31], and regression analysis [32] have provided valuable insights, they often neglect the inherent spatial heterogeneity present in geographic data. For instance, the effects of landscape fragmentation on species populations may differ significantly across regions due to local environmental conditions, necessitating a more nuanced analytical approach. Several studies have successfully integrated spatial heterogeneity into their analyses of landscape patterns and habitat quality. For example, a study by Hu et al. [33] employed geographically and temporally weighted regression (GTWR) and multiscale geographic weighted regression (MGWR) to analyze the relationship between landscape features and the spatial heterogeneity of habitat quality, demonstrating the importance of considering spatial contexts in ecological research. This paper aims to highlight the importance of incorporating spatial heterogeneity into the analysis of landscape patterns and habitat quality, proposing advanced spatial statistical methods that can capture the complex interactions between these variables.

The GeoDetector model emerges as an effective tool for identifying spatial heterogeneity and quantifying its driving mechanism [34,35]. This method not only assesses the relative importance of individual drivers, but also explores potential interactions among them, providing a more comprehensive understanding of the mechanism influencing habitat quality through landscape pattern. The GeoDetector has gained increasing application in both natural and social sciences [36–38]. Accordingly, this study employs the GeoDetector to investigate the driving mechanism underlying the impact of landscape pattern on habitat quality.

This study applies the InVEST model and landscape pattern indices to investigate the spatiotemporal dynamics of habitat quality and landscape configuration within the park from 2012 to 2022. Furthermore, the GeoDetector model is conducted to quantify the intricate relationship between these two variables. The research aims to (1) investigate the spatial heterogeneity and temporal trends in habitat quality within the NCTLNP and (2) explore the mechanism by which landscape pattern indices influence the spatial heterogeneity of habitat quality. The findings will contribute to a deeper understanding of the dynamic changes within the NCTLNP ecosystem, providing valuable insights for optimizing conservation management strategies for national park nature reserve systems.

2. Materials and Methods

2.1. Study Area

The NCTLNP is located in Northeast China (129°05′–131°18′ E, 42°38′–44°18′ N); the region straddles the border zone between Jilin and Heilongjiang provinces, forming a tri-border area with Russia and North Korea, as shown in Figure 1. Encompassing an area of approximately 14,100 km^2, the NCTLNP spans six administrative counties, Dongning, Hunchun, Wangqing, Muling, Ningan, and Tumen, while it is divided into three sub-areas: the core protection zone (approximately 51.95%), the general control zone (approximately 41.96%), and the population aggregation zone (approximately 6.09%). The topography of the NCTLNP is characterized by low mountains, valleys, and hills, with an average elevation below 1500 m. The region experiences a temperate continental monsoon climate, with an average annual temperature of 5 °C and approximate precipitation of 600 mm. This climate fosters a forest ecosystem dominated by temperate coniferous and broad-leaved mixed forests, with forest cover exceeding 90% of the total area. The NCTLNP serves as a critical habitat for biodiversity, boasting one species of first-grade nationally protected wild plants and fourteen species of first-grade nationally protected wild animals. Overall, the study area represents a significant biodiversity hotspot with an excellent ecological environment.

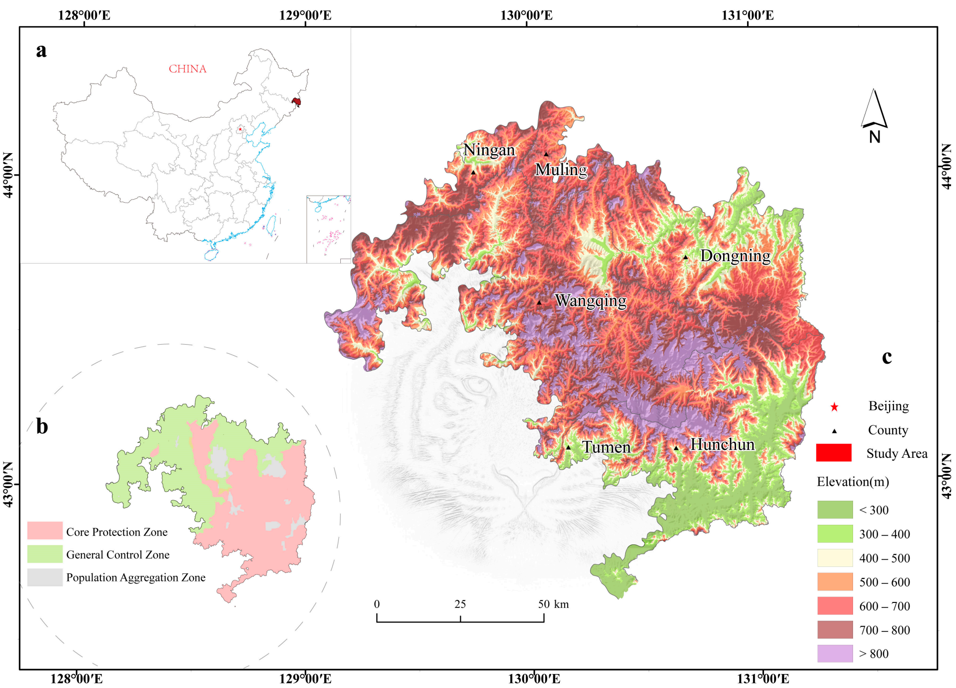

Figure 1. Spatial context of the study area: (**a**) location of the NCTLNP in China; (**b**) three management units of the NCTLNP; (**c**) topography of the NCTLNP.

2.2. Data Sources

There were three types of data in this study. (1) Land cover maps with a 30 m resolution for the years 2012, 2017, and 2022 were used as the basic data source. These maps were acquired from the CLCD dataset [39], developed by Wuhan University based on Landsat images from Google Earth Engine. The dataset includes seven land cover types within the NCTLNP: Cropland, Forest, Grassland, Water, Barren, Impervious, and Wetland. (2) Population density data for 2012, 2017, and 2022 were sourced from Worldpop (https://www.worldpop.org, accessed on 28 June 2024) with a resolution of 1000 m. This dataset was used to quantify the impact of human activities on habitats. (3) The administrative division data was defined according to the Northeast China Tiger and Leopard National Park Master Plan (2022–2030). In order to facilitate subsequent calculations, the projection coordinate system was unified as the WGS_1984_UTM_Zone_52N.

2.3. Methods

Figure 2 outlines the study framework, consisting of three stages: (1) Habitat quality assessment: Habitat quality was assessed using the InVEST model in 2012, 2017, and 2022 within the NCTLNP. (2) Landscape index calculation: Landscape indices were calculated using Fragstats in 2012, 2017, and 2022 to characterize landscape patterns within the NCTLNP. (3) Driving mechanism analysis: GeoDetector was employed to analyze the driving mechanisms of landscape patterns on habitat quality across multiple spatial and temporal scales.

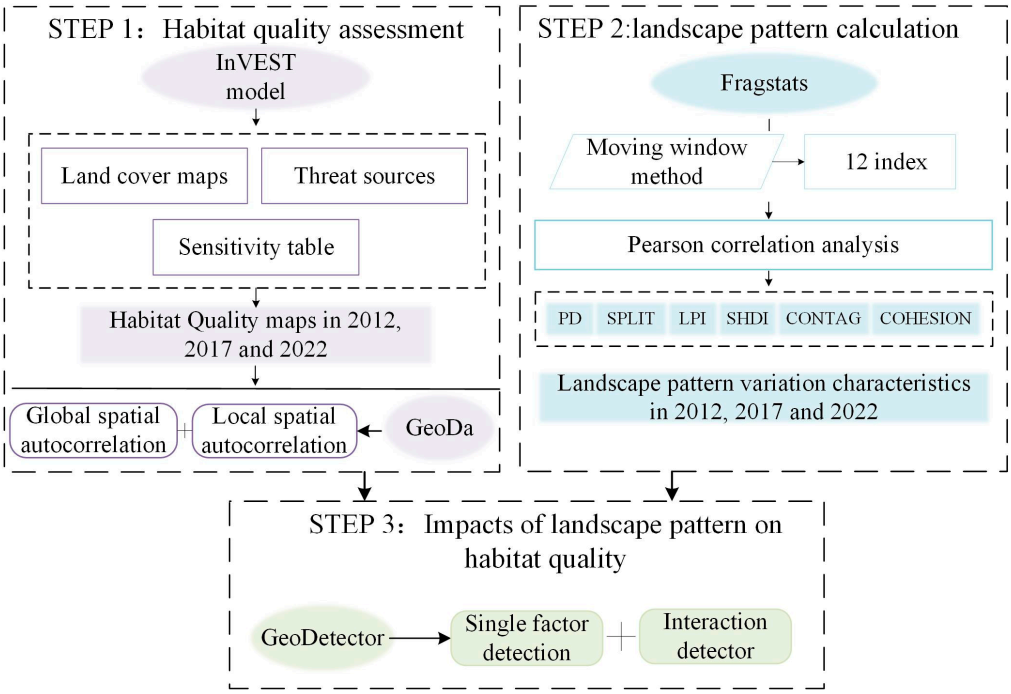

Figure 2. Framework of this study.

2.3.1. Habitat Quality Calculation

The Habitat Quality Module of the InVEST 3.11 was applied to assess habitat quality from 2012 to 2022. This module integrates land cover data with information on threats to biodiversity to estimate the extent and changes in habitat types over time. Leveraging findings from related studies and the InVEST model users' guide [40–43], a threat factor data table (Table 1) was developed, while Table 2 specifies the sensitivity of each habitat type to these threats.

Table 1. Threat factor parameter setting.

Threat	Max Distance	Weight	DECAY
Impervious	1	0.8	Exponential
Cropland	0.57	0.47	Exponential
Resident	2	0.7	Exponential
Barren	0.5	0.4	Exponential

Table 2. Sensitivity of land-cover types to each threat.

Land Cover	Habitat	Threat Factors			
		Impervious	Cropland	Resident	Barren
Cropland	0.5	0.45	0	0.5	0.1
Forest	1	0.84	0.5	0.8	0.2
Grassland	0.7	0.8	0.35	0.7	0.26
Water	0.8	0.85	0.4	0.75	0.2
Barren	0.1	0	0	0	0
Impervious	0	0	0	0	0
Wetland	1	0.86	0.4	0.75	0.33

Table 1 identifies impervious surface, cropland, resident population, and barren as threats that degrade habitat quality. Conversely, Table 2 categorizes forest, wetland, water, and grassland as high-quality habitats, assigning suitability scores of 1, 1, 0.8, and 0.7, respectively. Habitat quality is calculated by the following formula:

$$Q_{xj}= H_j(1 - \frac{D_{xj}^z}{D_{xj}^z+k^z}) \tag{1}$$

where H_j is the habitat suitability score of the land cover type j; z is the index describing the resolution, with a default value of 2.5; k is the semi-saturation constant, with a default value of 0.5; and D_{xj} denotes the habitat degradation of land cover type j in grid x within the study area, which is calculated as follows:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{W_r}{\sum_{r=1}^{R} W_r} \right) r_y i_{rxy} \beta_x S_{jr} \tag{2}$$

where y is all the rasters' on the threat raster graph of r; Y_r is a set of grid cells on r's threat raster map; R is the total number of threat factors; W_r and r_y denote, respectively, the weight and interference level to the habitat of threat factor r; β_x and S_{jr} denote, respectively, the resistance of grid x to interference and the sensitivity of the land cover type j to threat factor r; and i_{rxy} denotes the decay function of threat distance and threat intensity, ranging from 0 to 1. Impervious surfaces, cropland, residential areas, and barren exhibit exponential decay.

2.3.2. Landscape Pattern Calculation

With in-depth studies of landscape patterns, researchers have devised hundreds of landscape pattern indices to quantify various attributes of these patterns. Fragstats v4.2.1, a dedicated software program for landscape pattern analysis [44], allows for the calculation of dozens of rigorously validated landscape metrics. Given the unique landscape characteristics within the NCTLNP, twelve landscape pattern indices were chosen for analysis, as shown in Table 3. To identify the optimal resolution for capturing the spatial heterogeneity of these patterns, a scale analysis was conducted using a starting resolution of 30 m with increments of 10 m, ranging up to 300 m. As a result, a resolution of 250 m was determined to be the most suitable for landscape pattern indices. In addition, a Pearson correlation analysis was conducted on twelve landscape pattern indices, and highly redundant indices with correlations greater than 0.9 were removed to avoid multicollinearity. [45]. Finally, six indices at a 250 m resolution were chosen to characterize the landscape pattern: CONTAG for patch aggregation, SHDI for overall diversity, PD for patch density, LPI for patch dominance, COHESION for patch connectivity, and SPLIT for patch dispersion.

Table 3. Landscape pattern index description.

Index	Type	Description
CONTAG	Aggregation	Reflects different levels of patch aggregation
AI		Quantifies patch distribution and spatial aggregation in a landscape
SHDI	Diversity	Indicating that the landscape has a high information content and a rich variety of types
SHEI		Describes the degree of evenness in the distribution of different ecosystems within a landscape
LSI	Heterogeneity and Shape	Represents landscape patch shape complexity
NP		Expresses the heterogeneity of a landscape and is positively correlated with landscape fragmentation
PD		Reflects the degree of differentiation of the entire landscape
SHAPE		Reflects maximum combination of landscape type areas
AREA_MN		Reflects the one of the basic elements of landscape mosaics
LPI	Dominance	Reflects the dominance at the patch level
COHESION	Connectivity	Describes the physical connectivity of various patch types
SPLIT	Fragmentation	Describes the degree of dispersion between patches of the same type

2.3.3. Spatial Autocorrelation Analysis

Spatial autocorrelation quantifies the degree of spatial dependence between variables, revealing patterns of aggregation, randomness, and dispersion in spatial data [46]. In this study, we employed Global Moran's *I* and Local Moran's *I* to characterize the global and local spatial autocorrelation of habitat quality across the years 2012, 2017, and 2022 [47]. The calculation formulas are as follows:

$$Global\ Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (3)$$

$$Local\ Moran's\ I = \frac{n\left(X_i - \overline{X}\right)\sum_{j=1}^{m} W_{ij}\left(X_i - \overline{X}\right)}{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \quad (4)$$

where n is the total number of spatial units in study area; m is the number of spatial units geographically adjacent to the grid j; $i \neq j$, $S = 1/n\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2$; X_i and X_j represent the habitat quality value of spatial units i and j, respectively; W_{ij} represents the spatial weight matrix of units i and j; and $\overline{X}$ represents the average habitat quality value.

Global Moran's *I* ranges from −1 to 1, with a positive value indicating spatial clustering of habitat quality within the NCTLNP. Local Moran's *I* identifies four distinct cluster types of habitat quality: high–high and low–low clusters, representing areas with consistently high or low habitat quality, respectively; and high–low and low–high clusters, representing areas with inconsistently habitat quality, reflecting spatial heterogeneity, as visualized in a Local Indicators of Spatial Association (LISA) plot.

2.3.4. GeoDetector

GeoDetector is a method to measure the spatial stratified heterogeneity by statistical variance, which has been maturely applied to explore the driving mechanism of this heterogeneity in various fields. Its central idea is to quantify the correlation strength (q) between the dependent and explanatory variables by comparing the variance within strata and across the whole study area. GeoDetector offers a suite of methods for exploring spatial relationships, including single-factor and interaction detection [34]. In this study, we leverage GeoDetector to investigate the influence of landscape indices on habitat quality within the NCTLNP. The calculation formula as follows:

$$q = 1 - \frac{\sum_{i=1}^{L} N_i \sigma_i^2}{N\sigma^2} \tag{5}$$

where q represents the degree of explanatory force of a certain landscape index to the dependent variable, with a range from 0 to 1; i is the stratification of explanatory variable; N_i and N are the number of units in the stratification i and the whole area; and σ_i^2 and σ^2 indicate the exponential variance in the stratification i and the total variance.

In addition, this study utilized Table 4 as a reference to identify the potential interaction types between landscape indices and habitat quality in the NCTLNP.

Table 4. Diverse types of interaction detection.

Criteria	Interaction Detection Type
q(x1∩x2) < min(q(x1), q(x2))	Non-linear attenuation
min(q(x1), q(x2)) < q(x1∩x2) < max(q(x1), q(x2))	Single-factor non-linear attenuation
q(x1∩x2) > max(q(x1), q(x2))	Two-factor interaction enhancement
q(x1∩x2) = q(x1) + q(x2)	Mutual independence
q(x1∩x2) > q(x1) + q(x2)	Non-linear enhancement

3. Results

3.1. Variation Analysis of Habitat Quality

As shown in Figure 3, habitat quality within the study area remained consistently high from 2012 to 2022, with an average index exceeding 0.96. Excellent habitat conditions predominated, constituting approximately 94% of the total area. Conversely, areas classified as 'poor' or 'worst' accounted for a negligible proportion (0.05%), attesting to a stable habitat structure and overall optimal conditions. Moreover, spatial patterns of habitat quality were heterogeneous. Low-quality habitats were concentrated in population aggregation areas (e.g., Wangqing, Dongning, and Hunchun) experiencing rapid urbanization and associated disturbances. In contrast, the core protection and general control zones exhibited higher habitat quality due to reduced anthropogenic pressures.

As shown in Table 5, habitat quality within the study area exhibited dynamic changes between 2012 and 2022. Prior to the establishment of the NCTLNP (2012–2017), while 'excellent' habitat dominated, it experienced a decline of approximately 45.66 km^2, primarily within the general control zone. Conversely, areas with good and worst levels expanded between 24.5 km^2 and 10.61 km^2, indicative of negative anthropogenic pressures. Following the establishment of the NCTLNP pilot program in 2017, a notable shift occurred. 'Moderate', 'poor', and 'worst' habitats contracted, with a significant reduction of 45.32 km^2 in 'moderate' areas and subsequent reclassification to 'excellent'. This pattern is consistent with the broader trend in increased forest cover and reduced cropland. These findings suggest that ecological restoration measures, such as the NCTLNP's natural forest protection project, contributed to enhanced habitat quality.

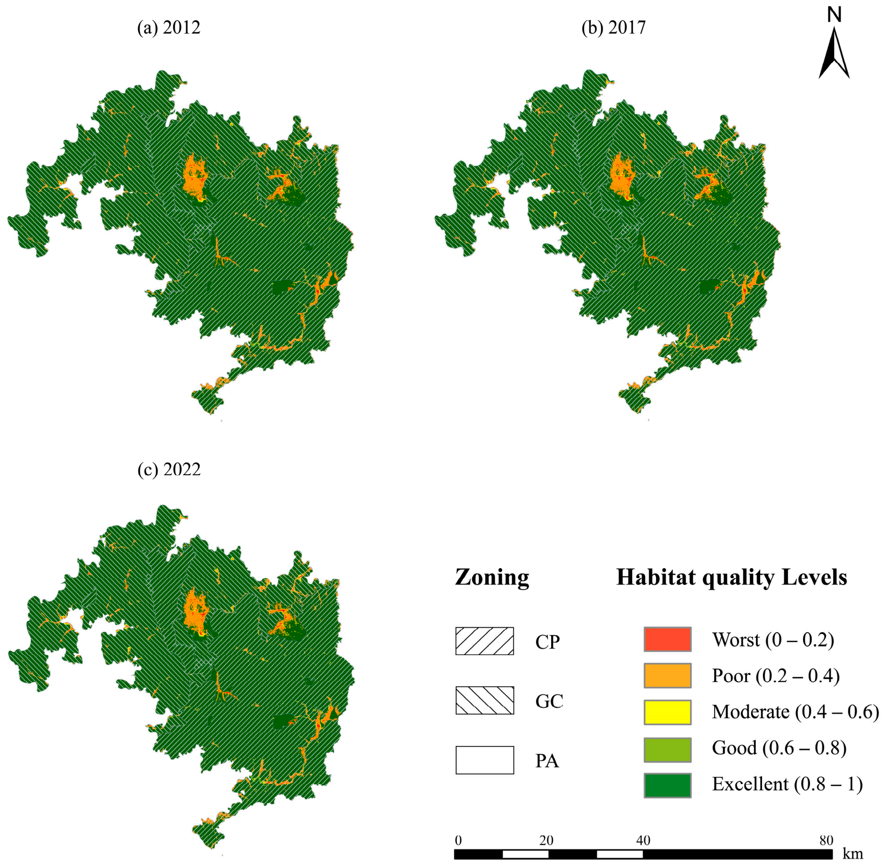

Figure 3. Variations in habitat quality from 2012 to 2022. (Note: CP = core protection zone; GC = general control zone; PA = population aggregation zone; Total = total area).

Table 5. Area (km^2) of different habitat quality levels in distinct zones from 2012 to 2022.

Levels	Zone	2012	2017	2022
		Area	Area	Area
Worst	CP	27.07	28.85	17.85
	GC	10.79	15.16	19.05
	PA	24.09	28.55	32.33
	Total	61.95	72.56	69.23
Poor	CP	0.01	0.04	0.09
	GC	0.30	0.99	0.21
	PA	0.90	1.98	0.06
	Total	1.21	3.01	0.36
Moderate	CP	170.50	162.07	143.83
	GC	173.74	189.15	172.59
	PA	331.33	333.08	322.56
	Total	675.57	684.30	638.98
Good	CP	22.23	27.11	25.00
	GC	14.84	28.75	31.22
	PA	15.51	21.22	21.45
	Total	52.58	77.08	77.67
Excellent	CP	7466.43	7468.16	7499.47
	GC	6011.37	5976.99	5987.96
	PA	550.53	537.52	545.94
	Total	14,028.33	13,982.67	14,033.37

Note: CP = core protection zone; GC = general control zone; PA = population aggregation zone; Total = total area.

3.2. Variation Analysis of Landscape Pattern

Landscape pattern dynamics within the NCTLNP were examined using a suite of indices from 2012 to 2022 (Figure 4). While overall landscape configuration remained relatively stable, specific metrics revealed notable temporal variations. The CONTAG index exhibited a general increase across all zones from 2012 to 2017, with an overall rise of 4.20%. However, from 2017 to 2022, a reversal occurred, with the CONTAG index declining in three zones, resulting in an overall decrease of 10.88%. The trends in CONTAG and SHDI were consistent, initially increasing by 5.74% but subsequently declining by 7.38%. Overall, the study area experienced 7.14% and 2.06% decreases in landscape aggregation and diversity, respectively, characterized by an increase in dominant landscape types within the core protection zone. Moreover, the core protection zone experienced significant declines of 1.17% in PD, indicative of reduced external disturbances and increased landscape homogeneity following the establishment of the national park. Furthermore, notable variations in landscape pattern indices emerged among different zones. The population aggregation zone experiencing decreased landscape aggregation, as evidenced by a 2.89% decline in CONTAG, while simultaneously demonstrating exacerbated fragmentation due to a 0.53% increase in SPLIT. In contrast, the consistent levels of CONHESION and LPI over the past decade point to the relative resilience of the landscape pattern in the NCTLNP.

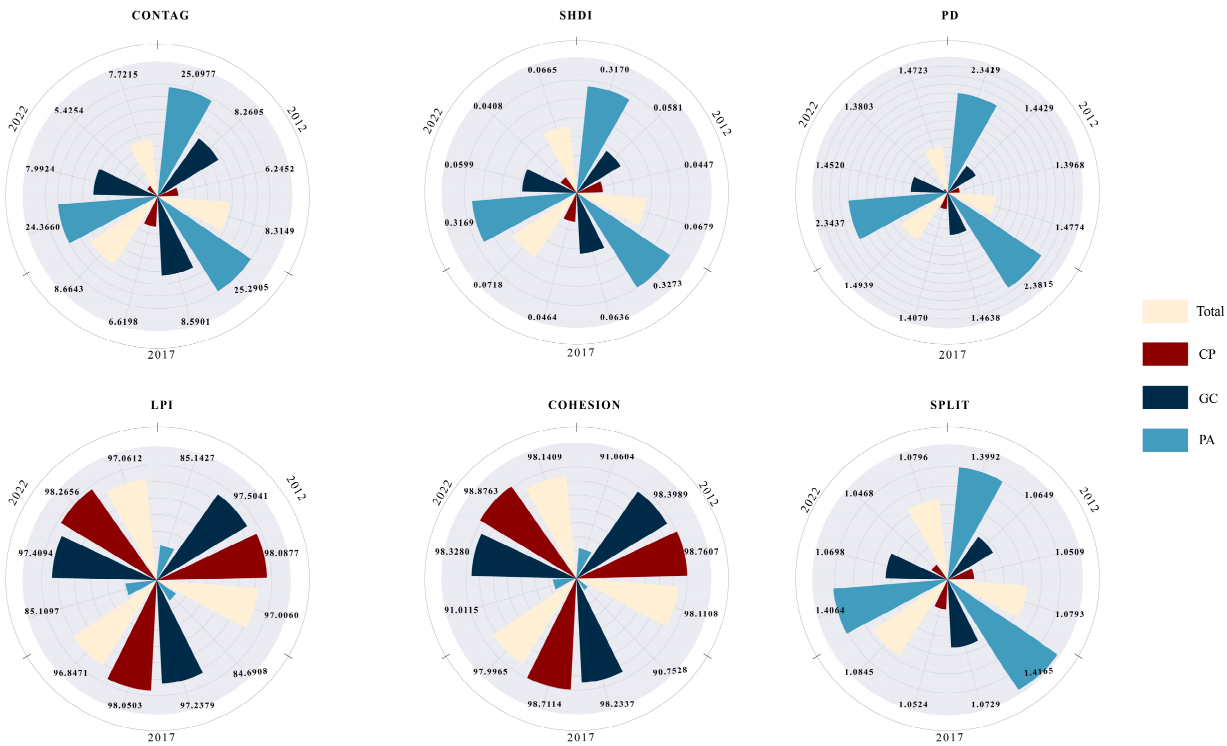

Figure 4. Variations in landscapes pattern from 2012 to 2022. (Note: CP = core protection zone; GC = general control zone; PA = population aggregation zone; Total = total area).

Spatial patterns of landscape pattern indices varied across the NCTLNP. The population aggregation zone exhibited heightened external disturbance and pronounced fragmentation, as evidenced by elevated values for CONTAG, PD, and SPLIT, coupled with reduced COHESION and LPI, indicating limited connectivity. In contrast, the core protection zone displayed lower fragmentation levels and increased landscape complexity. The general control zone exhibited intermediate characteristics, aligning with the overall study area.

3.3. Spatial Autocorrelation Analysis of Habitat Quality

To understand the spatial pattern of habitat quality within the NCTLNP, a global spatial autocorrelation analysis was conducted. As shown in Table 6, the Moran's *I* index for the three study years (2012, 2017, and 2022) was 0.652, 0.670, and 0.687, respectively, with corresponding Z-scores exceeding the critical value of 2.58, indicating statistical significance at the 1% level. These findings demonstrate that the habitat quality of the NCTLNP exhibited a significant positive spatial autocorrelation over the decade, characterized by a strong spatial clustering pattern. Furthermore, the increasing Moran's *I* value suggest that habitat quality has become more clustered over time.

Table 6. Global Moran's *I* of the habitat quality.

Year	2012	2017	2022
Moran's *I*	0.652	0.670	0.687
z	638.98	651.41	648.07
p	0.001	0.001	0.001

To further explore the spatial clustering patterns within the NCTLNP, a local spatial autocorrelation analysis was employed. As depicted in Figure 5, the NCTLNP predominantly exhibited low–low and high–low clustering patterns, with a high degree of spatial consistency over the decade. Low–low clusters were primarily concentrated in the population aggregation zone, which have experienced prolonged and intense anthropogenic pressures, resulting in a concentration of low-quality habitats. In contrast, high–low clusters were primarily located adjacent to low–low clusters, suggesting that although high-quality habitat patches exist, their distribution is fragmented and may be constrained or isolated by surrounding low-quality habitats. Moreover, the scarcity of low–high and high–high clusters suggests a relatively uniform distribution of habitat quality within the study area. This highlights the unique role of high–low clusters as ecological transition zones.

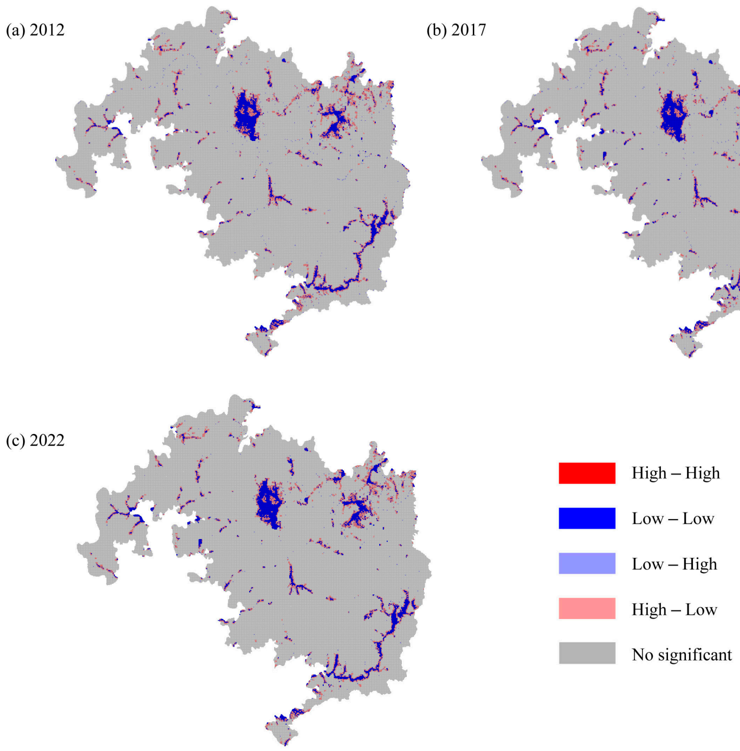

Figure 5. LISA clustering maps of habitat quality.

3.4. Geographic Detector Analysis of Habitat Quality and Landscape Pattern

To identify the primary landscape indices influencing habitat quality within the NCTLNP, a geographical detector was employed. As shown in Figure 6, all six factors exhibited significant explanatory force (greater than 0.2) in shaping habitat quality across the entire park from 2012 to 2022. Among these factors, SHDI, LPI, and COHESION consistently demonstrated the strongest influence, with average explanatory forces exceeding 0.34. This suggests that large contiguous forest areas within the NCTLNP generally correlate with high habitat quality. However, the notable influence of SHDI also highlights the importance of water bodies and wetlands in maintaining favorable habitats.

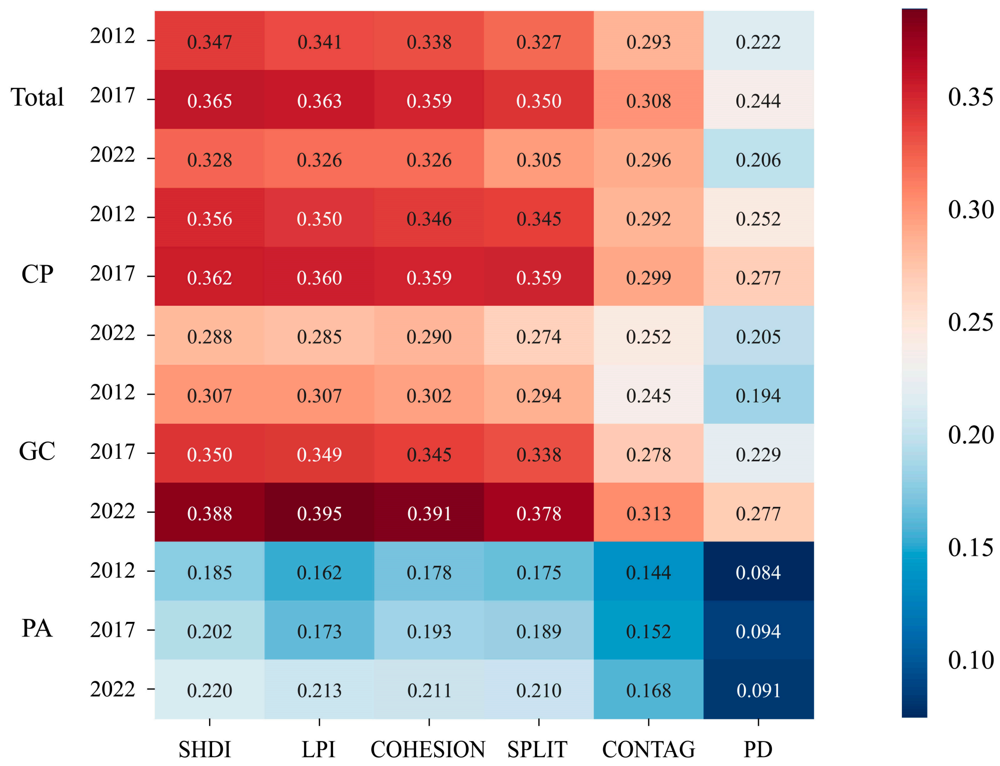

Figure 6. Single-factor detection results for the spatial heterogeneity of habitat quality. (Note: CP = core protection zone; GC = general control zone; PA = population aggregation zone; Total = total area).

The factors influencing habitat quality within the core protection zone closely mirrored those affecting the entire study area. While the relative importance of these factors fluctuated over time, the overall trends remained consistent. However, in 2022, habitat quality within the core protection zone was primarily influenced by landscape connectivity, as measured using the COHESION index. In contrast, the general control zone and population aggregation zone experienced a steady increase in the influence of all six factors. Within the general control zone, SPLIT index emerged as the vital determinant of habitat quality, with an average explanatory force of 0.347. As an ecological transition zone, the habitat quality in this region was significantly impacted by landscape fragmentation patterns. Additionally, the impact of landscape pattern indices on habitat quality within the population aggregation zone was more limited, ranging from 0.08 to 0.22, due to the predominant influence of human activities and economic development.

To understand the complex relationship between the landscape characteristics and habitat quality within the NCTLNP, we analyzed the interactions among various landscape indices from 2012 to 2022. As shown in Figure 7, the combined influence of multiple landscape factors on habitat quality distribution significantly exceeds those of individual factors, with minimal differences between interactions. This suggests that habitat quality is a complex outcome shaped by the interplay of various landscape factors. Particularly, the interaction between SHDI and CONTAG consistently emerged as the most influential factor across the entire park, emphasizing the critical roles of landscape diversity and aggregation in shaping ecological conditions within the NCTLNP. Over the decade, the interaction effect within the core protection zone initially increased but then declined, while it consistently rose in the general control zone and population aggregation zone. These shifts in factor interactions are directly tied to the spatial variation in the worst level of habitat quality. This negative change was driven by an increase in landscape diversity and a decrease in the dominance of specific habitat types. Collectively, these findings support the effectiveness of establishing the national park in fostering habitat improvement.

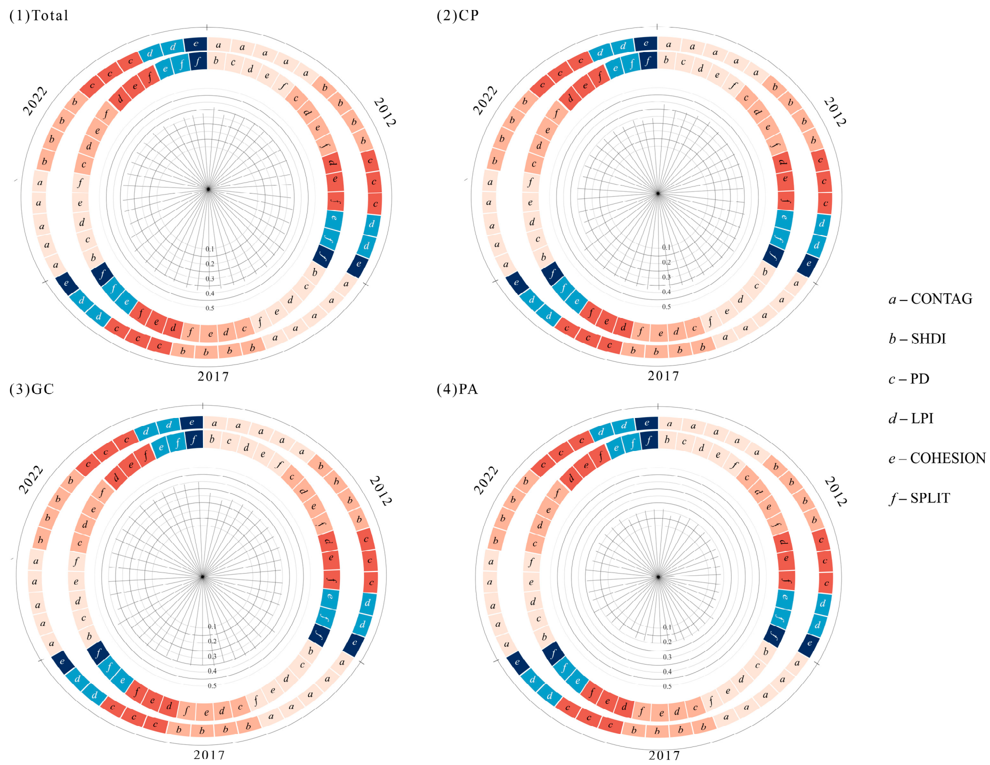

Figure 7. Interaction detection results for the spatial heterogeneity of habitat quality. (Note: CP = core protection zone; GC = general control zone; PA = population aggregation zone; Total = total area).

4. Discussion

4.1. Spatiotemporal Changes in Habitat Quality and Landscape Pattern in NCTLNP

The Northeast China Tiger and Leopard National Park (NCTLNP) in China provides the highest-quality habitat for Amur tigers and Amur leopards, hosting the largest wild breeding populations of these species. To preserve this biodiversity, the NCTLNP pilot program was launched in 2017 and became an official national park in 2021. Over 90% of the park is covered by forests, forming extensive and intact patches that are critical for habitat quality, but these areas are facing various threats [48].

Despite an overall improvement in habitat quality, significant variations exist between sub-regions of the park. This disparity arises from the park's formation through the consolidation of several pre-existing nature reserves, which had generally higher habitat quality compared to newly added areas. To address this, the Chinese government divided the park into the core protection, general control, and population aggregation zones [49]. The core zone, which contains large undisturbed habitats, boasts the highest habitat quality and minimal human interference. The general control zone, serving as a protective area around the core, supports species migration, but has slightly lower habitat quality. In contrast, the population aggregation zone—marked by higher population densities and human activities—suffers from the lowest habitat quality. Scattered human settlements spread these negative impacts across the park. The pilot program aims to improve habitat quality by concentrating populations through ecological relocation initiatives.

Between 2012 and 2022, the park experienced an initial decline in habitat quality, followed by a recovery. Before the pilot program in 2017, rapid growth and weak management contributed to habitat degradation and fragmentation. However, post-2017, government-led ecological management efforts—including the restoration of 400 hectares of prime forest and the planting of 2000 hectares of Korean pine-broadleaf forest—have gradually restored habitat quality [13]. Anthropogenic activities such as agriculture, mining, and unregulated deforestation have significantly altered the natural landscape, leading to notable changes in spatial patterns. To better understand how landscape patterns influence ecosystem health, we analyzed six landscape indices, namely SPLIT, SHDI, PD, LPI, CONTAG, and COHESION.

Land uses in the park tend to be scattered, particularly in the core and general control zones, which are predominantly forested. However, closer to populated areas, aggregation increases due to concentrated human activities and the presence of large continuous farmland. Although forest connectivity remains high overall, some sub-regions have fragmented, isolated patches of high-quality habitat with poor connectivity [50]. Between 2012 and 2022, the landscape experienced substantial fragmentation, especially before 2017. Over time, some smaller patches merged with larger areas, reducing fragmentation, but the SPLIT index shows that a degree of fragmentation persists. The core and general control zones exhibit relatively low landscape diversity due to their predominantly forested nature. In contrast, the population aggregation zone with a mix of residential buildings, agricultural fields, and vacant land have high landscape diversity. This diversity is crucial for assessing ecosystem resilience and planning for sustainable development. The establishment of the NCTLNP pilot has led to a reduction in the number of towns and villages. Consequently, villages have become more densely populated, while transition zones between sub-regions are less densely populated. The expansion of core protection and general control zones and the integration of existing large patches are expected to increase connectivity and improve overall habitat quality, benefiting both wildlife and ecological health.

4.2. Influence of Landscape Patterns on Habitat Quality

Understanding the spatial patterns of habitat quality has been a critical focus of global research, but the mechanisms behind these changes and their impact on habitat quality remain insufficiently understood. Human activities, particularly intensified land use, have driven substantial changes in landscape patterns, with anthropogenic factors influencing habitat quality more significantly than natural processes. Notably, from 2017 to 2022, habitat quality improved, largely due to the implementation of natural forest conservation projects and ecological compensation measures [40].

Among the landscape indices studied, the SHDI had the strongest explanatory power for habitat quality. In high-quality habitats, greater landscape diversity led to increased fragmentation, which embedded lower-quality habitats within better ones, ultimately reducing overall habitat quality. Conversely, in lower-quality habitats, landscape diversity could incorporate higher-quality patches, improving overall habitat conditions. Edge areas, which typically displayed higher SHDI values, were particularly vulnerable to low-quality habitat expansion due to human disturbances. Other key indices, such as the LPI and COHESION, also showed strong correlations with habitat quality. These metrics suggest that connectivity among large forest patches is crucial for expanding habitat space, particularly for species like ungulates [51]. Fragmentation, which reduces connectivity between habitat patches, significantly hampers animal movement, leading to a decline in habitat quality, consistent with previous studies.

Interaction analysis revealed that the combined effects of SHDI and CONTAG had the most significant influence on the spatial variation of habitat quality. In forest-dominated areas, where large, intact, and connected patches are the norm, these factors play a pivotal role in maintaining habitat integrity. In contrast, in areas with lower-quality habitats, such as human settlements, higher CONTAG values reflect the aggregation of degraded landscapes, which intensifies human pressures and reduces the available space for high-quality habitats. This process diminishes the positive spillover effects of adjacent high-quality habitats, resulting in an overall decline in habitat quality. Conversely, increased landscape fragmentation, as indicated by the SPLIT index, could improve habitat quality in lower-quality areas by creating more fragmented but better-distributed patches.

A study by Qi et al. [52] highlighted the relationship between human population density and species survival. They found that when population densities exceeded 400 individuals per square kilometer, the likelihood of tiger extinction rose significantly within 50 years. This suggests that in densely populated or industrial regions, increasing fragmentation may help mitigate negative impacts. On the other hand, in areas with high habitat quality, reducing fragmentation should be prioritized to maintain species viability.

In summary, the six landscape pattern indices analyzed in this study revealed distinct mechanisms driving changes in habitat quality, with SHDI exerting the most substantial influence. As land use intensifies and landscape patterns evolve, these indices will continue to shape habitat quality over time.

4.3. Limitations and Future Directions

While valuable insights were gained, the research has certain limitations. First, the land use data used to analyze the mechanisms influencing habitat quality was somewhat limited. Specifically, there was a lack of data on Korean pine-broadleaved mixed forests, which are essential habitats for tigers and leopards. Improving data accuracy and using higher-resolution data would strengthen the analysis and conclusions. Second, the study simulated habitat quality using the InVEST model, but it did not fully account for all ecosystem services. Future research should incorporate a broader assessment of ecosystem services to better evaluate the effectiveness of national conservation policies. Finally, geographical detectors are statistical tools that help understand the relative importance of different factors influencing habitat quality. Future research could explore the integration of machine learning techniques to refine the identification and assessment of these underlying mechanisms.

5. Conclusions

Landscape patterns in the NCTLNP have been significantly altered by human activities and land use changes, which have directly affected habitat quality. This paper aims to explore the influence of landscape patterns on habitat quality and proposes targeted conservation actions based on landscape pattern indices. Using the GeoDetector model, this study identifies the key drivers of habitat degradation. The results will provide valuable insights for developing effective conservation strategies for this critical biodiversity hotspot.

Our findings reveal significant spatial variation in habitat quality within the NCTLNP region. From 2012 to 2022, habitat quality within the NCTLNP remained consistently high, with stable habitat structure and favorable conditions. The establishment of the national park positively influenced habitat quality and landscape dynamics. While the core protection zone experienced improvements, the population aggregation zone continued to face challenges related to fragmentation and disturbance. Low-quality habitats in densely populated regions become increasingly clustered, as indicated by the increasing Moran's I. This highlights the need for targeted efforts to improve habitat quality in these areas. Furthermore, landscape factors significantly influenced habitat quality changes. SHDI was the primary driver of habitat quality variation, both in the entire study area and its sub-regions. The interaction between SHDI and CONTAG further explained habitat quality variation, especially in fragmented landscapes. These findings emphasize the importance of landscape heterogeneity in maintaining habitat quality and underscore the need for effective conservation strategies to address the negative impacts of human activities.

To improve habitat quality within the NCTLNP, conservation strategies should be adapted to the distinct characteristics of each functional zone. In the core protection zone, preserving habitat aggregation is crucial for preventing fragmentation and ensuring connectivity between habitats. In the general control zone, efforts should focus on ecological restoration, improving habitat quality, and re-establishing ecological corridors. In these zones, cultivated land and abandoned mining sites can be progressively converted into artificial forests, promoting forest patch continuity and mitigating fragmentation. In the population aggregation zone, such as town centers where agriculture and tourism dominate, integrating forestland into urban planning can help disperse dense human settlements, thereby reducing their negative impacts on habitat quality. By tailoring conservation initiatives to the specific conditions of each region, habitat quality can be enhanced, and the ecological integrity of the NCTLNP can be preserved.

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