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# Spatial and Temporal Changes of Habitat Quality and Its Influential Factors in China Based on the InVEST Model

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**Abstract:** The loss of biodiversity is one of the three global crises today. How to reduce habitat destruction and overexploitation to protect biodiversity is an urgent issue to be addressed. This study aims to explore the influential factors and driving mechanisms of habitat quality to find ways to reduce the interference of human activities on habitat quality. This paper evaluates the habitat quality in 30 provinces of China from 2010 to 2020 using the InVEST model and studies its geospatial differences by spatial auto-correlation. Then it investigates the influencing factors and driving mechanisms based on Geodetector and proposes strategies to improve habitat quality for different regions. The study shows that first, habitat quality is not distributed homogeneously in Chinese provinces, and habitat quality varies widely among different regions in the structure. Second, factors have different influences on habitat quality, which can be grouped into "key factors" and "auxiliary factors". Its driving forces vary greatly over time, with per capita water resources, nighttime light index, area of afforested land, forest area, and destructed forest area as key factors in both 2010 and 2020. Third, the factor pairs are all bifactor or non-linear enhanced, showing that two factors have a stronger combined effect on habitat quality than a single factor. In particular, factors such as per capita water resources and area of afforested land in very strong interactions with others. Fourth, corresponding strategies are proposed for different regions in China to improve habitat quality according to the analysis of the spatial inequality of habitat quality and its driving mechanism, providing a reference for relevant regions abroad.

**Keywords:** habitat quality; spatial and temporal variation; drive mechanism; Geodetector; China



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## 1. Introduction

Habitat quality is the ability of a habitat to offer suitable conditions for the survival of individuals or populations constantly [1,2] and shows the level of ecosystem services and biodiversity in a region [3,4]. Habitat quality, as an important indicator to measure the ecological environment, is essential to maintain the level of biodiversity [5] and is an important guarantee of regional ecological security. The rapid advance of urbanization has contributed to habitat fragmentation, degradation and even disappearance by human activities, affecting the material and energy circulation between habitats, significantly impairing habitat quality, and seriously threatening biodiversity and human well-being [6]. Therefore, exploring the spatial and temporal variations of habitat quality of the region and analyzing their spatial distribution characteristics, influential factors and driving mechanisms are helpful to formulate scientifically sustainable development countermeasures, with great significance for preserving biodiversity and maintaining the ecosystem balance [7].

The habitat quality evaluation method differs in different objects and spatial scales, and different data sources play a decisive role in the choice of evaluation methods. Early studies focused on the habitat quality evaluation of individuals and populations, mainly by field surveys [8] to obtain relevant parameters of habitat quality [9] and by constructing an index system for comprehensive evaluation [10,11]. Due to the relatively high cost of data collection, the application of the method is frequently limited to small areas and short time scales, making it hard to monitor the dynamics of habitat conditions of different types in different areas [12]. Recently with the improvement of 3S (RS, GIS, GPS) technology, the quantitative assessment of habitat quality at a regional scale [13,14] using ecological models has gradually emerged. The commonly used ones include MAXENT model [15,16], habitat suitability index (HSI) model [17,18], SoLVES model [19,20] and InVEST model [21,22]. Because of its advantages of high reliability, low data demand and easy access, high visibility of results [23,24], and significant correlation with biodiversity observations [25], the InVEST model is nowadays a widely used method for habitat quality studies [26–28], enabling the assessment of habitat quality at large scale and long time span. The studies available on habitat quality assessment cover various scales such as watersheds [29–31], provincial [32,33], urban agglomerations [34,35], metropolitan areas [36], cities [37,38], counties [39,40], nature reserves [41,42], and river corridors [43], focusing on the spatio-temporal variations of habitat quality [44,45] and the reply of habitat quality to land use changes [46,47]. The research is emerging to reveal the mechanisms driving spatio-temporal changes in habitat quality using geographic probe models [48,49].

In general, there is still room for further research and exploration in spite of numerous studies on the spatio-temporal changing characteristics, influential factors and conservation measures of habitat quality. First of all, most of the studies [29–43] focus on small and medium scales, and there is short of habitat quality evaluation at the national scale. The studies mostly analyze the habitat quality evaluation results in the whole study area, but not enough for the spatial inequality patterns of habitat quality in the entire study scope. Few studies [50] have been conducted to systematically review the spatial variation and spatial and temporal variation in habitat quality in each province of China from a geographic perspective. Secondly, the studies available have not analyzed the influential factors and driving mechanisms of habitat quality changes deeply enough. Most of the current studies have included natural environment, geographic location, anthropogenic disturbance, and socioeconomic influences in single-factor analysis models, while few studies have comprehensively explored the factors influencing habitat quality and their interactive effects. In particular, there are no studies on the geographical relationship between social activities and habitat quality [51]. Studies on the interaction of multiple influences and driving mechanisms on habitat quality using GeoDetector have focused on the influencing factors of human activities, which have rarely been covered before.

This study is conducted (1) to assess habitat quality at the national scale, identify and map hot and cold spots of habitat quality, and discover spatial and temporal changing patterns; (2) to detect the degree of influence and interaction of natural, economic, social, and land use factors on habitat quality focus on human activity-related factors; (3) to explore the drive mechanisms and propose reasonable management strategies and policy recommendations. Therefore, this paper conducts a study on 30 provinces in China. Firstly, it evaluates habitat quality by InVEST model, recognizes the spatial inequality of habitat quality using the spatial autocorrelation method, then explores the influential factors of habitat quality and its driving mechanism by Geo-Detector, and further proposes policy recommendations to supply reliable data for city administration and government policy.

## 2. Materials and Methods

### 2.1. Study Area: China

The study was conducted on 30 provincial administrations in China, excluding Tibet, Taiwan, Macau and Hong Kong (see Figure 1), because limited data were available. China is a vast country with a rich diversity of species that are complex in distribution. It has different landforms, low in the east and high in the west, roughly distributed in the stair-step shape and mainly covered by mountainous areas. The country is dominated by the typical monsoon climate, with a cold, dry wind in winter and a warm, humid wind in summer. More than 20 laws and regulations related to biodiversity conservation have been promulgated and revised in the past 10 years, providing a solid legal guarantee for biodiversity conservation. In October 2021, the first 5 national parks were established, and the construction of the national botanical garden system in Beijing and Guangzhou was started, combining in situ conservation and relocation conservation, which is a very effective way to protect biodiversity and shows the high importance the country attaches to biodiversity conservation. With urbanization in China developing rapidly, habitat quality is under increasing threat. Therefore, it is urgent to study the spatial inequality and influential factors of habitat quality in different regions to promote biodiversity in China.

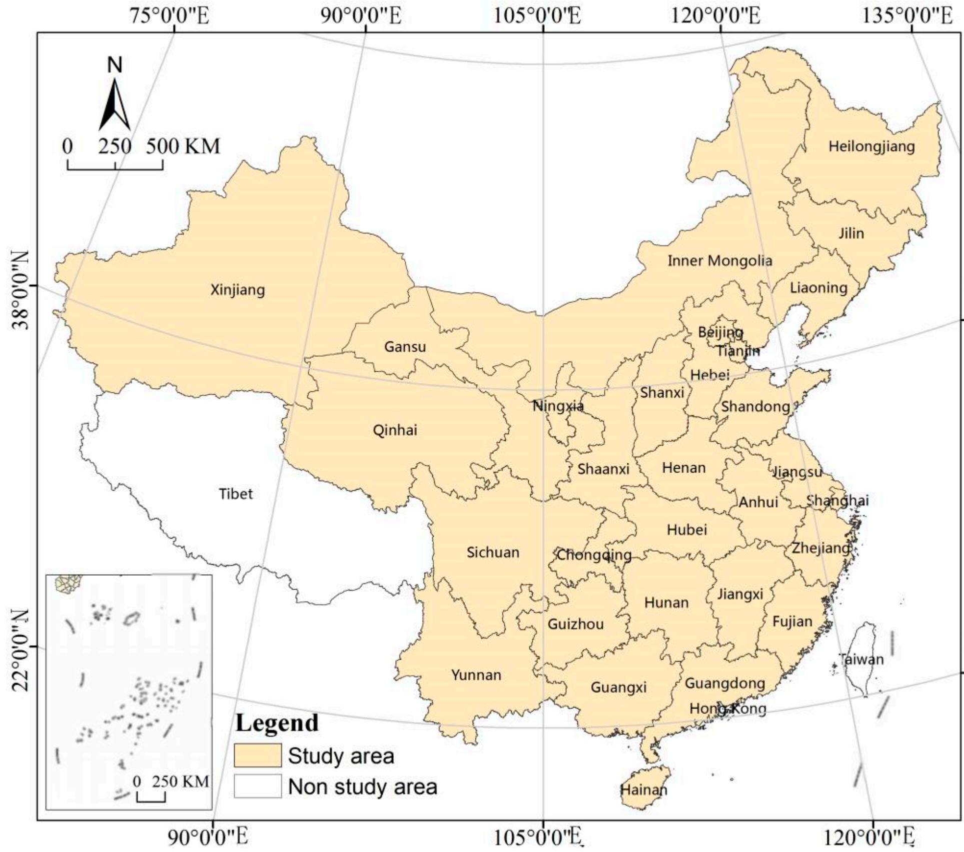


**Figure 1.** Study Area.

## *2.2. Research Methods*

### 2.2.1. Evaluation of Habitat Quality—InVEST Model

The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) model is an integrated approach for quantifying multiple ecosystem services, and its habitat quality module can be used to assess habitat quality through analyzing maps of land-use/land-cover (LULC) and the extent to which different land threaten biodiversity, making it an important tool for quantifying habitat quality [52]. In this research, the habitat quality module of InVEST 3.10 is adopted to investigate the spatial and temporal variation of habitat quality in 2010 and 2020 in 30 provinces across China. To obtain the habitat quality index value, it is necessary to calculate the habitat degradation degree first. Its calculations are available in the literature [49].

Based on the InVEST model user's guide [53], previous studies [54], and study area reality, this research set relevant parameters, including habitat threat factors (see Table 1) and the sensitivity of various types of land to threat factors (Table 2).

**Table 1.** Habitat threat factors.

| Threat Factors | Threat Distance/km | Threatened | Type of Declining |
|---|---|---|---|
| Urban land | 10 | 1.0 | exponential |
| Rural residential area | 8 | 0.8 | exponential |
| Other construction land | 9 | 0.9 | exponential |
| Cultivated land | 6 | 0.6 | linear |
| Bare land | 4 | 0.4 | linear |

**Table 2.** Sensitivity of land use types to the threat factors.

| Land Use Types | Habitat Suitability | Sensitivity | | | | |
|---|---|---|---|---|---|---|
| | | Urban Land | Rural Residential Area | Other Construction Land | Cultivated Land | Bare Land |
| Cultivated land | 0.3 | 0.8 | 0.6 | 0.7 | 0.0 | 0.4 |
| Forest land | 1.0 | 0.8 | 0.7 | 0.7 | 0.6 | 0.2 |
| Grassland | 1.0 | 0.7 | 0.5 | 0.6 | 0.5 | 0.6 |
| Water area | 0.9 | 0.7 | 0.6 | 0.7 | 0.4 | 0.4 |
| Construction land | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Bare land | 0.6 | 0.6 | 0.5 | 0.6 | 0.4 | 0.0 |

#### 2.2.2. Spatial Statistical Analysis

The spatial autocorrelation index is available for describing the regularity of the spatial distribution of a geographical phenomenon within a specific unit, mainly including global autocorrelation and local autocorrelation. Its calculations are available in the literature [55]. Spatial autocorrelation models can be used to investigate the spatial association and clustering characteristics of habitat quality [56], where the global spatial autocorrelation is used to describe the interaction of habitat quality throughout the study area and its correlation degree, while the local spatial autocorrelation decomposes the global spatial autocorrelation index to each study unit to examine the spatial correlation pattern and degree of habitat quality in each local area, and to visualize the local spatial differentiation.

To ascertain the spatial clustering features of habitat quality in 30 provinces of China, the measurement is conducted using global Moran's I and local Moran's I in the spatial statistics tool of ArcMap (ArcGIS10.2) in this study. Firstly, this paper uses global autocorrelation (Moran I) to determine whether there is clustering in the spatial pattern of habitat quality in the whole study area, and further determines its specific location and analyzes its spatial clustering characteristics by leveraging local autocorrelation (Anselin Local Moran I) [57].

#### 2.2.3. Driving Factors Analysis: Geodetector

GeoDetector [58] is an effective statistical approach to discover the spatial differentiation of geographical changes and disclose their influential factors. It can detect the different influence extent of factors in various spatial units and their mutual relations. It is now commonly used in many fields, such as ecology [59], geography [60], economics [61], and environmental science [62]. The GeoDetector [63] has four functional modules for detecting factors, interactions, risks and ecology, respectively. In the current study, factor detectors and interaction detectors are used to determine the degree of influence of each factor on the spatial inequality of habitat quality. Factor detection allows for the identification of the force of the influencing factor, and interaction detection enables us to explain the interaction between different pairs of influential factors.

Assume that the dependent variable ($Y_i$) and independent variable ($X_i$) respectively represent habitat quality and its influential factors. Factor detection results (q value) can be used to measure the level of spatial variation of $Y_i$ and the force of $X_i$ in explaining the spatial variation of $Y_i$. The use of the interaction detection results enables the identification of interactions of different driving factors, $X_i$, i.e., the analysis of whether the explanatory power of $Y_i$ is enhanced or diminished when the influential factors act together or are simply independent of each other. Five relationships emerge from the interaction between $X_i$ and $X_j$ [60].

According to data accessibility and spatial and temporal comparability, the average habitat quality index of all provinces is taken as the dependent variable in this study. Habitat quality is the outcome of the joint action of nature, economics, society, living, land use, industrial structure, science and technology innovation level, and other factors, and more complex effects may arise from the superposition of different factors. The natural environment leads to the general features of habitat distribution, and social activities play a dominant role in the variation of habitat quality [64]. Natural factors are often formed by nature over a long time, such as natural landforms and annual precipitation, and are little influenced by government policies and human activities in the short term. Therefore, this paper omits the natural factors that have been studied extensively in previous papers but focuses on the influential factors of human activities so as to propose reasonable improvement strategies. According to the research experience of Bai [64], Wang [65] and others, coupled with accessible and complete data, this research selects 14 indicators of action as the independent variables ($X_i$) in the 4 dimensions of economic level, natural condition, social activities, and land use, to investigate the influential factors and drive mechanism of habitat quality (see Table 3).

**Table 3.** Selection of indicators.

| Variable | Index | Code | Type |
|---|---|---|---|
| Dependent Variable ($Y_i$) | Habitat quality | Y | biodiversity |
| Independent Variable ($X_i$) | General public budget revenue (100 million yuan) | $X_1$ | Economic level |
| | Investment in gardening&greening (10,000 yuan) | $X_2$ | |
| | Average annual temperature (°C) | $X_3$ | Natural condition |
| | Forest area (10,000 hectares) | $X_4$ | |
| | Per capita water resources (cu.m/person) | $X_5$ | |
| | Air conditioner owned per 100 urban households (set) | $X_6$ | Social activities |
| | Nighttime light index (nW/(cm$^2$·sr) | $X_7$ | |
| | Inventions of domestic patents granted (piece) | $X_8$ | |
| | Number of national nature reserves (number) | $X_9$ | |
| | Forest Fires (case) | $X_{10}$ | |
| | Destructed Forest Area (hectare) | $X_{11}$ | |
| | Area of afforested land (10,000 hectares) | $X_{12}$ | Land use |
| | Area of green space (hectare) | $X_{13}$ | |
| | Per capita area of paved roads (sq.m) | $X_{14}$ | |

We hold that in the indicator system general public budget revenue and investment in gardening & greening mirror the government's potential and strength to support habitat quality [66]; the average annual temperature reflects the impact of natural condition; the forest area and per capita water resources reflect the advantages and disadvantages of natural resources; air conditioners owned per 100 urban households shows the indirect impact of building energy consumption [67], and the nighttime light index [68] can be employed for measuring the overall urbanization intensity [69]; inventions of domestic patent granted [70] reflect the indirect impact of scientific and technological innovation [71] on habitat quality; the number of national nature reserves shows the potential and strength of human protection of habitat quality; forest fires and the destructed forest area reflect the probability and severity of damages to habitat quality damage; the area of afforested land shows the influence of forestry production on habitat quality; the area of green space [72] reflects the ecological quality in the urban area; the per capita area of paved roads [73] reflects the potential effect of traffic on habitat quality. The study of $X_i$ and $X_j$ using GeoDetector presents the relationship between the spatial and temporal variation in habitat quality and economic level, natural condition, social activities, and land use and offers evidence for relevant policy formulation.

*2.3. Research Steps*

This research contains three aspects and seven steps (see Figure 2). One aspect is about habitat quality evaluating (1) download statistics to make raw data tables of independent variables (X) and dependent variables (Y); (2) evaluate habitat quality. The other side is spatial inequality analysis of habitat quality: (3) spatial statistical analysis of habitat quality (Y) was conducted using ARCGIS to obtain spatial differentiation. Finally, the driving factors analysis of habitat quality: (4) use Python to discretize continuous data of X and adopt quantile method to classify X; (5) import raw data of Y and classified data of X into the GeoDetector software for calculation. Compare each scheme in the results, and choose the one with the largest q-value as the final scheme when satisfying the same or higher significance level; (6) on the basis of the order of q value, establish the intensity of X's explanatory power, and calculate the average value of q of X that passes the significance test to get the intensity of the influence force; (7) analyze the factor interaction effect to reveal the drive mechanism and propose policy recommendations.

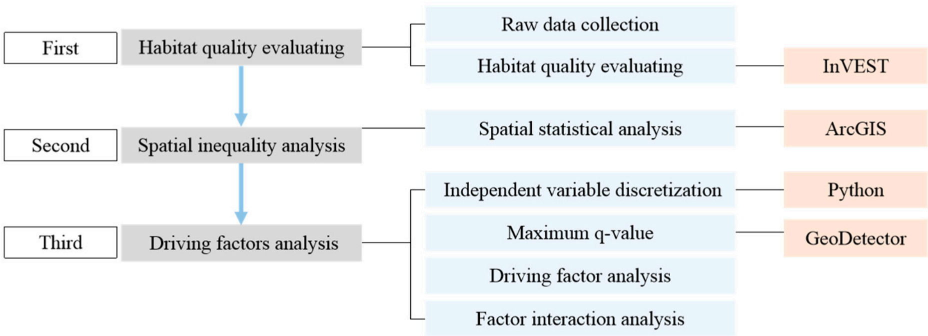


**Figure 2.** Technical flowchart.

*2.4. Data Sources*

The land use data used for the habitat quality assessment were obtained from the raster data sets of 2010 and 2020 with 1 km resolution accuracy [74]. The land use includes 6 primary types of construction land, cultivated land, water, forest land, grassland and bare land, a total of 25 secondary types. ArMap10.2 is used for data processing and graphics generation.

Influencing factor indicators mainly came from the China Statistical Yearbook (2011, 2021) [75], China Meteorological Yearbook (2011, 2021) [76], China Urban Construction Statistical Yearbook (2010, 2020) [77], and nighttime light data from China's long-term series of annual artificial nighttime light data sets (1984–2020) [78].

## 3. Results

*3.1. Analysis of Spatial and Temporal Variation in Habitat Quality*

3.1.1. Spatial and Temporal Variation in Habitat Quality

Habitat quality indexes in 2010 and 2020 were 0.671 and 0.665, respectively, and the average was 0.668, indicating good habitat quality in general. Based on the ArcGIS platform, the habitat quality was grouped into five levels, that is, low (0.000–0.297), relatively low (0.297–0.598), medium (0.598–0.941), relatively high (0.941–0.992) and high (0.992–1.000), by natural breaks to form a grading map (Figure 3). The figure shows that the habitat quality features obvious spatial inequality in the study scope, and the spatial pattern of habitat quality from 2010 to 2020 was stable in general. In 2020, for example, the areas with high values of habitat quality index were mainly in southwest China, south China, eastern Inner Mongolia, and the Daxinganling and Changbai Mountains in northeast China, accounting for 50.51% of the total study area. They were dominated by mountains, woodlands and hills, mostly with large vegetation cover, less human activities and high biodiversity levels. The areas with a relatively high value accounted for 0.57% of the total study area, a quite small percentage, distributed in spotty and band-like patterns and dominated by grassland. The areas with a medium value were in Xinjiang, western Inner Mongolia and northern Qinghai in northwest China, accounting for 24.12% of the total study area. The areas with a relatively low value were in the Northeast Plain, the Guanzhong Plain, the Sichuan Basin and the North China Plain, accounting for 21.55%. They were densely populated by cities and highly disturbed by human activities with a large portion of cultivated land. The distribution of low-value areas was highly consistent with that of construction land, and they featured a spotty pattern in distribution as the most ecologically fragile areas with the most intense human activities, accounting for 3.25% of the total.

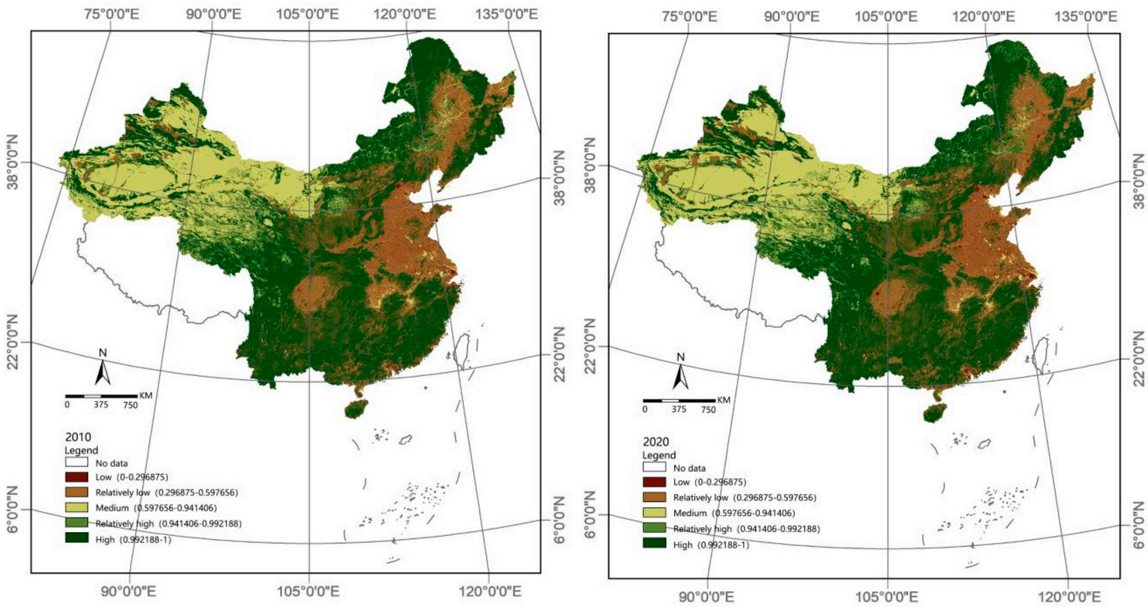


**Figure 3.** Spatial inequality of habitat quality in 2010 and 2020.

Most of the provinces experienced a decline in the index from 2010 to 2020, except for a few seeing an increase. The habitat quality index was characterized by a decline as a whole of 0.65%. Habitat quality in 26 provinces showed a decreasing trend, with large decreases in Heilongjiang, Shandong, Chongqing, and Guangxi. Habitat quality declined in two ways: first, the spatial expansion of urban construction resulted in the extension of the area with low habitat quality around the city to the peripheral regions, promoting the degradation of areas with high habitat quality, where the increased intensity of land use contributed to the expansion of threatening source land, and thus resulted in the degradation of habitat quality; second, the habitat suitability decreased, and habitat quality declined as forest land turned into other land types, grassland became construction land, cultivated land or unused land, and waters or unused land changed into construction land. Habitat quality showed a slight rise in Shanghai, Sichuan, Shaanxi and Qinghai, scattered in the distribution. It was directly related to the ecological project of restoring the forest, urban greening policy and ecological construction, where cultivated land was converted into grassland or forest land to improve habitat suitability.

The analysis of the proportion of different grades of habitat quality from 2010 to 2020 (Table 4) shows an increase in the share of low and relatively low grades of habitat quality while there was a decrease in the shared medium, relatively high and high grades, showing that the polarization of habitat quality and a decrease overall.

**Table 4.** Proportion of different grades of habitat quality.

| Grade | Habitat Quality | Proportion of Different Grades/% | |
|---|---|---|---|
| | | 2010 | 2020 |
| Low | 0.000–0.297 | 2.38 | 3.25 |
| Relatively low | 0.297–0.598 | 21.53 | 21.55 |
| Medium | 0.598–0.941 | 24.61 | 24.12 |
| Relatively high | 0.941–0.992 | 0.61 | 0.57 |
| high | 0.992–1.000 | 50.87 | 50.51 |

### 3.1.2. Spatio-Temporal Variation in Habitat Degradation

A high habitat degradation index indicates that the threat factor causes high potential damage to the regional habitat quality and a high probability of habitat quality degradation. The average habitat degradation index in 2010 and 2020 was 0.0111 and 0.0118, respectively, with a slight increase of 6.82%, indicating an increased probability of habitat quality decline. Figure 4 shows that habitat degradation was generally lower in the west and higher in the east and was advanced as the urban built-up area increased, with the highest habitat degradation in the Yangtze River Delta and the North China Plain. The reasons for the unequal spatial distribution are, firstly, the relatively high population density in these areas, the concentrated distribution of urban residential land as well as cultivated land, the high degree of damage from human activities, and the high probability of habitat quality degradation, and secondly, the fact that along with the expansion of urban and rural construction land, the habitat degradation in these areas was increasing and showed the expansion of degraded areas in space.

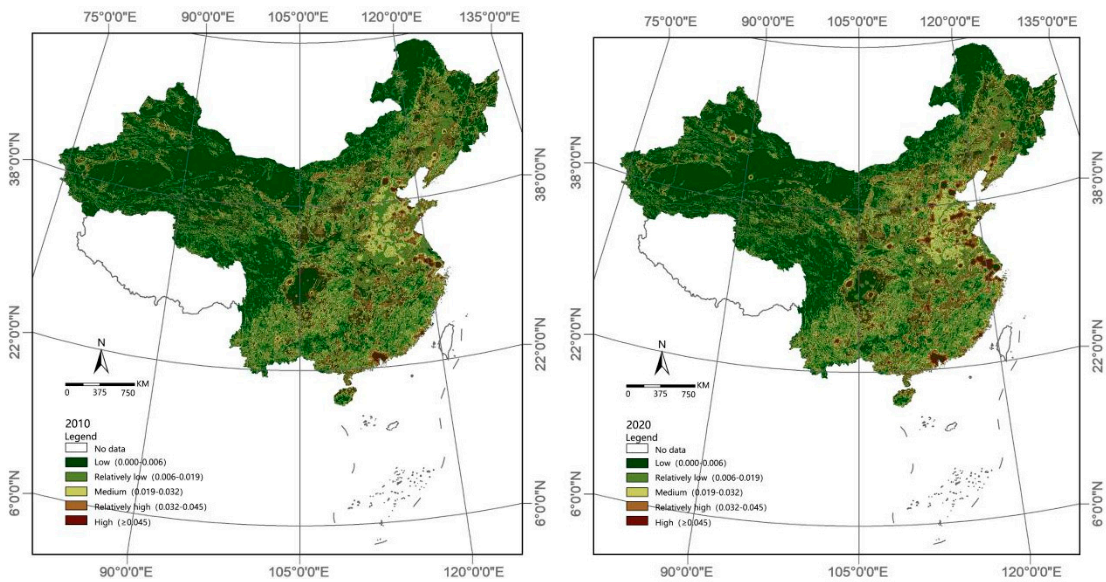


**Figure 4.** Spatial inequality of habitat degradation in 2010 and 2020.

Based on the assessment results, habitat degradation is classified into five levels: low (0–0.006), relatively low (0.006–0.019), medium (0.19–0.032), relatively high (0.032–0.045) and high (≥0.045). From 2010 to 2020, the areas with medium, relatively high and high habitat degradation increased, while the areas with low and relatively low degradation decreased (Table 5), indicating an increase in areas with a high probability of habitat degradation (areas with medium, high and relatively high degradation), a decrease in areas with a low probability of habitat degradation (areas with low and relatively low degradation), and an increased probability of overall habitat quality decline.

**Table 5.** Proportion of different degradation grades of habitat quality.

| Grade | Habitat Degradation | Proportion of Different Grades/% | |
|---|---|---|---|
| | | 2010 | 2020 |
| Low | 0.000–0.006 | 0.54 | 0.52 |
| Relatively low | 0.006–0.019 | 0.24 | 0.24 |
| Medium | 0.019–0.032 | 0.12 | 0.13 |
| Relatively high | 0.032–0.045 | 0.06 | 0.06 |
| high | ≥0.045 | 0.04 | 0.05 |

### *3.2. Spatial Statistical Analysis of Habitat Quality*

#### 3.2.1. Global Spatial Autocorrelation

The global spatial autocorrelation investigation shows a significant spatial clustering of habitat quality across the country. At a significance level of $p < 0.001$, the global Moran's I index of habitat quality in 2010 and 2020 was 0.5409 and 0.5546, respectively; the Z-scores were 4.5455 and 4.6479, respectively, indicating significant spatial clustering of habitat quality. The years 2010–2020 saw an increased Moran's I index, indicating a slightly strengthening trend in spatial clustering (see Figure 5).

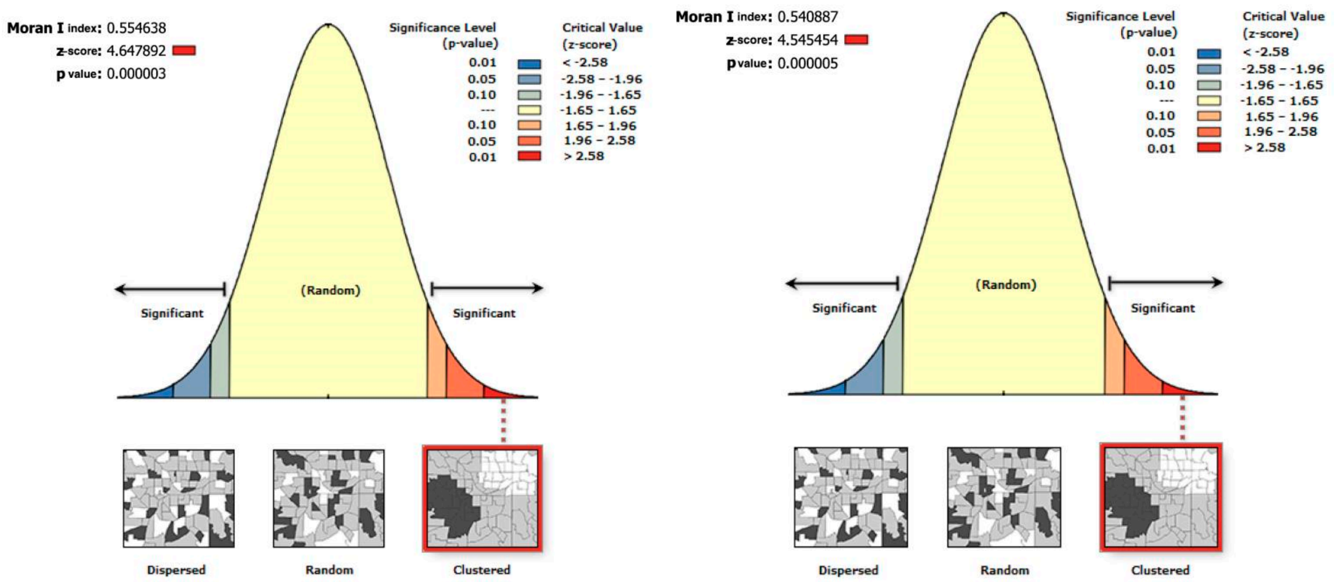


**Figure 5.** Global Moran's I analysis (2010–2020).

#### 3.2.2. Local Spatial Autocorrelation

The study area showed obvious spatial agglomeration characteristics of habitat quality (see Figure 6): the spatial clustering remained stable from 2010 to 2020, and the clustering status was dominated by high-high and low-low types, while the high-low and low-high clustering types were almost negligible, indicating high (low) clustering of habitat quality in space. Specifically, the areas with high-high clustering were continuously distributed in Guangxi and Yunnan in the southwestern study area, where natural resources are highly endowed with high habitat suitability; the areas with low-low clustering were concentrated in the eastern provinces, where the ecological environment is fragile with serious ecological degradation. Habitat quality generally showed a significant spatial dependence, with low-low clustering distribution consistent with that of low habitats and high-high clustering areas more concentrated than high habitats, showing a low degree of habitat fragmentation in these areas.

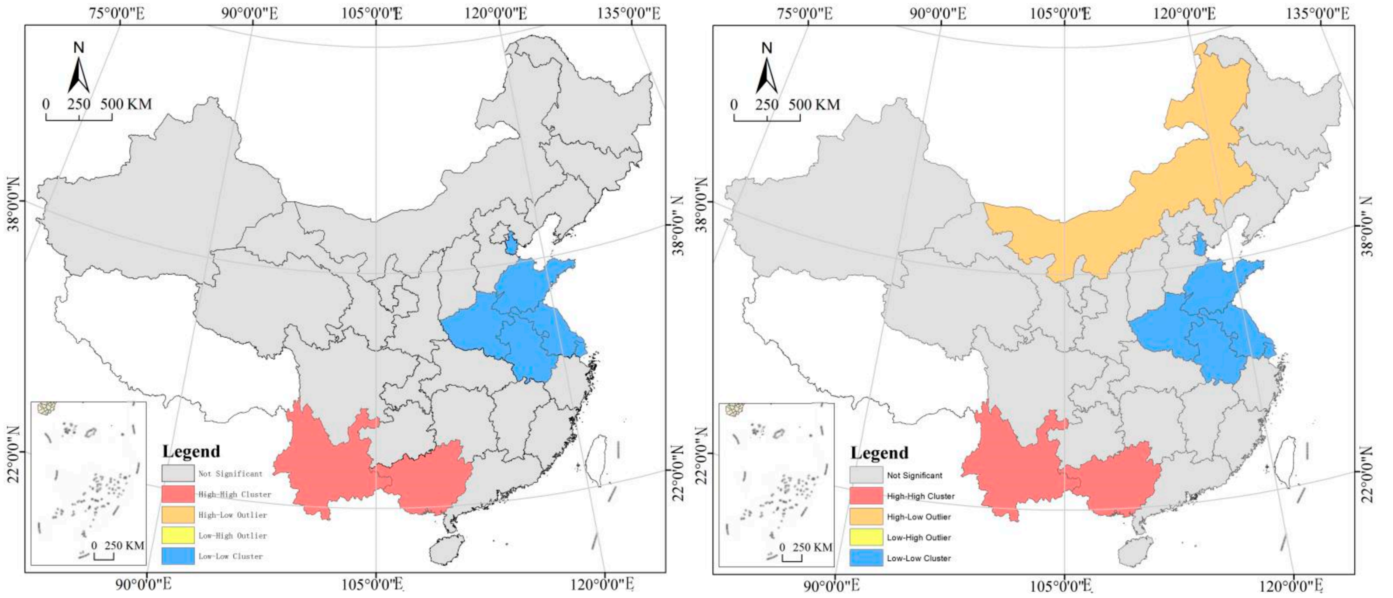


**Figure 6.** Local Moran's I analysis (2010–2020).

## *3.3. Analysis of Influential Factors of Habitat Quality*

### 3.3.1. Factor Analysis

In 2020, $X_2$ and $X_{14}$ can only pass a 10% significance test, while other factors can pass a 5% or more stringent significance test. Under the 5% significance condition, the influence factor intensity was ranked as $X_{10} > X_8 > X_5 > X_7 > X_{12} > X_{11} > X_4 > X_9 > X_1 > X_3 > X_{13} > X_6$. In 2010, $X_2$, $X_6$, $X_{13}$ and $X_{14}$ can only pass a 10% significance test, while other factors can pass a 5% or more stringent significance test. Under the 5% significance condition, the influence factor intensity was ranked as $X_5 > X_7 > X_{12} > X_4 > X_9 > X_{11} > X_3 > X_8 > X_1 > X_{10}$ (see Figure 7). From 2010 to 2020, the force of 8 factors increased, among which $X_8$, $X_{10}$ and $X_{14}$ have a greater enhancement; there are 6 factors that reduce the acting force, among which $X_9$, $X_{13}$ and $X_3$ weaken greatly (see Figure 8). It is worth noting that $X_2$ and $X_{14}$ always fails the significance test while $X_6$ and $X_{13}$ promoted to pass the 5% significance test.

Natural conditions had the greatest impact on habitat quality in 2010, while human activities had the greatest impact in 2020. The ranking of influential forces in 2010 and 2020 is quite different; the former is natural condition > land use > social activities > economic level, the latter is social activities > natural condition > land use > economic level (see Figure 9), and the influence of social activities is significantly enhanced.

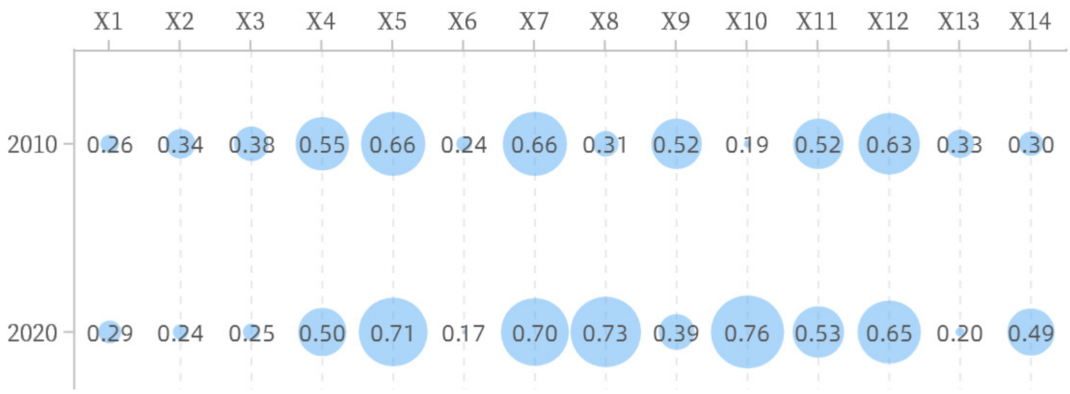


**Figure 7.** Analysis of influential factors.

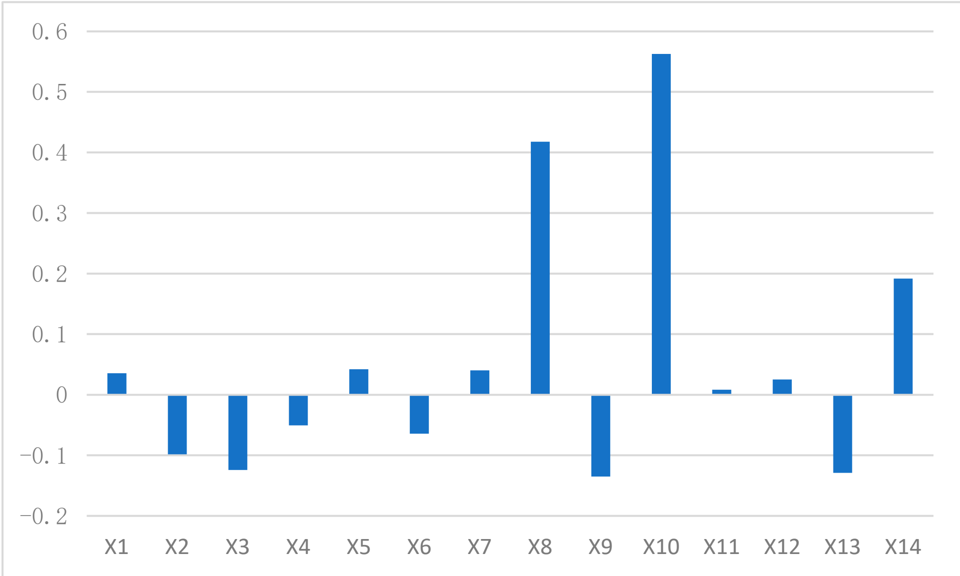


**Figure 8.** Influential factors variation from 2010 to 2020.

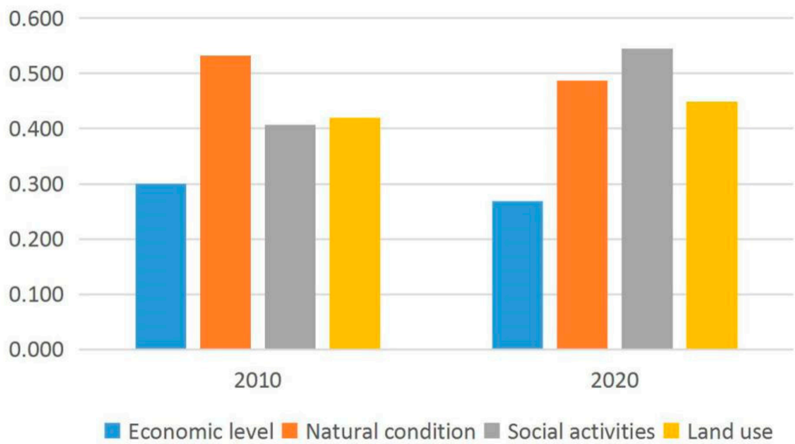


**Figure 9.** Analysis of driving forces.

The average value of the corresponding factor force (q-value) to habitat quality (y) is calculated to judge the influence on habitat quality. The average value of the 14 factors in 2020 was 0.47, while that in 2010 was 0.42.

### 3.3.2. Interaction Analysis

Under the 5% significance condition, 45 factor pairs were formed in 2010. The mean value of the interaction force was about 0.77, the least value was 0.45, and the crest value was 0.93; In 2020, 66 factor pairs were formed. The mean value of the interaction force was about 0.81, the least value was 0.31, and the crest value was 1.

Based on the average value of the interaction force of factors in 2010 and 2020 and keeping the relative balance of various factor pairs in quantity to the full, the factor pairs are divided into three categories: high, medium and low, with 0.8 and 0.9 as thresholds (see Table 6, Figure 10). Among these factors, per capita water resources ($X_5$) and area of afforested land ($X_{12}$) have strong interaction effects with others. In 2010 and 2020, the relationship between every two factors is bifactor or non-linear enhanced, and there is no independent and weakening relationship, which shows that there is a close relationship between every two factors and the combined effect of the two factors on habitat quality is stronger than that of the single factor.

**Table 6.** Analysis of the interaction factor pairs.

| | Quantity of Factor Pairs | | | | Interaction Intensity | | | Significant Interaction Factors |
|---|---|---|---|---|---|---|---|---|
| | Total | High | Medium | Low | Min | Max | Average | |
| 2020 | 66 | 22 | 19 | 25 | 0.31 | 1 | 0.81 | $X_5$, $X_{10}$, $X_{12}$ |
| 2010 | 45 | 5 | 18 | 22 | 0.45 | 0.93 | 0.77 | $X_5$, $X_7$, $X_{12}$ |

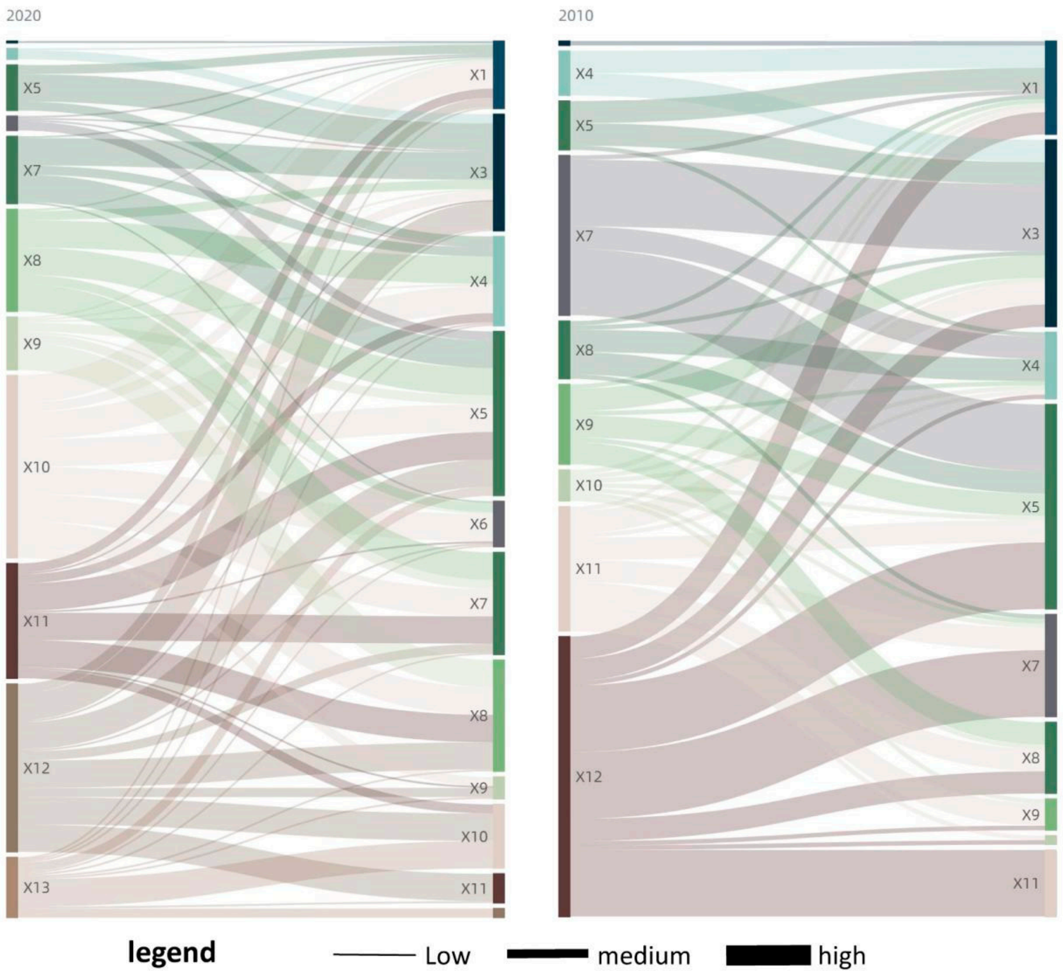


**Figure 10.** Analysis of interaction factors in 2020 and 2010.

It is worth noting that the interactions between per capita water resources ($X_5$) and area of afforested land ($X_{12}$) was the highest in 2010, reaching 0.9267. The result indicates that the interaction between per capita water resources and the area of afforested land has the largest role in promoting the growth of habitat quality in the initial phase of the research. In 2020, the interaction between per capita water resources ($X_5$) and inventions of the domestic patent granted ($X_8$) was the highest, reaching 0.9999. It indicates that with the continuous development of urbanization in China, the interactions between per capita water resources and inventions of the domestic patent granted are the main influencing force of habitat quality.

## 4. Discussion

### *4.1. Driving Mechanism*

The influential factors are divided into two grades according to the ranking and mean value of the factor forces, including "Key factors" and "Auxiliary factors." Among them, "Key factors" refers to the factors that both direct force and factor interaction force act. It is determined on the basis that the q value of the factor in 2010 and 2020 is greater than the average value. The direct force of "Auxiliary factors" is relatively weak, dominated by interaction, and the rest factors belong to this type (see Table 7). On this basis, the driving mechanisms of 14 influencing factors in four dimensions of economic level, natural conditions, social activities and land use on habitat quality are investigated (see Figure 11). The driving mechanisms of habitat quality vary greatly over time, with per capita water resources ($X_5$), nighttime light index ($X_7$), area of afforested land ($X_{12}$), forest area ($X_4$), and destructed forest areas ($X_{11}$) as key factors in both 2010 and 2020.

**Table 7.** Divided the influential factors: blue indicates "Key factors", and green indicates "Auxiliary factors".

| | 2020 | | 2010 | |
|---|---|---|---|---|
| 1 | $X_{10}$ | 0.756 | $X_5$ | 0.664 |
| 2 | $X_8$ | 0.732 | $X_7$ | 0.657 |
| 3 | $X_5$ | 0.706 | $X_{12}$ | 0.626 |
| 4 | $X_7$ | 0.697 | $X_4$ | 0.554 |
| 5 | $X_{12}$ | 0.651 | $X_9$ | 0.521 |
| 6 | $X_{11}$ | 0.526 | $X_{11}$ | 0.518 |
| 7 | $X_4$ | 0.503 | $X_3$ | 0.378 |
| 8 | $X_{14}$ | 0.495 | $X_2$ | 0.340 |
| 9 | $X_9$ | 0.386 | $X_{13}$ | 0.330 |
| 10 | $X_1$ | 0.295 | $X_8$ | 0.314 |
| 11 | $X_3$ | 0.253 | $X_{14}$ | 0.303 |
| 12 | $X_2$ | 0.242 | $X_1$ | 0.259 |
| 13 | $X_{13}$ | 0.201 | $X_6$ | 0.237 |
| 14 | $X_6$ | 0.172 | $X_{10}$ | 0.194 |

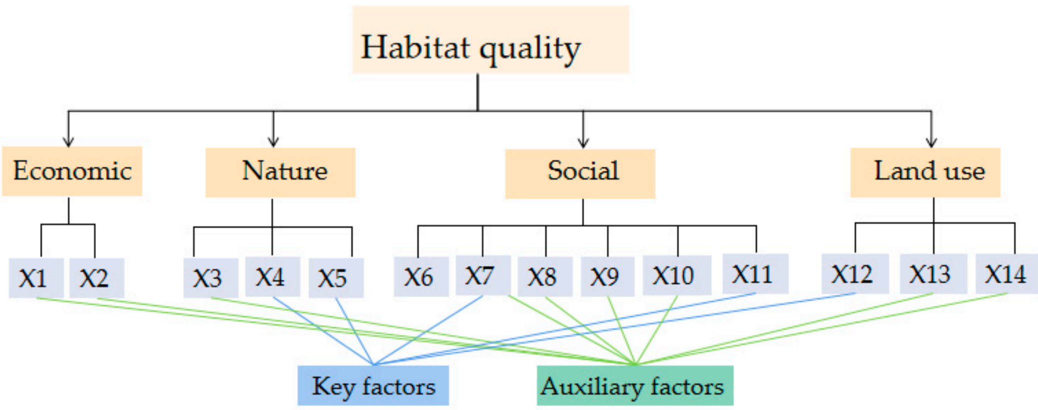


**Figure 11.** Analysis of habitat quality driving mechanism.

Some of the findings in this paper support the previous studies. For instance, Yang J et al. (2020) also found the spatial inequality of habitat quality in China [50]. The average annual temperature in terms of natural conditions has been the focus of scholarly attention [46], and in recent years, the nighttime light index in terms of social activities has received increasing attention [48]. Huang et al. (2020) suggested that technological innovation and fixed asset investment play a decisive role in mitigating the negative effects of urban and socioeconomic development on habitat quality [71]. But there are also some conclusions different or even contrary to the previous studies; for example, the study in this paper downplays the influence of the natural condition but highlights the influence of human factors on habitat quality. The factors such as destructed forest area, forest fires, number of national nature reserves, and air conditioners owned per 100 urban households in terms of social activities have received attention from few scholars. Contrary to the previous studies [79], this paper argues that the effect of population density on habitat quality is negligible, which may validate the claim of Jesús Zuñiga-Palacios et al. (2021) [80] that many of the species studied prefer relatively urbanized habitats to those that are less urbanized. It indicates that the factors affecting habitat quality are different at different scales. The new findings are of great significance for large-scale biodiversity conservation.

### 4.2. Policy Recommendations

China has made remarkable achievements in ecological progress. Although biodiversity conservation has been given sufficient attention at the national level, the corresponding regulatory measures are not sufficiently precise and synergistic and fail to address the spatial contradictions in habitat quality. As for the development trend, to "formulate policies and implement regulation on the basis of local conditions" has been the consensus of the industry, society and government [81], and to design differentiated policies in accordance with the spatial distribution of habitat quality and its drive mechanisms has become an urgent need.

For habitat quality conservation, its four driving roles at the economic level, natural conditions, social activities, and land use, as well as the interactions between them, should be taken into full account. According to the average force of the influential factors on habitat quality in 2010 and 2020, the influence of habitat quality was ranked as $X_5 > X_7 > X_{12} > X_4 > X_8 > X_{11} > X_{10} > X_9 > X_{14} > X_3 > X_2 > X_1 > X_{13} > X_6$ from the largest to the smallest in terms of force, where there was no significant difference from $X_5$ to $X_9$, so they were taken as core influential factors. With the average values of GDP per capita and habitat quality in China in the year 2020 as the benchmark, the study area is divided into four regions (see Figure 12), with the solution strategies proposed considering the specific conditions of various regions based on the previous studies (see Figure 13). The first quadrant includes Hubei, Guangdong, Fujian, Zhejiang, and Inner Mongolia, which are regions characterized by high GDP per capita and habitat quality. The fourth quadrant includes Chongqing, Shanghai, Beijing, Shandong, Tianjin and Jiangsu, which are regions characterized by high GDP per capita but lower habitat quality than the nationwide average. The first quadrant is mainly the regions in the south, and the fourth quadrant is mainly the regions in the north. The abundance of rainfall in the south is a major reason for its relatively high regional habitat quality. In terms of economic development level, these two regions are highly urbanized, and urban construction is already at a high level. For the provinces in these regions, they should develop advanced technologies ($X_8$, $X_{10}$ and $X_{11}$) including habitat restoration technologies, disaster monitoring technologies and disaster rescue technologies, and then improve lifestyles ($X_6$, $X_7$, $X_9$) and strengthen the guidance of low-carbon lifestyles, including using energy-saving products, reducing night-time activities and enhancing conservation awareness. Economically developed cities focus on the former, while less developed areas focus on the latter.

The second quadrant includes Shanxi, Qinghai, Gansu, Ningxia, Shaanxi, Sichuan, Yunnan, Guangxi, Hunan, Jiangxi, Hainan, Guizhou, Heilongjiang, and Xinjiang, which are regions with lower GDP per capita, but a higher habitat quality than the national average. The third quadrant is dominated by northern regions, including Anhui, Henan, Hebei, Jilin, and Liaoning, with GDP per capita and habitat quality both lower than the average. The regions in these two quadrants are characterized by incomplete industrialization and urbanization, and for them, urban construction is an important factor affecting their habitat quality. They should first promote a green economy ($X_1$, $X_2$) for development, including increasing public budgets, advocating a low-carbon economy, and increasing investment in greening. Secondly, they should advocate ecological development ($X_3$, $X_4$, $X_5$, $X_{12}$, $X_{13}$, $X_{14}$), including rational use of resources, expansion of green areas and optimization of land use structure. For cities with better economic development, the focus is on the former, while for underdeveloped areas, the focus is on the latter.

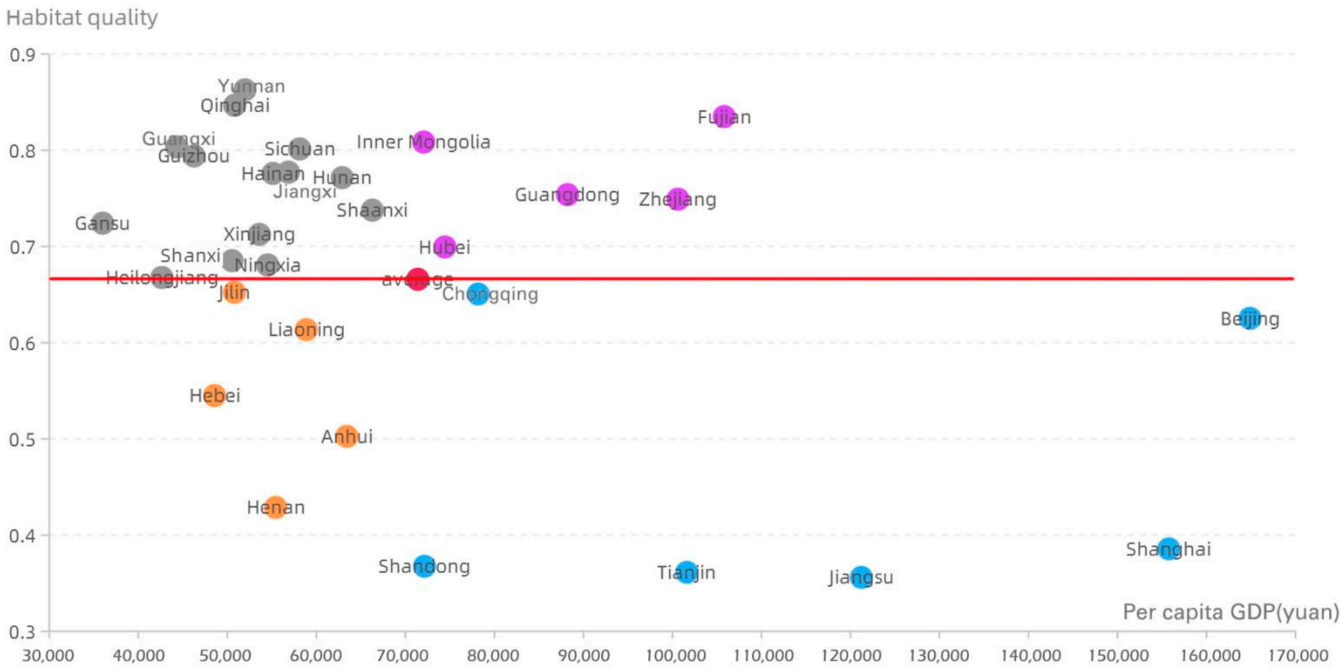


**Figure 12.** Regional division of improve habitat quality.

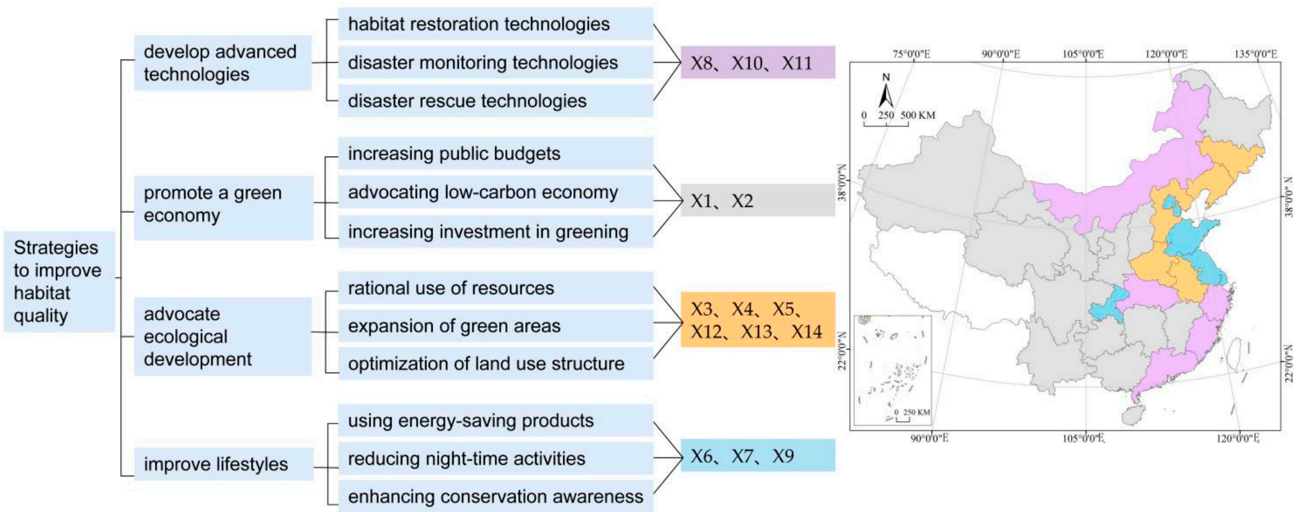


**Figure 13.** Strategies to improve habitat quality for different regions.

## 5. Conclusions

With the continuous progress of urbanization in China, human activities are increasingly interfering with land use and habitat quality, and there have been growing signs of habitat fragmentation, posing a great threat to biodiversity. The research on the driving mechanism of habitat quality and then guiding urban planning is of great practical significance. This paper empirically investigates the spatio-temporal variation from 2010 to 2020 and driving factors of habitat quality in Chinese provinces and proposes policy recommendations to improve habitat quality for different regions, to supply reliable data for city administration and government policy making.

The study shows that first, habitat quality is not distributed homogeneously in Chinese provinces, and habitat quality varies widely among different regions in the structure. Second, factors have different influences on habitat quality, with driving forces varying over time, but per capita water resources ($X_5$), nighttime light index ($X_7$), area of afforested land ($X_{12}$), forest area ($X_4$), and destructed forest area ($X_{11}$) are always key factors in 2010 and

2020; the factor pairs are all bifactor or non-linear enhanced, showing that there is a close relationship between every two factors and the two factors have a stronger combined effect on habitat quality than a single factor, including factors such as per capita water resources ($X_5$) and area of afforested land ($X_{12}$) in very strong interactions with others. Third, on the basis of the spatial inequality of habitat quality and its drive mechanism, corresponding strategies are proposed for four different region groups determined according to habitat quality and GDP per capita: developing advanced technologies, improving lifestyles, promoting a green economy, and advocating ecological development.

This research creates a new study perspective and scale for researchers in ecology, environmental science, and urban and rural planning to analyze the spatio-temporal variation of habitat quality and its influential factors. It contributes to uncovering the development pattern and driving mechanisms of habitat quality with great theoretical significance and, at the same time, provides valuable data for governments to formulate policies and city administration with great practical significance for the improvement of habitat quality in China. The methods and findings of this research also have a great reference value for studies of habitat quality change in cities and regions. The shortcoming of this study is that although the habitat module of InVEST model is relatively mature and has obtained good results in quantitatively and visually expressing the habitat quality in large and medium-scale areas, some of its parameters mainly come from the model manual and related research, which leads to the difficulty in field detection, verification and correction, making the results somewhat subjective, which requires further study in the future. This research explored the spatial inequality of habitat quality and its drive mechanism of 14 factors at the national spatial scale, and we will include more potential factors in further study to further reveal the driving mechanism of habitat quality so as to improve habitat quality and better protect biodiversity.

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