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The Impact of Human Activity Expansion on Habitat Quality in the Yangtze River Basin

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Abstract: Globally, natural habitats have suffered tremendous damage from human activities, a phenomenon that is increasingly evident in basin regions. The management of natural habitats in basin regions is dependent on understanding of the various impacts of human activities on these ecosystems. Despite the various studies that have been conducted on the effects of human activities on habitats in basin regions, there is still a lot of doubt regarding the impact of these activities on the quality of basin ecosystems. To fill this gap, this study employs a series of spatial analysis methods and logistic regression modeling to delve into the spatial and temporal patterns of human activities and habitat quality in the Yangtze River Basin (YRB) as well as the differences in the impacts of human activities on habitat quality in the sub-basins of the YRB. The findings indicate a 0.408% decline in the overall environmental quality of the YRB area from 2000 to 2020, accompanied by a 15.396% surge in human activities. Notably, the southeastern Qilian Mountains and the mountainous regions in the northwestern sector of the Sichuan Basin emerge as pivotal areas for habitat quality restoration. Conversely, the southwestern Qilian Mountains and the urban clusters in the Yangtze River Delta (YRD) face significant habitat quality deterioration. Spatial regression analyses reveal a noteworthy trend: the burgeoning human activities in the Yangtze River region pose a substantial threat to habitat recovery efforts. Further differential analyses focusing on the upper, middle, and lower basin segments underscore that human activities exert the most pronounced impact on habitat quality within the lower basin region, while the upper basin experiences the least influence. The implications of this study are manifold. It furnishes valuable policy insights for the comprehensive management and targeted preservation of habitats across the YRB. By delineating areas of habitat restoration and degradation and highlighting the differential impacts of human activities across basin segments, this research lays a solid foundation for informed decision making in habitat conservation and ecosystem management within the YRB.

Keywords: habitat quality; human activities; spatial analysis; spatial regression; Yangtze River Basin

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1. Introduction

Globally, the expansion of human activities is having a major impact on natural habitats, seriously threatening ecosystem function and integrity. Human activities, such as the expansion of impervious surfaces, agricultural practices, population growth, and economic development, are causing irreversible damage to natural habitats, with basin regions experiencing increasingly pronounced effects [1,2]. Understanding the intricate interplay between human activities and natural habitats within the Yangtze River Basin (YRB) is imperative given its status as the third-largest basin globally [3]. The ramifications of habitat degradation in this region are profound, potentially leading to ecosystem collapse, compromised water quality, climate instability, and threats to species survival.

Such challenges underscore the urgency of comprehensively assessing habitat quality and quantifying the impact of human expansion on it across the YRB [4–6]. At present, research on the spatial dynamic relationship between human activities and natural habitats within the Yangtze River Basin is still relatively weak. This knowledge deficit hampers the development of effective policies aimed at conserving biodiversity and managing basin resources sustainably. Addressing this gap necessitates a quantitative evaluation of habitat quality in the YRB and a thorough investigation into the varying impacts of human activity expansion across different regions. By conducting a rigorous assessment of habitat quality and its relationship to human activities, policymakers can gain invaluable insights into the conservation needs of the Yangtze River and devise evidence-based strategies for integrated basin management. These efforts are essential for safeguarding the ecological integrity of the YRB and ensuring the long-term sustainability of its diverse ecosystems.

Habitat quality (HQ) is a visual representation of the goodness of natural habitats in an area. It indicates the ability of an area's ecosystems to provide habitats for all organisms, including humans, and can provide a visual indication of biodiversity [2,7,8]. Measures of habitat quality are still inconsistent and focus mainly on field surveys and model assessments [9]. Field surveys are used to collect data manually to obtain species richness data within a geographic area of interest to calculate HQ [10], which can also be used to explore population structure [11]. This approach requires a great deal of time and effort, and collecting data in a vast study area such as the Yangtze River Delta Basin is particularly challenging [7]. Approaches to constructing models for assessment include integrating data from multiple sources to assess HQ models [12], pressure–state–response (PSR) assessment systems [13], and constructing regional HQ measurement models based on habitat attributes in the measurement area [14]. These methods are applicable to different regions and in some aspects cannot accurately reflect the specificity of regional ecosystem structure [15]. Recently, with the popularization of HQ models and the advancement of remote sensing imaging technology, the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model, a constructed ecosystem valuation model, has incorporated threat metrics in assessing ecosystem threats and has been used to scrutinize the importance of various ecosystems. The InVEST model employs threat metrics to measure ecosystem threats, and ecosystem suitability is assessed in high quality (HQ) to efficiently calculate regional HQ. It is capable of comprehensively assessing changes in HQ across a wide range of scales and time horizons, and it adapts well to changes in ecosystem structure. Previous studies have demonstrated its robustness in HQ assessment [2]. Previous studies have extensively assessed the spatial and temporal patterns of HQ at the national scale [16], the regional scale of small watersheds [17], the provincial scale [18], and the urban agglomeration scale [19]. However, HQ assessment at the regional scale of large watersheds is still lacking, especially for large watershed regions such as the Yangtze River Delta. Meanwhile, previous studies failed to reveal the differences in the impacts of human activities on habitat quality among different sub-watersheds, which makes it difficult to refine the integrated watershed management policy in a larger policy context. Therefore, analyzing spatial and temporal HQ patterns under sub-basins in the YRD region and the Yangtze River Basin is crucial for grasping the current status of habitat conservation in the region and predicting future trends.

Contemporary human activities (HA) have had a profound impact on HQ, leading to habitat loss and contributing to global climate change [20]. Humans have destroyed pre-existing natural ecosystems in order to develop land, build towns and cities, mine, and produce energy, resulting in the reduction or loss of wildlife habitats [21]. Human transportation and power infrastructure has cut up otherwise contiguous habitats into isolated fragments, affecting species migration, communication, and reproduction, and reducing biodiversity [22]. Human activities such as pollution, overgrazing, and deforestation degrade the quality of habitats and reduce their functions and services. Human activities such as industry, agriculture, and transportation emit large amounts of greenhouse gases, which lead to an increase in global temperatures, affecting the hydrological, soil, and vegetation conditions of habitats and threatening the adaptation and survival of species [23]. In previous studies, various methods, such as correlation modeling [20], panel regression modeling [20], and Geodetector [24,25], have been used to measure the extent of the impacts of HA on HQ, providing rich theoretical and methodological support for this study. However, previous studies lacked differential analysis of the specific impacts of HA on HQ in the upper, middle, and lower reaches of the Yangtze River, which largely hindered the implementation of targeted biodiversity conservation efforts [26]. Although spatial de-marginalization and spillover effects between HA and HQ are recognized, previous methods lacked the ability to accurately address these spatial dynamics, resulting in imprecise estimates [27]. Therefore, it is crucial to incorporate spatial effects when analyzing the impact of HA on HQ [2]. Existing studies have explored the effects of HA on HQ at the national, city cluster, and eco-regional scales and found predominantly negative impacts [2,28,29], but there are gaps in the understanding of these impacts at larger watershed regional scales, such as that of the Yangtze River Delta region. Therefore, it is necessary to conduct a detailed study of the changes in the impacts of HA on HQ in the upper, middle, and lower reaches of the Yangtze River Basin.

The Yangtze River, the third-largest river in the world, is well known for being China's largest basin region and a global leader in hydroelectric resources. The river traverses a vast geographic area with abundant natural wealth, diverse industrial chains, and a highly prosperous economic system [30]. The Yangtze River Basin (YRB) holds significant importance for China's socio-economic development and ecological security [3]. Presently, conservation efforts for the Yangtze River have garnered considerable attention both domestically and internationally [31]. However, the rapid development of the Yangtze River Economic Belt poses a serious threat to ongoing conservation initiatives and integrated YRB management. Therefore, studying the spatial relationship between human activities and HQ in the YRB can offer policy recommendations for promoting green and sustainable development within the economic zone. Additionally, it can provide valuable insights for enhancing Yangtze River conservation and integrated YRB management practices.

To tackle these challenges, this study conducted spatial analyses and investigated the spatial and temporal dynamics of the impacts of human activities on HQ in the Yangtze River Basin and its sub-basins using land-use data and the Human Footprint Index (HFI). The aim was to provide policy insights for integrated management and targeted habitat conservation measures in the Yangtze River Basin region [32]. By delineating areas of habitat restoration and degradation through the interpretation of data analysis results and emphasizing the different impacts of human activities on watershed segments (upper, middle, and lower), this study further advances the progress of integrated watershed habitat management, accelerates the progress of identifying vulnerable areas of habitats, and establishes a solid foundation for informed decision making on habitat conservation and ecosystem management within the YRB watershed. Therefore, this study had three primary objectives: (1) to assess spatial and temporal changes in habitat and human activities (HAs) within the YRB, (2) to investigate the spatial relationship between HA and HQ, and (3) to analyze changes in the effects of human activities on HQ.

2. Methods

2.1. Habitat Quality Measrements

Among many ecological assessment modeling methods, the InVEST model has significant advantages in spatial analysis and accuracy. This study evaluated HQ in the YRB using the HQ module of the InVEST model [33], which primarily relies on biodiversity and ecosystem structure indicators to gauge habitat and vegetation types along with their degradation status. It incorporates data on threat factor sensitivity and external threat intensity across various land-use types to model HQ [2,34,35]. In this study, the land-use data were reclassified to confirm their weights, and the sensitivity data were obtained by adding the threat factors of different types of land to habitat quality, as shown in Tables 1 and 2. Specific habitat indices were calculated using the following equation:

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

where H_j is the habitat suitability of land cover type j, D_{xj} is the degree of habitat degradation of raster cell x in land-use class j, j is a half-saturation constant, z is a constant, and Q_{xj} is the HQ, which usually ranges from 0 to 1, where the closer the value is to 1, the better the quality of the habitat.

Table 1. Threat sources and their weights.

Code	Threat Source	Maximum Distance (km)	Weight	Decay Type
I	Urban and rural construction land	12	0.28	Exponential
II	Other construction land	8	0.19	Exponential
III	Farmland	3	0.11	Exponential
IV	Desert	10	0.25	Exponential
V	Gobi	6	0.14	Exponential
VI	Bare	3	0.03	Exponential

Table 2. Habitat suitability and its relative sensitivity to different threat sources.

Land-Use Type		Habitat Suitability	Threat Source					
Code	Name		I	II	III	IV	V	VI
11	Paddy field	0.60	0.65	0.45	0.35	0.30	0.25	0.10
12	Arid land	0.40	0.60	0.40	0.30	0.30	0.30	0.20
21	Forest land	1.00	0.70	0.50	0.60	0.45	0.30	0.10
22	Shrubwood	1.00	0.60	0.40	0.40	0.35	0.20	0.10
23	Open forest land	1.00	0.90	0.80	0.70	0.65	0.30	0.10
24	Other forest land	1.00	0.85	0.75	0.70	0.65	0.30	0.10
31	High-cover grassland	0.80	0.55	0.60	0.50	0.80	0.35	0.10
32	Medium-cover grassland	0.75	0.60	0.70	0.55	0.85	0.40	0.10
33	Low-cover grassland	0.70	0.65	0.80	0.60	0.75	0.40	0.20
41	Graff	1.00	0.80	0.30	0.65	0.65	0.35	0.10
42	Lake reservoir	1.00	0.85	0.35	0.70	0.85	0.40	0.10
45	Bottomland	0.60	0.85	0.35	0.70	0.60	0.40	0.20
51	Urban land	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52	Rural residential land	0.00	0.00	0.00	0.00	0.00	0.00	0.00
53	Other construction land	0.00	0.00	0.00	0.00	0.00	0.00	0.00
61	Desert	0.10	0.10	0.10	0.10	0.10	0.10	0.10
62	Gobi	0.10	0.10	0.40	0.10	0.60	0.10	0.10
63	Bare	0.20	0.15	0.20	0.10	0.50	0.30	0.10
64	Marshland	1.00	0.60	0.60	0.70	0.60	0.35	0.20
67	Other	0.10	0.10	0.10	0.10	0.20	0.10	0.10

Drawing on prior research and referencing established methodologies [36], this study configured the model parameters necessary for operating the HQ module within the InVEST model. These parameters were tailored to the specific characteristics of the study area, as depicted in Tables 1 and 2.

2.2. Calculation of the Human Footprint Index

In this study, we utilized the Human Footprint Index (HFI) [37] to assess human activity strengths and weaknesses. This dataset comprises eight variables representing various aspects of human pressure on the built environment, including population density, nighttime lighting, farmland, pastureland, roads, railroads, and navigable waterways. Following Sanderson and Venter's methodology, annual dynamic data on the global terrestrial human footprint from 2000 to 2020 were developed. The magnitude of human activity intensity within each grid was calculated using the zonal statistics function of ArcGIS 10.8.

2.3. Hotspot Analysis

Hotspot analysis is often used to determine whether a geographic object has a statistically significant low or high value in its spatial distribution and is a type of local autocorrelation analysis that identifies the location of spatial clustering of high or low values for HQ in a study area [38]. Meanwhile, hotspot analysis has also been widely used to assess changes in demographic crime analysis, changes in market resources, changes in geosocial network trends, and changes in high and low values for HQ in the field of ecology and the environment [39]. Hotspots and coldspots denote statistically significant areas with high and low values, respectively. In hotspot analysis, confidence intervals of 90%, 95%, and 99% are typically used, with larger intervals indicating higher confidence levels. Hotspot analysis identifies areas of high (hotspots) and low (coldspots) values in geospatial data, offering insights into their statistical significance [40]. The formula for hotspot analysis is as follows:

$$G_i{}^*(d) = \frac{\sum_{j=1}^{n} w_{ij}x_j - E(\sum_{j=1}^{n} w_{ij}x_j)}{s\sqrt{\sum_{j=1}^{n} w_{ij}{}^2 (x_j - E(\sum_{j=1}^{n} w_{ij}x_j))^2}} \tag{2}$$

where $G_i^*(d)$ is the G_i^* statistic computed at a distance threshold d; w_{ij} is the spatial weight between point i and point j in geospatial space, which is usually determined based on the distance; x_j is the value of the attribute at point j; Σ denotes the summation of all the neighboring points j; $E\left(\sum_{j=1}^{n} w_{ij}x_j\right)$ is the expected mean value; and s is the standard deviation.

The value of the G_i^* statistic can be used to identify hot- and coldspots. If the value of $G_i^*(d)$ is greater than zero, this indicates that there is a spatial aggregation of attribute values at point i with those of the surrounding points, i.e., it is a hotspot. If the value of $G_i^*(d)$ is less than zero, the attribute value at point i is spatially dispersed from the attribute values at the surrounding points, i.e., it is a coldspot. The larger the absolute value of $G_i^*(d)$, the more significant the hotspot or coldspot. This is a basic formula for calculating spatial hotspots, and it can be extended and adjusted according to the specific situation in practical applications [41].

2.4. Bivariate Spatial Autocorrelation

Spatial autocorrelation analysis assesses potential interdependencies between variables within the same geographic area [42]. These dependencies typically fall into two main categories: global spatial autocorrelation (Global Moran's I) and local spatial autocorrelation (Local Indicators of Spatial Association, LISA). Global spatial autocorrelation characterizes the overall spatial distribution pattern to ascertain if the data exhibit spatial clustering. It quantifies the global spatial autocorrelation using Moran's I statistic, which has a range of [−1, 1]. A Moran's I value greater than 0 suggests positive spatial autocorrelation, with values closer to 1 indicating more similar aggregation patterns in the data. Local spatial autocorrelation analysis is another method based on global spatial autocorrelation, which identifies the presence of spatial agglomeration centers in a given geographic location. LISA analysis can help to determine in which regions data values are significantly similar to each other and the extent of these similarities. This helps to reveal spatial heterogeneity, i.e., data at different locations within a region may exhibit different patterns of aggregation [43]. Spatial autocorrelation analysis aids in comprehending the spatial distribution characteristics of data, facilitating a deeper understanding and interpretation of potential relationships among geographic data. Global and local spatial autocorrelation analyses provide different levels of insight that help to more precisely locate and understand patterns of aggregation and dispersion in spatial data. The following equation is used to calculate Moran's I values:

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n} (x_i - \overline{x})^2} \tag{3}$$

where I is Moran's I statistic; n is the total number of spatial cells; w is the sum of the spatial weights; x_i and x_j are the values of the variables at positions i and j, respectively; $\overline{x}$ is the mean value of the variable across all positions; and w_{ij} is the spatial weight between positions j.

Moran's I statistic takes values from −1 to 1. Positive values indicate spatial clustering (similar values close to each other), negative values indicate spatial discretization (different values close to each other), and values close to zero indicate that the spatial pattern is approximately random. This statistic is widely used in spatial analysis to assess the presence of spatial autocorrelation in a dataset. If the calculated Moran's I value is significantly different from the value expected under spatial randomness, this indicates the presence of spatial autocorrelation in the data [44].

2.5. Spatial Regression Model

This study introduces three spatial regression models at the global scale: the spatial lag model (SLM) [45], the spatial error model (SEM) [46], and the spatial error model with a spatial lag term (SEMLD) [47]. The SLM incorporates interactions of dependent variables and considers the effects of independent variables from neighboring geographic units on local units. SEM assumes spatial dependence in disturbance error terms, incorporating interactions of error terms between neighboring units. SEMLD enhances the explanatory power of SEM by adding a spatial lag term to the original model.

GWR (geographically weighted regression) is a spatial analysis method derived from the ordinary least squares (OLS) model [48]. It constructs a local regression equation for each research unit, typically a point or region in geospatial space. Unlike the traditional global OLS model, GWR considers the influence of spatial location, thus providing a more effective solution to spatial autocorrelation issues in model residuals [49]. One of the strengths of the GWR model is that it is able to capture the heterogeneity of data across geographic locations, which helps to analyze the causes of spatial heterogeneity [50]. GWR is thus widely used in ecological studies because ecosystems are usually significantly affected by geographic location, e.g., factors such as climate, soil type, and vegetation cover may have different effects in different locations. For this study, GWR analysis was employed to examine the impact of HA on HQ while focusing on spatial heterogeneity. This approach involves considering factors across various geographic locations to comprehend why certain areas may exhibit different effects on HQ. Through GWR modeling, the study aims to offer a more comprehensive understanding of how geographic factors influence HQ, thereby enhancing insights into spatial data variations and disparities [51]. GWR is introduced in this study to probe into the impact of HA on the spatial heterogeneity of HQ at local scales. By incorporating geographic coordinates into the sample data, GWR smoothens spatial irregularities based on the OLS model, enabling the exploration of HA effects on HQ for each geographic unit. Essentially, GWR facilitates the exploration of spatial heterogeneity in the impact of HA on HQ.

3. Materials

3.1. Data Sources

Human Footprint Indices (HFI) (obtained from global year-by-year human footprint data) were taken from the dataset collated by the UEMM Team (https://www.x-mol.com/groups/li_xuecao, accessed on 22 November 2023), YRB-related boundary data and land-use data, and the Resource and Environment Data Center of the Chinese Academy of Sciences [37,52–54] (http://www.resdc.cn, accessed on 23 November 2023). Other basic geographic data were obtained from the National Bureau of Surveying, Mapping, and Geographic Information of China (http://www.ngcc.cn, accessed on 25 November 2023). Detailed information is provided in Table 3.

Table 3. Data information.

Data Name	Data Resolution	Data Format	Data Sources
HFI	1000 m	Tif	https://www.x-mol.com/groups/li_xuecao
Land-use data	1000 m	Tif	http://www.resdc.cn
Boundary data	/	Shpfile	http://www.resdc.cn http://www.ngcc.cn

3.2. Study Area

Spanning approximately 1.8 million square kilometers, the Yangtze River Basin (YRB) stretches between latitudes 24°27′ and 35°54′ N and longitudes 90°13′ and 122°19′ E. It ranks as the world's third-largest river basin and encompasses nearly all of China, spanning 19 provincial-level administrative regions [2]. Figure 1 shows the information on the Yangtze River Basin in the study area. The YRB showcases distinct differences in longitude between its upper, middle, and lower basins. The middle and lower reaches, characterized by mountainous plateaus, boast abundant hydropower and forest resources. Meanwhile, the upper reaches of the middle YRB, such as Yunnan Province, are renowned for their tourism potential and serve as a key agricultural hub in China, benefitting from fertile terrain and a favorable climate. Conversely, the lower reaches, known as the Yangtze River Economic Belt, feature expansive geography, abundant water resources, dense populations, and robust economic development. This area serves as the nucleus of China's export-oriented economy and high-tech industries, attracting substantial industrial and population concentrations [7]. Marked differences in ecosystem composition across the upper, middle, and lower reaches of the YRB are attributable to variations in resource allocation and policies.

Population changes in the YRB are evident; in 2000, the population of the YRB was about 4 million [26]. Over the last two decades, the population of the YRB has steadily increased and now approaches 500 million. Notably, urbanization rates have surged, particularly in major cities like Shanghai, Chongqing, and Nanjing, witnessing rapid growth in urban populations and their share of the total population. Conversely, some rural areas inland may experience population decline. Economic transformations in the YRB are also evident. As early as 2000, the YRB stood as one of China's foremost economic regions, contributing significantly to the national GDP. Since 2000, the economy of the YRB has continued to grow at an average annual rate of over 7%. Cities in the YRB have seen significant development in manufacturing, finance, technology, and services, attracting large amounts of domestic and foreign investment. Some cities, such as Shanghai and Shenzhen, have become global economic centers, contributing to China's overall economic growth.

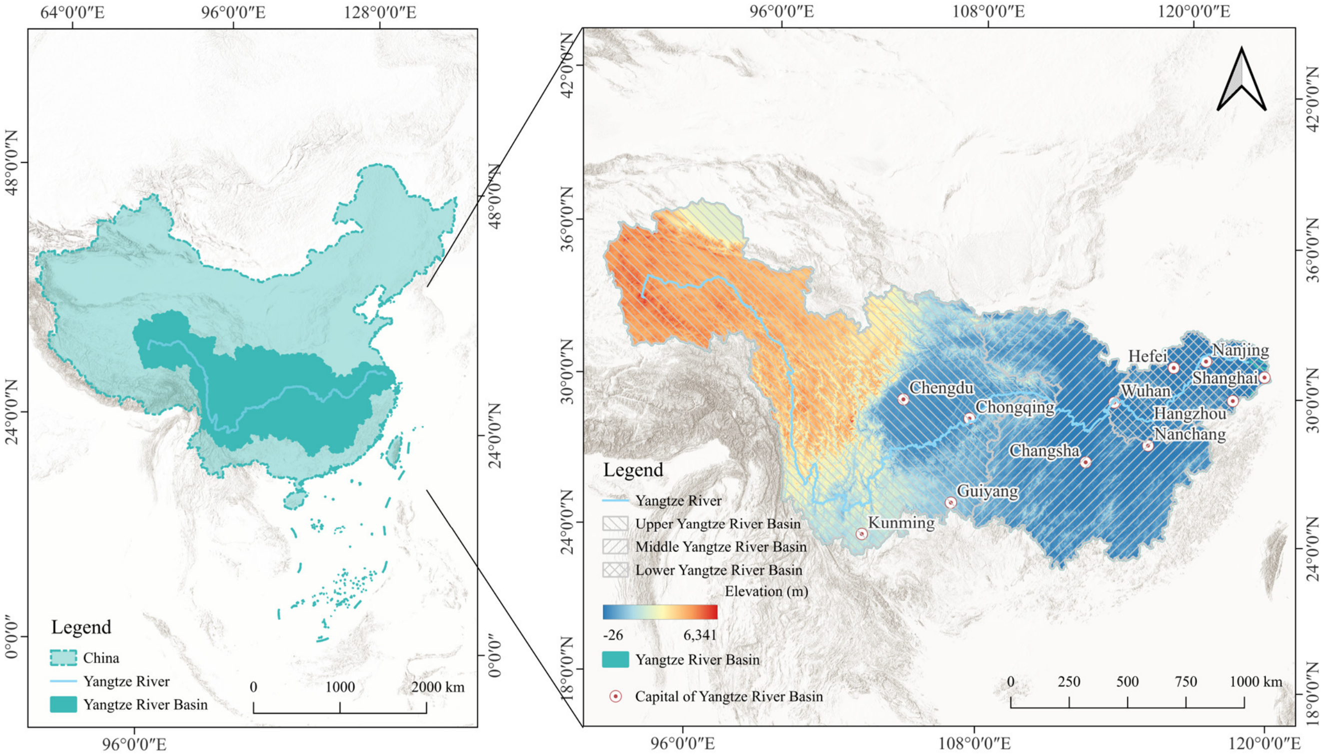

Figure 1. Map of study area.

4. Results

4.1. Spatiotemporal Patterns of HQ and HA

In the time series, the HQ of the YRB showed a slight decline from 0.736 in 2000 to 0.733 in 2020, with a value of 0.735 in 2010 (refer to Figure 2). Spatially, regions with higher HQ values are primarily situated in the mountainous and hilly areas surrounding the Daba Mountains, the Hengduan Mountains, the Sichuan Basin, and the southeastern urban agglomeration of the YRB. Conversely, areas with lower HQ values are predominantly found in the Sichuan Basin, the Yangtze River's source region, the Yangtze River Delta (YRD) region, and various large urban agglomerations in the middle reaches of the Yangtze River. These latter areas are primarily characterized by dense concentrations of arable and construction land.

Over time, the HA of the YRB has shown an increasing trend, with values of 11.211 in 2000, 11.566 in 2010, and 12.937 in 2020. Spatially (refer to Figure 3), areas with a higher human activity intensity are primarily concentrated in the Yangtze River Delta (YRD) urban agglomeration, the city agglomerations in the middle reaches of the Yangtze River, and the Sichuan Basin—regions that have been focal points of national development in recent years. Conversely, regions with a lower intensity of human activities are mainly situated in the upper reaches of the YRB, the Hengduan Mountains, the Daba Mountains, and the mountainous areas surrounding the Sichuan Basin. These areas, predominantly mountainous, offer fewer opportunities for development and construction.

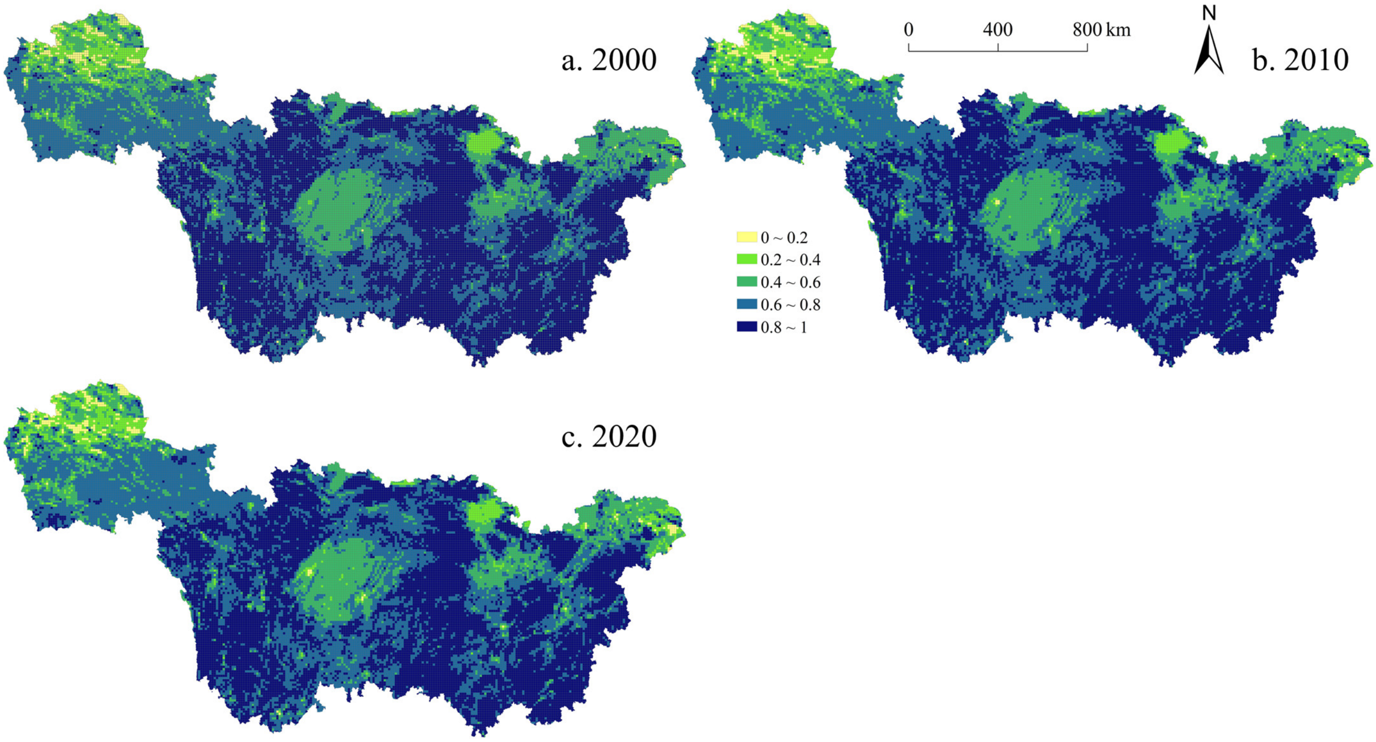

Figure 2. Spatial patterns of HQ during 2000–2020.

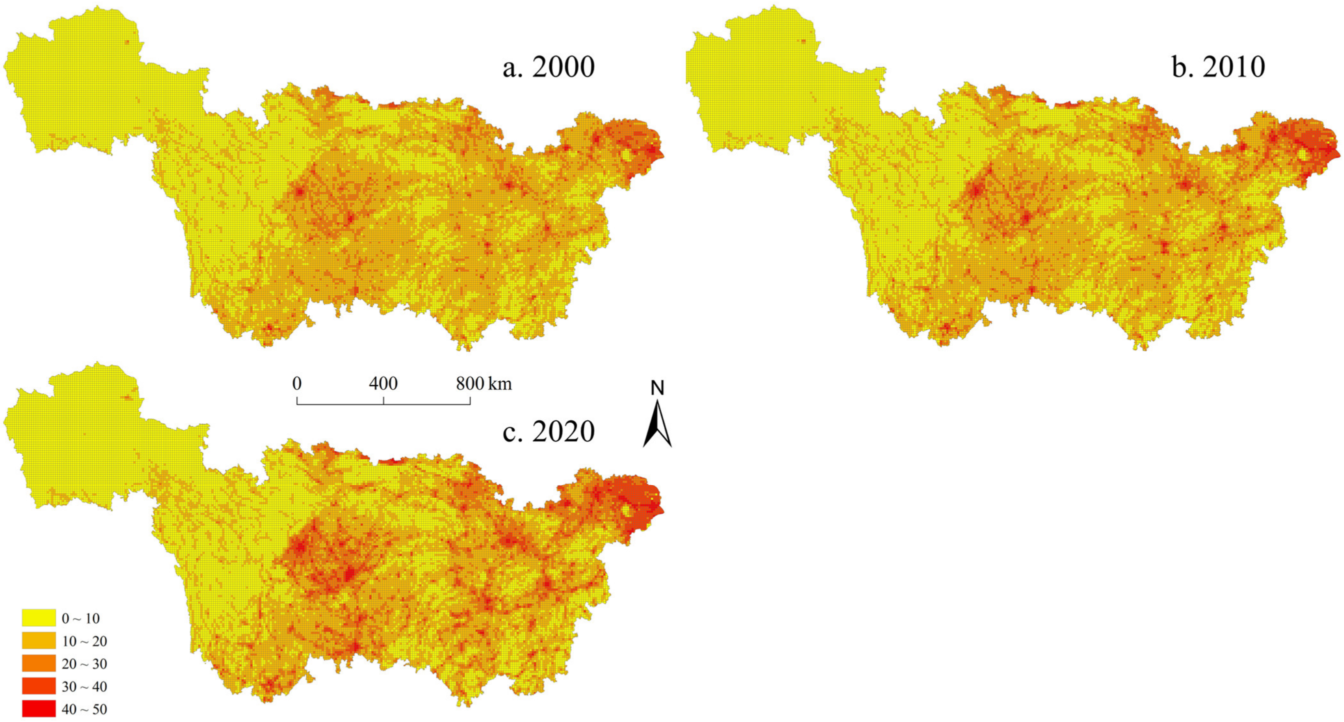

Figure 3. Spatial patterns of HA during 2000–2020.

Throughout the study period, in terms of spatial variation, the average HQ was highest in the middle basin (0.811), lowest in the lower basin (0.684), and intermediate in the upper basin (0.707). Conversely, the average HA level was highest in the lower basin of the Yangtze River (19.954), followed by the middle basin (13.794), and was lowest in the upper basin (9.683) (refer to Figure 4). In terms of the time series, the HQ of the upper basin of the YRB saw a slight increase of 0.004, or 0.567%, during 2000–2020, whereas those of the middle basin and the lower basin experienced decreases of 0.006 and 0.030, equivalent to 0.738% and 4.298%, respectively, over the same period. While HQ in the upper reaches showed a minor improvement, the most significant deterioration occurred in the lower reaches of the YRB. The intensity of human activities in the upper basin, middle basin, and lower basin all increased during 2000–2020 by 1.201, 1.911, and 4.383, with corresponding percentage increases of 13.019%, 14.626%, and 24.455%, respectively. This indicates a consistent upward trend in human activity intensity throughout the YRB, with the most pronounced increase observed in the lower basin region.

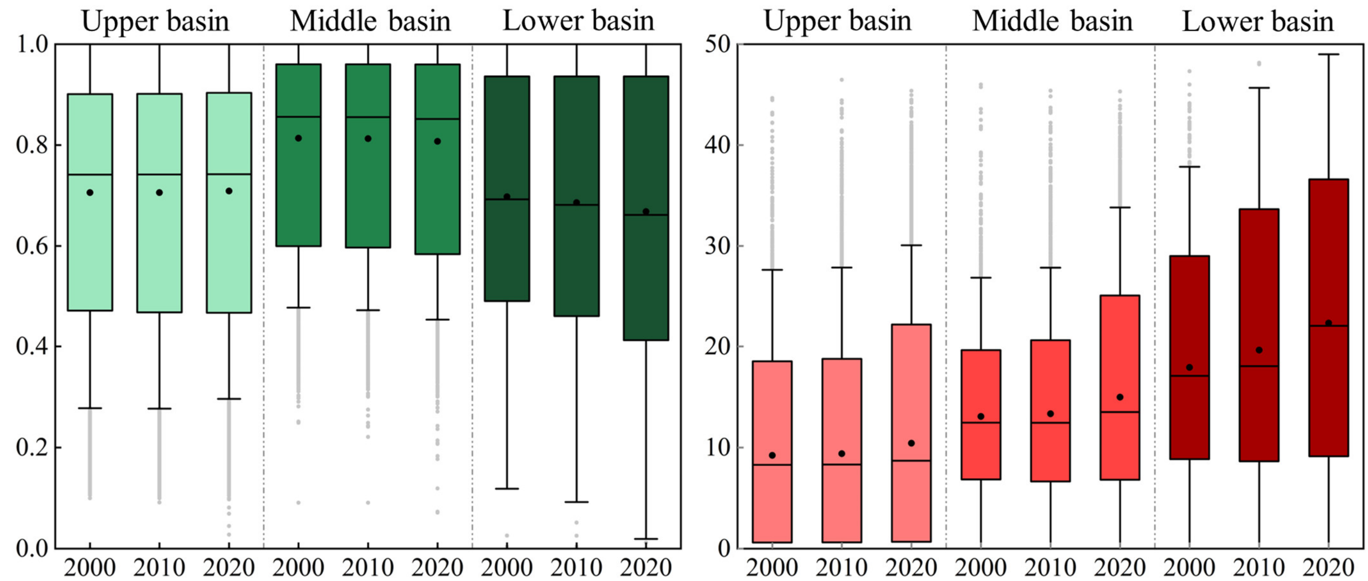

Figure 4. HQ and HA in different sub-basins during 2000–2020.

In addition, hotspot analysis was introduced in this study to visualize the spatial patterns of changes in HQ and HA illustrated in Figures 5 and 6. Between 2000 and 2010, the urban agglomeration of the Yangtze River Delta (YRD) experienced a significant decrease in HQ. Conversely, between 2010 and 2020, the southeastern Qilian Mountains and the mountainous areas in the northwestern part of the Sichuan Basin saw notable increases in HQ, while decreases were observed in the southwestern Qilian Mountains and the urban agglomeration of the Yangtze River Delta. Overall, over the 20-year period from 2000 to 2020, HQ notably declined in the southwestern Qilian Mountains and the urban agglomeration of the Yangtze River Delta, while it increased significantly in the southeastern Qilian Mountains and the mountainous areas of the northwestern Sichuan Basin. Between 2000 and 2010 and 2010 and 2020, HA witnessed significant increases in the Yangtze River Delta region, the urban agglomeration in the middle reaches of the Yangtze River, and the Sichuan Basin. Overall, during 2000–2020, HA rose significantly throughout the YRB, with the most pronounced increase observed in the Yangtze River Delta urban agglomeration.

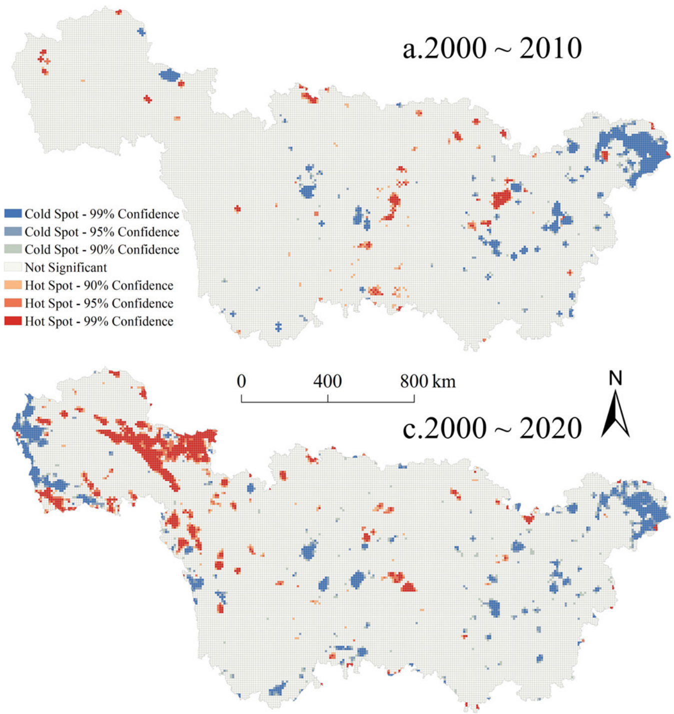

Figure 5. Hotspots of HQ changes during 2000–2020.

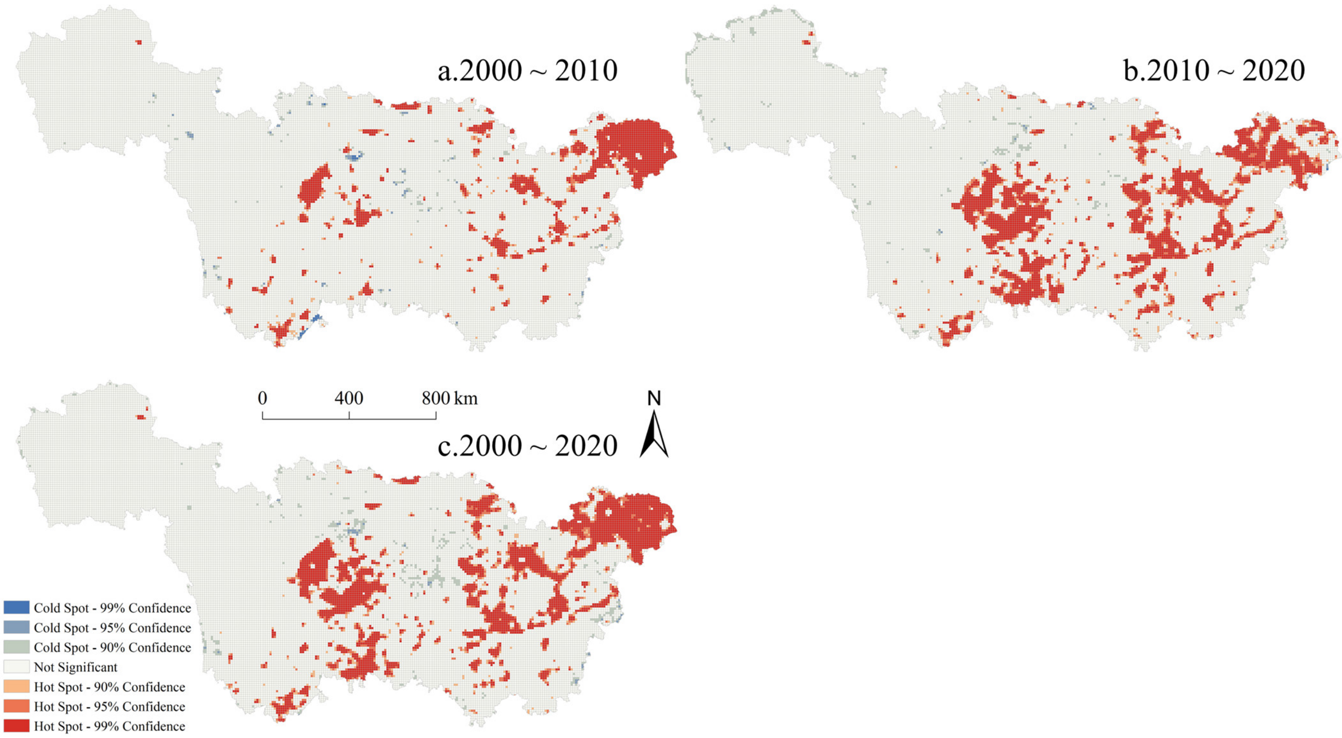

Figure 6. Hotspots of HA changes during 2000–2020.

4.2. Spatial Clustering Patterns of HQ and HA

Based on the global bivariate spatial autocorrelation results for HQ and HA in the YRB (Figure 7), the Moran's indices of −0.015, −0.059, and −0.135 were negative and significant at the 0.001 level during 2000–2020, indicating a negative correlation between HA and HQ. The Moran's index decreased by 0.120 during 2000–2020, demonstrating a decreasing trend over the study period. Meanwhile, the absolute z-values exhibited an increasing trend during the study period, rising by 50.82, suggesting a gradual enhancement in the negative correlation between HQ and HA.

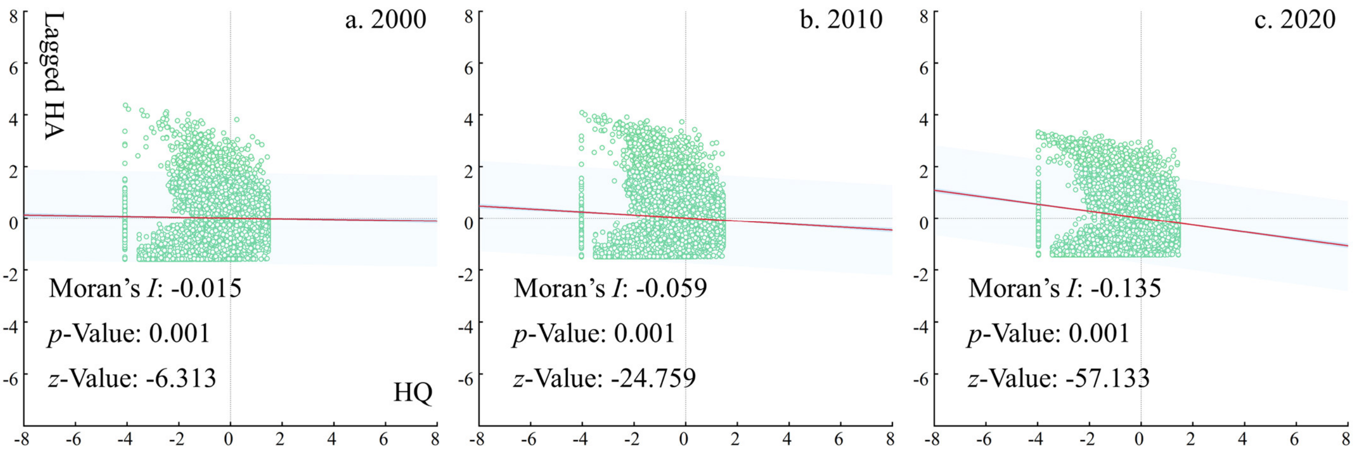

Figure 7. Bivariate Moran scatter plots for HQ and HA during 2000–2020.

Based on the findings from the bivariate spatial autocorrelation analysis, several distinct types of clustering patterns emerge in the Yangtze River Basin (YRB). The predominant types include high–low (high HQ and low HA) and low–high (low HQ and high HA) clusters. Over the study period, there was a notable decrease of 1.549% in the share of low–high clusters, suggesting a shift in spatial dynamics. Furthermore, as shown in Table 4, the low–low type (low HQ and low HA) experienced the most significant growth, increasing by 17.356% between 2000 and 2020 (Figure 8). Conversely, the high–high type (high HQ and high HA) represented the smallest agglomeration type, accounting for only 6.219% in 2020. The spatial distribution of these agglomeration types reveals distinct patterns. High HQ and high HA clusters are primarily concentrated in northwestern Guizhou and certain cities along the middle reaches of the Yangtze River. Interestingly, their distribution appears more dispersed, indicating that human activities in these regions have not significantly impacted HQ. Conversely, areas with low HQ and low human activity are mainly found in the upper basin of the YRB, suggesting natural limitations to human development in these regions. Regions characterized by low HQ and high human activity are clustered around the urban agglomerations of the Yangtze River Delta (YRD), the Sichuan Basin, and the vicinity of the Dabie Mountain Range. These areas exhibit intense human activities, resulting in considerable damage to HQ. On the other hand, regions with high HQ and low human activity are predominantly situated in mountainous areas in the western part of the Sichuan Basin and around the Hengduan Mountains. This part of the region is sparsely populated, and there is no significant destruction of HQ.

Table 4. Percentages for each cluster type.

Cluster Types	High–High	Low–Low	High–Low	Low–High
2000	7.680%	10.198%	16.590%	15.425%
2010	6.471%	10.334%	15.514%	15.317%
2020	6.219%	11.968%	16.446%	15.186%

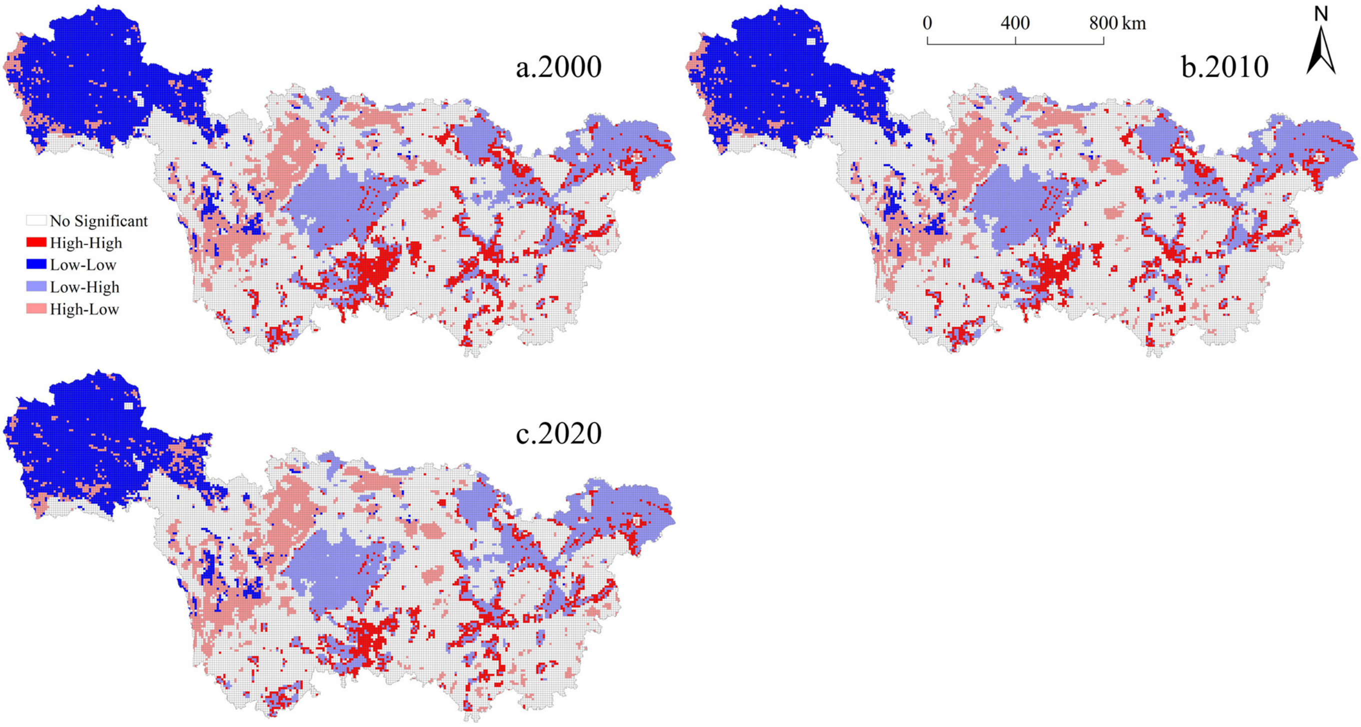

Figure 8. Bivariate LISA cluster maps of HQ and HA during 2000–2020.

4.3. Effects of HA on HQ

Given the significant spatial spillover effect of human activity (HA) on habitat quality (HQ), employing a spatial model becomes imperative. Initially, an ordinary least squares (OLS) model was utilized in this study, the results of which are presented in Table 5. However, the analysis revealed a notable spatial autocorrelation effect in the residual term of the OLS model, prompting consideration of a spatial regression model. Moreover, the relatively low R^2 in the OLS model suggests that it lacks interpretive power. Consequently, the structural equation model (SEM), the spatial lag model (SLM), and the spatial error model with a lagged dependent variable (SEMLD) were introduced to further explore the impact of HA intensity on HQ in the Yangtze River Basin (YRB) area. It is worth noting that all the models selected for this study passed the robust LM test, affirming their suitability for analysis. Additionally, the statistical values of the Breusch–Pagan test and the Koenker–Bassett test for all the models cleared the significance threshold, indicating the absence of heteroscedasticity in the independent variables (as detailed in Table 5). After evaluating various criteria, such as log-likelihood, the Akaike information criterion (AIC), and the Schwartz Bayesian information criterion (SC), the SEMLD model emerged as the one most suitable for this study. This choice ensured a robust analysis of the relationship between HA intensity and HQ in the YRB area, accounting for both spatial autocorrelation and lagged effects.

The regression analysis yielded insightful results regarding the impact of human activity (HA) on habitat quality (HQ) in the Yangtze River Basin (YRB) over time, as shown in Table 6. The effect of HA on HQ exhibited a gradual decline, with a peak value of -0.017 in 2000 and a significant regression coefficient of -0.017 ($p < 0.001$). This indicates that for every 1% increase in the intensity of human activity, HQ is expected to decrease by 0.017%. Furthermore, the regression coefficient of the spatial lag term also displayed a decreasing trend, reaching its maximum value of 1.033 in 2000. This suggests that for every 1% increase in HQ in the surrounding areas, HQ within the region itself would increase by 1.033%. It is noteworthy that the regression coefficients of the spatial error terms are significant across all years. This implies that the error terms of neighboring regions tend to influence the error terms of the focal region, with negative effects observed in 2000, 2010, and 2020. Such findings underscore the interconnectedness of habitat quality across spatial domains within the YRB, highlighting the importance of considering spatial dynamics in habitat management and conservation efforts.

Table 5. Diagnostic items of the ordinary least squares (OLS) method.

Diagnostic Item	2000	2010	2020
Moran's I (error)	234.5292 ***	235.517 ***	232.450 ***
LM (lag)	54,246.817 ***	54,171.908 ***	51,631.749 ***
Robust LM (lag)	169.289 ***	207.819 ***	218.046 ***
LM (error)	54,964.396 ***	55,428.354 ***	53,993.951 ***
Robust LM (error)	886.868 ***	1464.265 ***	2580.247 ***
Lagrange multiplier (SARMA)	55,133.685 ***	55,636.173 ***	54,211.996 ***
Breusch–Pagan test	352.618 ***	257.113 ***	284.895 ***
Koenker–Bassett test	193.9842 ***	135.763 ***	133.542 ***
Log-likelihood	7212.750	7064.670	7055.640
AIC	−14,421.500	−14,125.300	−14,107.300
SC	−14,405.300	−14,109.100	−14,091.100
R^2	0.005	0.014	0.043

Notes: *** $p \leq 0.001$.

Table 6. Regression results for the YRB.

Explanatory Variables	SLM			SEM			SEMLD		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
HA	−0.068 ***	−0.075 ***	−0.084 ***	−0.334 ***	−0.341 ***	−0.370 ***	−0.035 *** (0.002)	−0.035 *** (0.002)	−0.034 *** (0.002)
Constant	0.082 ***	0.085 ***	0.098 ***	0.795 ***	0.797 ***	0.814 ***	−0.017 *** (0.002)	−0.016 *** (0.002)	−0.013 *** (0.002)
Spatial lag term	0.908 ***	0.906 ***	0.895 ***				1.033 *** (0.002)	1.031 *** (0.002)	1.029 *** (0.002)
Spatial error term				0.914 ***	0.914 ***	0.908 ***	−0.677 *** (0.014)	−0.658 *** (0.014)	−0.657 *** (0.014)
Log likelihood	22,956.200	22,794.700	21,859.900	23,534.269	23,501.254	22,791.041	26,775.907	26,520.790	25,445.620
AIC	−45,906.300	−45,583.300	−43,713.900	−47,064.500	−46,998.500	−45,578.100	−53,545.800	−53,035.600	−50,885.200
SC	−45,882.000	−45,559.000	−43,689.600	−47,048.300	−46,982.300	−45,561.900	−53,521.500	−53,011.300	−50,860.900
R^2	0.773	0.773	0.762	0.785	0.789	0.782	0.812	0.811	0.800

Notes: *** $p \leq 0.001$. Numbers in parentheses denote standard deviations.

The study also delved into the specifics of different sub-basins within the Yangtze River Basin (YRB) using the SEMLD model, with diagnostic results affirming its efficacy. Tables 7–10 present the regression results for these sub-basins, which exhibited notable differences compared to the regression results for the entire YRB. Across all sub-basins, human activities consistently demonstrated predominantly negative effects on habitat quality (HQ). The smallest regression coefficients were observed in the lower basin, indicating that the negative impact of human activity on HQ was most pronounced in this region. In both the middle YRB and upper YRB, the negative effect of human activity on HQ was also significant. Specifically, in 2020, a 1% increase in human activity in the upper YRB led to a 0.024% decrease in HQ, while the same increase in the lower YRB resulted in a more substantial 0.147% decrease in HQ. Moreover, regarding the spatial lag term, all sub-basins exhibited a strong spatial spillover effect of HQ, with the middle basin of the Yangtze River displaying the most significant effect. Specifically, in the middle basin of the YRB, a 1% increase in human activity led to a 0.144% increase in HQ compared to 0.026% in the upper basin and 0.068% in the lower basin. These findings underscore the nuanced spatial dynamics of human activity and its impact on habitat quality within different regions of the Yangtze River Basin, emphasizing the importance of tailored conservation and management strategies at the sub-basin level.

Table 7. Regression results for the UYRB.

Explanatory Variables	SLM			SEM			SEMLD		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
HA	−0.016 ***	−0.023 ***	−0.038 ***	−0.207 ***	−0.219 ***	−0.269 ***	−0.026 *** (0.002)	−0.027 *** (0.003)	−0.024 *** (0.002)
Constant	0.069 ***	0.070 ***	0.078 ***	0.730 ***	0.733 ***	0.752 ***	−0.021 *** (0.002)	−0.020 *** (0.002)	−0.020 *** (0.002)
Spatial lag term	0.904 ***	0.905 ***	0.900 ***				1.035 *** (0.003)	1.035 *** (0.003)	1.035 *** (0.003)
Spatial error term				0.910 ***	0.911 ***	0.908 ***	−0.701 *** (0.017)	−0.695 *** (0.017)	−0.684 *** (0.017)
Log likelihood	13,739.000	13,663.200	13,222.500	13,905.673	13,866.005	13,541.526	16,159.919	16,074.237	15,572.295
AIC	−27,472.100	−27,320.400	−26,439.000	−27,807.300	−27,728.000	−27,079.100	−32,313.800	−32,142.500	−31,138.600
SC	−27,449.300	−27,297.600	−26,416.200	−27,792.100	−27,712.800	−27,063.800	−32,291.000	−32,119.700	−31,115.800
R^2	0.765	0.765	0.752	0.771	0.773	0.764	0.808	0.808	0.795

Notes: *** $p \leq 0.001$. Numbers in parentheses denote standard deviations.

Table 8. Regression results for the MYRB.

Explanatory Variables	SLM			SEM			SEMLD		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
HA	−0.317 ***	−0.304 ***	−0.297 ***	−0.494 ***	−0.471 ***	−0.467 ***	−0.141 *** (0.006)	−0.143 *** (0.006)	−0.147 *** (0.005)
Constant	0.263 ***	0.271 ***	0.308 ***	0.945 ***	0.940 ***	0.951 ***	0.061 *** (0.006)	0.070 *** (0.006)	0.098 *** (0.006)
Spatial lag term	0.786 ***	0.775 ***	0.737 ***				0.973 *** (0.005)	0.964 *** (0.005)	0.938 *** (0.006)
Spatial error term				0.864 ***	0.860 ***	0.842 ***	−0.593 *** (0.024)	−0.566 *** (0.024)	−0.555 *** (0.024)
Log likelihood	8357.070	8326.890	8188.990	8457.452	8445.305	8357.833	9103.311	9024.309	8791.379
AIC	−16,708.100	−16,647.800	−16,372.000	−16,910.900	−16,886.600	−16,711.700	−18,200.600	−18,042.600	−17,576.800
SC	−16,687.300	−16,627.000	−16,351.200	−16,897.000	−16,872.800	−16,697.800	−18,179.800	−18,021.800	−17,556.000
R^2	0.756	0.755	0.756	0.771	0.772	0.777	0.782	0.780	0.778

Notes: *** $p \leq 0.001$. Numbers in parentheses denote standard deviations.

Table 9. Regression results for the LYRB.

Explanatory Variables	SLM			SEM			SEMLD		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
HA	−0.210 ***	−0.215 ***	−0.261 ***	−0.309 ***	−0.346 ***	−0.382 ***	−0.052 *** (0.011)	−0.067 *** (0.010)	−0.086 *** (0.012)
Constant	0.215 ***	0.234 ***	0.299 ***	0.798 ***	0.813 ***	0.834 ***	0.008 (0.011)	0.031 (0.012)	0.061 *** (0.014)
Spatial lag term	0.801 ***	0.785 ***	0.733 ***				1.015 *** (0.011)	0.993 *** (0.012)	0.968 *** (0.013)
Spatial error term				0.867 ***	0.870 ***	0.843 ***	−0.567 *** (0.042)	−0.466 *** (0.042)	−0.471 *** (0.042)
Log likelihood	2033.750	2026.100	1844.520	2013.895	2024.201	1816.932	2295.148	2247.032	2036.960
AIC	−4061.500	−4046.200	−3683.030	−4023.790	−4044.400	−3629.860	−4584.300	−4488.060	−4067.920
SC	−4044.210	−4028.910	−3665.740	−4012.270	−4032.880	−3618.340	−4567.010	−4470.780	−4050.630
R^2	0.738	0.760	0.755	0.742	0.770	0.761	0.770	0.781	0.776

Notes: *** $p \leq 0.001$. Numbers in parentheses denote standard deviations.

Table 10. Regression results of SEMLD for the different sub-basins.

Explanatory Variables	Upper Basin			Middle Basin			Lower Basin		
	2000	2010	2020	2000	2010	2020	2000	2010	2020
HA	−0.026 *** (0.002)	−0.027 *** (0.003)	−0.024 *** (0.002)	−0.141 *** (0.006)	−0.143 *** (0.006)	−0.147 *** (0.005)	−0.052 *** (0.011)	−0.067 *** (0.010)	−0.086 *** (0.012)
Constant	−0.021 *** (0.002)	−0.020 *** (0.002)	−0.020 *** (0.002)	0.061 *** (0.006)	0.070 *** (0.006)	0.098 *** (0.006)	0.008 (0.011)	0.031 (0.012)	0.061 *** (0.014)
Spatial lag term	1.035 *** (0.003)	1.035 *** (0.003)	1.035 *** (0.003)	0.973 *** (0.005)	0.964 *** (0.005)	0.938 *** (0.006)	1.015 *** (0.011)	0.993 *** (0.012)	0.968 *** (0.013)
Spatial error term	−0.701 *** (0.017)	−0.695 *** (0.017)	−0.684 *** (0.017)	−0.593 *** (0.024)	−0.566 *** (0.024)	−0.555 *** (0.024)	−0.567 *** (0.042)	−0.466 *** (0.042)	−0.471 *** (0.042)
Log likelihood	16,159.919	16,074.237	15,572.295	9103.311	9024.309	8791.379	2295.148	2247.032	2036.960
AIC	−32,313.800	−32,142.500	−31,138.600	−18,200.600	−18,042.600	−17,576.800	−4584.300	−4488.060	−4067.920
SC	−32,291.000	−32,119.700	−31,115.800	−18,179.800	−18,021.800	−17,556.000	−4567.010	−4470.780	−4050.630
R^2	0.808	0.808	0.795	0.782	0.780	0.778	0.770	0.781	0.776

Notes: *** $p \leq 0.001$. Numbers in parentheses denote standard deviations.

The local-scale regression results depicted in Figure 9 reveal a notable scale dependence of the effect of human activity intensity on habitat quality (HQ). This highlights the significance of considering spatial scale when assessing this relationship. To address this, geographically weighted regression (GWR) was employed, extending from the ordinary least squares (OLS) model [55]. The superiority of the GWR model over the OLS model was evident from the Akaike information criterion (AIC) values in Table 11. Specifically, for the years 2000, 2010, and 2020, the AIC of GWR was substantially smaller than that of OLS, indicating the higher performance of the GWR model. Moreover, the R^2 of GWR surpassed that of the OLS model, signifying its enhanced explanatory power. The analysis revealed that the percentage of data with positive regression coefficients was consistently lower than that with negative coefficients, suggesting a prevailing negative impact of human activity intensity on HQ. Additionally, GWR underscored the spatial heterogeneity of this effect. Specifically, in the urban agglomeration area of the Yangtze River Delta (YRD), regression coefficients were predominantly negative, often with larger absolute values compared to other areas. In contrast, the Yangtze River source area exhibited mainly positive coefficients in 2000 and 2010, shifting to negative coefficients in 2020. Furthermore, a positive effect of human activity intensity on HQ gradually emerged over time, primarily observed in mountainous regions like the Daba Mountain Range and the northern region of Guizhou Province. These findings highlight the complex and dynamic nature of the relationship between human activity intensity and habitat quality across different spatial scales and regions within the study area.

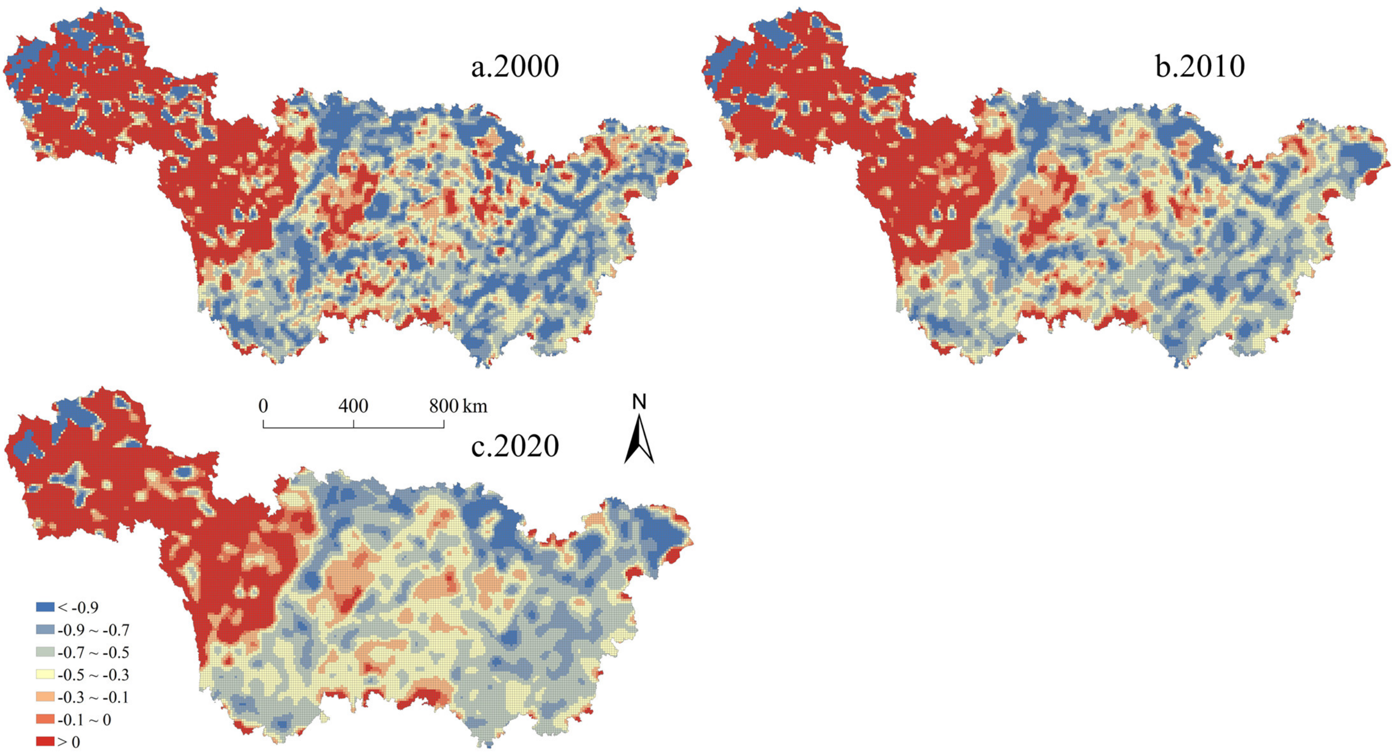

Figure 9. Spatial patterns of regression coefficients for HA during 2000–2020.

Table 11. R^2 and AICc values for OLS and GWR models.

Years	2000		2010		2020	
	GWR	OLS	GWR	OLS	GWR	OLS
AICc	−56,777.633	−14,421.500	−54,721.534	−14,125.300	−50,751.269	−14,107.300
R^2	0.884	0.005	0.857	0.014	0.816	0.043

5. Discussion

5.1. Impact of HA on HQ

This study provides a comprehensive assessment of the spatial and temporal variations in habitat quality (HQ) within the Yangtze River Basin (YRB), revealing a concerning trend of continuous degradation [26]. Significant disparities in HQ were observed across different areas of the YRB, closely linked to the spatial and temporal distribution of human activities [56]. As economic development progresses along the gradient from west to east within the Yangtze River Basin (YRB), the alluvial plains in the lower basin have emerged as focal points for population concentration and rapid economic growth [57]. However, this rapid expansion of human activity has come at the expense of natural habitats, resulting in substantial degradation of HQ in these areas. Over the period from 2000 to 2020, human activity increased significantly across the upper, middle, and lower basins of the Yangtze River, with the lower basin experiencing the most pronounced increase, reaching 24.455%. Despite this surge in human activity, HQ in the lower basin notably increased, indicating successful conservation efforts or mitigating factors in this region. However, the overall trend for HQ in the YRB is concerning. Apart from a slight increase in HQ observed in the upper basin, HQ in the middle and lower basins experienced significant declines, with the lower basin recording the most substantial decrease, reaching a maximum of 4.298% over the 20-year period. Of particular interest is the observation that while certain areas within the upper basin exhibited improvements in HQ over specific time periods, a downward trend was observed in the middle and lower basins. This nuanced understanding of the spatial and temporal evolution of ecosystem health in the YRB underscores the complexity of balancing economic development with environmental conservation efforts in a dynamic and rapidly changing landscape.

This study extensively examined the spatial relationship between human activity (HA) and habitat quality (HQ) in the Yangtze River Basin (YRB). It was found that in urban agglomeration areas, HA had a pronounced negative impact on HQ, indicating that the expansion of human activities has a more serious effect on ecosystems, disrupting the integrity and connectivity of regional ecosystems and resulting in habitat degradation [58]. In contrast, a slight improvement in HQ was observed in areas where HA expansion was less pronounced, such as mountainous regions. This variation in HA across the upper, middle, and lower reaches of the YRB is primarily influenced by the distribution of resources and other factors [59]. The upper basin of the YRB is characterized by low human activities due to resource scarcity, while the middle and lower basins are influenced by the abundance of resources and economic development levels. Intensive HA in urban agglomerations has led to a significant decline in environmental quality, which has had a strong adverse impact on the environment. Conversely, in mountainous areas, HA may contribute to the restoration of environmental quality through environmental protection measures. This suggests that the environmental changes in the YRB are a result of a combination of multiple factors, necessitating the adoption of measures tailored to local conditions to promote sustainable development while protecting and enhancing environmental quality [60]. Moreover, this study analyzed the variations in the impacts of HA expansion on HQ in different sub-basins. The results show that the negative effect of HA on HQ is strongest in the downstream region and smallest in the upper Yangtze River Basin. This finding provides crucial insights for developing targeted conservation measures in specific regions. By further investigating the mechanisms of how HA specifically affects HQ, we can devise more precise environmental management strategies to promote sustainable ecological development in the Yangtze River Basin. Expansion of human activities in specific sub-basins may lead to significant deterioration of HQ, while in other sub-basins there may be relatively small impacts on HQ. This variation suggests the need for site-specific ecological conservation and resource management measures to minimize the adverse effects of human activities on HQ [61]. In addition, HQ tends to have significant spatial spillover effects, which is consistent with findings from previous studies [2]. Spatial spillovers of human activities impact habitats, including ecosystem connectivity, migration and species dispersal, land-use change, climate change, diffusion of socio-economic activities, and policy and management practices, require that integrated ecosystem responses across regions be considered in research and management [62].

5.2. Policy Implications

Taken together, this study offers a thorough examination of the interplay between habitat quality (HQ) and human activities in the Yangtze River Basin (YRB), uncovering trends in spatial and temporal variations. It serves as a robust scientific foundation for future endeavors in ecological preservation and sustainable development, thus contributing significantly to the development of targeted environmental policies and ecosystem management strategies [63]. Policy recommendations grounded in the study's findings are set out below.

Given that habitat quality (HQ) has significant spatial spillover effects, policymakers should incorporate it into environmental protection strategies and promote synergistic regional development. Measures to reduce interregional spillover effects of adverse ecological impacts and achieve sustainable ecosystem health by promoting synergistic interregional development are recommended [64,65]. To address this issue, an ecological compensation mechanism could be established, such as the establishment of a Yangtze River Basin ecological compensation fund at the national level to support ecological environmental protection efforts in upstream areas, while upstream and downstream areas could be encouraged to establish ecological compensation agreements to clarify the compensation standards and modalities so as to realize a win–win situation for ecological environmental protection and economic and social development. In this way, a cross-regional ecological cooperation mechanism and a decision-making framework for eco-compensation could be established to ensure that habitat protection is not only effective at the local scale but also has a positive impact in the wider region.

Given the different levels of HQ in different regions, the implementation of differentiated ecological environmental protection and management measures is recommended [65]. The upper reaches of the Yangtze River Basin can strengthen soil and water conservation and ecological restoration by implementing projects such as returning farmland to forests, grasses, and wetlands to improve vegetation cover and ecological stability. The upstream area has more mountainous areas and should strictly control the development of mineral resources to reduce the damage of mining activities to the ecological environment and promote ecological agriculture and green planting technology, reduce agricultural surface pollution, and comprehensively realize the enhancement of habitat quality (HQ). In the middle reaches of the Yangtze River Basin, the decline in HQ is obvious, and the management of industrial pollution sources should be intensified, strict emission standards should be implemented, and enterprises should be promoted to carry out cleaner production and technological transformation, including strengthening of the construction and management of urban sewage treatment facilities, improvement of the sewage treatment rate and the rate of water reuse, and reduction in urban sewage pollution on the Yangtze River, while strengthening the management of agricultural face source pollution and slowing down the destruction of the habitat quality (HQ) in the middle reaches of the Yangtze River. The habitat quality of the lower reaches of the Yangtze River Basin itself is not encouraging, and the decline in its HQ is also more obvious. It is possible to strictly control urban expansion and land development and to rationally plan the urban layout and land-use structure so as to avoid negative impacts on the habitat quality of the Yangtze River Basin resulting from the reduction in animal and plant habitats resulting from uncontrolled urban expansion [66] The HQ damage in the downstream region is more serious, and the protection and restoration of wetlands along the river should be strengthened by establishing wetland nature reserves or wetland parks to improve the stability and service function of wetland ecosystems, and the comprehensive management of the water environment should be strengthened by implementing projects such as river dredging and water ecological restoration so as to improve the water quality and ecological environment of the lower reaches of the Yangtze River and to rectify the imbalance between balanced urbanization development and biodiversity protection.

5.3. Limitations and Future Plans

The study delves into the spatiotemporal patterns of human activities' impact on habitat quality in the YRB over the period 2000–2020. However, it acknowledges the following limitations: 1. In the era of rapid informatization and industrialization, there has been a surge in the exchange of people, information, and material flows. Nonetheless, this study has not examined the impact of HA on HQ from the perspective of remote coupling. Specifically, the study has not accounted for the potential influence of HA in the upper basin of the YRB on HQ in the lower basin areas. To address this gap, we aim to incorporate the remote coupling perspective in future research to enhance the analysis of the impact of HA on HQ. 2. This study primarily relied on cross-sectional data to investigate the effects of HA on HQ, overlooking the time-series perspective within a given region. To overcome this limitation, we plan to utilize panel data in future endeavors to gain insights into the regional variations in the impact of HA on HQ.

6. Conclusions

This study comprehensively analyzed the spatial and temporal patterns of human activities (HAs) and habitat quality (HQ) in the Yangtze River Basin, including its upper, middle, and lower reaches, from 2000 to 2020 using spatial analysis and spatial regression. The results showed that the overall HQ of the Yangtze River Basin gradually declined during the study period, while the overall HA significantly increased. Specifically analyzing the changes in the upper, middle, and lower reaches of the Yangtze River basin, the HQ of the upper Yangtze River basin increased by 0.567%, while that of the middle and lower reaches decreased by 0.738% and 4.298%, respectively. Meanwhile, the HA in the upper, middle, and lower basins increased by 13.019%, 14.626%, and 24.455%, respectively. It is noteworthy that the changes in HQ and HA showed obvious and consistent trends in the upper, middle, and lower basins. Locally, the low–low aggregation type increased by 17.356%, while all other aggregation types decreased, with the largest decrease of 79.230% being recorded for the high–high aggregation type. The spatial regression model at the basin-wide scale indicated that HA had a significant negative effect on HQ, and HQ exhibited a significant spatial spillover effect. However, the results of geographically weighted regression (GWR) at the local scale indicated that HA in mountainous areas had a positive effect on HQ. This study deepens our understanding of the spatial relationship between HA and HQ in the upper, middle, and lower reaches of the Yangtze River and the differences in the effects of HA on HQ changes. This study can serve as a case study of the effects of human activities on habitat quality in large basins.

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