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Major Role of Natural Wetland Loss in the Decline of Wetland Habitat Quality—Spatio-Temporal Monitoring and Predictive Analysis

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Abstract: Land use change significantly affects habitat quality, and the long time series exploration of dynamic variations in wetland habitat quality is of great significance to wetland conservation and management practices. Jingxin Wetland is located in the lower reaches of the Tumen River Basin, an important ecological function area in China. In recent years, under the influence of human activities and climate change, Jingxin Wetland has faced the threat of degradation and reclamation. This study investigated the dynamic evolution of habitat quality in Jingxin Wetland based on the CA-Markov model and the InVEST model at a long time scale and analyzed the drivers of habitat quality changes. Furthermore, habitat statuses under different policy orientations were explored using a multi-scenario development model. The results show that the total area of Jingxin Wetland exhibited a shrinking trend from 1964 to 2019, the wetland landscape was more fragmented, and the loss of natural wetland (marsh wetland) was serious. Consequently, wetland habitat quality has declined. According to scenario analysis, the study area should firmly follow the ecological conservation route in the future, through which the encroachment of human activities on wetlands can be effectively reduced and habitat conditions can be effectively improved. Both natural and economic development scenarios would result in the shrinkage of wetlands, which will extend the trend of declining habitat quality. It is noteworthy that the loss of wetland can be effectively reduced by implementing ecological conservation policies, which would reduce the degradation of wetland habitat quality. The results of this study can provide valuable references for wetland ecological conservation and ecological management practices.

Keywords: multi-scenario prediction; habitat quality; CA-Markov model; InVEST model; Jingxin Wetland

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1. Introduction

Habitat quality refers to the suitability of inland ecosystems for species survival and reproduction and economic development at a certain spatial and temporal scale [1]. It contributes to depicting the completeness and variety of terrestrial ecosystems [2], and also plays a substantial role in determining species' distribution patterns and in regulating the spatial dynamics in fragmented landscapes [3]; the greater the habitat quality, the greater the biodiversity of the ecosystem [4]. Therefore, habitat quality assessment is an important means of determining the level of regional ecological security and health.

Land use cover change (LUCC) is one of the most dominant factors in the dynamic evolution of habitat quality. The transformation of land use changes the circulation of material and energy flows between landscape patches, thereby altering the production and service capacity of habitats [5]. Land use intensity also leads to a shift in habitat quality [6], with high-intensity land use practices having the potential to cause dramatic shifts in the land over short periods, which in turn leads to habitat and species loss [7]. Wetlands are one of the three major ecosystems on Earth; they are the core of the regional landscape chain and control the ecological safety and health of entire regions [8]. Wetlands are susceptible to alteration due to the vulnerability of their ecosystems [9]. Changes in wetland types will lead to shifts in landscape connectivity within wetlands [10], which in turn may lead to habitat loss for flora and fauna [11]. An increasing number of wetlands are experiencing landscape fragmentation [12,13], which usually implies degradation of its ecological functions [14]. The fragmentation of wetland landscapes is characterized by reduced species richness and taxa diversity, and the fragmentation also poses the risk of reduced efficiency of ecosystem functions [15]. It can create isolated patches that support fewer species and may promote local extinction of species [16]. Therefore, wetland landscape fragmentation plays a major role in the degradation of ecological systems and the reduction in wetland habitat quality [17]. In recent years, studies on wetland habitat quality have often performed simulations using various models, such as the multi-scale integrated models of ecosystem services (MIMES) [18], habitat suitability index (HSI) [19], and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) [20]. Among these, InVEST models are currently the more mature and widely used, with advantages such as precise quantification, visualization of results, and low cost of application [21]. The habitat quality module of InVEST quantifies habitat quality by analyzing land use and the degree of threat to biodiversity at the raster scale, and it has been widely used in multi-scale quantitative assessment of habitat quality in nature reserves, watersheds, provinces, and urban agglomerations [22–24]. Rahimi et al. [25] assessed the response of water yield and habitat quality to land use change in Shadegan wetlands in southwestern Iran based on an InVEST model and found that land use change is a major factor contributing to the decline in habitat quality. Zhang et al. [26] assessed the dynamic evolutionary characteristics of coastal wetland habitat quality, and found that declining habitat quality is a serious threat to the habitats of rare species, such as *Grus japonensis*. Fu et al. [27] explored the response of future habitat quality to land use change in the Yellow River Basin based on scenario simulation, and found that high-intensity human activity (urban sprawl) is the main factor contributing to the decline in habitat quality. Thus, previous studies have revealed the response of wetland habitat quality to land use, providing clear ideas and insights for further in-depth study.

Current research on wetland habitat quality is mainly focused on the past and lacks predictions for different future scenarios. The cellular automata (CA) model is the most representative model for the geological field [28], and has been widely used in many research areas such as land use, geomorphological evolution, and urban growth and dispersal [29–31]. The CA-Markov model organically combines CA models and Markov models, integrating the ability of CA models to simulate the spatial variability of complex systems and the advantages of Markov models for long-term prediction [32]. This combined model not only improves the prediction accuracy of land use type transformation, but can also effectively simulate the spatial changes in land use patterns, thus offering improved scientific value and practicality [33,34]. Akin et al. used the CA-Markov model to simulate the dynamics of land use change in Mediterranean coastal wetlands, and found that the rapid development of agricultural activities led to significant habitat loss in ecologically sensitive areas [35]. Simioni et al. [36] applied the CA-Markov model to simulate land use and land cover in the Banhado Grande Wetland Reserve, Brazil, in 2030, and found that the increase in soybean cultivation posed a threat to the wetland ecosystem. Zhang et al. [37] used CA-Markov models and multi-scenario simulations to predict the future wetland evolution of nearly 30 wetlands in Guangxi, revealing future directions. All the above studies show that the CA-Markov model has good generalizability for the realistic simulation of wetland development trends. On the whole, it is of great relevance to explore the development and management of optimal wetland habitat quality through the simulation and prediction of habitat quality under future wetland land use change using a combination of the InVEST model and the CA-Markov model.

Jingxin Wetland is an important downstream branch of the Tumen River Basin, an important ecological function area in China. Situated on the frontier of China, Russia, and North Korea, Jingxin Wetland has abundant plant and animal species diversity and is an important habitat for migratory waterfowl. Known as a "Migratory Bird Station", it has good ecological protection measures and ecological services [38,39]. Jingxin Wetland is close to Northeast Tiger and Leopard National Park, which was approved by the Chinese government in 2021. However, past monitoring of landscape dynamics has revealed that Jingxin Wetland is affected by human disturbance, and more than 80% of natural wetlands have been transformed into artificial wetlands such as paddy fields, reservoirs, and ponds [40]. According to historical data, wetland types in the region are highly variable, with large fluctuations and uncertainties in wetland habitat quality. In this research, we hypothesized that a shift in wetland type would have a large impact on habitat quality. With this premise in mind, we conducted simulations of wetland types under multiple scenarios, and explored the dynamic evolution of wetland habitat quality in the long term. The findings have important implications for the conservation of wetland biodiversity and the maintenance of habitat functions for animals and birds.

2. Materials and Methods

2.1. Overview of the Study Area

Jingxin Wetland (42°31′–42°42′ N, 130°26′–130°37′ E) is located in the lower reaches of the Tumen River Basin in China (Figure 1). The study area is near the Sea of Japan, with a relatively humid climate and windy spring and autumn. The rainy season is mostly concentrated in July and August, with annual rainfall of 823.7 mm, annual average temperature of 5.6 °C, extreme maximum temperature of 36.3 °C, extreme minimum temperature of −32.5 °C, and a frost-free period of 156 days. The terrain in the study area mainly includes plains and hills, with lakes and wetlands distributed all over the area, and the main stream of the Tumen River flows from west to east through Jingxin Wetland. In addition to its unique location, the wetland is rich in natural resources and exceptionally rich in animal species, retaining many of the region's endemic species. In particular, it is an important species gene pool for wetland animals and a habitat for globally endangered waterfowl such as *Grus japonensis* and rare wildlife such as *Panthera tigris altaica* and *Oncorhynchus keta* [39–41].

2.2. Data Sources and Processing

In this study, in order to understand the changes in wetland habitat quality under different land use policies during different historical periods, we selected three years (1964, 1991, and 2019) of data for analysis. Land use data were obtained from high-resolution satellite images, including Corona remote sensing images from August and October 1964 with a resolution of 2.75 m, SPOT satellite images in April 1991 with a resolution of 10 m, and planet satellite imagery in September 2019 with a resolution of 3.125 m. The pre-processing of these 3 phases of remote sensing images were performed in ENVI 5.3 software, and object-oriented classification of images was conducted with the support of eCognition 9.0 software, uniform projection, a coordinate system, and resolution for all types of sites in ArcGIS 10.7 DEM data were obtained from the Geospatial Data Cloud (https://www.gscloud.cn/ (accessed on 5 February 2023)) platform, and extracted using ArcGIS 10.7 to obtain the slope. Annual precipitation, average annual temperature, per capita GDP, population density data, and other road traffic data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/ (accessed on 1 March 2023)). Population footprint data were obtained from the Human Footprint dataset published by Mu et al. [42]. Soil data were obtained from the National Earth System Data Center (https://soil.geodata.cn/ztsj.html (accessed on 1 March 2023)). The spatial resolution of all data was resampled uniformly to 10 m.

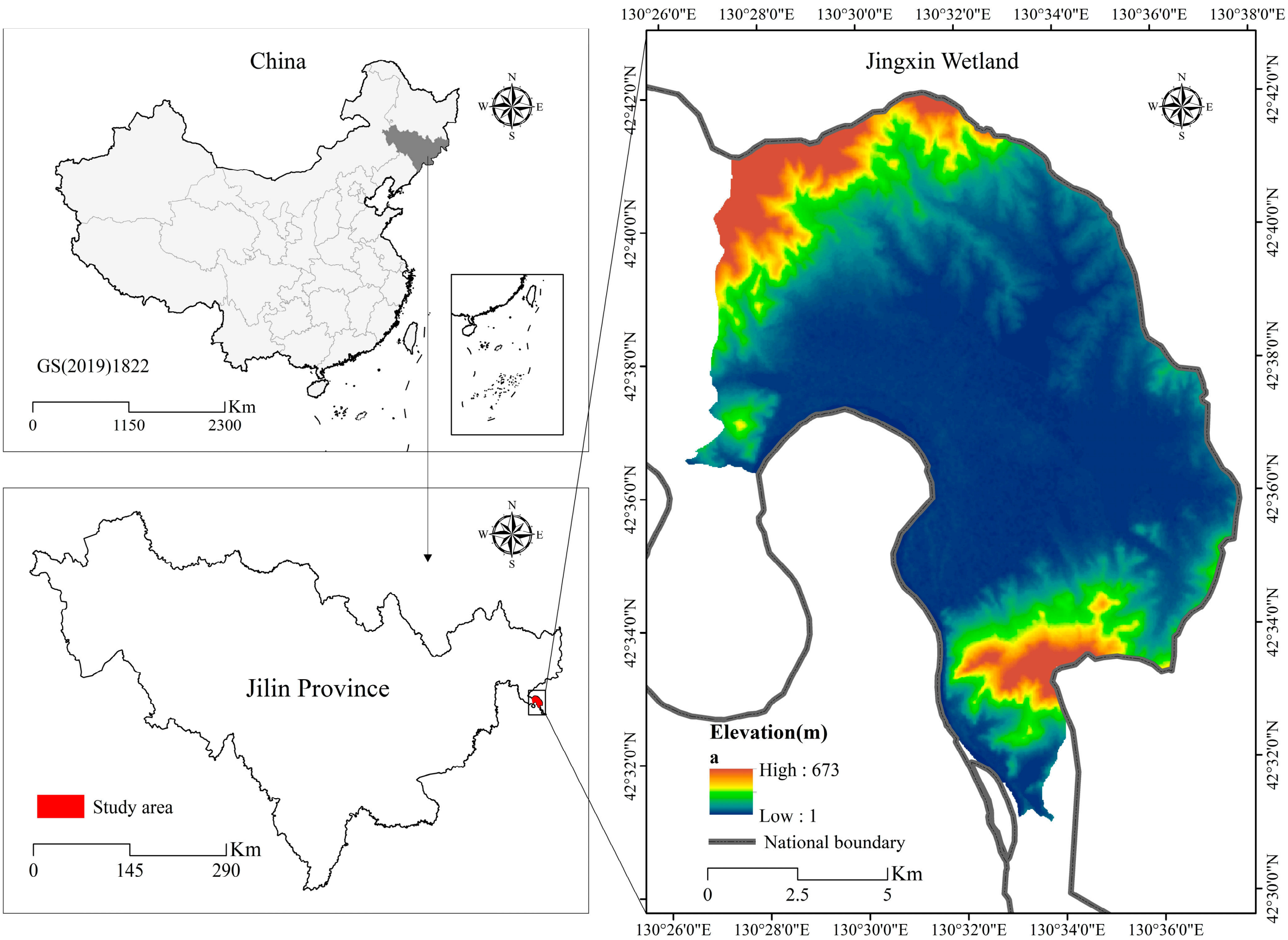


Figure 1. Location map of the study area.

2.3. Research Design

The research was conducted following three main steps (Figure 2): (1) Extraction of information from high-resolution images using object-facing classification, improvement in the accuracy of wetland land use classification, and exploration of the spatial and temporal changes in wetland land use. (2) Exploration of land use change under multiple scenarios. Based on the CA-Markov model, a high-precision simulation of wetland dynamics for the 2019–2047 period was performed under three scenarios: natural development scenario (NDS), economic development scenario (EDS), and ecological protection scenario (EPS). (3) Investigation of the response of habitat quality to land use change in Jingxin Wetland and identification of the drivers of habitat quality change based on the InVEST model.

2.3.1. Classification Method and Accuracy Validation

The preprocessing of the Corona and SPOT raw images was adopted from Liu et al., 2009 [43]. Images were pre-processed using eCognition Developer 9.3 software. Multi-scale segmentation was performed first, and the optimal segmentation scale was selected after several trials. The optimal segmentation scale can reduce patch redundancy and fragmentation and improve the purity of the target sample, thus increasing accuracy and runtime speed. Selecting feature values such as spectrum, texture, shape, and vegetation index of the object, preliminary land cover data for the study area were derived from the generated object collection samples and combined with random forest classifier calculations. According to the actual situation of land resource utilization in Jingxin Wetland, the national standards "Land Use Status Classification" (GB/T 21010-2017) [44] and "Wetland Classification" (GB/T 24708-2009) [45] were followed to establish a landscape classification system suitable for Jingxin Wetland (Table 1). With reference to the historical images and field data of Google Earth, misclassified features were re-corrected by visual interpretation, and the accuracy of the classification results was verified. The overall accuracy of the classification was determined to be above 90%, which meets the requirements of this study.

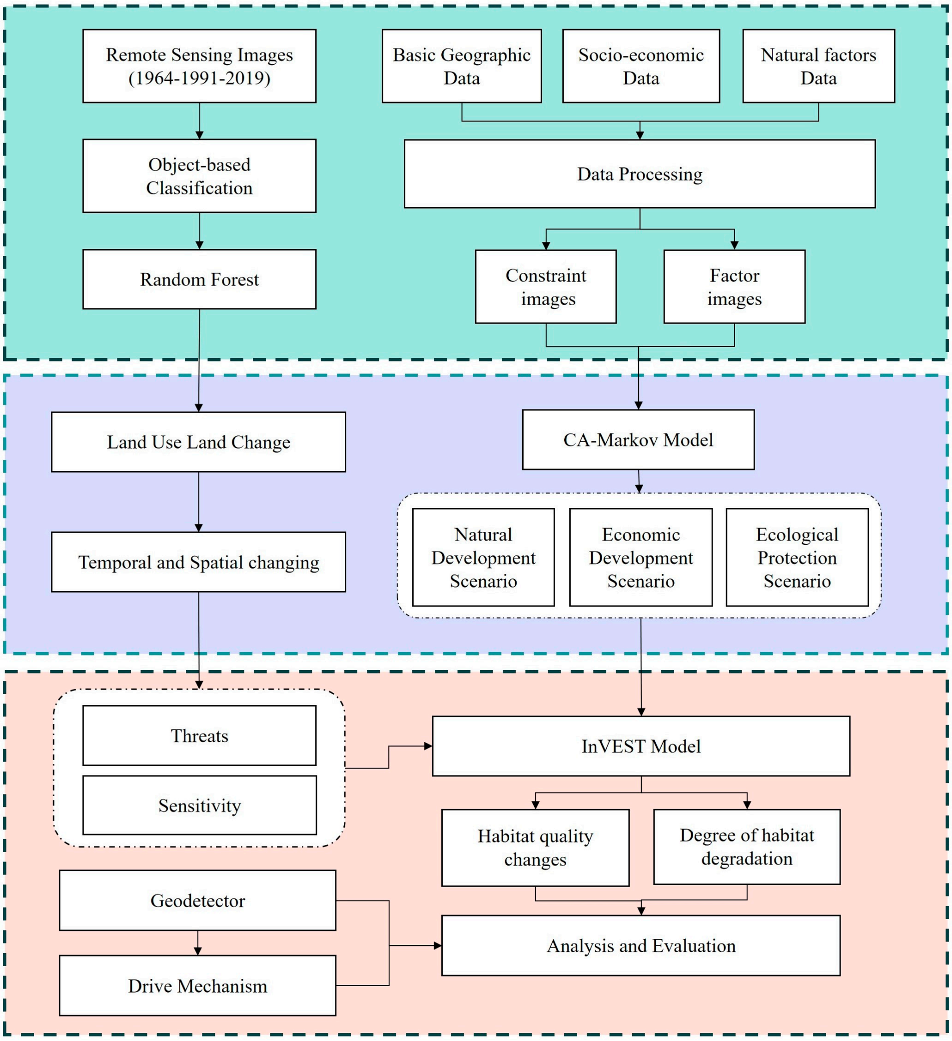


Figure 2. Research technology roadmap.

2.3.2. CA-Markov Simulation and Validation

In this study, the MCE module in IDRISI 17.02 software was used to produce a land use suitability atlas, and a 5 × 5 filter was used, i.e., a rectangular space of 5 × 5 cells around a metacell is considered to have a significant effect on the change in the state of that metacell. To ensure the reliability of the simulation results, the number of CA model iterations was set as 28. For model validation, we simulated the landscape pattern of Jingxin Wetland in 2019 under the natural growth scenario. The accuracy of the model to simulate changes in landscape patterns was tested using the Kappa index, with the following equation:

$$Kappa = (P_0 - P_c)/\left(P_p - P_c\right) \quad (1)$$

where: P_0 denotes the proportion of correct simulations; P_c denotes the proportion of correct simulations in the model random case; P_p denotes the proportion of correct simulations in the ideal classification case.

Table 1. Landscape classification system for Jingxin Wetland.

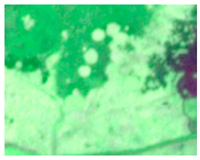
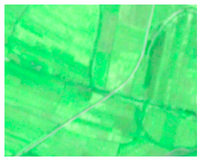
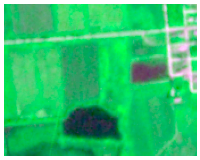
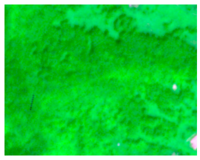
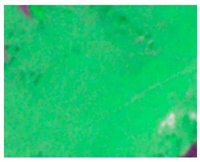
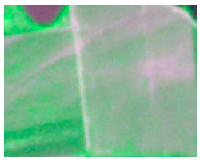
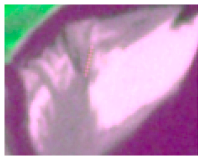
Category I	Category II	Description	Image
Natural Wetlands	Marsh	Long-term waterlogged, marsh and partly wet, aquatic or saline plant zones	
	River	Including rivers and their tributaries, streams and waterfalls	
	Lake	Wetlands consisting of natural depressions of varying sizes and shapes in the ground filled with water bodies	
Artificial wetlands	Paddy field	Land used for growing aquatic crops such as rice	
	Pond	Artificially excavated or naturally formed ponds with a storage capacity of less than 10^5 m^3 water surface enclosed by the shoreline of the normal water level	
	Reservoir	Water storage and power generation as the main function of the construction of artificial wetlands, with an area greater than 8 hm^2	
Forest		Land covered by trees, bamboos and shrubs	
Grassland		Land dominated by herbaceous plants	
Cropland	Dry land	Arable land without irrigation equipment, mainly relying on natural precipitation to grow dry crops	

Table 1. *Cont.*

Category I	Category II	Description	Image
Artificial Surface	Residential area	Land on which buildings and structures are constructed	
	Transportation Land	Land used for transportation and passage of ground lines, yards and stations, etc.	
Mudflats	River Manzanita	The part of the valley bottom beyond the river bed that is inundated during river floods	
Other land	Forest fire barrier	Open areas between forests and between forests and villages, schools, factories, etc. to prevent the spread of fire and to facilitate fire-fighting and rescue	

Using the CROSSTAB module in IDRISI software, the actual and predicted landscape type maps of Jingxin Wetland in 2019 were input to test the model accuracy. The run yielded a Kappa coefficient of 0.83 for 2019, showing that the model simulation is good and the validated CA-Markov model can be used to predict the landscape type in 2047.

2.3.3. InVEST Model

The biodiversity module of the InVEST model uses the level of habitat quality to represent changes in the persistence, resilience, and recovery of biodiversity; habitat quality and habitat scarcity are calculated by the model as a reflection of biodiversity [46]. Habitat change is considered to be a proxy for genetic, species, or ecosystem change, and the model assumes that areas with high habitat quality will better support all classes of biodiversity [47]. The InVEST model was developed by establishing a link between threat sources and habitat quality, considering the relative impact of threats (weights), the distance between the habitat grid and the threat, the degree to which the grid is legally protected, and the relative sensitivity of each habitat type to each threat. The degree of habitat degradation and habitat quality of the study area were obtained by calculating the negative impact of threat sources on habitat quality. The specific calculation process is as follows:

$$Q_{xj} = H_j \left(1 - \frac{{D_{xj}}^2}{{D_{xj}}^2 + k^2}\right) \tag{2}$$

where Q_{xj} represents the habitat quality of raster x in land use and land cover j; H_j represents the habitat suitability of land use and land cover j; k is the half-saturation constant, and when k = 0.5, the k value is equal to the D value; D_{xj} is the habitat stress level of raster x in landscape type j. The equation is as follows:

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} \left(\frac{W_r}{\sum_{r=1}^{R} W_r}\right) r_y i_{rxy} \beta_x S_{jr} \tag{3}$$

The stressor r in raster y on the habitat in raster x is i_{rxy}.

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{d_{rmax}}\right)(Linear) \tag{4}$$

$$i_{rxy} = exp\left[-\left(\frac{2.99}{d_{rmax}}\right)d_{xy}\right](Indexes) \tag{5}$$

where d_{xy} is the linear distance between raster x and y; d_{rmax} is the maximum action distance of threat factor r, which is the weight of threat factor; β_x is the accessibility level of raster x (1 represents extremely attainable level); S_{jr} is the sensitivity of landscape type j to threat factor r (the closer the value to 1, the higher the sensitivity).

The main parameters required to run the habitat quality model include the distance of threat factor effects and their weights, and the suitability and sensitivity of the habitat to each threat factor. Combining existing research results and taking into account the current situation in the study area [48–51], cultivated land, construction land, and transportation land, which have a greater impact on wetland types, were selected as ecological stressors. The suitability and sensitivity of each threat factor were assigned with reference to previous studies, as shown in Tables 2 and 3.

Table 2. Threat factor attributes.

Threats	Maximum Distance of Influence (km)	Weights	Type of Spatial Recession
Dry land	0.5	0.5	indexes
Paddy field	0.5	0.5	indexes
Residential area	2	0.7	indexes
Transportation Land	1	1	linear

Table 3. Sensitivity of landscape types to threat factors.

Land Use	Habitat Suitability	Dry Land	Residential Area	Transportation Land	Paddy Field
Transportation Land	0	0	1	0	0
Pond	0.9	0.6	0.8	0.6	0.2
Residential area	0	0	0	0	0
Dry land	0.4	0	0.3	0.3	1
Forest	0.9	0.3	0.5	0.7	0.8
Forest fire barrier	0	0	0	0	0
Reservoir	0.7	0.6	0.8	0.5	0.6
Paddy field	0.5	0.3	0.5	0.1	0
River	0.9	0.1	0.7	0.6	0.3
River Manzanita	0.1	0.1	0.2	0.1	0.1
Marsh	0.9	0.6	0.7	0.4	0.2
Lake	0.9	0.1	0.7	0.6	0.2
Grassland	0.6	0.5	0.2	0.5	0.8

2.3.4. GeoDetector

GeoDetector 2015 is a new statistical tool for detecting spatial differentiation, as well as revealing the driving factors behind it [52]. GeoDetector can effectively explain factors affecting the spatial heterogeneity of habitat quality. In this study, the interaction detector of the factor detector was used to detect the interaction between different variables of habitat quality. The explanatory power of each factor was measured using the q-value by quantifying the spatial heterogeneity of potential natural and anthropogenic factors. The expression is as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^{L} N_h \sigma_h^2 \quad (6)$$

where q indicates the explanatory power of the factor on habitat quality; h = 1, ..., L is the stratification of variable Y or factor X; N_h and N are the number of cells in stratum h and the whole region, respectively; σ_h^2 and σ^2 are the variances of Y values in stratum h and the whole region, respectively. The q-value is between 0 and 1, and a larger q indicates a stronger explanatory power of the factor.

2.3.5. Multiple Scenario Settings

The objective behind configuring these scenarios is to assess forthcoming alterations within Jingxin Wetland as influenced by distinct conditions. According to the local government's conservation planning for wetlands, combined with related studies [53,54], three scenarios were established, namely ecological protection, economic development, and natural development. Taking the same time interval as land use change, land use changes in 2047 under these three scenarios were explored. In this manner, the habitat quality change of Jingxin Wetland was determined. Natural development scenario (NDS) refer to situations that are not affected by national policies and natural disasters, where future trends in wetland change are consistent with the 1991–2019 trends. Economic development scenario (EDS) refer to the rapid development of the local economy and expansion of construction scale. Considering the dominant position of Jingxin Wetland in the Tumen River development strategy, the area of non-wetlands such as buildings and roads will inevitably increase, and the corresponding threats to wetlands will also gradually increase. It is thus necessary to explore the direction of development for which the Markov transfer matrix was adjusted to set the conversion rate from each wetland type to non-wetlands to increase by 50%, with no change in the interconversion rate for other wetland types. Ecological protection scenario (EPS) focuses on the protection of wetland ecology. In accordance with the "14th Five-Year Plan for Ecological Protection of Yanbian Prefecture" for the restoration of Jingxin Wetland, aiming to provide a reference for ecological conservation, ecological quality, and sustainable development, the conversion rate of each wetland type to non-wetland was set to be reduced by 50%, and a value of 0 was assigned to the accessibility of degraded sources in the Jingxin Wetland Core Reserve.

3. Results

3.1. Dynamic Evolution Characteristics of Wetland Types

The land use types in Jingxin Wetland primarily include natural wetlands (swamp wetlands), artificial wetlands (reservoirs, paddy fields), forests, grasslands, and dry fields, accounting for more than 90% of the total area of the region (Figure 3). Dramatic land use changes occurred from 1964 to 2019, with the type and scale of land use widely varying across periods. Among these, from 1964 to 1991, the area of lake wetlands and marsh wetlands showed a decreasing trend, accounting for a loss of nearly 525 ha of natural wetland (Figure S1). In contrast, the area of paddy field increased by 1667 ha and large reservoirs were constructed, significantly increasing the area of artificial wetlands. From 1991 to 2019, the landscape pattern of Jingxin Wetland evolved more dramatically, with a natural wetland loss of nearly 348 ha. Specifically, the rate of marsh wetland degradation increased, with the area of marsh wetland decreasing at a rate of 19.91 ha per year. The area of lake and pond showed small increases, the degradation of forest was also more pronounced, and the area of grassland increased at a rate of 60.59 ha per year. The extent of the artificial surface expanded even more, and dryland simultaneously increased at a rate of 33.22 ha per year. With the continuous expansion of transportation land, the spatial extent of land use change in Jingxin Wetland spread outward in a radial pattern, reflecting the increased intensity of human interference and more complex landscape types during the period.

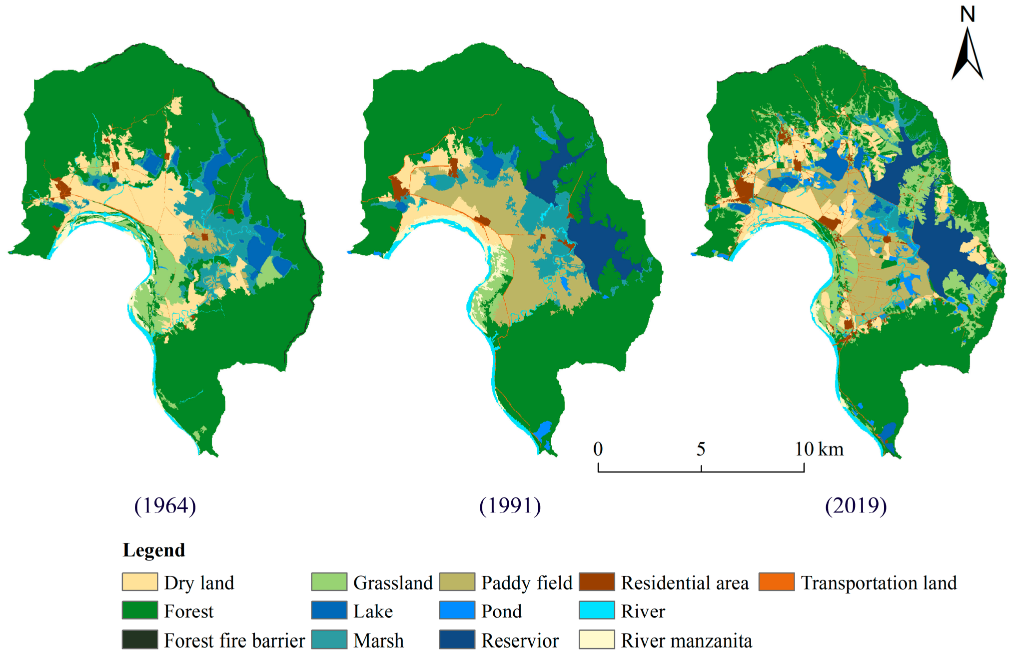


Figure 3. Spatial distribution of landscape types in 1964, 1991, and 2019 in Jingxin Wetland.

Frequent mutual land use transfers occurred in Jingxin Wetland during 1964–2019, mainly among swamp wetlands, artificial wetlands, and forests (Figure 4). From 1964 to 1991, artificial wetlands accounted for the largest land use type transfer, of which the main contributor was paddy fields, mainly dry fields (1055.2 ha) and swamp wetlands (230.9 ha), followed by reservoirs, which were mainly built on the basis of the original lake and swamp, with a total of 438.1 ha of lake and 390.5 ha of swamp wetland converted to reservoir area. A large loss of marsh wetlands occurred during 1991–2019, with a total transfer out of 845.3 ha, mainly through conversion to artificial wetlands such as paddy fields and ponds, and increased human use of marsh wetlands. The area of paddy fields was 336.2 ha, mainly shifting to dry fields, which fluctuated somewhat between conversions from and to paddy fields in different periods.

3.2. Spatial and Temporal Variation Characteristics of Wetland Types under Different Scenarios

Compared to the baseline scenario (2019), the ecological protection scenario presents the smallest degree of change in wetland land use (Figure 5). Under this scenario, the desired effect of ecological protection is achieved. Under the natural development and economic development scenarios, the area of non-wetland land use increases and the spatial scope of land use is more scattered. The natural development scenario continues the trend of fragmentation of wetland landscapes, which is mainly manifested in the continuous shrinkage of marsh wetland area (Figure S2), increase in the area of ponds and lakes, increase in the area of cultivated land, and decrease in the area of forest land. The ecological protection scenario results in better protection of the ecology of Jingxin Wetland, artificial surface expansion is effectively controlled, and encroachment on ecological land such as forest land and natural wetlands is minimal. Under the economic development scenario, the area of swamp wetlands shrinks dramatically, the area of ponds reaches its maximum, and the area of building land and transportation land expands significantly.

3.3. Habitat Quality Analysis

The habitat quality of Jingxin Wetland varied significantly among different periods due to changes in land use (Figure 6). From 1964 to 1991, the habitat quality of Jingxin Wetland showed an overall decreasing trend, with the decrease in areas having excellent quality, and the increase in areas having moderate and good quality (Figure 7). The largest change was observed in the area of excellent quality, which shifted mainly to areas of good and moderate quality. The area transferred out of poor habitat quality accounted for approximately 15% or more of the total transferred area. Habitat quality changed more significantly with land use expansion from 1991 to 2019, where the transfer out of areas with very good habitat quality accounted for more than 35% of the total transferred area. A major shift to areas of moderate quality was observed, and the transfer in of areas of poor habitat quality was greater than the transfer out, indicating a tendency for further deterioration of habitat quality with the evolution of the landscape pattern.

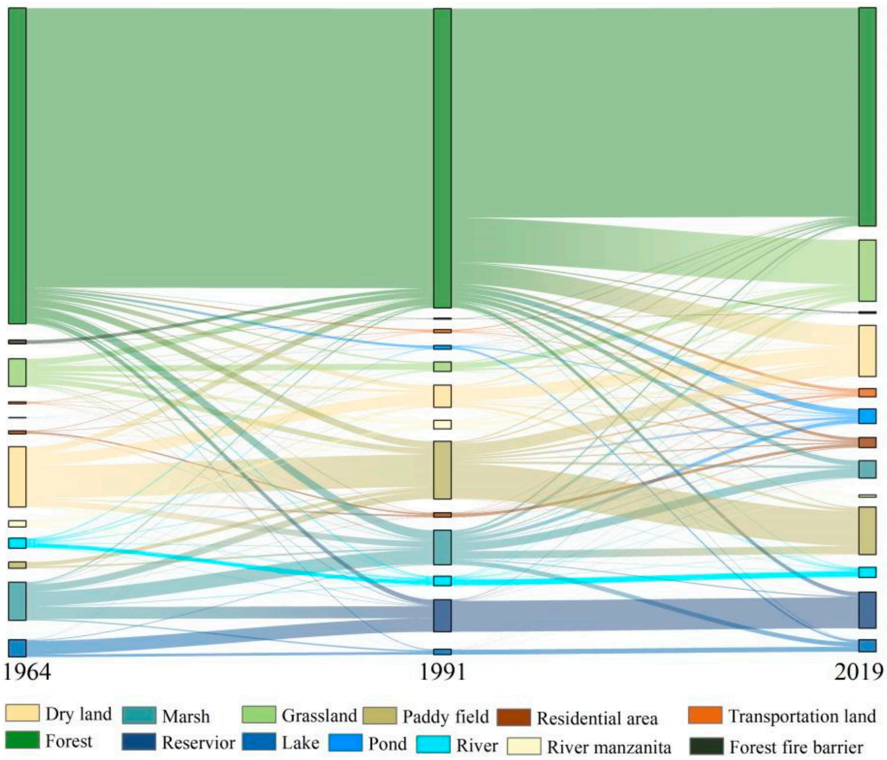


Figure 4. Sankey map of landscape type area transfer.

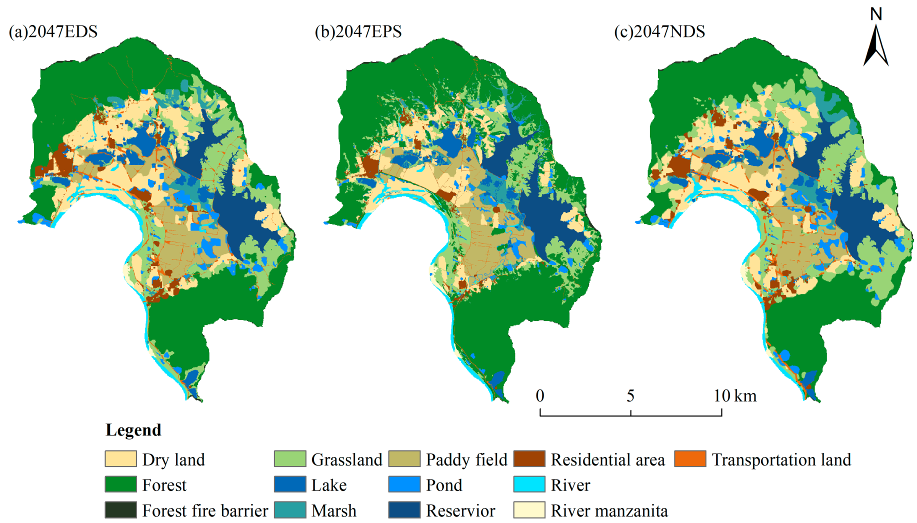


Figure 5. Projected results of landscape pattern in Jingxin Wetland in 2047 under different scenarios.

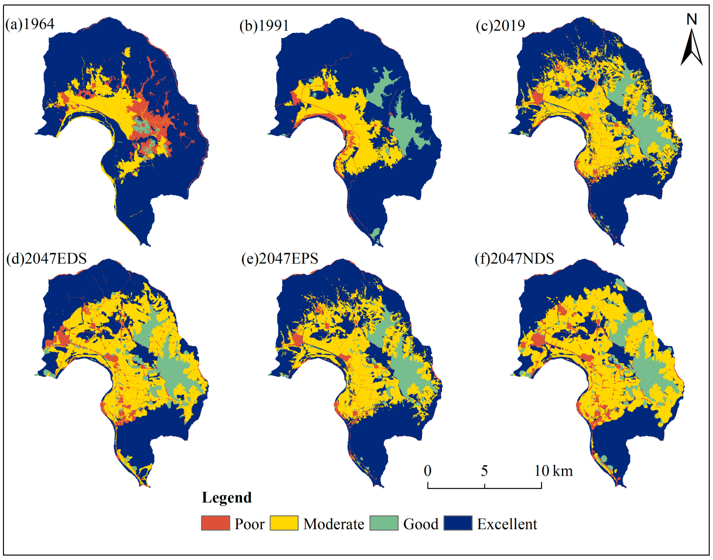


Figure 6. Spatial distribution pattern of habitat quality in different years.

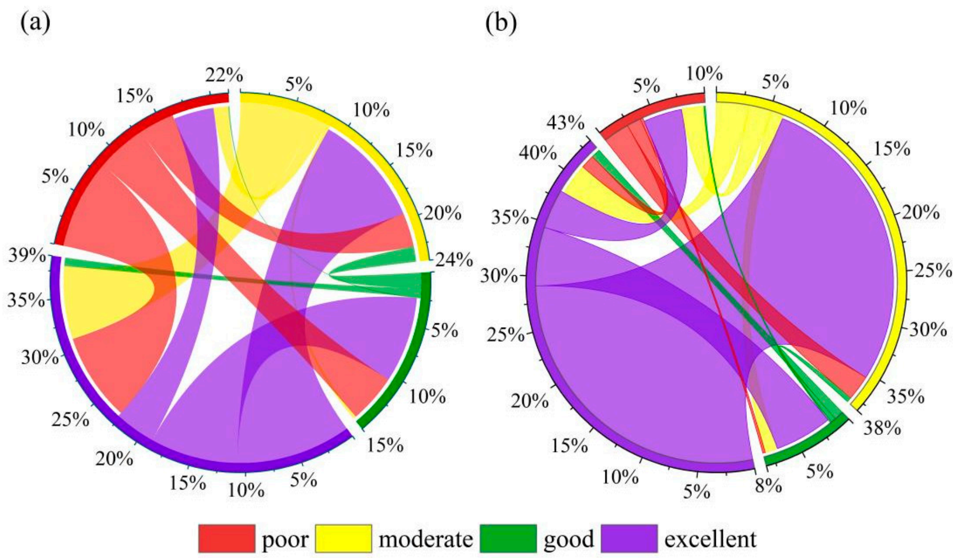


Figure 7. Habitat quality transfer chord diagram of Jingxin Wetland during 1964–2019. Note: (**a**) habitat quality transfer during 1964–1991; (**b**) habitat quality transfer during 1991–2019.

Significant differences can be observed in the area of habitat quality classes between scenarios in 2047 (Figure 8). The ecological protection scenario presents the largest area of excellent habitat quality and the smallest area of poor habitat quality. Habitat quality distribution patterns are similar under both the natural development and economic development scenarios. Nevertheless, there are also some characteristic differences in habitat quality due to the different focus of development, which has different impacts on landscape patterns. The economic development scenario has a larger area of poor grade habitat quality, whereas the natural development scenario shows a decrease in the area of excellent habitat quality, an increase in the area of moderate habitat quality, and a deterioration in the overall environmental ecological quality.

3.4. Degree of Habitat Degradation

The habitat degradation index expresses the magnitude of the level of stressors to which the species is exposed at the current regulatory level, thus reflecting the magnitude of the probability of habitat degradation and habitat quality reduction. The value of the habitat degradation index ranges from 0 to 1, indicating the relative level of habitat degradation of current land use. For a more visual description of habitat degradation trends, the natural breakpoint method was used to classify and compare the degree of habitat degradation (Figure 9).

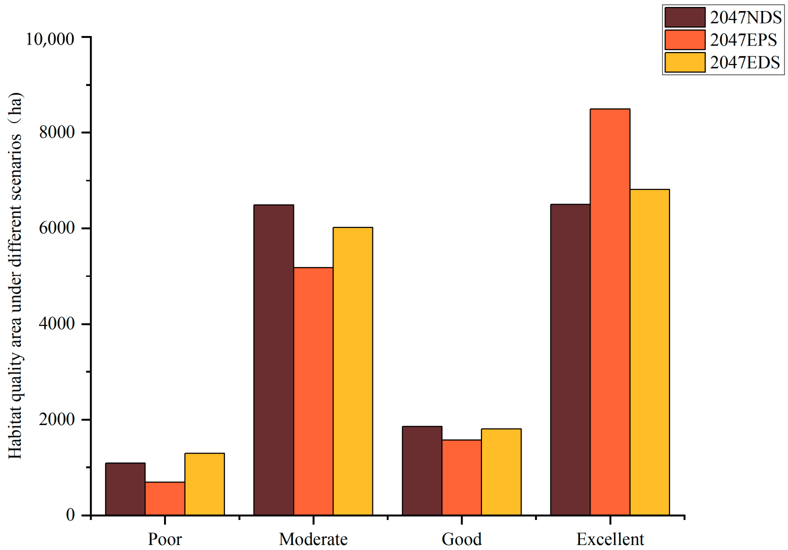


Figure 8. Comparison of habitat quality area in 2047 under different scenarios.

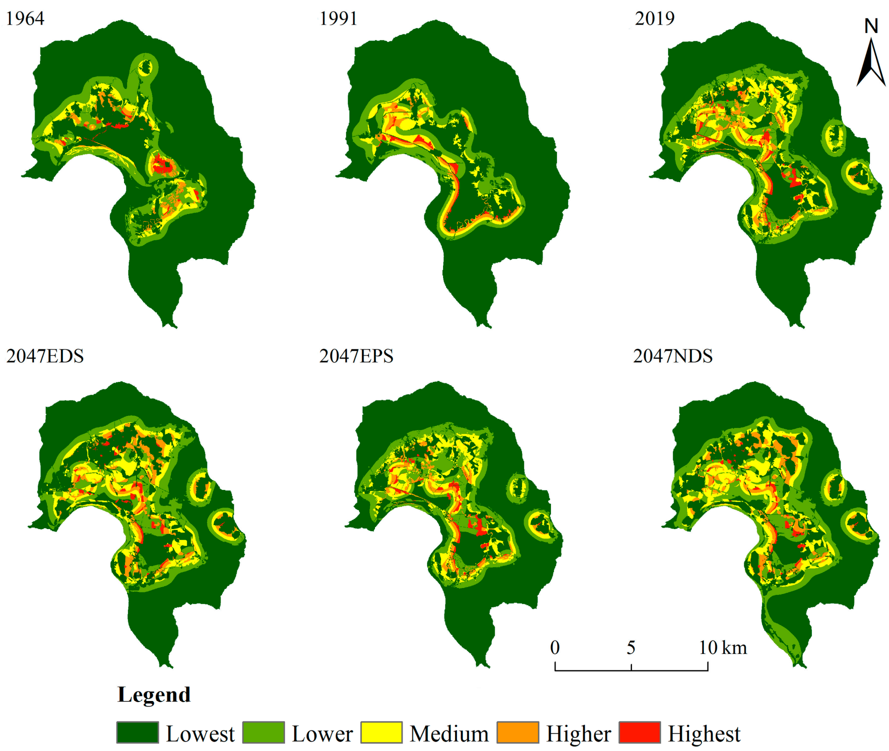


Figure 9. Spatial distribution pattern of habitat degradation in different years.

From 1964 to 1991, the area of lower and lowest degradation accounted for more than 90% of the total area, and the area of higher and highest degradation accounted for about the same percentage (Figure S3). From 1991 to 2019, the degradation pattern changed significantly, with the area of lower degradation and below shrinking to 84%, and the area of high degradation increasing to 10%. Habitat degradation shows little change under the future ecological protection scenario compared to 2019. Under the natural development scenario, the area of lowest degradation is the smallest and the areas of medium and higher degradation increase to 19%. Under the economic development scenario, the area of lowest degradation increases compared to the natural development scenario, and the area of highest degradation is the largest, increasing by 2%.

3.5. Possible Factors Affecting Changes in Habitat Quality

Changes in habitat quality in Jingxin Wetland are the result of a combination of human activities and natural factors. In this study, we selected 11 potential factors that can reflect the regional natural environment and human disturbance. According to the magnitude of the q-value of each driver (Figure 10a), the drivers were divided into three categories. The first category included x9 (Human Footprint) > x10 (DEM) > x2 (Slope) > x4 (POP), with q-values all above 0.2, representing the dominant drivers of habitat quality change. The second category included x6 (Distance from water) > x7 (Distance from railway) > x1 (Soil) > x5 (Gross Domestic Product), with q-values all above 0.1, representing important drivers of habitat quality change. The third category included x8 (Distance from main road) > x11 (Temperature) > x3 Rainfall, with relatively small q-values and weak explanatory power for habitat quality changes. The results of the interaction detector showed (Figure 10b) that two potential factors increase the explanatory power of habitat quality when acting together. The type of interaction is mainly expressed as a two-factor enhancement, and the explanatory power of the interaction is higher than the explanatory power of either factor alone. The most significant contribution of x9 (Human Footprint) to the interaction detection and the strongest interaction of x9 ∩ x7 further illustrate the important influence of human activities on habitat quality.

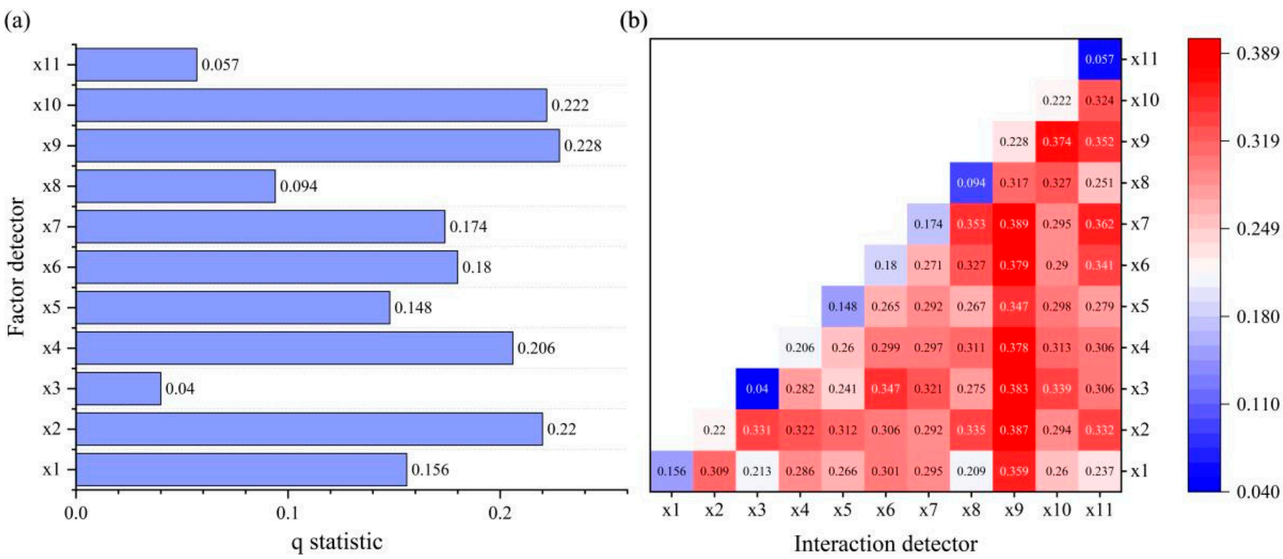


Figure 10. q statistical index and interaction results calculated using GeoDetector. Note: (**a**) q value of Factor detector; (**b**) Factor interaction detection results. x1 Soil, x2 Slope, x3 Rainfall, x4 Population density, x5 Gross Domestic Product, x6 Distance from water, x7 Distance from railway, x8 Distance from main road, x9 Human Footprint, x10 Digital elevation model, x11 Temperature.

4. Discussion

4.1. Impact of Wetland Type Change on Habitat Quality

From 1964 to 2019, habitat quality in Jingxin Wetland was sensitive to the shift in wetland type, with the loss of natural wetlands being the most significant factor in the decline of habitat quality. The most distinct change in Jingxin Wetland was observed after the construction of the Longshan Reservoir in the 1980s, resulting in the conversion of natural wetlands such as large swamp wetlands and lake wetlands into artificial wetlands (Figure 4). The construction of reservoirs disrupts the hydrological connectivity between lakes and leads to shrinkage of the lake [55], but it also provides objective hydrological conditions for the reclamation of paddy fields; large areas of dry land were reclaimed as paddy fields, which is also related to the local population's habit of eating rice [56]. LUCC alters the water recharge pathway of wetlands, reducing recharge by surface runoff. Human activities affect runoff regulation and the seasonal distribution of reservoirs, which also leads to the gradual reduction in wetland hydrological inflow. These changes in the water area affected the swamp landscapes distributed in Jingxin Wetland. Consequently, natural wetlands undergo degradation and wetland habitat quality declines, which further reflects the high explanatory power of the distance from the water for habitat quality in GeoDetector. From 1991 to 2019, influenced by anthropogenic water bundling, the area of pond and lake wetlands increased and wetland patches became more fragmented, both of which resulted in a decrease in the area of higher habitat quality and an increase in the extent of habitat degradation. The direct role of human activities on land use change has been made clearer through the validation of GeoDetector. The interaction of the human footprint with other factors has high explanatory power for habitat quality (Figure 10b), reflecting the trend of humans taking advantage of natural conditions and constantly pursuing socio-economic development, which exerts a significant impact on habitat quality. According to the projected results under different scenarios for 2047, the implementation of ecological protection measures can effectively control land use change, protect natural wetland resources, maintain habitat quality, and support a trend towards better ecological conditions. In contrast, under the natural development scenario and the economic development scenarios, wetland land use is more fragmented and habitat quality continues to decline. This corroborates the view that land use change in wetlands is a major factor influencing habitat quality [57].

4.2. Suggestions for the Development of Wetland Areas under Ecological Conservation Scenarios

In this study, among the land use projections for different future scenarios, the ecological protection scenario shows the best overall effect on habitat quality. This model enhances the protection of wetlands, in line with the development goals of local ecological civilization and ecological security. However, in the actual development process, the means of achieving sustainability between agricultural and economic development and wetland conservation have been a leading issue of concern for scholars [58,59]. In response to the human–land conflict revealed by the study results, the following measures can be taken in the future to weigh the contradiction between economic development and ecological protection, which would help in maintaining habitat quality and ecological safety in Jingxin Wetland. (1) Considering the continuous increase in artificial surfaces from 1964 to 2019 (Figure S1), the scale of construction land should be controlled scientifically through planning in the future. In principle, in line with the scale and layout of territorial spatial planning and urban development boundary control requirements, the potential of existing construction land should be vigorously explored, and the supply of land for construction should be strictly controlled to reduce the encroachment of wetlands during urban expansion [60]. (2) The agricultural area of the Jingxin Wetland is still the main land use area (Figure 3), with the single mode of social production for community residents. Food crops are an important source of economic income, and as the population increases, artificial wetlands such as paddy fields and ponds will inevitably be built around the natural wetland area. Therefore, in the process of implementing the policy of returning farmland to wetlands and forests, etc., corresponding ecological compensation measures should be introduced to enhance the participation of residents in wetland conservation efforts [61,62]. (3) Ecological conservation needs to rely on local residents. In wetland ecological protection and restoration projects, local residents should be assigned jobs such as forest rangers and wetland guards. At the same time, wetland eco-industries can be developed in the local area such that residents can enjoy the dividends of a better ecological environment [63].

4.3. Strengths and Limitations of the Study

In this study, object-oriented land cover classification algorithms based on high-resolution image data were used to achieve feature extraction of Jingxin Wetland, and the monitoring of spatial variations in the long time series of land use change in Jingxin Wetland was achieved. In terms of model coupling, the CA-Markov and InVEST models integrate new land use expansion analysis strategies to simulate changes in different types of land use patches with high accuracy. Using this combination, the problem of the accuracy of simulation data in the field of large-scale research can be overcome [64,65]. This study explored the dynamics of habitat quality changes in Jingxin Wetland from 1964 to 2019, and also predicted future habitat quality under different scenarios based on government ecological protection policies and economic development trends. The projected results provide a basis for ecological protection and restoration of Jingxin Wetland, as well as a reference for the management of wetlands in other protected areas. However, this study has some limitations. First, in the construction of the CA-Markov model suitability atlas, land use data, distance to water, temperature and precipitation, slope elevation, population density, gross economic product, and accessibility factors were considered, but other factors affecting human activities and socio-economic construction need to be further incorporated and the indicator system needs to be improved. Secondly, although long time series of regional habitat quality monitoring studies are useful for grasping the regional ecological change pattern, considering that the years selected in the study are far apart and span a wide range, the fluctuation in habitat quality within the time interval needs further in-depth study.

5. Conclusions

Based on the integration of the InVEST-CA-Markov model, this study investigated the response of wetland habitat quality to changes in wetland types at multiple past–present–future time scales. From 1964 to 2019, land use patterns in the Jingxin Wetlands tended to be more fragmented, the loss of natural wetland area directly led to the degradation of habitat quality, and the area of habitat degradation expanded. Human activities appeared as the most important driver of habitat quality decline. Regarding future scenarios, under the ecological conservation scenario, the expansion of non-wetland areas such as arable land and artificial surfaces will be curbed, the wetland area will be effectively maintained, and habitat quality will improve. In contrast, the quality of wetland habitats will deteriorate to varying degrees under both the natural and economic development scenarios, which is not conducive to wetland ecological conservation and sustainable development. Our study provides new insights into wetland conservation and ecological development, as well as a reference for the management of other wetland reserves.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151612415/s1. Figure S1. Average annual rate of change in the area of landscape types. Figure S2. Comparison of land use under different scenarios. Figure S3. Area share of different habitat degradation degrees in different years.

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