

Article

Ecological Vulnerability Assessment and Prediction in the Middle Reach of the West Liaohe River Basin

Chunhui Xu ^{1,*}, Cheng Han ¹, Qixin Liu ¹ and Yinghui Ye ²

¹ College of Geographic Science and Tourism, Jilin Normal University, Siping 136000, China; hancheng_vv@jlnu.edu.cn (C.H.); liuqx@jlnu.edu.cn (Q.L.)

² College of Geo-Exploration Science and Technology, Jilin University, Changchun 130026, China; yyh13@jlu.edu.cn

* Correspondence: dlxyxch@jlnu.edu.cn

Abstract

The middle reaches of the West Liaohe River Basin, a typical semi-arid to semi-humid transition and agro-pastoral ecotone in northern China, exhibit high ecological sensitivity, low resilience, and pronounced fragility. Despite growing concerns, existing studies in this region lack a comprehensive assessment paradigm that effectively couples inherent ecological attributes with nonlinear predictive modeling. To fill this gap, we developed an integrative framework that innovatively combined the SRP conceptual model with a stacking ensemble learning technique. This coupling is methodologically novel because it moves beyond linear assumptions, enables the detection of complex nonlinear response surfaces, and establishes a seamless analytical chain from historical evaluation to future projection. By selecting 13 indicators, including topography, climate, soil, vegetation, and socio-economic factors, the weight was determined by the comprehensive application of the analytic hierarchy process and entropy weight method, and the ecological fragility of the middle reaches of the West Liaohe River Basin from 2000 to 2020 was evaluated at multiple scales. The spatial differentiation driving factors were analyzed using a geographic detector. Therefore, an Ensemble Learning Regression model was used to simulate and predict the ecological fragility pattern in 2030. The results show that from 2000 to 2020, the ecological fragility of the study area showed a decreasing trend overall, with the Ecological Vulnerability Synthetical Index (EVSI) decreasing from 3.48 to 2.68, and the spatial pattern gradually shifting from “high in the northwest, low in the southeast” to “overall stability, local optimization.” The spatial agglomeration of ecological fragility gradually weakened, indicating that high-fragility areas tend to disperse and low-fragility areas expand in contiguous areas, and the ecosystem structure tends to develop towards equilibrium. The driving mechanism shows an evolution characteristic from “soil erosion dominated” to “biological abundance dominated,” with the impact of climate factors first increasing and then stabilizing, and the direct pressure from human activities continuously weakening. Under the assumption that historical trends continue, the ensemble learning model projects that by 2030, the ecological vulnerability pattern will be dominated by Mild and Moderate levels, with the area of extremely vulnerable regions significantly reduced to 0.36%. This study verified the applicability of the SRP model in transitional river basins, and the constructed “evaluation-driving mechanism-prediction” framework can provide a scientific basis for the ecological protection and adaptive management of the West Liaohe River Basin and provide a methodological reference for ecological fragility research in similar areas. However, limitations persist: the indicator system and weight assignment are subject to inherent subjectivity, and the 2030 scenario pro-

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jection based on the Stacking ensemble learning model relies on the BAU (Business-As-Usual) assumption, which fails to account for abrupt climate extremes or major policy shifts. Future studies should incorporate multi-scenario constraints to reduce predictive uncertainty.

Keywords: ecological vulnerability; West Liaohe River; SRP model; spatiotemporal evolution

1. Introduction

Under the dual drive of global climate change and rapid land use transformation, ecosystems are facing increasingly strong uncertainty and disturbance risks, and regional ecological security patterns show significant spatial heterogeneity and dynamic fluctuations. Ecological vulnerability, as a core concept for understanding the response of ecosystems to external stress, is usually defined as the susceptibility of the system to degradation under natural or human interference, as well as the set of abilities to maintain function, resist disturbance, and recover to an acceptable state. This concept is closely related to the “exposure-sensitivity-adaptability” paradigm and resilience theory [1–5]. In the context of risk governance and ecological management, vulnerability research is not only committed to identifying “where is more vulnerable” but also emphasizes revealing the mechanisms and processes of “why it is vulnerable, how to recover, and how to intervene,” thereby providing a scientific basis for delineating ecological protection red lines, prioritizing restoration, and formulating adaptive strategies [6,7].

The West Liaohe River Basin is situated in a critical zone of the northern agro-pastoral ecotone and ecological barrier, where hydrothermal conditions exhibit a transitional state from semi-arid to semi-humid. The spatiotemporal distribution of water resources is uneven, and coupled with changes in land use intensity and the implementation of ecological engineering projects, this has continuously pressured ecosystem functions such as water conservation, soil retention, and habitat provision, rendering it a typical ecologically fragile region [8–11]. Consequently, there is an urgent need to conduct systematic assessments and dynamic simulations of ecological vulnerability in this area to promote the sustainability of the human-environment system and optimize the ecological security pattern. In recent years, ecological research targeting the West Liaohe River Basin has progressed considerably. Regarding ecological carrying capacity and security patterns, Zheng et al. assessed the spatiotemporal evolution of ecological carrying capacity and constructed an ecological security pattern using spatial principal component analysis and the minimum cumulative resistance model [8]; Lyu et al. characterized the spatiotemporal changes in ecological security patterns based on ecosystem services and found that natural factors had stronger explanatory power for ecological sources and corridors than human activities [9]. In terms of land use and ecological element relationships, Duan et al. revealed trends of decreasing water bodies and grassland areas while increasing farmland areas within ecological land [10]. Regarding local ecological responses, Yan et al. found that river flow contributed more to riparian vegetation changes than climatic factors [11]. These studies have laid an important foundation for understanding the evolution of the basin ecosystem; however, several limitations remain. First, most studies have focused on historical state assessments and have not formed a complete research chain encompassing evaluation, driving-force analysis, and prediction. Second, the commonly used methods are predominantly linear or semi-linear models, which inadequately capture the nonlinear response relationships between ecological vulnerability and multiple driving factors. Furthermore, existing research has largely concentrated on the entire basin or the up-

stream source areas, while targeted studies on the middle reaches, a typical agro-pastoral transitional zone, remain relatively weak.

Driven by global changes and regional sustainable development issues, research on ecological vulnerability has gradually shifted from conceptual analysis and qualitative description to an integrated paradigm of “indicator system construction-spatial heterogeneity diagnosis-driving mechanism identification-scenario simulation prediction-governance strategy assessment” [1–7]. At the methodological level, the framework of ecological evaluation indicators has continuously evolved from PSR and DPSIR to multi-dimensional, comprehensive models. PSR and its extended models organize indicators through the causal chain of “pressure-state-response,” which can clearly reveal the formation mechanism of ecological and environmental problems and their logical relationship with management interventions, thus having strong intuitiveness and communicability in environmental performance evaluation and policy diagnosis. However, such models essentially rely on the linear causal assumption and often perform poorly in depicting nonlinear processes, multi-source driving mechanisms, and cross-scale feedback effects commonly existing in complex ecosystems. Simultaneously, the classification and weighting of indicators at different levels are more susceptible to researchers’ subjective judgments, thereby weakening the comparability and generalizability of different research results to some extent [12]. The VSD model provides a systematic and operational path for complex human-land system coupling research through a structured analysis of exposure, sensitivity, and adaptive capacity dimensions, and can flexibly integrate multi-source data to support multi-scale assessment, especially highlighting the interactive impacts of socio-economic and ecological systems [13–15]. However, the model still faces challenges in practical application, such as the weighting and interaction relationships between dimensions often relying on subjective judgments, lack of unified standards, and the subjectivity and uncertainty in the selection and standardization of indicators are often not fully quantified and reported [16,17]. In recent years, the SRP model has directly revealed a comprehensive risk pattern under the joint action of the natural background and human activities by juxtaposing the intrinsic attributes of the system (sensitivity and recovery) with external stresses. It has been applied and expanded in research on ecological and geological vulnerability [18–20].

At the level of evaluation methods, the reasonable determination of index weights and accurate identification of driving mechanisms are key to ensuring the scientificity and interpretability of the results. Subjective weighting methods (such as the analytic hierarchy process (AHP)) can effectively integrate domain knowledge [21–23]; Objective weighting methods (such as the entropy weighting method) rely on information entropy theory, allocate weights according to the degree of variation of index data, and help reduce subjective bias [24,25]. Spatial analysis methods (such as global and local spatial autocorrelation) can effectively reveal clustering patterns and spatial dependence of vulnerability [26,27]. The GeoDetector, based on the spatial differentiation consistency calculation factor, explains the explanatory power (q statistic), does not rely on linear assumptions, and can identify the interaction between factors, making it suitable for multi-factor driving analysis of ecological processes [28,29]. Ensemble learning models reduce the risk of overfitting by combining multiple base learners, effectively capturing the nonlinear relationship between ecological vulnerability and driving factors [30,31]. However, its prediction accuracy depends on sample representativeness, feature engineering, and hyperparameter optimization, and requires strict validation through cross-validation and independent data to ensure robust results [32].

To address the deficiencies of existing studies, which mainly focus on historical states, rely on linear or semi-linear methods, and lack targeted research on the typical agro-pastoral middle reaches, we propose an integrated “evaluation-driver-projection”

framework tailored to the West Liaohe River Basin. Specifically, we constructed an SRP-based indicator system with AHP-entropy weights to capture the natural and anthropogenic dimensions of vulnerability. We then applied GeoDetector to reveal how the dominant drivers and their synergistic interactions evolved over three decades (2000, 2010, and 2020). Finally, we employed a stacking ensemble model to simulate the 2030 vulnerability pattern under the BAU assumption. This framework not only tests the superiority of non-linear ensemble learning over traditional models in handling complex ecological responses but also identifies spatially explicit priority areas for future ecological restoration and adaptive management.

2. Materials and Methods

2.1. Overview of the Study Area

This study considers the middle reaches of the West Liaohe River Basin as the core area, covering two prefectural-level administrative regions, Chifeng City and Tongliao City in the Inner Mongolia Autonomous Region. The geographical coordinates range between 116°20' E–124°14' E and 41°08' N–45°22' N, with an area of approximately 146,100 square kilometers (Figure 1). The region is located at the southern end of the Daxing'an Mountains, the northern slope of the Yanshan Mountains, and the transition zone of Inner Mongolia Plateau. The landform shows significant east–west differentiation and transition characteristics. The north of Chifeng is mainly mountainous and hilly, accounting for approximately 70%, with a terrain that is higher in the west and lower in the east, with an altitude ranging from 300 to 2067 m. Tongliao in the south is mainly characterized by the West Liaohe River alluvial plain and the Korqin Sandy Land, with plains accounting for approximately 70% and sandy land accounting for approximately 46%, with an overall altitude between 120 and 550 m. This “north mountains, south sands, and central river valley” topographical pattern profoundly affects the structure and function of regional ecosystems.

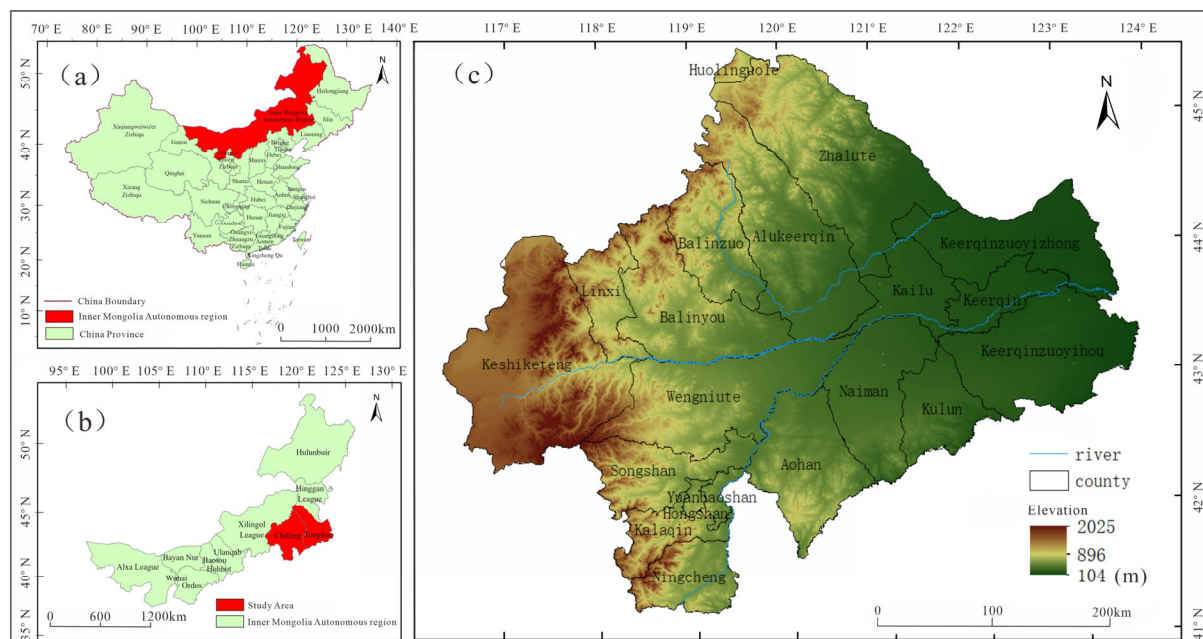


Figure 1. Location of the Study Area. (a) The location of Inner Mongolia Autonomous Region in China; (b) The location of the study area in the Inner Mongolia Autonomous Region; (c) Administrative division map of the study area.

This region has a temperate continental monsoon climate, with distinct characteristics of a transition from semi-arid to semi-humid climate. The average annual temperature ranges from 0 to 7 °C, with an average annual precipitation of 368 to 381 mm, decreasing from southwest to northeast, while the annual evaporation reaches as high as 1690 to 2000 mm, equivalent to 4 to 5 times the precipitation, with severe water deficit and prominent risks of drought and wind erosion. Winters are cold and long, summers have concentrated rainfall, and the temperature changes abruptly, with strong winds in spring and autumn, further exacerbating the volatility of the climate and increasing the sensitivity of ecosystems.

The river system is complex and consists of a dense network of rivers. The rivers within Chifeng belong to four major basins: the West Liaohe River, inland rivers, the Daling River, and the Luan River, whereas Tongliao is dominated mainly by the West Liaohe River system (accounting for approximately 59.5% of its total area). The main rivers include the West Liaohe, Laohe, and Wulijimuren rivers. The total water resources amount to approximately 7.645 billion cubic meters, but the per capita share is low, making this region water scarce. Lakes and reservoirs are widely distributed and serve both water supply and ecological regulation.

Land use is mainly for arable land, forest land, and grassland, and it is a typical ecologically fragile area with a complex agricultural and pastoral intersection in northern China, as well as an important water source conservation area on the Loess Plateau. As of 2022, the population density in the study area was approximately 47 people per square kilometer, significantly lower than the national average, with a per capita GDP of about 49,000 yuan, lower than the national average, and the economic structure is mainly traditional agriculture, pastoral industries, and resource-based industries. In recent years, under the combined impact of climate change and human activities, the region has been facing pressures such as water resource shortages, land desertification, and ecosystem degradation, and it is also a key implementation area for national ecological engineering projects (such as the “Three North” Shelterbelt, returning cultivated land to forests and grasslands). Therefore, conducting multi-scale assessments and dynamic simulations of ecological fragility in this region is of great significance for revealing the human-land coupling mechanism in transitional river basins and supporting the optimization of regional ecological security patterns.

2.2. Data Sources and Processing

The main data adopted in this study included topographic, meteorological, soil, socioeconomic, and other related thematic data from three periods: 2000, 2010, and 2020. The years 2000, 2010, and 2020 were selected based on two considerations: The decadal interval aligns with key national ecological policy milestones: 2000 marks the launch of the Grain-for-Green Program, 2010 corresponds to the end of the 11th Five-Year Plan, and 2020 represents the terminal year of the 13th Five-Year Plan, coinciding with the assessment phases of several ecological restoration projects in the West Liaohe River Basin. Furthermore, the 10-year step effectively smooths short-term interannual climatic fluctuations, allowing the identification of medium-term evolutionary trends and the underlying driving mechanisms of ecological vulnerability. The specific data sources and detailed information are listed in Table 1. The study area was the West Liaohe River Basin. Owing to its vast spatial range, all data were uniformly adopted in the China_2000_3_DEGREE_GK_Zone_40N coordinate system for efficient data processing and consistency with visualization, and were resampled in a grid format with a uniform resolution of 120 m to ensure spatial matching and computational comparability of the multi-source data. Simultaneously, during the research process, various data were converted to a uniform

format, missing values were handled, and spatial alignment was unified to ensure the scientificity and accuracy of subsequent model construction and analysis.

Table 1. Data Source Statistics Table.

Data Name	Resolution/m	Source
Topographic Data (DEM)	30	Geospatial Data Cloud Website
Annual average temperature	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center
Annual precipitation	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center
Annual evapotranspiration amount	500	Chinese Academy of Sciences Resource and Environmental Science Data Center
Land Use Type	30	Chinese Academy of Sciences Resource and Environmental Science Data Center
Soil Erosion Data	1000	National Earth System Science Data Center
Net Primary Vegetation Productivity	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center
NDVI Data	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center
Biodiversity richness	30	Calculated based on the “Technical Specification for Evaluation of Ecological Environment Condition (2015)”
Population Density	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center
Per capita GDP	1000	Chinese Academy of Sciences Resource and Environmental Science Data Center

2.3. Model and Method

This study established a methodological framework encompassing five modules: data preprocessing, indicator system construction, status assessment, driving force analysis, and integrated prediction (Figure 2).

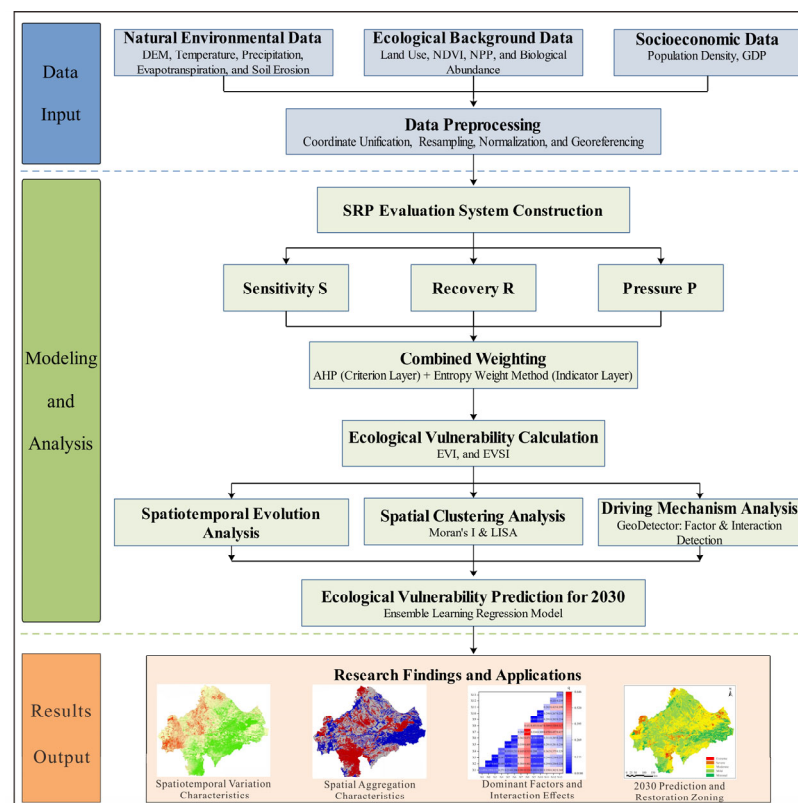


Figure 2. Methodological framework diagram.

2.3.1. Construction of the Ecological Vulnerability Evaluation System

The SRP model starts with three dimensions: ecosystem sensitivity, resilience, and external pressure, comprehensively measuring regional ecological vulnerability and systematically revealing the ecological vulnerability mechanism under the joint action of natural factors and human activities. Based on the SRP model framework and the ecological environment characteristics of the West Liaohe River Basin, this study constructed an ecological vulnerability evaluation system consisting of three criterion layers, seven element layers, and 13 indicator layers.

Ecological sensitivity characterizes the vulnerability and response of ecosystems to external disturbances and covers four elements: topography, meteorology, surface, and soil. The topography element selects three indicators: elevation, slope, and topographic undulation. The topography of the West Liaohe River Basin is complex, and these indicators directly affect the probability of soil erosion and the occurrence of geological disasters in the basin. Generally, the higher the elevation, steeper the slope, and greater the topographic undulation, the stronger the ecological sensitivity [33]. Three meteorological indicators were selected: annual precipitation, average annual temperature, and annual evapotranspiration. The basin is located in a transition zone from semi-arid to semi-humid, with significant spatial heterogeneity in the water and heat conditions in the region. Areas with less precipitation, abnormal temperatures, and high evapotranspiration are more prone to drought stress, leading to increased ecological sensitivity [5]. The surface element selects indicators of land use types, as different land use patterns directly determine the structure and functional stability of ecosystems. Unreasonable use significantly increases ecological sensitivity [34]. Soil elements are selected as indicators of soil erosion intensity, which directly reflect the surface's resistance to disturbances. Areas with severe erosion have fragile ecological backgrounds and significantly high sensitivity [35].

Ecological resilience reflects the self-repairing ability of ecosystems after disturbances and includes two elements: vegetation and vitality. Two indicators were selected for the vegetation element: net primary productivity (NPP) and vegetation coverage. NPP represents the energy fixation capacity of an ecosystem, whereas vegetation coverage reflects the protective function of the land surface. Both indicate the recovery potential of the ecosystem [36,37]. The vitality element selects a biological abundance index. Biodiversity is the foundation for maintaining ecosystem stability, and the higher the biological abundance, the stronger the system's resistance to disturbances and recovery [38].

The ecological pressure index characterizes the load imposed on the ecosystem by external factors, mainly human activities, specifically population density and GDP as two indicators. Population density directly reflects the intensity of human activities, whereas GDP represents the level of regional economic development, both of which reflect the degree of disturbance caused by human activities in the ecosystem. Generally, regions with high population densities and relatively developed economies face greater ecological pressures [12]. The specific composition of the ecological vulnerability evaluation system in the West Liaohe River Basin is presented in Table 2.

Table 2. Ecological Vulnerability Evaluation Index System in the Middle Reach of the West Liaohe River Basin.

Target Layer	Criterion Layer	Element Layer	Indicator Layer	Index Selection Criteria	Index Properties
Ecological Fragility Performance evaluation indicator system	Ecological sensitivity	Topography	Elevation (X_1)	Topographical characteristics directly affect the risk of soil erosion and other geological disasters such as landslides.	Forward
			Slope (X_2)		Forward
			Topographic undulation (X_3)		Forward
		Meteorology	Annual Precipitation (X_4)	Abnormal hydrothermal conditions exacerbate drought stress and increase the ecological sensitivity.	Negative
			Annual Average Temperature (X_5)		Negative
		Surface	Annual evapotranspiration (X_6)	Land-use patterns determine the structural and functional stability of ecosystems.	Forward
			Land Use (X_7)		Forward
	Ecological resilience	Soil	Soil Erosion (X_8)	Soil erosion intensity reflects surface resistance to disturbance and the ecological background.	Forward
			Net Primary Productivity of Vegetation (X_9)		Negative
		Vegetation	Vegetation Coverage (X_{10})	Vegetation productivity and coverage jointly characterize the potential for ecosystem restoration.	Negative
Ecological pressure level	Human Activity	Vigor	Biomass abundance (X_{11})	Biodiversity is the foundation for maintaining system stability and resistance to interference.	Negative
		Socioeconomic	Population Density (X_{12})	Population and economic intensity directly reflect the degree of human interference.	Forward
			GDP (X_{13})		Forward

The Ecological Vulnerability Index (*EVI*) is obtained by multiplying the standardized values of each indicator by their corresponding weights and summing the results (Formula 1). Based on the *EVI* calculation results, the *EVSI* was used to quantify and evaluate the overall ecological vulnerability level of the region (Formula (2)).

$$EVI = \sum_{i=1}^n X_{ij} \times w_i \quad (1)$$

$$EVSI = \sum_{i=1}^n P_i \times S_i / S \quad (2)$$

In this formula, *EVI* represents the ecological vulnerability index, X_{ij} represents the standardized value of the j th grid index of the i th indicator, and w_i represents the weight of the i th indicator. where *EVSI* represents the comprehensive ecological vulnerability index, n represents the number of grades, P_i represents the grade value, S_i represents the area of grade i , and S represents the total area of the study region.

2.3.2. Factor Weight Index Calculation

1. Analytic Hierarchy Process

Hierarchical analysis is an effective model for quantitatively describing multiple evaluation indicators, which can mathematically formalize the decision-maker's thinking process and transform their subjective qualitative judgments into quantitative analysis, thereby helping decision-makers maintain consistency in their thinking process [22]. The basic steps of hierarchical analysis are as follows: first, based on logical relationships, the evaluation objectives and criteria are divided into layers, generally divided into the objective, criterion, and scheme layers, to construct a hierarchical structure model. Second, for each evaluation indicator in the criterion layer, their importance is compared pairwise through expert consultation, questionnaires, and other methods, and use the 1–9 scale method is used to measure relative importance (for example, 1 indicates equal importance, 9 indicates absolute importance), and a judgment matrix (Formula 3) is constructed accordingly.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad (3)$$

In this case, a_{ij} represents the importance of index i relative to index j , which must satisfy $a_{ij} > 0$ and $a_{ij} = 1/a_{ji}$, respectively. By calculating the maximum eigenvalue $\lambda_{\max}$ of the matrix and its corresponding eigenvector W and normalizing the eigenvector, the obtained components are the relative weights of each criterion. After determining the weights, a consistency test was conducted to ensure the reliability of the judgments. The specific steps are:

- (1) Consistency index (CI) calculation:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (4)$$

$\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix, and n is the order of the matrix. The higher the CI value, the greater the inconsistency of the scale.

- (2) The average random consistency index RI is queried, which is the average of CI based on a large number of random reciprocal matrices and is a fixed value.
- (3) The consistency ratio (CR) is calculated as $CR = CI/RI$.

If $CR < 0.10$, the consistency of the judgment matrix is acceptable, and the obtained weights are reasonable; if $CR \geq 0.10$, it indicates that the consistency deviation is large, and it is necessary to re-perform pairwise comparisons and adjust the judgment matrix until the consistency test is passed [23].

2. Entropy Weight Method

The entropy weight method is an objective weighting method, the core principle of which is based on the degree of variation of each indicator data to determine its weight. Specifically, if the degree of variation in a certain indicator's value is greater (i.e., the entropy value is smaller), then the information quantity provided by the indicator in the evaluation system is greater, and its weight should also be correspondingly increased [24,25]. The calculation process mainly includes the following three steps: first, the entropy value of each indicator is calculated; second, the degree of variation of the indicator is determined according to the entropy value; finally, the final weight of the indicator is determined by comprehensively considering the degree of variation of all indicators.

The calculation process is as follows.

- (1) Data standardization: For the original data matrix X with m samples and n indicators, forward indicator standardization is as follows:

$$Z_{ij} = \frac{X_{ij} - \min(X_{1j}, \dots, X_{mj})}{\max(X_{1j}, \dots, X_{mj}) - \min(X_{1j}, \dots, X_{mj})} \quad (5)$$

Negative indicator standardization

$$Z_{ij} = \frac{\max(X_{1j}, \dots, X_{mj}) - X_{ij}}{\max(X_{1j}, \dots, X_{mj}) - \min(X_{1j}, \dots, X_{mj})} \quad (6)$$

Z_{ij} is the standardized value of the j th indicator of the i th sample, and X_{ij} is the value of the j th indicator of the i th sample before standardization. The standardized matrix Z was then obtained.

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mn} \end{bmatrix} \quad (7)$$

- (2) Calculate the weight ratio P_{ij} of the j th index value of the i th sample and obtain a new matrix P .

$$P_{ij} = z_{ij} / \sum_{i=1}^m z_{ij} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (8)$$

- (3) Calculate the entropy value e_j for the j th indicator:

$$e_j = -k * \sum_{i=1}^m P_{ij} * \ln(P_{ij}) \quad (9)$$

Among them, $k = 1/\ln(m)$, $k > 0$, $e_j \geq 0$.

- (4) Calculate the variation index d_j for the j th indicator as follows:

$$d_j = 1 - e_j \quad (j = 1, 2, \dots, n) \quad (10)$$

- (5) The entropy value w_j of the j th indicator is calculated as follows:

$$w_j = d_j / \sum_{j=1}^n d_j \quad (11)$$

This study adopts a weighting strategy that combines the Analytic Hierarchy Process (AHP) and Entropy Weight Method, where the criteria layer weights are determined by AHP, and the indicator layer weights are calculated using the Entropy Weight Method. This combined approach balances the logical rationality of the evaluation system at the macro framework level with the objectivity of indicator weighting. The AHP makes value judgments on the criteria layer based on expert experience, ensuring that the evaluation framework conforms to the intrinsic logic of ecological management. The Entropy Weight Method objectively assigns weights based on the actual degree of variation in the indicator data, effectively avoiding subjective bias. The combination of both ensures the strategic orientation rationality of the evaluation system and the scientific and dynamic adaptability of the indicator weights [39].

Considering the natural and socioeconomic features of the study area and incorporating expert judgments and published data, pairwise comparisons of the criterion layer factors were conducted to establish a third-order judgment matrix, with the results shown in Table 3.

Table 3. Criterion Layer judgment matrix.

Criterion Layer	S	R	P
S	1	4	2.5
R	0.25	1	0.6
P	0.4	1.67	1

The resulting weights for the criterion layers were $S = 0.605$, $R = 0.149$, and $P = 0.246$. The maximum eigenvalue $\lambda_{\max}$ is 3.036, and the consistency index $CI = (\lambda_{\max} - 3)/(3 - 1) = 0.018$. With the standard RI value of 0.58 for $n = 3$, the consistency ratio $CR = 0.018/0.58 \approx 0.031$, which is below 0.1, thus passing the consistency test. The weights of the indicators at the indicator layer were calculated using the entropy weight method, and the detailed values are presented in Table 4.

Table 4. Calculation Results of Indicator Layer Weight Index.

Index	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	X ₈	X ₉	X ₁₀	X ₁₁	X ₁₂	X ₁₃
Weight	0.0438	0.0578	0.0844	0.0673	0.0728	0.0696	0.1170	0.0923	0.0464	0.0520	0.0506	0.1271	0.1189

2.3.3. Spatial Autocorrelation Analysis

Moran's *I* is a statistical index for measuring spatial autocorrelation, used to analyze the degree of aggregation of similar or different values in geospatial data. Its value range is usually between −1 and 1, with positive values indicating a positive correlation (aggregation of similar values), negative values indicating a negative correlation (aggregation of different values), and 0 indicating a random distribution [26,27]. The distribution of Moran's *I* includes global Moran's *I* (Equation (12)) and local Moran's *I* (Equation (13)).

$$\text{Global Moran's } I \text{ index: } I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (12)$$

$$\text{Local Moran's } I \text{ index: } I = \frac{(x_i - \bar{x})}{s^2} \sum_j w_{ij} (x_j - \bar{x}) \quad (13)$$

In the formula, *I* represents Moran's *I* index; x_i and x_j represent the mean vulnerability index of the *i*th and *j*th grids, respectively; $\bar{x}$ represents the mean vulnerability; w_{ij} represents the spatial weight matrix; *S* represents the sum of the elements of the spatial weight matrix. The aggregation patterns were high-high, high-low, low-high, low-low, and not significant.

2.3.4. Geographical Detector

GeoDetector is a spatial statistical method based on the “factor force value (q value)” that detects the spatial differentiation characteristics and driving mechanisms of geographical phenomena. This method takes spatial hierarchical heterogeneity as the core and quantitatively describes the explanatory power of the influencing factors on the spatial distribution of the target variable by comparing the differences in variance within different layers and the overall variance [28,29]. This study introduced the GeoDetector model, selected the factor detection and interaction detection functional modules, and conducted a systematic analysis of the dominant factors and their synergistic effects on the spatial differentiation of ecological vulnerability to identify the relative contributions of different driving factors and their interactive effects.

1. Factor Detector: This detects the explanatory power of a single factor *X* on ecological vulnerability *Y*, with the degree of explanation represented by q-value. The higher the q-value, the stronger the explanatory power, and vice versa. Its formula is:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (14)$$

In the formula, $h = 1, \dots, L$ represents the stratification of variable *Y* or factor *X*; N_h and *N* are the number of units in layer *h* and the total area, respectively; σ_h^2 and σ^2 are the variances of *Y* values in layer *h* and the total area, respectively.

2. Interactive Detector: Whether the interaction of factors produces a composite superimposed effect on regional ecological fragility. The main types are listed in Table 5 below.

Table 5. Interaction Types.

Criterion	Interaction
$q(X1 \cap X2) < \text{Min}[q(X1), q(X2)]$	Nonlinear Attenuation
$\text{Min}[q(X1), q(X2)] < q(X1 \cap X2) < \text{Max}[q(X1), q(X2)]$	Single-factor nonlinear attenuation
$q(X1 \cap X2) > \text{Max}[q(X1), q(X2)]$	Two-factor enhancement
$q(X1 \cap X2) = q(X1) + q(X2)$	Independent
$q(X1 \cap X2) > q(X1) + q(X2)$	Nonlinear Enhancement

2.3.5. Ensemble Learning Regression Model

1. Random Forest

Random forest is an ensemble learning algorithm based on the bootstrap aggregation framework proposed by Breiman [40]. The basic principle is to use self-sampling to extract B subsets of samples from the original training set with replacement, each subset having the same size as the original set, and to train a decision tree separately. To reduce the correlation between trees, during the node splitting of each decision tree, only k candidate features are randomly selected from all p features, and the optimal segmentation features and thresholds are determined based on the square error minimization criterion. For regression problems, the final output of a random forest is the arithmetic mean of the predicted values of B trees:

$$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (15)$$

where $T_b(x)$ is the output of the b th regression tree on the input x . A single decision tree is constructed through recursive binary splitting, and the splitting criterion uses the reduction in the node-squared error:

$$\Delta \text{Err}(m, j, t) = \text{Err}(D_m) - \left(\frac{|D_m^{\text{left}}|}{|D_m|} \text{Err}(D_m^{\text{left}}) + \frac{|D_m^{\text{right}}|}{|D_m|} \text{Err}(D_m^{\text{right}}) \right) \quad (16)$$

In the formula, $\text{Err}(D) = \frac{1}{|D|} \sum_{i \in D} (y_i - \bar{y}D)^2$ is the mean square error of the samples within the node, and $\bar{y}D$ is the target mean of the node. Random forest reduces the overfitting risk of a single decision tree by introducing sample perturbation and feature perturbation, and its “out of bag” samples can provide an unbiased generalization error estimation.

2. XGBoost

XGBoost is an efficient implementation based on the gradient boosting framework and is a boosting ensemble method [41]. Unlike random forest parallel training, XGBoost sequentially adds decision trees, and each new tree fits the residuals of all previous trees. The objective function incorporates a regularization term based on minimizing the empirical risk in the following form:

$$L^{(t)} = \sum_{i=1}^n \ell(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (17)$$

Among them, ℓ is the differentiable loss function (commonly used in regression tasks), f_t is the prediction function of the t -th tree, the regularization term $\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \|w\|^2 + \alpha \|w\|_1$, T is the number of leaf nodes in the tree, w is the leaf weight, and γ, λ, α are the penalty coefficients. XGBoost uses a second-order Taylor expansion to approximate the loss function, thereby accelerating optimization using Newton’s method:

$$L^{(t)} \approx \sum_{i=1}^n (g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)) + \Omega(f_t) \quad (18)$$

In the equation, $g_i = \partial_{\hat{y}_{(t-1)}} \ell(y_i, \hat{y}_{(t-1)})$ and $h_i = \partial_{\hat{y}_{(t-1)}}^2 \ell(y_i, \hat{y}_{(t-1)})$ are the first-order and second-order gradients, respectively. During node splitting, XGBoost uses an ap-

proximate quantile algorithm to process continuous features and supports column sampling, parallelization, and the automatic learning of missing values.

3. LightGBM

LightGBM is also based on the gradient boosting framework but has been specifically optimized for large-scale data in terms of training efficiency and memory consumption [42]. The core improvements include: ① Histogram based algorithm: discretizing continuous feature values into a fixed number of bins, only traversing the boundaries of the bins when searching for the best splitting point, reducing the computational complexity from $O(\text{data volume} \times \text{feature count})$ to $O(\text{bucket count} \times \text{feature count})$; ② Leaf wise strategy: Unlike XGBoost's Level wise strategy, Leaf wise selects the leaf node with the highest splitting gain each time for splitting, which can reduce losses faster at the same depth, but needs to be combined with a maximum depth limit to prevent overfitting; ③ Single side gradient sampling (GOSS): retaining samples with larger gradients and randomly sampling samples with smaller gradients, reducing the training sample size; ④ Exclusive Feature Bundling (EFB): Bundling almost mutually exclusive sparse features into dense features to reduce feature dimensionality. The objective function of LightGBM is similar to that of XGBoost, but the variance gain is used in the split gain calculation:

$$\text{Gain} = \frac{1}{2} \left[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} + \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda} \right] - \gamma \quad (19)$$

where I is the current node sample set, I_L and I_R are the split left and right child nodes, respectively. This study also optimized the hyperparameters of LightGBM using Optuna, including the number of trees, maximum depth, learning rate, histogram binning, subsampling ratio, column sampling ratio, and $L1/L2$ regularization terms.

3. Results

3.1. Analysis of Spatiotemporal Differentiation Characteristics of Ecological Fragility

3.1.1. Spatial Differentiation Characteristics of Ecological Vulnerability

Before calculating ecological vulnerability, it is necessary to standardize the weight indicators according to the positive and negative properties of the indicators. Among them, land use type was treated as a qualitative indicator and quantified using the assignment method. The specific assignment rules were as follows: water areas were assigned a value of 0, forest areas a value of 0.2, grassland areas a value of 0.4, cultivated land areas a value of 0.6, urban, rural, industrial, mining, and residential land areas a value of 0.8, and unused land areas a value of 1. Based on formula (1) and the weights of each indicator, the EVI for the study area in 2000, 2010, and 2020 was calculated separately. By integrating the results of the three periods, ecological vulnerability was divided into five levels using the natural break method: minimal vulnerability ($0 < \text{EVI} \leq 0.263$), mild vulnerability ($0.263 < \text{EVI} \leq 0.298$), moderate vulnerability ($0.298 < \text{EVI} \leq 0.324$), severe vulnerability ($0.324 < \text{EVI} \leq 0.354$), and extreme vulnerability ($0.354 < \text{EVI} \leq 0.699$). The spatial distribution patterns of ecological vulnerability in each period are shown in Figure 3, and the area ratios of each level are presented in Figure 4. Based on formula (2) and the above classification results, the EVSI of the study area was calculated as 3.48 in 2000, 3.20 in 2010, and 2.68 in 2020, indicating that the overall ecological vulnerability of the region showed a decreasing trend during the study period.

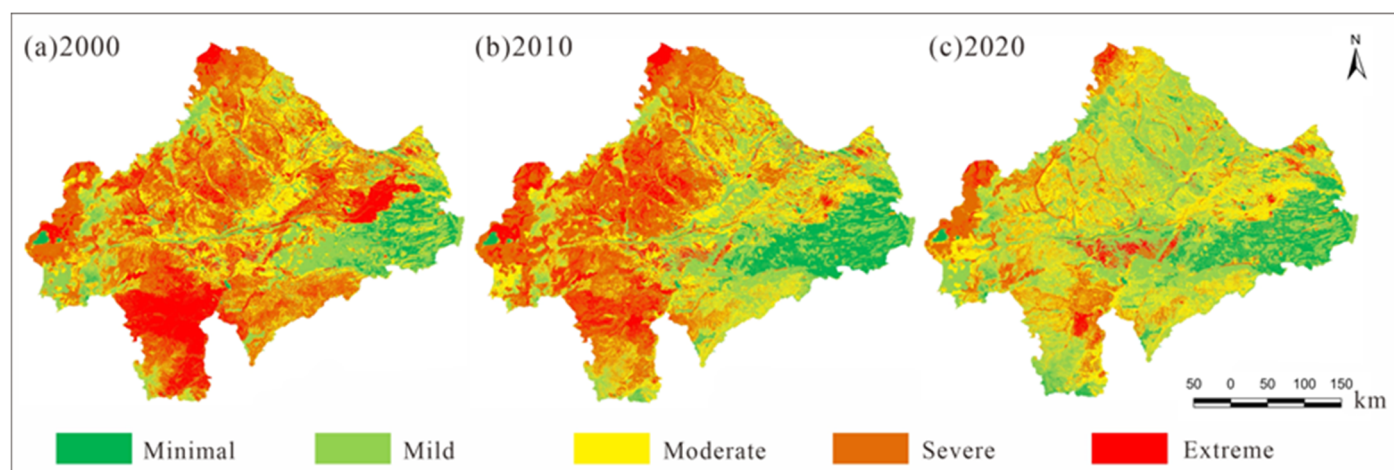


Figure 3. Spatial distribution of ecological vulnerability in the study area from 2000 to 2020.

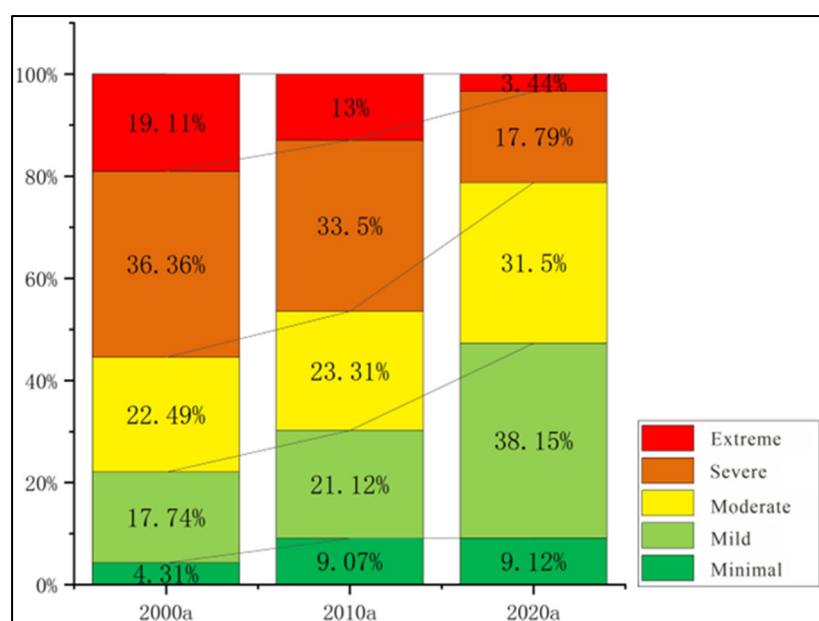


Figure 4. Proportion of Vulnerability at Different Levels from 2000 to 2020.

In 2000, the ecological and environmental vulnerability of the research area showed distinct spatial differentiation characteristics. Overall, the Severe vulnerability areas accounted for the majority, with an area ratio of 36.36%, widely distributed in the central and western parts of the research area, including Zhalute Banner, Ar Horqin Banner, Balin Left Banner, Balin Right Banner, Wengniute Banner, and Aohan Banner. Moderate-vulnerability areas accounted for 22.49% of the total area, mostly surrounding heavily vulnerable areas and forming a transition zone. The Extreme vulnerability areas accounted for 19.11% of the total area, mainly appearing in Songshan District, Hongshan District, Yuanbaoshan District, and Harqin Banner of Chifeng City, as well as Horqin District of Tongliao City. Mild vulnerability areas accounted for 17.74% of the total area, and were mostly located in the southeastern part with lower terrain and better water resource conditions. Minimal vulnerability areas had the smallest area, accounting for only 4.31% and were scattered around urban areas and riverbanks. Overall, vulnerability gradually increased from southeast to northwest, reflecting regional differences in the impact of natural conditions and human activities on the ecological environment.

In 2010, the severely vulnerable areas were still the type with the highest area proportion, accounting for 33.50% of the total area, and formed the background base of the

regional ecological environment. Moderately vulnerable areas followed, with a proportion of 23.31%, serving as an important transitional type. Mildly vulnerable areas also accounted for a significant proportion, reaching 21.12%. The Extreme- and minimal-vulnerability areas had smaller proportions of 13.00% and 9.07%, respectively. Compared to 2000, the highly vulnerable areas (including Severe and Extreme vulnerability areas) greatly shrank to the west, concentrated in the western part of the study area in a north–south direction, covering typical arid and semi-arid regions such as Baling Left Banner, Baling Right Banner, Wengniute Banner, Songshan District, Hongshan District, and Yuanbaoshan District in Chifeng City. Moderate vulnerability areas were widely interspersed among the highly vulnerable areas, forming a strip-like region running from northeast to southwest, connecting the central part of Chifeng City with the northwestern part of Tongliao City, playing a key transitional role. In contrast, the low-vulnerability areas (including Minimal and Mild vulnerability areas) were extensively distributed in large contiguous areas in the southeastern part of the study area, especially in the central and southern parts of Tongliao City and the southeastern edge of Chifeng City. Here, the terrain is relatively flat, water source conditions are better, and the ecological situation is more stable than in other regions.

In 2020, the spatial pattern of ecological vulnerability in the study area underwent significant changes, and the overall ecological condition showed an improving trend. Mild vulnerability areas have become the predominant type, accounting for 38.15% and occupying an absolute dominant position. Moderate vulnerability areas were followed by mild vulnerability areas, accounting for 31.50% of the total area. Together, they constitute the main body of this study. In contrast, the area of severe vulnerability significantly reduced, accounting for 17.79%, whereas the area of extreme vulnerability shrank dramatically, occupying only 3.44%. The Minimal vulnerability area maintained a stable proportion of 9.12%. Spatially, the low-vulnerability areas (Minimal and Mild vulnerability areas) cover a large, contiguous area in the southeastern part of the study area, especially in the central and southern parts of Tongliao City and the southeastern parts of Chifeng City, reflecting the most stable ecological conditions in this region. Moderate-vulnerability areas are mainly distributed in the northwestern part, serving as a vast transition zone connecting high- and low-vulnerability areas. The range of high-vulnerability areas (Severe and Extreme vulnerability areas) has been greatly reduced, scattered only in the westernmost and northern local areas of the study area, such as the ecological vulnerability areas in Keshiketeng Banner, Hongshan District, and Wengniute Banner. Overall, the study area shows a spatial differentiation feature of “southeast is superior, northwest is secondary, and local areas in the west are poor” in terms of vulnerability, and the overall ecological security pattern has been effectively improved.

3.1.2. Temporal Differentiation Characteristics of Ecological Fragility

1. 2000–2010: The overall ecological fragility tends to stabilize, with localized deterioration occurring

Between 2000 and 2010, the ecological vulnerability structure of the West Liaohe River Basin tended to stabilize overall, but locally showed a deterioration trend. From the perspective of area proportion changes (Figure 5), the area of Minimal vulnerability zones increased from 6290.13 km² in 2000 to 13,254.29 km² in 2010, with the proportion rising from 4.31% to 9.07%; the proportion of Mild vulnerability zones also increased from 17.74% to 21.12%, indicating that the ecology in some areas showed a recovery trend. The proportion of Moderate vulnerability zones remained relatively stable, slightly increasing from 22.49% to 23.31%. Although the proportion of Severe vulnerability zones decreased from 36.36% to 33.50%, the range of highly vulnerable zones shrank, but they were still the largest type of vulnerable area, posing a major threat to regional ecological security. At

the same time, the proportion of Extreme vulnerability zones decreased from 19.11% to 13.00%, reflecting that the extreme vulnerable state was somewhat alleviated.

From the transfer situation of vulnerability levels (Figure 6), the main transfers are among Moderate, Severe, and Extreme vulnerability levels, and it shows the characteristic of a small amount of transfer from higher levels to lower levels. Specifically, the area of transfer from Moderate vulnerability zones to Severe vulnerability zones accounts for 5.34% of the total area of the region, while the proportion of transfer from Severe to Moderate is 9.96%; the proportion of transfer from Severe to Extreme vulnerability is 3.76%, and the proportion of transfer from Extreme vulnerability to Severe is 7.88%. Overall, the net transfer ratio from higher vulnerability levels (Severe and Extreme) to lower levels is higher, which reduces the area of high vulnerability zones and correspondingly increases the area of low vulnerability zones.

From the monitoring results of ecological vulnerability changes (Figure 7a), areas with increased vulnerability are mainly distributed in the northwestern and central parts of the study area, showing scattered spatial distribution. This may be affected by human activities or local climate change, leading to a decrease in ecosystem stability. In contrast, areas with decreased vulnerability are concentrated and distributed in the eastern part of the study area and some river valley areas, reflecting that the region may have achieved significant ecological restoration effects through measures such as vegetation coverage improvement and soil and water conservation projects. The areas where the vulnerability level remains basically unchanged (the yellow part in the figure) are widely distributed in the western and transitional zones, indicating that the ecosystem status in these areas is relatively stable. Overall, the changes in ecological vulnerability show a spatial differentiation pattern of “improvement in the east and local deterioration in the central and western parts,” reflecting the complex interactions between ecological governance measures and human activities in the region.

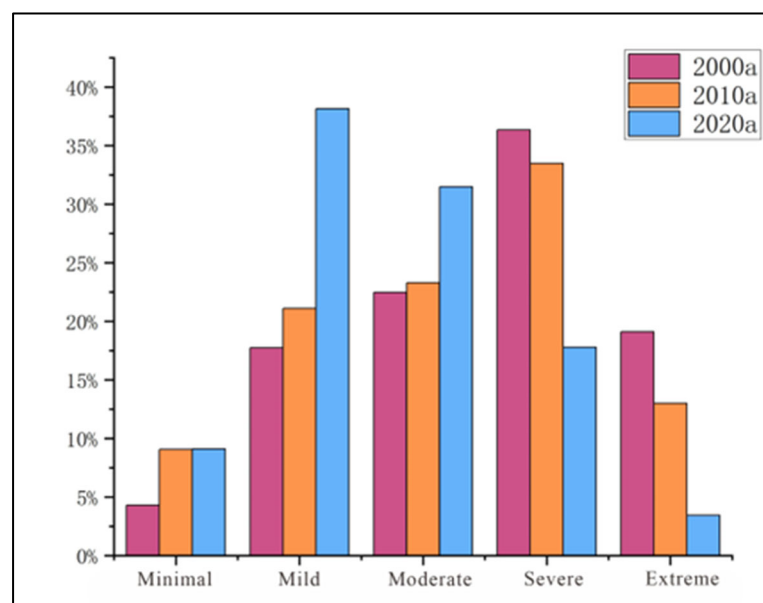


Figure 5. Proportion of ecological vulnerability levels from 2000 to 2020.

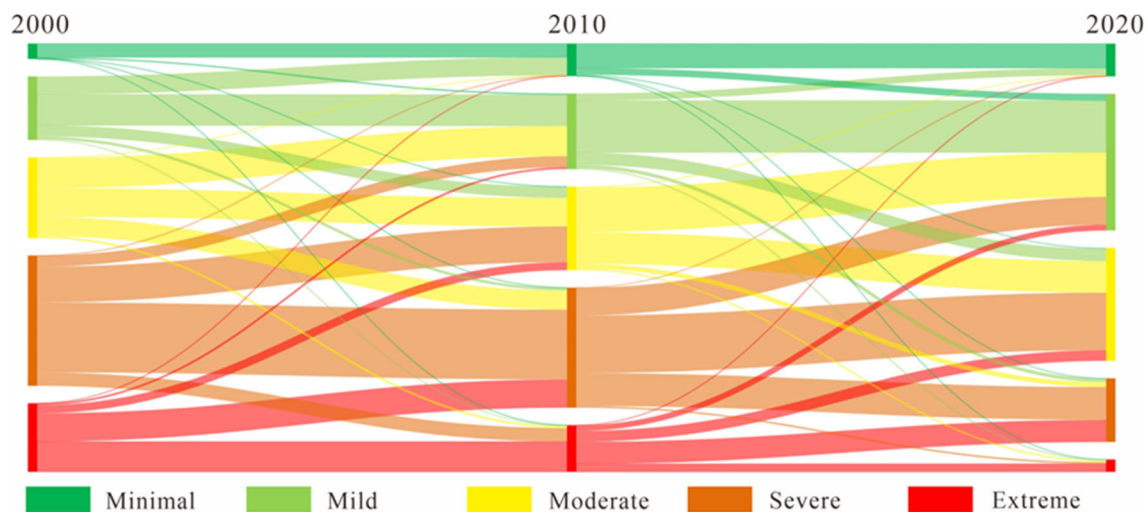


Figure 6. Sankey diagram of the change in ecological vulnerability at various levels in the study area from 2000 to 2020.

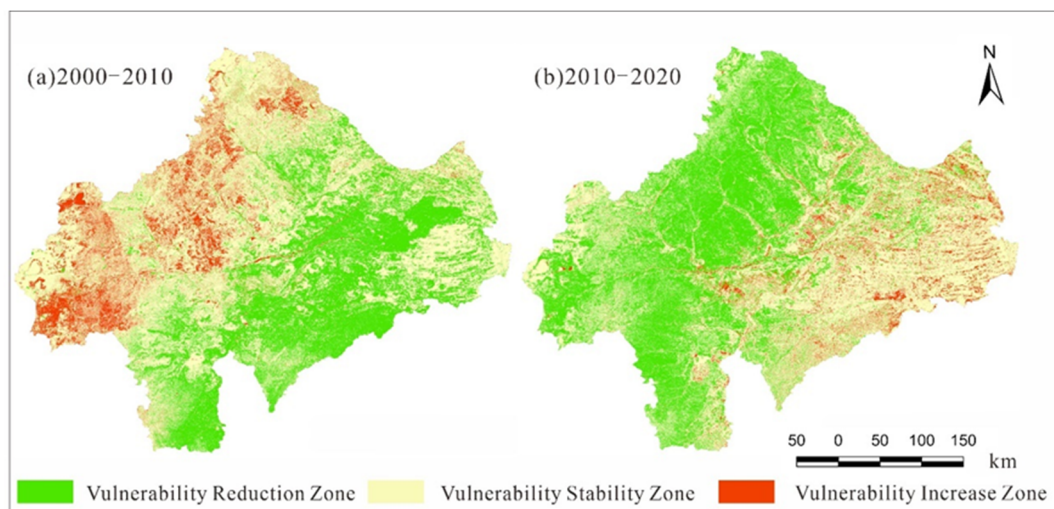


Figure 7. Monitoring Map of Ecological Vulnerability Changes in the Study Area from 2000 to 2020.

2. 2010–2020: Significant improvement in ecological quality and optimization of vulnerability structure

2010 to 2020 was a key period of significant improvement in the ecological quality of the West Liaohe River Basin. During this period, the ecological vulnerability structure underwent a fundamental transformation, shifting from primarily Moderate and Severe vulnerability to primarily Mild and Moderate vulnerability, with a significant optimization of the ecological security pattern.

From the perspective of area proportion (Figure 5), the proportion of Minimal vulnerability areas increased slightly from 9.07% to 9.12%, with the area remaining basically stable, indicating that the level of this area has approached saturation. The proportion of Mild vulnerability areas increased significantly from 21.12% to 38.15%, becoming the largest type of vulnerable area in terms of area, reflecting the significant effectiveness of ecological restoration measures. The proportion of Moderate vulnerability areas increased from 23.31% to 31.50%, with the area increasing by about 35.16%, becoming the second largest type of vulnerable area, playing an important transitional role in the ecosystem. At the same time, the proportion of Severe vulnerability areas decreased sharply from 33.50% to 17.79%, and the Extreme vulnerability areas shrank dramatically from 13.00% to 3.44%. The significant reduction in these two types of highly vulnerable areas directly

reflects the remarkable improvement in the ecological quality of the West Liaohe River Basin from 2010 to 2020.

From the perspective of the transition of vulnerability levels (Figure 6), the transfer during this period mainly occurred between Mild, Moderate, and Severe vulnerability levels, and showed the overall characteristic of a large-scale transfer from high-level vulnerability areas to low-level vulnerability areas. The specific proportions of the areas of each transfer direction to the total area of the region are as follows: the transfer from Moderate to Mild vulnerability areas accounts for 12.44%, and the transfer from Mild to Moderate accounts for 3.41%; the transfer from Severe to Moderate accounts for 16.03%, and the transfer from Moderate to Severe accounts for 1.37%; the transfer from Severe to Mild accounts for 7.73%, and the transfer from Mild to Severe accounts for 0.96%.

From the monitoring results of ecological vulnerability changes (Figure 7b), the spatial distribution pattern of ecological vulnerability in the study area during this period has shown a significant reversal, characterized by a sharp expansion of the improved areas and a significant contraction of the deteriorated areas. Large contiguous areas with reduced vulnerability levels are distributed, covering almost the entire central and western parts of the study area, mainly showing the transformation from the Extreme and Severe vulnerability areas in 2010 to the Moderate and Mild vulnerability areas in 2020. This trend indicates that the region may have improved the structure and function of the ecosystem and enhanced its ability to resist external disturbances over the past decade through the implementation of ecological protection and restoration projects such as returning cultivated land to forests and controlling soil erosion. Correspondingly, areas with basically unchanged or slightly increased vulnerability levels are interlaced in the central and eastern parts of the study area. The overall vulnerability level of this region is relatively low, mainly with Minimal and Mild vulnerability; the local increase in vulnerability may be related to continuous human activity pressures (such as overgrazing, mineral resource development) or local climatic aridification and other factors.

3.2. Analysis of Ecological Vulnerability Spatial Aggregation Characteristics

Based on formulas 12 and 13, this paper calculates the global and local Moran's I indices of ecological vulnerability in the study area, and draws the corresponding global Moran's I index map (Figure 8) and ecological vulnerability LISA cluster map (Figure 9).

As shown in Figure 8, the global Moran's I indices of ecological vulnerability in the study area for 2000, 2010, and 2020 were 0.855, 0.868, and 0.792, respectively. The scatter points are mostly concentrated in the "high-high" and "low-low" quadrants, indicating that ecological vulnerability has maintained spatial positive correlation within the study area, that is, both high-value and low-value areas show an aggregated distribution trend. From 2000 to 2010, the index slightly increased from 0.855 to 0.868, reflecting a slight enhancement in the spatial agglomeration of ecological vulnerability; while from 2010 to 2020, the index decreased from 0.868 to 0.792, indicating a significant weakening of its spatial agglomeration. This change reflects the continuous optimization of the spatial pattern of ecological vulnerability: high-vulnerability areas tend to disperse, low-vulnerability areas gradually expand, and the spatial distribution becomes more uniform.

Based on Figure 9, the ecological vulnerability of the study area has always been characterized by "high-high" and "low-low" agglomeration during the period from 2000 to 2020. Among them, the "high-high" agglomeration areas have gradually shifted from relatively concentrated distribution to dispersion, with the intensity of agglomeration tending to weaken; while the "low-low" agglomeration areas show a trend of expanding from local agglomeration to a larger contiguous area, reflecting the spatial response of ecological restoration and optimization of the ecological vulnerability pattern.

In 2000, based on the LISA clustering results (Figure 9a), it can be seen that the “high-high” clusters are mainly distributed on the north and south sides of the study area, with a relatively concentrated trend in the southern part of Chifeng City, indicating that these areas have a high ecological vulnerability and are highly correlated spatially, which may be closely related to local topographical undulations, arid climate, and human activity disturbances. At the same time, the “low-low” clusters are scattered in the northern part of the study area, showing an overall distribution pattern surrounding the “high-high” clusters, and forming a relatively obvious concentration area in the West Liaohe River Plain area of Tongliao City. Its formation may be attributed to flat terrain, relatively abundant water resources, and relatively stable land use patterns.

As of 2010, based on the LISA clustering results (Figure 9b), it can be seen that the “high-high” cluster has overall contracted westward, showing a distinct north–south strip-like distribution, mainly concentrated in the western and northern regions of Chifeng City; the “low-low” cluster, on the other hand, has expanded westward, presenting a wide east–west distribution, covering the central and southern regions of Tongliao City. Between the two clusters, there is a transition zone composed of “insignificant” areas, reflecting the gradient change characteristics of ecological fragility from high to low. This spatial pattern indicates that the aggregation trend of ecological fragility remained significant in 2010, but the high and low fragile areas were further separated spatially, the transition area expanded, and this reflects an intermediate state between ecosystem recovery and pressure distribution.

By 2020, based on the LISA clustering results (Figure 9c), it can be seen that the “high-high” cluster areas tend to be scattered, with the overall range of aggregation significantly reduced and the area greatly decreased, only scattered remnants remaining in the western and northern parts of the study area. The area of the “low-low” cluster areas is not significantly different from 2010, but the spatial distribution is more dispersed, and the continuity of aggregation has weakened. At the same time, the range of the “non-significant” areas in the middle has significantly expanded, becoming an important transitional zone connecting high and low vulnerability areas. This pattern change reflects the continuous weakening of positive spatial correlation of ecological fragility, the overall ecological quality of the region tends to be balanced, local heterogeneity is enhanced, further confirming the positive effects of ecological restoration measures in reducing the aggregation of high-risk areas and promoting the optimization of ecosystem spatial structure.

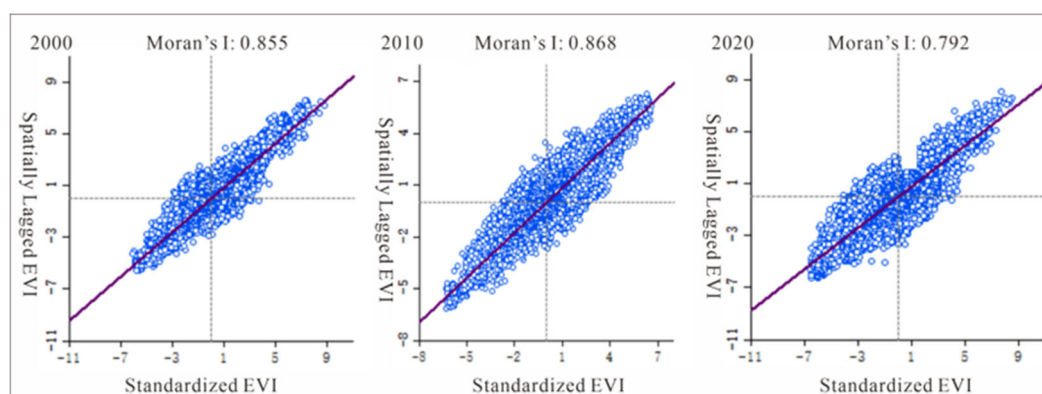


Figure 8. Global Moran's I Index Map.

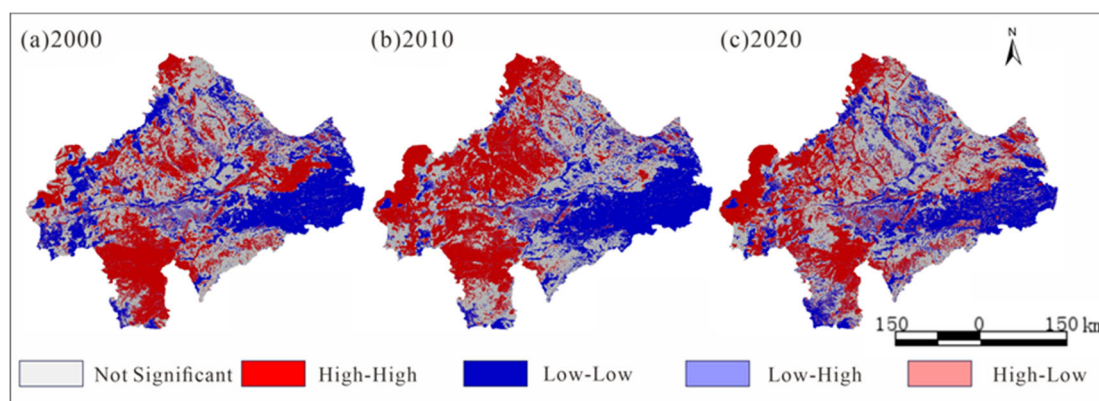


Figure 9. Local Spatial Autocorrelation (LISA) Clustering Map of Ecological Vulnerability.

3.3. Analysis of Ecological Vulnerability Driving Factors

To explore the spatial differentiation characteristics and main driving factors of ecological vulnerability in the study area, this study adopts the Geographical Detector method, taking the EVI as the dependent variable and 13 evaluation factors as independent variables for driving mechanism analysis. Firstly, all data are resampled into 1000 m $\times$ 1000 m grids and aligned, generating approximately 146,100 effective units. To meet the classification requirements of the Geographical Detector for independent variables, the driving factors are discretized as follows: elevation (X_1), annual precipitation (X_4), average annual temperature (X_5), annual evapotranspiration (X_6), net primary productivity of vegetation (X_9), biodiversity (X_{11}), population density (X_{12}), and GDP (X_{13}) are divided into 6 levels using the natural break method; soil erosion intensity (X_8) and vegetation coverage (X_{10}) are divided into 5 levels using the equal interval method; topographic relief (X_3) is divided into 5 levels using the natural break method; slope (X_{12}) is divided into 5 levels according to the intervals of 0–5°, 5–15°, 15–25°, 25–35°, and greater than 35°; land use types (X_7) are directly used in the original 6-category system. To maintain method compliance and improve interpretability, the dependent variable EVI is kept as a continuous value. The factor detection results are shown in Table 6.

In 2000, the q -value of soil erosion (X_8) was the highest (0.432), indicating that the degree of soil erosion is the primary factor determining the spatial differences in ecological vulnerability. Land use types (X_7 , 0.283) and biodiversity (X_{11} , 0.262) also have strong explanatory power, showing that human land use patterns and biodiversity status have an important impact on ecological vulnerability. The influence of population density (X_{12} , 0.220) and GDP (X_{13} , 0.201) is more pronounced, reflecting the pressure on the ecosystem from human socio-economic activities. The explanatory power of topographic factors (elevation, slope, undulation) and climatic factors (precipitation, temperature, evapotranspiration) is relatively weak, indicating that in 2000, ecological vulnerability was more directly affected by human activities and surface processes.

In 2010, biological abundance (X_{11}) became the main factor ($q = 0.386$), followed by annual precipitation (X_4 , 0.365) and soil erosion (X_8 , 0.362), indicating that ecological vulnerability was jointly dominated by biological conditions and natural water erosion processes. The explanatory power of annual precipitation increased significantly, and the average annual temperature (X_5) also jumped from the last position in 2000 to the 5th position (0.229), showing that the influence of climatic factors became prominent. The explanatory power of population density and GDP decreased sharply (to 0.020 and 0.047, respectively), and the impact of land use types also decreased (0.138), indicating that the relative role of direct human economic pressure decreased.

In 2020, the biological abundance (X_{11}) continued to rank first, and its explanatory power was further enhanced ($q = 0.468$). Soil erosion (X_8 , 0.397) remained the second most

important factor, and together they constitute the core driving force. The land use type (X_7) affected the recovery (0.223), which may reflect the effects of land use structure adjustment or ecological restoration projects. The explanatory power of climate factors such as annual precipitation and average temperature was lower than in 2010, but still higher than the level in 2000. The explanatory power of human socio-economic factors such as population density and GDP remained low, indicating that their direct driving effect on ecological vulnerability is no longer significant.

A comprehensive analysis of the trend of changes in the three-phase single-factor detection can be concluded that: the dominant driving factor has shifted from “soil erosion dominance” in 2000 to “biological abundance dominance” in 2010 and 2020; the influence of climate factors shows a “first rise then stabilize” characteristic, with the impact of climate factors (especially precipitation and temperature) reaching a peak in 2010, although their influence decreased from the peak in 2020, it was still significantly higher than in 2000; the human activity factor has shifted from direct pressure to indirect regulation, with significant impacts of factors such as population and GDP in 2000, while the explanatory power of such factors sharply declined after 2010, suggesting that the direct impact of human activities has weakened with the enhancement of ecological awareness or policy intervention; factors such as elevation, slope, and terrain undulation have ranked in the middle to lower positions in terms of explanatory power in all years, indicating that in the study area, terrain is not the main source of spatial differentiation of ecological vulnerability.

Table 6. Ecological Vulnerability Single Factor Detection Results.

Factor	2000		2010		2020	
	q Value	q-Value Sorting	q Value	q-Value Sorting	q Value	q-Value Sorting
Elevation X_1	0.149	6	0.308	4	0.105	5
Slope X_2	0.037	9	0.093	9	0.028	11
Topographic undulation X_3	0.036	10	0.098	8	0.027	12
Annual precipitation X_4	0.136	7	0.365	2	0.112	4
Annual average temperature X_5	0.019	13	0.229	5	0.054	9
Annual evapotranspiration X_6	0.039	8	0.115	7	0.07	6
Land Use Type X_7	0.283	2	0.138	6	0.223	3
Soil Erosion X_8	0.432	1	0.362	3	0.397	2
Vegetation Net Primary Productivity X_9	0.03	11	0.044	12	0.067	7
Vegetation coverage X_{10}	0.023	12	0.065	10	0.062	8
Biodiversity Abundance X_{11}	0.262	3	0.386	1	0.468	1
Population Density X_{12}	0.22	4	0.02	13	0.022	13
GDP X_{13}	0.201	5	0.047	11	0.047	10

The results of the interactive detection of ecological vulnerability driving factors in the middle reaches of the West Liaohe River Basin (Figure 10) show that the interaction explanatory power (q value) between all factors is significantly higher than the contribution of a single factor, indicating that the spatial differentiation of ecological vulnerability is mainly driven by the synergistic effect of multiple factors rather than the independent influence of a single factor. In the three periods of 2000, 2010, and 2020, the top six interaction types with the highest explanatory power are mainly “double-factor enhancement,” further confirming the universality of synergistic driving.

In 2000, ecological vulnerability was mainly dominated by soil erosion (X_8), which formed a significant “double factor enhancement” interaction effect with land use (X_7),

population density (X_{12}), GDP (X_{13}), elevation (X_1), annual precipitation (X_4), and biodiversity (X_{11}). At the same time, the interaction between land use type (X_7) and other factors was also prominent. By 2010, the interaction pattern had undergone a significant transformation. Soil erosion (X_8) and biodiversity (X_{11}) ($q = 0.625$), and annual precipitation (X_4) and biodiversity (X_{11}) ($q = 0.620$) became the most powerful interaction combinations in terms of explanatory power, indicating that the driving core had gradually shifted from soil erosion to the synergistic effect of biodiversity and climatic factors. The top five interaction types were all “double factor enhancement,” while the interaction between annual precipitation and land use (sixth) had already shown a “non-linear enhancement.” In 2020, the interaction between soil erosion (X_8) and biodiversity (X_{11}) was further enhanced ($q = 0.721$), followed by the interaction between land use (X_7) and soil erosion (X_8) ($q = 0.620$). As the most explanatory single factor, the interaction between biodiversity and other factors often presented a “non-linear enhancement,” highlighting its core position in the synergistic network. The interaction between land use and soil erosion also maintained a strong interaction effect.

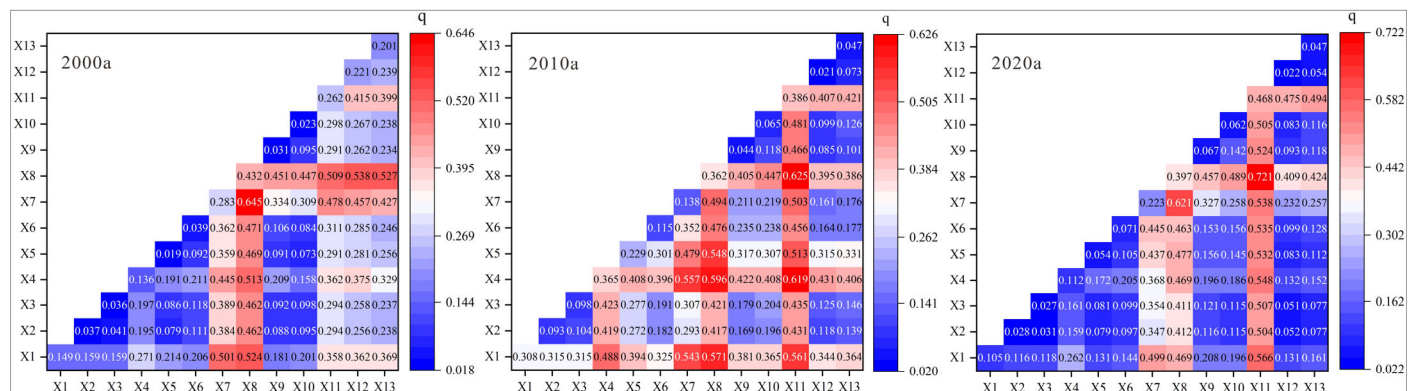


Figure 10. Two-factor interaction detection results for ecological vulnerability drivers.

3.4. Ecological Vulnerability Scenario Projection Based on Ensemble Learning

The model input features include three periods (2000, 2010, 2020) of basic topographic factors such as elevation, slope, and relief amplitude. Four spatial texture features— 31×31 and 51×51 window mean filtering, 9×9 window standard deviation, neighborhood difference, and gradient magnitude—were extracted to enhance the characterization of surface spatial heterogeneity, while redundant small-scale mean features were removed. To capture the synergistic driving effects among factors, pairwise interaction terms were constructed based on interaction detection results, selecting six factors: soil erosion, population density, GDP, elevation, annual precipitation, and land use. Additionally, the 2000 EVI value and the 2010–2000 EVI difference were incorporated into the continuous feature set as historical change information, strengthening the model’s memory of temporal evolution.

The model adopted a temporal extrapolation validation strategy, with strictly separated training, validation, and test sets. From the overlapping valid pixels across the three periods, stratified sampling was performed based on ΔEVI quantiles, dividing into 20 strata with equal sampling, yielding a total sample dataset of 2 million samples. These were split 8:2 into a training set (1.6 million) and a validation set (0.4 million), used for model training and hyperparameter tuning (with R^2 as the criterion and early stopping monitoring), respectively. The actual EVI data for the entire study area in 2020 were used as an independent test set to evaluate the model’s spatiotemporal extrapolation capability. With ΔEVI ($\text{EVI}_{2020} - \text{EVI}_{2010}$) as the core target, a Stacking ensemble framework was employed, using XGBoost, LightGBM, and Random Forest as base learners and LightGBM

as the meta-learner. LightGBM was chosen as the meta-learner because of its high computational efficiency via histogram algorithms, effective regularization to suppress overfitting, stronger nonlinear coupling capability compared to traditional meta-models, and its accuracy advantage verified in preliminary experiments. Optuna-Bayesian optimization was used to automatically search hyperparameters for the XGBoost and LightGBM base learners, maximizing validation R^2 . The search ranges for XGBoost were: number of trees (300–800), max depth (6–12), learning rate (0.01–0.1, log scale), subsample ratio (0.6–0.9), column subsample ratio (0.6–0.9), and L1/L2 regularization (0.01–1.0, log scale). The ranges for LightGBM were corresponding, with additional early stopping (10 rounds) to prevent overfitting. Each model ran 50 trials, and the parameter set yielding the highest validation R^2 was selected as the final configuration. For Random Forest, due to low parameter sensitivity, the number of trees was fixed at 300 and max depth at 12 to reduce computational cost.

After tuning, the three base learners and the meta-learner were combined into the Stacking model, which was retrained on the full training data using three-fold cross-validation with the direct (pass-through) mode enabled. To evaluate the ensemble performance, the predictive performance of each base learner on the same test set for 2020 EVI was compared (Table 7). Results showed that the ensemble model achieved a training R^2 of 0.923, validation R^2 of 0.808, and test R^2 of 0.853, with RMSE and MAE superior to any single base learner, indicating good generalization ability and prediction accuracy. Finally, this model was used to predict the 2030 EVI spatial distribution, and the resulting ecological vulnerability pattern for the study area in 2030 is shown in Figure 11.

Table 7. Performance comparison of different models in predicting 2020 EVI.

Model	Train R^2	Val R^2	Test R^2	Test RMSE	Test MAE
XGBoost	0.875	0.752	0.813	0.012	0.008
LightGBM	0.719	0.709	0.804	0.012	0.008
Random Forest	0.682	0.664	0.770	0.0133	0.009
Stacking Ensemble	0.923	0.808	0.853	0.011	0.007

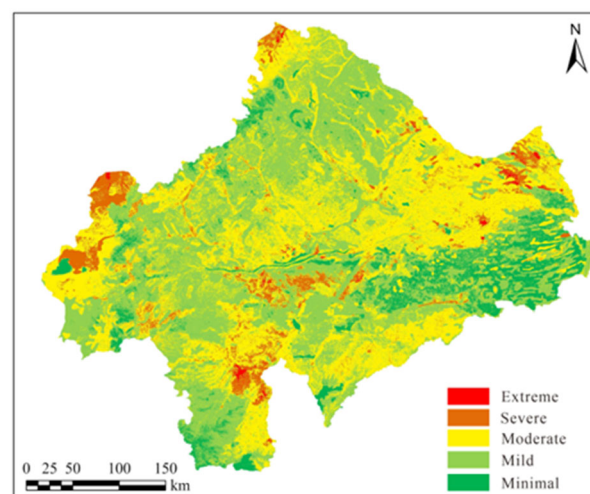


Figure 11. Predicted Ecological Vulnerability in 2030.

In 2030, the ecological vulnerability of the study area will mainly be mild and moderate. Among them, the mildly vulnerable areas are mainly distributed in a north–south direction in the western part of the study area, accounting for 43.41% of the total area; The moderately vulnerable areas are mainly distributed on the north and south sides of the eastern part of the study area, running in an east–west direction, accounting for 41.57% of

the total area. The micro fragile zone is mainly located in the eastern part of the study area, sandwiched between the moderate fragile zones on the north and south sides, and also extends in an east–west direction, accounting for 8.31% of the total area. The severely vulnerable areas are scattered on the east, west, and central parts of the study area, accounting for 6.35% of the total area. The extremely vulnerable areas have significantly shrunk to Keshiketeng Banner in the northwest mountainous area of the study area and Hongshan District in the south mountainous area, accounting for only 0.36% of the total area.

4. Discussion

4.1. Overall Decline in Ecological Vulnerability and the Phased Evolution of Its Driving Mechanisms

The research results show that the EVSI of the middle reaches of the West Liaohe River Basin from 2000 to 2020 decreased from 3.48 to 2.68, with the area of Extreme and Severe vulnerability zones significantly reduced, and the overall ecological vulnerability of the region showed a continuous downward trend. This change is not the result of the improvement of a single factor, but a comprehensive reflection of the continuous rebalancing of the “risk-recovery” relationship under the joint action of natural environment constraints, human activity regulation, and the enhancement of ecosystem resilience.

From the perspective of the theoretical framework, the vulnerability paradigm proposed by the IPCC holds that system vulnerability is jointly determined by exposure, sensitivity, and adaptive capacity (resilience). When the rate of increase in resilience is faster than that of risk exposure or sensitivity, the overall vulnerability level can show a downward trend. Turner et al. further pointed out in their research on human-environmental coupled systems that complex systems often achieve new stable states through phased adjustments under multiple disturbance backgrounds, rather than evolving along a unidirectional degradation path [2]. The continuous decline of EVSI in this study indicates that under the background of still existing climate fluctuations, the recovery capacity of the ecological system in the middle reaches of the West Liaohe River has been significantly enhanced, thereby offsetting part of the ecological risks brought by natural and human disturbances [43,44].

The analysis of driving mechanisms shows that the dominant factors of ecological fragility have undergone a clear stage-by-stage evolution during the study period. In 2000, soil erosion was the primary factor explaining the spatial differentiation of ecological fragility, reflecting that the regional ecosystem was still in a state dominated by surface processes. The combined effects of arid climate, strong wind erosion background, and unreasonable land use patterns directly restricted vegetation growth and ecosystem stability, thereby becoming the core driving force for the formation of fragility. This result is consistent with the conclusions of early studies on ecological fragility in semi-arid agricultural and pastoral areas [12]. With the continuous implementation of ecological governance measures such as returning cultivated land to forests and grasslands, soil and water conservation projects, and land use structure adjustment, the intensity of soil erosion has been effectively controlled, and its dominant role in ecological fragility has gradually weakened. After 2010, biological abundance became the factor with the highest explanatory power, and it was further strengthened in 2020, indicating a shift from “surface process dominance” to “biological structure and function dominance” as the limiting factor of the ecosystem. It is noteworthy that the mode of action of human activity factors has also changed significantly. In 2000, population density and GDP still had a strong explanatory power for ecological fragility, indicating that human activities affected the ecosystem in the form of direct pressure; however, after 2010, their explanatory power rapidly decreased, suggesting that under the background of ecological engineering and policy inter-

vention, the impact of human activities on ecological fragility has gradually shifted from “direct disturbance” to “indirect regulation.” This change is consistent with the research conclusions of recent years on the “weakening of human pressure and enhancement of ecological regulation” in the northern ecological engineering areas [5,9].

4.2. Ecological Significance of Weakened Spatial Agglomeration

The global Moran’s I index indicates that the spatial agglomeration of ecological vulnerability in the middle reaches of the West Liaohe River Basin slightly increased from 2000 to 2010, while it significantly weakened from 2010 to 2020, showing an overall trend of transformation from “intensified agglomeration” to “weakened agglomeration.” This change means that the spatial structure of ecological vulnerability in the study area is gradually evolving from early relatively continuous, patchy distributed high-risk areas to a “mosaic” risk pattern with alternating high and low vulnerability levels.

In this study, the decline of Moran’s I after 2010 does not mean the complete elimination of ecological risk, but rather that the highly vulnerable areas have gradually been divided into scattered patches from large-scale continuous distribution, while the low-vulnerable areas have formed larger contiguous expansions in space. This result is particularly evident in the LISA cluster map: the area of the traditional “high-high” aggregation has significantly shrunk, with spatial positions tending to be scattered, while the “low-low” aggregation has shifted from local clustering to regional expansion. Continuous distribution of highly vulnerable areas often has a stronger spatial transmission effect, and once disturbed by external factors, it is prone to trigger a cascade of ecological degradation. In the mosaic pattern, the highly vulnerable patches are isolated by low-vulnerable areas, and their risk diffusion paths are blocked, leading to a relative increase in the overall stability of the system [45]. Therefore, the reduction in spatial agglomeration of ecological vulnerability in this study, to some extent, reflects the improvement of the overall disturbance resistance of the ecological system in the middle reaches of the West Liaohe River Basin, as well as the structural effectiveness of ecological restoration measures at the spatial level.

However, the weakening of spatial agglomeration does not mean a reduction in governance difficulty. On the contrary, the high vulnerability areas have shifted from “massive concentration” to “scattered distribution” in space, indicating that ecological risks show stronger spatial fragmentation characteristics, which puts forward higher requirements for refined and zonal governance. Existing research has shown that in the practice of ecological governance at the basin scale, the initial phase of restoration often focuses on reducing the overall area of high-risk zones, while in the later stage, the focus of governance gradually shifts to the precise identification and differentiated intervention of local high-risk patches [46]. The spatial pattern evolution characteristics revealed by this study exactly reflect the phased feature of the transition from “area control” to “point-patch precise regulation” in the governance of ecological vulnerability in the middle reaches of the West Liaohe River Basin.

4.3. Limitations, Uncertainties, and Future Research Directions

The methodological limitations of this study are mainly reflected in three aspects. First, in the processes of indicator system construction and weight assignment, although the combined AHP-entropy weight method integrates both expert experience and objective data information, the completeness of indicator selection, the effectiveness of their representation across different spatial scales, and the subjective bias that is difficult to fully eliminate during weighting may all affect the absolute accuracy of the evaluation results. Second, the explanatory power of factors (q-statistic) in the GeoDetector is sensitive to the discretization scheme of continuous variables (e.g., the number of classes and the selection

of breakpoints); different discretization strategies may lead to minor changes in the ranking of factor importance, thereby affecting the stability of interpreting the driving mechanisms. Third, the prediction accuracy and robustness of the Stacking ensemble learning model depend heavily on the representativeness of training samples, the quality of feature engineering, and hyperparameter tuning. In real ecosystems, policy interventions or extreme climatic events often manifest as nonlinear abrupt changes, and such non-stationary processes are difficult to fully learn and extrapolate from historical data alone.

At the data level, inherent limitations are also evident in three respects. First, multi-source data exhibit significant differences in spatial resolution. Although they have been uniformly resampled to a 120 m grid to ensure spatial matching, the processes of downscaling or upscaling inevitably introduce information loss and exert a smoothing effect on spatial heterogeneity, which may impair the accurate characterization of local vulnerability extremes. Second, some socioeconomic data are aggregated at the county or prefectural level and then rasterized; their internal spatial differences are averaged out, making it difficult to precisely reflect the actual intensity of human activities at the township or village scale. Third, satellite-derived products such as NDVI and NPP are subject to interference from cloud cover, aerosol optical depth, and sensor degradation. Although data providers have performed atmospheric correction and quality flagging, uncertainties remain regarding the temporal consistency of vegetation indices in cloudy growing seasons or topographically complex areas.

It is particularly important to emphasize the assumption constraints underlying the scenario projections. The projection of ecological vulnerability for 2030 in this study is based on the assumption of continued historical trends, i.e., it presumes that core driving factors—including climatic trends, land-use policies, and socioeconomic growth rates—will maintain their historical rates of change. This assumption does not account for potential extreme drought events, sudden adjustments in ecological engineering policies, or other unforeseen systemic disturbances. Therefore, the 2030 projection should be strictly interpreted as a “reference scenario of trend extrapolation” rather than a deterministic forecast, and caution is warranted when applying it to local-scale decision-making.

The combined constraints from both methodological and data levels suggest that the vulnerability assessment results of this study, when used for fine-scale management decisions, should be regarded as regional-scale trend indications rather than absolute estimates at individual grid cells. To address the above limitations, future research could be improved in the following directions: incorporating multi-source observational data with higher temporal and spatial resolution; integrating variables such as the implementation intensity of major ecological projects and policy changes into the covariate system of the model; and constructing a simulation framework with multi-scenario constraints based on multi-scenario climate model data and various land-use planning schemes. These improvements would help to more comprehensively delineate the possible range of future ecological vulnerability changes, enhance the robustness of the assessment results, and strengthen their practical value for supporting regional adaptive management decisions.

5. Conclusions

1. The overall ecological quality continues to improve

Between 2000 and 2020, the ecological vulnerability in the middle reaches of the West Liaohe River Basin showed an overall decreasing trend, with the EVSI dropping from 3.48 to 2.68. Spatially, the distribution pattern of “high in the northwest and low in the southeast” gradually shifted to “overall stability and localized optimization.” In 2020, areas of light and moderate vulnerability had become the dominant type, accounting for a total of 69.65%, while areas of severe and extremely vulnerable had significantly decreased, re-

flecting the significant effectiveness of regional ecological protection and restoration measures.

2. The spatial agglomeration of ecological vulnerability weakens, and the pattern tends to be balanced

The global Moran index shows that the spatial agglomeration of ecological vulnerability slightly increased from 2000 to 2010, but significantly weakened from 2010 to 2020, indicating that the areas of high vulnerability tend to disperse and the areas of low vulnerability gradually expand, with the spatial structure of the ecosystem developing towards equilibrium. The LISA clustering results further reveal that the range of “high-high” aggregated areas has shrunk and become scattered, while the “low-low” aggregated areas have expanded continuously, with the ecological security pattern continuously optimizing.

3. The driving mechanism shows the evolution characteristics of “natural-biological” dominance and weakened impact of human activities

Geospatial probe analysis indicates that the dominant driving factor of ecological vulnerability has gradually shifted from soil erosion in 2000 to biodiversity in 2010 and beyond. The explanatory power of climate factors (annual precipitation, average annual temperature) reached a peak in 2010 and then tended to stabilize. The influence of human activity factors (population density, GDP) has continued to weaken, indicating that the implementation of ecological protection policies has effectively alleviated direct human interference. All factor interactions exhibit enhancement, indicating that ecological vulnerability is synergistically driven by multiple factors.

4. The overall ecological fragile pattern is stable, but there are still risks in some areas.

The Stacking ensemble learning model trained on historical data predicts that by 2030, the overall spatial pattern of ecological vulnerability in the middle section of the West Liaohe River Basin will remain stable, with further reduction in extremely vulnerable areas. However, local areas such as Wengniute Banner and Songshan District in Chifeng City will still maintain a high level of vulnerability and require continuous attention and key management.

Furthermore, due to the inherent limitations at both the data and methodological levels, the reliability and generalizability of our findings should be interpreted with caution. The 2030 projections are based on the BAU assumption and do not account for abrupt climate events or policy shifts; thus, they should be regarded only as trend references rather than deterministic predictions. Future studies should incorporate multi-scenario constraints to further enhance the robustness of the assessments.

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Abbreviations

The following abbreviations are used in this manuscript:

SRP	Sensitivity-Recovery-Pressure
EVSI	Ecological Vulnerability Synthetical Index
EVI	Ecological Vulnerability Index

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