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Ecological vulnerability Assessment in the Heilongjiang-Amur River Transboundary Basin

Wang Xinyuan[1,2], Cheng Hao[1,*], Li Fujia[1], Dashtseren Avirmed[3], Ganzey Kirill[4]

[1]Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing 100101, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China
[3]Institute of Geography and Geoecology, Mongolian Academy of Sciences, Ulaanbaatar 15170, Mongolia
[4]Pacific Geographical Institute, Far Eastern Branch of the Russian Academy of Sciences, Vladivostok 690041, Russia

***CORRESPONDING AUTHOR**
Hao Cheng
chenghao@igsnrr.ac.cn

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ABSTRACT

The Heilongjiang–Amur River Basin (HARB) is an important transboundary basin in Northeast Asia, characterized by complex and diverse ecosystems and facing significant environmental pressures. Assessing ecological vulnerability in this region is of great importance. This study adopts the Exposure–Sensitivity–Adaptive capacity (ESA) framework and applies the CRITIC–AHP weighting method to evaluate the spatial pattern of ecological vulnerability (EVI) in HARB in 2020 and identify its main influencing factors. The results show that the overall ecological vulnerability of the basin is relatively high, the average EVI in 2020 was 31.0. Areas with high vulnerability are mainly concentrated in the Gobi region of Mongolia, the Northeast China Plain, and parts of southern Russia. Soil retention, net primary productivity (NPP), and habitat quality index (HQI) are the key factors contributing to the spatial variation of EVI, which explained 63%, 42% and 40% of the variation, respectively. The Mongolian part of the basin shows relatively higher ecological vulnerability, which reflects the significant influence of arid climate and fragile land resources. These findings provide a scientific basis for ecological vulnerability management and transboundary cooperation in the HARB, and offer useful reference for developing sustainable ecological strategies in other transboundary river basins.

KEYWORDS

Ecological vulnerability assessment, ESA framework, Heilongjiang-Amur River Basin

1. INTRODUCTION

The Heilongjiang–Amur River Basin (HARB) is a key transboundary river basin in Northeast Asia, spanning China (43%), Mongolia (9%), and Russia (48%). It features complex geographical conditions and diverse ecosystems. In recent years, the basin has faced increasing ecological pressure due to the combined effects of climate change, land degradation, and human activities[1]. A systematic assessment of ecological vulnerability in the basin is crucial for identifying high-risk areas, developing targeted ecological protection strategies, and promoting cross-border cooperation and sustainable management[2].

Ecological vulnerability is an important indicator used to measure how sensitive an ecosystem is to external disturbances. It generally considers three components: exposure, sensitivity, and adaptive capacity[3]. In recent years, the methods for assessing ecological vulnerability have significantly advanced. Traditionally, researchers have used principal component analysis (PCA), various quantitative models, fuzzy comprehensive evaluation, and landscape pattern analysis[4]. While these methods have proven effective in specific contexts, they still have limitations in balancing subjective and objective factors[5]. To address this issue, this study integrates the CRITIC method[6] (which evaluates indicator importance based on inter-indicator correlation) with the Analytic Hierarchy Process (AHP)[7], combining both objective and subjective weighting approaches. This allows for a more comprehensive and balanced vulnerability assessment.

Existing research on the ecological vulnerability of the Heilongjiang–Amur River Basin has primarily focused on land cover change, water environment issues, and transboundary governance. Jia and Yang, using remote sensing data, revealed that agricultural expansion and forest fragmentation have significantly undermined ecosystem stability in the basin[8]. Luo et al. highlighted increasing challenges related to transboundary water pollution and ecological imbalance between China and Russia, noting the inadequacy of current monitoring and management mechanisms[9]. Dai et al. evaluated the cumulative impact of human activities at the regional scale and emphasized the need for a more coordinated transboundary ecological management system[10].

Previous studies on the ecological conditions of the HARB have mainly focused on local areas or single factors. There is still a lack of systematic vulnerability assessments based on a unified indicator system at a basin-wide scale, especially those using the most recent data.

Therefore, this study adopts the Exposure–Sensitivity–Adaptive capacity (ESA) framework and applies the CRITIC–AHP weighting method to assess the spatial pattern of ecological vulnerability in the HARB in 2020. It also identifies the main influencing factors and proposes targeted ecological management recommendations. The results aim to provide scientific support for enhancing the resilience of the basin's ecosystems and promoting transboundary environmental governance among China, Mongolia, and Russia.

2. RESEARCH METHODS

2.1 Study Area

The HARB covers an area of approximately 2.08 million square kilometers, spanning from 41.72°N to 55.90°N and from 108.05°E to 141.13°E. Its elevation ranges from sea level at the Tatar Strait, where the river flows into the ocean, to 2,565 meters in the Khentii Mountains of Mongolia[11]. The region is influenced by the East Asian monsoon, with cold winters and warm, rainy summers. Approximately 75% to 80% of the annual river runoff occurs during the summer.

The basin features distinct geographical and climatic characteristics. The western part is mountainous, including the Yablonovy Range and the Greater Khingan Mountains, and has a typical continental climate. The eastern part is lower in elevation and mainly consists of hills. The central region is dominated by broad plains, such as the Songnen Plain and the Sanjiang Plain, with a monsoon climate prevailing. Population density varies significantly between the northern and southern parts of the basin, and the extent of human activities also differs greatly across regions[12].

In addition to geographical and climatic differences, the HARB is also shaped by diverse socio-economic factors, exhibiting prominent transboundary characteristics. Agricultural expansion and urban development in China, forestry exploitation and mineral extraction in Russia, and pastoral land use in Mongolia have led to uneven ecological pressures across the region. Moreover, disparities in environmental policies and governance capacities among the three countries have further influenced the spatial pattern of ecological vulnerability. These factors collectively contribute to land degradation, wetland loss, and the decline of ecosystem services, thereby intensifying the ecological vulnerability of the basin[13].

Table 1. The selected indicators for ecological vulnerability in the HARB and their corresponding weights

Primary Goal	General criteria (weight)	Specific criteria (weight)	Positive (+) or Negative (-)
Ecological vulnerability	Exposure (0.392)	Building density (0.108)	+
		Population density (0.102)	+
		Extreme drought (0.056)	+
		Extreme humidity (0.065)	+
		Palmer Drought Index (0.061)	+
	Sensitivity (0.417)	Elevation (0.056)	+
		Terrain relief (0.026)	+
		Slope (0.041)	+
		Fractional vegetation cover (FVC) (0.070)	-
		Net primary productivity (NPP) (0.091)	-
		Soil retention amount (0.133)	-
	Adaptability (0.191)	Habitat quality index (HQI) (0.107)	-
		Proportion of protected areas (0.084)	-

2.2 Methods

Based on the ESA vulnerability assessment framework and taking both natural and human factors into account, this study developed an ecological vulnerability indicator system for the HARB (Table 1).

Given the significant differences in natural environments and socio-economic conditions among China, Mongolia, and Russia, the construction of the indicator system in this study emphasizes regional representativeness. Exposure indicators (e.g., population density, building density, and extreme drought/humidity indices) reflect anthropogenic pressures and climatic extremes; sensitivity indicators highlight the inherent ecological sensitivity, including topographic complexity, vegetation status (FVC, NPP), and soil retention capacity; adaptability indicators emphasize ecosystem resilience, primarily represented by habitat quality and the proportion of protected areas.

Each indicator has a different unit of measurement and influences regional ecological vulnerability in different ways. To ensure comparability among the 13 indicators, all data were normalized to a standard scale ranging from 0 to 1. The normalization formulas for positive and negative indicators are presented below as Equation(1) and Equation(2), respectively. For positive indicators, higher values indicate greater ecological vulnerability, while for negative indicators, higher values indicate lower vulnerability.

$$Z_{ij} = \frac{X_{ij} - Min(X_j)}{Max(X_j) - Min(X_j)} \quad (1)$$

$$Z_{ij} = \frac{Max\,(X_j) - X_j}{Max(X_j) - Min(X_j)} \quad (2)$$

Where X_{ij} is the original value of indicator j in the year i , Z_{ij} is the normalization value of j indicator in the year i , the range extends from 0 to 1. $Max\,(X_j)$ and $Min(X_j)$ is the maximum and minimum value of j indicator in the corresponding grid in research years.

In this study, the CRITIC [15] model and the Analytic Hierarchy Process (AHP[16]) method were combined to determine the comprehensive weights of the indicators in a more scientific and objective manner. The CRITIC method ensures objectivity by measuring the variability and contrast intensity among indicators, while the AHP method incorporates expert judgment to reflect region-specific ecological concerns. The combination of the two enhances the scientific robustness and regional applicability of the assessment. The calculation formulas for the indicator weights are presented below.

$$W_j = aW_{1j} + bW_{2j} \quad (3)$$

$$a = b = \frac{1}{2} \quad (4)$$

$$W_{1j} = (W_{11}, \ldots, W_{1j}), W_{2j} = (W_{21}, \ldots, W_{2j}) \quad (5)$$

Where W_j represents the weight of indicator j , W_{1j} is the weight of indicator j derived using the AHP technique, and W_{2j} is the weight of indicator j obtained through the CRITIC method. Here, j denotes the number of vulnerability indicators. The weights for exposure, sensitivity, and adaptive capacity are 0.392, 0.417, and 0.191, respectively (Table 1).

Currently, there is no universally accepted standard for classifying ecological vulnerability[17]. Therefore, based on the specific context of the HARB and insights from previous studies, this research divides the quantitative assessment results into five levels: Slight (<23.098), Light (23.099~29.031), Medium (29.032~34.351), Heavy (34.352~40.0), and Very heavy (⩾40.081). A higher ecological vulnerability value indicates a more fragile ecological environment.

The geographical detector is a statistical tool used to explore spatial heterogeneity, identify the driving factors behind observed differences, and analyze the interactions among various variables[18]. In this study, we used the "GD" package in R 4.2[19] to analyze the influencing factors of ecological vulnerability in the HARB region. The analysis was conducted through the differentiation and factor detection modules, as well as the interaction detection module of the geographical variables. In the factor detection process, the explanatory power of each driving factor for spatial variation was quantified using the following formula (Equation 6):

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

Where $h = 1$ and L is the stratification, i.e., classification or partitioning, of the variable Y or factor X; N_h and N are the number of cells in stratum h and the whole area, respectively; σ_h^2 and σ^2 are the variance of the Y values in stratum h and the whole area, respectively. q has the value range of [0,1], and the larger the value of q indicates that the stronger the explanatory power of Y is, i.e., the greater the degree of the factor's influence on spatial differentiation, and vice versa, the weaker it is.

3. RESULT AND DISCUSSION

3.1 EVI of HARB in 2020

In 2020, ecological vulnerability in the HARB region was mainly classified as moderate and severe. The proportions of areas with slight, mild, moderate, severe, and extreme vulnerability were 12.9%, 21.6%, 35.11%, 25.61%, and 4.77%, respectively.

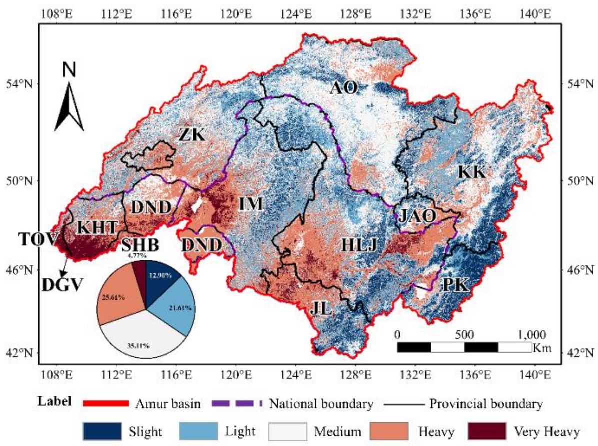

Figure 1. Ecological Vulnerability in the HARB Region in 2020 (ZK: Zabaykalsky Krai; PK: Primorsky Krai; KK: Khabarovsk Krai; JAO: Jewish Autonomous Oblast; AO: Amur Oblast; IM: Inner Mongolia; JL: Jilin; HLJ: Heilongjiang; TOV: Töv; SHB: Sükhbaatar; KHT: Khentii; DGV: Dornogovi; DND: Dornod)

Ecological vulnerability in the HARB region shows significant spatial variation. Areas with extremely high ecological vulnerability index (EVI) values are mainly located in the southwestern, southern, and eastern parts of the basin, particularly along the border between Heilongjiang Province in China and Russia. These high-vulnerability zones are especially concentrated in the Gobi region of Mongolia, as well as in urban centers and agricultural areas within China, such as the Sanjiang Plain (**Figure 1.**, the border region between northeastern Heilongjiang Province of China and Khabarovsk Krai of Russia.). At the provincial level, the five Mongolian provinces within the HARB exhibit relatively high average EVI values, all exceeding 35 (Figure 2).

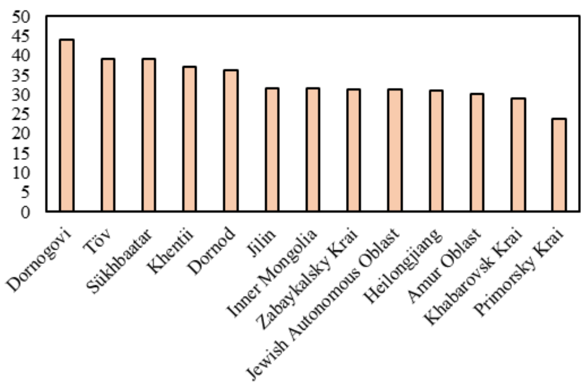

Figure 2. Average EVI by Province in the HARB Region in 2020

3.2 Explanatory Contribution of Each Factor to EVI

Using the geographical detector model, this study identified the dominant driving factors influencing ecological vulnerability in 2020. The results show that all 13 factors have a statistically significant impact on EVI variation. Among them, soil retention has the highest explanatory power, accounting for 63% of the variation in EVI (Figure 3). This is followed by net primary productivity and the habitat quality index, which explain 42% and 40% of the variation, respectively. Terrain relief, slope, the Palmer Drought Index, extreme wet events, and extreme dry events contribute between 12% and 36%. The remaining seven factors each explain less than 10% of the variation, with population density showing the lowest explanatory power at only 1%.

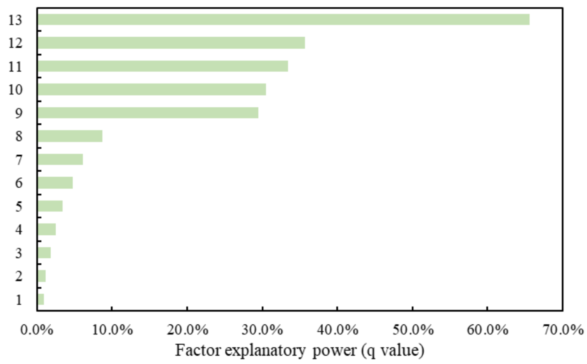

Figure3. The impact of various driving factors on EVI changes in 2020 and their average values. (For the vertical axis: 1-Extreme drought; 2-Population density; 3- Palmer Drought Index; 4-Building density; 5-Proportion of protected areas; 6-FVC; 7-Extreme humid; 8-Elevation; 9-Slope; 10-Terrain relief; 11-HQI; 12-NPP; 13- Soil retention amount)

3.3 Governance and policy responses for reducing ecological vulnerability

Reducing regional ecological vulnerability requires comprehensive and multi-dimensional strategies. First, it is essential to strengthen the coordinated management of both natural and human factors. This study identifies soil retention as the most important factor explaining variations in the Ecological Vulnerability Index (EVI) in the HARB region (q = 63%), suggesting that reducing soil erosion may be a key pathway to mitigating ecological vulnerability[20]. Measures such as promoting conservation agriculture and restoring riparian vegetation can help enhance soil retention capacity[21]. The significance of the habitat quality index (HQI) and net primary productivity (NPP) further indicates that reducing the intensity of agricultural activities and improving vegetation health are also important approaches for alleviating ecological vulnerability.

At the same time, as a major transboundary river basin in Northeast Asia, the HARB region encompasses China, Mongolia, and Russia—three countries that differ significantly in terms of ecological vulnerability, economic development models, and environmental protection efforts. In particular, Mongolia faces more urgent challenges related to ecological vulnerability, especially in the Gobi and grassland areas severely affected by drought and overgrazing. This study found that ecological vulnerability in Mongolian territory is generally high, especially in areas with poor soil retention and low net primary productivity.

To address these issues, Mongolia could strengthen the sustainable management of grassland ecosystems and optimize the structure of its livestock industry to mitigate grassland degradation. This may include promoting a grass-livestock balance system, establishing region-specific livestock carrying capacity standards, and encouraging practices such as designated grazing zones and rotational grazing. Additionally, the development of a grassland ecological compensation mechanism could enhance herders' engagement in ecological protection. For example, Mongolia could draw on China’s policy experiences such as “grazing ban for grassland recovery” and “conversion of cropland to wetlands” by piloting ecological restoration programs in high-vulnerability areas. These programs could offer financial incentives to support herders in reducing grazing intensity and participating in grassland monitoring and restoration efforts.

Moreover, the integrity of the basin's ecosystem requires the three countries to transcend administrative boundaries and establish a coordinated governance framework. To promote long-term ecological protection and collaborative governance in the HARB, we recommend establishing a joint ecological monitoring network among China, Mongolia, and Russia. This transboundary network could facilitate regular data sharing, synchronized observation protocols, and early warning systems for ecological risks. By integrating monitoring efforts, the three countries can improve their capacity to respond to environmental change and develop coordinated strategies for sustainable ecosystem management across the basin.

4. CONCLUSION

Unlike previous studies that focused on local areas or single ecological factors, this study provides a comprehensive, transboundary assessment of ecological vulnerability across the entire HARB using up-to-date multi-source data.

Based on multi-source data, this study applied the ESA ecological vulnerability assessment framework, the CRITIC–AHP weighting model, and the geographical detector method to systematically analyze the spatial and temporal characteristics of ecological vulnerability in the HARB region in 2020 and its underlying driving mechanisms. The results indicate that ecological vulnerability in the basin was relatively high (the average EVI in 2020 was 31.0) and exhibits significant spatial clustering, with high-vulnerability areas mainly located in the Gobi region, urban centers, and agricultural zones. The study also identifies soil retention, net primary productivity (NPP), and the habitat quality index (HQI) as the core factors driving the spatial pattern of ecological vulnerability, which explained 63%, 42% and 40% of the variation, respectively. Highlighting the critical roles of soil stability and vegetation health in shaping regional ecological vulnerability. However, it is important to note that this study focuses on large-scale ecological vulnerability assessment at the basin level. While the results indicate moderate to high vulnerability in the upstream areas, detailed field verification was beyond the scope of this work. Future research should incorporate ground-based investigations and localized monitoring to validate and refine the assessment outcomes in specific high-risk subregions.

These findings provide scientific support for cross-border cooperation in the HARB region and contribute to efforts aimed at reducing ecological vulnerability. Moreover, the proposed assessment framework offers valuable reference for promoting sustainable development in other similar transboundary regions worldwide.

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