

Article

Cryosphere Ecological Vulnerability in the Qilian Mountains Region: Trends, Drivers, and Adaptation

Xiaoya Yi ^{1,2,3}, Xingyu Xue ^{1,2,3}, Changsheng Lu ^{2,4}, Bowen Li ^{1,2,3}, Mengyuan Liu ^{1,2,3}, Jizu Chen ^{1,2,3}, Youyan Jiang ^{1,5} and Wentao Du ^{1,2,3,*}

- ¹ Northwest Institute of Eco-Environment and Resources, Chinese Academy of Sciences, Lanzhou 730000, China; yixiaoya@nieer.ac.cn (X.Y.); xuexingyu23@mails.ucas.ac.cn (X.X.); libowen@nieer.ac.cn (B.L.); liumengyuan25@mails.ucas.ac.cn (M.L.); chenjizu@lzb.ac.cn (J.C.); jiangyouyan1980@gmail.com (Y.J.)
- ² Qilian Mountains Field Research Station for Interactions Among Cryosphere and Multi-Spheres, China Meteorological Administration, Lanzhou 730000, China; 232085802165@lut.edu.cn
- ³ University of Chinese Academy of Sciences, Beijing 100049, China
- ⁴ School of Energy and Power Engineering, Lanzhou University of Technology, Lanzhou 730000, China
- ⁵ Lanzhou Regional Climate Center, Lanzhou 730000, China
- * Correspondence: duwentao@lzb.ac.cn

Highlights

What are the main findings?

- EVI of the Qilian Mountains region showed minor regional changes but more pronounced local shifts, with ecological pressure trending eastward.
- Natural factors have a greater impact on the EVI of the Qilian Mountains region than socio-economic ones, and a unique finding is the prominent influence of glacial meltwater volume and the Freeze–thaw disaster risk index.

What are the implications of the main findings?

- Ecological degradation is already apparent in certain localities, demanding urgent and enhanced measures for ecological protection and restoration. In the long run, enhancing vegetation coverage will be conducive to mitigating ecological vulnerability.
- The unexpected prominence of cryospheric elements as key drivers of ecological vulnerability offers a new perspective for guiding future ecological restoration strategies. Concurrently, monitoring key indicator thresholds is essential for informing targeted ecological management of the Qilian Mountains region.

Abstract

The rapid shrinkage of the climate-regulating cryosphere, driven by global warming and anthropogenic activities, underscores the urgency of understanding its impact on regional ecological vulnerability. This study develops a Sensitivity–Resilience–Pressure (SRP) model-based framework comprising 21 natural and socio-economic indicators, employs spatial autocorrelation and center of gravity migration to characterize spatiotemporal patterns in the Qilian Mountains region, and integrates Random Forests (RF) with Shapley Additive Explanations (SHAP) to identify key drivers. Results reveal a downward trend in the Ecological Vulnerability Index (EVI) from 2000 to 2020, with areas of very heavy vulnerability declining from 21.05% to 14.73%, indicating gradual ecological recovery. The study area exhibits moderate vulnerability, with the western region dominated by heavy and very heavy vulnerability, whereas the eastern region is characterized by potential and light vulnerability, indicating a high-west, low-east spatial pattern. A significant positive spatial autocorrelation is observed, revealing that areas with high vulnerability are highly clustered and primarily overlap with regions of high elevation and sparse vegetation. The



Academic Editor: Tao Chen

Received: 13 November 2025

Revised: 7 January 2026

Accepted: 8 January 2026

Published: 14 January 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

RF-SHAP analysis demonstrates that natural factors dominate the EVI, with fractional vegetation cover, biological abundance, glacial meltwater volume, annual precipitation, and the landscape diversity index emerging as the main drivers, and the EVI changing sequentially as each indicator approaches its threshold: 0.16, 56.57, 2.23 mm, 400.73 mm, and 0.39. In conclusion, although ecological vulnerability in the Qilian Mountains has declined, future management strategies should leverage these threshold effects to implement precise, indicator-based monitoring and regulation.

Keywords: cryosphere; ecological vulnerability index; driving factors; the Qilian Mountains region

1. Introduction

Ecological vulnerability, originating from natural hazard studies [1,2], was formally defined by Timmerman [3] as a system's susceptibility to hazardous events. Since the 1980s, the field has transitioned from theoretical conceptualization to quantitative assessment, gaining a pivotal role in climate change strategies [4,5]. In 2014, the IPCC AR5 established it as central to adaptation, integrating exposure, sensitivity, and adaptive capacity [6,7]. Research has since advanced toward identifying vulnerable regions and establishing robust, multi-scale frameworks, with increasingly diverse methods and study objects [8–10]. In this context, ecological vulnerability assessment serves as a critical diagnostic tool for identifying systemic fragilities, thereby guiding conservation strategies and reinforcing its significance in frontier environmental science [11,12]. While existing assessments have extensively covered arid and semi-arid zones, mountain and plateau environments, coastal systems, and urban agglomerations [13–16], regions dominated by the cryosphere remain comparatively underexplored. This oversight is critical, as the cryosphere exerts a profound influence on hydrology [17], climate [18], and biodiversity [19]; consequently, its degradation acts as a multiplier of ecological risk. Specifically, glacial retreat reduces runoff, intensifying droughts and ecological stress [20]; simultaneously, thawing permafrost releases greenhouse gases that accelerate warming and further cryosphere loss. These processes intensify the frequency of extreme weather and disasters [21], endangering both ecosystems and human well-being. Recognizing the ecological vulnerability of the cryosphere is crucial, as localized impacts from its decline can escalate into regional and global security threats. Therefore, urgent monitoring and protection are essential to safeguard vital water resources, biodiversity, and climate stability, thereby ensuring long-term social–ecological resilience.

A variety of ecological vulnerability indicator systems are now in use, notably the ESA (Exposure–Sensitivity–Adaptability) model [22], the PSR (Pressure–State–Response) model [23], the VSD (Vulnerability Scoping Diagram) model [24], the SRP (Sensitivity–Resilience–Pressure) model [25], DPSIRM (Driving force–Pressure–State–Impact–Response–Management) model [26], and the C-R (Cause–Result) model [27]. In contrast to frameworks like PSR and DPSIR that emphasize causal chains and management processes, the SRP model decomposes ecosystem responses into three interrelated yet functionally distinct components: sensitivity, buffering and recovery capacity, and external stress intensity. This approach better characterizes the comprehensive state of ecosystems under complex disturbances. In addition, SRP performs well in applications because it generalizes across a wide spectrum of systems encompassing distinct natural units like lake basins [28], plateaus [29], and karst [30], as well as complex human-dominated environments such as urban agglomeration [31] and areas defined by significant stressors like natural hazards [32]. It organizes assessment around the three core dimensions of sensitivity to disturbance, internal re-

silience of structure and function, and external pressure, supporting comprehensive, interpretable, and operable evaluations. Given that the Qilian Mountains region is characterized by high altitude and the coexistence of typical cryospheric elements—including glaciers, snow, and permafrost—ecological vulnerability depends not only on the magnitude of external stress but also heavily on intrinsic habitat sensitivity and the ability to recover from damage. By emphasizing resilience as an independent dimension, the SRP model is a superior framework for uncovering the vulnerability dynamics of cryospheric mountain ecosystems. Regarding methodology, both qualitative and quantitative techniques are common, including AHP (Analytic Hierarchy Process) [33], SPCA (Spatial Principal Component Analysis) [34], the CRITIC objective weighting method [35], the Entropy Weight Method [27], and FAHP (Fuzzy Analytic Hierarchy Process) [36]. Among these, the CRITIC method stands out as a robust, objective weighting technique particularly effective for multidimensional analysis. Distinct from subjective approaches, it determines indicator weights based entirely on the inherent characteristics of the data by simultaneously considering two aspects: the variability within each indicator and the correlations between them [37]. This dual approach ensures that the resulting weights are free from subjective bias, yielding to a more comprehensive and accurate evaluation that effectively captures the full informational content of the dataset [38,39]. The driving mechanisms of ecological vulnerability are characterized by inherent complexity and high dimensionality [40]. Traditional methods such as multiple regression, correlation, and geographic detector analysis are widely used but often underperform with high dimensionality, nonlinearity, and multicollinearity [41]. To overcome these limitations, machine learning, especially Random Forests (RF), offers superior predictive capabilities, efficiently handling large datasets without linear assumptions and remaining resilient to multicollinearity [42]. However, RF and similar models are often criticized as “black boxes”, which limits their interpretability [43]. SHapley Additive exPlanations (SHAP) remedies this by attributing feature contributions, clarifying global and local model behavior, and identifying thresholds [44,45], enhancing transparency and applicability. Applying the RF–SHAP model to ecological vulnerability research enables the quantification of the contributions and critical thresholds of factors affecting ecological vulnerability. Based on the thresholds of these driving factors, delineating ecological red lines and constructing an ecological vulnerability early-warning system can support the dual objectives of ecological conservation and sustainable human development.

The Qilian Mountains region, located on the Qinghai–Tibet Plateau, encompasses vital cryospheric elements (glaciers, permafrost, and snow) that serve as regulators of the regional hydrological and ecological cycles [46]. This area is pivotal for water resources and oasis evolution but remains vulnerable due to the dual pressures of climate change and human interference. Currently, the cumulative effects of global warming, glacier retreat, permafrost thaw, and cryospheric hazards are weakening its ecological carrying and buffering capacities [47]. However, existing research has largely relied on fragmented approaches, focusing on isolated components such as geology, hydrology, vegetation, or soil, rather than integrated systemic coupling [48–53]. Due to difficulties in obtaining cryospheric data, vulnerability studies often prioritize general natural and socio-economic factors while overlooking changes in glaciers, snow, and permafrost, leading to incomplete assessments of these fragile environments. Compounding this issue, there is a more profound research gap in developing threshold-based approaches for environmental management, which involves both identifying the critical tipping points of key drivers and translating these thresholds into practical strategies. This disconnects between fundamental analysis and applied management tools prevents research from effectively guiding conservation and policy-making. To address previous study limitations, we developed an SRP-based ecological vulnerability assessment for the Qilian Mountains region, integrating topography, vegetation, climate,

biodiversity, natural hazards, and human disturbance, and subsequently employed the RF-SHAP model for a quantitative analysis of the key influencing factors. This study aims to: (1) identify spatiotemporal characteristics of Ecological Vulnerability Index (EVI) in the Qilian Mountains cryospheric zone; (2) evaluate the influence of cryospheric elements on the vulnerability; (3) identify the threshold to guide strategies mitigating EVI in cryosphere-influenced regions for improved management and ecological resilience.

2. Data and Methods

2.1. Study Area

The Qilian Mountains region lies on the northeastern margin of the Qinghai–Tibetan Plateau (93°23′–104°18′E, 35°36′–40°34′N), at the junction of the Qinghai–Tibetan, Inner Mongolian, and Loess plateaus. Spanning Qinghai and Gansu, the range extends roughly 800 km east–west and 200–400 km north–south, with an approximate area of $1.88 \times 10^5 \text{ km}^2$ (Figure 1). Elevations range from approximately 4000 m to over 5800 m, accompanied by a pronounced vertical ecosystem zonation. The high altitude fosters a plateau continental climate with strong solar radiation and large diurnal ranges; hydrothermal conditions vary markedly spatially, forming a gradient transitioning from warm and wet in the east to cold and dry in the west. Mean annual temperature is approximately 5.64 °C and mean annual precipitation is roughly 251.83 mm. Vegetation exhibits distinct altitudinal belts controlled by elevation and moisture, with grasslands occupying approximately about 65% of the area.

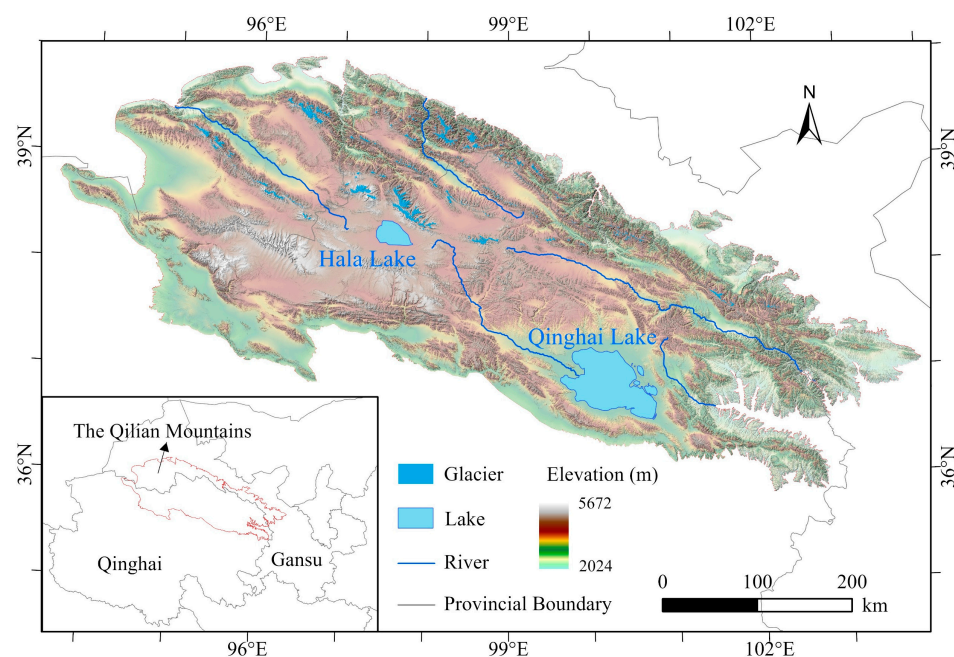


Figure 1. Location of the Qilian Mountains region.

Cryosphere components are widespread and exert first-order control on hydrology and ecosystem stability. According to the Second Chinese Glacier Inventory, the region contains 2683 glaciers with a total area of 1597.81 km² and an ice volume of ~84.48 km³ [54]. Notably, the contribution of glacial meltwater in river runoff increases from east to west [55]. In addition to glaciers, permafrost is also extensive, underlying about 47.51% of the landscape [56], and seasonal snow cover is widespread. Together, meltwater from glaciers, permafrost, and snow is a critical source of runoff for the region's river systems, including the Heihe, Shule, Shiyang, and the exorheic Datong River.

2.2. Data Sources

The data employed in this study consist principally of topographic, meteorological, soil, socio-economic, and other auxiliary datasets (Table 1). Most data cover the period from 2000 to 2020, with the exception of freeze–thaw disaster risk index (2000, 2010, 2019) and terrain data (2000, 2010, 2020). Missing station data were interpolated using Inverse Distance Weighting (IDW) to generate raster datasets. All data were clipped using the study area vector data, reprojected to the WGS_1984_Albers coordinate system, and resampled to a spatial resolution of 500 m. Taking into account data processing and visualization considerations, a 5 km × 5 km grid was adopted as the fundamental spatial unit of analysis. Weighted indicator data were used to generate the EVI, followed by the creation of a fishnet grid within the study area for spatial analysis. Notably, the 2019 freeze–thaw disaster risk index was used as a proxy for 2020. This substitution was made because the data series ends in 2019 and the variable exhibits significant stability and lag effects. All the above methods were implemented using ArcGIS 10.6 software.

Table 1. Ecological vulnerability evaluation indicator system in the Qilian Mountains region.

Target Layer	Category of Index	Element Layer	Indicator Layer	Indicator Code	Data Sources	Spatial Resolution	Type of Relationship
Ecological vulnerability	Ecological sensitivity	Terrain factor	Slope gradient	TF1	Resource and Environmental Science Data Platform	30 m	Positive
			Elevation	TF2		30 m	Positive
			Topographic relief	TF3		30 m	Positive
		Surface factor	Fractional vegetation cover	SU1	National Tibetan Plateau Data Center	250 m	Negative
			Snow cover duration	SU2	National Earth System Science Data Center	500 m	Negative
			Glacial meltwater volume	SU3	[57]	500 m	Negative
			Snow disaster index	SU4	National Earth System Science Data Center	500 m	Positive
			Freeze–thaw disaster risk index	SU5	Gansu Provincial Industry Technology Center of Intelligent Equipment and Big Data for Disaster Prevention	500 m	Positive
		Soil factor	Soil and water conservation capacity	SO1	[58]	1 km	Negative
			Soil erosion intensity	SO2	Resource and Environmental Science Data Platform	1 km	Positive
		Meteorological factor	Annual average temperature	MF1	National Cryosphere Desert Data Center	1 km	Negative
			Annual precipitation	MF2	National Cryosphere Desert Data Center	1 km	Negative
			Aerosol optical depth	MF3	National Earth System Science Data Center	1 km	Positive

Table 1. Cont.

Target Layer	Category of Index	Element Layer	Indicator Layer	Indicator Code	Data Sources	Spatial Resolution	Type of Relationship
Ecological vulnerability	Ecological resilience	Landscape structure	Landscape diversity index	LS	National Cryosphere Desert Data Center	30 m	Positive
		Ecological vitality	Hydrological index	EV1	National Cryosphere Desert Data Center	500 m	Negative
			Biological abundance	EV2	National Cryosphere Desert Data Center	500 m	Negative
			Thermal comfort index	EV3	China Meteorological Data Service Centre	500 m	Negative
	Ecological pressure	Social factor	Population density	SC1	WorldPop	1 km	Positive
			Herbage yield	SC2	Geographic Remote Sensing Ecological Network Platform	500 m	Negative
			Per capita GDP	SC3	Resource and Environmental Science Data Platform	1 km	Negative
			Artificial nighttime light index	SC4	National Tibetan Plateau Data Center	1 km	Positive

2.3. Ecological Vulnerability Index (EVI)

The SRP model is a comprehensive evaluation framework constructed based on ecosystem stability, aiming to assess the ecological vulnerability of specific regions. This study employs the SRP model to evaluate the ecological vulnerability of the Qilian Mountains region, considering its unique natural geographical environment and socio-economic development status. Additionally, the selection of evaluation indicators is guided by principles of scientific validity, representativeness, timeliness, availability, and operational feasibility. A total of 21 indicators were chosen across three dimensions: ecological sensitivity, ecological resilience, and ecological pressure, to develop a region-specific evaluation model (Table 1) (Figure 2).

Ecological sensitivity reflects the susceptibility of an ecosystem when subjected to internal and external disturbances [59]. The indicators for ecological sensitivity include topographic factors [13] (elevation, slope, and topographic relief) which serve as the fundamental topographic constraints on ecosystem stability; surface factors [60] (fractional vegetation cover, snow cover days, snow disaster index, glacial meltwater volume and freeze–thaw disaster risk index), which reflect the alpine and cryospheric characteristics of the region and regulate surface water resources and disturbance intensity, playing a pivotal role in shaping the initial ecological response to external forcing; soil factors [61,62] (soil conservation capacity and soil erosion amount) and meteorological factors [30,63] (annual average temperature, annual precipitation, and aerosol optical depth), which provide the macro-background for regional ecological patterns and are particularly critical in arid, semi-arid, or high-altitude regions. Ecological resilience represents the capacity of an ecosystem to self-regulate and recover from disturbances [64]. The selected indicators [65,66] for ecological resilience are landscape diversity index, hydrological index, biological abundance, and thermal comfort index, which influence the system’s recovery capacity from the perspectives of structure, water resources, material foundation, and environmental potential, respectively. Ecological pressure measures the stress imposed on ecosystems by socio-economic activities and human interventions [67], which is reflected through indicators [68,69] such as population density, herbage yield, artificial nighttime

light index and GDP per capita, collectively capturing external forces to characterize the stress imposed by human activities on the Qilian Mountains region ecosystem from the perspectives of resource utilization and spatial expansion.

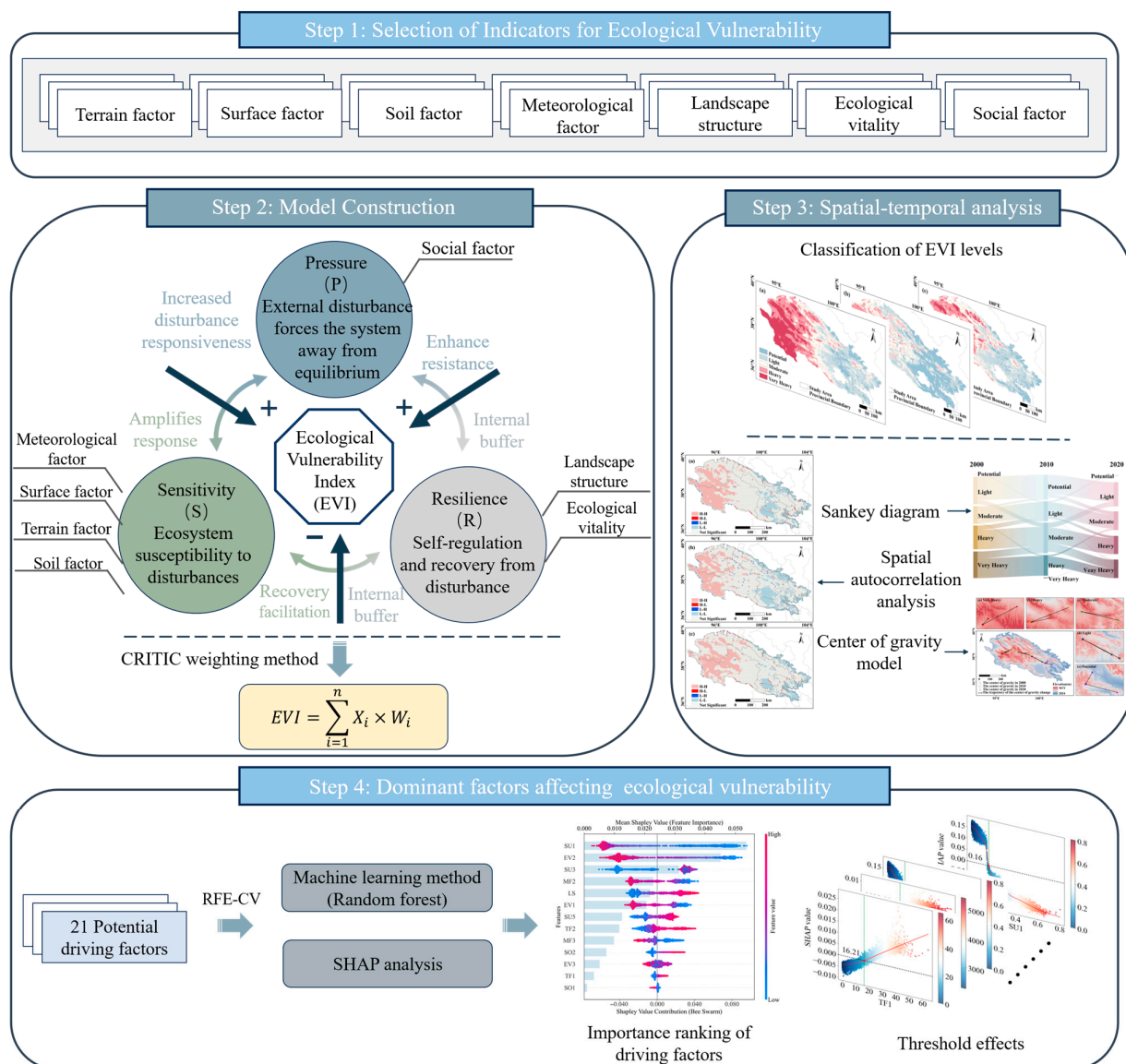


Figure 2. Flowchart of the Ecological Vulnerability Index (EVI) assessment process.

Ecological sensitivity reflects the strong response of ecological processes to climate change, cryospheric dynamics, and surface conditions. Ecological resilience functions as an internal buffering mechanism that regulates the impact of sensitivity on the actual environment; specifically, factors like landscape structure and ecological vitality determine a sensitive system's reorganization and stability after disturbance. Ecological pressure represents the intensity and duration of external stress, primarily stemming from human activities and socio-economic development, which can amplify or suppress vulnerability through interactions with sensitivity and resilience. Rather than functioning independently, these three dimensions form a coupled system: sensitivity dictates the initial reaction to disturbance, resilience governs the recovery trajectory, and pressure modifies disturbance mechanisms and resilience efficacy. Consequently, ecological vulnerability arises from the imbalance among these components, particularly when high sensitivity and intense external pressure coincide with insufficient resilience. In the model construction, indicators

are categorized into positive and negative indicators based on their characteristics, to more accurately assess the ecological vulnerability of the Qilian Mountains region.

2.4. The Ecological Vulnerability Assessment Methods

The original indicator data were standardized to eliminate the effects of dimensional heterogeneity and ensure comparability [70]. The positive indicators and negative indicators were standardized by Equations (1) and (2), where x'_i is the standardized value (ranging from 0 to 1), x_i represents the original measured value of the index factor i , and x_{imin} and x_{imax} represent the minimum and maximum values of the index i , respectively. All indicators were reprojected to an Albers equal-area conic projection and resampled to a 500 m $\times$ 500 m raster format to ensure spatial consistency.

$$x'_i = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \quad (1)$$

$$x'_i = \frac{x_{imax} - x_i}{x_{imax} - x_{imin}} \quad (2)$$

In the CRITIC weighting method, the allocation of weights is based on the volatility (comparative strength) and conflict (correlation) between evaluation indicators [71], the comparative strength is multiplied by the correlation value indicator to obtain the final weights by Equations (3) and (4):

$$P_j = S_j \sum_{i=1}^n 1 - r_{ij} \quad (3)$$

where P_j is the amount of information contained in the j -th indicator within the evaluation indicator system, S_j is the standard deviation of the j -th indicator, r_{ij} is the correlation coefficient between factors i and j .

$$W_j = \frac{P_j}{\sum_{j=1}^n P_j} \quad (4)$$

where W_j is the objective weight of the j -th indicator.

All raw data were sourced from authoritative national scientific data platforms and subjected to consistent pre-processing steps, thereby ensuring high reliability for weight calculation. Furthermore, in applying the CRITIC weighting method, the raster data used in this study comprised 964 rows and 1674 columns, resulting in a total of 1,613,736 pixels. Each pixel was considered an independent sample point for computation purposes. The large sample size adequately supports the CRITIC method in objectively deriving weights and ensures the statistical robustness of the results.

According to the CRITIC weight model, the ecological vulnerability index [72] is the sum of the weighted indicators. The final EVI value was obtained using Equation (5):

$$EVI = \sum_{i=1}^n X_i \times W_i \quad (5)$$

where EVI is the comprehensive Ecological Vulnerability Index value, X_i is the standardized value of indicator i , and W_i is the corresponding weight value of indicator i ($1 \leq i \leq n$).

To gain an intuitive understanding of the ecological vulnerability of the study area, the natural breaks method was used to classify EVI into five levels [73]. The specific classification criteria are: Level I is potential vulnerability ($EVI \leq 0.28$), level II is light vulnerability ($0.28 < EVI \leq 0.4$), level III is moderate vulnerability ($0.4 < EVI \leq 0.54$), level IV is heavy vulnerability ($0.54 < EVI \leq 0.67$), and level V is very heavy vulnerability ($EVI > 0.67$).

2.5. Spatial Analysis

Spatial autocorrelation analysis serves as a crucial method for investigating the spatial distribution patterns of geographic phenomena. It effectively determines whether geographic elements exhibit tendencies towards clustering or dispersion across space. This analytical approach is primarily categorized into two types: global spatial autocorrelation (Global Moran's I) and local spatial autocorrelation (Local Moran's I) by Equations (6) and (7). Global spatial autocorrelation is employed to assess spatial dependence across the entire study area, thereby revealing the overarching spatial distribution pattern of the region. Global Moran's $I \in [-1, 1]$; a positive value indicates positive spatial correlation (clustering), a negative value indicates negative correlation (dispersion), and a value of zero suggests no significant spatial autocorrelation. To analyze local spatial clustering, the Local Moran's I index was used to generate a LISA (Local Indicators of Spatial Association) map. Ecological vulnerability was classified into five clustering patterns within a 95% confidence interval: high–high clustering (H-H), high–low clustering (H-L), low–high clustering, low–low clustering (L-L), and not significant [66]. By applying spatial autocorrelation analysis, the distribution pattern and spatial heterogeneity characteristics of regional ecological environment vulnerability can be effectively elucidated.

$$\text{Global Moran's } I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (6)$$

$$\text{Local Moran's } I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n w_{ij} (x_j - \bar{x})}{s^2} \quad (7)$$

where n is the total number of elements; x_i and x_j represent the EVI values for the i -th and j -th units; $\bar{x}$ is the average EVI value across all units; w_{ij} is the spatial weight matrix; and s is the standard deviation.

2.6. RF–SHAP Interpretable Machine Learning Model

Random Forests algorithm, introduced by Breiman in 2001 [74], aggregates multiple decision trees to markedly improve predictive accuracy and stability, offering strong robustness while mitigating over-fitting. However, as a complex ensemble, its decision-making process exhibits a characteristic “black-box” nature that defies straightforward interpretation. Shapley Additive Explanations (SHAPs), grounded in game-theoretic Shapley values, decompose a model's output into the independent contributions of each input feature [75], thereby quantifying feature importance. By illustrating the internal logic of RF without compromising performance, SHAP substantially enhances model transparency and interpretability. The calculation formulas are shown in Equations (8) and (9):

$$f(x) = \phi_0(f, x) + \sum_{i=1}^p \phi_i(f, x) \quad (8)$$

$$\phi_i(f, x) = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(p-|S|-1)!}{p!} (f_x(S \cup \{i\}) - f_x(S)) \quad (9)$$

where S is a subset of the features used and p is the number of influencing factors in the model. $f_x(S)$ is the predicted value for subset S . The impact of the i -th factor on the prediction result of the model when given the input x is $\phi_i(f, x)$, which is computed using Equation (9).

Recursive Feature Elimination (RFE) is a powerful and widely applied feature selection technique [76]. Through an iterative process starting with all available features, it considers feature interactions while progressively eliminating the least significant ones. The model is retrained and evaluated in cycles until a target number of features or an ideal performance

threshold is met. Furthermore, integrating RFE with Cross-Validation (RFECV) enables the automatic determination of the optimal number of features [77]. This approach effectively prevents overfitting during the selection process while securing the optimal feature subset.

3. Result

3.1. The Temporal Characteristics of EVI

The EVI showed an initial decline followed by a rebound from 2000 to 2020, with mean EVI values of 0.49, 0.45, and 0.49 for the years 2000, 2010, and 2020, respectively. Over the 21 years, the annual mean EVI averaged 0.48, indicating a generally moderate level of vulnerability. To further analyze temporal dynamics, we quantified the proportional and absolute changes for each vulnerability class (Table 2). During the 2000–2010 period, the area proportions of potential and light vulnerability grew by 18.7% and 10.04%, respectively, while all other classes declined; very heavy vulnerability showed the largest decline at 20.6%. However, this improvement was partially offset between 2010 and 2020, as potential vulnerability contracted by 16.65% and very heavy vulnerability rebounded by 14.28%. Over the entire study period (2000–2020), areas classified as moderate vulnerable and very heavy vulnerability declined by $1.24 \times 10^3 \text{ km}^2$ and $1.19 \times 10^4 \text{ km}^2$, respectively, representing decreases of 0.66% and 6.32% of the total area. In contrast, potential, light, and heavy vulnerability expanded by $3.86 \times 10^3 \text{ km}^2$, $3.81 \times 10^3 \text{ km}^2$, and $5.49 \times 10^3 \text{ km}^2$, respectively, collectively increasing their total share by approximately 2%. Overall, while the study region exhibited a trend towards ecological improvement, the recovery process remains constrained and unstable.

Table 2. Coverage and area proportions of different ecological vulnerability classes in the Qilian Mountains region.

Classes	2000		2010		2020	
	Area/km ²	Percentage/%	Area/km ²	Percentage/%	Area/km ²	Percentage/%
Potential	13,739.75	7.29	48,961.00	25.99	17,598.75	9.34
Light	42,545.25	22.58	61,456.75	32.62	46,358.25	24.61
Moderate	48,226.25	25.60	37,496.00	19.90	46,986.00	24.94
Heavy	44,216.00	23.47	39,635.50	21.04	49,710.75	26.39
Very Heavy	39,663.75	21.05	848.50	0.45	27,744.00	14.73
Total	1.88×10^5	99.99	1.88×10^5	100.00	1.88×10^5	100.01

(Note: Percentages do not sum to 100% due to rounding of the proportions for each ecological vulnerability class).

A Sankey diagram (Figure 3) was used to quantify area transitions among vulnerability classes, revealing a predominant shift toward lower vulnerability grades during the 2000–2010 period. The most significant conversions were from light to potential vulnerability ($3.37 \times 10^4 \text{ km}^2$), from very heavy to heavy ($2.87 \times 10^4 \text{ km}^2$), and from heavy to moderate ($2.83 \times 10^4 \text{ km}^2$). By 2010, the potential, light, and very heavy vulnerability classes accounted for 25.99%, 32.62%, and 0.45% of the total area, respectively. Conversely, the 2010–2020 period exhibited a reversal in this trend, with transitions moving primarily toward higher vulnerability states. The largest shifts occurred from potential to light ($2.79 \times 10^4 \text{ km}^2$), moderate to heavy ($2.02 \times 10^4 \text{ km}^2$), and light to moderate ($2.28 \times 10^4 \text{ km}^2$). Consequently, the area proportions of potential and light vulnerability contracted, while those of moderate, heavy, and very heavy vulnerability expanded. While the aggregate regional vulnerability showed only minor fluctuations, these extensive internal transfers indicate pronounced volatility at the local scale.

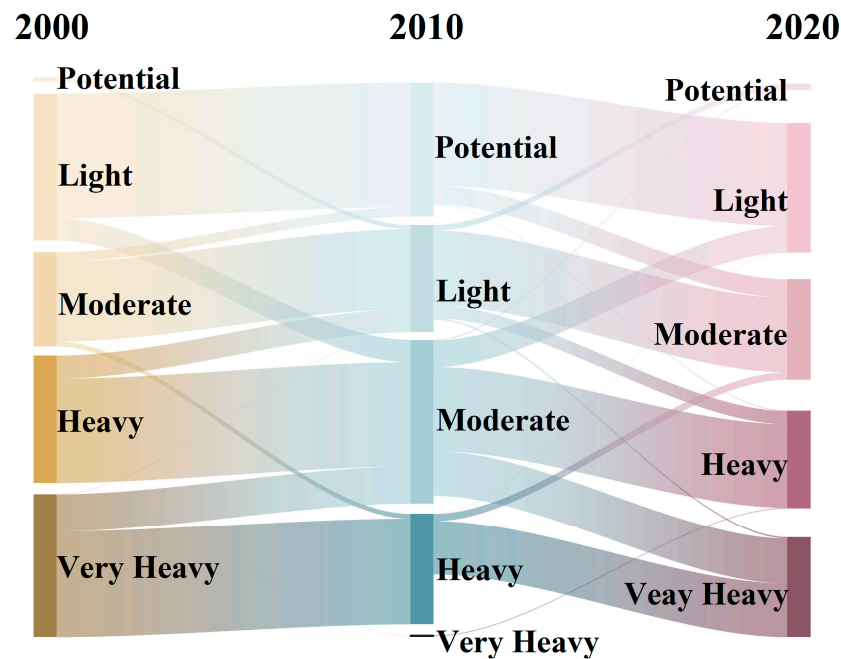


Figure 3. Area transfer flows among ecological vulnerability classes in the Qilian Mountains region during 2000–2010 and 2010–2020.

3.2. The Spatial Characteristics of EVI

The Qilian Mountains region is generally classified as moderately vulnerable, with over 70% of its total area comprising the light, moderate, and heavy vulnerability classes. Spatially, this vulnerability is not uniform, showing a clear decrease from the northwest to the southeast (Figure 4). Consequently, the western region is dominated by heavy and very heavy vulnerability, whereas the eastern region is defined primarily by potential and light vulnerability (Figure 5). Spatial autocorrelation analysis shows that the Moran's I index values were 0.76, 0.72, and 0.75 for the years 2000, 2010, and 2020, respectively. These values are significantly above zero, indicating an aggregated distribution: areas with similar vulnerability levels (high or low) are strongly clustered rather than being randomly distributed across the study region ($Z = 96.32, 91.50, 95.73, 101.23; p < 0.01$), indicating that some areas in the Qilian Mountains region bear significant ecological stress, while others benefit from better environmental conditions. The study area is dominated by high–high (H–H) and low–low (L–L) clusters, with nonsignificant areas as a secondary pattern, whereas high–low (H–L) and low–high [78] outlier values account for only a negligible share (Figure 6). Specifically, low–low (L–L) clusters, which are dominated by potential and light vulnerability, are primarily found in areas with relatively superior natural conditions. These include the overlap area between the study area and the Hexi Corridor, the southeastern Qilian Mountains region, and parts of Haibei Tibetan Autonomous Prefecture (Gangcha and Haiyan counties (hereinafter referred to as Haibei Prefecture), Hainan Tibetan Autonomous Prefecture (Gonghe County) (hereinafter referred to as Hainan Prefecture), and Haidong City. High–high (H–H) clusters are concentrated in the western Qilian Mountains region, largely overlapping areas of heavy and very heavy vulnerability, and cover most of Haixi Mongolian and Tibetan Autonomous Prefecture (Mangya City, Dachaidan Administrative Zone, Delingha City, and Dulan County) (hereinafter referred to as Haixi Prefecture) as well as Jiuquan City (Aksai Kazakh Autonomous County and Subei Mongol Autonomous County). This clustering phenomenon is driven by specific underlying factors, namely water resource limitations and surface instability. Spatially, the western cluster coincides with regions characterized by low annual precipitation (MF2), low fractional vegetation

cover (SU1), and high elevation (TF2). Imbalanced hydrothermal–vegetation coupling, characterized by vast bare ground and insufficient biomass to buffer against external shocks, acts as the primary natural driver of this high vulnerability. Additionally, the compounding effect of industrial activities like mining further intensifies the situation, solidifying the significant spatial clustering.

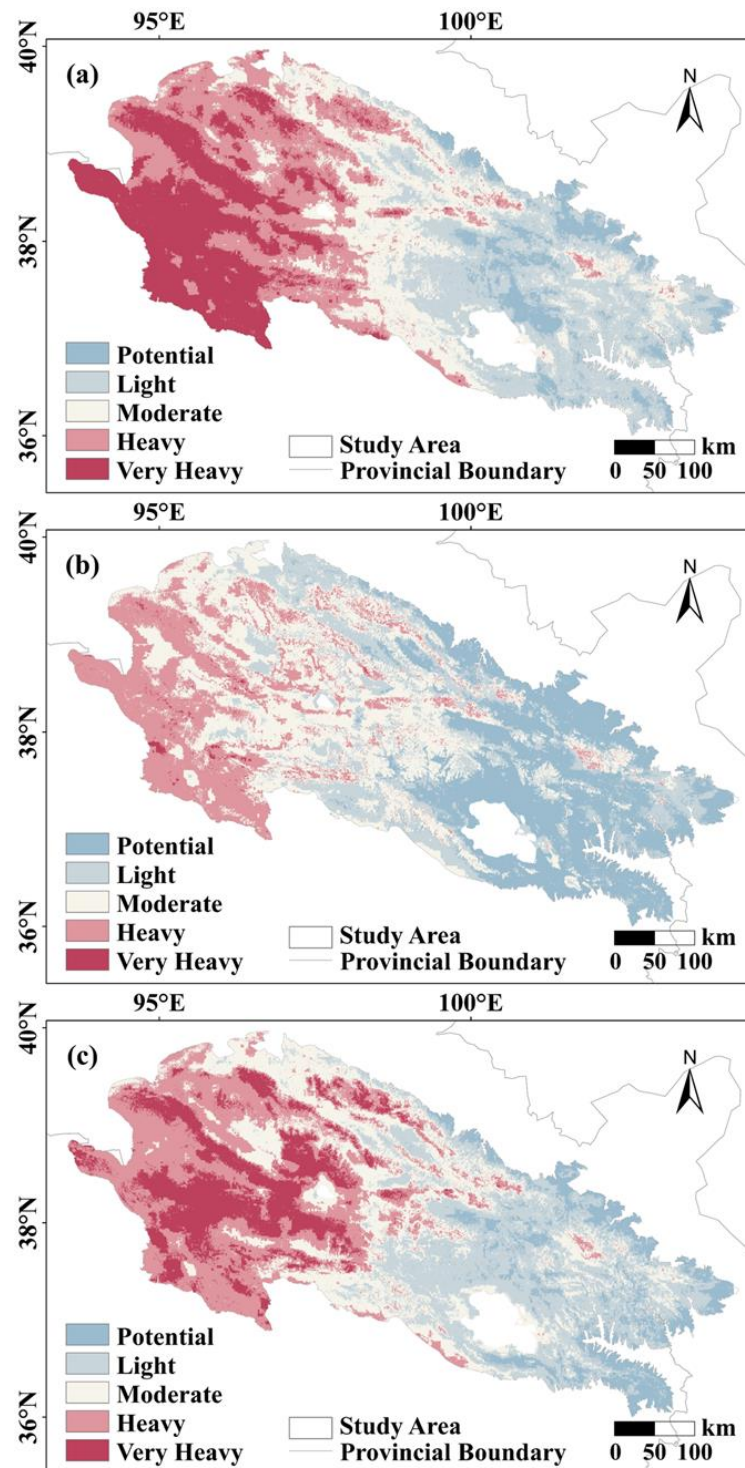


Figure 4. Spatial distribution of ecological vulnerability in the Qilian Mountains region in (a) 2000, (b) 2010, and (c) 2020.

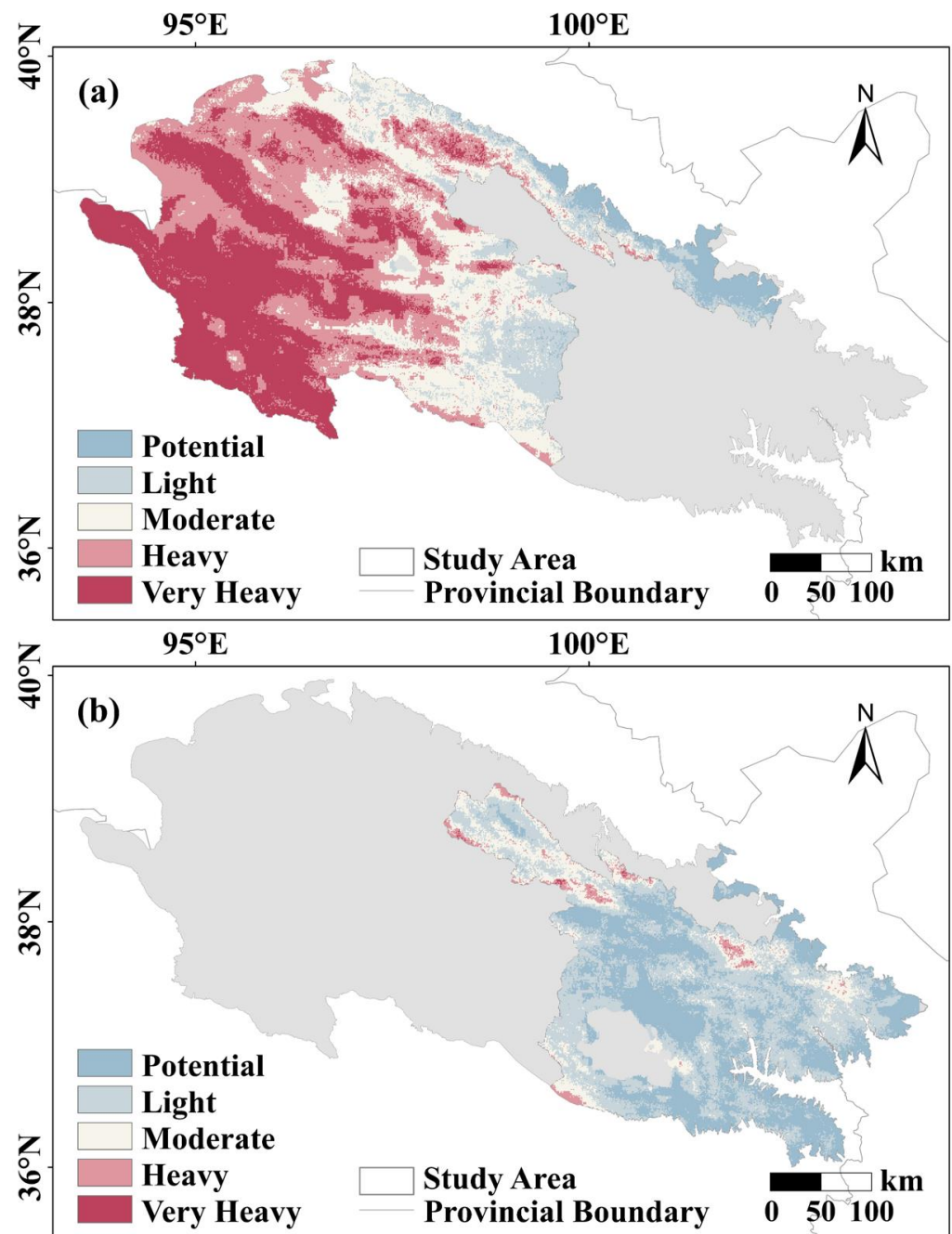


Figure 5. Spatial distribution of ecological vulnerability in the western (a) and eastern (b) Qilian Mountains region.

Additionally, a center of gravity model was applied to trace the directional evolution of vulnerability centers (Figure 7). Throughout the period, the centroids of light and moderate vulnerability displayed the largest migration distances, while the very heavy vulnerability experienced the most rapid acceleration in centroid movement. Overall, all vulnerability classes showed an eastward shift.

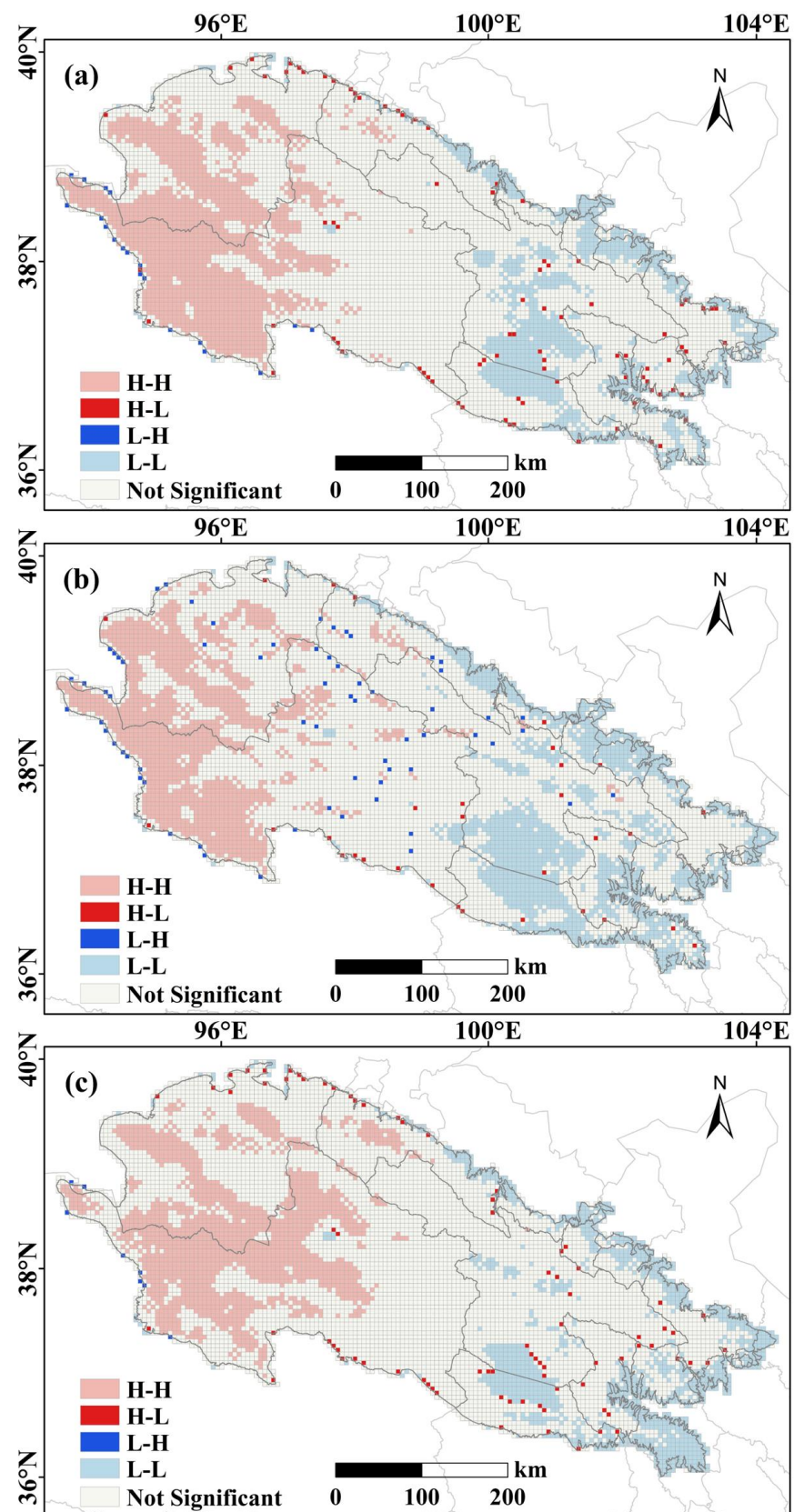


Figure 6. Moran's Indices of the EVI in the Qilian Mountains region for the years (a) 2000, (b) 2010 and (c) 2020.

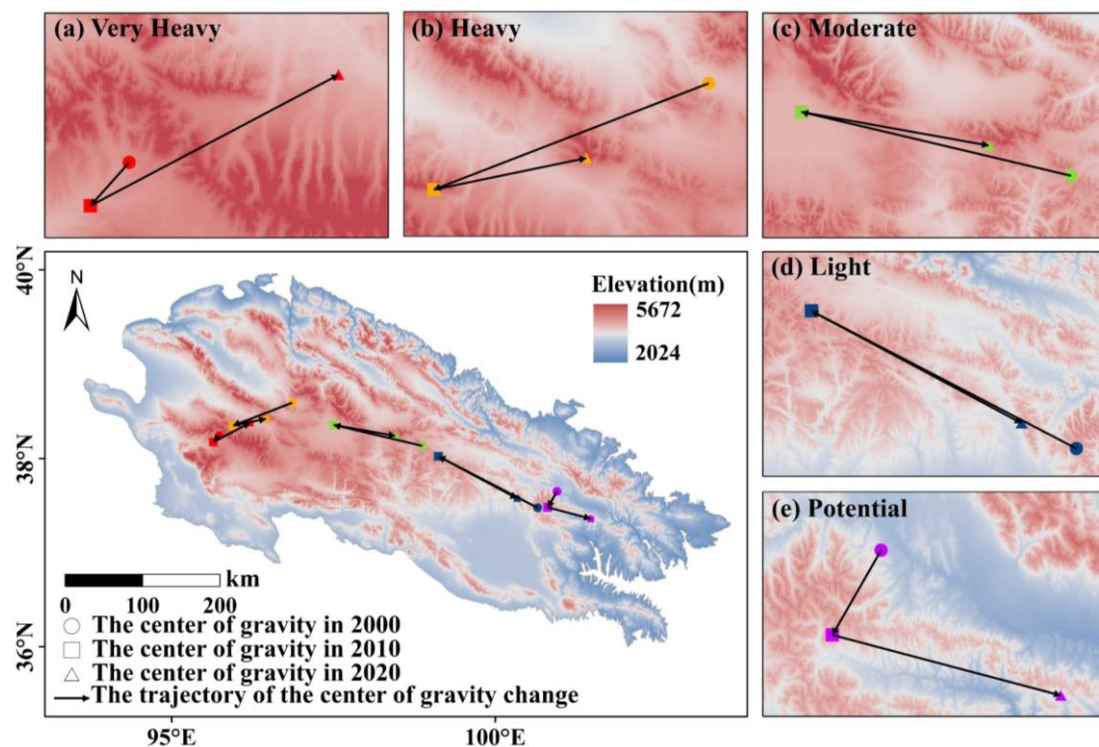


Figure 7. The center-of-gravity trajectory across ecological vulnerability levels in the QLMs (2000–2020) (a–e) follows very heavy, heavy, moderate, light, and potential, respectively.

It is important to note that ecological vulnerability in the Qilian Mountains region is distinctly localized due to spatial heterogeneity. The total potentially vulnerable area increased by 82.3% between 2000 and 2010, followed by a 44.1% decrease by 2020. However, this regional trend masks starkly different local outcomes (Figure 8). Some areas saw significant improvements; proactive policies such as the construction of water conservation forests and reclaimed water use in Xining caused its potentially vulnerable area to expand from 15.2% to 72.8%, while industrial and agricultural reforms allowed Haidong City to maintain a stable, optimized state where 70–80% of its land was consistently classified as having only light vulnerability. In contrast, other regions faced deterioration or complex challenges. Haixi Prefecture, which held 99.2% of the region’s very heavily vulnerable land in 2000, experienced significant fluctuations as its own very heavily vulnerable area dropped to 1.2% in 2010 before rebounding to 29.8% in 2020. The initial improvement was attributed to the success of ecological engineering, such as the program of “returning pastures to grasslands,” which significantly enhanced vegetation cover and brought about clear ecological restoration. Conversely, after 2010, the reduced contribution of glacial meltwater to surface runoff exacerbated water scarcity, and overgrazing became the main driver of ecological pressure, which worsened the ecological environment of Haixi Prefecture. Zhangye City underwent a worrying polarization, with its lightly vulnerable area shrinking by 89.3% as its very heavily vulnerable zone expanded by 158%, indicating escalating ecological risks. Meanwhile, consistent pressure from industry and energy projects in Jiuquan City caused that over 50% of its area remained heavily vulnerable throughout the period (Figure 9).

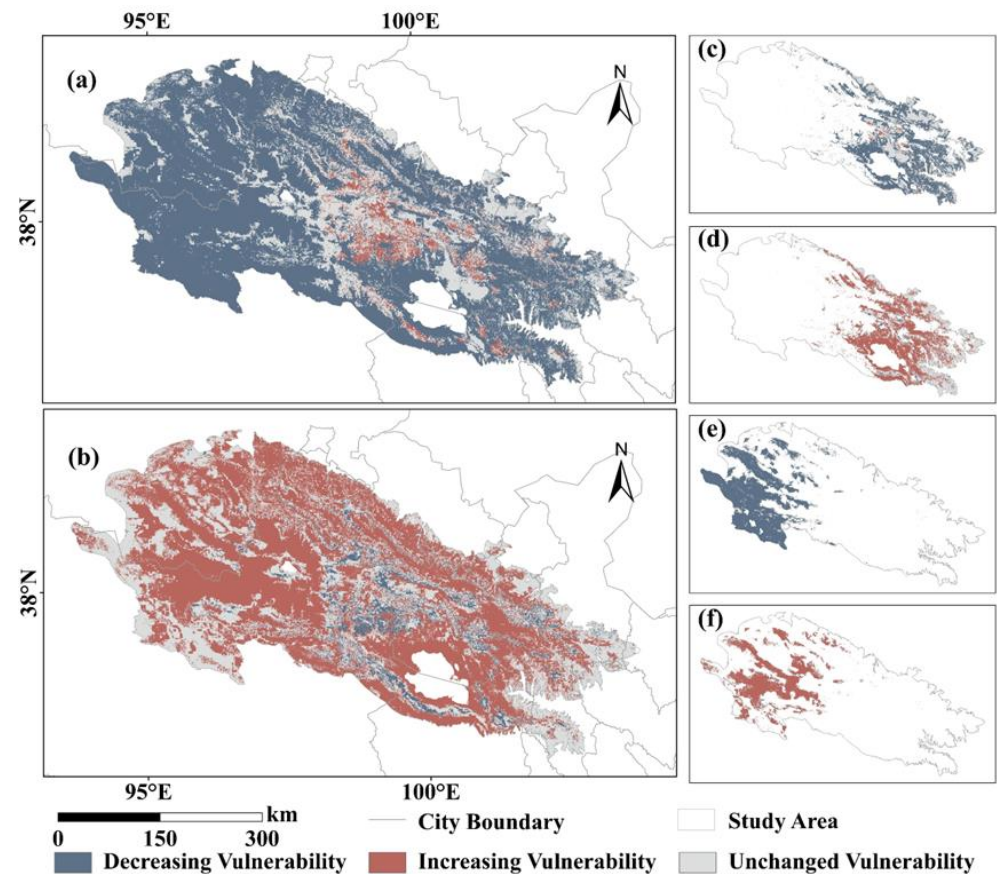


Figure 8. Spatiotemporal transitions of ecological vulnerability in the Qilian Mountains. (a,b) Overall grade transitions during 2000–2010 and 2010–2020; (c,d) changes specifically in potential vulnerability; and (e,f) changes in very heavy vulnerability for the same respective periods.

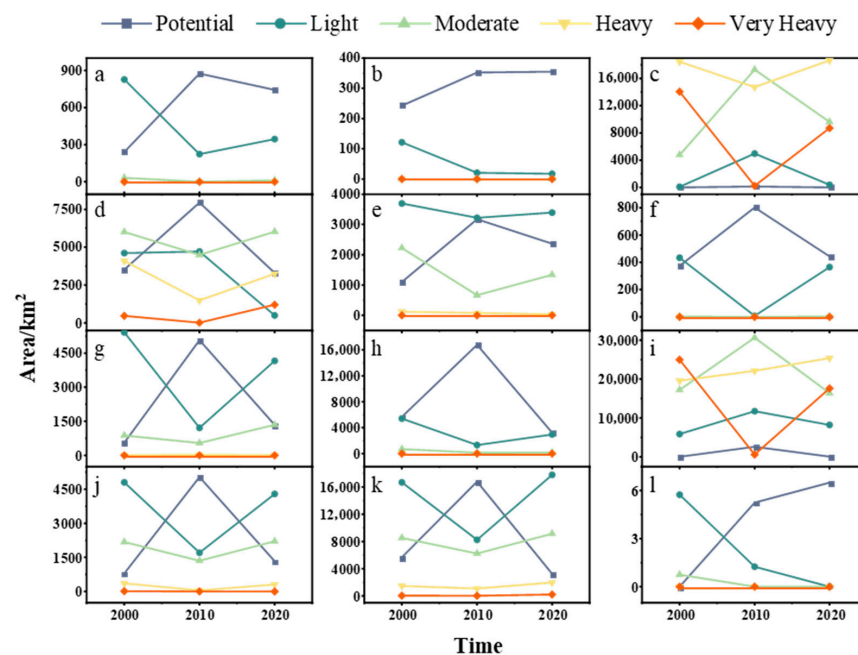


Figure 9. Dynamic changes in ecological vulnerability classes by administrative region from 2000 to 2020: (a) Lanzhou, (b) Baiyin, (c) Jiuquan, (d) Zhangye, (e) Wuwei, (f) Jinchang, (g) Xining, (h) Haidong, (i) Haixi Mongol and Tibetan Autonomous Prefecture, (j) Hainan Tibetan Autonomous Prefecture, (k) Haibei Tibetan Autonomous Prefecture, (l) Huangnan Tibetan Autonomous Prefecture.

3.3. The Driving Forces of the EVI

By employing Recursive Feature Elimination with Cross-Validation (RFECV) to select features, we identified 13 key variables driving ecological vulnerability in the study area, namely TF1, TF2, SU1, SU3, SU5, SO1, SO2, MF2, MF3, LS, EV1, EV2, EV3. The dataset was partitioned into training and testing sets with an 80:20 ratio. The validation results on the training set showed a coefficient of determination (R^2) of 0.9513, a root mean square error (RMSE) of 0.0424, and a mean absolute error (MAE) of 0.0328. Similarly, the testing set yielded an R^2 of 0.944, an RMSE of 0.0453, and an MAE of 0.0354. These results indicate that the RF model exhibits high stability and predictive accuracy across both datasets, providing quantitative support for the reliability of the subsequent SHAP interpretation. Based on the RF model and SHAP value quantification, we ranked the importance of explanatory variables in predicting the mean annual ecological vulnerability over the 21-year study period. Importance was quantified with mean SHAP values, which represent the marginal contribution of each indicator. The indicators, ranked from most to least influential, are SU1, EV2, SU3, MF2, LS, EV1, SU5, TF2, MF3, SO2, EV3, TF1, and SO1 (Figure 10). Among these, SU1, EV2, SU3, MF2, and LS stand out as the primary drivers of ecological vulnerability, with pronounced vulnerability shifts occurring near the thresholds of 0.16, 56.57, 2.23 mm, 400.73 mm, and 0.39, respectively. These thresholds represent critical tipping points in ecosystem stability. Fractional vegetation cover (SU1) of 0.16 characterizes extremely sparse surface vegetation and weak habitat resistance to disturbances, which, in turn, disrupts the energy balance and hydrological cycle and diminishes land surface stability. A biological abundance (EV2) of 56.57 implies a foundational ecological base that lacks sufficient resilience, making it prone to amplifying adverse responses under strong disturbances. Glacial meltwater (SU3) contribution levels around 2.23 mm reflect a deficient water supply from glaciers, which reduces the ecosystem resilience of both water availability and baseflow during the dry season, thus leading to a greater dependence on reservoir regulation. Similarly, annual precipitation (MF2) of 400.73 mm points to a hydrothermal pattern constrained by limited moisture and surplus energy. This tends to create an unstable regime characterized by sharp increases in runoff during intense precipitation events and, conversely, weak baseflow during other periods. A landscape diversity index below 0.39 typically signifies a landscape dominated by just one or two feature types. The resulting lack of functional redundancy limits buffering pathways, leaving the ecosystem vulnerable to disturbances such as pests or wildfires. Collectively, crossing these thresholds compromises the ecosystem's capacity to buffer against climate extremes, exacerbating risks of soil erosion, land degradation, and a decline in ecological functions, which can escalate localized impacts into systemic fluctuations.

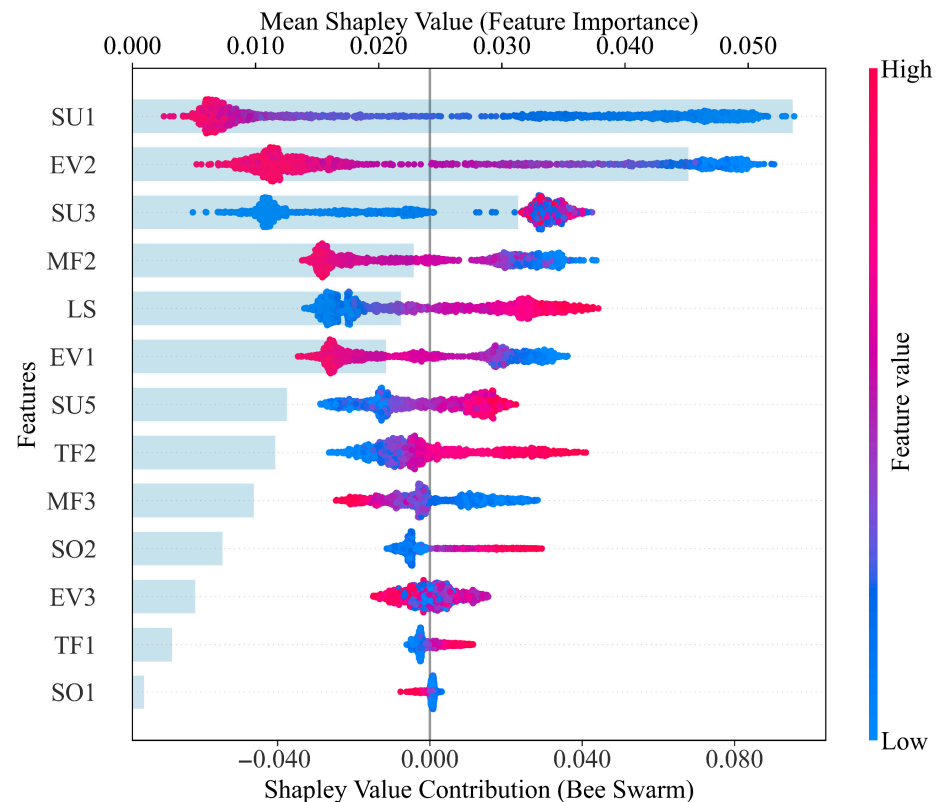


Figure 10. Importance ranking of environmental factors based on SHAP theory.

The driving factors influence ecological vulnerability to varying extents and in opposite directions, revealing pronounced trade-offs and synergies between individual drivers and the vulnerability index. SU1, EV2, MF2, EV1, MF3, EV3, and SO1 exhibit pronounced trade-off relationships with ecological vulnerability, whereas SU3, LS, SU5, TF2, SO2, and TF1 display synergistic relationships with ecological vulnerability. Taking SU1 as a prime example, data points associated with high FVC cluster at negative SHAP values, indicating that higher FVC reduces ecological vulnerability, and the opposite holds when FVC is low. Moreover, this mitigating capacity intensifies as FVC increases. It is worth noting that the response of ecological vulnerability to various driving factors exhibits influence thresholds. Therefore, based on the global feature importance of the driving factors, their critical response thresholds affecting ecological vulnerability were identified (Figure 11). For FVC, a critical inflection point occurs at 0.13; beyond this threshold, SHAP values drop sharply, indicating that vegetation expansion exerts a pronounced mitigating effect on ecological vulnerability. However, a saturation effect is observed as FVC continues to rise: below 0.6, SHAP values decline markedly, signifying substantial vulnerability reduction; yet, once FVC exceeds 0.6, the curve plateaus, implying diminishing marginal returns in vulnerability mitigation. Conversely, for SU3, once its value exceeds 2.23 mm, the associated SHAP value turns from negative to positive, indicating that additional meltwater within this interval makes a substantial positive contribution to regional ecological vulnerability. The SHAP value peaks at about 30 mm of melt runoff, signifying that glacial meltwater volume exerts its strongest aggravating impact on ecological vulnerability at this level. Broadly, EV2, MF2, EV1, MF3, EV3, and SO1 display trends analogous to that of FVC, showing nonlinear negative correlations, while LS, SU5, TF2, SO2 and TF1 exhibit nonlinear positive correlations with ecological vulnerability.

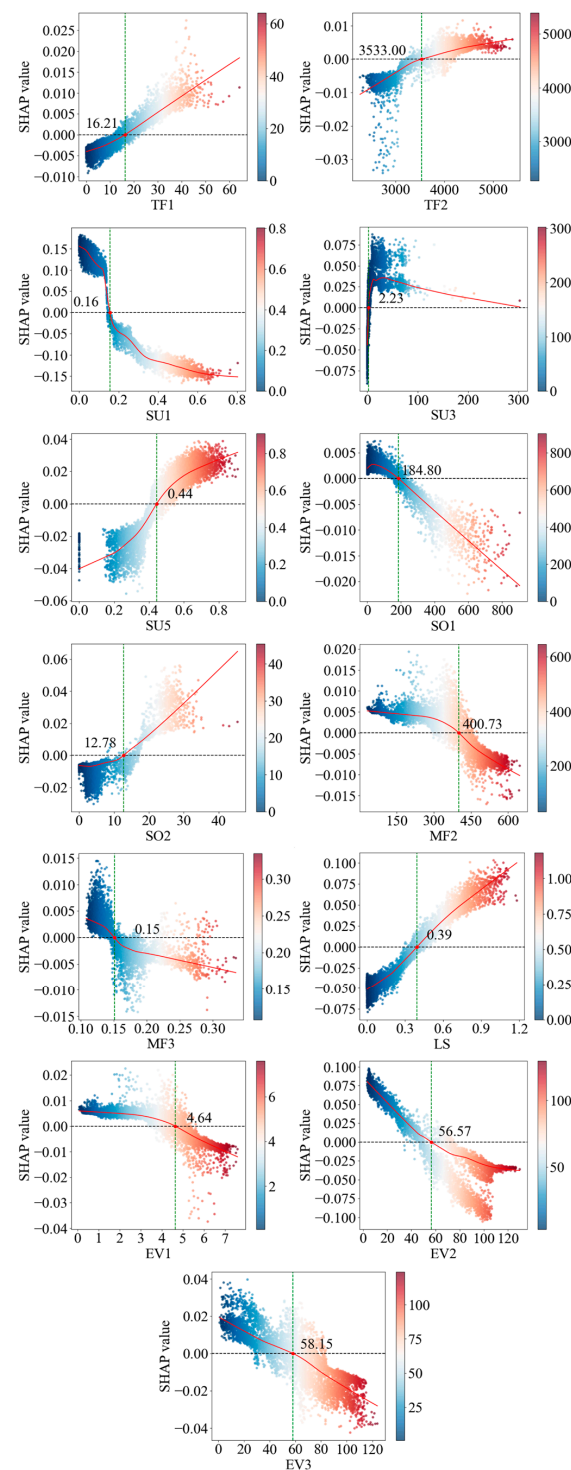


Figure 11. Partial dependence plots of the 13 selected drivers for ecological vulnerability assessment. The dark blue dashed line denotes a SHAP value of zero. The green dashed line corresponds to the value on the X-axis where the fitted curve crosses the zero SHAP line (red dot).

4. Discussion

4.1. The Spatio-Temporal Patterns of EVI

The Qilian Mountains region, a crucial critical functional zone for ecological protection in arid and semi-arid regions, has experienced fluctuations in ecological vulnerability driven by climate and economic pressures. The main trend over 21 years was a significant improvement followed by a partial rebound, leading to a slight net decrease in vulnera-

bility of 1.52% from 2000 to 2020. This result is consistent with existing research [79,80]. Initial efforts to protect the Qilian Mountains region were formalized in 1997 when Gansu Province promulgated the “Regulations on the Administration of Gansu Qilian Mountain National Nature Reserve” [81]. These foundational policies, which played a positive role in improving the ecological environment, were followed after 2000 by a series of large-scale ecological restoration projects, such as the “Grain for Green Program” and the “Natural Forest Protection Program [82]. These projects effectively increased the area of forests and grasslands. The conversion of unused land to ecological use improved the ecological environment and promoted the enhancement of habitat quality [83], which reduced the ecological vulnerability of the Qilian Mountains region between 2000 and 2010 (decreased by 8.9%). Although the study area actively advanced ecological civilization initiatives from 2010 to 2020, long-term, large-scale mining activities induced local vegetation destruction, soil erosion, and ground surface subsidence [84], ultimately damaging the ecological environment. Activities such as open-pit mining, road construction, and waste residue accumulation damaged surface structures and reduced vegetation cover [85]. This degradation undermines the vegetation’s ability to buffer soil stability, regulate water, and exchange energy, leaving the ecosystem increasingly sensitive to climate fluctuations and external disturbances. Concurrently, mining disturbances involve topsoil stripping and surface fragmentation, which significantly intensifies soil erosion and reduce soil and water conservation capacity, thereby hindering vegetation recovery and affecting local hydrological conditions [86,87]. In alpine and seasonal permafrost regions, the destruction of surface cover also amplifies ground temperature fluctuations and exacerbates freeze–thaw cycles, increasing associated hazards and reducing surface stability. Thus, the impact of mining activities on ecological vulnerability is not merely reflected in direct human pressure, but also generates significant indirect effects by altering key natural factors, thereby amplifying regional ecological vulnerability. This explains the phenomenon of rebounding or persistently high ecological vulnerability from 2010 to 2020; for instance, the area of high-level EVI in Zhangye City increased by 74.75% during this period. Furthermore, with accelerated economic development, some hydropower facilities have been illegally constructed and operated irregularly, tourism projects have been overdeveloped, and some enterprises prioritized economic returns over environmental responsibilities, with severely insufficient environmental investment; in addition, some departments have failed to adequately rectify prominent ecological and environmental problems, leading to environmental deterioration [47].

Situated on the northeastern Qinghai–Tibet Plateau, the spatial pattern of the EVI in the Qilian Mountains region follows the basic trend of large-scale geomorphic units [88]. High ecological vulnerability is mainly distributed in the northwestern part of the Qilian Mountains region, an area with higher altitude and low vegetation cover. In arid and semi-arid regions, when vegetation is reduced, the capacity of the land to intercept water and sustain biodiversity diminishes [89]. Combined with high evapotranspiration, this accelerates soil moisture depletion, potentially inducing land degradation should the water cycle be disrupted [90]. Simultaneously, reduced surface albedo and the loss of the cooling effect from transpiration drive regional warming, leading to issues such as glacier retreat and permafrost thaw [91,92]. A series of cascading effects stemming from low vegetation cover causes the ecosystem to be fragile. Low ecological vulnerability is concentrated in the southeastern Qilian Mountains region, representing 33.95% of the low-level EVI area in 2020, especially around Qinghai Lake, where a combination of favorable natural conditions and effective policies maintains ecosystem health. The region benefits from a lower average altitude, abundant rainfall, and rich biodiversity, which together support dense and healthy vegetation [93]. These natural advantages have been reinforced by

the implementation of national policies, such as the Grain for Green Program and Qilian Mountain Ecological Environmental Protection and Comprehensive Management Plan [94], which ensured effective ecological protection and maintained low vulnerability levels. By incorporating the center of gravity migration model, it was found that the centers of gravity for vulnerability zones of all grades generally shifted westward initially and then eastward, reflecting the dynamic and unbalanced state of the regional ecology. This suggests a transfer of environmental pressure from the west to the east. During the study period, EVI in the western region decreased by 1.84%, whereas it decreased by only 0.55% in the eastern region. This disparity may be attributed to enhanced land management, stricter conservation policies, or economic restructuring in the west [93]. In contrast, the eastern region likely faces heightened ecological pressures driven by multiple factors, including urbanization and agricultural expansion [95]. Furthermore, anthropogenic vegetation expansion has altered evapotranspiration, thereby exacerbating water resource conflicts [96], while recent increases in precipitation have led to spatiotemporal imbalances that enhanced vegetation sensitivity to moisture and affected plant growth [94].

4.2. Driving Forces of EVI

The driver analysis utilized RFE to select 13 out of the initial 21 indicators. The exclusion of most anthropogenic indicators reflects the region's sparse population, and limited economic interference, indirectly confirming that natural factors act as the dominant drivers of ecological vulnerability in the Qilian Mountains region. As illustrated in the figure, the primary drivers of ecological vulnerability in the Qilian Mountains region are SU1, EV2, SU3, MF2, and LS, with contribution rates of 21.8%, 18.36%, 12.74%, 9.29%, and 8.87%, respectively. This ranking underscores that vegetation properties and water regulation dynamics are the critical determinants of vulnerability. These findings align with existing research [60,97], confirming that ecological mechanisms in arid mountain areas are governed principally by biological and hydrological factors. Vegetation serves as the primary barrier against soil erosion and regulates surface energy and water cycles [98], while landscape diversity mitigates pressures from grazing and climate shocks [99]. The Qilian Mountains region's dominant vegetation, comprising alpine meadows and steppes, is characterized by a distinct duality. It is highly susceptible to the impacts of climate change, yet simultaneously demonstrates remarkable resistance and resilience when facing other environmental disturbances [100]. While our findings concur with previous studies regarding the core roles of SU1, MF2, and EV2 [25,69], a key distinction of this research is highlighting the pivotal role of glacial and freeze–thaw processes (SU3 and SU5). Glacial retreat and freeze–thaw cycles induce shifts in water availability that govern the entire ecosystem [101,102]. These shifts cause earlier summer runoff peaks and aggravate dry-season water shortages, thereby constraining vegetation growth and organic matter input [103]. While factors such as EV1, SU5, TF2, MF3 and SO2 are of intermediate rank, contributing 8.37%, 5.1%, 4.72%, 4%, and 2.98%, respectively, they jointly combine to form a key control nexus linking hydrological, geomorphological, and disaster factors. Specifically, SU5 degrades soil structure and diminish vegetation's anchoring ability, thus accelerating erosion [104]. TF2 acts as a limiting factor for glacial boundaries, thermal regimes, vegetation belts, and the limits of human access. MF3 influences radiation absorption, potentially suppressing photosynthesis and plant growth, particularly at high altitudes [105]. This, in turn, reduces vegetation stability and the ecosystem's carbon sink capacity [106], intensifying vulnerability. Similarly, a low or unstable EV1 undermines ecosystem stability and promotes soil erosion and vegetation degradation [107]. SO2 is not only a product of these dynamic processes but also serves as an amplifier [108]. Lower-ranking factors, such as

EV3, TF1, and SO1, which contribute only 2.08%, 1.31%, and 0.39%, respectively, are largely accounted for by these more dominant, higher-order variables.

Further analysis of these nonlinear thresholds illuminates the specific biophysical mechanisms through which these drivers operate. First, regarding ecosystem stabilizers SU1 and EV2, SHAP analysis highlights a critical inflection point for vegetation cover at 0.16. Below this level, the lack of root networks results in a state of instability that leaves the soil highly susceptible to erosion [98]. High biological abundance further reinforces stability by maintaining permafrost thermal regimes, preventing habitat fragmentation caused by ground subsidence [92]. Uniquely, the impact of SU3 reveals a transition from a beneficial resource to a potential hazard. Although meltwater is vital in arid zones [57], our results indicate that ecological vulnerability worsens when melt runoff surpasses the 2.23 mm threshold, a shift consistent with peak water hypothesis [101]. Excessive meltwater signals rapid, temperature-driven ablation, leading to irreversible glacial storage deficits and hydrological instability, including amplified runoff variability and flood risks, disrupting downstream ecosystems [57]. Regarding MF2, the beneficial impact on vulnerability weakens after reaching a threshold of approximately 400 mm. In arid and semi-arid environments, water is the primary constraint [60]. However, once precipitation exceeds this level, other factors such as temperature or soil nutrients may become the primary constraints [52]. Moreover, excessive precipitation in steep areas can trigger hydraulic erosion, counteracting the positive effects of increased moisture [109]. Finally, LS functions through a buffering mechanism rooted in the functional redundancy hypothesis. When LS value exceeds 0.39, the heterogeneous landscape provides diverse ecological niches and alternative pathways for energy flow [99]. This structural complexity facilitates risk dispersion during disturbances like droughts, thereby enhancing resilience.

Thresholds not only define the upper limits of an ecosystem's carrying capacity and the lower limits of its recovery, but they also provide quantitative boundaries for precision management [110]. As such, they function as an essential mediating variable for accurately assessing and managing regional ecological vulnerability [111]. Based on the nonlinear characteristics of the top five drivers identified by the RF-SHAP model, we propose refined eco-environmental management strategies. Given that SU1 is the dominant driver, the value of 0.16 serves as a critical physical threshold for soil retention and slope stability. Regions where $SU1 < 0.16$ lack essential root anchorage and face high risks of irreversible erosion. Therefore, these areas require a strict ban on grazing and human activity, designation as core ecological red line protection zones, and artificial interventions to restore surface stability [13]. Conversely, for regions where $SU1 > 0.16$, the focus must shift to enforcing a forage-livestock balance and scientific rotational grazing [65]. This aims to prevent ecosystem degradation back below the threshold caused by overuse and to secure sustained ecological benefits. Simultaneously, for regions where EV2 falls below 56.57, indicating a simplified trophic structure, the focus should transition from simple vegetation maintenance to improving habitat quality [19]. Through the introduction of native species, the conservation of key species habitats, and the construction of multi-layered community structures, the goal is to raise biodiversity levels beyond the 56.57 threshold. This elevation in biodiversity will enhance the ecosystem's ability to buffer against external disturbances. Our study further reveals that when SU3 exceeds 2.23 mm, ecological vulnerability increases significantly, marking a transition in ecological risk from resource scarcity to hydrological hazards. To address this in high-meltwater areas, hydraulic facilities should be utilized to capture excess summer runoff for ecological replenishment during low-flow periods, thereby balancing seasonal flow extremes. Furthermore, implementing early warning systems and abnormal runoff is crucial for improving the downstream ecosystem's resilience to climate amplification [80]. For LS and MF2, strategies should adhere to the

principles of structural optimization and water-constrained vegetation planning. In homogeneous habitats where LS is below 0.39, large-scale monocultures should be replaced by multi-layered restoration approaches. This shift aims to boost landscape heterogeneity and improve the system's resilience against risks. For arid and semi-arid regions where MF2 is below 400.73 mm, natural restoration should be prioritized, with a preference for low-water-consuming shrubs and grasses. It is crucial to prevent soil moisture depletion caused by indiscriminate high-density afforestation, thereby ensuring that ecological restoration remains sustainable within the water resource carrying capacity [65]. This understanding provides clear strategic direction: in low-threshold zones, interventions should prioritize elevating key ecological factors to maximize returns, whereas in high-threshold zones, the emphasis must shift to monitoring and early warning to prevent the ecosystem from crossing irreversible tipping points.

4.3. Limitation and Outlook

Ecological vulnerability assessments are vital for identifying regional environmental issues, yet the current research process still faces several inherent limitations. These limitations not only affect the accuracy of the assessment results but also constrain our deep understanding of the dynamic patterns of ecosystem change. Ecosystems are inherently complex and multidimensional systems. Although the factors chosen in the study of the Qilian Mountains region are representative, the actual influencing elements are substantially more numerous. This creates a discrepancy between the assessment results and the true state of the ecosystem. Additionally, the study period was set to 2000–2020 due to constraints related to data availability and quantifiability. Specifically, some key indicators, like freeze–thaw disaster risk index, were available only up to 2019. While the lack of more recent data (to 2025) is a limitation of our research, it also highlights an important avenue for future investigation. More critically, the evolution of ecological vulnerability is often a nonlinear process. The weighted index model employed in this study, however, presumes linear superposition. Consequently, it is insufficient for identifying or pre-empting nonlinear transitions, resulting in an inadequate representation of the underlying dynamic processes and threshold effects.

Future research on ecological vulnerability can be advanced by incorporating more current data, enhancing the precision of data fusion and analysis, and focusing on nonlinear processes and threshold identification. This is crucial for developing proactive ecological early-warning and adaptive management strategies. At the same time, conducting cross-regional comparative and validation studies to explore the common patterns and regional characteristics of ecological vulnerability will provide a more solid scientific basis for global-scale environmental protection.

5. Conclusions

This study addresses a critical gap in existing ecological vulnerability research, which has largely overlooked the influence of the cryosphere. Focusing on the Qilian Mountains region as a representative case, this research establishes an objective and comprehensive framework for evaluating the region's ecological vulnerability. This framework assesses the impacts of combined pressures from climate change, natural disasters, and human economic activities, thereby offering a novel approach to ecological vulnerability assessment for the Qilian Mountains region. The conclusions are as follows:

- (1) The region has undergone a clear transition in regional ecological vulnerability from high to low levels. This trend strongly suggests that the environmental governance policies enacted by local and national authorities have been highly effective, contributing to substantial ecological improvements and paving the way for sustainable

regional development. While the study area is characterized by a spatial pattern of high vulnerability in the west and low in the east, the environmental pressure in the eastern region is projected to rise gradually.

- (2) The dominant drivers of ecological vulnerability in the study area are natural factors. Notably, the distinct prominence of glacier and permafrost elements as key drivers of local vulnerability underscores the amplifying effect of climate change on alpine ecosystems, offering a new perspective for future ecological restoration strategies. Furthermore, enhancing vegetation coverage remains critical for mitigating ecological vulnerability.
- (3) Based on the validated reliability of the RF-SHAP model in quantifying feature contributions and nonlinear relationships, this study proposes a threshold-based, zone-specific management strategy. By implementing interventions in low-threshold zones and early warning monitoring in high-threshold zones, this strategy provides a scientific basis for constructing a regional ecological early-warning system and preventing the ecosystem from crossing irreversible tipping points.

Author Contributions: X.Y.: Conceptualization, Visualization, Data curation, Writing—original draft, Investigation. X.X.: Methodology, Software. C.L.: Methodology, Software. B.L.: Investigation, Validation. M.L.: Investigation, Validation. J.C.: Investigation, Validation. Y.J.: Supervision, Writing—review and editing. W.D.: Conceptualization, Writing—review and editing, Project administration, Funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Science Fund for Creative Research Groups of Gansu Province (No. 23JRRA567), the Natural Science Foundation of China (42471165, 42471157), West Light Foundation of The Chinese Academy of Sciences (xbzg-zdsys-202306), and the Program of the State Key Laboratory of Cryospheric Science and Frozen Soil Engineering, CAS (CSFSE-KF-2402).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Bertram, G.C.L.; Burton, I.; Kates, R.W.; White, G.F. The Environment as Hazard. *Geogr. J.* **1979**, *145*, 126. [\[CrossRef\]](#)
2. Ge, Y.; Zhang, H.; Dou, W.; Chen, W.; Liu, N.; Wang, Y.; Shi, Y.; Rao, W. Mapping Social Vulnerability to Air Pollution: A Case Study of the Yangtze River Delta Region, China. *Sustainability* **2017**, *9*, 109. [\[CrossRef\]](#)
3. Timmerman, P. *Vulnerability, Resilience and the Collapse of Society*; Royal Meteorological Society: London, UK, 1981.
4. Kasperson, J.X.; Kasperson, R.E.; Turner, B.L. Vulnerability to global environmental change. In *Social Contours of Risk*; Routledge: London, UK, 2012; Volume 2, pp. 245–285. [\[CrossRef\]](#)
5. Liu, Y.Q. *Spatial-Temporal Evolution and Ecological Vulnerability of Ecological Environmental Factors in Ulan Buh Desert*; Inner Mongolia Agricultural University: Inner Mongolia, China, 2022.
6. IPCC. Climate Change 2014: Impacts, Adaptation, and Vulnerability. In *Contribution of Working Group II to the Fifth Assessment Report*; Cambridge University Press: Cambridge, UK, 2014. (In Chinese)
7. Jiang, T.; Li, X.; Chao, Q.; Yuan, J.; Lin, E. Highlights and Understanding of Climate Change 2014: Impacts, Adaptation, and Vulnerability. *Progress. Inquisitiones Mutat. Clim.* **2014**, *10*, 157–166.
8. Ippolito, A.; Sala, S.; Faber, J.H.; Vighi, M. Ecological vulnerability analysis: A river basin case study. *Sci. Total Environ.* **2010**, *408*, 3880–3890. [\[CrossRef\]](#)
9. Lamsal, P.; Kumar, L.; Atreya, K.; Pant, K.P. Vulnerability and impacts of climate change on forest and freshwater wetland ecosystems in Nepal: A review. *Ambio* **2017**, *46*, 915–930. [\[CrossRef\]](#)
10. Pandey, R.; Bardsley, D.K. Social-ecological vulnerability to climate change in the Nepali Himalaya. *Appl. Geogr.* **2015**, *64*, 74–86. [\[CrossRef\]](#)

11. Logez, M.; Bouraï, L.; Tronquart, N.H.; Argillier, C. Ecological Vulnerability of Aquatic Ecosystems—A Review. *Environ. Manag.* **2024**, *75*, 192–204. [\[CrossRef\]](#)
12. Zhuang, L.; Huang, L.; Zhao, C.; Zheng, G.; Tang, W.; Zhou, D.; Zhu, J. Identification and assessment of the mudflat ecological vulnerability dominated by coastline evolution in Jiangsu. *Ecol. Indic.* **2024**, *168*, 112761. [\[CrossRef\]](#)
13. Li, Q.; Shi, X.; Wu, Q. Effects of protection and restoration on reducing ecological vulnerability. *Sci. Total Environ.* **2021**, *761*, 143180. [\[CrossRef\]](#)
14. Xiao, H.; Shao, H.; Long, J.; Zhang, S.; He, S.; Wang, D. Spatial-temporal pattern evolution and geological influence factors analysis of ecological vulnerability in Western Sichuan mountain region. *Ecol. Indic.* **2023**, *155*, 110980. [\[CrossRef\]](#)
15. Zhu, Y.; Hou, K.; Chang, Y.; Li, X.; Yang, K. Analysis of Ecological Vulnerability Control Strategies for Typical River Valley Cities in Northwest China: A Perspective of Spatial Heterogeneity. *Land Degrad. Dev.* **2024**, *35*, 5626–5647. [\[CrossRef\]](#)
16. Zhang, M.; Zhou, Y.; Sang, S. Vulnerability analysis of the economic-social-ecological complex system of Island tourism destinations. *PLoS ONE* **2025**, *20*, e0324714.
17. Gao, T.G.; Zhang, T.J.; Cao, L.; Kang, S.C.; Sillanpää, M. Reduced winter runoff in a mountainous permafrost region in the northern Tibetan Plateau. *Cold Reg. Sci. Technol.* **2016**, *126*, 36–43. [\[CrossRef\]](#)
18. Navas, A.; Ramírez, E.; Gaspar, L.; Lizaga, I.; Stott, T.; Rojas, F.; Latorre, B.; Dercon, G. The impact of glacier retreat on Andean high wetlands: Assessing the geochemical transfer and sediment provenance in the proglacial area of Huayna-Potosí (Bolivia). *Geomorphology* **2024**, *460*, 109250. [\[CrossRef\]](#)
19. Losapio, G.; Lee, J.R.; Fraser, C.I.; Gillespie, M.A.K.; Kerr, N.R.; Zawierucha, K.; Hamilton, T.L.; Hotaling, S.; Kaufmann, R.; Kim, O.S. Impacts of deglaciation on biodiversity and ecosystem function. *Nat. Rev. Biodivers.* **2025**, *1*, 371–385. [\[CrossRef\]](#)
20. Milner, A.M.; Khamis, K.; Battin, T.J.; Brittain, J.E.; Barrand, N.E.; Füreder, L.; Cauvy-Fraunié, S.; Gíslason, G.M.; Jacobsen, D.; Hannah, D.M.; et al. Glacier shrinkage driving global changes in downstream systems. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 9770–9778. [\[CrossRef\]](#)
21. Wright, S.N.; Thompson, L.M.; Olefeldt, D.; Connon, R.F.; Carpino, O.A.; Beel, C.R.; Quinton, W.L. Thaw-induced impacts on land and water in discontinuous permafrost: A review of the Taiga Plains and Taiga Shield, northwestern Canada. *Earth-Sci. Rev.* **2022**, *232*, 104104. [\[CrossRef\]](#)
22. Ding, L.K.; Hu, W.J.; Chen, B.; Loh, K.H.; Jilian, L.S.; Lee, L.K.; Qiu, S.T.; Gu, H.F.; Zheng, X.Q.; Liang, S.S.; et al. Ecological vulnerability assessment of tropical seagrass beds and coral reefs: A case study of Sibutu Archipelago, Malaysia. *Chin. J. Ecol.* **2022**, *41*, 2479–2488. [\[CrossRef\]](#)
23. Xue, L.Q.; Wang, J.; Zhang, L.C.; Wei, G.H.; Zhu, B.L. Spatiotemporal analysis of ecological vulnerability and management in the Tarim River Basin, China. *Sci. Total Environ.* **2019**, *649*, 876–888. [\[CrossRef\]](#)
24. Ye, H.; Bai, D.; Wang, J.L.; Tan, S.C.; Liu, S.Y. Assessment of Ecosystem Vulnerability in the Tropic of Cancer (Yunnan Section). *Remote Sens.* **2025**, *17*, 219. [\[CrossRef\]](#)
25. Luo, M.; Jia, X.; Zhao, Y.; Zhang, P.; Zhao, M. Ecological vulnerability assessment and its driving force based on ecological zoning in the Loess Plateau, China. *Ecol. Indic.* **2024**, *159*, 11658. [\[CrossRef\]](#)
26. Feng, Z.; Liu, X.P.; Zhang, J.Q.; Wu, R.; Ma, Q.Y.; Chen, Y.N. Ecological vulnerability assessment based on multi-sources data and SD model in Yinma River Basin, China. *Ecol. Model.* **2017**, *349*, 41–50. [\[CrossRef\]](#)
27. Tian, J.H.; Guo, C.C.; Wang, J.H. Quantitative Assessment of the Ecological Vulnerability of Baiyangdian Wetlands in the North China Plain. *J. Resour. Ecol.* **2021**, *12*, 814–821. [\[CrossRef\]](#)
28. Sun, Z.; Liu, Y.; Sang, H. Spatial-Temporal Variation and Driving Factors of Ecological Vulnerability in Nansi Lake Basin, China. *Int. J. Environ. Res. Public Health* **2023**, *20*, 2653. [\[CrossRef\]](#)
29. Zhang, X.Q.; Zheng, Y.P.; Yang, Y.; Ren, H.; Liu, J.W. Spatiotemporal evolution of ecological vulnerability on the Loess Plateau. *Ecol. Indic.* **2025**, *170*, 113060. [\[CrossRef\]](#)
30. Zhang, Y.Q.; Xiong, K.N.; Chen, Y.; Bai, X. Spatiotemporal changes and driving factors of ecological vulnerability in karst World Heritage sites based on SRP and geodetector: A case study of Shibing and Libo-Huanjiang karst. *npj Herit. Sci.* **2025**, *13*, 65. [\[CrossRef\]](#)
31. Jiang, B.H.; Chen, W.; Dai, X.A.; Xu, M.; Liu, L.F.; Sakai, T.; Li, S.L. Change of the spatial and temporal pattern of ecological vulnerability: A case study on Cheng-Yu urban agglomeration, Southwest China. *Ecol. Indic.* **2023**, *149*, 110161. [\[CrossRef\]](#)
32. Li, Y.H.; Fan, Q.; Wang, X.; Xi, J.C.; Wang, S.Y.; Yang, J. Spatial and Temporal Differentiation of Ecological Vulnerability Under the Frequency of Natural Hazard Based on SRP Model: A Case Study in Chaoyang County. *Geogr. Sci.* **2015**, *35*, 1452–1459. [\[CrossRef\]](#)
33. Wang, Z.Y.; Xiong, H.X.; Zhang, F.W.; Qiu, Y.; Ma, C.M. Sustainable development assessment of ecological vulnerability in arid areas under the influence of multiple indicators. *J. Clean. Prod.* **2024**, *436*, 140629. [\[CrossRef\]](#)
34. Bao, T.A.; Xi, G.L. Impact of grassland storage balance management policies on ecological vulnerability: Evidence from ecological vulnerability assessments in the Selinco region of China. *J. Clean. Prod.* **2023**, *426*, 139178. [\[CrossRef\]](#)
35. Das, U.; Behera, B. Geospatial assessment of ecological vulnerability of fragile Eastern Duars Forest integrating GIS-based AHP, CRITIC and AHP-TOPSIS models. *Geomat. Nat. Hazards Risk* **2024**, *15*, 2330529. [\[CrossRef\]](#)

36. Wu, C.S.; Huang, C.; Liu, G.H.; Liu, Q.S. Assessment of ecological vulnerability in the Yellow River Delta using the Fuzzy Analytic Hierarchy Process. *Acta Ecol. Sin.* **2018**, *38*, 4584–4595.
37. Wang, Z.; Zhong, Y.; Chai, S.L.; Niu, S.F.; Yang, M.L.; Wu, G.R. Product design evaluation based on improved CRITIC and Comprehensive Cloud-TOPSIS—Applied to automotive styling design evaluation. *Adv. Eng. Inform.* **2024**, *60*, 102361. [[CrossRef](#)]
38. He, S.; Nong, L.; Wang, J.; Zhong, X.; Ma, J. Revealing various change characteristics and drivers of ecological vulnerability in the mountains of southwest China. *Ecol. Indic.* **2024**, *167*, 112680. [[CrossRef](#)]
39. Aghaloo, K.; Sharifi, A. Balancing priorities for a sustainable future in cities: Land use change and urban ecosystem service dynamics. *J. Environ. Manag.* **2025**, *382*, 125460. [[CrossRef](#)]
40. Ayanlade, A.; Smucker, T.A.; Nyasimi, M.; Sterly, H.; Weldemariam, L.F.; Simpson, N.P. Complex climate change risk and emerging directions for vulnerability research in Africa. *Clim. Risk Manag.* **2023**, *40*, 100497. [[CrossRef](#)]
41. Santos, F.; Graw, V.; Bonilla, S. A geographically weighted random forest approach for evaluate forest change drivers in the Northern Ecuadorian Amazon. *PLoS ONE* **2019**, *14*, e0226224. [[CrossRef](#)]
42. Anees, S.A.; Mehmood, K.; Khan, W.R.; Sajjad, M.; Alahmadi, T.A.; Alharbi, S.A.; Luo, M. Integration of machine learning and remote sensing for above ground biomass estimation through Landsat-9 and field data in temperate forests of the Himalayan region. *Ecol. Inform.* **2024**, *82*, 102732. [[CrossRef](#)]
43. Wang, F.; Wang, Y.; Zhang, K.; Hu, M.; Weng, Q.; Zhang, H. Spatial heterogeneity modeling of water quality based on random forest regression and model interpretation. *Environ. Res.* **2021**, *202*, 111660. [[CrossRef](#)]
44. Wang, H.; Liang, Q.; Hancock, J.T.; Khoshgoftaar, T.M. Feature selection strategies: A comparative analysis of SHAP-value and importance-based methods. *J. Big Data* **2024**, *11*, 44. [[CrossRef](#)]
45. Zhou, M.; Li, Y. Spatial distribution and source identification of potentially toxic elements in Yellow River Delta soils, China: An interpretable machine-learning approach. *Sci. Total Environ.* **2024**, *912*, 169092. [[CrossRef](#)] [[PubMed](#)]
46. Gui, J.; Wang, X.F.; Li, Z.X.; Zou, H.M.; Li, A.J. Research on the response of vegetation change to human activities in typical cryosphere areas: Taking the Qilian Mountains as an example. *J. Glaciol. Geocryol.* **2019**, *41*, 1235–1243.
47. Li, X.; Gou, X.; Wang, N.; Sheng, Y.; Jin, H.; Qi, Y.; Song, X.; Hou, F.; Li, Y.; Zhao, C.; et al. Tightening ecological management facilitates green development in the Qilian Mountains. *Chin. Sci. Bull.* **2019**, *64*, 2928–2937. [[CrossRef](#)]
48. Gui, J.; Li, Z.; Xue, J.; Du, F.; Cui, Q. The effect of freeze-thaw action on the dynamic change of supra-permafrost water sources: A stable isotope perspective. *J. Environ. Manag.* **2024**, *356*, 120536. [[CrossRef](#)]
49. Guo, J.; Zheng, W.; Li, Y.; Su, Q.; Zhang, D.; Wei, S.; Sun, X.; Yang, F. Quantitative geomorphological analyses reveal late Cenozoic uneven tectonic expansion at the North Qilian Shan. *Earth Surf. Process. Landf.* **2025**, *50*, e70090. [[CrossRef](#)]
50. Li, T.; Zhao, J.; Wu, G.L. Glaciers retreat-induced gravelization encroached alpine hillside grassland: A case study in Qilian Mountain, China. *Catena* **2025**, *254*, 108905. [[CrossRef](#)]
51. Liu, Z.; Si, J.; He, X.; Jia, B.; Zhou, D.; Wang, C.; Zhu, X.; Qin, J.; Ndayambaza, B.; Bai, X. The impact of desertification on soil health stability in Semi-Arid alpine Regions: A case study of the Qilian Mountains in the northeastern Tibetan Plateau, China. *Ecol. Indic.* **2024**, *163*, 112098. [[CrossRef](#)]
52. Wang, X.; Pang, G.; Yang, M.; Wan, G.; Liu, Z. Precipitation changes in the Qilian Mountains associated with the shifts of regional atmospheric water vapour during 1960–2014. *Int. J. Climatol.* **2018**, *38*, 4355–4368. [[CrossRef](#)]
53. Zuo, Y.F.; Li, Y.H.; He, K.N.; Wen, Y.S. Temporal and spatial variation characteristics of vegetation coverage and quantitative analysis of its potential driving forces in the Qilian Mountains, China, 2000–2020. *Ecol. Indic.* **2022**, *143*, 109429. [[CrossRef](#)]
54. Sun, M.P.; Ma, W.Q.; Yao, X.J.; Zhang, M.J.; Li, Z.Q.; Qin, D.H. Assessment and spatiotemporal characteristics of service value of glaciers in the Qilian Mountains. *Acta Geogr. Sin.* **2021**, *76*, 178–190.
55. Tian, H.; Yang, T.; Liu, Q. Climate change and glacier area shrinkage in the Qilian mountains, China, from 1956 to 2010. *Ann. Glaciol.* **2014**, *55*, 187–197. [[CrossRef](#)]
56. Peng, C.Y.; Sheng, Y.; Wu, J.C.; Cao, W.; He, B.B. Simulation of the permafrost distribution in the Qilian Mountains. *J. Glaciol. Geocryol.* **2021**, *43*, 158–169.
57. Jin, Z.; Zhao, Q.; Qin, X.; Zhang, J.; Li, Y.; Liu, Y.; Chen, J. The cryosphere change will intensify the summer drought in Qilian Mountains, northeastern of the Tibetan plateau. *J. Hydrol. Reg. Stud.* **2023**, *47*, 101401. [[CrossRef](#)]
58. Li, J.; He, H.; Zeng, Q.; Chen, L.; Sun, R. Dataset of Soil Conservation Capacity Preventing Water Erosion in China (1992–2019). *Sci. Data Bank* **2023**, *10*, 319. [[CrossRef](#)]
59. Luers, A.L.; Lobell, D.B.; Sklar, L.S.; Addams, C.L.; Matson, P.A. A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. *Glob. Environ. Change* **2003**, *13*, 255–267. [[CrossRef](#)]
60. Wu, G.; Tian, J.; Feng, X.; Ren, Y.; Bao, W.; He, C.; Yu, T.; Wu, J. Spatiotemporal variation and driving factors of ecological vulnerability in arid and semi-arid regions: A case study of Ningxia, China. *Catena* **2025**, *259*, 109378. [[CrossRef](#)]
61. Wu, X.; Zhu, C.; Yu, J.; Zhai, L.; Zhang, H.; Yang, K.; Hou, X. Ecological Vulnerability in the Red Soil Erosion Area of Changting under Continuous Ecological Restoration: Spatiotemporal Dynamic Evolution and Prediction. *Forests* **2022**, *13*, 2136. [[CrossRef](#)]

62. Cai, Y.; Guo, X.; Liu, J.; Wang, D.; Zheng, J. Ecological geological vulnerability assessment in Northern Shanxi Province (China) based on sensitivity resilience pressure (SRP) model. *Sci. Rep.* **2025**, *15*, 8063. [\[CrossRef\]](#)
63. Zhang, H.; Liu, Y.; Li, J.; Tian, P.; Zhong, J.; Gong, H. Evaluation and analysis of coastal complex ecological resilience based on multidimensional data: A case study of East China Sea. *Ecol. Indic.* **2023**, *155*, 110981. [\[CrossRef\]](#)
64. Zou, T.H.; Chang, Y.X.; Chen, P.; Liu, J.F. Spatial-temporal variations of ecological vulnerability in Jilin Province (China), 2000 to 2018. *Ecol. Indic.* **2021**, *133*, 108429. [\[CrossRef\]](#)
65. Li, Y.; Xie, W.; Sui, K.; Zhang, D.; Wan, Q. Revealing various change characteristics and drivers of ecological vulnerability in the Luan river basin based on the SRP model. *Sci. Rep.* **2025**, *15*, 33021. [\[CrossRef\]](#) [\[PubMed\]](#)
66. Li, Y.; Liu, J.; Zhu, Y.; Wu, C.; Zhang, Y. Spatiotemporal Differentiation and Attribution Analysis of Ecological Vulnerability in Heilongjiang Province, China, 2000–2020. *Sustainability* **2025**, *17*, 2239. [\[CrossRef\]](#)
67. Zhang, X.; Wang, L.; Fu, X.; Li, H.; Xu, C. Ecological vulnerability assessment based on PSSR in Yellow River Delta. *J. Clean. Prod.* **2017**, *167*, 1106–1111. [\[CrossRef\]](#)
68. Wu, X.; Huang, X. Research on the geometric weighting-coupling degree method for the urban ecological environment vulnerability index. *Ecol. Indic.* **2024**, *162*, 112023. [\[CrossRef\]](#)
69. Zhang, Y.; Su, L.X. Ecological Vulnerability Assessment and Driving Factor Analysis in the Middle Section of Yellow River Basin Based on SRP Model. *Huan Jing Ke Xue Huanjing Kexue* **2025**, *46*, 5134–5144. [\[CrossRef\]](#)
70. Kang, H.; Tao, W.; Chang, Y.; Zhang, Y.; Xuxiang, L.; Chen, P. A feasible method for the division of ecological vulnerability and its driving forces in Southern Shaanxi. *J. Clean. Prod.* **2018**, *205*, 619–628. [\[CrossRef\]](#)
71. Chen, Y.L.; Shen, S.L.; Zhou, A.N. Assessment of red tide risk by integrating CRITIC weight method, TOPSIS-ASSETS method, and Monte Carlo simulation. *Environ. Pollut.* **2022**, *314*, 120254. [\[CrossRef\]](#)
72. Aubréville, A.; Chevalier, A. *Climats, Forêts et Désertification de l'Afrique Tropicale/Par A. Aubréville*; préface de Aug. Chevalier; Geographical, Maritime and Colonial Publishing Company: Paris, France, 1949.
73. Mu, X.; Kun, J.; Zhao, W.; Liu, S.; Wei, X.; Wang, B. Spatio-temporal changes of ecological vulnerability across the Qinghai-Tibetan Plateau. *Ecol. Indic.* **2021**, *123*, 107274. [\[CrossRef\]](#)
74. Breiman, L. Random Forests. *Mach. Learn.* **2001**, *45*, 5–32. [\[CrossRef\]](#)
75. Lundberg, S.; Lee, S.I. A Unified Approach to Interpreting Model Predictions. In Proceedings of the NIPS, Long Beach, CA, USA, 4–9 December 2017.
76. Demarchi, L.; Kania, A.; Cieżkowski, W.; Piórkowski, H.; Oświecimska-Piasko, Z.; Chormański, J. Recursive Feature Elimination and Random Forest Classification of Natura 2000 Grasslands in Lowland River Valleys of Poland Based on Airborne Hyperspectral and LiDAR Data Fusion. *Remote Sens.* **2020**, *12*, 1842.
77. Wang, Y.; Niu, R.; Lin, G.; Xiao, Y.; Ma, H.; Zhao, L. Estimate of soil heavy metal in a mining region using PCC-SVM-RFECV-AdaBoost combined with reflectance spectroscopy. *Environ. Geochem. Health* **2023**, *45*, 9103–9121. [\[CrossRef\]](#) [\[PubMed\]](#)
78. Lee, E.J.; Piao, D.; Song, C.; Kim, J.; Lim, C.-H.; Kim, E.; Moon, J.; Kafatos, M.; Lamchin, M.; Jeon, S.W.; et al. Assessing environmentally sensitive land to desertification using MEDALUS method in Mongolia. *For. Sci. Technol.* **2019**, *15*, 210–220. [\[CrossRef\]](#)
79. Zhang, Q.; Cao, G.C.; Zhang, L.L.; Zhao, M.L.; Li, J.T. Dynamic Evaluation Map and Driving Force Analysis of Ecological Environment Quality on the Southern Slope of Qilian Mountains Based on GEE. *Environ. Sci.* **2025**, *46*, 4534–4544. [\[CrossRef\]](#)
80. Zhang, X.Y.; Wei, W.; Zhou, L.; Guo, Z.C.; Li, Z.Y.; Zhang, J.; Xie, B.B. Analysis on spatio-temporal evolution of ecological vulnerability in arid areas of Northwest China. *Acta Ecol. Sin.* **2021**, *41*, 4707–4719. [\[CrossRef\]](#)
81. Feng, J.; Jiang, Z. Strategies to Protect Forestry in Qilian Mountain Nature Reserve. In Proceedings of the 2019 9th International Conference on Social Science and Education Research(SSER 2019), Kitakyushu, Japan, 25–27 October 2019; p. 4.
82. Lu, F.; Hu, H.; Sun, W.; Zhu, J.; Liu, G.; Zhou, W.; Zhang, Q.; Shi, P.; Liu, X.; Wu, X.; et al. Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 4039–4044. [\[CrossRef\]](#)
83. Zhang, Y.; Wang, R.H.; Lu, C.W.; Zhou, L.M. Simulation and prediction of habitat quality in the Qilian Mountain Nature Reserve. *J. Nanjing For. Univ. (Nat. Sci. Ed.)* **2024**, *48*, 135–144.
84. Qian, D.; Yan, C.; Xiu, L.; Feng, K. The impact of mining changes on surrounding lands and ecosystem service value in the Southern Slope of Qilian Mountains. *Ecol. Complex.* **2018**, *36*, 138–148. [\[CrossRef\]](#)
85. Yuan, M.; Ouyang, J.; Zheng, S.; Tian, Y.; Sun, R.; Bao, R.; Li, T.; Yu, T.; Li, S.; Wu, D.; et al. Research on Ecological Effect Assessment Method of Ecological Restoration of Open-Pit Coal Mines in Alpine Regions. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7682. [\[CrossRef\]](#)
86. Xing, Z.; Peng, S.; Du, W.; He, Y.; Chong, S.; Feng, F.; Yu, P.; She, C.; Xu, D. Hydrogeological changes caused by opencast coal mining in steppe zone: A case study of Shengli 1 open-pit coal mine. *Desalination Water Treat.* **2018**, *121*, 126–133. [\[CrossRef\]](#)
87. Krabbenhoft, K.; Kirby, D.; Biondini, M.; Halvorson, G.; Nilson, D. Topoedaphic unit analysis: A site classification system for reclaimed mined lands. *CATENA* **1993**, *20*, 289–301. [\[CrossRef\]](#)

88. Wang, C.; Zhu, Y.; Wu, Z.; Xu, X. Ecological Vulnerability Evaluation and Change Analysis of the Tianshan Area Along the Pipeline of the “West-to-East Gas Transmission” Project Based on the SRP Model. *Sustainability* **2025**, *17*, 4301. [\[CrossRef\]](#)
89. Ouyang, Z.; Zheng, H.; Xiao, Y.; Polasky, S.; Liu, J.; Xu, W.; Wang, Q.; Zhang, L.; Xiao, Y.; Rao, E.M.; et al. Improvements in ecosystem services from investments in natural capital. *Science* **2016**, *352*, 1455–1459. [\[CrossRef\]](#) [\[PubMed\]](#)
90. Li, M.; Wu, P.; Ma, Z.; Pan, Z.; Lv, M.; Yang, Q.; Duan, Y. The Increasing Role of Vegetation Transpiration in Soil Moisture Loss across China under Global Warming. *J. Hydrometeorol.* **2022**, *23*, 253–274. [\[CrossRef\]](#)
91. Zhang, Y.; Gao, T.; Kang, S.; Shangguan, D.; Luo, X. Albedo reduction as an important driver for glacier melting in Tibetan Plateau and its surrounding areas. *Earth-Sci. Rev.* **2021**, *220*, 103735. [\[CrossRef\]](#)
92. Jin, X.-Y.; Jin, H.-J.; Iwahana, G.; Marchenko, S.S.; Luo, D.-L.; Li, X.-Y.; Liang, S.-H. Impacts of climate-induced permafrost degradation on vegetation: A review. *Adv. Clim. Change Res.* **2021**, *12*, 29–47. [\[CrossRef\]](#)
93. Bao, R.; Ma, H.; Zhang, W. Ecological vulnerability evaluation and driving factors analysis of the southern foothills of the Qilian Mountains. *J. Qinghai Univ.* **2025**, *43*, 101–120.
94. Yang, X.; Zhang, Z.; Zhou, H.; Liu, F.; Yu, H.; Zhao, B.; Wang, X.; Li, H.; Shi, Z. Social–Ecological Factors and Ecosystem Service Trade-Offs/Synergies in Vegetation Change Zones of Qilian Mountain National Park During 2000–2020. *Remote Sens.* **2025**, *17*, 1402. [\[CrossRef\]](#)
95. Zhang, L.; Yang, L.; Zohner, C.M.; Crowther, T.W.; Li, M.; Shen, F.; Guo, M.; Qin, J.; Yao, L.; Zhou, C. Direct and indirect impacts of urbanization on vegetation growth across the world’s cities. *Sci. Adv.* **2022**, *8*, eabo0095. [\[CrossRef\]](#)
96. Fang, Z.; Ding, T.; Chen, J.; Xue, S.; Zhou, Q.; Wang, Y.; Wang, Y.; Huang, Z.; Yang, S. Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Sci. Total Environ.* **2022**, *831*, 154967. [\[CrossRef\]](#)
97. Zhang, B.T.; Li, Z.X.; Feng, Q.; Lu, Z.X.; Zhang, B.J.; Cheng, W.J. Evolution of ecosystem service values in Qilian Mountains based on land-use change from 1990 to 2020. *Acta Ecol. Sin.* **2024**, *44*, 4187–4202. [\[CrossRef\]](#)
98. Liu, X.R.; Feng, T.J.; Zhang, Y.F.; Liu, Y.B.; Wang, P. Vegetation restoration affects soil hydrological processes in typical natural and planted forests on the Loess Plateau. *J. Hydrol.* **2025**, *650*, 132465. [\[CrossRef\]](#)
99. Hallett, L.M.; Stein, C.; Suding, K.N. Functional diversity increases ecological stability in a grazed grassland. *Oecologia* **2017**, *183*, 831–840. [\[CrossRef\]](#) [\[PubMed\]](#)
100. Willis, K.J.; Jeffers, E.S.; Tovar, C. What makes a terrestrial ecosystem resilient? A complex set of biotic and abiotic factors determines the resilience of an ecosystem. *Science* **2018**, *359*, 988–989. [\[CrossRef\]](#) [\[PubMed\]](#)
101. Huss, M.; Hock, R. Global-scale hydrological response to future glacier mass loss. *Nat. Clim. Change* **2018**, *8*, 135–140. [\[CrossRef\]](#)
102. Qin, J.; Ding, Y.; Shi, F.; Cui, J.; Chang, Y.; Han, T.; Zhao, Q. Links between seasonal suprapermafrost groundwater, the hydrothermal change of the active layer, and river runoff in alpine permafrost watersheds. *Hydrol. Earth Syst. Sci.* **2024**, *28*, 973–987. [\[CrossRef\]](#)
103. Kang, E.S. Review and Prospect of Studies on Hydrology of Cold and Dry Regions in China. *J. Glaciol. Geocryol.* **1998**, *20*, 238–244. [\[CrossRef\]](#)
104. Sun, B.Y.; Ren, F.P.; Ding, W.F.; Zhang, G.H.; Huang, J.Q.; Li, J.M.; Zhang, L. Effects of freeze-thaw on soil properties and water erosion. *Soil Water Res.* **2021**, *16*, 205–216. [\[CrossRef\]](#)
105. Shu, Y.; Liu, S.; Wang, Z.; Xiao, J.; Shi, Y.; Peng, X.; Gao, H.; Wang, Y.; Yuan, W.; Yan, W.; et al. Effects of Aerosols on Gross Primary Production from Ecosystems to the Globe. *Remote Sens.* **2022**, *14*, 2759. [\[CrossRef\]](#)
106. Yue, X.; Unger, N. Aerosol optical depth thresholds as a tool to assess diffuse radiation fertilization of the land carbon uptake in China. *Atmos. Chem. Phys.* **2017**, *17*, 1329–1342. [\[CrossRef\]](#)
107. Terwayet Bayouli, O.; Zhang, W.; Terwayet Bayouli, H. Combining RUSLE model and the vegetation health index to unravel the relationship between soil erosion and droughts in southeastern Tunisia. *J. Arid. Land* **2023**, *15*, 1269–1289. [\[CrossRef\]](#)
108. Masroor, M.; Sajjad, H.; Rehman, S.; Singh, R.; Hibjur Rahaman, M.; Sahana, M.; Ahmed, R.; Avtar, R. Analysing the relationship between drought and soil erosion using vegetation health index and RUSLE models in Godavari middle sub-basin, India. *Geosci. Front.* **2022**, *13*, 101312. [\[CrossRef\]](#)
109. Zeng, W.; Tian, Y.; Zhai, J.; Sun, W.; Sun, Y.; Li, R.; Yang, Q. Soil erosion resilience under climate extremes: Disentangling the impacts of vegetation restoration and rainfall intensification across China. *Ecol. Indic.* **2025**, *178*, 113994. [\[CrossRef\]](#)
110. Groffman, P.M.; Baron, J.S.; Blett, T.; Gold, A.J.; Goodman, I.; Gunderson, L.H.; Levinson, B.M.; Palmer, M.A.; Paerl, H.W.; Peterson, G.D.; et al. Ecological Thresholds: The Key to Successful Environmental Management or an Important Concept with No Practical Application? *Ecosystems* **2006**, *9*, 1–13. [\[CrossRef\]](#)
111. Scheffer, M.; Carpenter, S.; Foley, J.A.; Folke, C.; Walker, B. Catastrophic shifts in ecosystems. *Nature* **2001**, *413*, 591–596. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.