Spatial-temporal variations of ecological vulnerability in the Tarim River Basin, Northwest China: Postprint

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Abstract

As the largest inland river basin of China, the Tarim River Basin (TRB), known for its various natural resources and fragile environment, has an increased risk of ecological crisis due to the intensive exploitation and utilization of water and land resources. Since the Ecological Water Diversion Project (EWDP), which was implemented in 2001 to save endangered desert vegetation, there has been growing evidence of ecological improvement in local regions, but few studies have performed a comprehensive ecological vulnerability assessment of the whole TRB. This study established an evaluation framework integrating the analytic hierarchy process (AHP) and entropy method to estimate the ecological vulnerability of the TRB covering climatic, ecological, and socioeconomic indicators during 2000–2017. Based on the geographical detector model, the importance of ten driving factors on the spatial-temporal variations of ecological vulnerability was explored. The results showed that the ecosystem of the TRB was fragile, with more than half of the area (57.27%) dominated by very heavy and heavy grades of ecological vulnerability, and 28.40% of the area had potential and light grades of ecological vulnerability. The light grade of ecological vulnerability was distributed in the northern regions (Aksu River and Weigan River catchments) and western regions (Kashgar River and Yarkant River catchments), while the heavy grade was located in the southern regions (Kunlun Mountains and Qarqan River catchments) and the Mainstream catchment. The ecosystems in the western and northern regions were less vulnerable than those in the southern and eastern regions. From 2000 to 2017, the overall improvement in ecological vulnerability in the whole TRB showed that the areas with great ecological improvement increased by 46.11%, while the areas with ecological degradation decreased by 9.64%. The vegetation cover and potential evapotranspiration (PET) were the obvious driving factors, explaining 57.56% and 21.55% of the changes in ecological vulnerability across the TRB, respectively. In terms of ecological vulnerability grade changes, obvious spatial differences were observed

in the upper, middle, and lower reaches of the TRB due to the different vegetation and hydrothermal conditions. The alpine source region of the TRB showed obvious ecological improvement due to increased precipitation and temperature, but the alpine meadow of the Kaidu River catchment in the Middle Tianshan Mountains experienced degradation associated with overgrazing and local drought. The improved agricultural management technologies had positive effects on farmland ecological improvement, while the desert vegetation in oasis-desert ecotones showed a decreasing trend as a result of cropland reclamation and intensive drought. The desert riparian vegetation in the lower reaches of the Tarim River was greatly improved due to the implementation of the EWDP, which has been active for tens of years. These results provide comprehensive knowledge about ecological processes and mechanisms in the whole TRB and help to develop environmental restoration measures based on different ecological vulnerability grades in each sub-catchment.

Full Text

Preamble

Spatial-temporal ecological variations vulnerability in the Tarim River Basin, Northwest China

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Abstract: As China' s largest inland river basin, the Tarim River Basin (TRB) is characterized by abundant natural resources and a fragile environment, facing increasing ecological crisis risks due to intensive exploitation and utilization of water and land resources. Since the implementation of the Ecological Water Diversion Project (EWDP) in 2001 to save endangered desert vegetation, growing evidence has shown ecological improvement in local regions, yet few studies have conducted comprehensive ecological vulnerability assessments of the entire TRB.

This study established an evaluation framework integrating the analytic hierarchy process (AHP) and entropy method to estimate the ecological vulnerability of the TRB, incorporating climatic, ecological, and socioeconomic indicators during 2000–2017. Using the geographical detector model, we explored the importance of ten driving factors on the spatial-temporal variations of ecological vulnerability. Results showed that the TRB ecosystem was fragile, with more than half of the area (57.27%) dominated by very heavy and heavy grades of ecological vulnerability, while 28.40% of the area exhibited potential and light grades. Light-grade ecological vulnerability was distributed in the northern regions (Aksu River and Weigan River catchments) and western regions (Kashgar River and Yarkant River catchments), whereas heavy grades were located in the southern regions (Kunlun Mountains and Qarqan River catchments) and the Mainstream catchment. Ecosystems in the western and northern regions were less vulnerable than those in the southern and eastern regions.

From 2000 to 2017, overall ecological vulnerability in the TRB improved, with areas showing great ecological improvement increasing by 46.11%, while areas with ecological degradation decreased by 9.64%. Vegetation cover and potential evapotranspiration (PET) were the primary driving factors, explaining 57.56% and 21.55% of the changes in ecological vulnerability across the TRB, respectively. Regarding ecological vulnerability grade changes, obvious spatial differences were observed in the upper, middle, and lower reaches due to varying vegetation and hydrothermal conditions. The alpine source region of the TRB showed clear ecological improvement due to increased precipitation and temperature, but the alpine meadow of the Kaidu River catchment in the Middle Tianshan Mountains experienced degradation associated with overgrazing and local drought. Improved agricultural management technologies had positive effects on farmland ecological improvement, while desert vegetation in oasis-desert ecotones showed a decreasing trend due to cropland reclamation and intensive drought. Desert riparian vegetation in the lower reaches of the Tarim River was greatly improved due to the EWDP, which has been active for decades. These results provide comprehensive knowledge about ecological processes and mechanisms in the entire TRB and help develop environmental restoration measures based on different ecological vulnerability grades in each sub-catchment.

Keywords: ecological vulnerability; ecological improvement; ecological degradation; AHP-entropy method; climate change; human activities; Tarim River Basin

1 Introduction

In the context of climate change and human activities, comprehensive quantification of the degrees to which natural and human systems experience hazards, disturbances, and pressures has received widespread attention [?]. In arid and semi-arid areas where desert ecosystems are fragile and water conditions dominate, intensive human activities aggravate water resource crises [?] and ecological environment deterioration [?]. Therefore, evaluating ecosystem vulnerability is essential for achieving sustainable economic development and environmental protection in these regions [?].

The concept of "vulnerability" was previously used in social sciences and has recently been applied to ecological fields (e.g., ecological vulnerability, environmental vulnerability, and ecosystem vulnerability) [?]. It has various similar expressions (e.g., risk, sensitivity, and fragility) and inverse concepts (e.g., resilience, adaptability, adaptive capacity, and stability) [?]. In ecological contexts, "vulnerability" refers to the possibility of an ecosystem suffering from hazards, disturbances, or pressures over time and space [?], or the risk of severe ecosystem destruction [?]. However, establishing evaluation criteria systems and developing assessment models remain key challenges. The key indicators of ecosystem assessment vary across space, time, and conditions, encompassing not only current socioeconomic and ecological indicators but also spatial-temporal indicators that describe dynamic ecosystem variations at different scales. With the development of remote sensing (RS) and geographic information systems (GIS), land surface parameters such as land use/land cover (LULC), land surface temperature, normalized difference vegetation index (NDVI), vegetation coverage, and topographic conditions have been widely used as key indicators to describe ecosystem status and process changes [?, ?, ?, ?].

Numerous models and methods have been developed for quantitative ecological vulnerability assessment, including the analytic hierarchy process (AHP) [?], principal component analysis (PCA) [?, ?], entropy method [?, ?], fuzzy assessment model [?], grey model [?], and artificial neural network model [?]. However, most of these models determine indicator weights based on prior knowledge or empirical methods. Improperly set weight coefficients can lead to overestimation or underestimation of ecological effects during assessment. The entropy method, with its strong mathematical theoretical basis, determines ecological indicator weights according to the degree of variation of each index [?]. Compared with various subjective weighting models, its greatest advantage is removing human interference effects on indicator weights [?], though it ignores expert knowledge and decision-maker preferences. The AHP method is a mathematical technique that develops weights through pairwise comparisons among criteria in a hierarchical structure [?]. It comprehensively considers expert opinions and judgments and is commonly integrated with objective weight methods to incorporate expert knowledge in decision-making [?, ?]. Therefore, combining AHP and entropy methods leverages both subjective and objective approaches, reasonably recognizing each indicator' s effects on environmental vulnerability.

The Tarim River Basin (TRB) is a typical inland river basin in Northwest China characterized by arid and semi-arid climates and fragile ecosystems. The TRB' s ecological environment has continuously deteriorated since 1960 due to climate change and intensive human activities [?]. Agricultural oasis expansion has aggravated deforestation and increased irrigation, while excessive water resource development and inefficient utilization have led to water crises and ecological degradation, affecting sustainable development of social, economic, and natural ecosystems. To restore the desert ecosystem and improve ecological quality in riparian zones, the local government launched the ecological water diversion project (EWDP) in 2001 to transport water to the middle and lower reaches of the Tarim River and its tributary system [?]. Many studies have evaluated EWDP' s ecological effects using field investigations, site observations [?, ?], and remote sensing monitoring [?, ?], but results showed varying extents and ranges of environmental quality influence after ecological restoration implementation [?, ?, ?]. [?] found that the TRB' s environmental quality did not improve, with several regions severely deteriorating due to excessive agricultural water consumption and extensive economic development without regard for ecological environment indicators. Previous studies focused more on the middle and lower reaches, while upstream regions and mountain ecosystem fragility and sensitivity were not considered in ecological vulnerability assessment. The main ecological problem in the TRB is the uncertainty of ecological vulnerability when considering interactions among the inland water cycle, eco-environment, and socioeconomic factors. Therefore, establishing a comprehensive indicator system including meteorological, hydrological, ecological, and economic parameters and evaluating ecological vulnerability at the basin scale is essential.

This paper establishes an assessment index system using RS and GIS technology, incorporating ten indicators related to climate change, ecological environments, and socioeconomic conditions. An evaluation framework based on the AHP-entropy method estimates the TRB' s ecological vulnerability at the basin scale, analyzing spatial-temporal vulnerability grade changes and their driving factors at the catchment scale during 2000–2017.

2.1 Study Area

The Tarim River, located in Xinjiang Uygur Autonomous Region, is China' s longest inland river (total length of 1321 km) [?]. The TRB is surrounded by mountains on three sides: the Tianshan Mountains to the north, Karakoram Mountains to the west, and Kunlun Mountains to the south. The Taklimakan Desert, China' s largest desert, covers the vast central region of the TRB (Fig. 1 [Figure 1: see original paper]). The TRB has an extremely dry climate with mean annual precipitation of 15–65 mm, above-freezing temperature (AFT) of 10°C–12°C, and potential evapotranspiration (PET) of 2000–3000 mm. Vegetation is densely distributed in alpine and oasis areas but sparsely distributed in the narrow riparian zone across main and branch channels. The main land use types derived from the 2017 LULC map include grassland (24.69%), forestland (8.03%), cropland (4.69%), water body (1.27%), build-up land (0.48%), and other land use types including Gobi, desert, bare land, bare rocks, gravels, and glaciers (60.85%).

Rainfall, seasonal snowfall, and glacier meltwater in mountainous areas are the major water sources in this inland water cycle. Nine headstreams flow into the Tarim River' s main branch, dividing the TRB into nine sub-catchments and one Mainstream catchment (Fig. 1). Currently, only three headstreams (Hotan River, Yarkant River, and Aksu River) maintain hydraulic connections with the Tarim River' s main branch.

2.2 Derivation of Ecological Vulnerability Indicators

This study selected ten indicators: three climate indicators (precipitation, AFT, and PET), four ecological indicators (vegetation cover, soil erosion, landscape diversity, and water density), and three socioeconomic indicators (population density, food production, and livestock density). Indicator formulas are shown in Table S1. Variance inflation factors for all indicators were below 10 (Table 1), indicating reliable collinearity levels [?]. The "landscape diversity" indicator was generated using Fragstats software (version 4.2), while the other nine indicators were processed using ArcGIS and R software (version 3.5.2). All nine catchments except desert catchments were used for ecological vulnerability assessment.

2.2.1 Climate Indicators

Daily meteorological data (air temperature, sunshine hours, wind speed, and relative humidity) for Xinjiang stations during 2000–2017 were acquired from the China Meteorological Data Service Centre (http://data.cma.cn). These data were interpolated to 10-km grids using the Meteorological Distribution System for High-Resolution Terrestrial Modeling (MicroMet) [?]. The daily gridded PET dataset was calculated using the Penman-Monteith equation (Table S1) with interpolated meteorological data. The annual cumulative AFT was calculated by accumulating daily maximum temperatures above 0°C. Annual cumulative precipitation and PET were obtained from daily gridded datasets. All indicators were resampled to 500-m resolution using the bilinear method [?].

2.2.2 Ecological Indicators

The monthly MOD13A1 enhanced vegetation index (EVI) product (Collection 6; 500 m$\times$500 m) during 2000–2017 was acquired from NASA' s Land Processes Distributed Active Archive Centre (https://lpdaac.usgs.gov). Annual EVI was calculated using the maximum value composite method, and annual vegetation cover was calculated using pixel dichotomy methods (Table S1).

Soil texture (sand, silt, and clay) data were obtained from the soil particle-size distribution dataset at 1:100,000 scale [?], and soil organic carbon data were downloaded from the World Soil Database (Version 1.2; 1 km$\times$1 km resolution) [?]. Slope and aspect parameters were calculated from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) product (http://srtm.csi.cgiar.org). The soil erosion indicator was estimated using the Revised Universal Soil Loss Equation (Table S1), an effective and widely used empirical model for soil erosion risk assessment [?].

LULC maps for 2000, 2010, and 2017 were generated by the Chinese Academy of Sciences from the China National Land Cover Database (ChinaCover) at 30-m resolution [?]. ChinaCover, based on Landsat TM/ETM and HJ satellite imagery, employs an object-based approach with extensive field data, achieving overall accuracy greater than 86% [?]. The six LULC types shown in Figure 1 were extracted from ChinaCover Level I, consistent with IPCC classes [?]. Forestland included shrubland, and wetland was reclassified as water body. LULC vector maps were transformed to 500-m raster images using the bilinear method, then Shannon' s diversity index was applied to estimate landscape diversity (Table S1).

Water availability data for five administrative prefectures (Bayingol Mongolian Autonomous Prefecture, Aksu Prefecture, Kashgar Prefecture, Hotan Prefecture, and Kizilsu Kirgiz Autonomous Prefecture) in the TRB for 2000, 2010, and 2017 were obtained from the Xinjiang Water Resources Bulletin (http://slt.xinjiang.gov.cn/) issued by the Department of Water Resources of Xinjiang Uygur Autonomous Region [?, ?, ?]. The administrative boundary at catchment scale was rasterized to 500-m pixel size, and water availability density was partitioned into each pixel of different catchments. River length proportion and water body area in each pixel were extracted from the LULC map. Water availability weight in each pixel was calculated based on distance from the river, LULC, and slope [?].

2.2.3 Socioeconomic Indicators

Population density, livestock density, and food production data for 46 counties or cities in the TRB were collected from the Xinjiang Statistical Yearbooks (2000–2017) [?]. Food production included grain crops (wheat, maize, rice, and beans), oil crops, vegetation, potato, and melons. Food production (unit: t) was converted to food calories (unit: kcal) to unify evaluation criteria across crops (Table S1). Different livestock species (cattle, horse, sheep, donkey, and pig) were converted to standard sheep units (Table S1). Ratios of population density, livestock density, and food production data to county (or city) area were calculated following Table S1 equations, then associated with county name attribution fields in the vector data of county (city)-level administrative boundaries. Vector datasets were rasterized to 500-m resolution using the bilinear method.

2.3.1 Standardization of Indicators

To evaluate different indicators in dimensionless form, indicators with positive and negative effects were standardized using Equations 1 and 2 [?], respectively:

For positive effects: $y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$

For negative effects: $y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$

where y_{ij} is the standardized result of the ith evaluating pixel on the jth indicator; x_{ij} is the original pixel value; and $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum of x_j, respectively. Positive-effect indicators were AFT, PET, soil erosion, population density, and livestock density, while negative-effect indicators were precipitation, vegetation cover, landscape diversity, water density, and food production.

2.3.2 Calculating Indicator Weights

This study first applied the AHP method to allocate subjective weights through expert pairwise comparisons, then used the entropy method to obtain objective weights based on indicator variation degrees. Finally, the integrated AHP-entropy method derived final weights.

Step 1: Calculating subjective weights with AHP.

The pairwise comparison judgment matrix was established based on composite opinions from three experts in ecological, agricultural, and water resource management departments, representing local field experience [?]. The consistency ratio (CR) was 0.067, below the 0.100 threshold, indicating reasonable matrix consistency [?].

Step 2: Calculating objective weights with the entropy method.

Ten indicators were estimated using the entropy method following these formulas [?, ?]. First, the proportion of standardized indicators was defined by Equation 3: $p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}$. Second, entropy H_j and weight W_e were calculated using Equations 4 and 5: $H_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln(p_{ij})$ and $W_e = \frac{1-H_j}{\sum_{j=1}^{n}(1-H_j)}$, where p_{ij} represents the proportion of the ith pixel of the jth indicator; H_j is the entropy of the jth indicator; W_e is the weight of the jth indicator; m is the total number of estimating pixels; and n is the number of evaluation indicators.

Step 3: Integrating AHP-entropy weights.

The overall combined weight was calculated using Equation 6: $w_j = \frac{W_a \times W_e}{\sum_{j=1}^{n} W_a \times W_e}$, where w_j represents the combined weight; W_a is the subjective weight from AHP; and W_e is the objective weight from entropy. Clearly, $\sum_{j=1}^{n} w_j = 1$ and $w_j \geq 0$ for $j = 1, 2, \dots, n$. Indicator weights are shown in Table 2 .

2.3.3 Determining Evaluation Grades

The natural breaks (Jenks) method [?], implemented automatically in ArcGIS, was used to obtain ecological vulnerability grades by minimizing intragroup variation and maximizing intergroup variation. Ecological vulnerability grades were reclassified into five levels: potential (0.26-0.54), light (0.54-0.64), medium (0.64-0.69), heavy (0.69-0.75), and very heavy (0.75-0.85).

Grade changes were defined as: "Up 1 grade" when ecological vulnerability transformed from one low level to one high level; "Up 2 grades" when transforming from one low level to two high levels; "Down 1 grade" when transforming from one high level to one low level; and "Down 2 grades" when transforming from one high level to two low levels.

2.3.4 Geographical Detection Method (GDM)

The geographical detection method is a variance analysis technique that detects spatial differentiation and reveals driving factors [?], successfully used to quantitatively analyze ecological vulnerability driving factors [?]. This study used the factor detector module to quantify driving factor x' s contribution to spatial-temporal differentiation of ecological vulnerability through the q-value, calculated as: $q_x = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$, where q_x is the explanatory power of driving factor x; SSW and SST are within-sum-of-squares in layer h and total sum of squares, respectively; h ($h = 1, 2, \dots, L$) is the category number of driving factor x; L is the number of categories; N_h and N are unit numbers for layer h and the whole region, respectively; and σ_h^2 and σ^2 are variances of ecological vulnerability in layer h and the whole region, respectively. Larger q-values indicate greater explanatory power.

To obtain discrete intervals for continuous independent variables in GDM, driving factors were converted using the natural breaks (Jenks) method [?] in ArcGIS. GDM calculations were performed in R software (version 3.5.2) using the 'geodetector' package.

3.1 Spatial Distribution of Ecological Vulnerability

Overall ecological vulnerability values in the TRB slightly decreased from 0.686 ($±0.090)*to*0.666(±$0.096) during 2000–2017 (Fig. 2 [Figure 2: see original paper]), indicating slight ecological environment improvement. As more than half the study area is dominated by desert and desertification regions, the overall ecological vulnerability grade remained relatively high, with areas above the heavy grade accounting for approximately 57.27% of the total area (Fig. 2d). The potential grade had the smallest average area (6.87%) (Fig. 2d), mainly distributed in mountainous grasslands or croplands along riparian zones (Fig. 2a–c). From 2000 to 2017, area proportions at potential and light grades increased by 57.86% and 39.60%, respectively, while the heavy grade decreased by 25.83% (Fig. 2d). Area proportions at medium and very heavy grades remained relatively stable, with change rates of -5.61% and -5.97%, respectively. Thus, the TRB' s ecological environment slightly improved, with continually increasing areas at potential and light grades and decreasing areas at heavy grade.

Comparing spatial patterns across catchments, ecological vulnerability grades showed overall decreasing trends from upstream to downstream, from mountainous to alluvial plain areas, and from west to east. The Yarkant River and Aksu River catchments in upstream regions with abundant precipitation and glacier meltwater had better ecological environments with higher vegetation cover (Fig. 3 [Figure 3: see original paper]). In the Yarkant River catchment, approximately 52.84% of the area was classified as light grade in 2017 (Fig. 3b). Conversely, the Kunlun Mountains catchment had the worst ecological environment, with very heavy-grade fragile regions exceeding 50.00% of total catchment area due to sparse vegetation and limited river flow.

Areas of potential and light grades obviously increased in the Yarkant River, Kashgar River, Hotan River, and Aksu River catchments, while heavy-grade areas significantly decreased in the Kashgar River and Yarkant River catchments from 2000 to 2017 (Fig. 3). Ecological vulnerability grades upgraded from medium to light in the Kashgar River and Weigan River catchments, and from heavy to medium in the Hotan River and Kaidu River catchments.

Statistics based on LULC and geomorphic parameters (altitude and slope) are shown in Figure 4 [Figure 4: see original paper]. Cropland had lower ecological vulnerability values than grassland and forestland (Fig. 4a), as crops in agricultural oases typically receive abundant irrigation water, making vegetation cover less sensitive to decreasing precipitation or severe drought. Regarding terrain parameters, ecological vulnerability values showed negative relationships with altitude (Fig. 4b) and slope (Fig. 4c). Mid-mountain regions at 2500–3500 m elevation with 25°–35° slopes had the best ecological conditions, showing the lowest vulnerability values (0.645 ($\pm$0.048)–0.620($\pm$0.053)).$In contrast, lowland regions below 1500 m elevation with slopes less than 5° had the most f$

3.2 Spatial-temporal Variations of Ecological Vulnerability

Distribution maps of ecological vulnerability changes during 2000–2010, 2010–2017, and 2000–2017 were used to analyze spatial-temporal variations (Fig. 5 [Figure 5: see original paper]). Negative ecological vulnerability values represent improvement, while positive values indicate degradation. From 2000 to 2010, approximately 36.06% of the TRB area showed great improvement (changes from -0.06 to -0.02), and 57.18% showed slight improvement (changes from -0.02 to 0.00) (Fig. 5d). Improved regions were primarily alpine grassland and cropland (Fig. 5a). Ecological degradation regions accounted for 6.76% of total area, mainly distributed in the Kaidu River catchment mountains, middle Tarim River reaches (Luntai County), and Qarqan River catchment croplands (Qiemo County).

From 2010 to 2017, ecological improvement slowed, with 12.97% of total area showing great improvement (Fig. 5d). Mountain grassland ecological environments exhibited slight improvement, including in the Kaidu River catchment, but upstream river reach croplands generally degraded (Fig. 5b). During 2000–2017, great ecological improvement occurred in about 46.11% of catchment area, while approximately 9.64% showed ecological degradation (Fig. 5d). Significant improvement mostly occurred in alpine grasslands surrounding catchments, and river-adjacent cropland ecological environments also improved (Fig. 5c). Spatial degradation distributions from 2000–2017 were similar to those from 2000–2010. Additionally, transition zones between cropland and forestland showed discontinuous degradation in the Aksu River and Yarkant River catchments, and desert riparian forest in the Tarim River middle reaches also showed significant degradation.

Spatial-temporal grade variations during 2000–2010, 2010–2017, and 2000–2017 are displayed in Figure 6 [Figure 6: see original paper]. Overall, approximately 80.00% of total area maintained stable grades. Most ecological improvement regions upgraded by one level. During 2000–2017, about 21.33% of total area increased by one grade, while only 1.65% decreased by one grade (Fig. 6d). The most significant environmental improvements occurred in the Kashgar River, Yarkant River, and Hotan River catchments. Regions improving by one level were mainly distributed in grasslands of the West Tianshan Mountains, Karakoram Mountains, Kunlun Mountains, and Altun Mountains, as well as alluvial plains in the Kaidu River, Weigan River, Kashgar River, Yarkant River, and Hotan River catchments. However, ecological vulnerability downgraded by one grade in the Middle Tianshan Mountains, Tarim River middle reaches, and southeast Taklimakan Desert margin (Qiemo County).

3.3 Impacts of Driving Factors on Ecological Vulnerability in the TRB

The influences of climatic, ecological, and socioeconomic factors on ecological vulnerability were analyzed using q-values (Table 3). In the entire TRB, ecological factors had the greatest impacts, while socioeconomic factors had the lowest (Table 3). Individual driving factor influences from high to low were: vegetation cover > PET > water density > precipitation > landscape diversity > AFT > population density > food production > soil erosion > livestock density. Vegetation cover had the highest q-value (0.5756), primarily explaining spatial heterogeneity of ecological vulnerability. PET (q-value = 0.2155) was the second most important factor. Water density and precipitation q-values exceeded 0.1000, indicating their relative importance. Population density, food production, and livestock density q-values were below 0.0100, showing smaller impacts.

In catchments with better ecological environments (Weigan River, Aksu River, Kashgar River, and Yarkant River), vegetation cover was the most important factor affecting spatial-temporal vulnerability variations, indicating that better vegetation growth in mountainous regions improves ecological environments. However, PET had the highest influence in the Qarqan River catchment (q-value = 0.5191), followed by the Kunlun Mountains catchment (q-value = 0.3304) and Hotan River catchment (q-value = 0.3084), implying that increased drought is a major ecological limitation in these regions. In the Kaidu River and Hotan River catchments, livestock density played more important roles, explaining 11.17% and 10.28% of ecological vulnerability changes, respectively, indicating that overgrazing significantly affects ecological balance in mountain regions.

4.1 Comparison of Spatial-temporal Variations Between AHP-entropy Method and Remote Sensing Vegetation Index

Many studies have found increasing vegetation greenness trends for both grassland and cropland across most Xinjiang regions based on MODIS or GIMMS datasets over recent decades [**?**, **?**, **?**, **?**], consistent with our findings. The annual maximum MODIS EVI represented vegetation greenness from 2000 to 2017 in the TRB (Fig. 7a [Figure 7: see original paper]). Results indicated that upstream river and cropland regions had more significantly increasing trends than mountain ranges. EVI decreasing trends were mainly located in grasslands of the Middle Tianshan Mountains and Tarim River middle reaches. Overall, MODIS EVI spatial-temporal patterns were similar to AHP-entropy method ecological vulnerability results.

4.2.1 Spatial-temporal Changes in Grassland Ecological Vulnerability

Except for the Kaidu River catchment, eight catchments showed positive vegetation growth trends in grassland based on MODIS EVI (Fig. 7b [Figure 7: see original paper]). Alpine grassland greening positively affected ecological environments, especially in upstream regions of the Kashgar River and Yarkant River catchments (Fig. 5c). Grassland in highland or lowland arid regions is most sensitive to short-term climate fluctuations and most severely degraded by human activities like overgrazing or clearing [?]. Many studies indicate that increased grassland vegetation index is mainly due to increased precipitation rather than rising temperature in Northwest China' s arid regions [?, ?]. With climate shifting from warm-dry to warm-wet since the 1980s in Xinjiang [?], increasing grassland vegetation growth trends have positively improved ecological environments around the TRB, particularly in the Karakoram Mountains, Kunlun Mountains, and Altun Mountains. In arid regions, grassland recovers from drought more easily than shrubland when receiving supplemental water [?]; therefore, ecological water transport has positively promoted grassland regeneration in the Tarim River middle and lower reaches.

4.2.2 Spatial-temporal Changes in Cropland Ecological Vulnerability

MODIS EVI for TRB cropland rapidly increased from 0.16 ($\$\pm 0.03) to 0.31 (\pm 0.12), especially in the Kaidu River a$ a), respectively (Fig. 9a [Figure 9: see original paper]). As cropland here deeply depends on human management, ecological vulnerability continuously decreased, likely related to agricultural management progress.

From 2000 to 2017, cropland area continuously increased from 2.98×10^{3} to 4.04×10^{3} km^2, mainly converted from forestland and grassland. Agricultural reclamation concentrated in upstream catchments (Kashgar River, Yarkant River, Aksu River, Weigan River, and Kaidu River) and the Tarim River upper and middle reaches. The greatest reclamation occurred in Kashgar River and Yarkant River oases, accounting for 40.00% of total cropland area converted from forestland (Fig. 8d). Significant cropland increase from forestland conversion implies greater water consumption for agricultural irrigation and less for natural vegetation (Fig. 9b).

4.2.3 Spatial-temporal Changes in Forestland Ecological Vulnerability

MODIS EVI increase rates for forestland in upstream catchments (Yarkant River, Kashgar River, and Aksu River) were much higher than in the Mainstream catchment (Fig. 7d), suggesting better upstream forestland ecological environments than desert riparian forest in the Mainstream catchment. Although Mainstream catchment forestland EVI showed obvious growth trends (Fig. 7d), sporadic vegetation degradation was found in the Tarim River middle reaches (Fig. 5a–c). The middle stream water transport dike cut off the river overflow mechanism, impacting desert riparian community self-renewal and degrading ecological environments. [?] also noted decreasing fractional vegetation trends along the Tarim River middle stream in 2000 and 2013, consistent with our study.

In the Tarim River lower reaches, runoff from the main branch and Konqi River generally raised groundwater tables and promoted rapid desert riparian forest regeneration within 300 m of riverbanks [?, ?, ?]. However, restored riparian vegetation scope was closely related to surface water receiving area. With the EWDP implemented in a 'line style' pattern from 2000 to 2017, riparian vegetation was restored along river channels and ecological environments improved (Fig. 5).

4.3 Impacts of Climate Change on Ecological Vulnerability

Over the past half-century, Xinjiang' s annual mean temperature and precipitation showed obvious growth trends based on meteorological station and reanalysis datasets [?, ?]. Although warming remained stable and precipitation slightly decreased during 1997–2015, drought severity increased, especially in South Xinjiang [?]. In this study, AFT exhibited a significant increasing trend (0.008°C/a, $P < 0.05$; Fig. 10a [Figure 10: see original paper]), but precipitation showed no significant trend (1.6 mm/a, $P > 0.05$; Fig. 10b) in the TRB during 2000–2017. Warming trends without significant precipitation increases intensified water resource stress. Spatially, AFT and PET showed decreasing trends in surrounding mountains but significant increasing trends in the Tarim River middle reaches (Fig. 10a and b). Precipitation increased in western regions but decreased in eastern regions, with cooling-wetting trends in high mountains and warming-drying trends in low basins.

Climate conditions benefited mountain grassland ecological environments in upstream regions (Kashgar River, Yarkant River, Hotan River, and Kunlun Mountains catchments) with fewer human activities (Fig. 5c). However, increased AFT and decreased precipitation in the Middle Tianshan Mountains aggravated overgrazing grassland degradation, negatively affecting ecological environments. Significantly increasing PET occurred in the Tarim River middle and lower reaches (Luntai and Yuli counties) and around the southern desert edge (Qiemo County) (Fig. 10c). Previous studies show PET based on ground meteorological stations around the TRB also increased from 1994 to 2010 due to increasing wind speed and vapor pressure deficit [?, ?], consistent with our results. Moreover, increased irrigation water withdrawal in agricultural oases may positively affect PET [?].

4.4 Impacts of Water Resource Changes on Ecological Vulnerability

Climate warming has caused significant river runoff growth trends since 1960 in the Tarim River headwaters [?, ?, ?]. Snow and glacier meltwater are primary runoff sources, accounting for 48.20% of total water volume [?]. Recently, Kaidu River and Aksu River runoff supplied by rainfall and seasonal snowmelt in the Middle Tianshan Mountains showed decreasing trends, possibly related to precipitation decreases [?]. Conversely, glacier meltwater effects from air temperature were more remarkable in the Karakoram Mountains and Kunlun Mountains. In the Yarkant River, where glacier meltwater contributed about 50.00% to runoff, significantly rising summer temperatures accelerated glacial shrinkage and increased runoff from 1996 to 2006 [?].

Water density indicator variations showed that western TRB regions (Yarkant River and Kashgar River catchments) had the most abundant water resources. Water density values significantly increased in the Yarkant River, Kashgar River, Hotan River, and Kunlun Mountains catchments, but decreased in the Weigan River and Aksu River catchments (Fig. 10d), consistent with runoff variations in these major source rivers. Decreased runoff combined with increased cropland area and agricultural water use may increase water stress in northern TRB catchments, while increased runoff provides more water resources for natural vegetation and agricultural irrigation in western and southwestern regions.

Agricultural water in the TRB, accounting for 96.50% of total water consumption, increased from 215.00×10^{8} m^3 in 2000 to 313.56×10^{8} m^3 in 2017 (Fig. 9b). Groundwater use for agriculture increased from 13.13×10^{8} m^3 in 2005 to 40.49×10^{8} m^3 in 2017 (Fig. 9b). Increased groundwater exchange dynamics were significantly altered by water-saving irrigation applications [?]. However, water saved by drip irrigation was used to expand cropland area, stressing ecological water use in the Tarim River lower reaches. Ecological water remained above the mean value (3.65×10^{8} m^3) during 2003–2010, then decreased to the lowest value of 1.20×10^{8} m^3 in 2012 with progressive agricultural water consumption (Fig. 9b). The Mainstream catchment had the largest desert riparian forest area, accounting for 23.34% of total forestland area (Fig. 8c), and these forestlands relied heavily on ecological water transport. As wet environments are required for germination and seedling growth, river overflow could activate crown seeds and soil seed banks [?, ?].

4.5 Impacts of Socioeconomic Changes on Ecological Vulnerability

As shown in Table 3, livestock played the most significant role in ecological vulnerability in the Kaidu River catchment. The Kaidu River catchment's grassland area ranked second largest in the TRB (Fig. 8a) and represents an important animal husbandry base in Xinjiang. Overgrazing capacity in spring-autumn pastures increased from 30.10% to 50.00% during 1985–2007, with most meadow overloads exceeding 100.00% in the Bayanbulak grassland [?]. Overgrazing decreased grassland quality and retarded restoration, causing continuous ecological environment degradation in the Middle Tianshan Mountains.

5 Conclusions and Suggestions

This study selected ten climatic, ecological, and socioeconomic indicators to estimate ecological vulnerability in the TRB using the AHP-entropy method for 2000, 2010, and 2017. Results showed ecological environment improvement in most TRB regions, with improvement degree decreasing from northwestern to southeastern regions. Vegetation cover and PET were the primary driving factors, explaining 57.56% and 21.55% of ecological vulnerability changes, respectively. Climate change benefited most mountainous regions, but overgrazing aggravated grassland degradation in the Kaidu River catchment. Agricultural oasis ecological environments improved with better management technologies, while oasis-desert ecotones showed sporadic degradation due to cropland reclamation and intensive drought.

Therefore, rational water and land resource use in agricultural oases is urgent, and moderate land reclamation should be executed in western and southwestern regions with abundant water resources. This study provides a comprehensive framework for better understanding ecological vulnerability at the basin scale, directly supporting ecological managers and governments in decision-making for similar arid and semi-arid areas with limited water resources and fragile environments.

We suggest different ecological protection and restoration measures based on varying ecological vulnerability characteristics in the TRB. Agricultural development should be strictly controlled and water use efficiency enhanced in Aksu River and Weigan River catchment oases to mitigate decreased water resources and intensified drought. In the Kaidu River catchment' s mountain grasslands, measures should actively restore grassland and rebuild forage-livestock balance through fencing, rotational grazing, and compensatory seed planting. In western (Yarkant River and Kashgar River catchments) and southwestern (Hotan River catchment) regions with abundant water resources, cropland reclamation from grassland and forestland should be moderate to avoid disrupting ecological water flow into the Tarim River main branch. In the Mainstream catchment, more attention should focus on intensive forest rehabilitation from agriculture and protecting *Populus euphratica* seedlings to restore natural vegetation cover and water body area.

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Appendix

Table S1. Indicator system of ecological vulnerability in Tarim River Basin

Indicator	Calculation formula	Formula description
Climate indicator		
Above-freezing temperature (AFT) (unit: °C)	$AFT = \sum_{i=1}^{n} T_i$	T_i is daily temperature above zero (°C); n is number of corresponding days.
Precipitation (PRE; unit: mm)	$PRE = \sum_{i=1}^{n} PRE_i$	PRE_i is daily precipitation on ith day (mm); n is day number ($n = 365$).
Potential evapotranspiration (PET; unit: mm)	$PET = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1+0.34U_2)}$	R_n is net radiation ($MJ/(m^2 \cdot d)$); G is soil heat flux ($MJ/(m^2 \cdot d)$); γ is psychrometric constant (kPa/°C); T is mean temperature (°C); U_2 is wind speed (m/s); e_s is saturation vapour pressure (kPa); e_a is actual vapour pressure (kPa); Δ is slope of vapour pressure curve (kPa/°C).
Ecological indicator		
Vegetation cover	$VC = \frac{EVI - EVI_0}{EVI_s - EVI_0}$	EVI_s is value at highly dense vegetation fraction; EVI_0 is value for bare soil.
Soil erosion (SE; unit: t/hm^2)	$SE = R \times K \times LS \times C \times P$	R is rainfall erosivity factor ($t \cdot hm^2 \cdot h/(hm^2 \cdot MJ \cdot mm)$); K is soil erodibility factor; LS is topographic factor; C is vegetation cover factor; P is erosion control practices factor.
Landscape diversity	$LD = -\sum_{i=1}^{m} P_i \ln(P_i)$	P_i is proportion of area for patch type i in landscape (%); m is number of patch types.

Indicator	Calculation formula	Formula description
Water density (WD; Unit: mm)	$WD = \frac{L_r + S_l + Q_w \times W_Q}{3}$	L_r is river length (m); S_l is water body area (m^2); Q_w is available water resource (m^3); W_Q is weight of available water resource.
Socioeconomic indicator		
Population density (POP; unit: person/hm^2)	$POP = \frac{POP_{total}}{A}$	POP_{total} is urban and rural population (person); A is county area (hm^2).
Food production (FOOD; unit: calorie/hm^2)	$FOOD = \frac{\sum_{i=1}^{n} M_i \times EP_i \times E_i}{A}$	i is production category (1 to n); M_i is product yield per category i (t); EP_i is edible percentage of product by category (%); E_i is calories per 100 g of product (calorie/g); A is county area (hm^2).
Livestock density (LS; unit: head/hm^2)	$LS = \frac{\sum_{i=1}^{n} LS_i \times L_i}{A}$	i is livestock type (1 to n); LS_i is livestock of type i (head); L_i is converted ratio of standard sheep; A is county area (hm^2).

Note: Figure translations are in progress. See original paper for figures.

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