Remote Sensing Assessment of Ecosystem Health and Key Driving Factors in Xinjiang (Postprint)

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Abstract

As the largest provincial-level administrative region in China by land area, the Xinjiang Uygur Autonomous Region features diverse ecosystem structures and abundant animal and plant species resources, representing an important biodiversity hotspot research area in Northwest China. This study took the Xinjiang Uygur Autonomous Region as the research object, integrated regional characteristics with the advantages of quantitative remote sensing data (real-time availability, easy accessibility, and periodicity), and selected four single-factor indicators: Normalized Difference Vegetation Index (NDVI), animal species richness, aridity, and human disturbance index. Based on the "Vigor-Organization-Resilience" ecological health assessment model, this study quantitatively constructed a remote sensing-dominated regional comprehensive ecological health assessment index for Xinjiang. Furthermore, the Geographical Detector method was employed to ascertain the influence degree of different environmental driving factors on ecological health in Xinjiang, and long-term temporal series application analysis and validation of this method were conducted at the county-level administrative region scale. The results indicated: (1) The ecological health level in Xinjiang was demarcated by the Tarim River-Yarkant River basin, with the ecological health level in Northern Xinjiang being significantly higher than that in Southern Xinjiang, exhibiting prominent spatial heterogeneity and agglomeration characteristics. (2) The influence degree of various environmental factors on ecological health in Xinjiang was as follows: Normalized Difference Vegetation Index (0.645) > human disturbance index (0.512) > animal species richness (0.414) > aridity (0.116). (3) From 2000 to 2018, the overall ecological health level in Xinjiang demonstrated a gradual upward trend, with the most significant changes occurring in Manas County, Hutubi County, and Changji City of Changji Hui Autonomous Prefecture, as well as Fuhai County and Fuyun County of Altay Prefecture.

Full Text

Remote Sensing Assessment and Key Driving Factors of Ecosystem Health in Xinjiang

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Abstract: As China' s largest provincial-level administrative region by land area, the Xinjiang Uygur Autonomous Region exhibits diverse ecosystem structures and abundant flora and fauna resources, representing an important biodiversity hotspot in northwestern China. This study focuses on Xinjiang, leveraging regional characteristics and the advantages of quantitative remote sensing data—including real-time availability, ease of acquisition, and periodic coverage—to select four single-factor indicators: Normalized Difference Vegetation Index (NDVI), animal species richness, drought severity, and human disturbance index. Based on the "Vigor-Organization-Resilience" ecological health assessment model, we quantitatively constructed a regional comprehensive ecological health remote sensing assessment index for Xinjiang dominated by remote sensing data. Furthermore, using the Geodetector method, we identified the influence degree of different environmental driving factors on Xinjiang' s ecological health and applied this method at the county administrative level for long-term temporal analysis and validation. The results demonstrate that: (1) Xinjiang' s ecological health level, with the Tarim River-Yarkant River basin as the boundary, shows significantly higher levels in northern Xinjiang than in southern Xinjiang, exhibiting pronounced spatial differentiation and agglomeration characteristics. (2) The impact degree of environmental factors on Xinjiang' s ecological health follows the order: NDVI (0.645) > human disturbance index (0.512) > animal species richness (0.414) > drought severity (0.116). (3) From 2000 to 2018, Xinjiang' s overall ecological health level showed a gradually increasing trend, with the most significant changes occurring in Manas County, Hutubi County, and Changji City of Changji Hui Autonomous Prefecture, as well as Fuhai County and Fuyun County in Altay Prefecture.

Keywords: ecological health assessment; single-factor index; Geodetector; driving factors; dynamic analysis; Xinjiang

1 Introduction

Ecological and environmental issues have become another severe challenge facing the global community after climate change, with countries worldwide actively conducting ecological health assessment research at various scales [1]. The concept of ecosystem health was proposed by Rapport in the context of global ecosystem degradation, referring to an ecosystem' s capacity to maintain its organizational structure, self-regulation, and self-recovery over time [2]. Early scholars defined ecosystem health primarily from the perspective of ecosystem self-health, considering an ecosystem healthy if it possessed self-recovery capabilities when encountering external stress [3]. With disciplinary development, researchers proposed that ecosystem health should consider not only the ecosystem itself but also its capacity to provide services to humans [4]; in this sense, ecosystem health equates to ecosystem sustainability. Costanza proposed that ecosystem health comprises "vigor," "organization," and "resilience," which has become the most widely accepted definition internationally [5].

Regarding assessment methods, current ecological health assessment approaches mainly include two types: indicator species methods and index system methods [6]. The former relies on key indicator groups' quantity, diversity, and physiological indicators to describe ecosystem health status. While this method can intuitively reflect ecosystem health levels through indicator species status, it has numerous limitations, such as unclear selection criteria for indicator species, inappropriate monitoring parameter selection, and insufficient monitoring scale refinement [7]. Compared with the indicator species method, the index system method integrates multiple ecosystem indicators to reflect ecosystem processes, highlighting the evolutionary relationship between ecological health and human services/regional environments while more accurately reflecting ecosystem carrying capacity and recovery ability after stress [8]. In recent years, ecological health assessment research has trended toward refined development, with assessment methods for different ecosystems increasingly perfected. Benjamin et al. [10] proposed the Ocean Health Index concept as a new simplified approach for evaluating marine health status. Langat et al. [11] investigated the role of forest resources in local community livelihoods in Kenya, recommending consideration of human factors when assessing forest ecosystem health. Wang Lixin et al. [12] combined grassland ecosystem community characteristics and degradation succession patterns with key ecological processes at the plant-atmosphere interface to establish a comprehensive index for evaluating grassland ecosystem health.

Most current ecosystem health assessment indicator selection focuses on artificial statistics and field survey data, as well as secondary processed indirect data, which often have limitations such as overly long update cycles for target-level statistical data, insufficiently refined assessment units, and difficulty obtaining basic data—particularly for naturally extreme areas inaccessible to humans where manual data acquisition is extremely difficult. Remote sensing technology offers technical advantages for describing macro-scale ecological conditions, including real-time, rapid, and periodic monitoring indicators, along with large-area, intuitive, and unrestricted geographic coverage. Fully utilizing remote sensing observation indicators for ecosystem monitoring and assessment is crucial for improving ecological assessment result quality. For instance, China' s Ministry of Ecology and Environment releases the Ecological Status Index (EI), which includes five indicators, four of which are obtained from remote sensing data. In 2013, Xu Hanqiu [13] proposed a new remote sensing ecological index (RSEI) based on quantitative remote sensing parameters, which was subsequently applied and widely recognized in ecological assessment studies of the Beipan River Basin [14], Qing River area [15], and Gansu region [16], demonstrating the enormous potential of quantitative remote sensing products in regional ecological assessment.

Xinjiang, located in an arid region of northwest China with fragile ecology, is also a key area for biodiversity conservation. Establishing an effective ecological health assessment system tailored to local conditions is crucial for promoting sustainable regional development. This study leverages the advantages of quantitative remote sensing data, adopts the internationally recognized "Vigor-Organization-Resilience" ecosystem health assessment model, and selects NDVI, drought severity, animal species richness, and human disturbance index as assessment indicators. By constructing a comprehensive ecological health remote sensing assessment index dominated by quantitative remote sensing data, this study quantitatively and intuitively reflects Xinjiang' s ecological health level and its changes, providing a useful reference for remote sensing indicator selection in regional ecological health assessment.

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2 Materials and Methods

2.1 Data Sources and Preprocessing

NDVI and land surface temperature products at 1 km resolution were obtained through the Google Earth Engine (GEE) platform, specifically the MOD13A2 and MOD11A2 products. These are generated from MODIS Level 1B data after atmospheric and aerosol correction, with production processes considering adjacent pixel effects, low viewing angles, and cloud/shadow influences. The data quality is highly recognized in the industry and widely applied [17], meeting the precision requirements for indicator construction in this study. Land cover classification data adopted the 30 m resolution land cover classification product constructed by the "Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences" [18]. Animal species richness data comprised Xinjiang bird and mammal species distribution data, spatialized based on actual distribution ranges from the "Xinjiang Bird List" [19] and "Xinjiang Mammal (Mammalia) List" [20]. Data sources and information are detailed in .

To ensure temporal and spatial consistency in calculations, this study processed all data as follows: For NDVI, the maximum value composition method was applied annually to obtain the research area' s NDVI, avoiding impacts from different vegetation growth stages (Xinjiang' s vegetation peaks in July-August [29]). Land surface temperature data underwent similar maximum value composition processing. For drought severity calculation using the Temperature-Vegetation Drought Index (TVDI) method, dry and wet edge equations were fitted using annual maximum value composite data. The resulting drought severity data were resampled to 10 km resolution using cubic convolution for spatial scale uniformity. Animal species richness data, originally literature-based, were converted to 10 km resolution raster format after vector grid processing. Although different richness value intervals had abrupt boundaries, these vertical and parallel boundaries were not further smoothed to maintain relationship accuracy and objectivity. Human disturbance index calculations referenced 建设用地当量 (construction land equivalent) conversion coefficients for different land cover types in Xinjiang , with results resampled to 10 km resolution using cubic convolution.

2.2 Assessment Methods

2.2.1 Assessment Indicator Selection This study' s regional ecological health assessment system primarily includes three components: Vigor (capacity to maintain self-health under stress, EV), Organization (self-regulation capacity, EO), and Resilience (self-recovery capacity, ER) [5]. For "Vigor," vegetation parameters are crucial indicators reflecting ecosystem energy or activity. Among numerous vegetation parameters, NDVI is most widely used, having close relationships with plant biomass, leaf area index, and vegetation coverage [21]; thus, NDVI was selected to characterize the "Vigor" indicator. For "Organization," biodiversity is directly linked to ecosystem structural complexity, and species richness is the most intuitive manifestation of biodiversity. Moreover, animals have broader activity ranges and stronger habitat dependence than plants; therefore, bird and mammal species richness was used to characterize the research area' s ecosystem complexity and diversity. For "Resilience," ecosystem resilience primarily refers to the capacity to restore original structure and function after external disturbance [5]. Research proves human activity impacts are crucial regulatory factors for regional ecological levels [22], and Xinjiang, as a key ecologically fragile area in western China, is more sensitive to external interference. Water sources are indispensable components for life on Earth, and regional drought severity directly affects biodiversity distribution and ecosystem balance. Therefore, this study selected human disturbance index and drought severity to characterize ecosystem disturbance degree and further construct the "Resilience" indicator.

To prevent information overlap among the four selected indicators from affecting assessment accuracy, multicollinearity diagnosis was applied. When the Variance Inflation Factor $VIF < 10$ (i.e., tolerance $TOL > 0.1$), selected indicators have no significant multicollinearity. Results showed good independence among the four indicators without information overlap .

2.2.2 "Vigor-Organization-Resilience" Model Construction (1) Vigor ($EV = NDVI$). After calculating NDVI using maximum value composition, data were resampled to 10 km resolution using cubic convolution for consistency with other indicators.

(2) Organization ($EO = ASR$). Xinjiang bird and mammal species distribution data were based on actual distribution ranges recorded in the "Xinjiang Bird List" and "Xinjiang Mammal (Mammalia) List." All species distribution information was digitized into vector grids, with species distribution quantities counted per grid to generate animal species richness (ASR) data.

(3) Resilience (ER). Resilience was constructed by combining drought severity and human disturbance index. First, drought severity was calculated using the Temperature-Vegetation Drought Index (TVDI) method, which reflects soil moisture conditions by establishing relationships between NDVI and land surface temperature [23]. The calculation formula is:

$$TVDI = \frac{TS - TS_{min}}{TS_{max} - TS_{min}}$$

where TS is the land surface temperature of any pixel; $TS_{min} = c + (d \times NDVI)$ represents the minimum land surface temperature (wet edge) for a given NDVI, with c and d as wet edge fitting equation coefficients; $TS_{max} = a + (b \times NDVI)$ represents the maximum land surface temperature (dry edge) for a given NDVI, with a and b as dry edge fitting equation coefficients. The fitted dry and wet edge equations are:

$$S_{max} = -50.35NDVI + 332.97, R^2 = 0.86$$
$$S_{min} = 26.25NDVI + 282.28, R^2 = 0.87$$

Drought severity (DI) is expressed as:

$$DI = 1 - TVDI_{max}$$

Human disturbance index calculation referenced the "construction land equivalent" concept proposed by Xu Yong et al. [24] to reflect human activity impact intensity on land surfaces. Different land use types were assigned conversion coefficients based on human activity intensity . The calculation formula is:

$$HDI = \frac{CLE}{S} \times 100$$

$$CLE = \sum_{i=1}^{n} SL_i \times CI_i$$

where HDI is the land surface human disturbance index; S is the total regional area; CLE is the construction land equivalent area; SL_i is the area of land use type i; CI_i is the construction land equivalent conversion coefficient for land use type i.

The final "Resilience" construction form is:

$$ER = \frac{1}{HDI + DI}$$

After calculating all single-factor indicators, the polar difference method was applied for standardization to unify dimensions. The comprehensive ecological health remote sensing assessment value for each evaluation unit is calculated as:

$$EH = EV \times EO \times ER$$

where EH represents the ecological health remote sensing assessment value; EV, EO, and ER represent ecological vigor, organization, and resilience, respectively. The indicator system is detailed in .

2.2.3 Driving Factor Analysis Method To further explore the influence strength of various factors on Xinjiang' s ecological health assessment results, this study employed Geodetector' s factor detector and interaction detector to examine relationships between evaluation indicators and targets. Geodetector is a statistical method for detecting spatial heterogeneity and revealing underlying driving forces [25], comprising four sub-modules: risk detector, factor detector, ecological detector, and interaction detector.

The factor detector' s physical meaning is expressed through q values (single indicator' s influence degree on ecological health) and p values (significance test level, i.e., explanatory power). Larger q values indicate greater influence of the single-factor indicator on comprehensive assessment results, while larger p values indicate weaker explanatory power. The interaction detector's physical meaning explains interactions between different single factors—whether different single-factor indicators independently affect assessment result Y, and if not, whether their interaction increases or decreases explanatory power for Y [26]. The factor detector' s q value expression is:

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

where $h = 1, 2, ...$; L is the stratification of dependent variable Y or single factor X; N_h and N are unit numbers in layer h and the entire region, respectively; σ_h^2 and σ^2 are variances of Y values in layer h and the entire region, respectively. Interaction detector interaction types are shown in .

3 Results and Analysis

3.1 Spatial Distribution Characteristics

3.1.1 Spatial Distribution of Single-Factor Indicators The spatial distribution of single-factor assessment indicators is shown in [Figure 2: see original paper]. Xinjiang' s NDVI distribution generally features high values in the west and northwest, low values in the east and southeast. High-value areas are mainly distributed on the northern and southern slopes of the Tianshan Mountains, the Altai Mountains, and oasis areas around the Taklamakan Desert. Low-value areas are primarily in the eastern and southeastern regions, including the Taklamakan, Kumtag, and Lop Nur deserts and Gobi areas with low vegetation coverage. Human-disturbed areas are concentrated in northern Tianshan, Altai Mountains, and the edges of the Taklamakan Desert, with the most significant impacts on the northern and southern slopes of the Tianshan Mountains and Altai Mountains. Eastern and southern regions, with large desert and Gobi areas, have minimal human activity due to difficult development conditions and low development value. High animal species richness areas are concentrated in northern Xinjiang, with hotspots in the Altai Mountains, western Tianshan, and western Junggar Mountains. Southern Xinjiang shows relatively low animal species richness, particularly in the Kunlun Mountains where high altitude imposes numerous survival limitations. Due to wildlife's strong mobility, especially birds' extensive activity ranges, animal species richness exhibits large-area diffusion patterns. Drought severity across Xinjiang is significantly higher in plains and basins than in mountainous areas, with relatively low severity only in the northern Altai, central Tianshan, and southern Kunlun Mountains, forming a belt-like distribution from west to east. Other regions generally show high drought severity.

3.1.2 Spatial Distribution of Ecological Health Assessment Results The spatial distribution of Xinjiang' s ecological health remote sensing assessment index is shown in [Figure 3: see original paper]. Xinjiang' s ecological health level shows significant north-south polarization, with obvious spatial heterogeneity distribution characteristics from north to south. Using the Tarim River-Yarkant River basin as the boundary, northern Xinjiang' s ecological health level is significantly higher than southern Xinjiang. Specifically, high-value areas are concentrated in the Altai Mountains, Tianshan Mountains, and oasis areas around the Tarim Basin; low-value areas are mainly distributed in the Tarim Basin, Junggar Basin, Turpan Basin, and Lop Nur region dominated by desert and Gobi terrain. The Kunlun Mountains in southern Xinjiang show the lowest ecological health assessment index in the entire region, with sharp differentiation from surrounding areas. The spatial distribution characteristics of Xinjiang' s comprehensive ecological health assessment results correspond well with three of the four single-factor indicators (excluding human disturbance). For positive indicators (NDVI and animal species richness), their high/low value distribution aligns with comprehensive assessment results, while the negative indicator (drought severity) shows opposite distribution characteristics. Although human disturbance is a negative indicator, its spatial distribution trend highly coincides with comprehensive assessment results, closely related to humans' "optimal selection" tendency when choosing activity areas—human activities preferentially occur in regions with higher ecological health levels. Due to the lack of smoothing treatment for species richness data, the final ecological health assessment index results contain abrupt boundaries, but this does not affect overall assessment results.

3.1.3 Driving Factor Analysis of Ecological Health Assessment Analysis results based on factor detector and interaction detector are shown in and . Regarding factor detection, all four single-factor indicators have p values < 0.01, indicating sufficient explanatory power for Xinjiang' s ecological health assessment results. Based on q values, the influence ranking of single-factor indicators is: NDVI (0.645) > human disturbance index (0.512) > animal species richness (0.414) > drought severity (0.116), demonstrating that vegetation parameters are the primary factor affecting Xinjiang' s ecological health level, while drought severity has relatively minimal influence. Regarding factor interactions, except for the nonlinear enhancement between animal species richness and drought severity, all other factor pairs show bivariate enhancement, indicating that single-factor indicators mainly have synergistic and nonlinear synergistic effects on ecological health levels, with no independent factors. This confirms that Xinjiang' s ecological health level results from interactions among multiple environmental factors rather than being dominated by any single factor.

3.2 Dynamic Changes and Driving Factors (2000-2018)

Xinjiang contains 98 county-level administrative units. Based on the proposed assessment method, county-level ecological health remote sensing assessment results were obtained. Using ArcGIS 10.2's zonal statistics and the Jenks natural breaks classification method, all counties were divided into five levels: excellent, good, moderate, poor, and bad, to analyze dynamic changes in Xinjiang' s ecological health from 2000 to 2018.

Annual assessment results show that Xinjiang' s ecological health level exhibits obvious spatial agglomeration characteristics. Areas with excellent/good ecological health are concentrated in the Yining region centered on Yining County and Gongliu County, and the Altay region centered on Habahe County and Burqin County. Areas with poor/bad ecological health are concentrated in Hotan, Kashgar, and Bayingolin Mongol Autonomous Prefecture. This spatial distribution pattern largely depends on Xinjiang's geographic environment. The Yining and Altay regions contain the western Tianshan Mountains and entire Altai Mountains, respectively, with high original ecological quality and rich biodiversity. Additionally, national plans to construct ecological priority zones in the Altai and Tianshan regions have further improved ecological health levels in these areas. Hotan, Kashgar, and Bayingolin Mongol Autonomous Prefecture contain large desert areas (Taklamakan, Kumtag, and Lop Nur), resulting in overall fragile ecological health in these regions.

From 2000 to 2018, Xinjiang' s overall ecological health level showed a gradually increasing trend, with 2010 being the lowest year and showing large gaps with previous assessment periods. The most significantly changed areas were Manas County, Hutubi County, and Changji City in Changji Hui Autonomous Prefecture, and Fuhai County and Fuyun County in Altay Prefecture and their surrounding counties. Counties in Hotan, Kashgar, and Bayingolin Mongol Autonomous Prefecture showed relatively small changes, consistently remaining at the "bad"level. The Yining region and northern Altay counties (Habahe, Burqin, and Altay City) maintained excellent/good levels throughout 2000–2018, with well-preserved ecological health status.

Mean values of single-factor indicators and ecological health assessment indices from 2000 to 2018 are shown in . Among the four single-factor indicators during this period, NDVI showed the most significant change with an overall increase of 0.11, while other indicators had relatively small change amplitudes not exceeding 0.05. The overall increase in Xinjiang' s ecological health assessment index corresponded to the NDVI change trend, indicating that vegetation parameter changes were the main reason for the overall improvement in Xinjiang' s ecological health level. Geodetector analysis results for 2000–2018 show that the influence degree of single-factor indicators on assessment results followed the order: NDVI > human disturbance index > animal species richness > drought severity, with pairwise interactions existing between indicators, mainly manifesting as linear synergy and nonlinear synergy.

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4 Conclusions

Based on the "Vigor-Organization-Resilience"ecological health assessment model, this study selected NDVI, drought severity, animal species richness, and human disturbance index to construct a comprehensive ecological health remote sensing assessment index dominated by quantitative remote sensing data. Compared with traditional ecological health assessment methods, this approach leverages remote sensing data advantages more fully, offering wide coverage, convenient data acquisition, shorter update cycles, and more refined evaluation results. Additionally, through the Geodetector model, we analyzed the intrinsic driving degree of various environmental factors on Xinjiang' s ecological health level and clarified interactions between different single-factor indicators. Comparison with existing Xinjiang ecological assessment results [30] shows high consistency in overall distribution trends. Overall, this study provides a useful reference for improving regional ecological health assessment methods.

Based on the analysis results, the following conclusions are drawn: (1) Xinjiang' s ecological health level shows obvious spatial differentiation and agglomeration characteristics, with the Tarim River-Yarkant River basin as the boundary—

northern Xinjiang' s ecological health level is significantly higher than southern Xinjiang. High-value areas are concentrated in the Yining and Altay regions, while low-value areas are concentrated in Hotan, Kashgar, and Bayingolin Mongol Autonomous Prefecture. (2) Geodetector analysis reveals that among the four single-factor indicators for assessing Xinjiang' s ecological health, their influence degree on comprehensive assessment results follows the order: NDVI > human disturbance index > animal species richness > drought severity, with interactions existing between all indicator pairs, mainly showing synergistic and nonlinear synergistic effects. (3) Affected by regional geographic environment, Xinjiang' s ecological health level from 2000 to 2018 showed the most significant changes in Manas County, Hutubi County, and Changji City of Changji Hui Autonomous Prefecture, and Fuhai County and Fuyun County of Altay Prefecture. (4) Overall, Xinjiang' s current ecological health situation remains concerning. As a typical ecologically fragile area in northwestern China, Xinjiang' s ecosystems are sensitive to external interference, difficult to recover after damage, and challenging for artificial intervention—characteristics that should receive sufficient attention from local governments.

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5 Discussion

This study still has several issues requiring further discussion: (1) Resilience indicator construction depends on land cover classification data, so its precision is affected by classification accuracy and types. (2) Animal species richness indicator construction relies on literature-recorded data with low update frequency, which may introduce errors in long-term temporal series analysis. (3) To unify spatial resolution among single-factor indicators, this study used cubic convolution to aggregate remote sensing data from 1 km resolution to 10 km resolution. While cubic convolution increases the number of neighboring pixels involved in calculation to achieve optimal resampling results and is a high-precision algorithm for remote sensing image processing, it still causes some degree of information loss.

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