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Assessment of Grassland Degradation Extent in Bayinbuluk Grassland, Tianshan Mountains, Xinjiang over the Past 35 Years (Postprint)

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Abstract

Numerous studies have utilized vegetation coverage and productivity indicators to assess grassland ecosystem degradation; however, individual evaluation indices are mutually independent, making comprehensive assessment of different grassland degradation degrees difficult. This study, taking the Bayinbuluke grassland in central Tianshan, Xinjiang as the research object, proposes a remote sensing assessment method for grassland degradation based on the coupling of normalized sub-indicators. Three sub-indicators—grassland vegetation coverage, average grass layer height, and total grass yield—were selected, and principal component analysis was employed to determine the weights of these sub-indicators. The Min-Max normalization method was introduced to process the data and construct a comprehensive evaluation index, the Grassland Degradation Index (GDI). Ultimately, the degradation degree of the Bayinbuluke grassland in Tianshan, Xinjiang from 1986 to 2021 was assessed through Landsat imagery inversion and reasonable classification of GDI change rates. The results indicate that: (1) GDIg exhibits the strongest correlation with NDVI. (2) In 2021, non-degraded areas of the Bayinbuluke grassland accounted for 60.51% of the total area; significant differences in grassland degradation degree were observed among different grassland types; spatially, degradation exhibited an intensifying trend from basin areas toward mountainous regions. (3) Through radiometric normalization methods, the GDIrs model can be applied to other years; the degradation degree of the Bayinbuluke grassland improved significantly from 2000 to 2009, while slight fluctuations occurred from 2009 to 2021. The research findings will provide data support and theoretical foundation for guiding the assessment of degradation degree and protecting the grassland ecosystem in Bayinbuluke.

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Full Text

Evaluation of Grassland Degradation Degree in the Bayinbuluk Grassland of the Tianshan Mountains, Xinjiang over the Past 35 Years

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Abstract

Numerous studies have evaluated grassland ecosystem degradation using vegetation coverage and productivity indicators. However, individual evaluation indices are independent of each other, making comprehensive assessment of different grassland degradation degrees challenging. This study proposes a remote sensing evaluation method for grassland degradation based on standardized sub-index coupling, using the Bayinbuluk grassland in the central Tianshan Mountains of Xinjiang as the research area. Three sub-indices were selected: grassland vegetation coverage, average grass layer height, and total grass yield. Principal component analysis was employed to determine the weights of these sub-indices, and the Min-Max standardization method was introduced to construct the Grassland Degradation Index (GDI). The degree of degradation in the Bayinbuluk grassland of the Tianshan Mountains from 1986 to 2021 was ultimately assessed through Landsat image inversion and reasonable classification of the GDI change rate. The results demonstrate that GDIg exhibits the best correlation with NDVI. In 2021, the proportion of undegraded area in Bayinbuluk grassland accounted for 60.51% of the total area, with significant differences in degradation degree among various grassland types. Spatially, degradation intensified from basins toward mountainous regions. The GDIrs model can be applied to other years through radiometric calibration. The degradation degree of Bayinbuluk grassland improved significantly from 2000 to 2009 and experienced slight fluctuations from 2009 to 2021. These findings provide robust data support and a theoretical foundation for guiding the evaluation of grassland degradation degree and protecting the grassland ecosystem in Bayinbuluk.

Keywords: grassland degradation; Landsat imagery; Min-Max standardization; Grassland Degradation Index; regression model; Bayinbuluk grassland

Introduction

Grassland constitutes a vital component of China's terrestrial ecosystems, covering 41.67% of the national land area, with various natural grasslands spanning approximately 3.9×10^{8} hm^2 and usable area of 2.8×10^{8} hm^2, primarily distributed in central and western regions. Xinjiang ranks among China's five major grassland animal husbandry provinces, with a gross natural grassland area of 5.6×10^{7} hm^2 and usable area of 4.8×10^{7} hm^2, ranking third nationally. Grassland area accounts for approximately 34.44% of Xinjiang's total area. However, influenced by natural and anthropogenic factors, 34.44% of China's natural grasslands are experiencing varying degrees of degradation. Compared with the 1980s, vegetation coverage in Bayinbuluk grassland has decreased from 89.4% to 30%~50%, with degraded area reaching 1.79×10^{6} hm^2, accounting for 19.61% of the total grassland area. China has implemented major ecological projects including the "Grazing Withdrawal and Grassland Restoration" program and grassland ecological compensation mechanisms to focus on restoration and management of degraded grasslands.

Given the vast expanse of grasslands, field surveys alone cannot meet large-scale evaluation requirements due to long monitoring cycles and heavy workloads. Consequently, remote sensing technology has been widely applied to grassland monitoring. Most grassland ecosystem studies have utilized indicators such as vegetation index, vegetation coverage, and vegetation productivity to evaluate grassland condition. For instance, Wu et al. used the CASA model to estimate the spatiotemporal distribution of net primary productivity in the Tianshan region of Xinjiang and analyzed its driving factors, revealing that net primary productivity in the Tianshan Mountains is spatially characterized by high values in the west and low values in the east, decreasing from north to south. Regarding grassland degradation or health assessment, Du et al. selected vegetation coverage, aboveground biomass, and edible forage ratio as indicators to construct a grassland degradation index, monitoring degradation in the middle and upper reaches of the Heihe River over 30 years. The results indicated a pattern of intensified degradation, local improvement, and overall deterioration. Zhao et al. constructed a PSR (Pressure-State-Response) model to build a health evaluation system for alpine pastoral ecosystems in Gannan Tibetan Autonomous Prefecture, demonstrating a clear negative trend in alpine grassland health. Lu et al. used the CVOR index to assess the health of Bayinbuluk alpine grassland ecosystems, finding that health status gradually recovered from "generally unhealthy" in 2005 to "healthy" in 2015, with degradation shifting from severe to moderate. Wu et al. explored a remote sensing-based method for reference coverage extraction and grassland degradation evaluation, addressing issues such as lack of reference systems and misapplication of remote sensing data in large-scale grassland degradation assessment. Li et al. selected coverage, total yield, and edible grass yield as indicators combined with Kriging interpolation in ArcGIS to analyze grassland degradation in Gansu Province, revealing degraded grassland area of 1.79×10^{6} hm^2, accounting for 69.65% of the province's total grassland area.

Grassland degradation degree is reflected in changes in vegetation coverage, aboveground biomass, edible grass ratio, grassland degradation indicator species, and soil organic matter content. Although numerous studies have analyzed different indicators, degradation characterization indices are complex and limited by various survey techniques. Individual indices remain independent of each other, and establishing a comprehensive evaluation index system represents a key challenge. Calculating weight values for sub-indices to achieve organic integration of different indicators is crucial for improving grassland monitoring accuracy. Therefore, this study selected vegetation coverage, total grass yield, and average grass layer height as three indicators, introduced the Min-Max standardization method to process sub-indices, and constructed the Grassland Degradation Index (GDI). Using 1980s grassland census data as an undegraded reference, we established a comprehensive evaluation index for grassland degradation through inversion of medium- to high-resolution Landsat imagery and calculated the change rate of GDI to characterize grassland degradation. This approach aims to establish a comprehensive remote sensing assessment index for grassland degradation, address the low efficiency of large-scale monitoring, and evaluate degradation in Bayinbuluk grassland since the 1980s.

1.1 Study Area Overview

Bayinbuluk grassland is located in the northwestern Tianshan Mountains south of Hejing County, Bayingolin Mongol Autonomous Prefecture, Xinjiang Uygur Autonomous Region. It extends 292 km from east to west and 108 km from north to south, comprising the Dayouerdusi Basin, Xiaoyouerdusi Basin, and the middle Tianshan Mountains, with elevations ranging from 1624 m to 4606 m. The climate is typical alpine, characterized by frequent rain and snow, long winters, and short summers, with an average annual temperature of -4.8°C and snow depth of 137 d and 45 cm. The grassland types are dominated by swamp meadows, alpine meadows, and alpine steppes. Dominant plant species include Kobresia capillifolia, Polygonum viviparum, Stipa purpurea, and Festuca kryloviana.

1.2 Data Sources and Processing

This study utilized remote sensing data and ground survey data relevant to the research. Grassland census data from the 1980s and 2021 ground survey data were obtained from the Bayinbuluk Grassland Ecosystem Research Station of the Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences. Selected remote sensing images were Landsat TM, Landsat ETM+, and Landsat OLI data with cloud cover controlled within approximately 10% and acquisition dates closest to field sampling times to maintain temporal consistency. Landsat data were obtained from the Geospatial Data Cloud (https://www.gscloud.cn). ENVI 5.3 software was used for radiometric calibration, atmospheric correction, and boundary cropping. Ground survey data were processed using ArcGIS 10.6 tools: Add Data to add coordinate points, and Extraction Values to Points to extract values. Digital elevation model (DEM) data were processed through mosaicking, boundary cropping, and format conversion using ArcGIS 10.6.

1.3 Model Construction

1.3.1 Regression Analysis Regression analysis is a statistical method that attempts to explain one or more dependent variables using independent variables. In nonlinear regression models, one type can be transformed into a linear model through variable transformation, known as curve regression or curve fitting, with the general form:

$$y_i = f(\theta, x_i) + e_i$$

where y_i is the dependent variable (explained variable), $f(\theta, x_i)$ is the parameter estimation equation, and e_i is the error function, which is minimized after fitting.

1.3.3 Principal Component Analysis Common methods for determining index weights include expert scoring, principal component analysis, and cluster analysis. However, expert scoring incorporates excessive subjective judgment. Principal Component Analysis (PCA) is a mathematical statistical method that transforms a set of correlated variables into a set of linearly uncorrelated variables through orthogonal transformation, concentrating most information in variables with higher contribution rates. Multiple studies have demonstrated that applying PCA to determine weights for grassland degradation sub-indices is scientifically sound and accurate.

1.3.4 Accuracy Assessment Model accuracy was measured using validation point RMSE. Root Mean Square Error (RMSE) measures the deviation between observed and true values, with greater sensitivity to outliers due to higher weighting of larger errors. The calculation formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(GDI_g - GDI_{rs})^2}$$

where RMSE represents root mean square error, n represents sample size, GDI_g represents actual calculated values from ground survey points, and GDI_{rs} represents remote sensing fitted values. Smaller RMSE values indicate better model accuracy when evaluating inversion model precision.

1.4 Index System

1.4.1 Vegetation Indices Normalized Difference Vegetation Index (NDVI) is the most widely used vegetation index, effectively reflecting vegetation status with simple calculation and extensive research foundation. Additionally, this study introduced other vegetation indices: Difference Vegetation Index (DVI), Ratio Vegetation Index (RVI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), and Three-band Gradient Difference Vegetation Index (TGDVI), with calculation formulas provided in Table 1.

Table 1 Vegetation indices and calculation formulas

Index Name	Calculation Formula
NDVI	$(R_{nir} - R_{red})/(R_{nir} + R_{red})$
DVI	$R_{nir} - R_{red}$
RVI	R_{nir}/R_{red}
EVI	$2.5 \times (R_{nir} - R_{red})/(R_{nir} + 6.0 \times R_{red} - 7.5 \times R_{blue} + 1)$
SAVI	$(1 + L) \times (R_{nir} - R_{red})/(R_{nir} + R_{red} + L)$, where $L = 0.5$
TGDVI	$\begin{cases} R_{nir} - R_{red} - \frac{\lambda_{red} - \lambda_{green}}{\lambda_{nir} - \lambda_{green}} \times (R_{red} - R_{green}), & \text{if } TGDVI > 0 \\ 0, & \text{if } TGDVI \leq 0 \end{cases}$

Note: R_{nir} represents near-infrared band; R_{red} represents red band; R_{blue} represents blue band; R_{green} represents green band; λ_{nir} represents near-infrared wavelength; λ_{red} represents red wavelength; λ_{green} represents green wavelength; L is soil adjustment coefficient.

1.4.2 Grassland Degradation Index (GDI) Grassland Degradation Index (GDI) is a common indicator for evaluating grassland degradation at large scales. This study's GDI is a weighted composite of vegetation coverage, total grass yield, and average grass layer height, representing a digital expression of grassland vegetation status with a value range of [0,1]. The calculation formula is:

$$GDI_g = \sum_{i=1}^{n} v_i \times w_i$$

where GDI_g represents ground survey point grassland degradation index, n represents number of indicators, v_i represents standardized value of indicator i, and w_i represents weight of indicator i.

1.4.3 Grassland Degradation Classification Standard Using 1980s grassland quadrat survey data as the undegraded reference standard and referencing the "Classification Index of Natural Grassland Degradation, Sandification, and Salification" (GB 19377-2003) and previous research, single-indicator classification thresholds for vegetation coverage reduction rate (undegraded <10%, light degradation 11%-20%, moderate degradation 21%-30%, severe degradation >30%), average grass layer height reduction rate (undegraded <10%, moderate degradation 11%-20%, severe degradation 21%-50%), and total grass yield reduction rate (undegraded <10%, moderate degradation 11%-20%, severe degradation 21%-50%) were weighted and averaged to obtain comprehensive GDI classification thresholds. The study area's grassland degradation was divided into four levels: undegraded, light degradation, moderate degradation, and severe degradation.

2 Results and Analysis

2.1 Calculation of Grassland Degradation Index in the 1980s

Reference baseline values for grassland degradation were determined based on 1980s grassland census data. Bayinbuluk grassland in the Xinjiang Tianshan Mountains comprises three grassland types: alpine meadow, alpine steppe, and swamp meadow, with 23 plant species (Table 2). Grassland types were finely classified by combining remote sensing imagery and field survey plots. The 1980s census data were used to calculate reference GDI values (Table 3). The maximum GDI value appeared in alpine meadow types with Kobresia capillifolia and forbs, indicating the best vegetation condition. The minimum GDI value appeared in alpine steppe types with Festuca kryloviana and Agropyron cristatum, indicating the poorest vegetation state. Overall, alpine meadow and swamp meadow vegetation conditions were better than alpine steppe.

Table 2 Main plant species

Grassland Type	Main Plant Species
Alpine Meadow	Carex oxyleuca, Caragana jubata, Kobresia capillifolia, Carex stenocarpa, Polygonum viviparum
Alpine Steppe	Carex turkestanica, Koeleria macrantha, Festuca kryloviana, Leymus ovatus, Agropyron cristatum, Iris loczyi, Stipa purpurea, Artemisia dracunculus, Secale sylvestre, Artemisia frigida, Stipa subsessiliflora
Swamp Meadow	Carex stenophylla, Hordeum bogdanii, Juncus compressus

Table 3 1980s grassland census dataset

Grassland Type	Plant Community Composition	GDIg
Alpine Meadow	Kobresia capillifolia, forbs	0.67

Grassland Type	Plant Community Composition	GDIg
Alpine Steppe	Festuca kryloviana, Agropyron cristatum	0.21
Swamp Meadow	Hordeum bogdanii, Juncus compressus	0.58

2.2 Calculation of Grassland Degradation Index in 2021

A total of 40 ground survey points were collected in 2021, including 20 alpine meadow sample points, 15 alpine steppe sample points, and 5 swamp meadow sample points. Vegetation coverage was obtained through visual estimation, with each sample plot containing 1 m × 1 m quadrats. Total grass yield was obtained through clipping method to measure fresh weight, and average grass layer height was calculated as the mean height of multiple species within the sample plot.

2.3 Remote Sensing Model for Grassland Degradation Index

Three variables (vegetation coverage, average grass layer height, and total grass yield) were standardized and processed through principal component analysis. Two principal components were extracted, and coefficients in the comprehensive scoring model were calculated through component matrix and variance contribution rates of sub-indices (Table 4). After normalization and averaging, the weights for vegetation coverage, average grass layer height, and total grass yield were 0.46, 0.24, and 0.30, respectively. The calculation formula is:

$$GDI_g = 0.46 \times C_i + 0.24 \times H_i + 0.30 \times Y_i$$

where GDI_g represents ground survey point grassland degradation index, C_i represents standardized vegetation coverage of community i, H_i represents standardized average grass layer height of community i, and Y_i represents standardized total grass yield of community i.

Table 4 2021 modeling plot dataset

Grassland Type	Sample Points	GDIg Range
Alpine Meadow	20	0.31-0.68
Alpine Steppe	15	0.18-0.45
Swamp Meadow	5	0.42-0.61

Among seven vegetation indices, TGDVI showed the highest correlation with GDIg, with a Pearson correlation coefficient of 0.682 (sig<0.01). Among five regression models (linear, exponential, logarithmic, quadratic, power), the linear function model showed the best fit ($R^2 = 0.553$). The GDIrs calculation equation is:

$$GDI_{rs} = 0.830 \times NDVI_{2021} + 0.086 \quad (R^2 = 0.553, RMSE = 0.145)$$

where GDI_{rs} represents remote sensing fitted value of grassland degradation index and $NDVI_{2021}$ represents NDVI value in 2021.

Model accuracy was verified using the remaining 20 sample points. RMSE was 0.145, indicating high inversion model accuracy suitable for grassland degradation assessment.

2.4 Current Degradation Status of Bayinbuluk Grassland

In 2021, Bayinbuluk grassland degradation classification was dominated by undegraded status, with undegraded area accounting for 60.51% of total area and degraded area accounting for 39.49%. Severe, moderate, and light degradation areas accounted for 14.71%, 12.55%, and 12.23% of total area, respectively.

Among the three grassland types, alpine meadow had the largest area but also the most severe degradation. Severe degradation area in alpine meadow accounted for 21.19% of its total area, greater than alpine steppe's 14.39%. Undegraded area in alpine steppe accounted for 91.54% of its total area, greater than alpine meadow's 49.06% and swamp meadow's 41.61%. Alpine meadow degradation was more severe than alpine steppe and swamp meadow, while alpine steppe showed the lightest degradation.

Due to the special intermontane basin topography of Bayinbuluk grassland with large elevation differences, grassland is mainly distributed within three elevation gradients: 1624-2347 m, 2347-2663 m, and 2663-2980 m (Figure 2). In the 1624-2347 m and 2980-3322 m elevation gradients, severe degradation grassland accounted for 63.03% and 57.32% of grassland area within each gradient, respectively, indicating serious degradation in mountainous and plain areas. In the 2347-2663 m and 2663-2980 m elevation gradients, undegraded grassland accounted for 73.40% and 75.03% of grassland area within each gradient, respectively, indicating lighter degradation in high-altitude basin areas.

Figure 2 [Figure 2: see original paper] Degradation area map of different altitude gradients

2.5 Application of GDI Model for Grassland Degradation Assessment

The GDIrs model can be applied to assess grassland degradation in earlier years. Due to lack of historical ground survey data, direct application to other years requires radiometric calibration of GDIrs values. NDVI values from 20 sample points were extracted, and regression analysis was performed to obtain radiometric calibration models:

$$NDVI_{2021} = 0.901 \times NDVI_{2000} - 0.014 \quad (R^2 = 0.682, RMSE = 0.104)$$

$$NDVI_{2021} = 0.922 \times NDVI_{2009} + 0.070 \quad (R^2 = 0.680, RMSE = 0.104)$$

Band calculations were performed on NDVI values from 2000 and 2009 using these formulas, and results were substituted into equation (2) to calculate GDIrs values. Degradation degree was determined through classification of GDIrs change rate, evaluating degradation characteristics over the past 35 years.

Table 5 Index weight coefficients

Index	1980s Model Coefficient	2021 Model Coefficient	1980s Weight	2021 Weight	Average Weight
Vegetation Coverage	0.48	0.44	0.47	0.45	0.46
Grass Layer Height	0.22	0.26	0.23	0.25	0.24
Total Grass Yield	0.30	0.30	0.30	0.30	0.30

Table 6 Grassland degradation in 2000, 2009, and 2021

Degradation Level	2000 Area (%)	2009 Area (%)	2021 Area (%)
Undegraded	38.69	64.51	60.51
Light Degradation	25.82	12.23	12.23
Moderate Degradation	21.19	12.55	12.55
Severe Degradation	14.30	10.71	14.71

The results clearly show (Table 6) that since 2000, Bayinbuluk grassland degradation has improved. From 2000 to 2009, the proportions of severe, moderate, and light degradation areas decreased by 5.58%, 8.64%, and 13.59%, respectively, while undegraded area increased by 25.82%, indicating significant improvement. From 2009 to 2021, changes were minimal: severe and light degradation areas increased by 4.00% and 0.27%, respectively, while moderate degradation and undegraded areas decreased by 0.45% and 4.00%, respectively, showing slight fluctuations but maintaining undegraded area larger than degraded area.

3 Discussion

3.1 Error Analysis of Grassland Degradation Remote Sensing Assessment

The GDIrs model fitting degree of $R^2 = 0.553$ is moderate. Errors mainly arise from three aspects: (1) Bayinbuluk remote sensing imagery has large cloud cover, and images closest to ground sampling time were selected, but temporal heterogeneity still exists between data; (2) Sample quadrats of 1 m × 1 m are too small, and spatial heterogeneity can cause assessment errors; (3) Too few sample points may lead to overfitting and assessment errors.

Regarding the baseline reference system for grassland degradation, using maximum values of evaluation indicators as ideal plot parameters is an important approach but may result in underestimated degradation. Some scholars have selected starting years as background values, but degradation status in starting years is difficult to accurately determine. To better approximate actual undegraded conditions, this study assigned reference values based on 1980s grassland type categories, controlling degradation background values within an appropriate range.

3.2 Applicability of GDI Model for Grassland Degradation Assessment

Current remote sensing applications in grassland ecosystems suffer from low quantitative inversion accuracy. The GDIrs model constructed in this study addresses the scientific challenge of quantitative grassland degradation assessment. Its application to earlier years fills gaps in continuous time series studies caused by missing historical data, offering greater temporal advantages and providing a data foundation for guiding grassland ecosystem protection with higher universality for long-term degradation assessment. By introducing weights for multi-index integration, the model improves remote sensing assessment efficiency for grassland degradation, meeting application needs for grassland ecosystem management.

Compared with other scholars' grassland degradation remote sensing assessments, this study uses 1980s grassland background values as reference and characterizes degradation degree through GDIrs change rate. However, several issues require deeper consideration: (1) Radiometric calibration for earlier years may introduce errors from non-uniform atmospheric backgrounds. Classifying different precipitation years and comparing grassland changes under the same precipitation background could improve model accuracy. (2) Bayinbuluk grassland has high elevation, making it difficult to find cloud-free multi-temporal imagery for long-term studies. This study ensured approximately 10-year intervals but requires further validation of model temporal stability.

3.3 Influencing Factors of Grassland Degradation

Vegetation growth is closely related to climatic factors. Studies show that from 1961 to 2015, temperature in the Kaidu River Basin of the Tianshan Mountains increased at a rate of $0.167°C \cdot (10a)^{-1}$, while precipitation increased at $0.167°C \cdot (10a)^{-1}$. Liu et al. found that after the mid-1980s, Bayinbuluk experienced warming and increased precipitation, resulting in overall "warm-humid" climate conditions during the study period. Research indicates that Xinjiang grassland net primary productivity is positively correlated with precipitation and temperature. The warming and humidification trends in Bayinbuluk have contributed to vegetation recovery, consistent with findings that Xinjiang grassland NPP showed a fluctuating upward trend from 2000 to 2016. However, the slight fluctuation in degradation degree from 2009 to 2021 aligns with research showing that although Xinjiang's climate showed warm-humid configuration after the 1980s, the "warm-humidification" trend slowed after 2009, leading to non-linear vegetation increase.

Human activities have complex and variable impacts on grasslands. Cao et al. found through principal component analysis that human activities were the dominant factor affecting vegetation change in the Cele oasis-desert transition zone. Besides livestock increase causing grassland degradation, current grassland protection measures include enclosure for rest, seasonal grazing, rotational grazing, and forage reseeding under the "Grazing Withdrawal and Grassland Restoration" program. The specific contribution of human activities to grassland degradation improvement requires further scientific analysis.

4 Conclusions

This study constructed a GDIrs model to evaluate grassland degradation in Bayinbuluk grassland over 35 years, improving remote sensing monitoring efficiency. The main conclusions are:

1. The comprehensive index is a weighted average of vegetation coverage, average grass layer height, and total grass yield. Introducing this index improves remote sensing evaluation efficiency for grassland degradation.

2. TGDVI showed the highest correlation with GDIg ($R^2 = 0.553$), making the model suitable for remote sensing assessment of Bayinbuluk grassland degradation.

3. In 2021, undegraded area accounted for 60.51% of total area. Alpine meadow showed the most severe degradation, while alpine steppe showed the lightest degradation. Spatial distribution exhibited intensifying degradation from basins to mountains.

4. Using radiometric calibration to assess earlier years extends the temporal scale. Results show significant improvement from 2000 to 2009 and slight fluctuations from 2009 to 2021.

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