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Integrated Remote Sensing Evaluation of Grassland Degradation Using Multi-Criteria GDCI in Ili Prefecture, Xinjiang, China

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Abstract

As an important ecological barrier and animal husbandry resource base in arid and semi-arid areas, grassland degradation directly affects regional ecological security and sustainable development. Ili Prefecture is located in the western part of Xinjiang, China, and is a typical grassland resource-rich area. However, in recent years, driven by climate change and human activities, grassland degradation has become increasingly serious. In view of the lack of comprehensive evaluation indicators and the inconsistency of grassland evaluation grade standards in remote sensing monitoring of grassland resource degradation, this study takes the current situation of grassland degradation in Ili Prefecture in the past 20 years as the research object and constructs a comprehensive evaluation index system covering three criteria layers of vegetation characteristics, environmental characteristics, and utilization characteristics. Net primary productivity (NPP), vegetation coverage, temperature, precipitation, soil erosion modulus, and grazing intensity were selected as multi-source indicators. Combined with data sources such as remote sensing inversion, sample survey, meteorological data, and farmer survey, the factor weight coefficient was determined by analytic hierarchy process. The Grassland Degeneration Comprehensive Index (GDCI) model was constructed to carry out remote sensing monitoring and evaluation of grassland degradation in Yili Prefecture. With reference to the classification threshold of the national standard for grassland degradation, the GDCI grassland degradation evaluation grade threshold (GDCI reduction rate) was determined by the method of weighted average of coefficients: non-degradation (0–10%), mild degradation (10–20%), moderate degradation (20–37.66%) and severe degradation (more than 37.66%). According to the results, between 2000 and 2022, non-degraded grasslands in Ili Prefecture covered an area of 27,200 km^2, representing 90.19% of the total grassland area. Slight, moderate, and severe degradation accounted for 4.34%, 3.33%, and 2.15%, respectively. Moderately and severely degraded areas are primarily distributed in agro-pastoral transition zones and economically developed urban regions, respectively. The results revealed the spatial and temporal distribution characteristics of grassland degradation in Yili Prefecture and provided data basis and technical support for regional grassland resource management, degradation prevention and control and ecological restoration.

Keywords: arid and semi-arid areas; fractional vegetation coverage; net primary productivity; livestock quantities; analytic hierarchy process; grade threshold

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Academic Editor: Jane Southworth

Received: 23 June 2025
Revised: 28 July 2025
Accepted: 1 August 2025
Published: 4 August 2025

Citation: Xing, L.; Jin, D.; Shen, C.; Zhu, M.; Wu, J. Integrated Remote Sensing Evaluation of Grassland Degradation Using Multi-Criteria GDCI in Ili Prefecture, Xinjiang, China. *Land* **2025**, *14*, 1592. https://doi.org/10.3390/land14081592

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1. Introduction

Grassland ecosystems play an irreplaceable role in maintaining biodiversity, regulating climate, conserving water resources, and supporting the development of animal husbandry [1,2]. The Ili Kazakh Autonomous Prefecture (hereinafter referred to as "Ili Prefecture"), located in western Xinjiang, is an important area of natural grassland resources and a core region for animal husbandry in China [3,4]. In recent years, influenced by a combination of climate change, population growth, and intensified human activities, grassland degradation has occurred in some areas of Ili Prefecture, manifested in declining vegetation cover, reduced biomass, and soil degradation, among other ecological issues [5,6]. Conducting systematic and scientific remote sensing monitoring and comprehensive assessment of grassland degradation in Ili Prefecture is of great practical significance and strategic value, as it not only helps to understand the trends of regional ecological changes, but also supports the sustainable use of grassland resources and the implementation of ecological protection and restoration projects [7–12].

Currently, field surveys are the primary method for monitoring grassland degradation [13–15]. Although field survey data are highly accurate, they are time-consuming, labor-intensive, and limited in spatial coverage, with long monitoring cycles and low efficiency [13,14]. In contrast, remote sensing technology offers advantages such as short update cycles, rapid data acquisition, and wide observation coverage, providing strong technical support for large-scale, rapid, and accurate assessment of grassland conditions [16–19]. Remote sensing-based assessment methods mainly include vegetation index analysis, net primary productivity (NPP) models, geostatistical analysis, and multi-indicator comprehensive evaluation. However, these methods still face a series of challenges: on one hand, some studies do not fully consider the complexity of grassland ecosystems, with overly simplistic indicator selection that fails to reflect the multidimensional nature of degradation [20–22]. On the other hand, technical bottlenecks remain in the integration of multi-source data and scale consistency processing, which affect the spatial and temporal accuracy and scientific validity of the assessment results [23,24]. In addition, the quantification of anthropogenic disturbance factors, such as grazing intensity and land use change, still lacks standardized methods and sufficient data support [25].

In grassland degradation monitoring and assessment, the determination of degradation thresholds is key to achieving quantitative identification and classification [26,27]. However, there is currently no unified standard for threshold definition. Different studies often set critical indicator values based on empirical methods, statistical distribution approaches, or expert judgment, leading to subjectivity and poor regional applicability in the classification of degradation levels [26]. In recent years, with the introduction of new methods such as machine learning [28], geographically weighted regression [29], and multi-temporal remote sensing analysis [23], threshold determination has gradually moved toward greater quantification and objectivity. Nonetheless, issues such as adaptability across different grassland ecological types, model generalization capability, and interpretability still require further improvement [23,28,30].

To address the above challenges, this study takes Ili Prefecture as the research area and integrates multi-temporal remote sensing imagery (2000–2020), meteorological observations, field surveys, and socio-economic data to construct a comprehensive indicator system encompassing vegetation conditions, environmental factors, and human disturbances. Based on this, remote sensing-based monitoring and comprehensive assessment of grassland degradation are conducted. The study aims to address three key scientific issues:

(1) How to construct a regionally adapted, multi-dimensional indicator system that reflects both the state and the drivers of degradation;

(2) How to identify and quantify the dominant natural and anthropogenic drivers of grassland degradation;
(3) How to establish appropriate degradation classification thresholds based on multi-source data and spatial variability.

The outcomes are expected to provide theoretical support and technical guidance for the scientific assessment, prevention, and ecological restoration of grassland degradation in arid and semi-arid regions.

2. Materials

2.1. Study Area

The Ili Kazakh Autonomous Prefecture is located in the western part of the Xinjiang Uygur Autonomous Region, China [31], with geographical coordinates approximately between 42°11′–44°59′ N and 80°09′–84°56′ E (Figure 1). It lies between the western section of the Tianshan Mountains and the Ili River Valley and represents a typical mountain–valley transitional zone in China [32,33]. The prefecture covers a total area of about 269,000 square kilometers, with terrain that descends from west to east. It features diverse landforms, including mountains, hills, valleys, and plains, which together create a rich variety of ecological environments [34]. Ili Prefecture has a typical temperate continental climate, influenced by moisture transported from the Atlantic Ocean [24]. It exhibits pronounced monsoonal characteristics and distinct vertical climatic zonation. The annual average temperature ranges between 5 °C and 10 °C, while annual precipitation decreases from west to east, ranging from approximately 200 to 800 mm, making it one of the regions in Xinjiang with the most abundant precipitation and favorable ecological conditions [35]. The Ili River Basin is rich in water resources, and the main soil types include meadow soil, chestnut-calcareous soil, and gray-calcic soil, providing excellent conditions for natural grassland growth [36]. Grasslands are one of the main land use and ecosystem types in Ili Prefecture, widely distributed across mountainous areas, river valleys, and hilly regions. They cover more than 60% of the total land area, with temperate desert steppe, mountain meadow steppe, and alpine steppe being the most representative types [37].

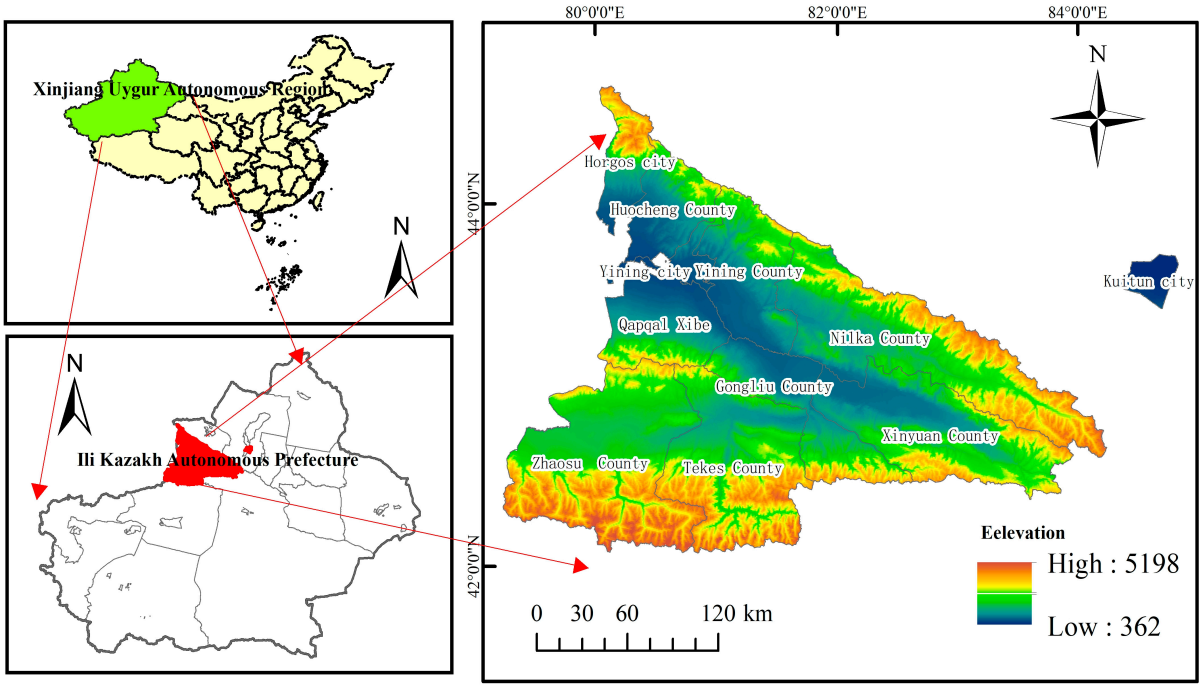


Figure 1. Location of study area.

2.2. Data Sources and Procession

The Moderate Resolution Imaging Spectroradiometer (MODIS) is mounted on both the Terra and Aqua satellites. This study use MODIS land products, specifically the surface reflectance products MOD09Q1 and MOD09A1 [38]. MOD09Q1 provides 8-day composite surface reflectance data at a 250 m spatial resolution and includes MODIS Bands 1 and 2 (Band 1: 630–670 nm; Band 2: 841–876 nm). MOD09A1 offers 8-day composite reflectance data at a 500 m resolution and includes Bands 3 to 7 (Band 3: 459–479 nm; Band 4: 545–600 nm; Band 5: 1230–1250 nm; Band 6: 1628–1652 nm; Band 7: 2105–2155 nm). To ensure consistency in spatial resolution, the MOD09Q1 data were resampled to 500 m. In this study, MODIS data from the years 2000 and 2022 were selected. The data underwent preprocessing steps including mosaicking, reprojection, format conversion, and boundary clipping. These data were primarily used for vegetation cover estimation.

The land cover classification data used in this study is based on the MODIS MCD12Q data product [39]. This product adopts the IGBP classification system, which divides the Earth's surface into 17 categories [40]: water bodies, evergreen needleleaf forests, evergreen broadleaf forests, deciduous needleleaf forests, deciduous broadleaf forests, mixed forests, closed shrublands, open shrublands, woody savannas, savannas, grasslands, permanent wetlands, croplands, urban and built-up lands, cropland/natural vegetation mosaics, permanent snow and ice, and barren or sparsely vegetated lands. The spatial resolution of the product is 500 m. After reprojection and clipping of the data, the categories of woody savannas, savannas, and grasslands were selected as the study scope of grasslands in Ili Prefecture.

Net Primary Productivity (NPP) refers to the amount of organic matter accumulated by producers per unit of time and space after subtracting the organic matter consumed by respiration [41]. It is one of the key indicators for reflecting grassland vegetation growth and assessing the health of grassland ecosystems. Specifically, this study uses the MOD17A3H product from MODIS for the years 2000 and 2022 [42], which provides annual NPP data at a spatial resolution of 500 m. The above-mentioned MODIS data is freely provided by NASA's Earth Observing System (EOS) Data Center (https://lpdaac.usgs.gov/, accessed on 5 November 2024).

Precipitation and temperature data are derived from the ERA5 global climate reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) via its official website (http://www.ecmwf.int/, accessed on 8 December 2024) [43,44]. The study selected the annual average temperature at 2 m above the surface, total annual precipitation, and soil moisture content at a depth of 0–7 cm.

SRTM (Shuttle Radar Topography Mission) is a space shuttle radar topographic mapping mission carried out aboard the U.S.-launched Space Shuttle Endeavor [45]. The mission lasted from 11 February to 22 February 2000, collecting data over approximately 11 days. It covered more than 80% of the Earth's land surface between 60° N and 60° S, acquiring over 119 million square kilometers of three-dimensional radar data. The data underwent processing steps including registration, interferogram generation, flat-earth removal, phase unwrapping, baseline determination, and ground height calculation, ultimately producing the SRTM DEM data. This study uses the SRTM3 version of the SRTM DEM [45,46], which is provided by the CGIAR Consortium for Spatial Information (CGIAR-CSI) at http://srtm.csi.cgiar.org/, accessed on 12 December 2024. Based on this DEM data, topographic factors such as slope length and slope gradient were derived.

The data on livestock development from 2000 to 2022 for various counties and cities in the Ili Kazakh Autonomous Prefecture of Xinjiang is sourced from the Xinjiang Statistical Yearbook. It includes the number of major livestock species in the administrative regions under Ili Prefecture (such as Yining City, Kuitun City, Huocheng County, Qapqal Xibe

Autonomous County, Tekes County, Nileke County, etc.). The year-end inventory numbers of cattle, sheep, horses, donkeys, and other livestock are used as characteristic indicators of grassland utilization.

3. Methodology

3.1. Indicator System

To scientifically assess the status of grassland degradation in the Ili Kazakh Autonomous Prefecture, it is particularly important to establish a comprehensive evaluation indicator system tailored to the region's characteristics. This system (Table 1) is based on a triadic driving mechanism of "natural conditions–vegetation response–human disturbance" and is divided into three primary criteria layers: vegetation characteristics, environmental characteristics, and utilization characteristics. These are further refined into sub-criteria layers such as community-scale indicators, climate and soil conditions, and grazing status. The system fully takes into account the dynamic changes in the structure and function of grassland ecosystems, while also addressing the coupling between ecological processes and human disturbances. It demonstrates strong regional adaptability and practical applicability.

Table 1. Evaluation index system for grassland degradation in Ili Prefecture.

Criterion Level	Sub-Criterion Level	Indicator Level	Data Sources
Vegetation Characteristics	Community Scale	Net Primary Productivity (NPP)	MOD17A3H
		Fractional vegetation cover (FVC)	MOD09Q1 and MOD09A1
Environmental Characteristics	Climatic Conditions	Annual Mean Temperature	ERA5 global climate reanalysis dataset
		Total Precipitation	ERA5 global climate reanalysis dataset
	Soil Conditions	Soil Erosion Modulus (SEM)	SMCD12Q, MOD09Q1, MOD09A1, SRTM DEM, ERA5 global climate reanalysis dataset and so on
Utilization Characteristics	Grazing Conditions	Livestock Quantities	Xinjiang Statistical Yearbook

3.2. Fractional Vegetation Cover

Fractional vegetation coverage is a direct indicator for assessing whether grassland resources are undergoing degradation [47]. Due to the significant linear correlation between vegetation coverage and the Normalized Difference Vegetation Index (NDVI), the pixel dichotomy model is used to approximate the estimation of vegetation coverage (F) in Ili Prefecture. The specific calculation formula is shown in Equation (1) [48]:

$$F = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100\% \quad (1)$$

In the equation, F represents fractional vegetation coverage, $NDVI_{min}$ is the minimum NDVI value in the study area (corresponding to bare soil), and $NDVI_{max}$ is the maximum NDVI value or the NDVI of pure vegetation pixels in the study area. To improve the accuracy of coverage estimation, grassland types are used as zoning criteria for calculating F. Finally, the estimation results are validated using ground truth points corresponding to the same time period.

3.3. Soil Erosion Modulus

Soil erosion modulus can effectively reflect the capacity of grasslands to conserve soil and water, and it is also an important indicator of the state of grassland ecosystems. In this study, a modified version of the Revised Universal Soil Loss Equation (RUSLE) is used to calculate the soil erosion modulus of grasslands in Ili Prefecture [49], as shown in Equation (2) [50]:

$$A = R \cdot K \cdot LS \cdot C \cdot P \tag{2}$$

In this equation, A represents the average annual soil erosion modulus, indicating the average amount of soil loss per unit area over a given time and space scale ($t/(km^2 \cdot a)$); R is the rainfall erosivity factor ($MJ \cdot mm/(km^2 \cdot h \cdot a)$); K is the soil erodibility factor ($t \cdot hm^2 \cdot h/(km^2 \cdot MJ \cdot mm)$); L and S are the slope length and slope steepness factors, respectively; C is the cover and management factor; P is the support practice factor. A p value of 0 indicates no erosion, while a value of 1 means no soil conservation measures were taken. In this study, empirical values are assigned based on land cover types: forest = 0.9, water bodies = 0, wetlands = 0, shrubs = 0.9, snow and glaciers = 0, cultivated land = 0.5, grassland = 0.9, and bare land/urban built-up areas = 1.

Rainfall erosivity (R) is a potential driver of soil erosion. Based on the method proposed by Zhang et al. [51], rainfall erosivity is determined using annual precipitation, with the specific formula shown in Equation (3):

$$R_\alpha = a P_\alpha^\beta \tag{3}$$

In this formula, R_α is the rainfall erosivity in year α, and P_α is the annual precipitation in year α (mm). The model parameters α and β are set to 0.0534 and 1.6548, respectively.

The soil erodibility factor K is used to reflect the sensitivity of soil to erosion. It is estimated using the EPIC model proposed by Williams et al. [52]. The specific Equation (4) is as follows:

$$\begin{aligned} K = 0.1317 \times \{0.2 \ & +0.3exp[-0.0256SAN(1 \\ & -SIL/100)]\} \times (SIL/(CLA+SIL))^{0.3} \times [1-0.25C/(C \\ & +exp(3.72-2.95C))] \times [1-(0.7SN)/(SN \\ & +exp(-5.51+22.9SN))] \end{aligned} \tag{4}$$

In the formula, SAN represents the percentage of sand (%), SIL is the percentage of silt (%), CLA is the percentage of clay (%), C is the organic carbon content in the soil (%), and SN is calculated as $1 - \mathrm{SAN}/100$.

The LS factor is calculated using the algorithm specified in the LS factor component of the Chinese Soil Loss Equation (CSLE), as prescribed by China's Water Resources Census. The calculation is shown in Equations (5) and (7):

$$L = (\lambda/22.1)^m \tag{5}$$

$$m = \begin{cases} 0.2 & \theta \le 1^\circ \\ 0.3 & 1^\circ < \theta \le 3^\circ \\ 0.4 & 3^\circ < \theta \le 5^\circ \\ 0.5 & \theta > 5^\circ \end{cases} \tag{6}$$

$$S = \begin{cases} 10.8sin\theta + 0.03 & \theta < 5^\circ \\ 16.8sin\theta - 0.50 & 5^\circ < \theta < 10^\circ \\ 21.9sin\theta - 0.96 & \theta \ge 10^\circ \end{cases} \tag{7}$$

In the formulas, λ represents slope length (m); m is the slope length exponent; θ denotes slope angle (°).

The cover and management factor C reflects the influence of land use type and vegetation cover on soil erosion. It is calculated based on the relationship between C and vegetation cover F, as proposed by Cai et al. [53], shown in Equation (8).

$$C = \begin{cases} 1 & F = 0 \\ 0.6508 - 0.3436 \times lgF & 0 < F < 78.3\% \\ 0 & F \geq 78.3\% \end{cases} \quad (8)$$

3.4. Degradation Comprehensive Index Model

To comprehensively reflect the overall status of grassland degradation in the Ili Prefecture, a Grassland Degradation Comprehensive Index (GDCI) model was developed. This model is based on key factors such as vegetation cover, net primary productivity (NPP), annual average temperature, total precipitation, soil erosion modulus (SEM), and livestock numbers. Before constructing the model, all indicators were normalized using the min-max standardization method to eliminate the influence of different units of measurement. Among these indicators, the soil erosion modulus, which reflects the degree of soil degradation, is treated as a reverse indicator in the model since higher values indicate more severe degradation. Therefore, its standardized value is inverted (i.e., 1 − SEM) to ensure consistency in indicator direction—where larger values represent lower levels of degradation. For weight determination, the Analytic Hierarchy Process (AHP) was used to construct a judgment matrix and assign reasonable weights based on the relative importance of each factor in the grassland degradation process. Finally, the GDCI model Equation (9) is constructed by performing a weighted summation of the standardized indicator values, enabling a quantitative assessment of the overall grassland degradation status.

$$\begin{aligned} GDCI = {} & 0.2742 \times NPP + 0.165 \times FVC + 0.1076 \times (1 - TEM) \\ & + 0.1052 \times PRE + 0.1315 \times (1 - SEM) \; + \; 0.2168 \times (1 - LIV) \end{aligned} \quad (9)$$

3.5. Determination of Grassland Degradation Grade Thresholds

In our study, the Grassland Degradation Grade Thresholds refer to the classification boundaries used to divide grassland into different degradation levels (e.g., non-degraded, slightly degraded, moderately degraded, severely degraded) based on the values of the integrated index (GDCI). According to the Classification Index for Degradation, Desertification, and Salinization of Natural Grasslands (GB19737-2003) (2003) [54], the single-factor criteria for net primary productivity (NPP), fractional vegetation cover (FVC), soil erosion modulus and so on are listed in Table 2. These criteria are used as the initial threshold standards for individual degradation indicators and serve as a reference and supplement to the degradation thresholds of the GDCI model. Since the thresholds for non-degraded and slightly degraded levels are the same across the three single indicators, the GDCI thresholds for these two levels are set to match those of the individual indicators. However, because the upper threshold for the moderately degraded level varies among the three indicators, a weighted average is calculated using the corresponding GDCI factor weights to determine the final threshold. The GDCI threshold values for each degradation level are then used to assess the grassland degradation status in Ili Prefecture (Table 3).

Table 2. Evaluation criteria for single indicators of grassland degradation in Ili Prefecture.

Primary Indicator	Secondary Indicator	Non-Degraded	Slightly Degraded	Moderately Degraded	Severely Degraded
Vegetation Characteristics	Reduction rate of relative percentage of Net Primary Productivity (NPP) (%)	0–10	11–20	21–50	>50
	Reduction rate of relative percentage of fractional vegetation cover (FVC) (%)	0–10	11–20	21–30	>30
Environmental Characteristics	Increase rate of relative percentage of annual average temperature (%)	0–10	11–20	21–30	>30
	Reduction rate of relative percentage of total precipitation (%)	0–10	11–20	21–30	>30
	Increase rate of soil erosion modulus (SEM) (%)	0–10	11–20	21–30	>30
Utilization Characteristics	Increase rate of relative percentage of livestock quantities (%)	0–10	11–20	21–40	>40

Table 3. Thresholds for grassland degradation levels in Ili Prefecture.

Grassland Degradation Level	GDCI Change Rate (X)
Severely Degraded	>37.66%
Moderately Degraded	20% < X ≤ 37.66%
Slightly Degraded	10% < X ≤ 20%
Non-Degraded	≤10%

4. Results

4.1. Spatial Distribution of Grassland Status, Environmental Conditions and Utilization Intensity

Net Primary Productivity (NPP) and fractional vegetation cover (FVC) were used to reflect the status of grassland vegetation. From 2000 to 2022, areas where NPP decreased by less than 10% accounted for 92.0% (Figure 2a) of the total grassland area, and areas where FVC decreased by less than 10% accounted for 86.9% (Figure 2b).

Environmental characteristics, including annual mean temperature, total precipitation, and soil erosion modulus, were used to reflect the environmental conditions of grassland. From 2000 to 2022, there was almost no change in the annual mean temperature across the entire study area, with a growth rate of less than 10% (Figure 2c). However, there was significant spatial variation in precipitation. Areas where total precipitation decreased by more than 30% accounted for the largest proportion—56.8% of the total area—mainly distributed in Tekes County, Gongliu County, and Xinyuan County. Areas with a 20–30% decrease in total precipitation accounted for 35.8%, mainly distributed in Horgos City, Huocheng County, and Yining City. Areas with a decrease of less than 20% accounted for 7.4%, mainly located in Yining City (Figure 2d). Areas where the soil erosion modulus decreased by less than 10% accounted for 96.1% of the total grassland area (Figure 2e).

Livestock quantities were used to reflect utilization characteristics. From 2000 to 2022, livestock numbers increased in every county (Figure 2f). Horgos City, Yining City, and Nika County saw increases of over 40%; Gongliu County, Xinyuan County, and Tekes County saw increases of 20–40%; Huocheng County, Yining County, and Zhaosu County experienced increases of 10–20%. Only Qapqal Xibe Autonomous County had an increase of less than 10%.

4.2. Grassland Degradation Assessment Results and Accuracy Evaluation

To assess the accuracy of the current grassland degradation classification results, a field survey was conducted in 2022 across the grasslands of Ili Prefecture. Based on observations of grassland growth conditions in typical areas since 2000 and the current status of vegetation and degradation at the time of the survey, ground-truth samples were interpreted and classified into four levels: non-degraded, slightly degraded, moderately degraded,

and severely degraded. A total of 111 ground validation points were collected. The overall classification accuracy reached 71.17% (see Table 4). Among the categories, the slightly degraded level had the highest accuracy at 76%, while the moderately degraded level had the lowest accuracy at 63.64%. The accuracy for the non-degraded and severely degraded categories was 70.97% and 69.23%, respectively. Considering that ground validation is subject to a degree of subjectivity in interpretation, the accuracy of the grassland degradation classification can be considered relatively satisfactory. Therefore, the GDCI-based assessment of current grassland degradation is generally consistent with actual conditions and has practical value in application.

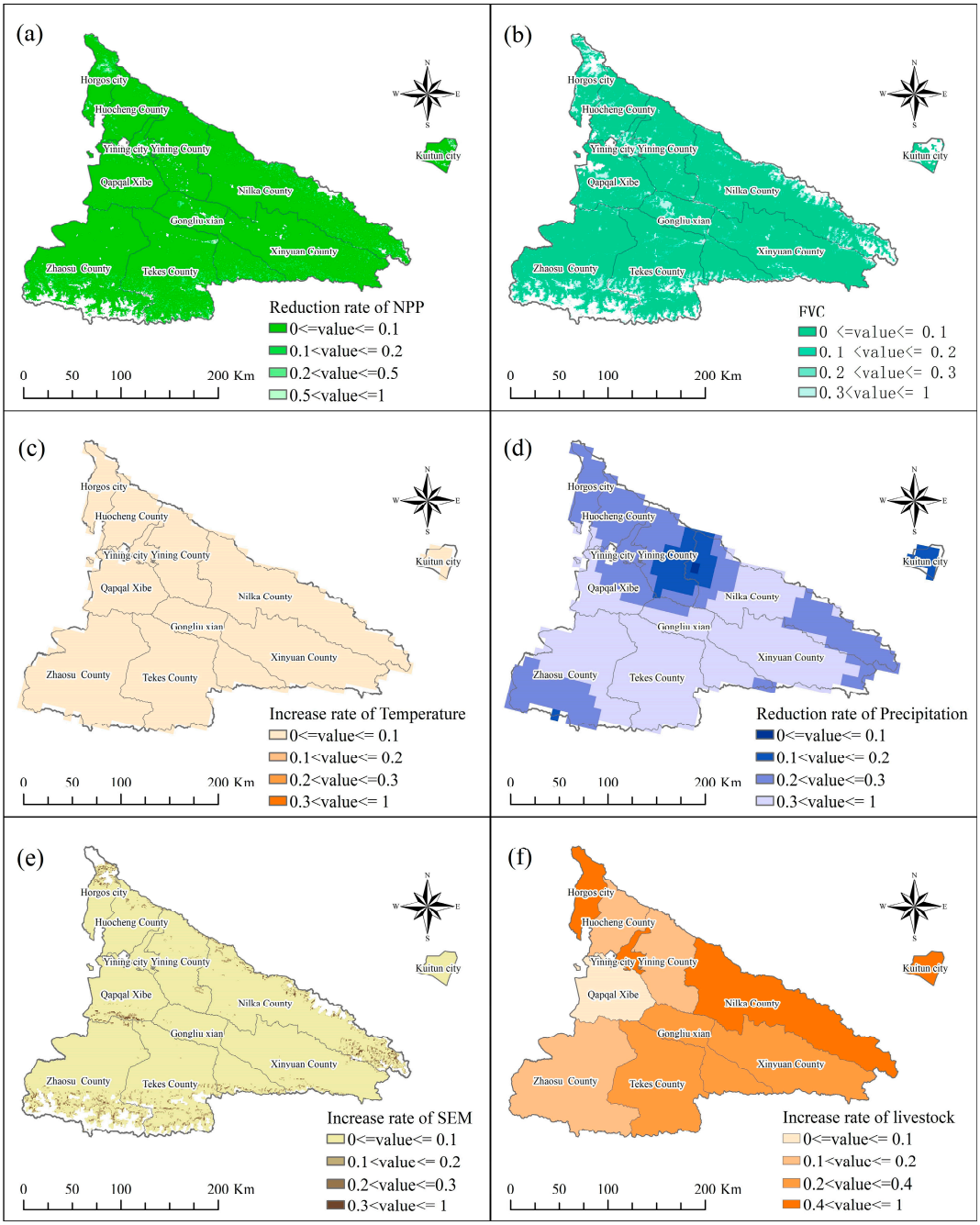


Figure 2. Temporal trends in the rates of change in individual factors from 2000 to 2022. (**a**) Reduction rate of Net Primary Productivity (NPP); (**b**) reduction rate of fractional vegetation cover (FVC); (**c**) increase rate of annual average temperature; (**d**) reduction rate of total precipitation; (**e**) increase rate of soil erosion modulus (SEM); (**f**) increase rate of livestock quantities.

Table 4. Accuracy of Current Grassland Degradation Assessment.

Grassland Degradation Level	Number of Validation Points	Correct Classifications	Accuracy
Severely Degraded	13	9	69.23%
Moderately Degraded	11	7	63.64%
Slightly Degraded	25	19	76.00%
Non-Degraded	62	44	70.97%
Overall	111	79	71.17%

4.3. Spatial Distribution of Grassland Degradation

From 2000 to 2022, the non-degraded grassland area in Ili Prefecture totaled 27,200 km^2, accounting for 90.19% of the total grassland area. The degraded grassland area amounted to 3000 km^2, representing 9.81% of the total, with degradation levels in order of increasing severity being: slightly degraded (1300 km^2, 4.34%), moderately degraded (1000 km^2, 3.33%), and severely degraded (700 km^2, 2.15%) (Figure 3). Slightly degraded areas are mainly distributed in Nilka County, Tekes County, and Zhaosu County. These counties are key grassland pastoral areas with vast grassland resources. Moderately degraded areas are primarily located in Nilka County, Kuitun City, and Yining County. These areas lie mostly within agro-pastoral transition zones, characterized by mixed land use where cropland and grassland are interwoven. Severely degraded areas are mainly found in Kuitun City, Horgos City, and Yining City. These are economically developed urban areas in Ili Prefecture with high population densities and rapid urbanization.

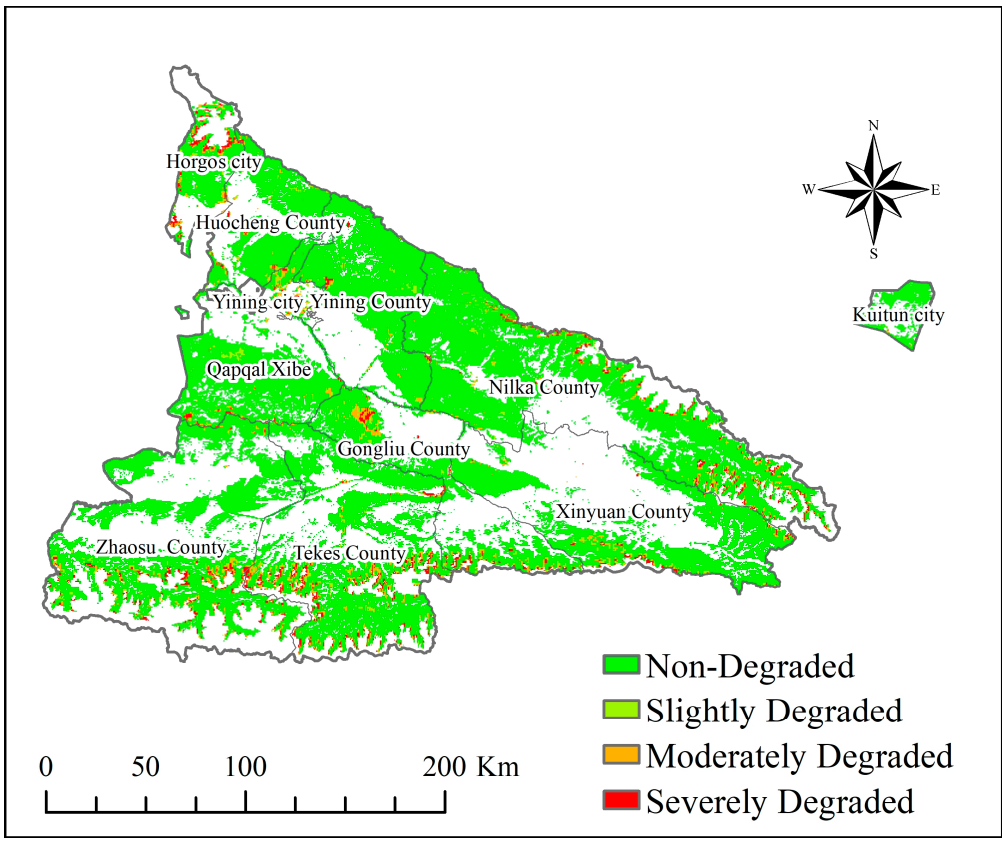


Figure 3. Grassland degradation status map of Ili Prefecture in 2022.

5. Discussion

Slightly degraded areas are key grassland pastoral areas. Although there is some grazing pressure, most degradation is mild and the ecological foundation remains relatively

sound [55]. In these regions, grassland management has been strengthened through practices such as rotational grazing, designated grazing bans, and rational control of livestock density, which have helped slow the degradation process and indicate strong potential for ecological restoration [56]. Moderately degraded areas are all mostly with agro-pastoral transition zones. Agricultural expansion has increasingly encroached on natural grasslands, intensifying the degree of degradation [55,57,58]. Notably, although Kuitun City is relatively small in area, the combined area of moderately and severely degraded grasslands exceeds that of non-degraded grasslands, highlighting the severity of degradation in this region. Farmland development, transportation infrastructure, and human disturbances have significantly altered the original structure and functions of grasslands, increasing ecosystem vulnerability [59]. Severely degraded areas are economically developed urban areas. With ongoing urban expansion and infrastructure development, large areas of grassland have been occupied, resulting in severe ecological damage [36]. Furthermore, these areas have highly developed livestock industries with large livestock inventories, leading to prolonged overgrazing—a major anthropogenic driver of severe degradation [60]. Additionally, relatively low precipitation and high evaporation intensify water limitations in these areas, further weakening the resilience of grassland ecosystems and exacerbating degradation trends [60].

This study addresses several key scientific issues related to grassland degradation assessment, particularly the challenge of integrating multiple ecological, environmental, and anthropogenic factors into a unified evaluation framework. Unlike previous studies that primarily relied on single indicators such as vegetation cover or NPP [20–22], this study proposes a comprehensive indicator system based on the "natural conditions–vegetation response–human disturbance" mechanism. By doing so, it offers a more holistic understanding of degradation processes in ecologically fragile regions like Yili Prefecture.

Although this study provides a relatively comprehensive evaluation of grassland degradation over the past two decades, several limitations should be acknowledged to guide future improvements. Given that MODIS data has been consistently available since 2000, the study selected the period from 2000 to 2022 for a 20-year dynamic assessment. However, the lack of earlier baseline data, such as grassland conditions in the 1980s, may introduce temporal biases in interpreting long-term degradation trends. Future research should explore the spatiotemporal fusion and assimilation of multi-source remote sensing data—such as integrating AVHRR, Landsat, and other historical datasets—to extend the monitoring time span and enable more continuous and long-term assessments.

Moreover, while this study focuses on key indicators such as vegetation cover, net primary productivity (NPP), and soil erosion modulus, grassland degradation also manifests in dimensions like forage quality, species composition (e.g., proportion of edible forage species), and desertification processes. These factors are currently difficult to capture using remote sensing data alone. Future work should aim to enrich the indicator system by incorporating ground-based observations or ancillary data sources to improve the ecological comprehensiveness and accuracy of the Grassland Degeneration Comprehensive Index (GDCI).

In addition, although the GDCI model and its indicator framework were developed specifically for Yili Prefecture, the structure based on the "natural conditions–vegetation response–human disturbance" triadic mechanism demonstrates good potential for scalability. By adjusting the indicator selection and weightings according to local environmental and socio-economic characteristics, this evaluation framework can be extended to other grassland regions facing similar degradation challenges. It offers not only a flexible tool for regional assessment but also a scientific basis for supporting grassland conser-

vation planning, ecological restoration strategies, and sustainable land use policies in broader contexts.

6. Conclusions

This study developed a Grassland Degeneration Comprehensive Index (GDCI) using MODIS and other multi-source remote sensing data to assess grassland degradation in Ili Prefecture. The index integrates key indicators reflecting vegetation condition, ecological environment, and utilization intensity, providing a reliable and coherent framework for regional degradation monitoring.

Results show that from 2000 to 2022, 90.19% of grasslands remained non-degraded. Slight, moderate, and severe degradation accounted for 4.34%, 3.33%, and 2.15% of the total grassland area, respectively, with distinct spatial patterns—pastoral zones, agro-pastoral transition zones, and urban regions.

The GDCI method proved effective and accurate in capturing degradation dynamics. Future work will focus on refining the indicator system and analyzing socio-economic drivers—such as policy and population distribution—to strengthen the scientific basis for sustainable grassland management in the region.

Author Contributions: Data curation, L.X.; formal analysis, L.X.; methodology, L.X.; writing—original draft, L.X.; writing—review and editing, D.J., C.S., M.Z., and J.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Third Xinjiang Scientific Expedition Program (Grant No. 2022xjkk0405), the National Natural Science Foundation of China (42301460, 42271313) and the Central Public-interest Scientific Institution Basal Research Fund, China (JBYW-AII-2024-19, JBYW-AII-2024-12).

Data Availability Statement: Dataset is available upon request from the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

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