Comprehensive Grassland Degradation Monitoring by Remote Sensing in Xilinhot, Inner Mongolia, China

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Abstract: Grassland degradation is a complex process and cannot be thoroughly measured by a single indicator, such as fractional vegetation cover (FVC), aboveground biomass (AGB), or net primary production (NPP), or by a simple combination of these indicators. In this research, we combined measured data with vegetation and soil characteristics to establish a set of standards applicable to the monitoring of regional grassland degradation by remote sensing. We selected indicators and set their thresholds with full consideration given to vegetation structure and function. We optimized the indicator simulation, based on which grassland degradation in the study area during 2014–2018 was comprehensively evaluated. We used the feeding intensity of herbivores to represent the grazing intensity. We analyzed the effects of climate and grazing activities on grassland degradation using the constraint line method. The results showed degradation in approximately 69% of the grassland in the study area and an overall continued recovery of the degraded grassland from 2014 to 2018. We did not identify any significant correlation between temperature and grassland degradation. The increase in precipitation promoted the recovery of degraded grassland, whereas increased grazing may have aggravated degradation. Our findings can not only improve the scientific quality and accuracy of grassland degradation monitoring by remote sensing but also provide clear spatial information and decision-making help in sustainable management of grassland regions.

Keywords: grassland degradation; monitoring standard; climate driving; grazing intensity; constraint line

1. Introduction

Grassland plays a key role in the supply of ecosystem services (ES) for human society, which not only provide provision services (e.g., meat, milk) but also provide regulation and support services such as climate regulation, soil conservation, wind protection and sand fixation, water conservation, as well as cultural services such as recreation [1,2]. Grassland is a rich and renewable natural resource. Its continued degradation will negatively affect productivity and result in the deterioration of grassland ecosystem functioning and also affect the circulation of trace elements [3,4]. At present, it is an impending issue for enhancing grassland management, identifying the mechanism of grassland productivity decline, and uncovering the pattern of grassland ecosystem service functions. Scientific
monitoring of grassland degradation therefore forms an important foundation for the sustainable development of grassland [5].

In recent years, remote sensing has become an indispensable tool in regional and global monitoring of grassland degradation. Because hyperspectral remote sensing is limited by low coverage and high cost [6,7], multispectral imaging remains an important data source in remote sensing. Selecting an appropriate evaluation index is a prerequisite in grassland degradation monitoring by remote sensing and is the basis for establishing related standards. Widely used indicators at present include fractional vegetation cover (FVC), normalized difference vegetation index (NDVI), and net primary production (NPP), etc. [8,9]. For example, Zhou et al. evaluated the degradation dynamics of grassland in China in 1982–2010 with NPP and grass coverage as the main indicators [10]. Using hyperspectral data to simulate FVC, Wiesmair et al. assessed the degree of grassland degradation in the study area and proposed suggestions for grassland management [11].

Grassland degradation is a complex process that is manifested in many ways, including grassland structure and function [12]. Regional complexity prevents the use of a single indicator such as NDVI or NPP as sufficient means to accurately monitor grassland degradation. It thus has been necessary to perform comprehensive grassland degradation monitoring using vegetation and soil characteristics. Zhang et al. used measured data along with the evaluation indicators of temperature vegetation dryness index, vegetation cover, biomass, and ecosystem service values to study grassland degradation in the Altay region of China [13]. Han et al. adopted species composition, degree of grassland desertification, and aboveground biomass (AGB) as indicators to comprehensively analyze grassland degradation in Northeast Inner Mongolia, China [14]. The monitoring of grassland degradation has evolved from the use of a single factor or a straightforward combination of these factors to composite indicators. A lack of a unified standard in monitoring, however, remains a problem in this field [15].

At present, research both in China and the international community has focused on factors influencing grassland degradation. Climate factors and human activities are considered to be important causes of grassland degradation [16,17]. Sun et al. discussed the effects of climate and grazing on the desertification of alpine grasslands in Northern Tibet [18]. With potential NPP to characterize the climatic influence as well as the difference between actual NPP and potential NPP to characterize human perturbations, Gang et al. quantitatively assessed the relative contributions of climate and human activities to global grassland degradation [19]. Such a methodology has been broadly applied in research [20,21]. Nonetheless, the use of NPP to quantify the degree of grassland degradation in this method oversimplifies the evaluation and suffers from drawbacks. Researchers also have studied the influence of policy on grassland degradation. Liu et al. investigated the influence of the Subsidy and Incentive System for Grassland Conservation on grassland degradation in Inner Mongolia, China [22]. Although correlation analysis still plays a dominant role in terms of research methods [23], it does not adequately reveal the complex relationship between grassland degradation and the influencing factors, and it needs to be optimized and improved.

Looking at the research progress in China and other countries, individual evaluation factors, such as FVC and AGB or their simple combinations, are still the primary evaluation indicators used for grassland degradation, and a lack of a comprehensive evaluation system and method is evident. The monitoring standards which are readily applicable at the regional or global scale based on remote sensing have not been established. Conventional linear methods do not work well to elucidate the complex mechanism of grassland degradation, and the study of factors influencing grassland degradation remains difficult. This study aims to develop a set of integrated standards applicable to regional grassland degradation monitoring with reference made to relevant standards and then analyze the influence of climate factors and grazing activities on grassland degradation by the constraint line method instead of simple linear analysis and conventional spatial analysis.
2. Material and Methods

2.1. Study Area

The Inner Mongolia Autonomous Region is the northern border of China, adjacent to Russia and Mongolia, and is an important part of construction of the Belt and Road. This study examined typical steppe of Xilinhot (Figure 1), located in the Xilingol League of the Inner Mongolia Autonomous Region, China, and near Mongolia. The geographic coordinates of the study area are 43°02′−44°52′N and 115°18′−117°06′E. Located at the heart of the Inner Mongolia Plateau, the area is elevated in the south and low in the north, with an average altitude of 988.5 m. It has a cool temperate, semi-arid continental climate. Most of the study area is covered by typical steppe, with a wide distribution of communities whose foundation species are *Leymus chinensis* (Trin.) Tzvel. and *Stipa grandis* P. Smirn. Representative plants include *Stipa grandis* P. Smirn., *Leymus chinensis* (Trin.) Tzvel., *Cleistogenes squarrosa* (Trin.) Keng, *Allium ramosum* Linn., and *Artemisia scoparia* Waldst. et Kit. [9,24]. The Xilingol Grassland National Nature Reserve is located mostly in the city of Xilinhot, Xilingol League of the Inner Mongolia Autonomous Region, China. With a total land mass of approximately 580,000 hectares, the reserve makes up the core of the Xilingol Grassland, an area of relatively well-conserved natural grassland and part of the Eastern Steppe of Eurasian Steppe. This is a typical study site for a grassland natural reserve in China and the rest of the world [24].

![Figure 1. Location of the study area.](image)

2.2. Data Sources and Preprocessing

We collected field samples in the study area during July and August of 2017 and 2018. We set up a total of 42 sample sites. Samples collected included biomass, litterfall, and soil layers at 0−20 cm soil depth. The parameters measured included biomass (dry mass), litterfall dry mass, soil bulk density (SBD), and soil organic carbon (SOC). We obtained MOD13Q1 data from LAADS DAAC (https://ladsweb.modaps.eosdis.nasa.gov). Monthly precipitation data, average monthly temperature data, and solar radiation data were from the China Meteorological Sharing Service...
System (http://data.cma.cn). The Shuttle Radar Topography Mission (SRTM) digital elevation data (90 m) were acquired from Geospatial Data Cloud (http://www.gscloud.cn). China’s soil dataset simulated for terrestrial conditions was from the Cold and Arid Regions Science Data Center at Lanzhou (http://westdc.westgis.ac.cn). Data for The Xilingol Grassland National Nature Reserve of Inner Mongolia were from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). Basic information regarding administrative zones and roads was from the National Geomatics Center of China (http://ngcc.cn/ngcc/). Mongolia boundary data were obtained from Mongolia’s statistical information service website (http://www.1212.mn).

We extracted NDVI and enhanced vegetation index (EVI) values from MOD13Q1 data and processed the data to a maximum value composite. We reconstructed the NDVI images using the harmonic analysis of time series. We performed spatial interpolation on temperature and precipitation data by introducing terrain factors according to the ANUSPLIN method.

2.3. Methodology

2.3.1. Linear Trend Analysis

The LTA method was used to analyze the overall variation trend of the grassland degradation [25].

\[
y = a \times x + b
\]

where \( x \) is the time, \( y \) is the parameter that undergoes changes, \( a \) is the slope of the trendline, and \( b \) is the intercept. The slope \( a \) is calculated by the least squares method and denotes the variation trend of each parameter.

\[
a = \frac{n \times \sum_{i=1}^{n} ix_i - \left( \sum_{i=1}^{n} i \right) \times \left( \sum_{i=1}^{n} x_i \right)}{n \times \sum_{i=1}^{n} i^2 - \left( \sum_{i=1}^{n} i \right)^2}
\]

where \( n \) is the number of years in the study period and \( x_i \) is the value of the parameter in each pixel (or region). When \( a < 0 \), it means the parameter represented by the pixel (or region) is decreasing. When \( a > 0 \), it means the parameter represented by the pixel (or region) is increasing.

2.3.2. Grazing Intensity Indicator

We calculated the feeding intensity of herbivores using the improved Terrestrial Ecosystem Regional (TECO-R) model and used this as the indicator for grazing intensity [26,27]. We defined feeding intensity of herbivores as the ratio of carbon stock in the biomass ingested by herbivores to the carbon stock in total AGB. We calculated feeding intensity using the following equation for the dynamic change in the carbon stocks found in aboveground and underground plant parts:

\[
\frac{d q_{LW}}{dt} = a_{LW} \times NPP - \frac{(1 + e_a) \times q_{LW}}{t_{LW}}
\]

where \( e_a \) is the feeding intensity of herbivores (dimensionless) and \( q_{LW} \) is the carbon stock (kg C/m²) in AGB, which is calculated using the dry mass of AGB simulated by NDVI and the measured average carbon conversion factor (0.368 kg C/kg) [28]. Both \( t_{LW} \) (turnover time of stem and leaf) and \( a_{LW} \) (a dimensionless quantity indicating the proportion of NPP attributed to aboveground plant parts) were generated by the TECO-R model.

2.3.3. Constraint Lines

Grassland degradation is influenced by numerous synergic factors, including human activities, climate, and environmental conditions. Linear analysis alone does not adequately describe these complex interplays. Therefore, we adopted a constraint line method to analyze the impact of climate factors and grazing activities on grassland degradation [29]. We used the Origin program to draw the
constraint lines by breaking the dataset into fractiles and divided the range of data on the x-axis into 100 equal columns. We set the data point at 99.9% of each column as the boundary to remove outliers. We then performed fitting based on the curve features [30]. On the basis of error distribution theory, we selected data in the 5% to 95% range for analysis to eliminate errors introduced by noise in the remote-sensing images [31].

3. Grassland Degradation Estimation

3.1. Monitoring Framework

We selected necessary indicators (FVC, AGB, NPP, and SOM) and an auxiliary indicator (SBD) based on the Chinese National standard “the Parameters for Degradation, Sandification, and Salification of Rangelands (GB 19377-2003)” and other relevant research [32], taking into consideration the monitoring feasibility of the indicators. Using the established standard for grassland degradation monitoring by remote sensing (Table 2), we calculated the percent change in each indicator and assigned a degree of grassland degradation. If three or more necessary indicators indicated degradation, we used the highest degree of degradation among the necessary indicators as the degree of grassland degradation. If two necessary indicators indicated degradation, we assigned the degree of grassland degradation based on the auxiliary indicator. If only one necessary indicator indicated degradation, the grassland was considered lightly degraded. If no necessary indicator indicated degradation, the grassland was considered undegraded (Figure 2).

3.2. Indicator Simulation

3.2.1. AGB and SBD

We constructed a back-propagation artificial neural network (BP-ANN) model [33,34], using field measurement data to simulate the AGB and SBD at 0–20 cm depth. The factors initially selected included terrain factors (digital elevation model, slope, aspect), meteorological factors (temperature T, precipitation P), soil factors (clay and gravel content of surface soil), and vegetation indices (NDVI, EVI). We adopted the mean impact value (MIV) method to select factors with > 85% contribution as the indicators included in the modeling (Table 1). We set up 84 samples (repeated measurement based on 42 sampling sites from 2017 to 2018) for the simulation of AGB. We used 70% of these sites for training, 15% for validation, and 15% for testing. We also simulated SBD at 0–20 cm depth based on the BP-ANN method.
| Factor     | AGB Cumulative Contribution (%) | SBD at 0–20 cm depth Cumulative Contribution (%) |
|------------|--------------------------------|-------------------------------------------------|
| NDVI       | −0.0363 22.63                  | EVI −0.0655 31.98                                |
| Clay       | 0.0263 39.03                   | Clay 0.0437 53.32                                |
| Sand       | 0.0257 55.06                   | Aspect 0.0318 68.85                              |
| P          | 0.0226 69.15                   | P 0.0164 76.86                                  |
| EVI        | 0.0158 79.00                   | NDVI 0.0163 84.81                               |
| Aspect     | −0.0141 87.79                  | T 0.0125 90.92                                  |
| T          | −0.0134 96.15                  | Sand −0.0087 95.17                              |
| DEM        | −0.0057 99.70                  | Slope −0.0067 98.44                             |
| Slope      | −0.0005 100                    | DEM −0.0032 100                                 |

Note: The factors selected for the construction of the back-propagation artificial neural network (BP-ANN) model for aboveground biomass (AGB; those with >85% contribution) are normalized difference vegetation index (NDVI), clay, sand, P, enhanced vegetation index (EVI), and aspect. The factors selected for the construction of the BP-ANN model for soil bulk density (SBD) at 0–20 cm depth (those with >85% contribution) were EVI, clay, aspect, P, NDVI, and T.

We used the coefficient of determination $R^2$ and the root-mean-square error (RMSE) to evaluate the training outcome. For the AGB model, the $R^2$ given by the training set was 0.8, and the RMSE was 340.5 kg ha$^{-1}$. The $R^2$ given by the validation set was 0.69, and the RMSE was 572.22 kg ha$^{-1}$. For the SBD model (at 0–20 cm depth), the $R^2$ given by the training set was 0.59, and the RMSE was 0.093 g cm$^{-3}$. The $R^2$ given by the validation set was 0.7, and the RMSE was 0.081 g cm$^{-3}$. With reference to the relevant research [33,35], we found the constructed BP-ANN model to be highly accurate and to meet the simulation demand.

3.2.2. SOM

The TECO-R model combines the strengths of Carnegie–Ames–Stanford approach (CASA) and vegetation and soil carbon transfer (VAST) models in regional-scale applications. It has been applied to the evaluation of carbon stock in terrestrial ecosystems in Australia and the USA as well as China, and the simulation results have been in clear agreement with measured values [26,36,37]. A common practice is the use of this model with the van Bemmelen factor to realize the conversion of soil organic carbon into SOM at a regional scale [38,39]. Here, we first simulated soil organic carbon using the TECO-R model and converted it to SOM using the following equation:

$$\text{SOM} = \text{SOC} \times 1.724$$  \hspace{1cm} (4)

where SOM denotes soil organic matter and SOC denotes soil organic carbon. The van Bemmelen factor adopts its general value of 1.724.

3.2.3. FVC

We simulated FVC using the following dimidiate pixel model [40]:

$$C_i = \frac{\text{NDVI} - \text{NDVI}_{\text{soil}}}{\text{NDVI}_{\text{veg}} - \text{NDVI}_{\text{soil}}} \times 100$$  \hspace{1cm} (5)

where $C_i$ represents the FVC (%) of pixel $i$ in the grassland; NDVI$_{\text{soil}}$ is the NDVI of the area without vegetation or completely covered by bare soil, which is denoted by the minimum NDVI of the pixel within $i$ years; and NDVI$_{\text{veg}}$ stands for the NDVI of the pixel completely covered by vegetation, which is represented by the maximum NDVI of the pixel in the grass vegetation within $i$ years.
3.2.4. NPP

The CASA model takes meteorological factors into full consideration and has been used extensively in the assessment and study of regional and global terrestrial NPP [41]. Researchers have validated the accuracy of NPP simulated by CASA [42,43]. Such research has shown a good linear relationship between the simulated NPP value and the measured data. Therefore, in this study, we used the CASA model to simulate NPP:

\[
NPP(x, t) = APAR(x, t) \times \varepsilon(x, t) \tag{6}
\]

\[
APAR(x, t) = SOL(x, t) \times FPAR(x, t) \times 0.5 \tag{7}
\]

\[
\varepsilon(x, t) = \varepsilon_{\text{max}} \times T(x, t) \times W(x, t) \tag{8}
\]

where \(NPP(x, t)\) is the net primary production of pixel \(x\) in month \(t\) (g·C·m\(^{-2}\)); \(APAR(x, t)\) is the photosynthetically active radiation absorbed by pixel \(x\) in month \(t\) (MJ·m\(^{-2}\)); \(\varepsilon(x, t)\) is the actual light use efficiency of pixel \(x\) in month \(t\) (g·MJ\(^{-1}\)); \(SOL(x, t)\) is the total solar radiation on pixel \(x\) in month \(t\) (MJ·m\(^{-2}\)); \(FPAR(x, t)\) is the ratio of incident photosynthetically active radiation absorbed by the vegetation layer, which is calculated by NDVI and simple ratio index (SR); the value 0.5 indicates the ratio of photosynthetically active radiation utilisable by plants to total solar radiation; \(\varepsilon_{\text{max}}\) represents the maximum light use efficiency of plants (a dimensionless quantity); and \(T(x, t)\) and \(W(x, t)\) stand for the temperature stress factor and water stress factor of pixel \(x\) in month \(t\) [26].

3.3. Estimation Standard

We set the thresholds for the necessary indicators and an auxiliary indicator of grassland degradation assessment based on the Parameters for Degradation, Sandification, and Salification of Rangelands (GB 19377-2003) and relevant research, and we established a standard for grassland degradation monitoring by remote sensing (Table 2).

| Category          | Indicator | UD  | LD  | MD  | SD  |
|-------------------|-----------|-----|-----|-----|-----|
| Necessary indicator | FVC       | 0–10| 10–20| 20–30| >30 |
|                   | AGB       | 0–10| 10–20| 20–50| >50 |
|                   | NPP       | 0–10| 10–20| 20–40| >40 |
|                   | SOM       | 0–10| 10–20| 20–40| >40 |
| Auxiliary indicator | SBD       | 0–10| 10–20| 20–30| >30 |

Note: UD, undegraded grassland; LD, lightly degraded grassland; MD, moderately degraded grassland; SD, severely degraded grassland. Each range used in the classification of grassland degradation degree is not inclusive of the value on the left side, but it does include the values on the right side. The necessary indicators are calculated as the percent reduction relative to the UD, whereas the auxiliary indicator (SBD) is calculated as the percent increase relative to the UD.

Figure 3 shows the functional compartments of The Xilingol Grassland National Nature Reserve. The reserve was established in 1985 and was given the rank of national nature reserve in 1997. The area was divided into core zones, buffer zones, and experimental zones. The core zones were not open to any organization or individual, and the buffer zones were open only to scientific research and observation. In this study, we used the annual averaged indicator values for the core zones (A, C1, C2, C3, E2) of the typical steppe in the nature reserve in 2014–2018 as the reference benchmark of undegraded grassland. The degree of grassland degradation was assessed on this basis.
4. Results

4.1. Grassland Degradation Degree

4.1.1. Spatial–Temporal Distribution

We comprehensively monitored the degree of grassland degradation between 2014 and 2018 using the established standard (Table 2). The results are shown in Figure 4. It should be noted that since the grassland coverage of study area is close to 90%, the distinction between grassland and non-grassland areas is no longer made in light of relevant studies [26,44].

![Functional zoning of The Xilingol Grassland National Nature Reserve](image)

**Figure 3.** Functional zoning of The Xilingol Grassland National Nature Reserve. Regions in the figure are labeled as follows: A, core area of Pingdingshan mountain grassland; B, core area of Xieertala River wetland; C, core areas of Ih Uul typical steppe; D, core areas of Abuduertu spruce, aspen, and birch forests; E, core areas of Haliut typical steppe; F, core area of Bayanbaolige typical steppe.

**Figure 4.** Spatial distribution of grassland degradation for the 2014–2018 period.

In general, grassland degradation in the study area exhibited an uneven and patched spatial distribution, with areas of different degrees of degradation mixed together. Only some locations exhibited large areas with the same degree of degradation. This patched distribution pattern increased the difficulty of grassland restoration and management.
From 2014 to 2018, degraded grassland in the northern and central parts of the study area underwent a gradual recovery. In most cases, the degree of degradation was restored from severe to moderate or even light. In the southern part of the study area, the grassland condition showed deterioration. Some of the undegraded areas became moderately or even severely degraded. In terms of the entire study area, the eastern part showed the most serious signs of degradation and was always in a moderately or severely degraded state. This required the immediate management and restoration of the region.

The different degrees of grassland degradation and the percent area they occupy in the study area are shown in Table 3 for 2014–2018. We calculated the average percent area of grassland with various degrees of degradation for the past five years (2014–2018). Approximately 31.06% of grassland in the study area was undegraded, 29.4% was lightly degraded, 7.38% was moderately degraded, and 32.16% was severely degraded. In other words, about 69% of grassland in the study area showed variable degrees of degradation. In terms of severity, the degradation was polarized, with equal proportions of lightly degraded and severely degraded areas, each accounting for about one-third of the study area.

Table 3. Percent of grassland area with different degrees of degradation in 2014–2018.

|       | UD  | LD  | MD  | SD  |
|-------|-----|-----|-----|-----|
| 2014  | 24.69 | 16.69 | 6.77 | 51.16 |
| 2015  | 32.56 | 22.82 | 6.86 | 37.77 |
| 2016  | 33.76 | 22.56 | 4.59 | 39.10 |
| 2017  | 31.45 | 35.76 | 14.43 | 18.36 |
| 2018  | 32.86 | 49.16 | 4.26 | 13.72 |

NOTE: UD, undegraded grassland; LD, lightly degraded grassland; MD, moderately degraded grassland; SD, severely degraded grassland.

In Table 3, the percent of MD area is 14.43 in 2017, which is different from other values. As a whole, the grassland in the study area was in a state of continuous recovery from 2014 to 2018, during which climate factors and human activities provided favorable conditions. According to our analysis, the percent of SD area decreased from 2014 to 2016, and the grassland restoration cumulative effect may have increased the percent of MD area obviously in 2017. More SD and MD recovered to LD during 2017–2018, so the percent of MD area significantly reduced in 2018. This may be the reason for the change.

4.1.2. Restoration of Degraded Grassland

We calculated the transfer matrix of grassland degradation in the study area during 2014–2018 (Table 4). As the analysis showed, about 5.45% of the lightly degraded areas were restored to undegraded, about 4.98% of the moderately degraded areas were restored to undegraded or lightly degraded, and about 44.9% of the severely degraded areas were restored to undegraded, lightly degraded, or moderately degraded. Overall, about 55.33% of grassland was recovering, and 20.28% showed signs of deterioration. In the 2014–2018 period, grassland in the study area underwent a continual recovery.

Table 4. Transfer matrix of grassland degradation during 2014–2018.

|       | UD  | LD  | MD  | SD  |
|-------|-----|-----|-----|-----|
| UD    | 8.93 | 12.67 | 0.68 | 2.23 |
| LD    | 5.45 | 7.67 | 0.62 | 2.83 |
| MD    | 2.19 | 2.79 | 0.31 | 1.25 |
| SD    | 15.72 | 26.67 | 2.51 | 7.48 |

NOTE: UD, undegraded grassland; LD, lightly degraded grassland; MD, moderately degraded grassland; SD, severely degraded grassland.
We calculated the interannual trend of grassland degradation in the study area by the slope of the linear trend for the period 2014–2018 (Figure 5). The grassland in the study area showed an overall recovery. The northern and the central parts were in a good recovery state, whereas the southeastern part showed some deterioration. The process of grassland restoration was not linear, as degradation occurred again during the course of the study. This signified the complex and nonlinear influencing factors of grassland degradation, and the need to further study the driving mechanisms of grassland degradation.

Figure 5. Interannual trend of grassland degradation: (a), (b), (c), and (d) changes in grassland for 2014–2015, 2014–2015, 2014–2015, and 2014–2015, respectively; (e) overall change in grassland for 2014–2018. Better: recovery of grassland; worse: deterioration [45].

4.2. Influence Factors

4.2.1. Climate Driving

We used the values of necessary and auxiliary indicators averaged over the past five years to characterize the degree of grassland degradation. We analyzed the relationship between climatic factors and grassland degradation by the constraint line method and explored the influence of climatic factors on grassland degradation. This analysis showed rather small fluctuations (about 0.42–0.75 °C) in the monthly and annual average temperature of the study area during the peak season of vegetation growth for 2014–2018. We could not identify an apparent relationship between these temperature fluctuations and the degree of grassland degradation. Therefore, in the following paragraphs, we only discuss the impact of precipitation on grassland degradation.

Figure 6 shows the relationship between the degree of grassland degradation and monthly average precipitation and annual average precipitation for the study area during the peak season of vegetation growth in 2014–2018. We observed a constraint relationship between precipitation and the degree of grassland degradation; as precipitation increased, grassland became less degraded. During the peak season of vegetation growth, when the monthly average precipitation exceeded 70 mm or the annual average precipitation exceeded 300 mm, degraded grassland showed clearer signs of recovery. This indicated that an increase in precipitation promoted the restoration of degraded grassland. In contrast, the constraint relationship between precipitation and grassland degradation did not guarantee continued restoration of degraded grassland as precipitation continued rising. Instead, it implied the promotion of grassland restoration by precipitation.

Figure 6. Relationship between the degree of grassland degradation and precipitation.
Precipitation variables often correlate with different ranges of altitude. The study showed that the precipitation decreased gradually with the elevation in the study area (Figure 7). According to the study, this relationship also had a significant impact on grassland degradation. As shown in Figure 7c, the grassland became less degraded with higher elevation. This may suggest that, due to more rainfall, grasslands at higher elevations had greater endurance to drought and grazing.

Figure 6. Constraint relationship between precipitation and grassland degradation: (a) constraint relationship between monthly average precipitation and the degradation degree (%) of grassland during peak season of vegetation growth; (b) constraint relationship between annual average precipitation and the degradation degree (%) of grassland.

Figure 7. Constraint relationship considering the altitude of grassland: (a) constraint relationship between monthly average precipitation and the altitude during peak season of vegetation growth; (b) constraint relationship between annual average precipitation and the altitude; (c) constraint relationship between the degradation degree (%) of grassland and the altitude.

Figure 8 shows changes in monthly average precipitation and annual precipitation in the study area during the peak season of vegetation growth for 2014–2018. We observed an increase in both quantities. During this period, the study area was marked by large interannual variations in monthly average precipitation during the peak season of vegetation growth. We saw less precipitation in the years 2014, 2015, and 2016 and very high precipitation in 2018 during the peak season of vegetation growth. The annual average precipitation of the study area for 2014–2018 was 300 mm. Except for the low precipitation in 2017, precipitation in the other years was high, especially for 2018, which had more abundant precipitation compared with the previous four years. These factors may have contributed significantly to good restoration progress of grassland in the study area in 2014–2018.
was one of the important factors leading to grassland degradation. Reducing the grazing pressure to an appropriate level might promote grassland restoration. This finding was consistent with the results of previous research [48–50] and suggested that overgrazing was one of the important factors leading to grassland degradation. Reducing the grazing pressure to an appropriate level might promote grassland restoration.

4.2.2. Grazing Intensity

We used feeding intensity of herbivores to quantify the grazing intensity. We used the values of necessary and auxiliary indicators averaged over the past five years to characterize the degree of grassland degradation. We then analyzed the relationship between grassland degradation and grazing intensity by the constraint line method and explored the influence of grazing intensity on grassland degradation. We observed a constraint relationship between grazing intensity and grassland degradation (see Figure 9). As grazing intensity increased, grassland degradation worsened. This result was in agreement with those found in previous research [48–50] and suggested that overgrazing was one of the important factors leading to grassland degradation. Reducing the grazing pressure to an appropriate level might promote grassland restoration.

As shown in Figure 10, the grazing intensity in the study area was decreasing in general. The grazing intensity in 2017 and 2018 showed a significant decrease as compared with the previous three years. According to the report of the local grassland management department, the carrying capacity of natural pasture in the typical steppe in Xilingol had achieved negative growth by 2017, creating favorable conditions for grassland recuperation. This finding was consistent with the results of our present research. Analyzing the relationship between grazing intensity and grassland degradation,
continued reduction in grazing intensity might have directly promoted the smooth restoration of grassland in the study area.

5. Discussion

5.1. Comparing with Relevant Research

Monitoring grassland degradation using remote sensing is mainly achieved by establishing a relationship between the vegetation indexes and grassland degradation evaluation indicators. Previewing relevant research, vegetation indexes such as NPP, FVC, AGB, etc. were the general evaluation indicators. However, most studies of grassland degradation at the regional scale ignore soil characteristics. Grassland degradation is a complex changing process and can be perceived most intuitively as changes in grassland vegetation, such as reduced plant height, density, and biomass; increased number of toxic weeds; and decreased number of edible grass species [51]. Thus, the indicators characterizing plant attributes are the most important and direct measures for evaluating grassland degradation. Extensive work has been performed on the degradation of regional grassland using vegetation change [52]. The process of grassland degradation, however, was also accompanied by changes in soil characteristics, such as increased SBD, decreased SOM, and soil thinning [53,54]. We may not be able to observe the same amount of degradation in the grassland soil as in grassland vegetation, but it would require the same comprehensive assessment as the latter if we wanted more accurate monitoring of grassland degradation. At present, most of the studies that incorporate soil characteristics into grassland degradation assessment focus on sample plot scale. For example, Coutinho et al. carried out some studies about the soil physical and chemical properties of grassland degradation on some degraded sites of rupestrian grassland in Brazil [55]. In this study, soil characteristics were taken into the monitoring standards of regional-scale grassland degradation.

In addition, linear analysis and spatial analysis are the main methods to study the influence factors of grassland degradation. An increasing number of studies have indicated that the influence of climate, grazing, and other factors on grassland degradation is nonlinear. For instance, based on the plots in semiarid grassland on the Colorado Plateau near Flagstaff, Arizona, Souther et al. studied the complex response of grasslands to grazing and gave advice on grassland management [56]. The constraint line method used in this study is beneficial to the analysis of the influence mechanism of grassland degradation.
5.2. Academic Value of Study

This study took a broad approach to the multiple vegetation and soil changes manifested during grassland degradation and developed a set of standards for the remote-sensing monitoring of regional-scale grassland degradation on the basis of vegetation and soil characteristics. The research results can promote the comprehensive understanding of grassland degradation.

This study provided a reference standard for undegraded grassland, which could serve as a scientific reference for related research. The selection of suitable UD as a reference benchmark formed the scientific basis for the assessment of grassland degradation, but in practice, the selection criterion was inconsistent. In studies at the sample plot level, scholars have used enclosed grassland as the reference benchmark for UD and have assigned degrees of grassland degradation based on grazing intensity [57]. For the study of grassland degradation monitoring at the regional level, it has been difficult to find an undegraded natural sample plot, and the selection of a reference benchmark became challenging [58,59]. As specified in the national standard, the Parameters for Degradation, Sandification, and Salification of Rangelands (GB 19377-2003), the benchmark of UD included vegetation characteristics and surface and soil conditions for an area with the same type of grassland in a nearby grassland nature reserve that shared identical moisture and thermal conditions as the region under monitoring. In this study, we selected grassland in the core area of The Xilingol Grassland National Nature Reserve as the standard for undegraded grassland. Some grassland degradation might have occurred in the study area, but the core zone was under strict management and showed almost no sign of degradation. Thus, it was an appropriate reference benchmark.

5.3. Sustainable Management of Grassland

As an important basic resource for social and economic development, the sustainable management of grassland is a scientific work requiring long-term research. Continued grassland degradation will negatively affect productivity and result in the deterioration of grassland ecosystem functioning, which has become the major challenge for sustainable management of grassland. To promote the sustainable recovery of degraded grassland, the scientific monitoring of grassland degradation is a fundamental work.

Research on the driving mechanism of grassland degradation and recovery can provide decision-making support for related departments. According to the study, the abundant precipitation may have contributed significantly to good restoration progress of grassland. Thus, we propose that related departments improve the grassland management system, establish a meteorological monitoring system, and carry out artificial rain in local areas with low precipitation. The study also showed that continued reduction in grazing intensity might have directly promoted the smooth restoration of grassland. Therefore, we recommend that related departments set grazing intensity thresholds according to grassland degradation degree, thus promoting sustainable use of grassland.

5.4. Limitations and Future Research Directions

Weed species will become rampant as grassland ecological functions, such as structure, energy cycle, and material exchange, gradually deteriorate with the degradation of the grassland ecosystem. These species will gradually replace the dominant grass species and foundation species. This change in grassland vegetation structure is also an important feature of grassland degradation [60]. Due to the limitations of current data acquisition, the feature was not considered in this study. However, it is necessary to further improve the grassland degradation standard system with the enrichment of available data.

To make monitoring practical, we also omitted certain indicators more suitable for studies on the sample plot scale, such as total oxygen content and percent area of rat holes, from the selection. These indicators cannot be readily quantified on the regional or even larger scale. These factors might affect research results and produce uncertainties. In the future, more evaluation indexes including
vegetation structure should be introduced to establish a more comprehensive grassland degradation evaluation system, so as to evaluate grassland degradation more accurately.

Actually, there are many factors affecting grassland degradation and recovery. Due to data and time, we only analyzed the influence of climate factors and grazing intensity on grassland degradation. From a management point of view, it could be interesting to consider some other factors in grassland degradation and recovery. For example, the use of fertilization and even alien species may help to improve the forage quality, as well as grassland restoration. Future work will delve into the research on influence factors and mechanisms of grassland degradation and restoration.

6. Conclusions

In this study, we developed a set of standards for the remote-sensing monitoring of regional-scale grassland degradation on the basis of vegetation and soil characteristics. We performed a field investigation of the typical steppe in Xilinhot in Inner Mongolia, China, to comprehensively assess the grassland degradation of this region during 2014–2018. We analyzed the temporal and spatial distribution and evolution trend of grassland degradation. We studied the effect of climate and grazing intensity on grassland degradation using the constraint line method. Increased precipitation and a reduction in grazing pressure to an appropriate level promoted the restoration of degraded grassland. These results could help devise grassland management policy by local departments. This comprehensive method effectively improved monitoring accuracy and provided new ideas for related research. To make the monitoring system more scientific, future work should focus on the enrichment of indicators and the use of measured data to set indicator thresholds that reflect regional differences.

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