

Article

Monitoring Temperate Typical Steppe Degradation in Inner Mongolia: Integrating Ecosystem Structure and Function

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Abstract

Under the combined effects of climate change, overexploitation, and intense grazing, temperate steppe in northern China is experiencing increasing deterioration, which is typified by a shift from structural degradation to functional disruption. Accurately tracking steppe degradation using remote sensing technology has emerged as a crucial scientific concern. Prior research failed to integrate ecosystem structure and function and lacked reference baselines, relying only on individual indicators to quantify degradation. To resolve these gaps, this study established a novel degradation evaluation index system integrating ecosystem structure and function, incorporating vegetation community distribution and proportions of degradation-indicator species to define reference states and quantify degradation severity. Analyzed spatiotemporal evolution and drivers across the temperate typical steppe (2013–2022). Key findings reveal (1) non-degraded and slightly degraded areas dominated (75.57% mean coverage), showing an overall fluctuating improvement trend; (2) minimal transitions between degradation levels, with stable conditions prevailing (59.52% unchanged area), indicating progressive degradation reversal; and (3) natural factors predominated as degradation drivers. The integrated structural–functional framework enables more sensitive detection of early degradation signals, thereby informing more effective steppe restoration management.

Keywords: temperate typical steppe; steppe degradation indicators; hydrothermal zones; degradation reference baseline; multi-source remote sensing data



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1. Introduction

Grasslands are the largest and most widely distributed terrestrial ecosystem on the planet, accounting for 20% of the world’s total land area [1]. It plays an irreplaceable role in promoting the global carbon cycle, guarding regional ecological security, and maintaining ecological balance and stability [2]. As the largest terrestrial ecosystem, grassland is the important material basis for the development of animal husbandry in China and the most important ecological security barrier [3].

Located in the middle of the Inner Mongolia Plateau, the temperate typical steppe of Xilingol is an important part of the temperate steppe of the Eurasian continent, which is not only an important ecological barrier in northern China but also the core area for the economic development of Inner Mongolia and the national supply of livestock products [4].

The temperate typical steppe of Xilingol is located in the continental arid and semi-arid monsoon area, rich in grass resources, a sensitive area to climate change, and a fragile ecosystem area [5]. Choosing a reasonable and effective way to quantitatively monitor and scientifically evaluate the steppe degradation in the local temperate typical steppe area is the first condition for repairing and managing the steppe degradation in the region.

Grassland degradation is a global environmental issue, fundamentally representing the process by which ecosystems undergo structural disruption and functional decline under the dual pressures of climate change and human activities. Ecosystem structure forms the foundation of ecosystems, encompassing the composition of biotic communities (species composition and diversity) and abiotic environments (soil). Studies indicate that grassland degradation in Inner Mongolia has led to a significant reduction in plant species richness and Shannon diversity, with community structure being disrupted [6]. Additionally, grassland degradation markedly diminishes soil quality, reducing microbial abundance and diversity [7]. Ecosystem function, representing the integrated expression of ecological processes and the services they provide, declines as a direct consequence of structural degradation. Research indicates that as degradation intensifies, the ecosystem's water conservation capacity diminishes and its carbon sequestration ability weakens [8]. Thus, grassland degradation is a complex process manifesting in multiple forms, including structural and functional alterations [9].

Accurate monitoring of regional grassland degradation is the basis for strengthening grassland conservation and restoration and improving grassland ecological quality [10]. Some studies have compared the differences in the classification of degradation using single indicators such as net primary productivity (NPP), fractional vegetation cover (FVC), and above-ground biomass (AGB) and found that the use of any one of these indicators to evaluate grassland degradation cannot objectively reflect the real situation of the degradation degree of grassland [9]. Therefore, any single remote sensing indicator has limitations when quantitatively assessing grassland degradation, as it cannot objectively and accurately reflect the complexity and heterogeneity of the region. In addition to selecting vegetation degradation indicators that are most sensitive to grassland degradation and show changes earliest, soil degradation indicators with delayed responses should also be incorporated. This is because grassland degradation results from the combined effects of soil, vegetation, and other interacting factors. And given that an increase in the number of degraded grass species may occur during the degradation process, which in turn affects the structure of grassland community composition, showing little or no increase in overall AGB and FVC. Consequently, monitoring grassland degradation based solely on vegetation indices and other quantitative estimates of vegetation characteristics carries inherent uncertainty. It is necessary to incorporate indicators reflecting ecosystem function and structure to rule out cases of false recovery in grasslands. Therefore, when monitoring grassland degradation, only by integrating ecosystem structure and function can a comprehensive assessment of the degradation status of grassland ecosystems be made, providing more comprehensive scientific basis for subsequent formulation of precise ecological management strategies.

Assessment of grassland degradation necessitates establishing appropriate reference baselines to accurately determine degradation status. Building upon a well-constructed degradation evaluation index system, temporal analysis of ecosystem structural and functional dynamics can provide deeper insights into degradation processes [11]. The successive successful launches of China's terrestrial resource satellites, particularly hyperspectral scientific and operational satellites, have enabled advanced monitoring of steppe community composition and species identification through remote sensing. Hyperspectral remote sensing provides data with high spectral resolution, enabling more precise identification of

degraded species compared to multispectral data. However, due to the limited coverage capacity of hyperspectral remote sensing data, it is impossible to obtain long-term time-series data covering the study area. Therefore, information on degraded indicator species can only be used to establish a reference baseline. Such reference baselines should clearly characterize the optimal community structure and ecological functions representative of non-degraded steppe ecosystems. At present, study on the application of remote sensing techniques for monitoring steppe degradation has seen fewer approaches to finding or establishing a reference baseline, and no methodology or theoretical system has yet been developed. Most of the existing studies, which are limited by the availability of remote sensing image data, take steppe degradation as a given in order to carry out studies on changes in steppe vegetation. This approach does not take into account the effects of temporal and spatial fluctuations in climatic and hydrothermal conditions on vegetation communities, which may be a normal fluctuation within the resilience of ecosystems rather than the occurrence of degradation. Therefore, the establishment of a reference baseline that takes into account both structure and function is extremely important for determining whether and to what extent steppes are degraded.

In conclusion, scholars both domestically and internationally have conducted extensive research on regional grassland degradation monitoring. However, current challenges persist: (1) degradation indicators struggle to simultaneously account for ecosystem structure and function, failing to bridge reliable ground-based experiments with efficient remote sensing technologies; (2) reference baselines remain difficult to establish and often neglect the impact of hydrothermal fluctuations on vegetation communities.

Building upon this foundation, our study first evaluates regional hydrothermal conditions and conducts ecological zoning. We then develop a comprehensive degradation assessment framework for typical steppe ecosystems by selecting indicators from both structural and functional perspectives. This system incorporates vegetation community distribution and the prevalence of degradation-indicator species, while accounting for climate variability and hydrothermal fluctuations, to establish scientific reference baselines for steppe degradation and enable quantitative severity evaluation. Finally, we analyze the spatiotemporal patterns and driving factors of degradation from 2013 to 2022. This study provides significant scientific guidance and practical implications for effectively controlling steppe degradation, maintaining sustainable steppe ecosystem development, and formulating regional ecological conservation strategies.

2. Study Area and Materials

2.1. Study Area

The Xilingol Typical Steppe, located in the eastern part of the Inner Mongolia Plateau, constitutes a vital component of the Eurasian continental steppe region and represents the most emblematic area of China's Temperate Typical Steppe. Situated within a continental arid-semi-arid monsoon zone, this steppe exhibits extreme sensitivity to climate change. Its vegetation community structure, species composition, and ecosystem possess high typicality and representativeness among comparable steppe ecosystems. Furthermore, this region serves as the core implementation zone for major ecological initiatives such as the National Grassland Ecological Conservation Subsidy and Reward Policy. The state has implemented multiple measures for ecological restoration and conservation, enabling research findings to directly inform national ecological governance decisions. Selecting this area for study allows results to effectively reflect the universal patterns of typical steppe ecosystems in China and globally, significantly enhancing the extrapolation value and application potential of research outcomes.

The temperate typical steppe in Xilingol, Inner Mongolia, serves as both a crucial ecological barrier and a significant pastoral base in northern China, representing one of the most important steppe ecosystems in the region. Situated in the central-eastern part of Xilingol League ($43^{\circ}1'43.5''$ – $46^{\circ}43'54.5''$ N, $113^{\circ}27'29.3''$ – $119^{\circ}12'40.2''$ E) (Figure 1), this steppe ecosystem covers three banners (Abaga, East Ujimqin, and West Ujimqin) and Xilinhot City. This temperate steppe is located in the continental arid and semi-arid monsoon zone, featuring long, cold winters and short, cool summers. The annual average temperature ranges between -1°C and 3°C , with abundant sunshine and high evaporation rates. Annual precipitation varies from 250 to 350 mm, showing a decreasing trend from northeast to southwest [12], with most rainfall concentrated during summer months. The terrain consists primarily of a flat plateau with an average elevation of about 1000 m. The diverse soil types, including chernozem, chestnut soil, and meadow soil, provide favorable conditions for steppe vegetation growth while remaining vulnerable to wind and water erosion. The steppe boasts rich grass species resources, producing high-quality forage with substantial yield. It maintains remarkable biodiversity and vital ecosystem functions. For centuries, these steppes have sustained nomadic livelihoods while providing abundant forage resources for large-scale sedentary animal husbandry. However, the steppe ecosystem now faces increasing degradation threats due to combined pressures from human activities and climate change.

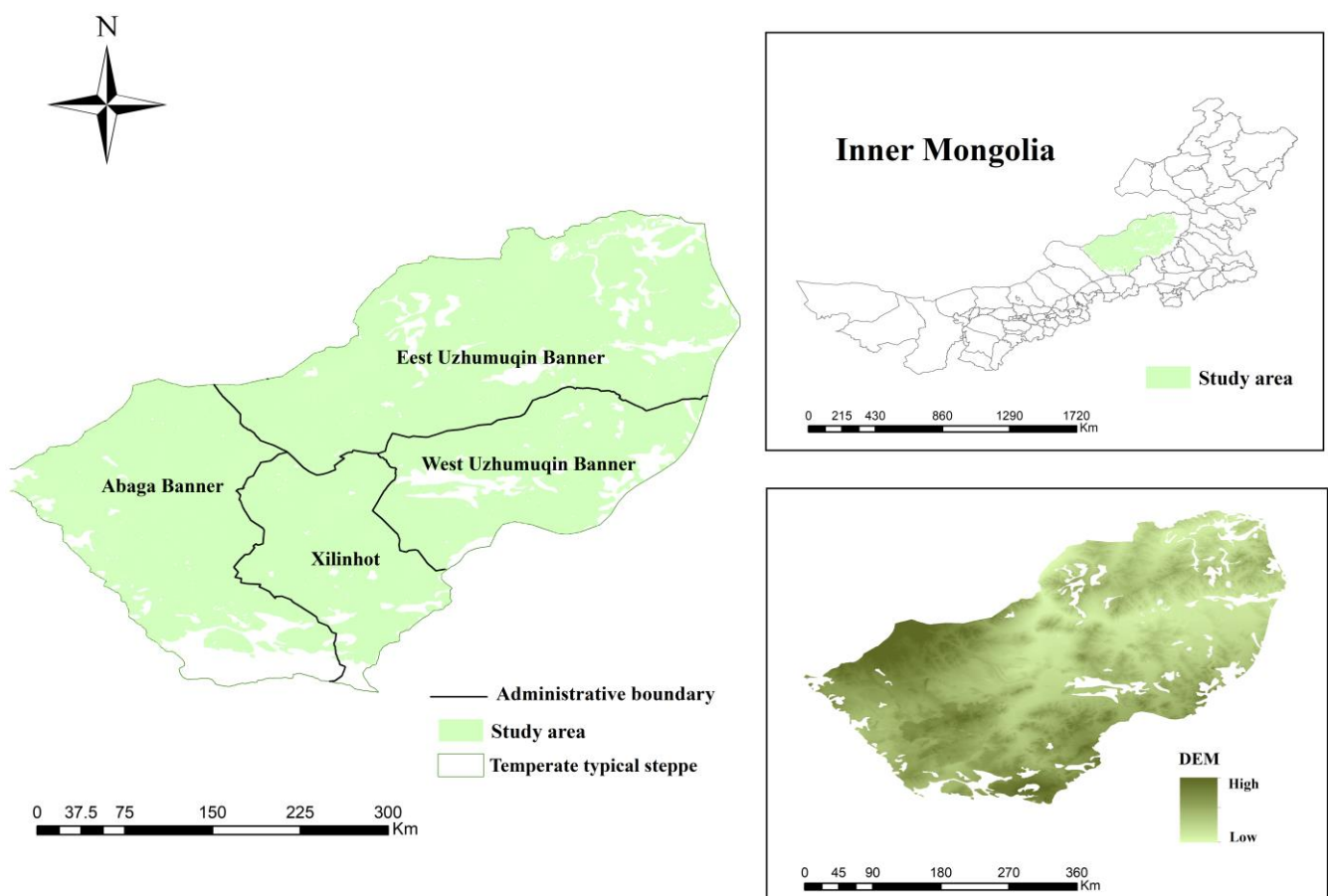


Figure 1. Location of the study area.

2.2. Data Sources and Preprocessing

This study incorporates multi-source remote sensing data, with detailed specifications provided in Table 1. The NDVI data were synthesized from the annual maximum values, the LST data were synthesized from the mean values of the months of the vegetation

growing season (from June to August each year), the annual total precipitation data were obtained by summing the monthly total precipitation, the annual mean temperature data were obtained by averaging the monthly mean temperatures for each of the 12 months of the year, and the hyperspectral data were preprocessed by radiometric calibration and atmospheric correction. The hyperspectral data used in this study comprised a total of 56 scenes. In addition to performing radiometric calibration and atmospheric correction, bands containing minimal ground information due to factors such as ultraviolet absorption and water vapor absorption were removed. Ultimately, 120 bands located within atmospheric transmission windows were retained. All data were standardized to the same coordinate system (GCS_WGS_1984), and the spatial resolution was resampled to 30 m $\times$ 30 m.

In preliminary work for this study, field surveys were conducted to delineate natural vegetation types in the Xilingol temperate steppe region. Guided by the principle of covering major vegetation communities within the study area, field investigations combined topographic maps with vegetation type maps, utilizing GPS positioning technology. Plot sizes were set at 30 m $\times$ 30 m to match the spatial resolution of ZY1-02D/02E satellite imagery. Within each plot, 1 m $\times$ 1 m subplots were randomly distributed using a nested plot design. This approach minimized matching errors between plots and remote sensing pixels while ensuring accuracy for multi-source data integration.

To enhance the applicability and reference value of remote sensing monitoring results in steppe resource surveys and related research, this study strictly adhered to ecological ground survey protocols. Building upon a systematic review of relevant literature, multi-year continuous ground measurements were conducted in the temperate typical steppe region of Xilingol, Inner Mongolia. Measurement content included plant community characteristics, community composition structure, and spectral information of degradation indicator species. Building upon existing research, this study systematically analyzed and constructed a long-term sequential distribution dataset for the region's primary vegetation communities. By comparing this dataset with vegetation type maps and field survey results, the accuracy of extracted vegetation community information was effectively validated.

Table 1. Sources of principal data.

Data Name	Resolution	Data Source
Digital Elevation data (DEM)	30 m	STRM elevation data products (https://search.earthdata.nasa.gov)
Normalized Difference Vegetation Index (NDVI)	30 m	National Science & Technology Infrastructure (https://nesdc.org.cn)
Land Surface Temperature (LST)	1000 m	(https://search.earthdata.nasa.gov)
Land Use Type	30 m	China Annual Land Cover Dataset (CLCD)
Soil Type	1:1 million	Chinese soil dataset (v1.1) based on the World Soil Database (HWSD), (https://data.tpdc.ac.cn)
Monthly Total Precipitation Monthly Mean Temperatures	1000 m	ERA5 Dataset Google Earth Engine (GEE) cloud-based platform
Evapotranspiration (ET)	500 m	MODIS MOD16A2 Dataset Google Earth Engine (GEE) cloud-based platform
ZY-1 02D and ZY-1 02E high-resolution data	30 m	The China Aero Geophysical Survey and Remote Sensing Center for Natural Resources (AGRS)
Grazing Intensity	1000 m	National Science & Technology Infrastructure (https://nesdc.org.cn)
Population Density	1000 m	(https://landscan.ornl.gov/)

3. Study Method

The methodological framework of this study is presented in Figure 2. We develop an integrated steppe degradation evaluation system incorporating both structural and functional ecosystem attributes. The system establishes degradation reference baselines and grades degradation through the premise of taking into account the hydrothermal conditions of the study area.

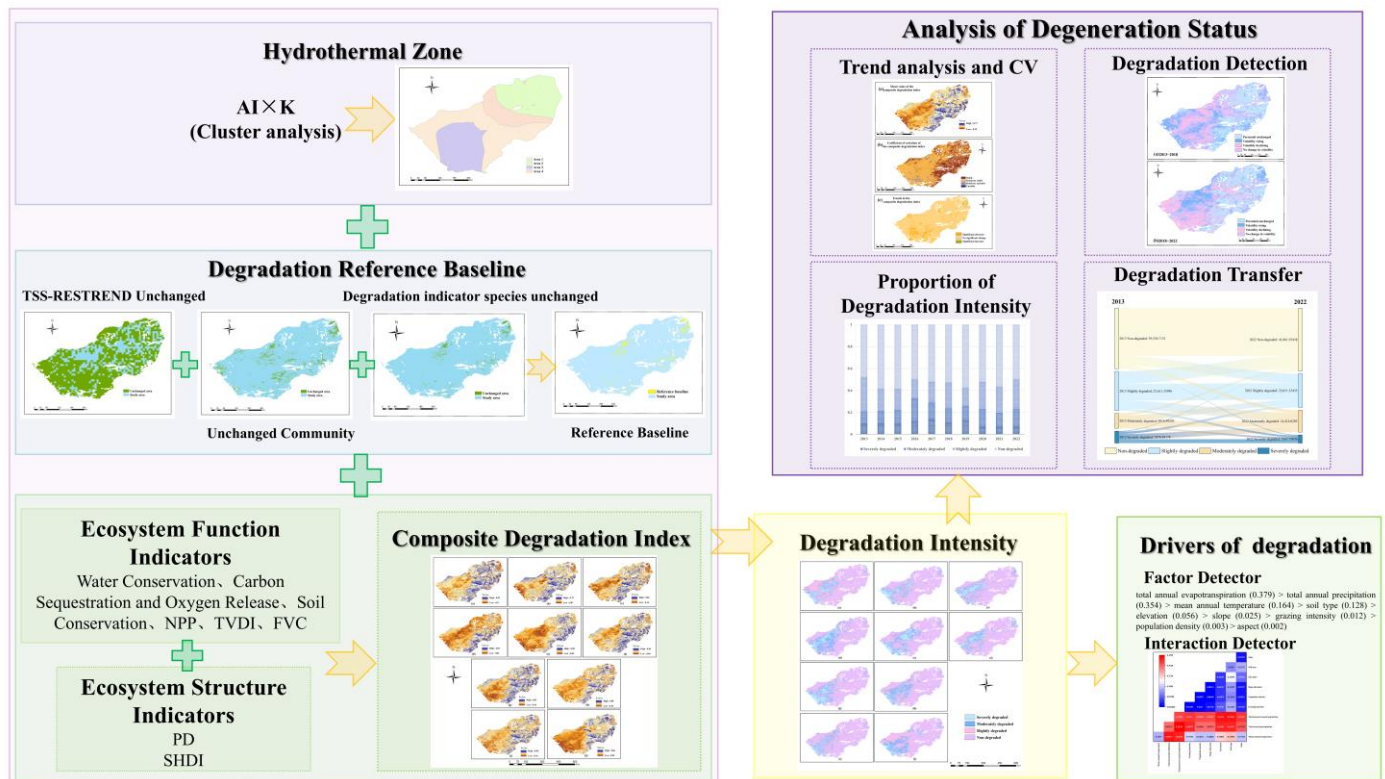


Figure 2. The flow chart of this study.

3.1. Steppe Degradation Indicators and Weights

3.1.1. Indicators of Steppe Ecosystem Structure

The Xilingol temperate typical steppe in Inner Mongolia serves as a crucial ecological barrier for North China, functioning as a key zone for desertification control and biodiversity conservation.

This study utilizes the vegetation community distribution dataset derived from field measurements introduced in Section 2.2 to calculate landscape fragmentation and Shannon diversity of vegetation communities within the study area, thereby representing changes in steppe ecosystem structure.

The patch density (PD) characterizes the degree of fragmentation in a landscape, reflecting to some extent the intensity of anthropogenic disturbance on the landscape. A higher fragmentation index indicates greater degradation of the landscape [13].

$$PD = \frac{N_i}{A_i} \quad (1)$$

In the formula, PD is the fragmentation index of landscape i , N_i is the number of patches of landscape i , and A_i is the total area of landscape i .

The Shannon diversity index (SHDI) is a method for measuring species diversity within a community, considering both the number of species and the evenness of their

distribution. A higher value indicates greater species diversity in the community, while a lower value indicates lower diversity.

$$SHDI = - \sum (P_i) \cdot \ln(P_i) \quad (2)$$

P_i is the proportion occupied by landscape patch type i [13].

3.1.2. Indicators of Steppe Ecosystem Function

In this study, we used the dimidiate pixel method to estimate the FVC, which calculates the proportion of vegetation in each image by analyzing the spectral features of each image in the remote sensing image and decomposing it into vegetated and non-vegetated components [14]. The formula for calculating FVC is

$$FVC = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (3)$$

where $NDVI_{max}$ and $NDVI_{min}$ are the $NDVI$ values with 95% probability of occurrence and 5% probability of occurrence in the study area, respectively.

NPP of vegetation refers to the total amount of organic matter fixed by net photosynthesis minus the total amount of organic matter consumed by plant respiration, and is a direct reflection of the productivity of vegetation, vegetation communities, and vegetation ecosystems under natural conditions [15]. The CASA model was used in this study to calculate NPP [16].

$$NPP = APAR(s, t) \times \varepsilon(x, t) \quad (4)$$

$$APAR(s, t) = SOL(x, t) \times FPAR(x, t) \times 0.5 \quad (5)$$

$$\varepsilon(x, t) = T_{\varepsilon 1} \times T_{\varepsilon 2} \times W_{\varepsilon} \times \varepsilon_{max} \quad (6)$$

where x represents a single pixel, t represents a month, $APAR(s, t)$ represents the photo synthetically active radiation (gC/m^2) absorbed by pixel x in month t , and $\varepsilon(x, t)$ represents the actual light energy utilization (gC/MJ) of single pixel x in month t . $SOL(x, t)$ denotes the total solar radiation at pixel x in month t ; $FPAR(x, t)$ denotes the absorption ratio of photosynthetically active radiation at pixel x in month t . The constant 0.5 denotes the proportion of total solar radiation that can be utilized by vegetation. ε_{max} is the maximum light energy utilization efficiency, and ε_{max} is different for different vegetation. The actual light energy utilization efficiency was calculated by temperature stress coefficients $T_{\varepsilon 1}$, $T_{\varepsilon 2}$ and moisture stress coefficients W_{ε} and ε_{max} [16].

Water conservation is closely related to factors such as precipitation, evapotranspiration, surface runoff, and vegetation cover type. In this paper, the water balance method and the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model are used to calculate the water conservation in the study area. The annual water yield module of the InVEST model is based on the principle of water balance, which sets the total annual rainfall minus the total annual actual evapotranspiration of the water resources in the raster cell as the total annual water yield [17].

$$Y(x) = \left[1 - \frac{AET(x)}{P(x)} \right] \times P(x) \quad (7)$$

where $Y(x)$ is the water production (mm) of x in the raster cell; $AET(x)$ is the actual annual evaporation (mm) of x in the raster cell; and $P(x)$ is the annual precipitation (mm) of x in the raster cell.

After calculating the water yield using the InVEST model, the water yield was corrected based on topographic indices, flow coefficient, and soil saturated hydraulic conductivity to finally obtain the water conservation [18]. The correction formula is

$$Retention = \min\left(1, \frac{249}{V}\right) \times \min\left(1, \frac{0.9 \times TI}{3}\right) \times \min\left(1, \frac{K}{300}\right) \times Y \quad (8)$$

Retention is the water conservation (mm); *V* is the flow coefficient; *TI* is the topographic index; *K* is the soil saturated hydraulic conductivity (cm/d); and *Y* is the annual water yield (mm).

The study used the Universal Soil Loss Equation (USLE) to calculate the potential soil erosion and actual soil erosion and hence soil conservation using the formula:

$$USLE = R \times K \times LS \times P \times C \quad (9)$$

$$RKLS = R \times K \times LS \quad (10)$$

$$SD = RKLS - USLE \quad (11)$$

SD is the soil conservation amount ($\text{t} \cdot \text{hm}^{-2} \cdot \text{h}^{-1} \cdot \text{a}^{-1}$); *RKLS* is the potential soil erosion intensity ($\text{t} \cdot \text{hm}^{-2} \cdot \text{h}^{-1} \cdot \text{a}^{-1}$); *USLE* is the actual soil erosion intensity ($\text{t} \cdot \text{hm}^{-2} \cdot \text{h}^{-1} \cdot \text{a}^{-1}$); *R* is the rainfall erosivity factor ($\text{MJ} \cdot \text{mm} \cdot \text{hm}^{-2} \cdot \text{h}^{-1} \cdot \text{a}^{-1}$); *K* is the soil erodibility factor ($\text{t} \cdot \text{MJ}^{-1} \cdot \text{mm}^{-1} \cdot \text{h}$); *LS* is the topography factor, dimensionless, where *L* is the slope length factor and *S* is the slope degree factor; *C* is the vegetation cover and crop management factor, dimensionless, with a range of values from 0 to 1; and *P* is the factor of soil and water conservation measures, dimensionless, with a range of values from 0 to 1 [19].

Carbon sequestration and oxygen release in steppe ecosystem includes two parts: carbon sequestration, which refers to the process of fixing atmospheric CO_2 in the ecosystem through biological processes, and oxygen release, which refers to the process of releasing O_2 from a substance through complex chemical changes. For the production value of organic matter in vegetated ecosystems is often characterized by NPP. Research shows that according to the chemical equation of photosynthesis of green vegetation ($6\text{CO}_2 + 6\text{H}_2\text{O} \rightarrow \text{C}_6\text{H}_{12}\text{O}_6 + 6\text{O}_2$), it can be seen that vegetation can fix 1.63 kg CO_2 and release 1.19 kg O_2 for every 1 kg of organic matter produced. The unit is g C/m²·year

$$\text{CO}_2(\text{fixation} + \text{release}) = \text{NPP} \times (1.63 + 1.19) \quad (12)$$

Sandholt et al. in their study on the use of surface temperature-vegetation index triangle feature space to study soil moisture, proposed the use of the temperature-vegetation drought index (TVDI) to represent soil dry and wet conditions [20].

$$\text{TVDI} = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \quad (13)$$

$$T_{\max} = a_1 + b_1 \times \text{NDVI} \quad (14)$$

$$T_{\min} = a_2 + b_2 \times \text{NDVI} \quad (15)$$

where *T* denotes the surface temperature value of any pixel; *T_{max}* denotes the maximum temperature corresponding to a certain *NDVI*, which can be obtained by linearly fitting the *NDVI* to the dry side; *T_{min}* denotes the minimum temperature corresponding to a certain *NDVI*, which can be obtained by linearly fitting the *NDVI* to the wet side, and *a₁*, *b₁* and *a₂*, *b₂* are the coefficients of the linear fit for the dry side and the wet side, respectively.

3.1.3. Indicator Weights

There are several ways to calculate indicator weights. Three objective weighting techniques, namely entropy weighting, coefficient of variation weighting, and principal component analysis, are used in this study to determine weights for each indicator in Sections 3.1.1 and 3.1.2 to prevent subjective weighting.

The entropy method is a critical approach for determining indicator weights in multi-index evaluation systems. Based on information entropy theory, this method calculates each indicator's entropy value to assess its relative importance, where lower entropy values indicate higher information disorder and greater variability, thus warranting higher weights in the comprehensive assessment [21]. The coefficient of variation, defined as the ratio of standard deviation to mean, quantifies sample stability and dispersion. This objective weighting approach effectively reduces subjectivity-induced uncertainties during indicator assignment [22]. PCA is fundamentally a statistical dimensionality reduction method that transforms correlated original variables into uncorrelated components through orthogonal transformation [23]. In remote sensing ecological monitoring, PCA concentrates maximal feature information into the leading components, enabling selective retention of fewer principal components than original variables to enhance analytical efficiency.

The entropy method, principal component analysis, and coefficient of variation method are all objective weighting approaches, yet each has limitations and yields inconsistent results. Directly applying any single method may introduce bias into the derived weights. To ensure robustness in the final indicator weights, Monte Carlo simulation is introduced to make decisions based on the three weighting methods discussed earlier.

Monte Carlo simulation obtains potential weighting results through repeated random sampling and calculation of probability distributions [24]. It assumes known probability distributions for input variables and enhances the reliability of output through multiple sampling, especially when the output depends on multiple variables [25]. Its fundamental purpose is to quantify uncertainty in indicator weights and assess the impact of this uncertainty on final conclusions within a probabilistic framework, thereby demonstrating the robustness and reliability of research findings. Furthermore, by testing 95% confidence intervals, scientifically sound and robust weighting results are obtained. To date, it has been applied across numerous fields [26]. The Monte Carlo triangular probability distribution function comprises the minimum, maximum, and mean values of individual steppe degradation weights. With 1000 simulation iterations, the mean value is calculated from the results of these simulations to obtain the comprehensive weight value for steppe degradation assessment in typical steppe areas (Table 2).

Table 2. The final indicator weighting results.

Indicator	Weight
Soil Conservation	0.2535
Water Conservation	0.1923
Carbon Sequestration and Oxygen Release	0.1175
Net primary productivity (NPP)	0.1175
Fractional vegetation cover (FVC)	0.0915
Temperature vegetation dryness index (TVDI)	0.0652
Patch density (PD)	0.0655
Shannon diversity index (SHDI)	0.0970

3.2. Hydrothermal Zone Delineation

The temperate typical steppe of Inner Mongolia, located in China's arid and semi-arid zone, represents a region with prominent hydrothermal constraints where vegetation distribution is governed by temperature-precipitation patterns. These hydrothermal factors simultaneously regulate vegetation growth and drive steppe degradation processes. Within the atmosphere-biosphere-pedosphere continuum system, two critical indicators, mean annual air temperature and annual soil water deficit, exhibit strong correlations with plant growth and distribution. Following Ni et al., their product is defined as the hydrothermal product index, serving as an integrated metric for temperature-moisture balance assessment [27].

$$K = T \times \frac{SD}{100} \quad (16)$$

where K is the hydrothermal product index, T is the average annual air temperature ($^{\circ}\text{C}$), and SD is the annual soil water deficit ($P - ET$). When $K > 0$, it indicates synchronous variations in hydrothermal conditions, with higher values representing better hydrothermal matching. Conversely, $K < 0$ signifies opposing trends in hydrothermal factors, reflecting an imbalance in hydrothermal coordination. This may manifest as regions with scarce precipitation and intense evapotranspiration or areas with insufficient thermal resources and cold climates, leading to poor hydrothermal resource matching. The greater the absolute value of K , the more severe the hydrothermal imbalance.

The aridity index, based on atmospheric water balance, accurately reflects the annual climatic moisture conditions of a region and holds greater practical significance for agricultural applications [28].

$$AI = \frac{ET}{P} \quad (17)$$

where AI is the dryness index; ET is the evapotranspiration (mm) and P is the precipitation (mm). The higher aridity index value indicates a drier climate and greater hydrothermal imbalance in a region, while a lower value corresponds to more humid conditions.

The study of hydrothermal zoning essentially involves aggregating spatially contiguous regions with similar climatic characteristics, representing a common application of clustering methods in geographic space. Since the hydrothermal product index (K) of the study area is consistently negative, it indicates a significant imbalance in hydrothermal matching. To highlight regional differences, the absolute value of K was multiplied by the aridity index (to amplify variations in hydrothermal conditions). Subsequent cluster analysis was conducted to better distinguish between high- and low-value zones. Based on the clustering results, the study area was initially divided into three hydrothermal zones: high-value clusters, low-value clusters, and non-significant areas. Due to the large longitudinal span of the non-significant zone, it was further subdivided into two regions to ensure scientific rigor and alignment with actual conditions, resulting in a final classification of four hydrothermal zones.

The hotspot analysis method employed in this study is the local Getis-Ord G_i^* index, a spatial autocorrelation metric calculated based on a spatial weight matrix [29]. By computing z -scores and p -values for each pixel in the dataset, this method identifies spatially clustered locations of either high-value or low-value elements.

$$G_i^* = \frac{\sum_{j=1}^n W_{ij} X_j - \bar{X} \sum_{j=1}^n W_{ij}}{S \sqrt{\frac{n \sum_{j=1}^n W_{ij}^2 - \left(\sum_{j=1}^n W_{ij} \right)^2}{n-1}}} \quad (18)$$

where G_i^* is the z-score, X_j is the attribute value of element j , W_{ij} is the spatial weight between element i and element j , and n is the total number of elements, where $\bar{X}$ and S are calculated as follows:

$$\bar{X} = \frac{\sum_{j=1}^n X_j}{n} \quad (19)$$

$$S = \sqrt{\frac{\sum_{j=1}^n x_j^2}{n} - (\bar{X})^2} \quad (20)$$

A statistically significant positive z-score indicates that higher values correspond to more intense clustering of hotspots, with increasing z-score values reflecting tighter spatial aggregation of high-value clusters. Conversely, a statistically significant negative z-score demonstrates that lower values represent stronger clustering of cold spots, where decreasing z-scores denote more concentrated low-value clustering patterns.

3.3. Establishment of Degradation Baseline

This study first utilizes time-series segmentation and residual trend analysis (TSS-RESTREND) based on long-term remote sensing monitoring data to identify pixels with unchanged attributes at large scales. TSS-RESTREND is currently a highly robust and reliable tool for assessing steppe vegetation degradation, particularly in arid and semi-arid regions such as typical steppes. Its core principle lies in separating the effects of climate change (primarily precipitation) on vegetation from non-climatic factors like human activities. This approach prevents normal fluctuations in steppe vegetation caused by climate change from being misinterpreted as degradation. Since TSS-RESTREND utilizes 1000 m-resolution data, its results are large-scale in nature. Further refinement of the degradation reference baseline requires integration with community distribution data and indicator species for degradation (Figure 3).

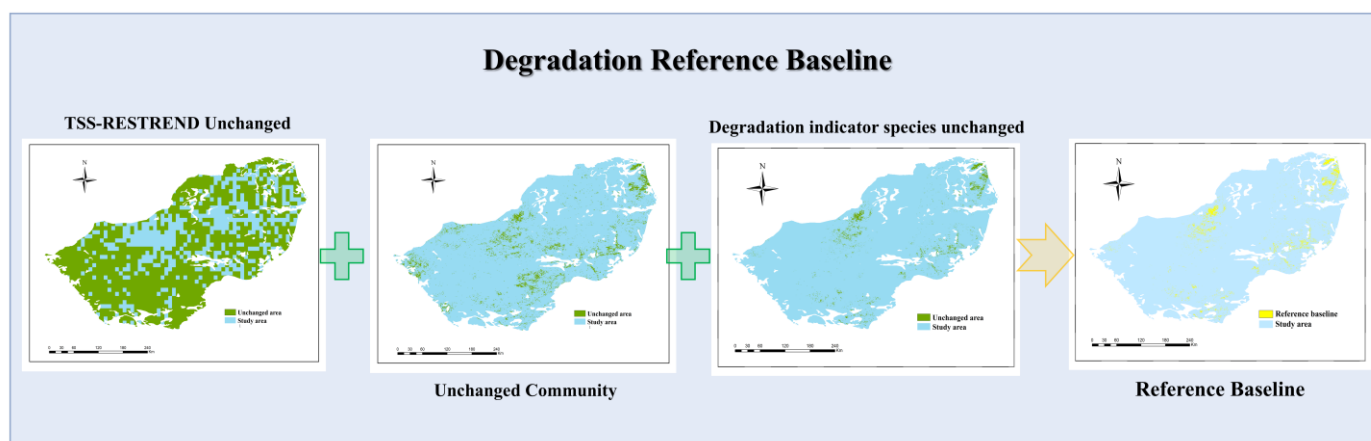


Figure 3. Flowchart for constructing a degradation reference baseline.

The Time Series Segmentation and Residual Trend (TSS-RESTREND) method was first proposed by Burrell Evans for analyzing vegetation changes across Australia [30]. This method isolates the influence of climatic factors on vegetation NDVI to assess the extent of human impacts on vegetation dynamics.

The TSS-RESTREND method first employs the BFAST algorithm to identify breakpoints within the NDVI time series during the study period. Notably, the BFAST implementation in TSS-RESTREND operates on Vegetation-Precipitation Relationship (VPR) residuals rather than raw NDVI time series, with its seasonal component disabled in the application. For each segmented period, the Chow test criterion evaluates the impact of discordant years on vegetation NDVI. When the F-test ($\alpha = 0.05$) indicates that BFAST-detected discor-

dant years did not alter vegetation structure, these breakpoints are rejected and adjacent segments are merged [31]. The specific merging logic follows four defined scenarios.

(1) If a pixel has a significant VPR ($\alpha = 0.05$) and there are no significant breakpoints in the VPR residuals ($\alpha = 0.05$), it satisfies all the criteria of the standard RESTREND analysis described above.

(2) When a significant breakpoint is detected in the VPR residuals, a Chow test is applied to the VPR. For pixels with significant breakpoints in the VPR residuals ($\alpha = 0.05$) but no significant breakpoints in the VPR ($\alpha = 0.05$), a segmented RESTREND is applied:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i z_i \quad (21)$$

where x_i is the year, z_i is a dummy variable (0 or 1), β_0 is the intercept, β_1 is the slope, β_2 is the offset term at the breakpoint, and β_3 is the slope at the breakpoint.

(3) If a pixel has a distinct break in the VPR, it may indicate a significant structural change in the ecosystem during the study period [32]. Therefore, it is not reasonable to assume that rainfall has the same effect on both sides of the breakpoint, and the time series NDVI_{max} is separated and new VPR is recalculated separately on either side of the breakpoint. To allow comparison of different accumulation and offset cycles across breakpoints, the optimal precipitation is converted to standardized scores by Burrell et al. [30].

$$z_i = \frac{x_i - \mu}{\sigma} \quad (22)$$

where z_i is the standardized score, x_i is the observed value, μ is the mean over the cumulative period of the entire time series, and σ is the standard deviation. The multiple regression is then fitted to the time series standard scores:

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \beta_3 x_i z_i \quad (23)$$

where x_i is the precipitation standard term calculated in the above equation, z_i is a dummy variable (0 or 1), β_0 is the intercept, β_1 is the slope, β_2 is the offset term at the breakpoint, and β_3 is the slope at the breakpoint. For a pixel, the change in pixel greenness needs to include the change in residuals.

(4) Pixels that do not meet the above conditions are considered unsuitable for the TSS-RESTREND.

The distribution of vegetation communities serves as both a crucial regulator of ecosystem functioning and a key structural indicator for steppe degradation assessment. Under combined pressures from climate change and anthropogenic activities, understanding spatiotemporal dynamics in plant community distribution has become a focal research priority in ecological remote sensing monitoring.

This study utilized existing community distribution data (as described in Section 2.2) to select pixels where communities remained unchanged from 2013 to 2022 as reference baseline pixels for further screening based on TSS-RESTREND results. These pixels satisfied the criteria of stable community composition and structure, enabling the degradation reference baseline to be narrowed down and precisely delineated from the perspective of unchanged ecosystem structure.

Spectral unmixing technology was employed to extract species abundance information within the study area. In hyperspectral remote sensing for ecological monitoring, each pixel represents a mixed pixel containing varying proportions of grass species. Spectral unmixing is essential to resolve species distribution patterns. Establishing an end-member spectral library is a critical step in hyperspectral remote sensing unmixing. This library contains pure spectra of various ground objects, ensuring that collected spectral data covers

all potential land cover types within the study area. It serves as the foundation for training and applying subsequent spectral unmixing algorithms.

Eight grass species occur within the study area: *Leymus chinensis*, *Stipa grandis*, *Achnatherum splendens*, *Artemisia frigida*, *Caragana microphylla*, *Cleistogenes squarrosa*, *Alhium ramosum*, and *Artemisia capillaris*. Field spectroscopic measurements were conducted for eight grass species and background soils, acquiring over 300 spectral curves. Species-specific curves were averaged to generate representative spectra. Using linear interpolation, all field-measured spectra (eight species and background soil) were resampled to 400–2500 nm at 1 nm intervals. These were then resampled to hyperspectral image bands via spectral response functions to establish a spectral library.

This study employs a deep convolutional unmixing network comprising an encoder and decoder. The encoder compresses input image data into a low-dimensional latent feature space, while the decoder reconstructs the original input from this latent representation. By constraining the latent space dimensionality below the input data dimensions, dimensionality reduction is achieved. Unmixing is performed through re-encoding in this compressed latent space, effectively separating distinct vegetation components. The decoder generates reconstructed images from latent representations, enabling validation of unmixing accuracy against original inputs.

$$Y_{F \times N} = M_{F \times K} \cdot A_{K \times N} + E_{F \times N} \quad (24)$$

The observed mixed pixel matrix Y (dimensions $F \times N$) is derived from the product of the endmember matrix M ($F \times K$) and the abundance coefficient matrix A ($K \times N$), with E ($F \times N$) representing residual errors: $Y = MA + E$. The objective of spectral unmixing is to reconstruct Y by optimizing A while accounting for E .

Using the results obtained through spectral unmixing, non-degraded areas were identified based on the proportion of degradation indicator species as specified in the national standard Parameters for degradation, sandification and salification of rangelands (GB19377-2003) [33].

The final selection process identifies the intersection of areas where community composition remains unchanged and the proportion of indicator species for degradation is low. This area serves as the reference baseline for steppe degradation. It must simultaneously meet three criteria: no change in large-scale attributes, stable steppe vegetation community structure, and a proportion of indicator species for degradation that complies with the non-degraded requirements specified in the national standard GB19377-2003 [33]. Only such areas qualify as reference baselines for steppe degradation. Failure to meet any one of the above three conditions indicates non-compliance with the criteria for undegraded steppe, rendering the area ineligible as a reference baseline for steppe degradation.

3.4. Degradation Delineation

Based on the above methodology, areas where steppe ecosystems are not degraded are identified, the composite degradation index corresponding to the area is extracted, and the mean minus the standard deviation of the composite degradation index corresponding to these areas is used as the critical value between non-degraded and slightly degraded. Combining the National Standard GB19377-2003 (Parameters for degradation, sandification and salification of rangelands) [33], the degradation of each hydrothermal region was classified as non-degraded, slightly degraded, moderately degraded and severely degraded, and the spatial pattern, spatial and temporal changes and evolutionary patterns of steppe degradation were analyzed.

3.5. Analysis Methods

3.5.1. Trend Analysis

Trend analysis is the use of ordinary least squares to fit the slope of the mean of an annual variable over a certain time frame, using the *Slope* to reflect the trend of each raster [34]. The calculation formula is as follows:

$$\text{Slope} = \frac{n \times \sum_{i=1}^n X_i - \sum_{i=1}^n X_i \times \sum_{i=1}^n i}{n \times \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (25)$$

where i is the year number, n is the length of the time series studied, and X_i is the annual mean for year i (X is the variable to be analyzed). If *Slope* is greater than 0 it means that the trend of the variable X for that image element in the time series is increasing and vice versa.

3.5.2. Coefficient of Variation Analysis

The coefficient of variation, also known as the coefficient of dispersion, can be used to quantify the inter-annual variability of degradation indicators to assess the stability of grassland ecosystems in different regions.

$$C_v = \frac{\sigma}{x} \quad (26)$$

where C_v is the coefficient of variation, σ is the standard deviation over a certain period of time, and x is the average value over a certain period of time, the smaller the coefficient of variation indicates that the degree of fluctuation is smaller and more stable, and vice versa the degree of fluctuation is larger and more unstable. The C_v values are divided into four classes: relatively stable ($C_v \leq 0.1$), stable ($0.1 < C_v \leq 0.2$), unstable ($0.2 < C_v \leq 0.3$), and very unstable ($C_v > 0.3$).

3.5.3. Degradation Detection

To monitor steppe degradation dynamics in Xilingol typical steppe during 2013–2022, this study implemented a reclassification and coding scheme for degradation intensity by integrating transition matrix analysis with coding methods, following established research protocols. The degradation intensity was numerically coded (4: non-degraded, 3: slightly degraded, 2: moderately degraded, 1: severely degraded) to construct degradation transition matrices, which quantitatively characterize the spatial-temporal transitions of steppe degradation across the study area. Conduct degradation detection by partitioning the 2013–2022 timeframe into two distinct periods. The formulation is presented using the years 2018 to 2022 as an example.

$$\text{dynamic} = 10000 \times \text{reclass}_{2018} + 1000 \times \text{reclass}_{2019} + 100 \times \text{reclass}_{2020} + 10 \times \text{reclass}_{2021} + \text{reclass}_{2022} \quad (27)$$

dynamic is the change in degradation class and *reclass* is the reclassification number for the period 2013–2022. Based on the changes in reclassification numbers, the changes in degradation class were categorized into four main trends: perennial unchanged, no change in volatility, volatility rising, and volatility declining (Table 3).

3.6. Drivers of Steppe Degradation

In order to deeply explore the driving factors affecting steppe degradation in the temperate typical steppe of Xilingol, Inner Mongolia, a series of influencing factors were comprehensively selected and analyzed from the perspectives of both natural and anthropogenic factors with reference to relevant studies [35]. Elevation, slope, slope direction, soil type, total annual precipitation, average annual temperature, and total annual evapo-

transpiration are natural factors, and grazing intensity as well as population density are anthropogenic factors. Referring to relevant studies, the natural breakpoint method of treatment was adopted to classify slope, slope direction, and elevation indicators into 9 categories, soil type into 33 categories, and all other indicators into 6 categories.

Table 3. Coding table for reclassification of steppe degradation intensity changes in typical steppe.

Type of Changes	Form of Coding	Description
Perennial unchanged	Identical classification numbers	No change in degradation intensity
No change in volatility	Classification numbers with endings same as the first	No change at the beginning or end of the degradation intensity
Volatility rising	Classification numbers with endings bigger than the first	Last year of degradation > first year
Volatility declining	Classification numbers with endings smaller than the first	Last year of degradation < first year

Geodetector is statistical method for detecting spatial dissimilarity and revealing the driving forces behind it, with the central idea being that if an independent variable has a significant effect on a dependent variable, then the spatial distributions of the independent and dependent variables should be similar [36]. The Geodetector consists of four detectors: factor detector, risk detector, ecological detector, interaction detector. In this study, factor detector and interaction detection are used to analyze the effects of natural as well as anthropogenic factors on grassland degradation.

The factor detector focuses on detecting the spatial dissimilarity of Y ; and on detecting to what extent a factor X explains the spatial dissimilarity of attribute Y , measured by the q value, with the expression:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (28)$$

where $h = 1, \dots, L$ is the stratification, categorization or partitioning, of the variable Y or factor X ; N_h and N are the number of cells in stratum h and the whole region, respectively; σ_h^2 and σ^2 are the variance of the Y values in stratum h and the whole region, respectively [37].

The interaction detector is used to identify interactions between different risk factors X_s , to assess whether factors X_1 and X_2 , when acting together, increase or diminish the explanatory power of the dependent variable Y , or whether the effects of these factors on Y are independent of each other. The evaluation is done by first calculating the q value of the two factors X_1 and X_2 for Y : $q(X_1)$ and $q(X_2)$, respectively, and calculating the q value when they interact (the new polygonal distribution formed by tangent of the two layers of the superposition variables X_1 and X_2): $q(X_1 \cap X_2)$, and comparing $q(X_1)$, $q(X_2)$, and $q(X_1 \cap X_2)$ [38].

4. Results

4.1. Characteristics of Spatial and Temporal Changes in the Composite Degradation Index

The change in the composite degradation index in the last 10 years is shown in Figure 4, from which it can be seen that the spatial distribution of the composite degradation index is not uniform, the differentiation characteristics are more obvious, and the whole shows a decreasing trend from the northeast to the southwest. Among them, the eastern and southern parts of East and West Urumqin Banners remained high during the 10 years because they are adjacent to the meadow steppe and have more precipitation, which is more suitable for the growth of vegetation. The value of the composite degradation index in the western part of Abaga Banner has remained low throughout the 10 years, probably

due to the fact that the region borders on desert steppe and has a dry climate and scanty precipitation, which is unsuitable for the growth and development of vegetation.

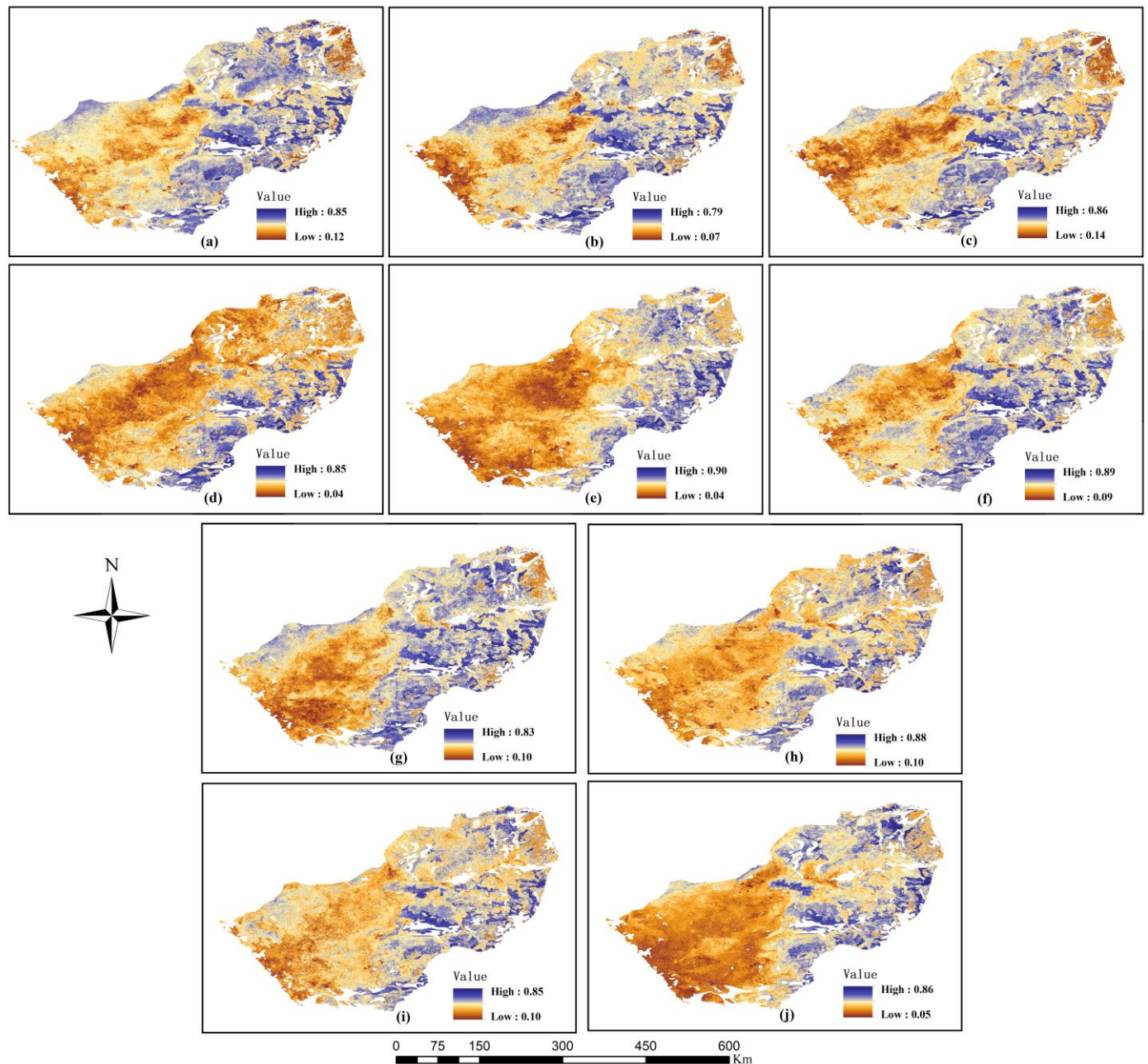


Figure 4. (a–j) Composite Degradation Index for the years 2013 to 2022.

The coefficient of variation of the composite degradation index in the study area ranges from 0 to 1, with a mean of 0.125, indicating spatial heterogeneity (as shown in Figure 5b). The area proportions for different variation levels, ranked from largest to smallest, are relatively stable (69.70%) > stable (27.27%) > relatively unstable (2.96%) > unstable (0.06%). This demonstrates that most areas of the typical steppe region tended to be stable over the 10-year period, with a small portion showing higher variability, primarily distributed in the southwestern part of Abaga Banner. Overall, the stability shows a decreasing trend from east to west. Based on the trend analysis results (Figure 5c), most of the study area experienced non-significant changes. Areas with significant increases clustered in the eastern part of East Ujimqin Banner, while areas with significant decreases clustered in the southwestern part of Abaga Banner.

From the above analysis, it can be seen that, because of the distinct differentiation features of the composite degradation index in the study area, it is inaccurate to choose a uniform degradation standard to classify the degradation intensity in the whole study area, which may lead to the area with a lower composite degradation index (for example, Abaga Banner) being in a state of heavy degradation in the whole area, which is not in line with the actual situation. Therefore, after zoning using the hydrothermal conditions of the study area, it would be more reasonable to develop reference baselines for degradation analysis based on each zone.

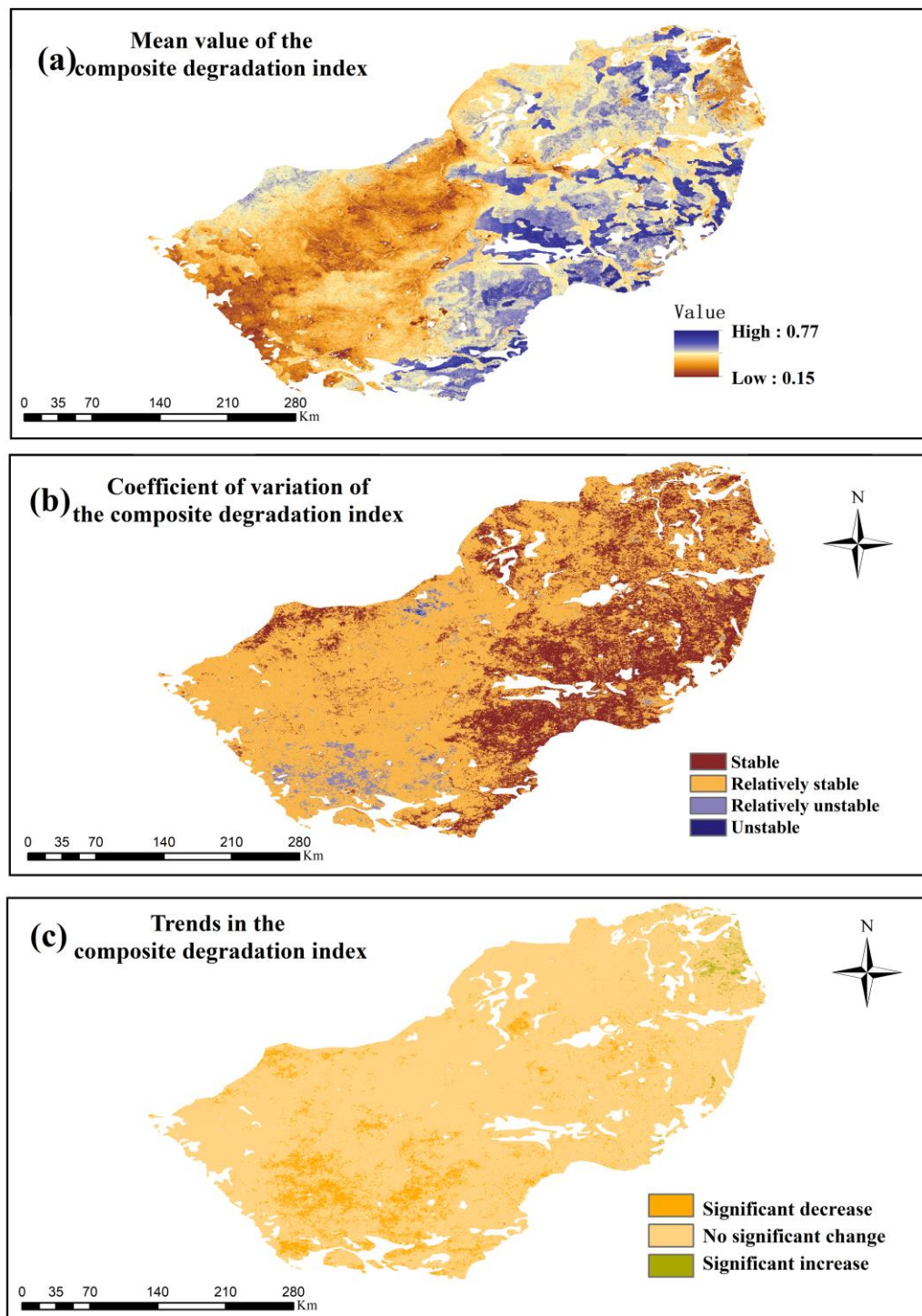


Figure 5. (a) Mean value; (b) Coefficient of variation; (c) Distribution of change trends of the steppe composite degradation index for the years 2013 to 2022.

4.2. Spatial and Temporal Analysis of the Current Status of Steppe Degradation

4.2.1. Time Series Segmentation and Residual Trend Method Results

Based on β_1 and significance level α in the above regression relationship [39,40], the trend of NDVI is categorized into 9 classes based on the linear fit of NDVI residuals to the time series using the α value of the F-test (Table 4). The trend level of NDVI decline is categorized into four levels, D1 ($\alpha < 0.01$), D2 ($0.01 \leq \alpha < 0.025$), D3 ($0.025 \leq \alpha < 0.05$) and DNC ($0.05 \leq \alpha < 0.1$), respectively. The trend level of NDVI increase is categorized into four levels, I1 ($\alpha < 0.01$), I2 ($0.01 \leq \alpha < 0.025$), I3 ($0.025 \leq \alpha < 0.05$), and INC ($0.05 \leq \alpha < 0.1$). NSC is the significance level does not pass ($\alpha > 0.1$), indicating no change in NDVI (Figure 6).

Table 4. Classification of NDVI Changes.

Grade Name	Direction of Change	Significance
I1	Slope > 0	$\alpha < 0.01$
I2	Slope > 0	$0.01 \leq \alpha < 0.025$
I3	Slope > 0	$0.025 \leq \alpha < 0.05$
INC	Slope > 0	$0.05 \leq \alpha < 0.1$
D1	Slope < 0	$\alpha < 0.01$
D2	Slope < 0	$0.01 \leq \alpha < 0.025$
D3	Slope < 0	$0.025 \leq \alpha < 0.05$
DNC	Slope < 0	$0.05 \leq \alpha < 0.1$
NSC		$\alpha > 0.1$

The extracted NSC represents large-scale areas showing no change, requiring further refinement of the degraded reference baseline using community distribution data and the proportion of degraded indicator species. The purpose of TSS-RESTREND's trend identification component is to pinpoint regions where characteristics hold steady on a broad scale, eliminating typical variations in steppe vegetation brought on by climate change that could be confused with degradation. Establishing the reference baseline for steppe degradation requires this step. However, the degradation baseline delineation is finished before the steppe degradation categorization, indicating a sequential process.

4.2.2. Results of Community Distribution Changes

Annual monitoring of community changes from 2013 to 2022 was conducted using land use transition matrices to quantify decadal shifts. Integrated multi-year data (Figure 7) revealed areal changes: *Achnatherum splendens* community, *Cleistogenes squarrosa* community, and *Leymus chinensis*-forb meadow community decreased in coverage, while *Stipa krylovii* community, *Stipa grandis* community, and *Leymus chinensis* rhizomatous grass community expanded.

In terms of total area changes, the overall area of the six communities showed fluctuating changes but none of the changes were significant. The proportions of area occupied by each community in 2013 were *Cleistogenes squarrosa* community (22.1%), *Stipa grandis* community (29.9%), *Achnatherum splendens* community (13.3%), *Stipa krylovii* community (17.8%), *Leymus chinensis* rhizomatous grass community (14.2%) and *Leymus chinensis*-forb meadow community (2.7%). The proportions of area occupied by each community in 2022 were *Cleistogenes squarrosa* community (20%), *Stipa grandis* community (30.1%), *Achnatherum splendens* community (13.1%), *Stipa krylovii* community (18.4%), *Leymus chinensis*-

sis rhizomatous grass community (13.9%) and *Leymus chinensis*-forb meadow community (3.8%), respectively.

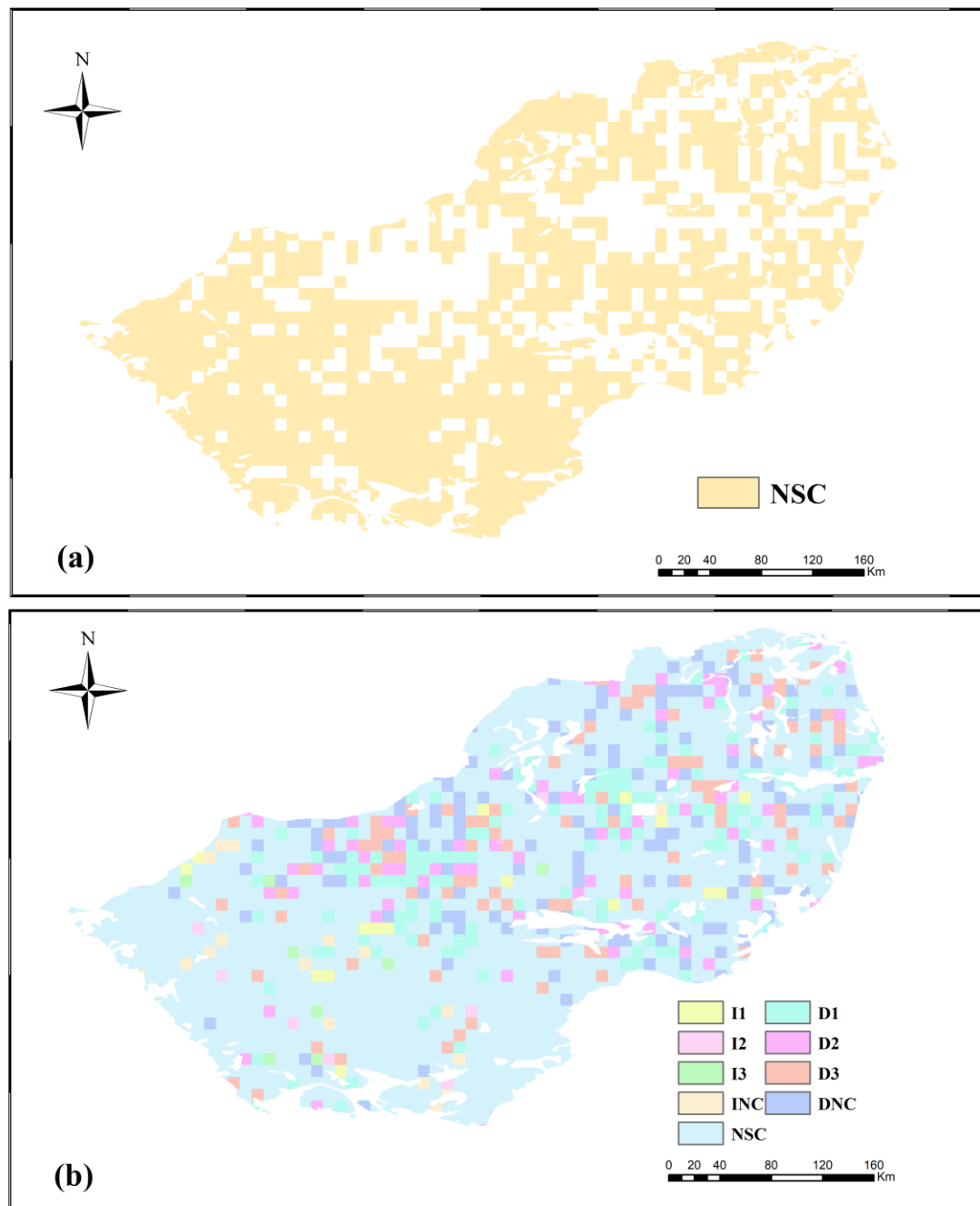


Figure 6. (a) Unchanged area detected by TSS-RESTREND; (b) TSS-RESTREND result.

Notably, the reduction in *Cleistogenes squarrosa* community (an indicator of steppe degradation) and the expansion of typical steppe dominant species (*Stipa grandis* community and *Stipa krylovii* community) suggest gradual steppe recovery. The areas where no changes occurred in the community structure from 2013 to 2022 were ultimately identified as regions with unchanged steppe ecosystem structure. These areas meet the criteria for stable community composition and structure, establishing a baseline for subsequent steppe degradation assessment and grading.

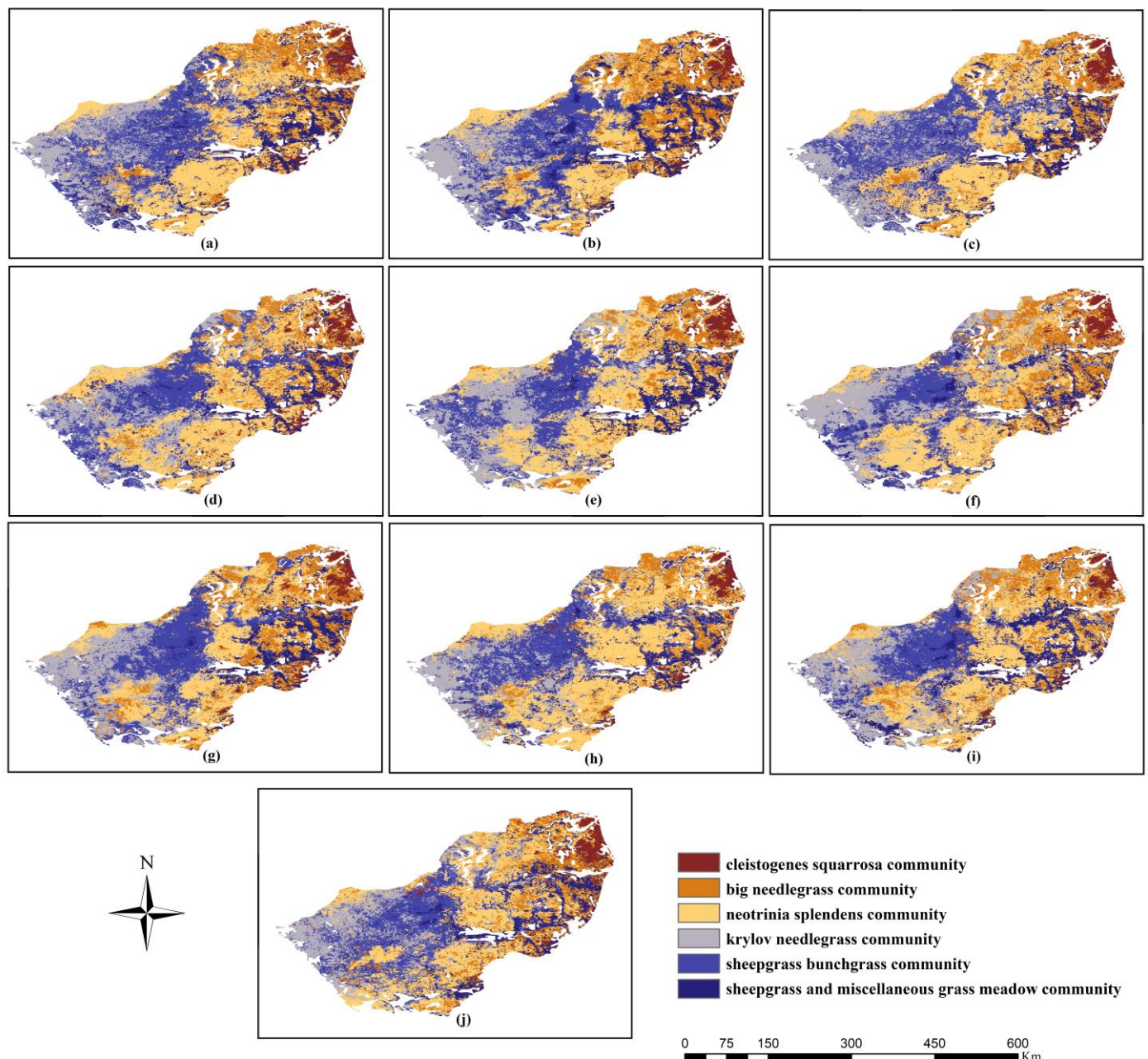


Figure 7. (a–j) Changes in community composition for the years 2013 to 2022.

4.2.3. Extraction of Degradation Indicator Species and Establishment of Reference Baseline

This study utilizes domestically produced hyperspectral satellite data and field-measured grass species spectra to construct a convolutional neural network model. This enables the identification of typical vegetation species within a given region, extracting their distribution information and proportion within the community. Degradation classification was performed using the proportion of degradation indicator species specified in the national standard GB19377-2003 [33]. Non-degraded areas were selected, and by combining the two aforementioned reference baseline methods, the overlapping regions were chosen as the final reference baseline results, as shown in Figure 8.

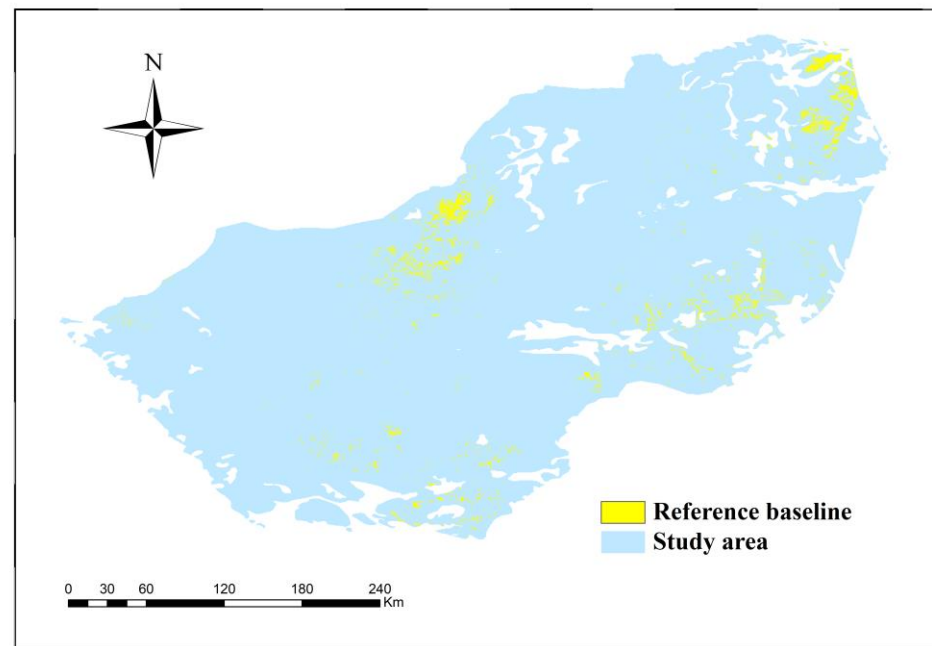


Figure 8. Steppe degradation reference baseline area.

4.2.4. Spatial and Temporal Analysis of Degradation

Spatially (Figure 9), non-degraded and slightly degraded areas are primarily concentrated in the eastern and southern parts of East Ujimqin Banner and West Ujimqin Banner, adjacent to meadow steppe, with minor distributions also found in the southern parts of Abaga Banner and Xilinhot City. Moderately degraded areas are clustered in parts of Xilinhot City and Abaga Banner, with smaller distributions also occurring in the central part of West Ujimqin Banner. Severely degraded areas are notably concentrated in the western part of Abaga Banner, adjacent to desert steppe, and are also distinctly distributed along the border areas between East Ujimqin Banner, Abaga Banner, and Xilinhot City.

This study utilized ground survey data and relevant domestic and international literature to compile a distribution map of degraded sampling points within the study area in recent years [41] (Figure 10). The marked sampling points in the map indicate steppe degradation levels determined by field measurements of indicators such as vegetation cover, grass community height, and soil properties. Due to inconsistent spatial scales among sampling points, precise pixel-level correspondence with remote sensing imagery was unfeasible. Therefore, verification was not conducted at the pixel scale but instead focused on spatial consistency comparisons based on the overall degradation patterns across the study area.

By comparing the degradation result map delineated in this study with the distribution map of degradation sampling points, it is evident that the degraded areas identified in this research spatially cover the degradation sampling points recorded during field surveys. This characteristic is particularly pronounced in the border areas between East Ujimqin Banner, West Ujimqin Banner, and Xilinhot City, as well as throughout Abaga Banner. Furthermore, spatial comparisons indicate that the overall steppe condition in West Ujimqin Banner is superior to that in Abaga Banner and Xilinhot City, with relatively smaller degraded areas. This finding aligns with the degradation distribution reflected by field sampling points, thereby validating the rationality of this study's degradation monitoring results at the regional scale.

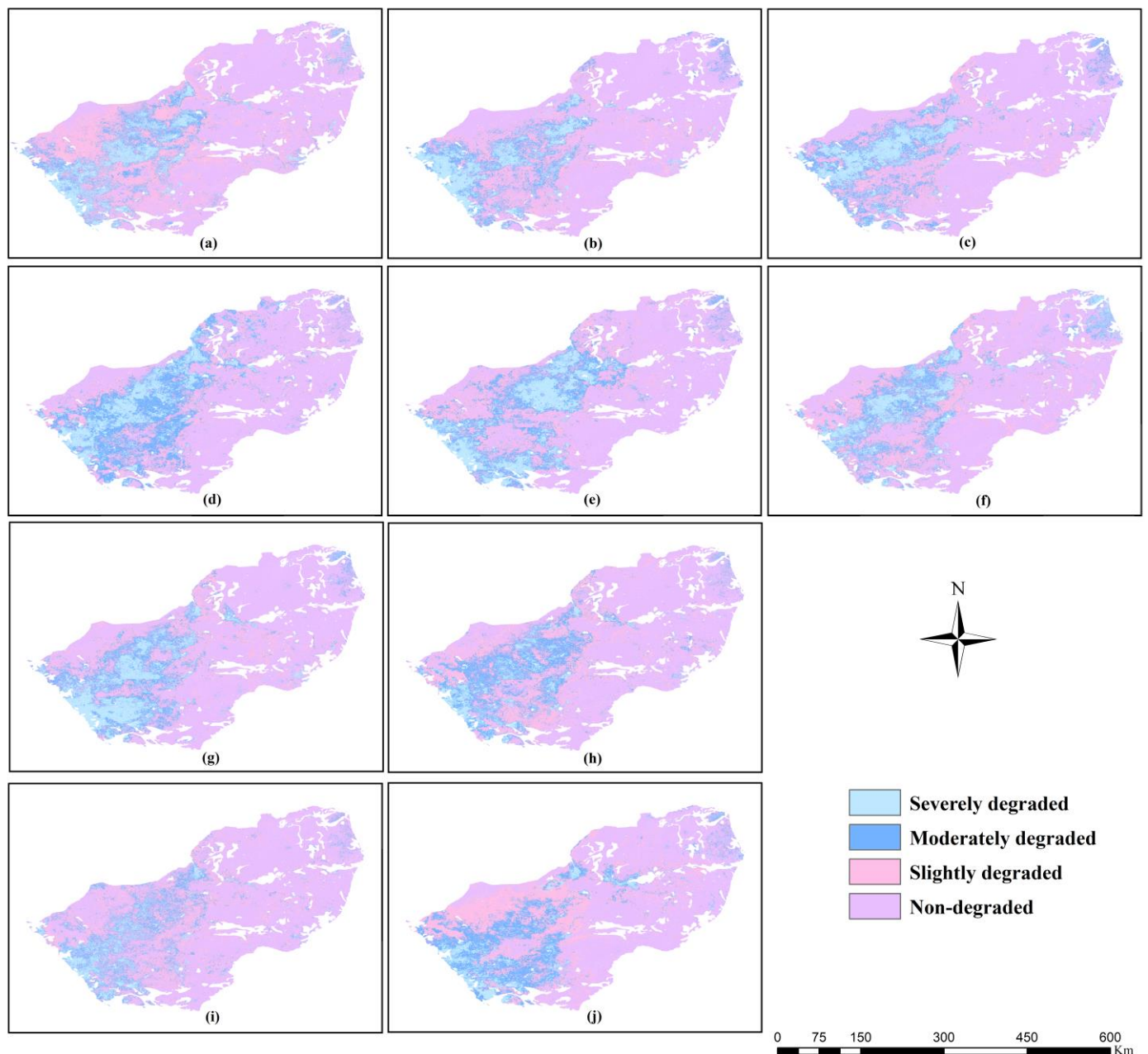


Figure 9. (a–j) Spatial distribution of degradation intensity for the years 2013 to 2022.

Regarding the proportion of steppe degradation intensity across different periods (Figure 11), from 2013 to 2022, the typical steppe region was dominated by non-degraded and slightly degraded steppe, averaging 75.57% (non-degraded: 53.58%, slightly degraded: 21.98%). Over the past decade, non-degraded steppe first increased, then sharply decreased, followed by fluctuating increases, rising from 47.89% to 49.87%. Degraded steppe showed an initial decrease, followed by a sharp surge, and then a decrease, declining from 52.11% to 50.13%. In terms of the increase in proportion, non-degraded steppe increased by 1.98% compared to the baseline, while severely degraded steppe decreased by 3.05%. This indicates a fluctuating improvement trend in the study area's steppe from 2013 to 2022, signifying gradually improving steppe conditions. Spatially, West Ujimqin Banner and the southeastern part of Xilinhot City largely maintained their previous state, remaining non-degraded throughout 2013–2022. In the southern part of West Ujimqin Banner, steppe conditions gradually improved, shifting from moderately degraded to slightly degraded,

with a small portion further transitioning to non-degraded. Most areas of East Ujimqin Banner were initially dominated by slightly degraded and non-degraded steppe; by the end of the study period, nearly all had transitioned to non-degraded, showing marked improvement and gradual recovery of steppe conditions.

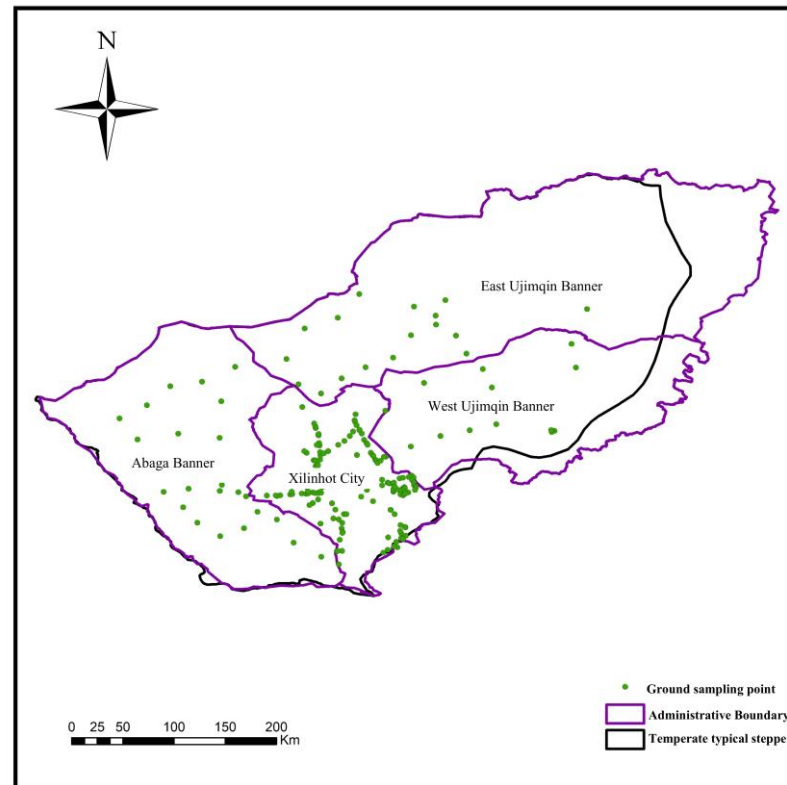


Figure 10. Distribution map of degraded sampling points.

The spatiotemporal distribution of steppe degradation intensity changes in the typical steppe from 2013 to 2022 is demonstrated in Figure 12. Overall, degradation intensity remained relatively stable across periods, with no significant changes predominating (2013–2018: 61.08%; 2018–2022: 57.96%, average 59.52%). These stable areas were widely distributed but showed clustering in southern and eastern West Ujimqin Banner, the central part of East Ujimqin Banner as well as southern Xilinhot City that largely maintained non-degraded status based on spatial distribution analysis. Areas showing improved degradation intensity (indicating reduced degradation) accounted for 25.03% (2013–2018) and 21.46% (2018–2022), averaging 23.25%, primarily located in eastern East Ujimqin Banner near meadow steppes and border areas between West Ujimqin, Abag Banner and Xilinhot City. Notably, areas with improving trends exceeded those showing worsening conditions, suggesting an overall positive shift potentially linked to local ecological conservation measures like the Grain-for-Green program and grazing exclusion.

The Sankey diagram of degradation transitions during 2013–2022 (Figure 13) reveals that non-degraded areas consistently increased, primarily transitioning from slightly and moderately degraded zones. Severely and slightly degraded areas all decreased, with slightly degraded showing the most significant reduction, largely shifting to non-degraded. Overall, the transition dynamics demonstrate net gains for non-degraded areas (inflow > outflow) and net losses for slightly and severely degraded (outflow > inflow) across the typical steppe region.

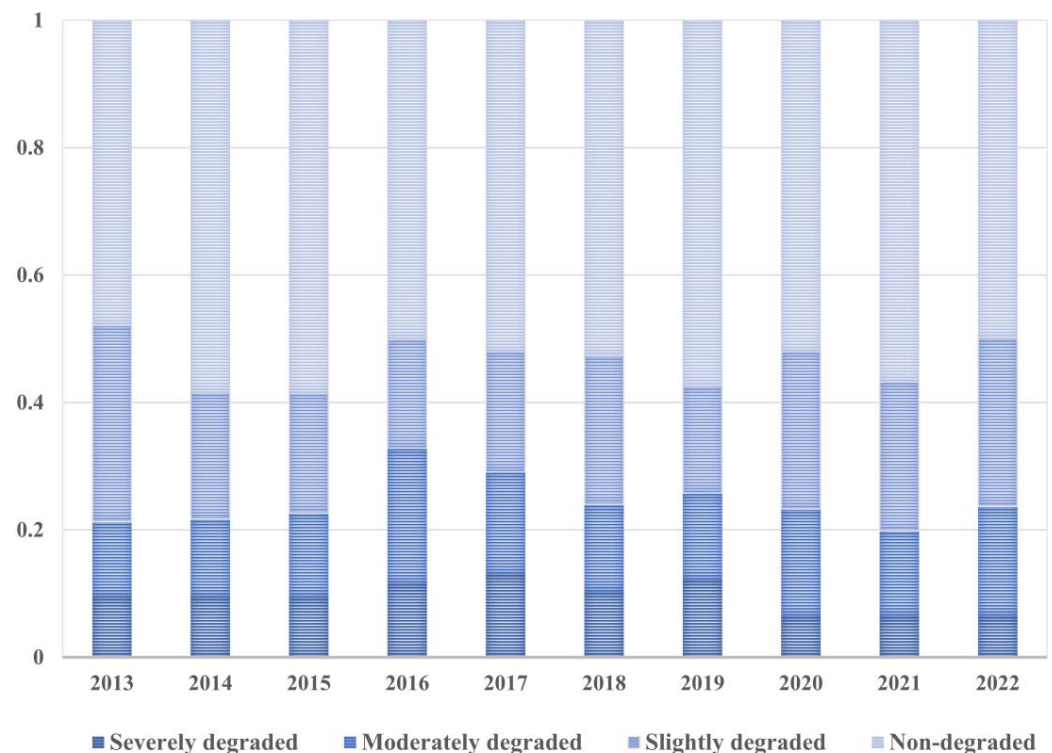


Figure 11. Area proportions by degradation intensity for the years 2013 to 2022.

From an ecological perspective, the proportion of non-degraded steppe in the study area increased by 1.98% and the proportion of severely degraded steppe decreased by 3.05% between 2013 and 2022. Furthermore, the results of degradation level transitions indicate that the inflow of non-degraded steppe exceeded the outflow. These changes suggest that the ecosystem structure and function of the typical steppe area in Xilingol, Inner Mongolia, are gradually recovering. Specifically, community structure becomes more stable, leading to increased species richness. This, in turn, enhances the ecosystem's functions such as water conservation and soil retention. Ultimately, this process boosts the ecosystem's resistance and resilience, enabling it to better maintain community stability and core functions when facing disturbances like short-term climate fluctuations and grazing pressure. This ensures the sustainable development of the steppe ecosystem.

At the policy implementation level, spatial-scale degradation trends (such as the southeastern part of West Ujimqin Banner maintaining non-degraded status and the overall improvement in East Ujimqin Banner) further validate the effectiveness of steppe ecological conservation projects undertaken in recent years by the province where the study area is located. Since 2013, local authorities have consistently implemented management measures such as "grazing bans and rest periods" and "grass-livestock balance": In the southeastern part of West Ujimqin Banner, designated as a "core grazing ban zone," the steppe community structure has remained stable due to the long-term absence of grazing disturbance, consistently maintaining a non-degraded state. Meanwhile, in Eastern Ujimqin Banner, scientifically managed carrying capacities have alleviated overgrazing pressures on steppes, facilitating the gradual restoration of mildly degraded steppes to non-degraded conditions.

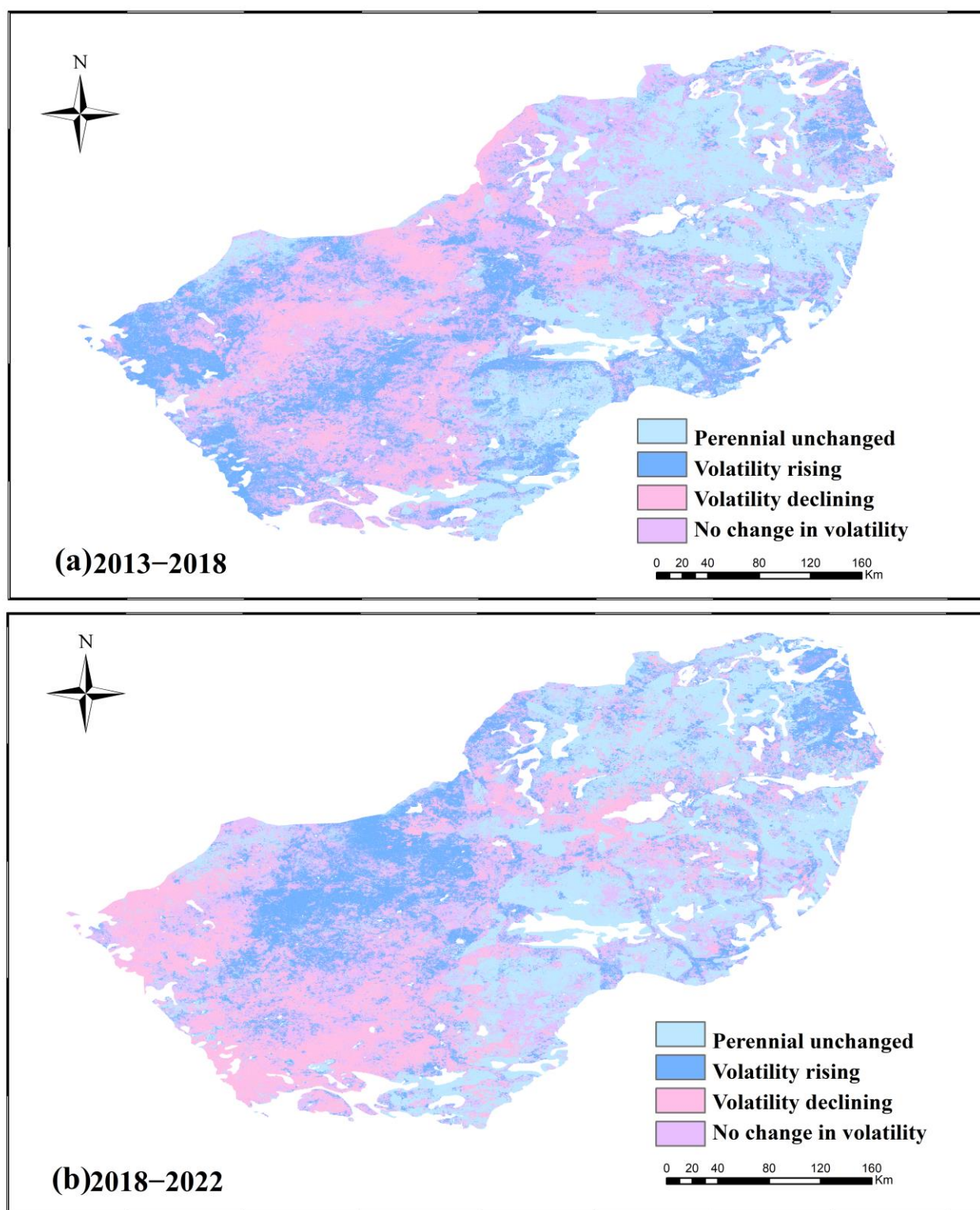


Figure 12. (a) Detection of changes in steppe degradation intensity from 2013 to 2018; (b) Detection of changes in steppe degradation intensity from 2018 to 2022.

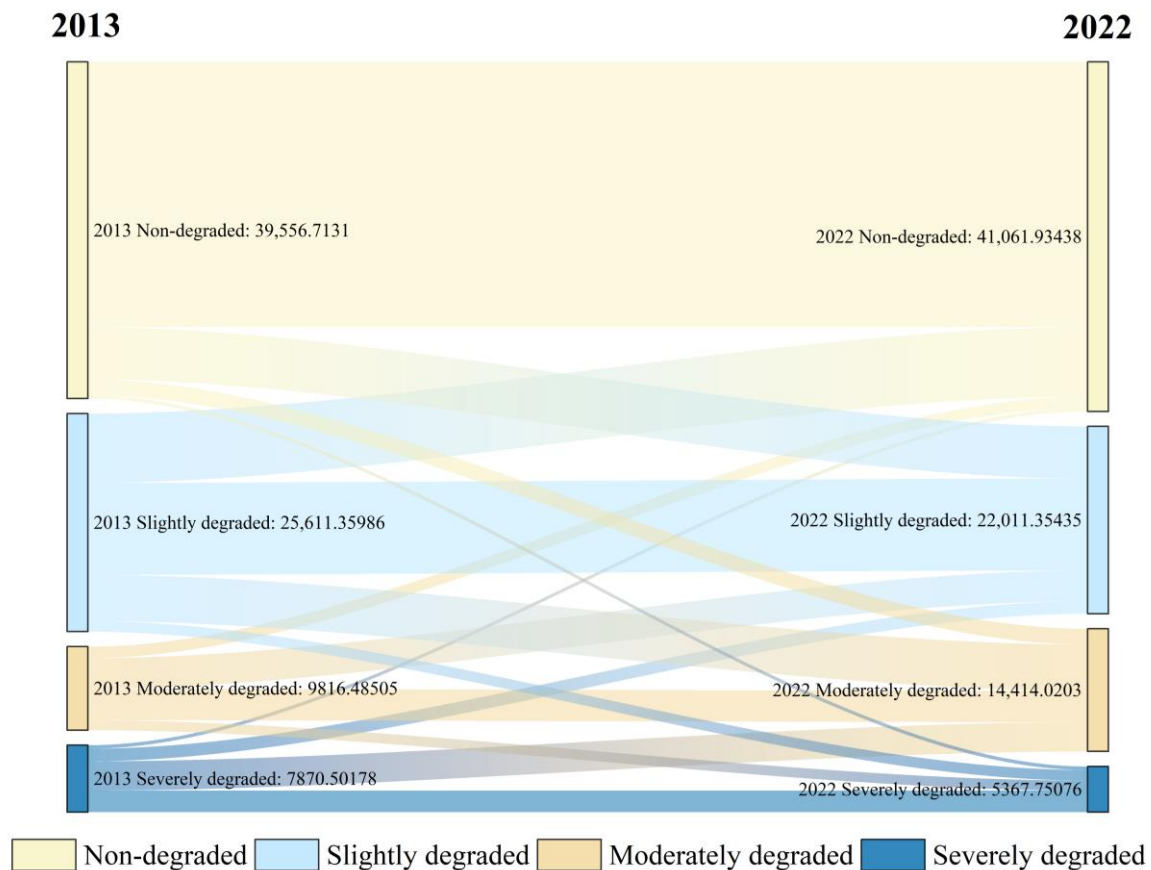


Figure 13. Sankey diagram of degradation transfer for the years 2013 to 2022.

4.3. Steppe Degradation Driving Factor Analysis

Based on factor detector analysis, this study quantified the influence of nine driving factors (categorized into natural and anthropogenic) on steppe degradation. The explanatory power (q-value) of each factor was ranked as follows: total annual evapotranspiration (0.379) > total annual precipitation (0.354) > mean annual temperature (0.164) > soil type (0.128) > elevation (0.056) > slope (0.025) > grazing intensity (0.012) > population density (0.003) > aspect (0.002). Among natural drivers, total annual precipitation and evapotranspiration were predominant ($q > 0.30$), while grazing intensity was the primary anthropogenic driver ($q = 0.012$). Natural factors exerted greater influence than anthropogenic factors on degradation during 2013–2022. Collectively, soil type, total annual precipitation, total annual evapotranspiration, and mean annual temperature were identified as the core drivers of integrated degradation grade changes in the typical steppe region.

The interaction effects between paired driving factors on steppe degradation are demonstrated in Figure 14. The top five interactive combinations with the highest explanatory power (q-values) are: annual precipitation $\cap$ annual evapotranspiration (0.45134) > annual precipitation $\cap$ mean temperature (0.42917) > annual evapotranspiration $\cap$ soil type (0.42864) > annual evapotranspiration $\cap$ elevation (0.4243) > mean temperature $\cap$ annual evapotranspiration (0.42192). These q-values exceed those of any single factor, confirming that synergistic interactions amplify degradation impacts in the typical steppe. Critically, the interaction between anthropogenic and natural factors significantly increased the q-value, as exemplified by grazing intensity $\cap$ annual total evapotranspiration (0.3931), indicating substantially enhanced impacts on steppe degradation. This demonstrates that combined natural and anthropogenic effects amplify steppe degradation in the study area.

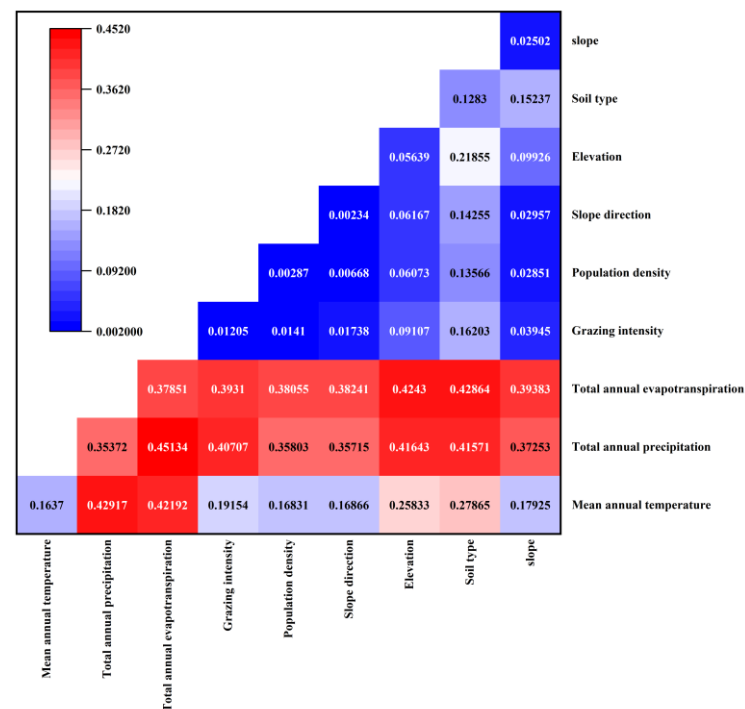


Figure 14. Interaction Factor Detector results.

5. Discussion

5.1. Steppe Degradation Assessment Methodology

Steppe degradation assessment indicators form the critical foundation for achieving precise ecological monitoring. Current research predominantly relies on trend changes in remote sensing vegetation parameters such as FVC [10] and NPP [42,43] to identify ecosystem degradation. However, these indicators exhibit significant response lag to degradation processes, often only becoming detectable when vegetation cover and biomass have already declined markedly. By this stage, ecosystems are frequently in an irreversible state of degradation. Research further notes that relying solely on declining FVC trends to delineate degraded areas fails to adequately account for critical characteristics such as soil property degradation and loss of dominant species, potentially leading to underestimation of actual degradation severity [10]. Although remote sensing technology offers advantages in large-scale, long-term monitoring, its assessment accuracy remains constrained by the singularity of indicators and requires further improvement [44]. While ground surveys can effectively capture parameters such as soil attributes and community structure that remote sensing struggles to detect [45], they struggle to meet the demands for spatially continuous and temporally dynamic monitoring.

To overcome these limitations, this study innovatively integrates ground-based measurement data with multi-source remote sensing data to establish a monitoring indicator system for steppe degradation that simultaneously reflects both structural and functional characteristics of ecosystems. By synthesizing multidimensional information including vegetation community composition, soil properties, and ecosystem functions, this system enables more comprehensive identification of degradation signals, thereby significantly enhancing the accuracy of steppe degradation assessment and early warning capabilities.

5.2. Steppe Degradation Reference Baseline

Previous studies on steppe degradation have largely neglected the establishment of reference baselines. Many studies [42,46] rely solely on the significance level of trends in a single indicator (FVC, NPP) as the criterion for degradation assessment. This approach fails

to adequately consider the multifaceted impacts of steppe degradation, potentially leading to situations where some vegetation has already transformed into degraded indicator species while still exhibiting high vegetation cover. Consequently, steppe degradation may be underestimated. Other studies [47] typically set a fixed historical period (such as the starting year of a time series) as the baseline for degradation assessment. This approach is highly sensitive to the choice of baseline period. If this period experienced abnormal climatic conditions (extreme drought or wet years), it introduces systematic bias, leading to distorted assessment results. Furthermore, some studies [48] directly apply simplistic grading to steppe degradation indices to determine regional degradation levels, lacking sufficient consideration of degradation process mechanisms. This study innovatively proposes a method for constructing a reference baseline for steppe degradation. This method quantitatively assesses the impact of hydrothermal fluctuations on vegetation (based on TSS-RESTREND), integrates changes in steppe vegetation communities and the proportion of degradation indicator species, and accounts for multidimensional shifts in ecosystem structure and function. It spatially delineates degradation reference baseline zones, effectively eliminating evaluation biases caused by climate change. This significantly enhances the scientific rigor and accuracy of degradation monitoring, providing a reference for establishing baselines for temperate typical steppe globally.

5.3. Dynamic Changes in Steppe Degradation

This study calculates a composite degradation index based on vegetation, soil, and steppe ecosystem function. The findings hold significant importance for understanding degradation patterns in the typical steppe region of Xilingol and implementing effective degradation prevention measures. The classification of steppe degradation intensity has long been a research focus among scholars. Due to the large study area, which borders desert steppes to the west and meadow steppes to the east, significant climatic variations exist across the typical steppe region, resulting in considerable divergence in water and heat conditions. To ensure accuracy and scientific rigor in steppe degradation classification, this study divides the region into four distinct hydrothermal zones based on climatic variations. Degradation criteria are established for each zone, with degradation intensity transitioning smoothly and naturally across zone boundaries. This demonstrates the validity of the hydrothermal zoning approach employed in this study.

Through evaluation and analysis, it was found that typical steppe areas exhibit a spatial characteristic of gradually decreasing from northeast to southwest, consistent with previous research findings [49,50]. This is primarily due to the western part of the study area being adjacent to desert steppes, where vegetation growth conditions are inherently poor, while the eastern part borders meadow steppes with more favorable conditions for vegetation growth and development. The classification results indicate that the degradation status of typical steppe areas gradually improves over time, consistent with studies by [51,52]. Both slightly degraded and severely degraded areas decreased in proportion, while the proportion of non-degraded areas increased. Furthermore, large areas of moderately and severely degraded steppes showed a trend of transitioning toward slightly degraded or non-degraded conditions. Most non-degraded steppes within the study area remain in good condition. The southern part of West Ujimqin Banner and the central-eastern regions of East Ujimqin Banner both maintain non-degraded status. Degradation intensity in the northern part of Xilinhot City and the border areas between Xilinhot, East Ujimqin, and West Ujimqin Banner show signs of improvement.

This is closely linked to the Inner Mongolia Autonomous Region's comprehensive launch of the Grazing Reduction and Grassland Restoration Project, full implementation of the Grassland Ecological Protection Subsidy and Reward Policy, and execution of

multiple grassland ecological restoration projects [53], all aimed at achieving sustainable development of grassland resources.

5.4. Drivers of Degradation

Some findings in existing research align with the results presented in this paper. For instance, scholars have indicated that over the past four decades, climate change has been the primary factor influencing the dynamics of the Xilingol steppe [49,51]. However, other studies have reached differing conclusions. For example, some studies argue that human activities are the main drivers of steppe degradation in Xilingol, while the impact of climate change is relatively minor [46,54].

Regarding the discrepancies in the conclusions, this paper analyzes the potential reasons as follows: First, the temperate typical steppes of Inner Mongolia are located in an arid and semi-arid monsoon region, where ecosystems are highly sensitive to changes in water and heat conditions. This sensitivity may lead to a more pronounced contribution of climatic factors to steppe degradation in regional-scale analyses. Second, the study area features a small proportion of urban land and low population density. With the gradual implementation of national and local policies such as grazing cessation and ecological compensation programs, grazing intensity has been effectively controlled, reducing direct human pressure on grasslands. Consequently, human activities may exert a lesser overall impact than natural factors.

Additionally, we acknowledge potential limitations at the data and methodological levels. The proxy indicators of human activity employed in this study, such as population density and low-resolution grazing intensity data, are constrained by spatial resolution and representational capacity. These limitations may underestimate the impact of human activity by failing to adequately capture locally intense grazing or other anthropogenic disturbances. In future research, incorporating higher-precision data, such as spatially disaggregated livestock inventories and human activity identification based on high-resolution remote sensing, will facilitate more accurate quantification of human factors in steppe degradation.

5.5. Limitations and Future Work

This study has certain limitations. Regarding data selection, although both natural factors and human activities were comprehensively considered, data completeness remains insufficient, particularly for livestock data. Since such data primarily originates from statistical yearbooks and lacks rasterized products, and given this study's focus on a 30 m resolution scale, forcing the introduction of statistical-level livestock data may compromise the accuracy and scientific validity of results due to scale mismatch.

Furthermore, steppe degradation is a long-term cumulative process. Although this study combined field surveys with literature data to obtain degraded sampling points for verification, spatial mismatches between sampling points and remote sensing pixels prevent pixel-level accuracy validation. Consequently, comparisons can only be made at the regional scale through spatial pattern consistency analysis, a method that inherently involves a degree of subjectivity.

In subsequent study, we will focus on acquiring or developing rasterized livestock data products with spatial attributes to enhance the accuracy and reliability of such data. Concurrently, we will explore more objective validation methods to strengthen the credibility of steppe degradation monitoring results, thereby advancing research in this field toward greater robustness.

6. Conclusions

This study systematically monitored the degradation status of the temperate typical steppe in Xilingol, Inner Mongolia, from 2013 to 2022. Based on ground surveys and multi-source remote sensing data, it integrated ecosystem structure and functional characteristics. By comprehensively applying trend analysis, change detection, and geographic detector methods, the spatio-temporal patterns and driving mechanisms of steppe degradation were revealed. Results indicate that during this period, the degradation status of Xilingol's temperate typical steppe showed an overall improvement trend.

Analysis indicates that on an interannual scale, the composite degradation index for this region shows an upward trend. Spatially, it exhibits a distribution pattern that gradually decreases from northeast to southwest, with most areas maintaining stable or relatively stable degradation states. Over the past decade, degradation intensity in the typical steppes of Xilingol have primarily been non-degraded or slightly degraded. Despite interannual fluctuations, the overall trend has been positive. This improvement is closely linked to the Inner Mongolia Autonomous Region's comprehensive implementation of the Grazing Ban and Grassland Restoration Project, the Grassland Ecological Protection Subsidy and Reward Policy, and the advancement of multiple ecological restoration projects. It reflects the significant effectiveness of ecological protection and restoration measures in this region. The study also indicates that natural factors are the primary drivers of steppe degradation, exerting a greater influence than human activities.

In summary, this study has clarified the spatiotemporal distribution characteristics of degradation in the temperate typical steppes of Xilingol. It has validated the rationality and scientific validity of monitoring results at the regional scale, providing methodological references for monitoring degradation in temperate typical steppes. Furthermore, it offers a scientific basis for the efficient and precise implementation of ecological conservation and restoration efforts.

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