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Ecological Restoration and Zonal Management of Degraded Grassland Based on Cost–Benefit Analysis: A Case Study in Qinghai, China

Ziyao Wang [1,2], Feng Li [1,2,*], Donglin Xie [1,2], Jujie Jia [2], Chaonan Cheng [1,2], Jing Lv [3], Jianhua Jia [4], Zhe Jiang [3], Xin Li [5] and Yuxia Suo [6]

[1] Department of Landscape Architecture, School of Architecture, Tsinghua University, Beijing 100084, China; wangziyao@mail.tsinghua.edu.cn (Z.W.)
[2] Ecological Restoration Research Center, School of Architecture, Tsinghua University, Beijing 100084, China
[3] Land Consolidation and Rehabilitation Center, Ministry of Natural Resources, Beijing 100035, China
[4] Qinghai Forestry Engineering Supervision Center Co., Ltd., Xining 810003, China
[5] Qinghai Grassland Improvement Experimental Station, Hainan 813000, China
[6] Qinghai Forestry Engineering Consulting Co., Ltd., Xining 810003, China
* Correspondence: feng_li@tsinghua.edu.cn

Abstract: The Qinghai–Tibetan Plateau (QTP) has the largest area of natural grassland in China, and continuous grassland degradation poses a serious threat to regional ecological security and sustainable resource management. It is essential to comprehensively evaluate the cost–benefit differences and drivers of grassland degradation across various zones to enhance sustainable management practices. This study presents a zonal management framework for the ecological restoration of degraded grasslands based on cost–benefit analysis, specifically applied to Qinghai in the Northeastern QTP. The results indicate: (1) Although the overall NDVI of grasslands shows an upward trend, some areas still exhibit significant degradation. (2) Cost–benefit analysis can divide degraded grasslands into four types of Ecological Management Zones (EMZs): high-cost–high-benefit zone, high-cost–low-benefit zone, low-cost–low-benefit zone, and low-cost–high-benefit zone. (3) The driving factors of grassland degradation show significant differences in different EMZs. Based on these research findings, differentiated spatial planning and management strategies for grassland ecological restoration were developed for each EMZ. This study not only provides a scientific methodology for grassland ecological restoration but also offers important insights for the sustainable management of grassland resources in the QTP and other ecologically sensitive areas.

Keywords: degraded grasslands; ecological restoration; cost–benefit analysis; ecological management zones; sustainable management strategies

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Citation: Wang, Z.; Li, F.; Xie, D.; Jia, J.; Cheng, C.; Lv, J.; Jia, J.; Jiang, Z.; Li, X.; Suo, Y. Ecological Restoration and Zonal Management of Degraded Grassland Based on Cost–Benefit Analysis: A Case Study in Qinghai, China. *Sustainability* **2024**, *16*, 11123. https://doi.org/10.3390/su162411123

Academic Editor: Antonio Boggia

Received: 29 October 2024
Revised: 8 December 2024
Accepted: 17 December 2024
Published: 18 December 2024

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1. Introduction

Grasslands are one of the main types of terrestrial ecosystems [1,2]. They play a crucial role in climate regulation, water retention, biodiversity conservation, and soil conservation [3,4], and they also serve as the foundation for livestock development, holding substantial economic value [5,6]. The Qinghai–Tibet Plateau (QTP) hosts the densest distribution of natural grasslands in China [7]. The 2023 research data indicate that the total grassland area of the QTP reaches 1.28 million km^2 [8]. The unique geographical location and climatic conditions make the QTP highly susceptible to external environmental disturbances, resulting in a fragile and sensitive ecological environment [9]. Presently, grassland degradation on the QTP remains severe, endangering regional ecological security and threatening the livelihoods of local communities [10].

Quantitative assessment and dynamic monitoring of grassland growth conditions enhance our understanding of the spatiotemporal distribution patterns of grassland degra-

dation, providing the foundation for formulating grassland ecological restoration strategies [11]. Remote sensing technology offers effective means for the continuous and rapid assessment of grassland resources, particularly suitable for extensive, intricate terrains, and inaccessible regions such as the QTP [10,12]. The Normalized Difference Vegetation Index (NDVI), a widely used indicator in remote sensing data, exhibits a highly significant linear correlation with vegetation coverage [13], accurately reflecting vegetation growth conditions and their annual variations [14,15]. Employing time-series NDVI data for trend analysis to assess historical dynamic changes in grassland vegetation cover has become a key method for monitoring and identifying grassland degradation [16].

National-level efforts are essential to achieving the goal of curbing grassland degradation [17,18]. A crucial step involves delineating Ecological Management Zones (EMZs) and developing spatial planning for ecological restoration based on the distinct characteristics of different zones [19,20]. Since the reform and opening up, a series of ecological restoration projects (ERPs) have been conducted in the QTP by the Chinese government. These projects aim to conserve and restore natural environments, working towards the goal of sustainable development [21,22]. Existing studies indicate that these ERPs have generally increased vegetation coverage on the QTP, effectively curbing grassland degradation in recent years [23,24]. However, grassland ecosystems in certain regions continue to face degradation risks due to the combined impacts of global climate change and human activities [13]. Rational implementation of ERPs, with comprehensive consideration of cost-effectiveness, is crucial for further improving grassland ecosystem quality on the QTP [25]. At present, cost–benefit analysis is extensively employed in research connected to ecological restoration planning. For example, Xu, et al. [26] utilized a comprehensive analysis of the costs and benefits to identify priority areas for combating desertification in Northern China, subsequently proposing diverse land-restoration strategies. Zhao, et al. [27] combined cost–benefit analysis with multi-objective optimization methods to propose spatial patterns and construction sequences for ERPs under different scenarios. Dong, et al. [28] proposed a comprehensive evaluation method for the prioritization of ecological restoration of abandoned mines based on cost–benefit analysis. In summary, constructing an EMZ identification framework based on cost–benefit analysis provides a scientific basis for the patterns, tasks, and priorities of ERPs, which is of great significance for optimizing resource allocation and enhancing the overall benefits of ecological restoration [29–31]. However, current research on degraded grassland ecological restoration still has limited exploration regarding cost–benefit analysis and EMZs [32], posing challenges for decision-makers in developing precise spatial planning and sustainable grassland ecological restoration strategies.

There is growing evidence that grassland degradation is driven by a confluence of factors, including climate change and human activities [33]. Due to the differing natural and socioeconomic conditions in various study areas, these influencing factors exhibit significant regional differences in the mechanisms driving grassland degradation [12,34]. Therefore, attribution analysis of grassland degradation is critically important, as it provides scientific support for the formulation of more targeted and efficient grassland ecological restoration strategies [9]. Researchers have developed various statistical methods to quantify the influencing factors of grassland degradation in recent years, such as mixed linear regression models [35], geographically weighted regression models [36], random forest models [37], and geographic detectors. Among these methods, the geographic detector uniquely offers the capability to analyze the driving forces underlying the spatial variation of a single factor's impact on the dependent variable and to quantitatively evaluate the interaction between two variables [38]. Thus, it has found widespread application in grassland degradation studies [13,39]. Despite this, the geographic detector still has certain limitations in the spatial discretization and stratification techniques of data [40]. In response to this challenge, Song, et al. [41] proposed the Optimized Parameter Geographic Detector (OPGD), significantly improving the accuracy and reliability of model evaluations by optimizing model parameters. However, most current studies on the attribution analysis

of grassland degradation evaluate the study area as a whole, neglecting the distinctions in the influence of driving factors on the grassland degradation process within different EMZs. This may result in insufficient effectiveness and the targeting of grassland ecological restoration strategies during implementation.

Situated in the northeastern region of the QTP, Qinghai is recognized as one of China's five principal pastoral domains [42]. While the overall ecological quality of grasslands in Qinghai has improved in recent years, severe degradation persists in some areas, significantly hindering local sustainable development [43]. Taking Qinghai as a case study, this research systematically investigates the cost–benefit evaluation methods for the ecological restoration of degraded grasslands and the driving mechanisms of grassland degradation. It offers detailed decision-making support for local ecological restoration practices and crucial insights for the sustainable management of grassland resources in the QTP and other ecologically sensitive regions. The objectives of this study are: (1) to evaluate the current status of grassland degradation in Qinghai based on trend analysis of NDVI from 2000 to 2020; (2) to delineate different EMZs for significantly degraded grasslands using cost–benefit analysis; and (3) to analyze the driving mechanisms of diverse factors on grassland degradation within different EMZs and propose targeted ecological restoration spatial planning and management strategies.

2. Study Area and Data

2.1. Study Area

Qinghai, located in Western China, is an important part of the QTP (Figure 1A). It spans approximately 722,300 km^2, and its administrative divisions include eight prefecture-level cities. The topography of Qinghai generally features elevated terrain in the northern and southern regions, transitioning to lower elevations in the central area, with an average altitude surpassing 3000 m (Figure 1B). Furthermore, Qinghai is an indispensable component of China's ecological security barrier within the QTP, serving an irreplaceable role in ensuring national ecological security and supporting ecological construction.

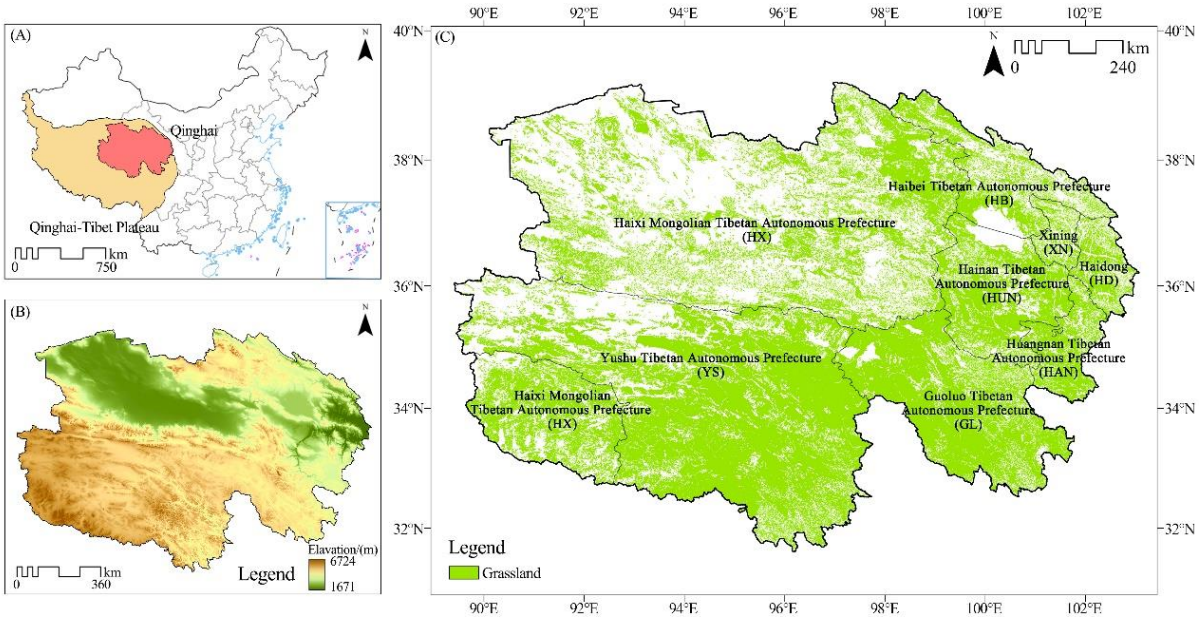


Figure 1. Study area (**A**) location; (**B**) elevation; (**C**) grassland distribution.

In 2020, the grassland area of Qinghai is approximately 395,000 km^2, accounting for 56.70% of the province's land area and 10.72% of China's grassland area (Figure 1C). Grasslands are crucial for maintaining key ecological functions such as soil conservation, water retention, and climate regulation. Due to the extreme fragility of the ecological environment and the intensifying impacts of climate change and human activities, certain

areas in Qinghai Province are experiencing severe grassland degradation. Consequently, developing detailed spatial planning for the ecological restoration of degraded grasslands is crucial for achieving sustainable development in the region.

2.2. Data Sources

This study incorporated spatial datasets from multiple sources. The types, formats, and spatial resolutions of the above data are detailed in Table 1.

Table 1. Data sources.

Data Type	Data Format	Data Source	Spatial Resolution
Land use/land cover	Raster	RESDC. [a]	30 m
Normalized Difference Vegetation Index	Raster	USGS. [b]	500 m
Digital elevation model	Raster	GDCP. [c]	1 km
Precipitation	Raster	RESDC. [a]	1 km
Temperature	Raster	RESDC. [a]	1 km
Evapotranspiration	Raster	RESDC. [a]	1 km
Soil organic carbon	Raster	TPDC. [d]	1 km
Cation exchange capacity	Raster	TPDC. [d]	1 km
Clay fraction	Raster	TPDC. [d]	1 km
GDP	Raster	RESDC. [a]	1 km
Population density	Raster	RESDC. [a]	1 km
Nighttime lighting index	Raster	TPDC. [d]	1 km
Grazing intensity	Raster	TPDC. [d]	1 km
Road, water area, residential area	Shapfile	NBGD. [e]	/

Notes: [a] Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn, accessed on 1 May 2024); [b] United States Geological Survey (www.usgs.gov, accessed on 1 May 2024); [c] Geospatial Data Cloud Platform (http://www.gscloud.cn, accessed on 1 May 2024); [d] National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdc.ac.cn, accessed on 1 May 2024); [e] National Basic Geographic Database (http://www.webmap.cn, accessed on 1 May 2024).

First, the spatial extent of grasslands in the study area was determined using the 2020 land-use/land-cover (LULC) data. Then, annual NDVI data from 2000–2020 were used to assess the trends in vegetation cover changes in grasslands. The NDVI data were sourced from the MODIS dataset (MOD13A1), with a spatial resolution of 500 m and a temporal resolution of 16 days. The maximum synthesis method was applied to generate annual data for each summer (June to September) using the Google Earth Engine (GEE) platform. Based on this, NDVI data were extracted within the spatial boundaries of the study area's grasslands using ArcGIS Pro 3.0 to generate a time series of NDVI data for 2000–2020. Furthermore, various raster and vector data (as detailed in Table 1) were used for cost–benefit and driving factor analyses, all of which were converted to a common spatial reference (WGS_1984_Web_Mercator), and the spatial resolution of the raster data was resampled to 500 m × 500 m.

3. Methods

This study presents an integrated framework that incorporates NDVI trend analysis, cost–benefit analysis, and the OPGD model to aid in the ecological restoration of degraded grasslands. The framework is structured into three technical steps (Figure 2). First, by analyzing NDVI trends from 2000 to 2020 within the study area, we pinpointed the spatial distribution of degraded grasslands. Second, we classified these degraded areas into four types of EMZs through cost–benefit analysis. Third, employing the OPGD model, we explored the influence of various driving factors on grassland degradation across different EMZs.

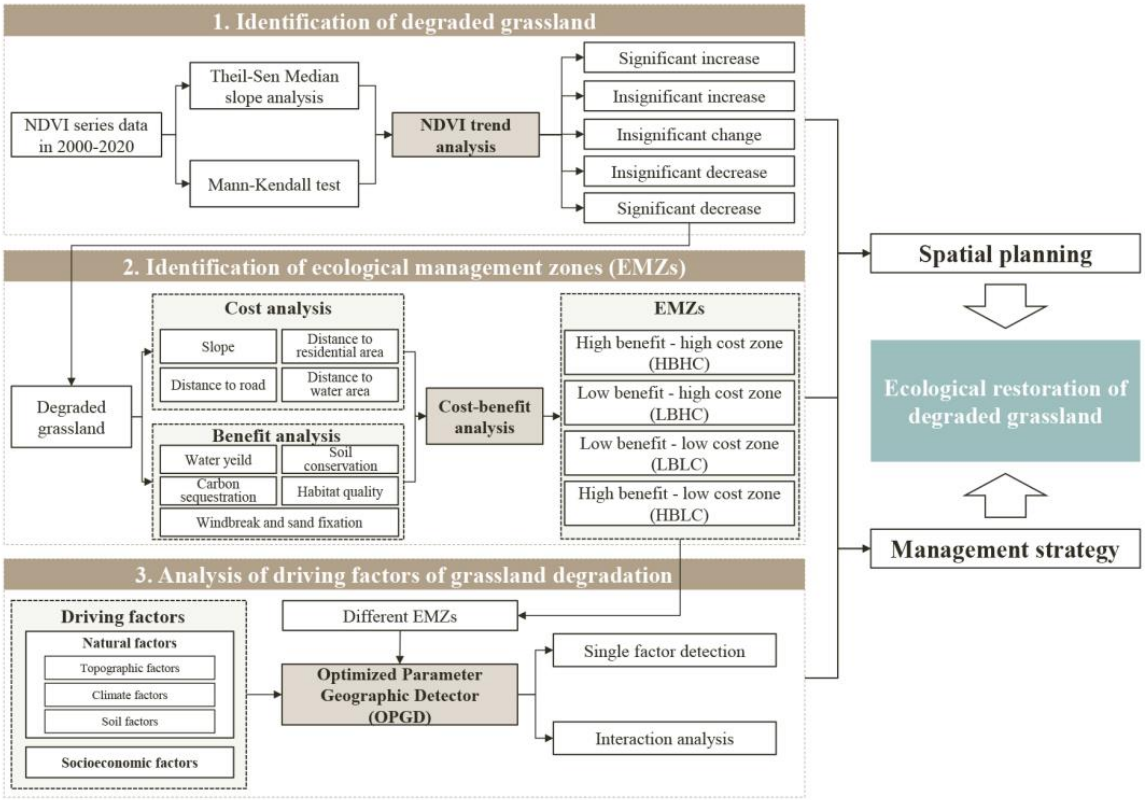


Figure 2. Research framework.

3.1. NDVI Trend Analysis of Grasslands

This study comprehensively uses the Theil–Sen Median Slope Analysis and the Mann–Kendall statistical test to evaluate the NDVI change trends of grasslands in the study area from 2000 to 2020 and test their significance. This method can calculate the NDVI change for each pixel over a specific period and is robust to missing outlier values. It has been widely applied in studies analyzing long-term NDVI change trends [13,44].

The following formula was used for the Theil–Sen Median slope analysis:

$$Slope = Median\left[\frac{(x_j - x_i)}{(j - i)}\right], \forall j > i \tag{1}$$

where *Slope* represents the trend of NDVI, $Slope < 0$ indicates a decreasing trend, and $Slope > 0$ signifies an increasing trend. j and i represent different years, with $j > i$. x_j and x_i are the NDVI values in year j and year i.

On this basis, we employed the Mann–Kendall statistical test to evaluate the significance of the observed trends [45], and its calculation formula is as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & S < 0 \end{cases} \tag{2}$$

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} sgn(x_j - x_i) \tag{3}$$

$$sgn(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \tag{4}$$

$$Var(S) = \frac{n(n-1)(2n+15)}{18} \quad (5)$$

where Z is the standardized test statistic. n is the number of time series data, which is 21 in this study. sgn is the function symbol. x_j and x_i represent the NDVI values in year j and year i.

According to the above analysis, the trend of NDVI was classified into five categories in this study, which were significant increase ($Slope > 0.0005$, $|Z| > 1.96$), insignificant increase ($Slope > 0.0005$, $|Z| \leq 1.96$), insignificant change ($-0.0005 \leq Slope \leq 0.0005$), insignificant decrease ($Slope < -0.0005$, $|Z| \leq 1.96$), and significant decrease ($Slope < -0.0005$, $|Z| > 1.96$).

3.2. Identification of EMZs Based on Cost–Benefit Analysis

The significant decrease in NDVI within a specific area indicates a continuous decline in grassland vegetation coverage and productivity. Therefore, these areas are typically considered significantly degraded grasslands, requiring necessary ecological restoration measures to improve grassland growth conditions. Hence, based on the trend analysis results, this study defined degraded grasslands as areas where NDVI showed a significant decreasing trend.

This study proposes an EMZ analysis framework for degraded grassland restoration based on cost–benefit analysis to ensure the scientific and effective implementation of ecological restoration projects. Ecological restoration costs and benefits of degraded grasslands were evaluated at the pixel scale, and the grasslands were classified into different EMZs using the quadrant model. We selected four cost indicators and five benefit indicators for the cost–benefit analysis. By consulting several local experts, scholars, and decision-makers in the field of ecological restoration in Qinghai, the relative importance between pairs of different indicators was clarified. The Analytic Hierarchy Process (AHP) was then used to construct a judgment matrix and calculate the weight values for each indicator (Table S6).

3.2.1. Cost Analysis

Due to the difficulty in obtaining pixel-level data on ecological restoration investment costs, we selected four indicators—slope, distance to residential areas, distance to roads, and distance to water areas—as evaluation indicators for the cost of ecological restoration of degraded grasslands. *Slope* significantly influences vegetation growth and the execution of projects. Areas with gentler slopes generally incur lower costs for ecological restoration efforts [46]. Proximity to residential areas, roads, and water areas allows for easier access to manpower, transportation, and water resources [28,47]. Therefore, the distances to residential areas, roads, and water areas are considered important indicators, widely used by researchers to assess the costs associated with ecological restoration [48–50].

3.2.2. Benefit Analysis

This study referenced previous research and used the Restoration Potential of Degraded Systems (RPDS) to assess the benefits of ecological restoration of degraded grasslands [26]. This method highlights the potential benefits that can be realized following ecosystem restoration. Its specific calculation formula is as follows:

$$RPDS = \max\left(\frac{ES_p - ES_a}{ES_p}, 0\right) \quad (6)$$

where ES_a and ES_p are the actual and potential value of various ecosystem services, with ES_p defined as the 90th percentile of the frequency distribution of these services in the grasslands of Qinghai.

In this study, five types of ecosystem services—water yield, carbon sequestration, soil conservation, habitat quality, and windbreak and sand fixation—were selected as evaluation indicators for analyzing RPDS. This selection is primarily based on three criteria: (1) these ecosystem services are widely recognized as representative of the grassland ecosystems

in Qinghai [48,51,52]; (2) these ecosystem services are explicitly listed as key types in the relevant policies and plans of Qinghai; (3) data availability. The model and calculation methods for ES assessment are shown in Table 2, while the tables of biophysical parameters used in the InVEST model are provided in the Supplementary Materials.

Table 2. ES assessment models.

ES	Model	Calculation Method
Water yield	Water yield services are calculated using the Water Yield (WY) module of the InVEST model.	$Y(x) = \left(1 - \frac{AET(x)}{P(x)}\right) \times P(x)$ where *Y(x)* is the annual water yield (mm); *AET(x)* is the annual actual evapotranspiration (mm); and *p(x)* is the annual precipitation (mm).
Carbon sequestration	As the basis of ecosystem material and the energy cycle, net primary productivity (NPP) can directly reflect the carbon storage capacity of vegetation [53]. This study uses NPP to represent carbon sequestration services.	The NPP data used in this study were obtained from the MOD17A3HGF annual composite datasets from the United States Geological Survey (www.usgs.gov). The datasets have a 500 m spatial resolution.
Soil conservation	Soil conservation services are calculated using the Sediment Delivery Ratio (SDR) module of the InVEST model.	$SC = R \times K \times LS(1 - C \times P)$ where *SC* is the actual soil conservation (t/ha); *R* is the rainfall erosivity $(MJ \cdot mm \cdot (ha \cdot h)^{-1})$; *K* is the soil erodibility $(t \cdot h \cdot (MJ \cdot mm)^{-1})$; *LS* is the slope length–gradient factor, which is calculated from the DEM data in the model with reference to the InVEST model manual; *C* is the vegetation cover management factor; and *p* is the support practice factor.
Habitat quality	Habitat-quality services are calculated by the Habitat Quality (HQ) module of the InVEST model.	$Q_{xj} = H_j\left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z + K^z}\right)\right]$ where Q_{xj} is the habitat quality index of raster *x* in LULC type *j*; H_j is the habitat suitability of LULC type *j*; D_{xj} is the threatened degree of raster *x* in LULC type *j*; *k* is the half-saturation constant; and *z* is the model default value.
Windbreak and sand fixation	The Revised Wind Erosion Equation Model (RWEQ) can estimate regional soil wind erosion over extended time periods with high spatial and temporal resolution [28] and is used in this study to evaluate windbreak and sand fixation services.	$WSF = S_{LQ} - S_L$ where *WSF* is annual sand fixation per unit area (kg/m^2); S_{LQ} is the potential amount of wind erosion of non-vegetation cover; and S_L is the actual wind erosion.

3.2.3. Identification of EMZs

The above indicators were divided into five levels (classification methods are detailed in the Supplementary Materials), assigned values from 1 to 5 from low to high, and weighted according to Table 2. Next, the evaluation results were processed using the Z-score standardization method, which allows for the delineation of four types of EMZs, corresponding to the four quadrants [54]. The four types of EMZs were high benefit—high-cost zone (HBHC), low benefit—high-cost zone (LBHC), low benefit—low-cost zone (LBLC), and high benefit—low-cost zone (HBLC).

3.3. Analysis of Driving Factors for Grassland Degradation Using OPGD

3.3.1. Selection of Driving Factors

Drawing on past research and data availability [13], we selected 12 natural and socioeconomic factors to examine the driving mechanisms of grassland degradation, and the natural factors included topographic factors, climate factors, and soil factors (Table 3).

Table 3. Driving factors of grassland degradation.

Type		Driving Factors	Abbreviation
Natural factors	Topographic factors	Altitude	ALT
		Topographic relief index	TRI
	Climate factors	Precipitation	PRE
		Temperature	TEM
		Evapotranspiration	EVP
	Soil factors	Soil organic carbon	SOC
		Cation exchange capacity	CEC
		Clay content	CLAY
Socioeconomic factors		GDP	GDP
		Population density	POP
		Nighttime lighting index	NLI
		Grazing intensity	GRI

3.3.2. OPGD Model

The geographic detector model is a statistical method used to explore spatial differentiation and identify the underlying driving factors [38]. Traditional geographic detector models necessitate manual discretization of continuous variables, which results in subjectivity and poor discretization. The OPGD model addresses this issue by selecting the optimal parameter combination (classification method and number of classes) for spatial discretization [41,55]. The OPGD model was constructed using the "GD" package in R, and the driving factors of degraded grasslands were analyzed from both single-factor and interaction detection perspectives.

First, the aforementioned 12 driving factors were used as explanatory variables, while the degree of grassland degradation (negative NDVI trend value) within different EMZs served as the dependent variable. Subsequently, the spatial data were classified using five methods: equal breaks, natural breaks, quantile breaks, geometric breaks, and standard deviation breaks, with the number of classes ranging from 4 to 15. The OPGD model was used to identify the parameter settings with the highest explanatory power (q value) for different factors influencing grassland degradation and to perform both single-factor and interaction detection analyses. Finally, Pearson correlation analysis was used as a supplementary tool to the OPGD model to identify potential positive or negative correlations between the dependent variable and each driving factor.

4. Result

4.1. Identification of Degraded Grasslands

4.1.1. Trends of Grassland NDVI

This study quantitatively assessed grassland NDVI trends in Qinghai from 2000 to 2020, classifying them into five levels (Figure 3A). The findings indicated that the majority of grasslands demonstrated an increasing NDVI trend during 2000–2020. Areas with significantly and insignificantly increased NDVI trends encompassed 29.9% and 37.0% of the total grassland area, respectively, located primarily in the lower elevations of the eastern and northern regions. Areas with insignificant changes in NDVI accounted for approximately 18.1% of the total grassland area, concentrated in the northwestern portion. Areas with significantly and insignificantly decreased NDVI represented 2.3% and 12.7% of the total grassland area, respectively, predominantly located in the southern part of Qinghai.

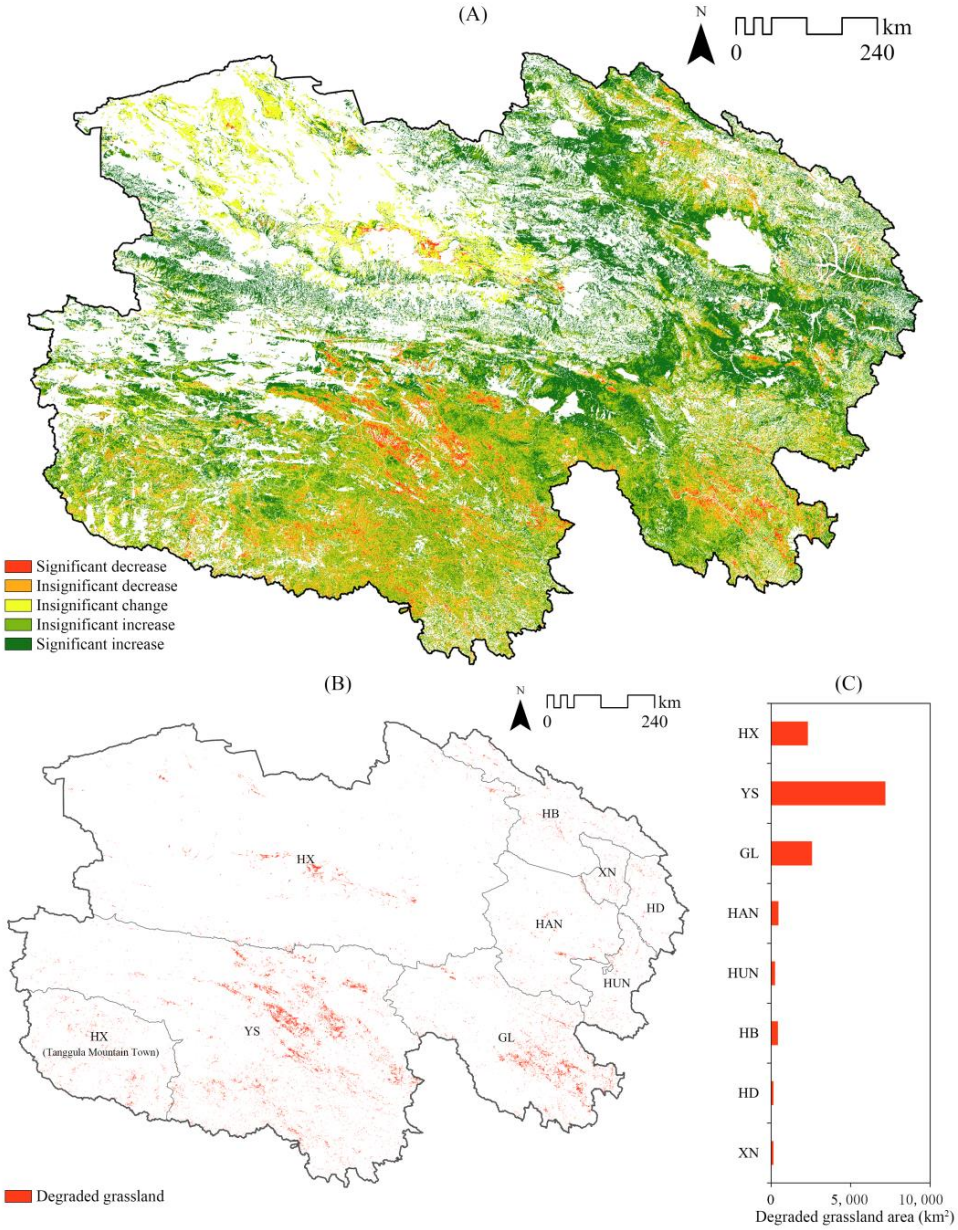


Figure 3. NDVI trend of grasslands and distribution of degraded grasslands. (**A**) NDVI trend of grasslands; (**B**) spatial distribution of degraded grasslands; (**C**) area of degraded grassland in different cities.

4.1.2. Spatial Distribution of Degraded Grasslands

Based on the trend analysis, we identified areas with a significant decrease in NDVI as degraded grasslands. Figure 3B,C show the spatial distribution and area of degraded grasslands across prefecture-level cities. The results indicated that the distribution of degraded grasslands within each city showed strong spatial heterogeneity. YS had the largest area of degraded grasslands (7183 km^2, 53.5% of the total), followed by GL (2566 km^2, 19.1%) and HX (2310 km^2, 17.2%). The remaining cities collectively comprised 10.2% of the total degraded grassland area.

4.2. Identification of EMZs for Degraded Grasslands

4.2.1. EMZs for Degraded Grasslands Based on Cost–Benefit Analysis

This study conducted a quantitative evaluation of the costs and benefits for the ecological restoration of degraded grasslands in the study area, leading to the delineation of EMZs based on these assessments. The results of the cost and benefit assessment are shown in Figure 4A,B. Overall, the restoration cost showed a distribution pattern of lower costs in the west and higher costs in the east. High-cost areas were mainly distributed in the western parts of HX and YS, while low-cost areas were primarily found in the eastern parts of YS and southeastern GL, and they were also widely distributed in HB, XN, and HD. The restoration benefits exhibited a distribution pattern of higher benefits in the northwest and lower benefits in the southeast. High-benefit areas were mainly in HX and Northern YS, while low-benefit areas were primarily in Southeastern YS, GL, and HUN.

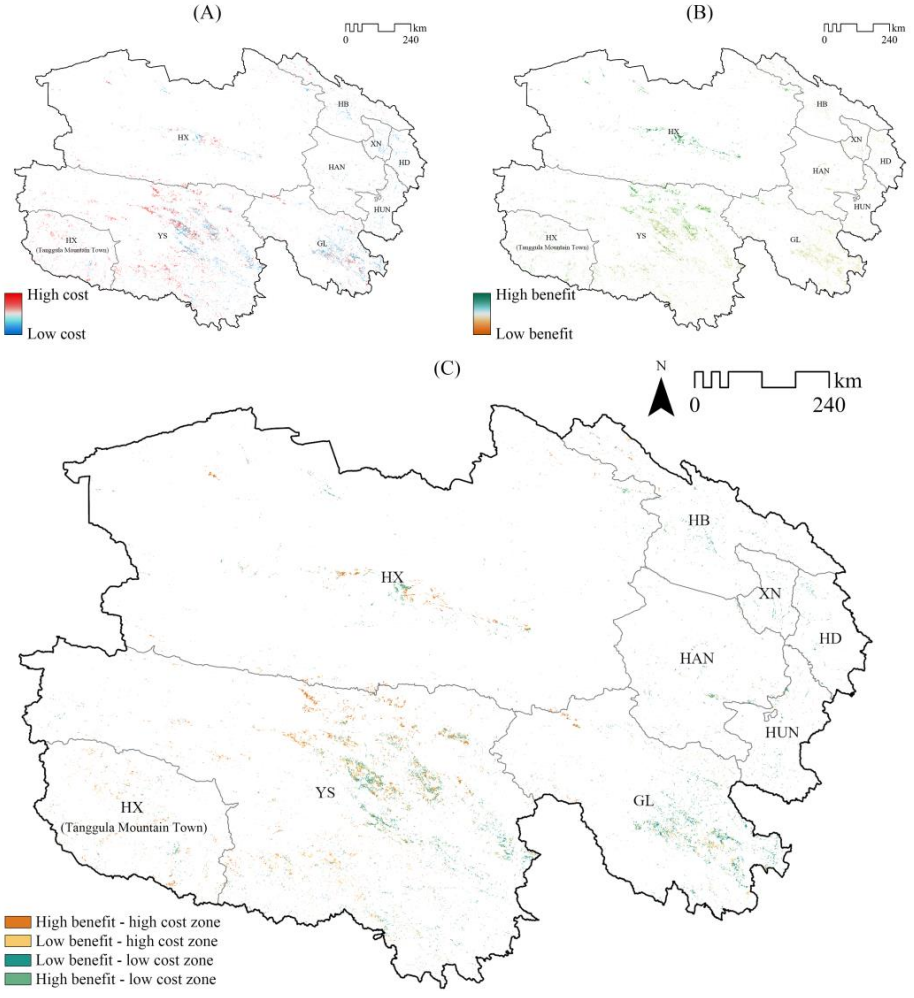


Figure 4. EMZs of degraded grassland based on cost–benefit analysis. (**A**) Spatial pattern of restoration costs; (**B**) spatial pattern of restoration benefits; (**C**) spatial pattern of EMZs.

Based on cost–benefit analysis, this study classified the degraded grasslands into four types of EMZs (Figure 4C). The area of HBHC was approximately 3327 km^2, primarily located in the central part of HX, the northern part of YS, and Tanggula Town. LBHC covered about 3450 km^2, primarily in Southern YS and Southeastern GL. The area of LBLC was approximately 3606 km^2, concentrated in the southeastern part of YS and within GL, with small areas also found in Southern HB, Southern HAN, and within XN. HBLC covered about 3053 km^2, predominantly located in the central and northern parts of HX and Central YS, with smaller areas in Northern HB and Central HAN.

4.2.2. Distribution of EMZs in Different Prefecture-Level Cities

Prefecture-level cities play a crucial role in the planning and execution of ecological restoration projects. They are responsible for formulating and implementing local ecological policies and regulations, as well as overseeing and assessing the progress and impact of ecological restoration efforts. Therefore, we calculated the distribution of various EMZs within each prefecture-level city (Figure 5).

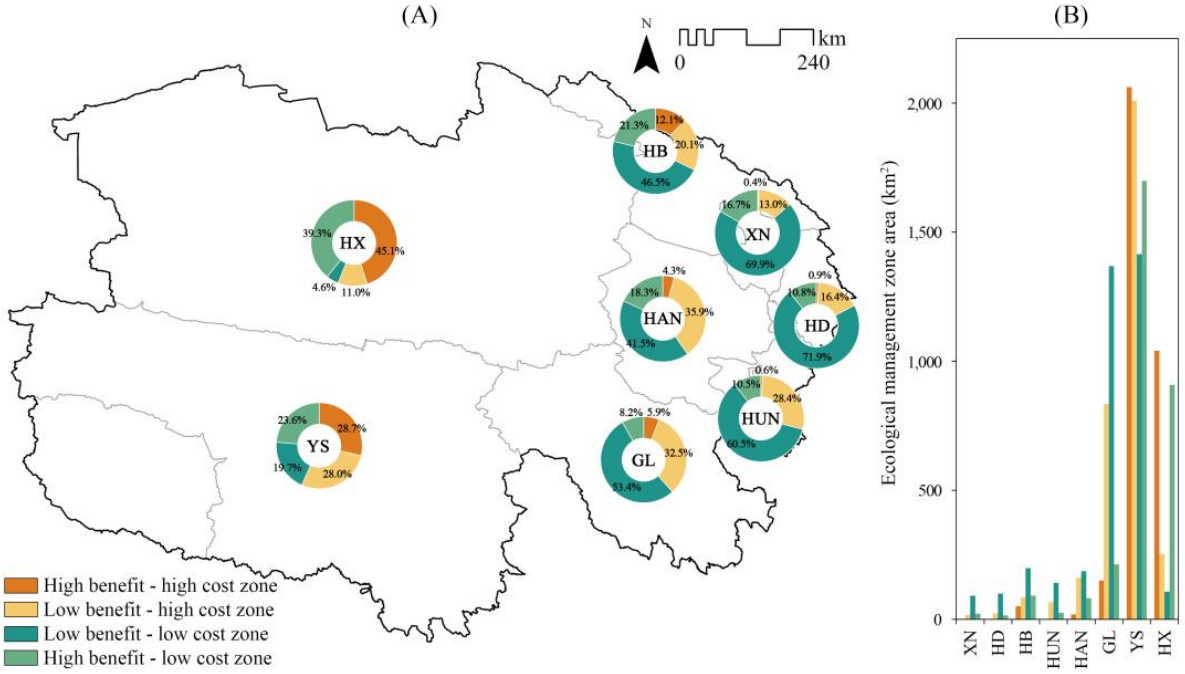


Figure 5. Distribution of various types of EMZs within different prefecture-level cities. (**A**) Proportion of each type of EMZ; (**B**) area of each type of EMZ within different prefecture-level cities.

It was evident that the areas and proportions of EMZs varied significantly across different prefecture-level cities. In YS, the areas of various EMZs were relatively large and balanced, with areas in decreasing order: HBHC (2061 km^2), LBHC (2009 km^2), HBLC (1699 km^2), and LBLC (1414 km^2). In GL, LBLC (1369 km^2) and LBHC (834 km^2) were dominant, accounting for 53.4% and 32.5%, respectively. In HX, HBHC (1041 km^2) and HBLC (908 km^2) were dominant, together accounting for about 85% of the area. In the remaining cities, the areas of various EMZs were relatively small, but their proportions varied. In HB, the proportions of the area from largest to smallest were LBLC, HBLC, LBHC, and HBHC, accounting for 46.5%, 21.4%, 20.1%, and 12.1% of the area. In XN and HD, the main types of EMZs were LBLC and HBLC, together accounting for more than 80% of the area. In HAN and HUN, LBHC and LBLC were the dominant EMZs, together accounting for more than 75% of the area.

4.3. Analysis of Driving Factors of Grassland Degradation in Different EMZs

4.3.1. The Impact of Different Driving Factors on Grassland Degradation

Single-factor detection was employed to investigate the impact of various driving factors on grassland degradation (Figure 6). The findings revealed that all factors significantly influenced grassland degradation ($p < 0.01$), although the explanatory power of each factor varied greatly across different EMZs. Detailed statistical test results were shown in Table S8.

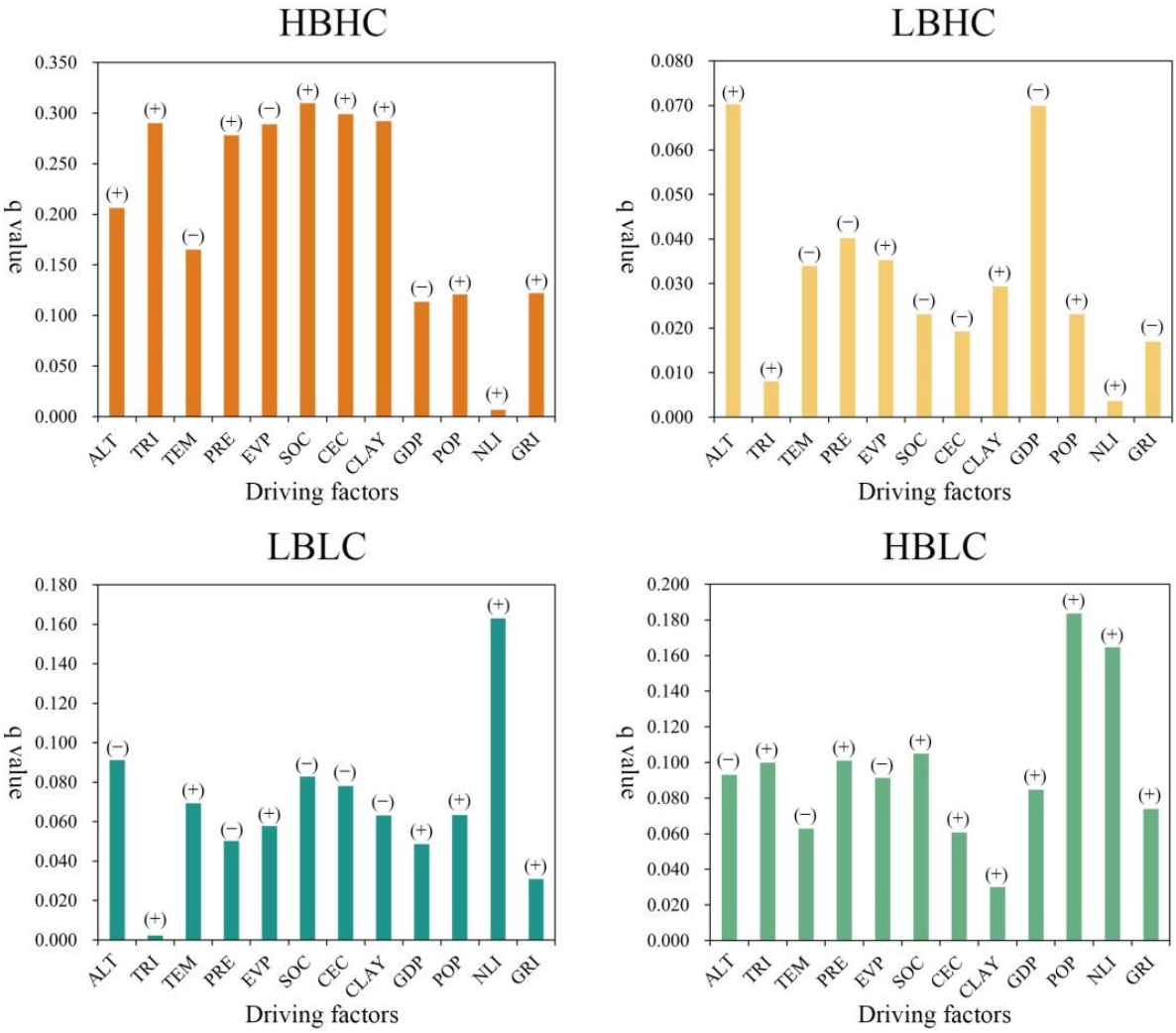


Figure 6. Result of single-factor detection results. HBHC: high benefit—high-cost zone; LBHC: low benefit—high-cost zone; LBLC: low benefit—low-cost zone; HBLC: high benefit—low-cost zone. Notes: (+)/(−) for positive/negative correlation.

Specifically, in HBHC, the q values of the three soil factors—SOC, CEC, and CLAY—were relatively high (q = 0.310, 0.299, and 0.292), indicating high sensitivity of grassland degradation to changes in soil factors. Topographic and climate factors also had high q values, with ALT, TRI, and PRE positively correlated with grassland degradation, and the other two factors negatively correlated. The explanatory power of socioeconomic factors was lower than other categories.

In LBHC, ALT was the dominant factor (q = 0.070, positively correlated), indicating that higher altitude leads to more severe grassland degradation. GDP also had relatively high explanatory power (q = 0.070, negatively correlated), indicating moderate economic development can inhibit grassland degradation in this area. The remaining factors had relatively low explanatory power.

In LBLC, NLI was the dominant factor (q = 0.163), and all socioeconomic factors were positively correlated with grassland degradation, suggesting that human activities have contributed to its intensification in this area. The q values for soil factors were relatively high, with SOC, CEC, and CLAY having values of 0.083, 0.078, and 0.063, respectively. The q values for climate factors were slightly lower than those for soil factors, with TEM and EVP positively correlated with grassland degradation, and PRE negatively correlated. Among the topographic factors, ALT exhibited a higher explanatory power for grassland degradation (q = 0.091, negatively correlated), while the q value for TRI was relatively low.

In HBLC, socioeconomic factors were the dominant factors for grassland degradation, especially POP and NLI, with q values as high as 0.184 and 0.165, both positively correlated with grassland degradation, indicating that population growth further degraded the grassland ecosystem in this area. PRE and TRI also had relatively high explanatory power (q = 0.101 and 0.100, positively correlated). Among soil factors, SOC had a q value of 0.105, while the other two factors had relatively low explanatory power.

4.3.2. Interaction of Driving Factors

Building on single-factor detection, this study further explored the interactions between pairs of driving factors (Figure 7). The findings revealed that the q values for interactions between any two factors were higher than those for individual factors, indicating that grassland degradation was amplified by the interaction of driving factors.

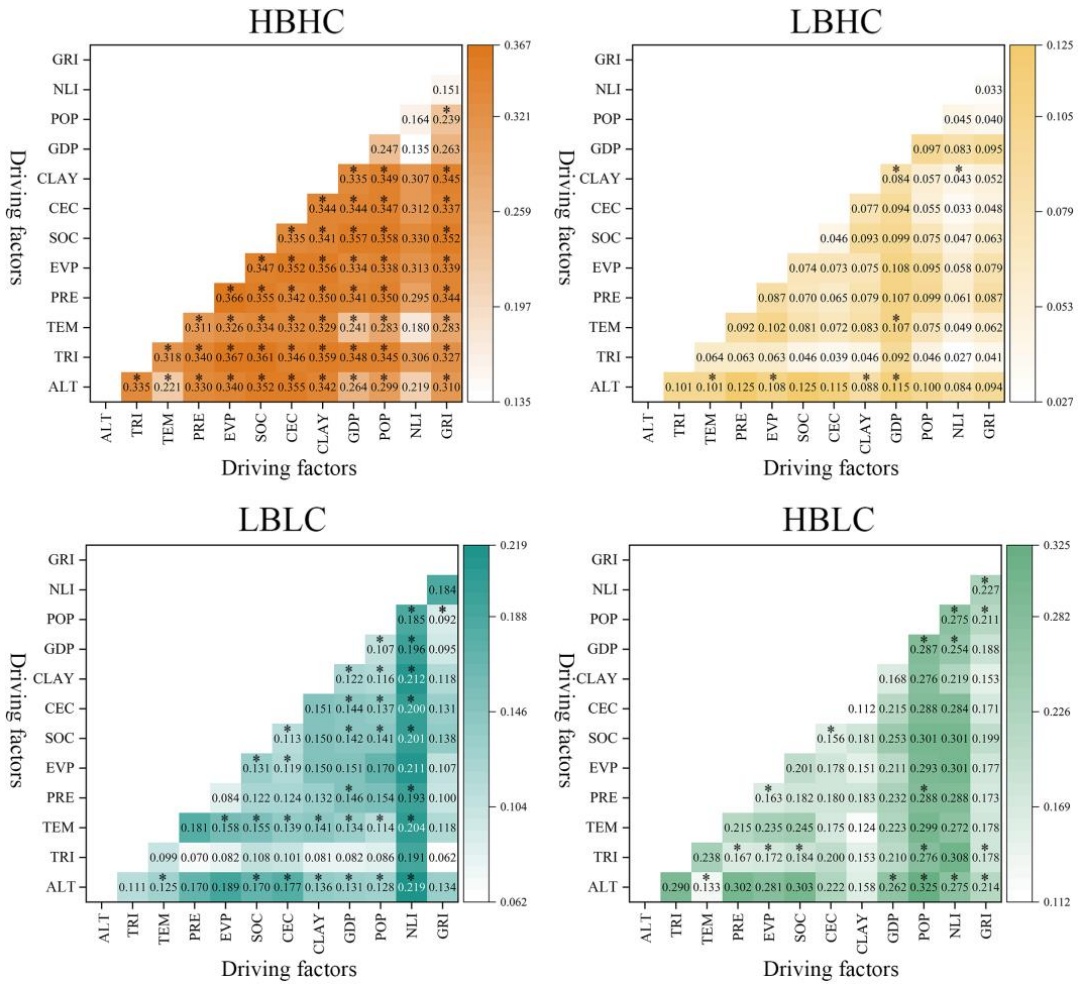


Figure 7. Result of interaction detection results. HBHC: high benefit—high-cost zone; LBHC: low benefit—high-cost zone; LBLC: low benefit—low-cost zone; HBLC: high benefit—low-cost zone. Notes: Those marked with * are bilinear enhanced, or else they are non-linearly enhanced.

Specifically, in HBHC, most driving factors exhibited bi-enhancement relationships. The three most influential interactions, in terms of explanatory power, were TRI and EVP (q = 0.367), PRE and EVP (q = 0.366), and TRI and SOC (q = 0.361). Soil factors showed strong interactions with other types of factors, further demonstrating the dominant role of soil factors in grassland degradation within this EMZ. Although the explanatory power of socioeconomic factors on grassland degradation was relatively low in single-factor detection, the q values of interactions between socio-economic factors and other categories of factors were at a higher level in interaction detection.

In LBHC, most driving factors exhibited nonlinear enhancement relationships. The three most influential interactions were ALT and PRE (q = 0.125), ALT and SOC (q = 0.125), and ALT and CEC (q = 0.115). Furthermore, the interaction between GDP and other factors was relatively strong, suggesting that in this area, the interactions between ALT, GDP, and other factors significantly influence grassland degradation.

In LBLC, the three most influential interactions were NLI and ALT (q = 0.219), NLI and CLAY (q = 0.212), and NLI and EVP (q = 0.211), indicating that the interactions between NLI and other factors had a strong impact on grassland degradation within this EMZ. At the same time, the interaction between ALT and climate and soil factors was also relatively high, further highlighting the significant impact of ALT on grassland degradation in this region.

In HBLC, most driving factors exhibited nonlinear enhancement relationships. The three most influential interactions were POP and ALT (q = 0.325), NLI and TRI (q = 0.308), and ALT and SOC (q = 0.303), emphasizing the significant impact of socioeconomic and topographic factors on grassland degradation. Although the q value of TRI was slightly higher than ALT in single-factor detection, its interactions with other factors were generally weaker. This indicates that among the topographic factors, ALT had a more significant impact on grassland degradation through its interactions with other factors.

5. Discussion

5.1. Comparison of the Impact of Driving Factors on Grassland Degradation

Scientifically identifying EMZs enables more efficient and accurate implementation of ecological restoration projects under limited financial resources [26]. However, existing studies have not adequately understood the differences between various EMZs [48]. Based on the above research results, we conducted a comparative analysis of grassland degradation responses to various driving factors within different EMZs.

Specifically, in areas with a significant decline in grassland NDVI (i.e., degraded grasslands), the influence of various driving factors on degradation varied significantly. In all four EMZs, topographic factors, particularly ALT, strongly explained the degree of degradation in degraded grasslands. In high-cost areas, ALT was positively correlated with degradation, while in low-cost areas, it was negatively correlated. This indicated that the NDVI of degraded grasslands was sensitive to altitude, with higher altitudes exacerbating degradation in high-cost areas. Conversely, in low-cost areas, where human activities such as overgrazing were more prevalent, lower altitudes were more impacted, leading to greater grassland degradation [56]. Additionally, we found that altitude, through interactions with other factors, had a more pronounced impact on grassland degradation, consistent with previous research [57].

Climate factors had higher explanatory power for grassland degradation in HBHC compared to other EMZs, indicating greater sensitivity to climate factors in this area. Additionally, although single-factor detection results for climate factors in the other three EMZs were relatively low, their interactions with topographic or socioeconomic factors were high. This indirectly reflected the complex effects of climate change on grassland degradation [58].

Soil factors had high explanatory power for grassland degradation in HBHC and LBLC, with strong interactions between soil factors and socioeconomic factors (POP and NLI). This suggested that human activities might reduce soil organic matter content,

making soil more susceptible to erosion by wind and water, thereby exacerbating grassland degradation [59,60].

Socioeconomic factors had high explanatory power for grassland degradation in HBLC and LBLC and were positively correlated with degradation. This indicated that in areas with lower ecological restoration costs, human activities exacerbated grassland degradation. Meanwhile, in different EMZs, interactions between socioeconomic factors and other types of factors were high, further emphasizing the significant impact of human activities on grassland degradation in the QTP [61].

5.2. Insights for Spatial Planning and Management Strategies for Degraded Grasslands

Delineating EMZs based on cost–benefit analysis offers reliable information for the ecological restoration of degraded grasslands [32], enhances the precision and differentiation in the decision-making process [62], and serves as a foundation for developing sustainable grassland ecological restoration strategies. Additionally, prefecture-level cities, as important administrative divisions in China, are key carriers for implementing policies and measures related to territorial spatial ecological restoration planning [63]. In view of this, we formulated detailed management strategies for different EMZs and linked them with various prefecture-level cities to provide decision-making support for local governments in developing differentiated grassland ecological restoration spatial planning and management strategies (Figure 8).

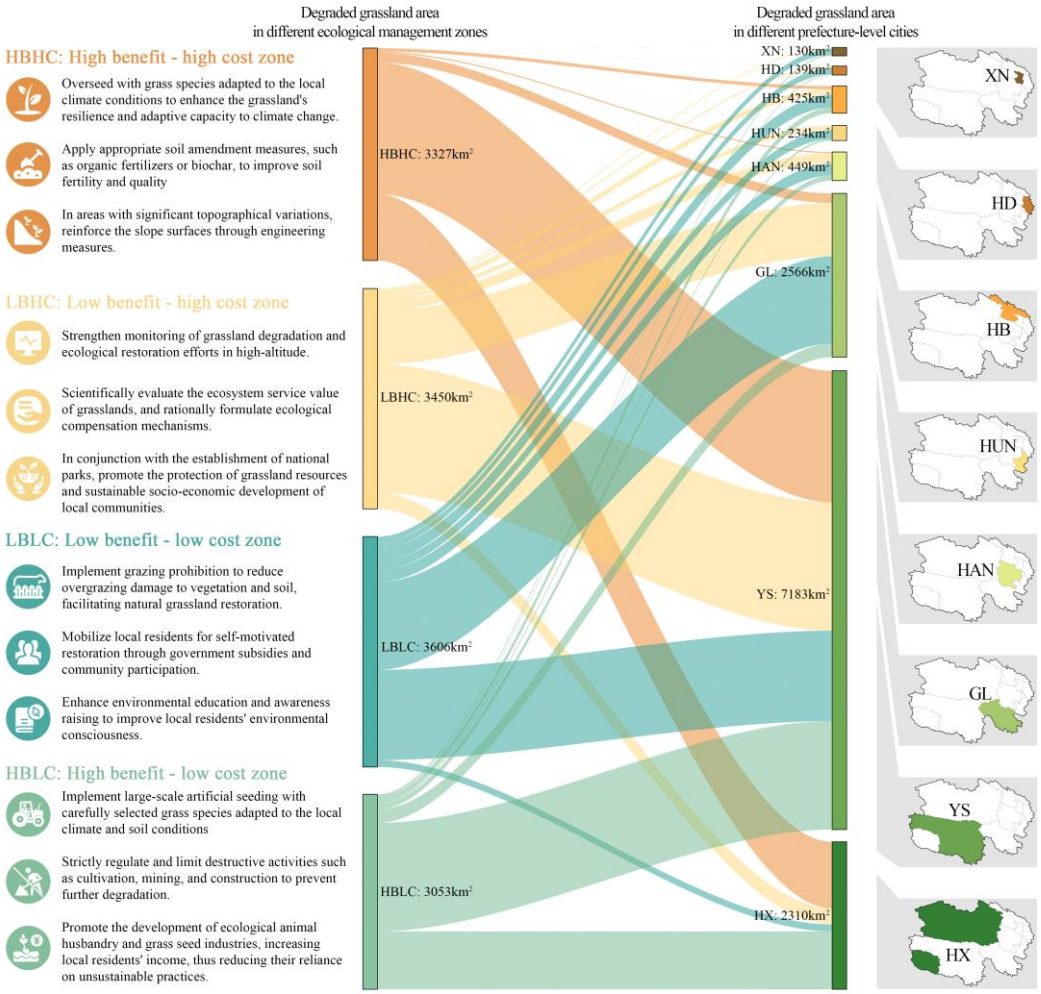


Figure 8. Management and planning strategies for degraded grasslands. HBHC: high benefit—high-cost zone; LBHC: low benefit—high-cost zone; LBLC: low benefit—low-cost zone; HBLC: high benefit—low-cost zone.

For HBHC, although the cost was relatively high, the benefits were substantial. Considering the sensitivity of grassland degradation in this area to topographic, climate, and soil factors, we propose the following management strategies: First, reseed grass species adapted to local climatic conditions in areas with severe grassland degradation to increase vegetation cover and enhance adaptability to climate change. Second, improve soil conditions by applying organic fertilizers and other methods to enhance soil structure and fertility. Third, in areas with significant topographic relief, employ engineering measures to stabilize slopes, reduce soil erosion, and create favorable microenvironments for plant growth.

For LBHC, due to the relatively high restoration costs and limited benefits, large-scale ecological restoration projects may be less effective. Based on this, we recommend: First, strengthen grassland degradation monitoring in high-altitude areas by combining remote sensing technology with ground surveys to regularly assess dynamic changes in grassland degradation, thereby improving the accuracy and efficiency of ecological restoration and reducing unnecessary costs. Second, scientifically assess the ecosystem service value of grasslands and, based on this, develop targeted ecological compensation policies that engage governments, enterprises, and the public to form a collaborative and shared ecological protection mechanism. Third, considering that these grasslands are primarily located in the Sanjiangyuan National Park, we suggest developing a specialized plan for grassland resource protection alongside the park's construction, integrating grassland restoration with eco-tourism and green agriculture industries, thereby promoting both grassland protection and the sustainable development of the local economy [64].

For LBLC, the cost was low, and the benefits were also modest due to the favorable baseline conditions of the grassland resources. Consequently, ecological restoration of degraded grassland in this zone should primarily rely on natural recovery. Considering the sensitivity of grassland degradation to socioeconomic factors, we propose the following management strategies: First, implement grazing bans to mitigate overgrazing damage to vegetation and soil, promoting natural grassland recovery. Second, mobilize local residents to participate in ecological restoration through government subsidies and community involvement. Third, strengthen ecological and environmental education to enhance environmental awareness among local residents [65].

For HBLC, with its high ecological restoration benefits and low costs, it is a priority area for implementing ecological restoration projects. We recommend the following management strategies: First, due to the severe damage to the original ecosystem and the relatively flat terrain, conduct large-scale artificial seeding with suitable grass species to promote rapid recovery of the grassland ecosystem [66]. Second, since unreasonable human activities may exacerbate grassland degradation, destructive activities such as cultivation and mining should be strictly limited [39]. Third, through the implementation of ecological restoration projects, develop ecological animal husbandry and grass seed industries to increase local residents' income and promote industrial transformation.

5.3. Strengths, Limitations, and Future Directions

This study establishes a framework for ecological restoration and zonal management of degraded grasslands, based on cost–benefit analysis, to delineate EMZs in accordance with the restoration costs and benefits of degraded grasslands across different regions. This helps optimize resource allocation and develop tailored restoration strategies. The framework not only guides grassland ecological restoration in Qinghai but is also applicable to other regions worldwide facing land degradation, fostering a balance between economic development and ecological protection. Due to the intensifying global climate change and land degradation challenges, the results of this study offer scientific evidence for policymakers and have substantial cross-regional applicability, playing a key role in advancing the United Nations Sustainable Development Goals (SDGs).

Although this study offers an innovative perspective on the spatial planning and sustainable management of degraded grassland ecological restoration, it has certain limitations that need to be addressed in future research. Firstly, due to data availability constraints,

the cost analysis mainly reflects the direct costs of implementing ecological restoration projects and may not fully account for indirect costs, such as income loss for herders due to grazing bans. Therefore, future research should further scientifically assess the indirect costs of ecological restoration, constructing a comprehensive evaluation indicator system that considers multiple dimensions such as economic losses of herders, costs of industrial structure adjustment, infrastructure investment costs, etc., while calibrating and verifying the assessment results through social surveys. In addition, this study proposed detailed ecological restoration strategies for different EMZs. Although these strategies are effective and well-targeted, they may face certain challenges and limitations. On the one hand, the analysis of influencing factors in this study primarily focuses on areas where grasslands have undergone significant degradation. While this approach can more directly and effectively guide the development of ecological restoration strategies, it lacks a comparative analysis with non-degraded grasslands in Qinghai. Future research could explore the driving mechanisms behind NDVI changes between degraded and non-degraded grasslands, offering a more comprehensive perspective for the sustainable management of grassland resources. On the other hand, the consistency of these strategies with current ecological restoration planning and management policies at the municipal level has not been fully validated. Future research should strengthen interactions among research teams, government, and other stakeholders, adjusting and refining the EMZ identification results to improve the practicality and adaptability of the research outcomes.

6. Conclusions

This study constructed a comprehensive framework integrating NDVI trend analysis, cost–benefit analysis, and the OPGD model, with Qinghai as a case study. The research focused on three aspects: identifying degraded grasslands, identifying EMZs, and analyzing driving factors influencing grassland degradation to support the ecological restoration of degraded grasslands.

By analyzing the NDVI trend of grasslands in Qinghai from 2000 to 2020, this study found that although the overall NDVI of grasslands showed an increasing trend, some areas still experienced significant degradation. The degraded grasslands were mainly located in the southern part of Qinghai. Through cost–benefit analysis, the degraded grasslands were further subdivided into four EMZs. Additionally, through the OPGD model analysis, significant differences were found in the driving factors of grassland degradation across different EMZs. Topographic factors had strong explanatory power for grassland degradation in all four EMZs, while socioeconomic factors mainly influenced grassland degradation through interactions with other factors.

Based on these analyses, differentiated spatial planning and management strategies for grassland ecological restoration were developed for each EMZ. These research findings not only provide valuable guidance for the sustainable management of grassland resources in Qinghai but also contribute to balancing the relationship between ecological protection and socioeconomic development, thereby fostering long-term sustainability in the region.

Although this research provides valuable insights, some limitations remain in the selection of cost analysis indicators and the implementation of ecological restoration strategies. Future studies could focus on further refining the indirect cost evaluation system and integrating ecological restoration strategies with territorial spatial planning.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su162411123/s1, Table S1: Table of biophysical parameters for each LULC class in the water yield evaluation; Table S2: Table of biophysical parameters for each LULC class in the soil conservation evaluation; Table S3: Threats and their maximum distance of influence and weights.; Table S4: The sensitivity of habitat types to each threat; Table S5: Classification standard of cost analysis indicators; Table S6: Indicator system of cost-benefit analysis of degraded grassland; Table S7: Interaction between driving factors; Table S8: Single factor detection statistical results; Figure S1: NDVI in the study area from 2000 to 2020; Figure S2: Results of the assessment of benefit indicators; Figure S3: Results of the assessment of cost indicators.

Author Contributions: Conceptualization, Z.W. and F.L.; methodology, Z.W.; software, Z.W. and D.X.; validation, Z.W., F.L. and D.X.; formal analysis, J.J. (Jujie Jia); investigation, Z.W., C.C. and J.J. (Jianhua Jia); resources, J.L. and Z.J.; data curation, Z.W., X.L. and Y.S.; writing—original draft preparation, Z.W.; writing—review and editing, F.L.; visualization, F.L.; supervision, Z.W. and F.L.; project administration, F.L.; funding acquisition, Z.W. and F.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Project of the National Natural Science Foundation of China, grant number 71734006, the Postdoctoral Fellowship Program of CPSF, grant number GZC20231226, and the National Key Laboratory of Forestry and Grassland Bureau for Urban and Rural Garden and Landscape Construction and the Fundamental Research Funds for the Central Universities, F grant number BFUKF202410.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: Author Jianhua Jia was employed by Qinghai Forestry Engineering Supervision Center Co., Ltd. and author Yuxia Suo was employed by Qinghai Forestry Engineering Consulting Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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