Spatiotemporal Variation and Driving Forces of Ecological Quality in the Ili Grassland Based on the Remote Sensing Ecological Index: Implications for Sustainable Ecotourism

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Abstract: The Ili Grassland is an important ecological security barrier in northwestern China and a region with abundant ecotourism resources. Scientifically evaluating the spatiotemporal variations in ecological environmental quality and identifying its key driving factors are essential for regional ecological conservation and sustainable ecotourism development. In this study, MODIS remote sensing data from 2000 to 2025 were used to construct the Remote Sensing Ecological Index (RSEI) based on four ecological indicators, including greenness, wetness, dryness, and heat. Principal component analysis (PCA) was applied to integrate these indicators, while the Sen's slope estimator combined with the Mann–Kendall (Sen+MK) trend analysis was employed to characterize the spatiotemporal dynamics of ecological environmental quality. Furthermore, the optimal parameters-based geographical detector (OPGD) model was used to identify the dominant driving factors influencing ecological environmental quality.The results showed that: (1) From 2000 to 2025, the ecological environmental quality of the Ili Grassland was mainly characterized by moderate and good levels. Areas with high ecological quality were primarily distributed in the central-eastern and southern mountainous grassland regions, whereas low-quality areas were mainly concentrated in the northwestern part of the study area. (2) The mean RSEI exhibited a slight decreasing trend during the study period. Ecological environmental quality experienced an initial fluctuating improvement followed by a continuous decline; however, the overall ecosystem maintained relatively high stability. (3) The Sen+MK analysis indicated that non-significant improvement and non-significant degradation dominated the study area, suggesting that the ecological environment underwent gradual and low-intensity changes without extensive ecological degradation. (4) The OPGD results revealed that annual precipitation, annual mean temperature, and tourism economic factors were the primary drivers of spatial differentiation in ecological environmental quality. All driving factors exhibited either bivariate enhancement or nonlinear enhancement effects, indicating that regional ecological patterns were jointly shaped by natural environmental conditions and tourism-related human activities.These findings provide

scientific support for ecological conservation, ecotourism planning, and sustainable regional development in the Ili Grassland.

Keywords: Remote Sensing Ecological Index (RSEI); ecological environment quality; Sen–Mann–Kendall trend analysis; Optimal Parameters-based Geographical Detector (OPGD); driving factors; Ili Grassland

1. Introduction

The ecological environment is fundamental to human survival and socioeconomic development, and its quality plays a critical role in global sustainability and human well-being[1]. However, rapid global climate change and accelerated urbanization have exerted increasing pressures on ecological systems[2]. Current research on ecological environmental quality mainly focuses on ecological risk assessment[3], ecological environmental quality evaluation[4], and ecological security assessment[5]. Existing approaches for evaluating ecological environmental quality include grey relational analysis[6],ecological footprint analysis[7], environmental indices (EI)[8], and fuzzy comprehensive evaluation methods [9]. Nevertheless, the selection of evaluation indicators and the determination of indicator weights often involve subjective judgments[10], and some indicators are difficult to acquire, limiting the objectivity and applicability of these methods.The Remote Sensing Ecological Index (RSEI), initially proposed by Xu[11], is a comprehensive ecological quality assessment framework developed based on remote sensing data and has been widely applied in ecological environmental quality evaluation. RSEI integrates four fundamental ecological dimensions, namely greenness (Normalized Difference Vegetation Index, NDVI), wetness (Wet), dryness (Normalized Difference Built-up and Soil Index, NDBSI), and heat (Land Surface Temperature, LST). These indicators are integrated through the Principal Component Analysis (PCA) method[12], resulting in a normalized ecological quality index ranging from 0 to 1.

In recent years, with the rapid development of remote sensing technology, its application in regional ecological monitoring and assessment has become increasingly widespread, making it an indispensable technical approach for evaluating regional ecological conditions[13]. Ecological environmental quality assessment based on the Remote Sensing Ecological Index (RSEI) has gradually become a research hotspot[14]. This approach has been extensively applied in various ecosystems, including urban areas, rural regions, wetlands, and coastal zones[15], and numerous modified RSEI frameworks have been developed to improve its adaptability to diverse geographical environments. By integrating four key ecological indicators, namely greenness, wetness, dryness, and heat, RSEI provides an effective tool for the quantitative assessment of ecological environmental quality. Previous studies have demonstrated that RSEI can effectively identify the spatiotemporal variations in ecological quality across different landscape types, including ecological evolution processes in regions such as the Yellow River Basin, eastern urban areas of China, and arid grassland ecosystems in northwestern China[15]. Recent studies conducted in the Ili region have shown that climate change and intensified human activities have significantly accelerated grassland degradation, resulting in reduced vegetation coverage and declining ecological quality[16]. Studies in Xinjiang have further confirmed that RSEI is an effective approach for long-term ecological monitoring and assessment in arid and semi-arid environments[17]. Moreover, RSEI has been successfully applied in typical grassland ecosystems, such as the Hulunbuir Grassland, to investigate the spatiotemporal evolution characteristics of ecological quality changes[18]. This study adopts the Remote Sensing Ecological Index (RSEI) not only because of its extensive application in ecological quality assessment but also because of its strong relevance to the fundamental attributes of ecotourism[19]. The development of ecotourism destinations relies heavily on ecological integrity, landscape attractiveness, environmental comfort, and ecosystem stability. In this context, the four core components of RSEI correspond closely to the key dimensions of ecotourism quality assessment. Specifically, greenness (NDVI) reflects vegetation coverage and landscape aesthetic value, which are essential for shaping the attractiveness of grassland landscapes[20]. Wetness (Wet) characterizes ecosystem water conditions and habitat suitability, thereby indicating the capacity of regional ecosystems to maintain ecological functions. Dryness (NDBSI) represents land degradation intensity and surface exposure conditions and is closely associated with ecosystem vulnerability. Land surface temperature (LST) reflects regional thermal comfort and environmental stress levels, both of which directly influence tourist experiences and ecosystem resilience[21].

The Geographical Detector (GD) model is primarily used to detect and quantify spatial differentiation characteristics[22]. It consists of four major detectors, including factor detection, interaction detection, risk detection, and ecological detection. However, conventional GD has certain limitations, particularly regarding the influence of data discretization on the accuracy and reliability of analytical results. To overcome this limitation, the Optimal Parameters-based Geographical Detector (OPGD) was proposed[23]. By optimizing the discretization parameters and improving the robustness of spatial factor detection, OPGD has been increasingly applied in ecological and environmental studies. For example, OPGD has been successfully employed to evaluate ecological environmental quality in the Dabie Mountain region of Anhui Province[24]. In addition, Zhao et al. (2024) applied OPGD to investigate vegetation coverage changes in urban agglomerations of southern Sichuan Province and achieved effective results[25].

However, several limitations remain in existing studies. First, most previous research has focused primarily on urban areas, wetlands[15], and forest ecosystems, while grassland ecosystems, particularly those located in arid and semi-arid regions, have received comparatively limited attention. Second, existing studies have mainly concentrated on the assessment of ecological environmental quality itself, whereas systematic investigations into the impacts of ecological quality changes on ecotourism development and the coupling relationships between ecological quality and ecotourism remain insufficient. Third, long-term monitoring studies focusing on ecological spatiotemporal dynamics over periods exceeding two decades are still relatively scarce. This limitation is particularly evident in ecologically sensitive grassland systems, such as the Ili Grassland, where continuous and long-term evaluations of ecological quality remain inadequate.

To address the aforementioned research gaps, this study develops an RSEI-based ecological quality assessment framework specifically designed for arid and semi-arid grassland ecosystems. The proposed framework aims to evaluate the characteristics of regional ecological quality variations and further explore their potential implications for ecotourism development, with particular emphasis on long-term ecological sustainability, spatial heterogeneity, and ecological pressures associated with tourism activities. Remote sensing technology provides a revolutionary approach for long-term ecological monitoring over large spatial scales due to its advantages in macro-scale observation, rapid information acquisition, strong dynamic monitoring capability, and relatively low operational costs. As an emerging comprehensive ecological assessment model, the Remote Sensing Ecological Index (RSEI) integrates multiple key ecological parameters and provides an intuitive representation of overall regional ecological quality[26]. Applying RSEI to evaluate the spatiotemporal variations in ecological quality of the Ili Grassland can not only overcome the limitations of traditional assessment methods in terms of subjectivity and spatial continuity, but also enable objective and quantitative evaluation of ecological resource conditions. Furthermore, it can reveal the processes and spatial differentiation patterns of ecological environmental changes, thereby providing scientific support for ecotourism planning and management. In this study, ecological quality is considered a fundamental environmental condition underlying ecosystem stability and is regarded as an important proxy dimension for evaluating the sustainability and spatial suitability of ecotourism development. Therefore, the primary focus of this research is the variation in ecosystem ecological conditions, while regional tourism value is indirectly examined through the ecological suitability and sustainability implications reflected by the RSEI assessment results.

Based on the above considerations, this study aims to achieve the following objectives: (1) to develop an RSEI-based ecological quality assessment framework and examine its relevance to sustainable ecotourism development; (2) to investigate the spatiotemporal evolution characteristics of ecological environmental quality in the Ili Grassland; and (3) to identify the key driving factors and reveal the mechanisms underlying variations in ecological environmental quality.

2. Study Area and Data Sources

2.1. Study Area

The Ili Kazakh Autonomous Prefecture is located in the northwestern part of Xinjiang Uygur Autonomous Region, China. It is an important component of the core area of the Silk Road Economic Belt and serves as a significant ecological security barrier and a region rich in ecotourism resources in northwestern China. The study area is geographically located approximately between 80°09′E–91°01′E and 42°14′N–49°10′N, covering a total area of approximately 268,400 km². The study area is characterized by a temperate continental climate, with pronounced vertical climatic differentiation caused by the combined effects of complex topography and prevailing westerly circulation. The mean annual temperature ranges from approximately 2 to 10 °C, while annual precipitation generally varies between 100 and 800 mm. The Ili River Valley receives relatively abundant precipitation, ranging from 400 to 800 mm annually, with some high-altitude mountainous areas exceeding 800 mm. In contrast, precipitation decreases substantially in the eastern and southern regions. The Ili Kazakh Autonomous Prefecture contains diverse ecosystem types, including alpine glaciers, forests, grasslands, wetlands, rivers, deserts, and oases. It is one of the most biodiverse regions in Xinjiang and represents an important water conservation area and grassland ecological functional zone in China. In recent years, rapid tourism development and intensified human activities have increased ecological pressures in some areas, including grassland degradation, ecological disturbance, and land-use changes. Therefore, investigating the spatiotemporal variations in regional ecological environmental quality is of great significance for promoting high-quality ecotourism development and strengthening regional ecological security. In this study, the Ili Kazakh Autonomous Prefecture was selected as the study area, including Yining City, Kuytun City, Khorgos City, Yining County, Chabuchaer Xibe Autonomous County, Huocheng County, Gongliu County, Xinyuan County, Zhaosu County, Tekes County, and Nilka County (Fig 1).

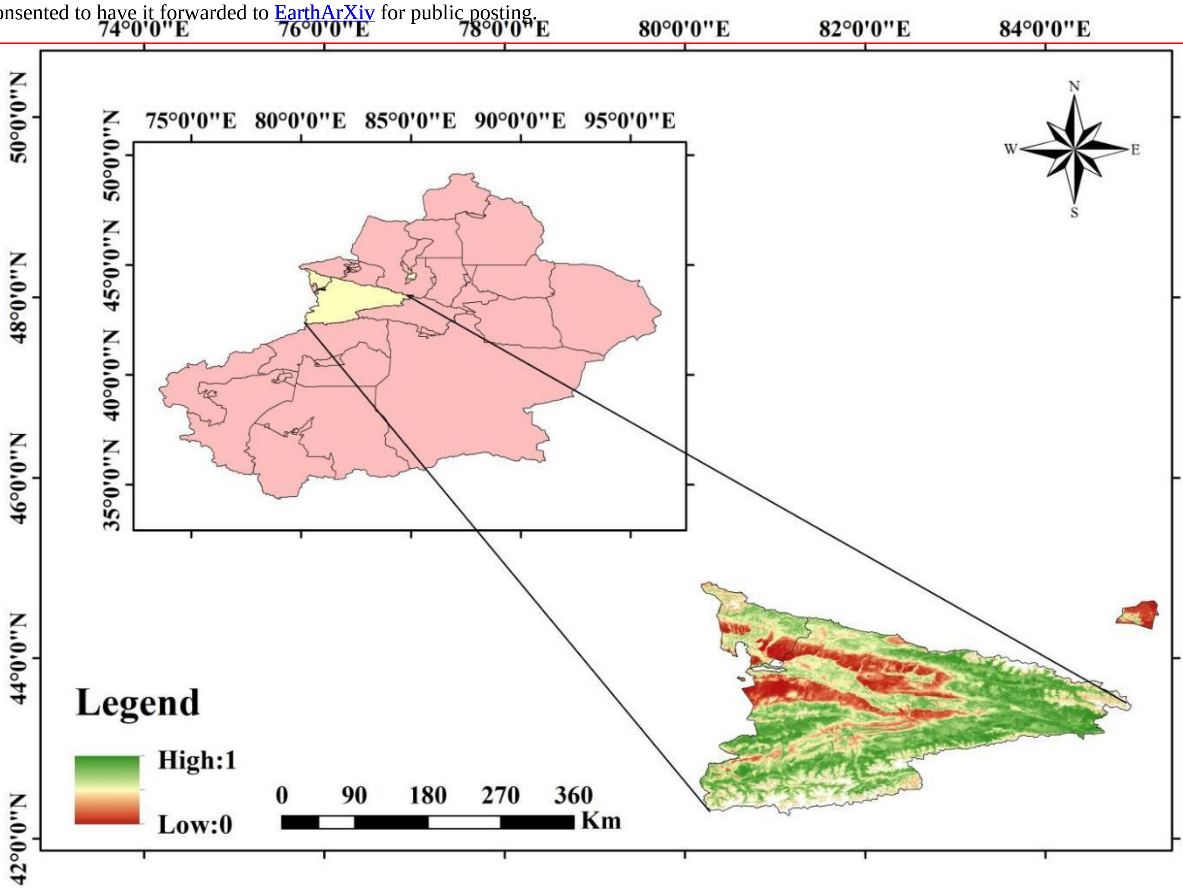


Fig 1. Study area.

2.2. Data sources

To characterize the long-term ecological evolution patterns of the Ili Grassland, the primary analysis was conducted using MODIS satellite remote sensing images acquired at five-year intervals, including the years 2000, 2005, 2010, 2015, 2020, and 2025. This temporal sampling strategy was adopted to highlight ecological changes at a five-year scale while minimizing the influence of short-term interannual variability caused by extreme climatic fluctuations, temporary land-use changes, and potential noise in remote sensing observations. Furthermore, to validate the robustness of the long-term trends identified from the interval-based analysis, a complete annual time series from 2000 to 2025 was additionally analyzed and compared with the results derived from the five-year interval dataset. The study period continuously covered 2000–2025, and all annual datasets were used without temporal gaps. To ensure data quality, all remote sensing images were acquired during the peak vegetation growing season (June–September) of each target year, with cloud cover below 10%. Cloud-contaminated pixels were removed using the quality assessment (QA) band provided by the Google Earth Engine (GEE) platform. Radiometric calibration, atmospheric correction, and image clipping were subsequently performed, and representative annual composites were generated using the median compositing method. All raster datasets, including MODIS products and digital elevation model (DEM) data, were processed in the Google Earth Engine (GEE) platform using the WGS 84 geographic coordinate system (EPSG:4326). Because the MODIS products used in this study have different original spatial resolutions (500 m and 1 km), all datasets were first harmonized into a consistent spatial and temporal framework before constructing the Remote Sensing Ecological Index (RSEI). Specifically, all raster layers were reprojected to the same geographic coordinate system and resampled to a unified spatial resolution of 500 m to ensure consistency among the ecological indicators. Detailed information on the datasets used in this study is provided in Table 1.

To investigate the driving factors influencing ecological environmental quality in the Ili Grassland, this study employed the Optimal Parameters-based Geographical Detector (OPGD) model based on previous research[27]. The RSEI was selected as the dependent variable, while annual precipitation, annual mean temperature, gross domestic product (GDP), population size, number of tourist attractions, tourist arrivals, domestic tourism revenue, and inbound tourism revenue were selected as independent variables[28]. The panel data of socioeconomic indicators for the Ili Kazakh Autonomous Prefecture during 2000–2025 were mainly obtained from the *China Statistical Yearbook*, *Xinjiang Statistical Yearbook*, *Ili Kazakh Autonomous Prefecture Statistical Yearbook*, as well as statistical bulletins and bulletins on national economic and social development published by counties (cities) within the study area. In addition, supplementary data processing was conducted for individual missing records. For indicators with missing values in certain years, linear interpolation was applied to ensure the continuity and completeness of the temporal data series.

Table 1. Details of MODIS datasets used in this study.

Products	Time Quantum		Time Resoiution	Platform	Version	Row Number
MOD09A1	3.01-5.31	6.01-8.31	8days	Terra	V061	h23v04,v05
MOD11A2	3.01-5.31	6.01-8.31	8days	Terra	V061	h24v05,v05
MOD13A1	3.01-5.31	6.01-8.31	16days	Terra	V061	h25v05,v05

3. Methods

3.1. Research methods

3.1.1. Indicator Calculation

Following the RSEI framework proposed by Xu (2013) and considering the characteristics of grassland ecosystems, four core ecological indicators were selected, including greenness, wetness, dryness, and heat. Principal component analysis (PCA) was applied to six periods of MODIS satellite imagery to generate the integrated ecological quality index, namely the Remote Sensing Ecological Index (RSEI). The RSEI values range from 0 to 1, with higher values indicating better ecological quality. By applying PCA, the ecological conditions of the study area can be comprehensively characterized through the integration of dryness, heat, wetness, and greenness components[29]. This approach provides an effective means of evaluating overall ecological status by combining multiple ecological indicators rather than relying on a single indicator, as adopted in previous studies. The four components of RSEI, namely dryness, heat, wetness, and greenness, are represented by the Normalized Difference Built-up and Soil Index (NDBSI), Land Surface Temperature (LST), wetness index (Wet), and Normalized Difference Vegetation Index (NDVI), respectively.

1. Greenness Index

Vegetation growth reflects the interactions between vegetation and the natural environment. The greenness index is an integrated indicator that characterizes vegetation health and growth conditions, and it is also influenced by vegetation biomass, vegetation coverage, and leaf area index (LAI). The Normalized Difference Vegetation Index (NDVI) is widely used to quantify vegetation coverage and growth status by representing vegetation greenness based on the near-infrared (NIR) and red (RED) spectral bands[30]. The calculation of NDVI is expressed as Equation (1):

$$NDVI = \frac{(NIR - \mathrm{Re}d)}{(NIR + \mathrm{Re}d)} \qquad (1)$$

MODIS corresponding bands:
Red: Band 1 (620–670 nm)
NIR: Band 2 (841–876 nm)

2. Humidity Index

In ecological environmental studies, the wetness index is a key indicator that reflects water conditions in soils, water bodies, and vegetation, and is closely associated with ecological changes[31]. Based on MODIS data, the Normalized Difference Moisture Index (NDMI) is commonly used to characterize surface moisture conditions, and its calculation is expressed as Equation (2)[32].

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \qquad (2)$$

3. Dryness Index

The dryness component was characterized using the Normalized Difference Built-up and Soil Index (NDBSI), which integrates the spectral information of built-up surfaces and bare soil[33]. The calculation of NDBSI is expressed as Equation (3):

$$NDBSI = \frac{IBI + SI}{2} \qquad (3)$$

where IBI represents the Index-Based Built-up Index and SI represents the Soil Index. To reduce spectral interference from water bodies, water pixels were masked before index calculation.

4. Heat Index

In this study, daytime land surface temperature (LST_Day_1km) from the MOD11A2 product was selected to represent the heat component of the RSEI. Daytime LST was chosen because it can more effectively capture the effects of solar radiation, surface heating, evapotranspiration stress, and vegetation thermal responses during the main active growth period of grassland ecosystems. Compared with nighttime LST, daytime observations provide a more sensitive indicator of surface thermal stress associated with ecological quality assessment. A notable feature of thermal infrared remote sensing is its capability to measure land surface temperature (LST)[34]. Previous satellite-based urban heat island studies have demonstrated a strong relationship between satellite-derived LST and actual surface temperatures[35]. In the MODIS-based Remote Sensing Ecological Index (RSEI), the heat component is represented by LST, which can be directly obtained from the MODIS MOD11 series products. The calculation process is shown in Equations (4)–(6).

$$LST = \frac{T}{\left[(1 + \frac{\lambda T}{\rho}) \ln \varepsilon\right]} \qquad (4)$$

$$T = \frac{K_2}{\ln(\frac{K_1}{L} + 1)} \qquad (5)$$

$$L = gain \times DN + bias \qquad (6)$$

In Equations (4)–(6), L represents the radiance converted from MODIS data, where gain is the gain value corresponding to the thermal infrared band, and bias is the offset value, both of which can be obtained from the MODIS image metadata. DN denotes the digital number of the MODIS thermal infrared band. T is the brightness temperature, while K_1 and K_2 are the pre-set calibration constants of the MODIS sensor. λ is the central wavelength of the corresponding thermal infrared band, ρ is a constant approximately equal to $1.438 \times 10^{-2} mK$, and ε is the land surface emissivity.

3.1.2. Construction of the Remote Sensing Ecological Index (RSEI)

Principal component analysis (PCA) is a statistical transformation method that converts a set of correlated observed variables into a new set of linearly independent variables through orthogonal transformation, thereby effectively reducing the dimensionality of the dataset[36]. In addition, spatial PCA does not rely on researchers' prior knowledge or subjective experience, which can reduce the influence of human-induced bias to some extent[37]. It should be noted that PCA is a statistical dimensionality reduction approach, and the component loadings derived from PCA represent variance-based weights rather than direct ecological causal relationships. Previous studies have demonstrated that the PCA-based weighting scheme of RSEI is consistent with field-measured ecological conditions in arid and semi-arid regions[11]. In this study, PCA was applied to integrate multiple ecological indicators and construct a comprehensive Remote Sensing Ecological Index (RSEI)[38]. The four ecological indicators were concentrated into one or two principal components, allowing all indicators to be integrated and represented by a single composite index. Therefore, during RSEI construction, PCA can effectively reduce the uncertainty of subjective or method-dependent weighting assignments, thereby improving the reliability of the RSEI assessment. Because the selected ecological indicators have different dimensions and units, normalization was performed before PCA. Accordingly, all indicators were transformed into a standardized range of 0–1, and the normalization method is expressed as Equation (7).

$$NI_i = \frac{(I_i - \mathrm{I}_{min})}{(\mathrm{I}_{max} - \mathrm{I}_{min})} \qquad (7)$$

In Equation (7), NI_i is the normalized value, I_i is the original pixel value, and I_{max} and I_{min} are the maximum and minimum values of the indicator across the study area. According to the statistical principles of PCA, the first principal component (PC1) captures the most important information from all the principal components.

Therefore, the results of PC1 were selected in this study to represent the original Remote Sensing Ecological Index ($RSEI_0$). To improve analytical efficiency, the first principal component was normalized and the positive and negative values were inverted to obtain the RSEI, as shown in Equations (8) and (9).

$$RSEI_0 = 1 - PC1 \qquad (8)$$

$$RSEI = \frac{(RSEI_0 - RSEI_{0\,min})}{(RSEI_{0\,max} - RSEI_{0\,min})} \qquad (9)$$

In Equations (8) and (9), RSEI represents the Remote Sensing Ecological Index of the study area. Ecological quality is positively correlated with the RSEI value, and the maximum and minimum RSEI values are denoted as $RSEI_{0\,max}$ and $RSEI_{0\,min}$, respectively.

The RSEI provides an effective indicator for characterizing regional spatiotemporal ecological quality due to its advantages in data accessibility, computational methodology, and practical applicability. The framework of RSEI calculation and its interpretation are illustrated in Fig 2.

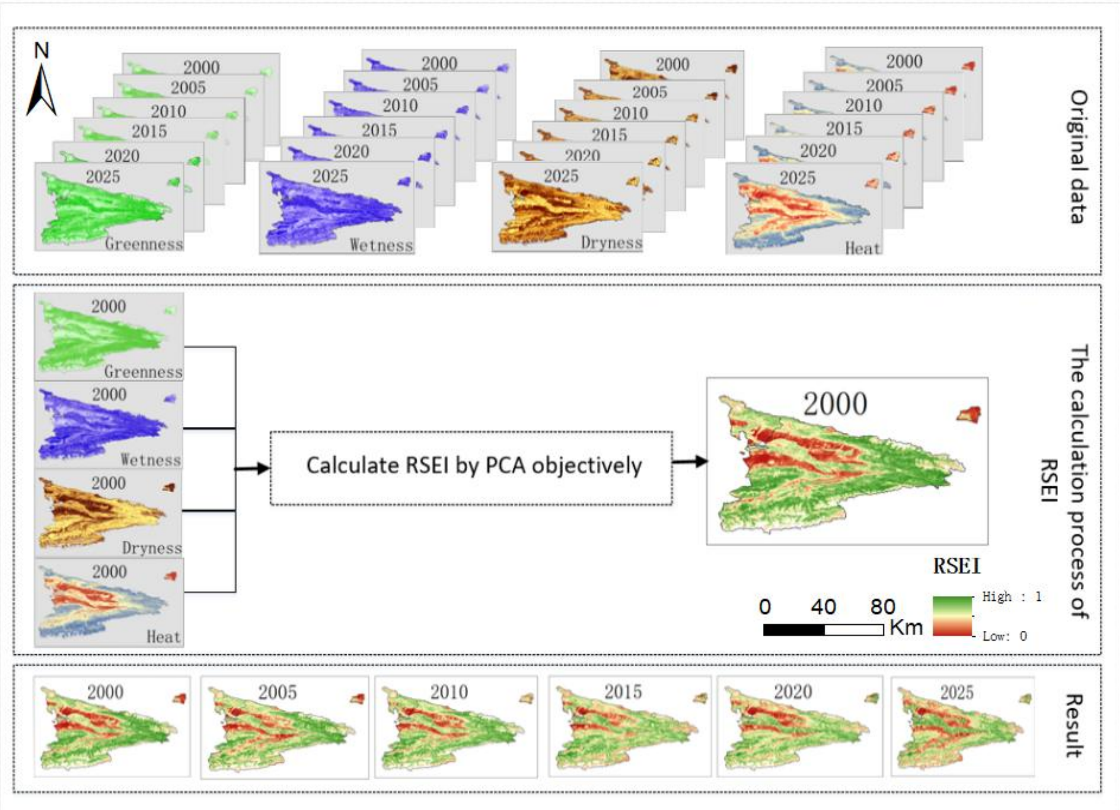


Fig 2. Flowchart of the Remote Sensing Ecological Index (RSEI) calculation process.

3.1.3. Sen’s slope estimation and mann-kendall test

The Sen–Mann–Kendall method is widely used for long-term time series analysis. The Theil–Sen estimator quantifies trend magnitude and direction, while the Mann–Kendall (MK) test evaluates statistical significance. As non-parametric methods, they are robust to outliers and distribution-free, making them suitable for trend detection in ordered data. The corresponding trend classification criteria are shown in Table 2, and the calculation formula is given as follows[39]

$$\mathrm{Sen} = \mathrm{median}\left(\frac{\mathrm{DRSEI_j} - \mathrm{DRSEI_i}}{\mathrm{j} - \mathrm{i}}\right) \tag{10}$$

$$Z = \begin{cases} S - \dfrac{1}{\sqrt{\mathrm{var}\,(s)}} & S > 0 \\ 0 & S = 0 \\ S + \dfrac{1}{\sqrt{\mathrm{var}\,(s)}} & S < 0 \end{cases} \tag{11}$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\left(a_j - a_i\right) \tag{12}$$

$$\mathrm{sgn}\left(a_j - a_i\right) = \begin{cases} +1 & \left(a_j - a_i > 0\right) \\ 0 & \left(a_j - a_i = 0\right) \\ -1 & \left(a_j - a_i < 0\right) \end{cases} \tag{13}$$

In the above equations, Sen represents the magnitude and direction of change in RSEI. When Sen> 0, RSEI exhibits an increasing trend; when Sen< 0, it indicates a decreasing trend; and when Sen= 0, RSEI remains stable over time. Z denotes the standardized test statistic used to assess the significance of the trend, while sgn() represents the sign function. The terms $\mathrm{a_j}$ and $\mathrm{a_i}$ correspond to the observed values at time points j and i , respectively.

Table 2. Trend of Sen+MK method.

Sen	MK salience	Trend type determination	Ecological meaning explained
Sen≥0.0005	Z>1.96	Significant increase（SI）	persistent and statistically significant increasing trend
	Z≤1.96	not significantly increased（NSI）	The indicator shows an overall increasing trend, although the change is not statistically significant
-0.0005<Sen<0.0005	-	basically stable (BS)	The indicator exhibits minor fluctuations with no evident trend.
Sen≤-0.0005	Z≤1.96	not significantly decreased(NSD)	The indicator shows a decreasing trend, but the change is not statistically significant.

Z＞1.96	Significant decrease （SD）	The indicator exhibits significant degradation

3.1.4. SCS+C terrain correction formula

To reduce the influence of topographic effects in mountainous areas, a terrain correction was applied using the SCS+C model based on DEM-derived slope and aspect. This method effectively minimizes illumination differences caused by terrain variability[40].The topographic correction was performed on the Google Earth Engine (GEE) platform using DEM-derived slope and aspect information. The C-correction model was applied to reduce terrain-induced radiometric distortion in the mountainous environment.The formula is as shown in Equation (14)-(17).

$$L_{corr}=L_{orig}\cdot\frac{\cos\theta_s\cos\theta_i+C}{\cos\theta_i+C} \quad (14)$$

$$\cos\theta_i=\cos\theta_s\cos\theta_t+\sin\theta_s\sin\theta_t\cos(\phi_s-\phi_t) \quad (15)$$

$$C=\frac{b}{a} \quad (16)$$

(17)

L_{corr} ： Terrain-corrected reflectance

L_{orig} ： Original remote sensing reflectance

θ_s ： solar zenith angle

θ_i : illumination angle

C: Empirical correction parameter

3.1.5. Geographical Detector Based on Optimal Parameters (OPGD)

The Optimal Parameters-based Geographical Detector (OPGD) model can identify the optimal combination of spatial data discretization methods, spatial stratification schemes, and spatial scale parameters, thereby enhancing the exploration of underlying driving mechanisms of geographical phenomena and improving the identification of spatial heterogeneity and variable interactions[25]. By automatically searching for optimal parameter combinations through algorithmic optimization, OPGD improves computational efficiency, reduces subjectivity in parameter selection, and enhances the robustness of analytical results. Compared with the conventional Geographical Detector model, OPGD overcomes several limitations, including dependence on expert experience for parameter combination selection, relatively low computational efficiency, and potential biases caused by subjective spatial discretization[23]. In this study, the OPGD analysis was conducted using the geographical detector package in R.

4. Results

4.1. PCA results

The principal component analysis (PCA) results of the four ecological indicators for the six selected years in the Ili grassland region are presented in Fig 3. As shown in the figure, the contribution rates of PC1 to the RSEI in 2000, 2005, 2010, 2015, 2020, and 2025 were 76.16%, 69.32%, 67.77%, 66.82%, 67.22%, and 66.54%, respectively. Compared with the other principal components, PC1 captured and integrated the characteristic information of all ecological indicators more effectively. Therefore, this study used only PC1 to construct the RSEI, as the first principal component is generally considered to represent the dominant gradient of ecological quality variations[41].

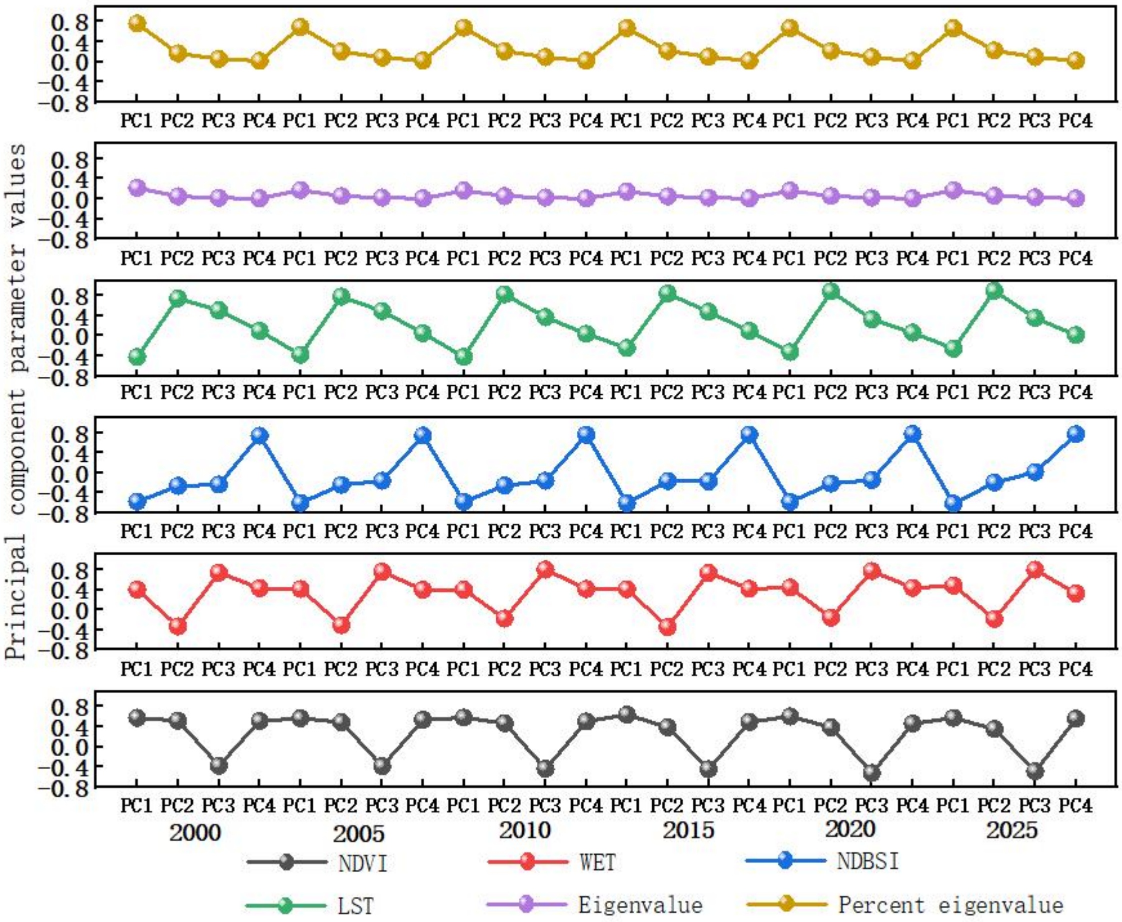


Fig 3. Principal component analysis results of the indicators in 2000, 2005, 2010, 2015, 2020, and 2025.

4.2. Spatiotemporal Distribution of Eco-Environmental Quality

To further investigate the spatiotemporal distribution characteristics of ecological environmental quality in the Ili Grassland, the ecological environmental quality of the study area was classified into five levels according to the relevant criteria[42], as presented in Table 3.

Table 3. RSEI classification criteria.

Level	Poor	Fair	Moderate	Good	Excellent
Interval	[0,0.2]	(0.2,0.4]	(0.4,0.6]	(0.6,0.8]	(0.8,1]

The mean RSEI values in 2000, 2005, 2010, 2015, 2020, and 2025 were 0.566, 0.547, 0.576, 0.557, 0.544, and 0.513, respectively. During the study period, the ecological quality of the Ili Grassland exhibited a trend characterized by "an initial fluctuating increase followed by a continuous decline." The mean RSEI values fluctuated between 0.513 and 0.576 from 2000 to 2025, showing an overall decreasing tendency. Specifically, the RSEI decreased from 0.566 in 2000 to 0.547 in 2005, and subsequently increased to the highest value of 0.576 in 2010. After 2010, ecological quality gradually deteriorated, with the RSEI values declining to 0.557, 0.544, and 0.513 in 2015, 2020, and 2025, respectively. These results indicate that the ecological environment quality of the Ili Grassland experienced a slight degradation trend during the study period, accompanied by a gradual decline in ecosystem stability.

The spatial distribution of ecological quality in the Ili grassland from 2000 to 2025 exhibited distinct regional differentiation characteristics (Fig 4). Throughout the study period, ecological quality was predominantly characterized by the Moderate and Good levels. Areas classified as Moderate, Good, and Excellent were mainly distributed in the central, eastern, and southern mountainous grassland regions of the study area. These regions are characterized by complex topography, relatively favorable precipitation conditions, high vegetation coverage, and strong ecosystem stability. In contrast, areas with Poor and Fair ecological quality were primarily concentrated in the northwestern part of the study area. Specifically, in 2000, areas with relatively high ecological quality showed a continuous spatial distribution pattern, with Good and Excellent classes widely distributed in the central and eastern regions, while areas with low ecological quality were mainly scattered in the northwestern and northern marginal areas. In 2005, low-quality ecological areas expanded to some extent, with some regions shifting from the Moderate level to Fair and Poor levels, indicating increased ecological pressure in localized areas. By 2010, ecological quality improved, with a notable expansion of high-quality areas. The spatial extent of the Excellent and Good classes increased, and the RSEI reached its highest value during the study period. After 2015, areas with lower ecological quality gradually expanded, particularly in the northwestern and northern regions, while the distribution areas of Good and Excellent classes declined. By 2025, the areas of Poor, Fair, Moderate, Good, and Excellent ecological quality levels were 5457.903 km^2 (10.15%), 12797.752 km^2 (23.81%), 14618.224 km^2 (27.19%), 14507.081 km^2 (26.99%), and

6375.804 km² (11.86%), respectively (Table 4). Among them, the Moderate and Good levels accounted for the largest proportions, indicating that the ecological environment quality of the Ili grassland remained dominated by moderate and relatively favorable conditions. However, the increasing proportion of low-quality areas suggests that ecological degradation risks have intensified in the study area.

Overall, the spatial pattern of ecological quality in the Ili grassland remained relatively stable from 2000 to 2025; however, a gradual transition from high-quality ecological areas toward medium- and low-quality areas was observed. Regions with better ecological conditions were primarily associated with higher vegetation coverage and favorable hydrothermal conditions, whereas areas with lower ecological quality were mainly affected by the combined effects of arid climatic conditions, grassland degradation, and anthropogenic pressures.

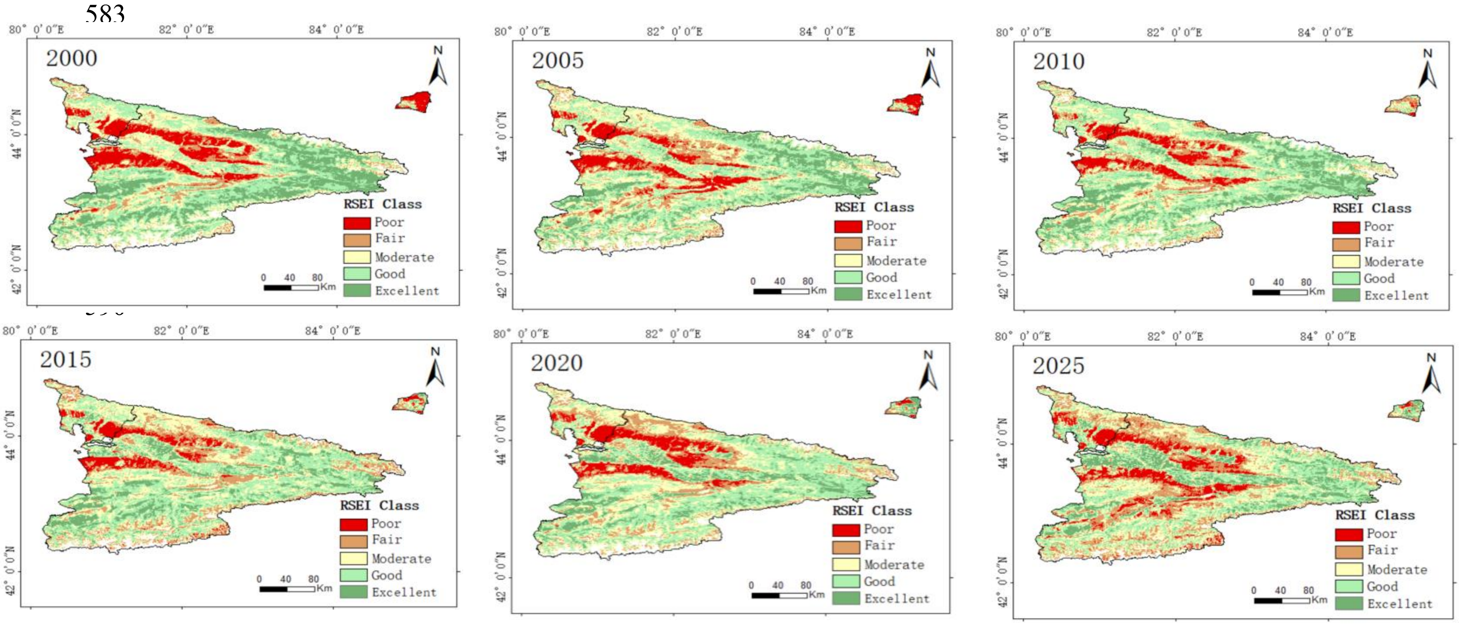


Fig 4. Spatial distribution of RSEI levels from 2000 to 2025.

Table 4. Areal distribution of RSEI classes in the study area (km², %).

RSEI Level	2000		2005		2010		2015		2020		2025	
	Area	Per	Area	Per	Area	Per	Area	Per	Area	Per	Area	Per
Poor[0-0.2]	6372.784	12.18	5032.281	9.61	4230.001	8.13	3430.256	6.46	4560.055	8.66	5457.903	10.15
Fair(0.2-0.4]	6315.145	12.07	8198.106	15.65	6945.453	13.36	9527.203	17.94	8927.874	16.95	12797.752	23.81
Moderate(0.4-0.6]	12817.284	24.49	15206.516	29.04	13705.524	26.35	15147.907	28.52	15397.275	29.23	14618.224	27.19
Good(0.6-0.8]	16563.84	31.65	16823.2	32.12	18737.844	36.04	18147.288	34.17	17603.053	33.42	14507.081	26.99
Excellent(0.8-1.0]	10263.179	19.61	7110.459	13.58	8385.676	16.12	6852.375	12.91	6185.519	11.74	6375.804	11.86

Total	52332.232	100	52370.562	100	52004.498	100	53105.029	100	52673.776	100	53756.764	100

4.3. Dynamic changes in ecological environment quality from 2000 to 2025

In this study, the Google Earth Engine (GEE) platform was utilized to derive the RSEI values of the Ili grassland from 2000 to 2025 using Equations (8) and (9). Furthermore, high-quality RSEI remote sensing images within the study area were selected through the GEE platform for subsequent remote sensing data processing. The temporal dynamics and current status of RSEI were then analyzed using the Sen's slope estimator combined with the Mann–Kendall (Sen+MK) trend analysis method. Fig 5 presents the spatial distribution maps of RSEI in the Ili grassland from 2000 to 2025.

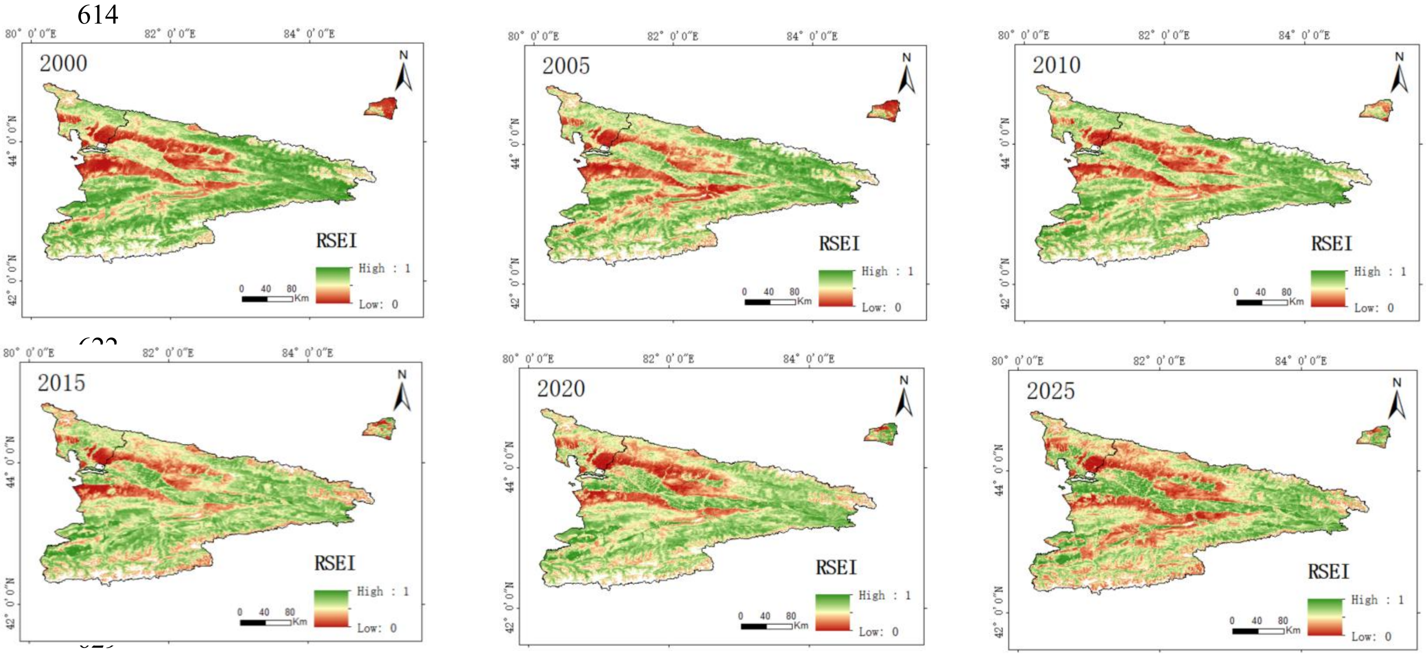


Fig 5. RSEI remote sensing images from 2000 to 2025.

The Sen+MK analysis results (Fig 6) indicate that the RSEI of the Ili grassland exhibited a pattern characterized by "a weak overall improvement trend with significant localized spatial heterogeneity," reflecting the complex responses of grassland ecosystems to climatic fluctuations and grazing pressures. The maximum and minimum values of the Sen's slope were 0.05 and −0.03, respectively, indicating a narrow and approximately symmetrical range of variation. This suggests that the study area experienced a gradual and low-intensity ecological adjustment process over the past 25 years (2000–2025), rather than a systematic ecological transformation or ecosystem collapse. The Mann–Kendall (MK) trend classification results further demonstrate that NSI (Non-Significant Improvement) and NSD (Non-Significant Degradation) were the dominant change types, further confirming that weak improvement was the prevailing trend in the study area. In addition, the magnitude differences between the extreme values of SD (Significant Degradation) and SI (Significant Improvement) were relatively small, suggesting that the extreme intensities of ecological degradation and restoration were statistically comparable. This indicates that no catastrophic ecological collapse occurred within the study region. Overall, during 2000－2025, the Ili grassland ecosystem remained in a stage of "slight positive fluctuations under high ecosystem stability," indicating that the region maintained ecological stability while exhibiting a certain degree of improvement. Therefore, sustainable ecotourism management strategies should be implemented in the future to achieve a balanced integration of ecological conservation and tourism development.

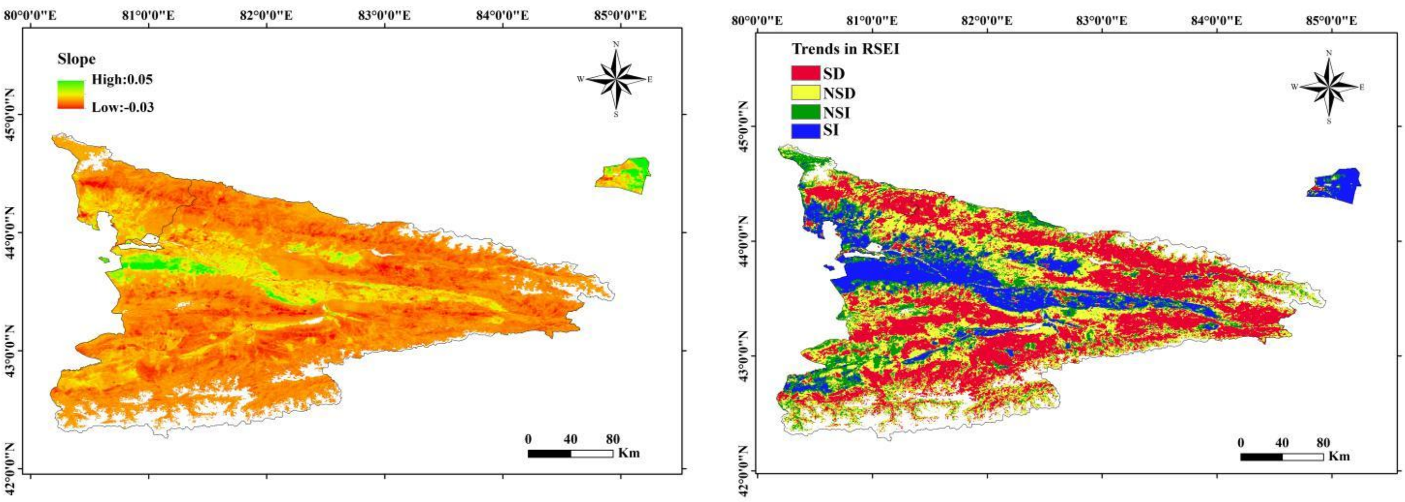


Fig 6. Evolution trend of ecological environment quality in the Ili grassland from 2000 to 2025.

4.4. Driving factor analysis

4.4.1. Single-factor analysis results

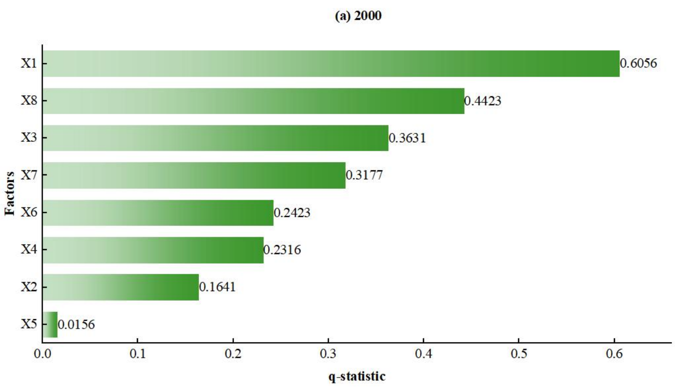
The Optimal Parameter Geographical Detector (OPGD) was applied in R version 4.3.2 to investigate the explanatory power of individual influencing factors (Fig 7). In the OPGD model, a p-value less than 0.05 indicates statistical significance. The q-statistic represents the explanatory power of factor X for the dependent variable Y; a higher q-value indicates stronger explanatory ability, implying a greater contribution of the factor to the spatial and temporal differentiation of ecological quality. All selected factors in this study exhibited significant effects on ecological quality ($p < 0.05$). Table 5 presents the q-statistic detection results for each driving factor. Based on the temporal analysis of the results, natural climatic factors and tourism economic factors alternately dominated the spatial differentiation of ecological quality in the study area.

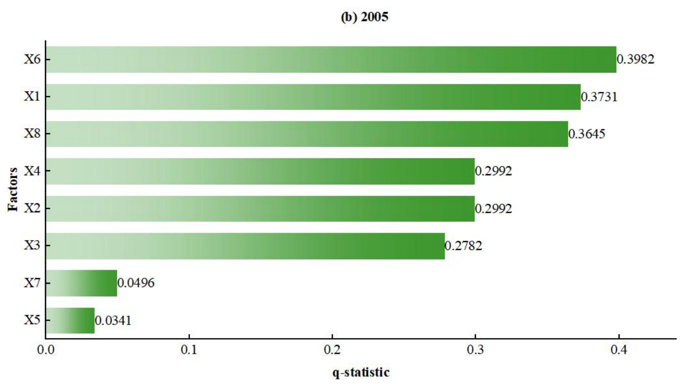
Among these factors, annual precipitation exhibited the strongest explanatory power for ecological quality in 2000 and 2010, with q-values reaching 0.6056 and 0.5669, respectively. In contrast, annual average temperature became the dominant factor in 2020, achieving the highest q-value of 0.7388. These results are closely related to the geographical and climatic characteristics of the Ili grassland. Although Ili is located in an arid and semi-arid region, the influence of the westerlies creates a unique "humid island" climate, where precipitation and thermal conditions directly regulate vegetation growth, succession processes, and the ecological background conditions of grassland ecosystems. Therefore, natural climatic factors played a fundamental and strong driving role during most periods.

Notably, the driving effects of socioeconomic and tourism-related factors became increasingly prominent over time, exhibiting distinct characteristics of phased intensification. In 2005, tourist arrivals (Tourists) emerged as the most influential factor, with a q-value of 0.3982. In 2015, gross domestic product (GDP) showed the strongest explanatory power, with a q-value of 0.4391. By 2025, domestic tourism revenue became the dominant driving factor, reaching a q-value of 0.5457. These findings highlight that, during the rapid development of ecotourism in the Ili grassland, human economic activities and tourism development have exerted crucial influences on the spatial pattern of local ecological quality. Other factors, including population size, inbound tourism revenue, and the number of scenic spots, also showed significant explanatory power for ecological quality; however, their q-statistics exhibited relatively pronounced interannual fluctuations. Overall, the ecological quality of the Ili grassland was jointly driven by the combined effects of the natural climatic foundation and ecotourism-related economic activities.

Table 5. Q-statistic detection results for driving factors.

Order		2000	2005	2010	2015	2020	2025
	Factor	q-Value	q-Value	q-Value	q-Value	q-Value	q-Value
1	Annual precipitation	0.6056	0.3731	0.5669	0.2526	0.1981	0.2141
2	Annual average temperature	0.1641	0.2992	0.1289	0.2684	0.7388	0.2785
3	Gross Domestic Product	0.3631	0.2782	0.2388	0.4391	0.2221	0.2326
4	Population	0.2316	0.2992	0.3611	0.0794	0.4009	0.1294
5	Number of scenic spots	0.0156	0.0341	0.1093	0.3081	0.2902	0.0089
6	Tourists	0.2423	0.3982	0.0586	0.0914	0.2198	0.0075
7	Domestic tourism revenue	0.3177	0.0496	0.1241	0.0914	0.4032	0.5457
8	Inbound tourism revenue	0.4423	0.3645	0.1541	0.2873	0.2131	0.3004





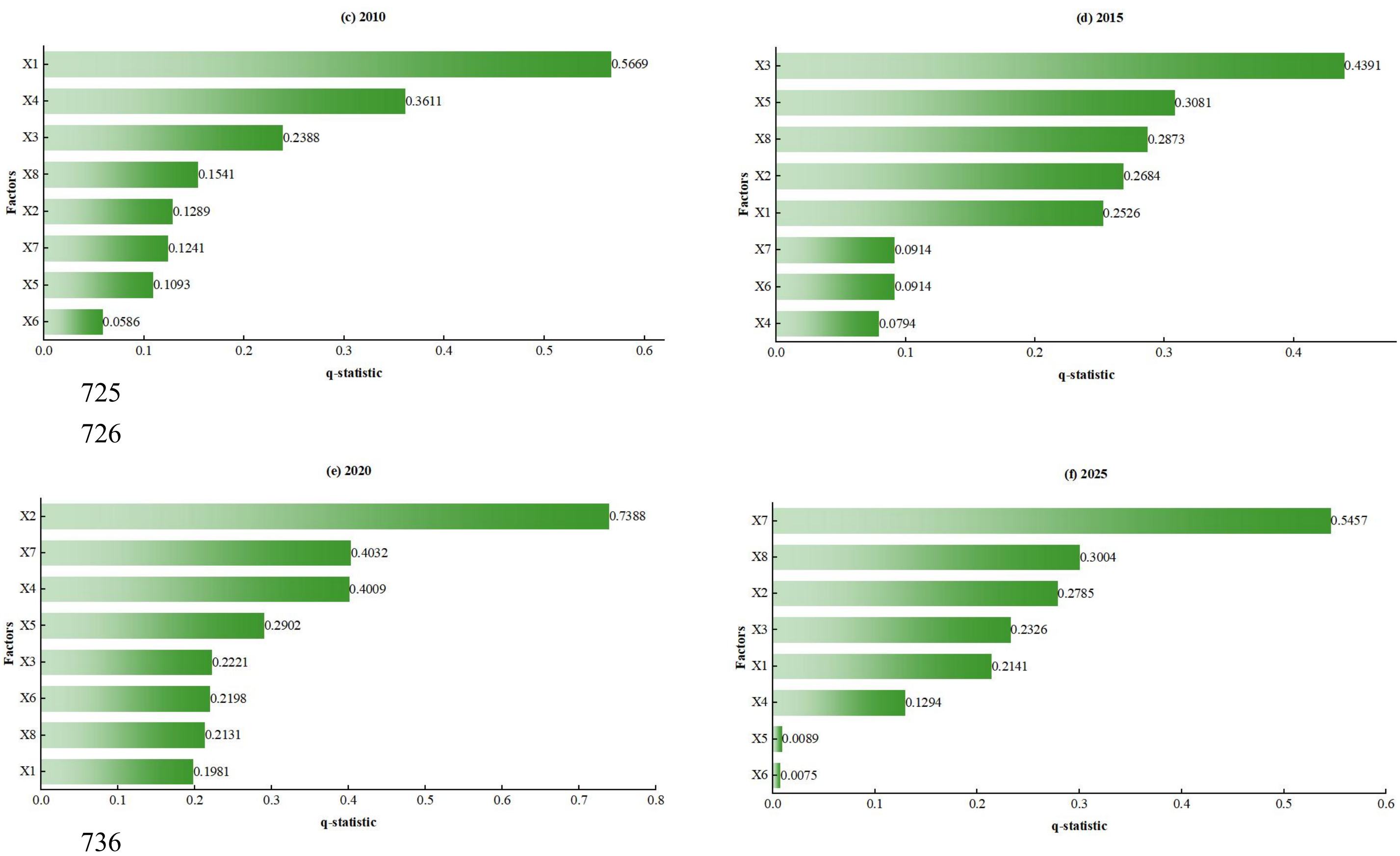


Fig 7. Single-factor detection results from the optimal parameters-based geographical detector (OPGD).

4.4.2. Interaction detection results

Figure 8 presents the interaction detection results among the driving factors. The analysis indicates that the interaction between any two factors exhibited significantly greater explanatory power for the ecological quality of the Ili grassland than any individual factor alone. All interaction types were characterized by either bivariate enhancement or nonlinear enhancement. Overall, the interactions between natural climatic factors (annual precipitation and annual average temperature) and socioeconomic as well as tourism-related factors showed the strongest effects, with q-values generally remaining at high levels. Specifically, in 2000, the interaction between annual precipitation and GDP exhibited the strongest explanatory power ($q = 0.9679$). In 2005 and 2025, the interaction between annual precipitation and domestic tourism revenue dominated, with q-values reaching 0.8548 and 0.9185, respectively. In 2010 and 2020, the strongest interactions were observed between annual average temperature and domestic tourism revenue ($q = 0.8836$) and between annual average temperature and population size ($q = 0.8221$), respectively. In 2015, the interaction between the number of scenic spots and inbound tourism revenue demonstrated a strong nonlinear enhancement effect ($q = 0.8793$). These results clearly demonstrate that the spatial differentiation of ecological quality in the Ili grassland was not driven by isolated individual factors, but rather resulted from the deep coupling and synergistic amplification between the natural ecological foundation and human economic activities dominated by ecotourism development.

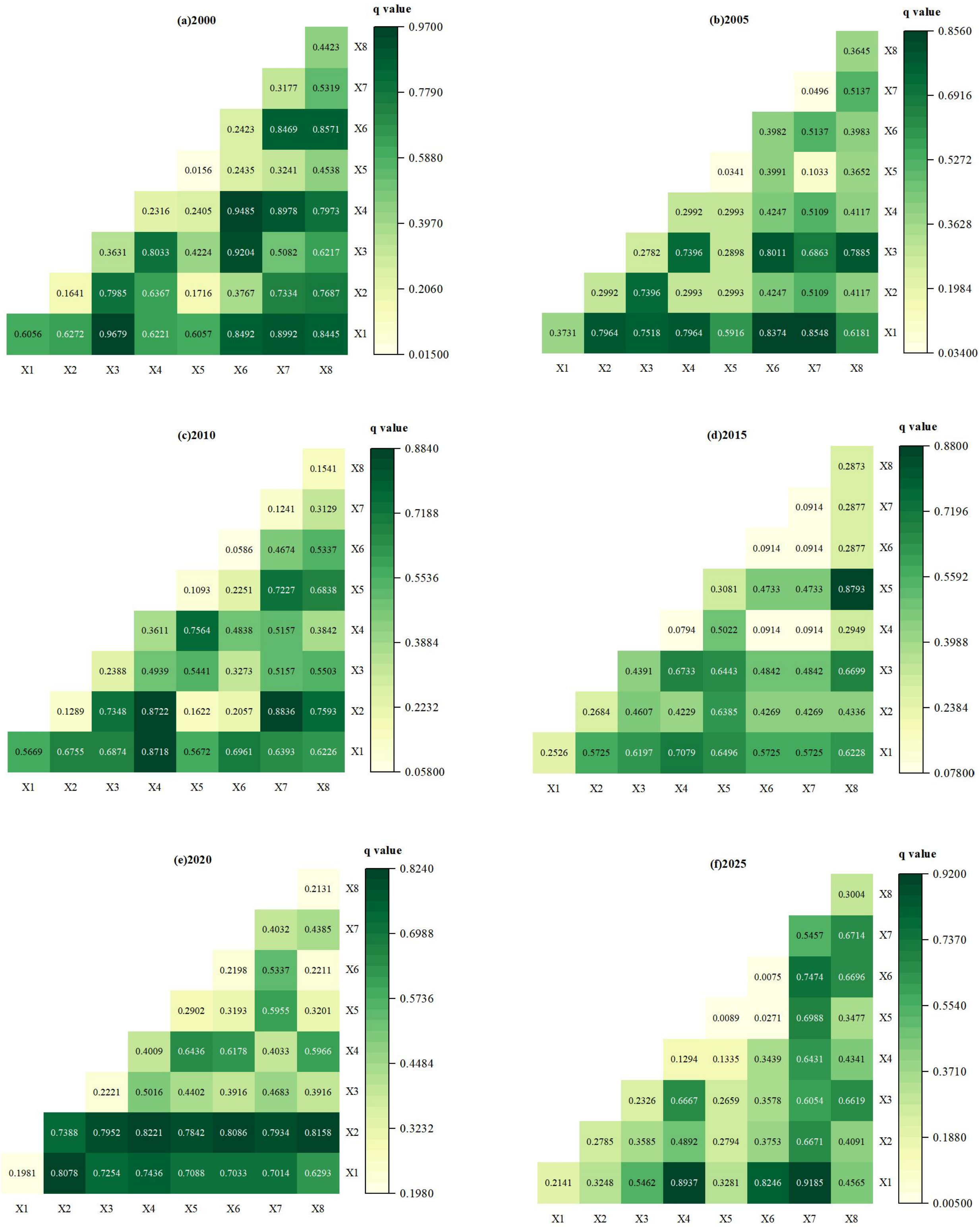


Fig 8. Interaction detection results among driving factors (X1 = Annual precipitation; X2 = Annual average temperature; X3 = Gross Domestic Product; X4 = Population; X5 = Number of scenic spots; X6 = Tourists; X7 = Domestic tourism revenue; X8 = Inbound tourism revenue).

5. Discussion

5.1. Spatiotemporal distribution characteristics of RSEI

Accurately assessing regional ecological environmental quality and timely identifying trends in ecological and environmental changes are of great significance for the long-term sustainable development of the Ili grassland and regional ecotourism. To achieve harmonious coexistence between ecotourism development and ecological conservation while maintaining grassland ecosystem stability, it is essential to scientifically plan tourism and economic development and provide strict protection for the region's core ecological environment. Previous studies have demonstrated that the Remote Sensing Ecological Index (RSEI) is an objective, large-scale, and widely applied comprehensive evaluation method for assessing regional ecological quality [43]. Based on the RSEI analysis conducted in this study, the overall ecological quality of the Ili grassland exhibited a distinct spatial differentiation pattern, characterized by "higher quality in the central-eastern and southern regions and lower quality in the northwestern region." Areas with relatively favorable ecological conditions (Moderate, Good, and Excellent levels) were mainly distributed in the central-eastern and southern mountainous grassland regions, where complex terrain, relatively abundant precipitation, and higher vegetation coverage provide favorable ecological conditions[44]. In contrast, areas with relatively poor ecological conditions (Poor and Fair levels) were primarily located in the northwestern marginal areas, where ecological quality was jointly affected by arid climatic conditions, grassland degradation, and anthropogenic pressures.

The Ili Kazakh Autonomous Prefecture is located in an arid and semi-arid region. Although its unique climate is shaped by topographic conditions and the circulation of the westerlies, its ecosystem remains highly sensitive to anthropogenic activities, particularly the rapidly developing tourism industry, as well as climate change. From the perspective of the temporal dynamics of the Ili grassland, the mean RSEI values fluctuated between 0.513 and 0.576 during 2000 – 2025, indicating a slight degradation process characterized by "an initial fluctuating increase followed by a continuous decline." Particularly after 2015, the area of low-quality ecological regions gradually expanded, while high-quality ecological regions showed a decreasing trend under the combined influence of potential environmental and anthropogenic pressures. However, the Sen+MK trend analysis further revealed substantial internal differences within the study area. The overall ecological change was dominated by Non-Significant Improvement (NSI) and Non-Significant Degradation (NSD), with relatively small differences in extreme change magnitudes. No catastrophic ecological collapse occurred; instead, the ecosystem remained in a stage of slight positive fluctuations under high systemic stability. Under these circumstances, regions with favorable natural conditions and relatively abundant precipitation, particularly the central-eastern and southern areas, maintained better vegetation greenness (NDVI) and moisture conditions (Wet), effectively buffering localized degradation pressures and allowing the overall ecological status to remain within a relatively stable range.

A comprehensive spatiotemporal assessment of ecological quality in the study area can provide valuable insights into the interactive feedback mechanisms between long-term ecological evolution and regional development. Over the past 25 years, this spatiotemporal analysis has visually revealed the evolutionary characteristics of RSEI levels in the Ili grassland. Although high-quality ecological regions have faced potential risks of transition toward medium- and low-quality levels, this gradual and low-intensity adjustment process indicates that the region has maintained relatively strong ecological resilience. Although the RSEI of the Ili grassland has shown a slight declining trend in recent years, Moderate and Good ecological quality areas have remained the dominant categories. This spatiotemporal evolution pattern suggests that, under the deep coupling between natural climatic conditions and ecotourism-oriented economic activities, the overall ecological condition of the region has maintained a relatively favorable foundation. These findings also highlight that future planning should pay particular attention to vulnerable areas undergoing transitions from high to low ecological quality levels, thereby ensuring the sustainable and high-quality development of ecotourism in the Ili grassland.

5.2. Factors influencing ecological environment quality

Identifying the key factors driving the spatiotemporal variations in ecological quality of the Ili grassland can provide valuable references for regional ecological conservation decision-making and ecotourism planning. In this study, the analysis based on the Optimal Parameter Geographical Detector (OPGD) revealed that natural climatic factors and tourism-related economic factors alternately dominated the spatial differentiation of ecological quality in the study area. Natural variables, such as annual precipitation and annual average temperature, exhibited strong explanatory power in multiple years. The Ili grassland is located in an arid and semi-arid region; however, the influence of the westerlies has created a unique “humid island” climate, in which precipitation and thermal conditions directly determine vegetation growth succession and the ecological baseline of grassland ecosystems. Previous studies have also demonstrated that climate change has significantly intensified the ecological evolution and degradation processes of grassland ecosystems in the Ili region and other arid areas[16]. Other socioeconomic factors also exerted significant influences on ecological quality, and their driving effects became increasingly prominent over time. With the rapid development of tourism and economic activities, tourist arrivals became the dominant driving factor in 2005, GDP exhibited the strongest influence in 2015, and domestic tourism revenue emerged as the primary driving factor in 2025. These findings indicate that human economic activities and tourism development have played crucial roles in shaping the spatial pattern of ecological quality in the Ili grassland.

This study demonstrated that changes in ecological quality were influenced by the combined effects of multiple factors rather than being independently driven by a single factor. The interactions between natural climatic factors (annual precipitation and annual average temperature) and socioeconomic as well as tourism-related factors exhibited the strongest impacts on ecological quality, with all interaction types characterized by either bivariate enhancement or nonlinear enhancement. For example, the interaction between annual precipitation and domestic tourism revenue dominated in 2005 and 2025, whereas the interaction between annual precipitation and GDP showed the strongest effect in 2000. This pattern may be attributed to the fact that precipitation and thermal conditions constitute the ecological carrying capacity foundation of the region, while human economic activities dominated by ecotourism exert additional influences on this natural foundation. In regions with favorable hydrothermal conditions, ecosystems generally exhibit stronger resilience and are better able to support tourism activities. Conversely, in areas with fragile ecological foundations, intensive tourism development and population concentration may pose increasing pressures on ecosystem stability. These findings are consistent with previous studies[27], further demonstrating that the spatial differentiation of ecological quality in the Ili grassland resulted from the deep coupling and synergistic amplification between the natural ecological foundation and human tourism-related economic activities.

5.3. Implications for ecotourism

The analysis of the spatiotemporal evolution and driving mechanisms of ecological quality in the Ili grassland provides several important implications for the sustainable development of regional ecotourism. First, a spatially differentiated and dynamic tourism management strategy should be implemented. Given that the central-eastern and southern mountainous grassland regions exhibit relatively high ecological quality and favorable hydrothermal conditions, these areas should be designated as key ecological conservation zones and high-quality low-impact ecotourism experience areas, with strict restrictions on intensive infrastructure development. In contrast, ecologically fragile areas with low RSEI values, such as the northwestern marginal regions, require scientifically regulated grazing and tourism activities, accompanied by proactive grassland ecological restoration measures. Second, it is necessary to establish a coordinated mechanism linking tourism economic development with ecological thresholds. The driving factor analysis demonstrated that tourist arrivals, domestic tourism revenue, and inbound tourism revenue became dominant or critical drivers at specific periods, such as 2005 and 2025. Moreover, the interactions between socioeconomic factors and annual precipitation as well as annual average temperature consistently exhibited significant synergistic enhancement effects. These findings indicate that the rapid expansion of the tourism industry has exerted substantial influences on the ecological pattern of grassland ecosystems. Therefore, future tourism planning should strictly adhere to ecological protection thresholds, implement dynamic carrying-capacity regulation mechanisms for scenic areas, and prevent irreversible ecological pressures caused by excessive commercialization and disorderly development. Finally, ecological tourism management should enhance risk monitoring and climate adaptation resilience. Tourism planning should fully consider the potential risks associated with fluctuations in hydrothermal conditions under global climate change. Strengthening ecological monitoring along major tourism routes and within scenic areas, and establishing an early-warning mechanism for the coupled "natural–tourism–socioeconomic" system, are essential for achieving high-quality ecotourism development guided by effective ecological conservation.

5.4. Limitations and future prospects

It should be acknowledged that the use of MODIS data in this study has certain limitations. For example, its moderate spatial resolution (500 m to 1 km) may not fully capture fine-scale spatial heterogeneity within mountainous grassland landscapes, including fragmented pasture patches, narrow river corridors, localized tourism facilities, and small-scale ecotourism resource characteristics. Therefore, in regions with complex terrain and highly heterogeneous land-cover patterns, the mixed pixel effect may occur, potentially affecting the local accuracy of ecological quality assessments and the evaluation of ecotourism resource suitability[45]. Nevertheless, the primary objective of this study was to assess long-term regional ecological dynamics and large-scale sustainability patterns rather than to conduct fine-scale mapping of tourism infrastructure. Given its excellent temporal continuity and long-term historical observations, MODIS data remain suitable for large-scale ecological trend monitoring. Future studies could integrate higher-resolution datasets, such as Landsat or Sentinel imagery, to further improve the spatial accuracy of ecological quality assessments in mountainous grassland regions[45].

6. Conclusion

This study utilized the Google Earth Engine (GEE) platform and MODIS remote sensing data to construct the Remote Sensing Ecological Index (RSEI). By integrating the Sen's slope estimator combined with the Mann–Kendall (Sen+MK) trend analysis method and the Optimal Parameter Geographical Detector (OPGD), this study systematically assessed the spatiotemporal evolution characteristics and driving mechanisms of ecological quality in the Ili grassland from 2000 to 2025. The results indicated that:

(1) Temporally, the mean RSEI values of the Ili grassland during 2000, 2005, 2010, 2015, 2020, and 2025 were 0.566, 0.547, 0.576, 0.557, 0.544, and 0.513, respectively. Overall, the ecological quality exhibited a changing trend characterized by "an initial fluctuating increase followed by a continuous decline," indicating a

slight degradation of the ecological environment. The Sen+MK analysis further revealed that the study area was primarily dominated by Non-Significant Improvement (NSI) and Non-Significant Degradation (NSD), suggesting that the ecosystem remained in a gradual and low-intensity adjustment stage with relatively high ecological stability.

(2) Spatially, the ecological quality of the study area was predominantly characterized by the Moderate and Good levels. Areas with high ecological quality were mainly distributed in the central-eastern and southern mountainous grassland regions, whereas areas with lower ecological quality were primarily concentrated in the northwestern region. In the future, differentiated ecological conservation and tourism management strategies should be implemented to strengthen the protection of key ecological areas, regulate tourism development and anthropogenic disturbances in ecologically fragile regions, and promote the coordinated integration of ecological conservation and tourism development.

(3) The OPGD results demonstrated that ecological quality differentiation was jointly driven by natural climatic factors and tourism-related economic factors. Annual precipitation and annual average temperature exhibited strong explanatory power during most periods, while the influences of socioeconomic factors, such as tourist arrivals, GDP, and domestic tourism revenue, gradually increased over time. The interaction detection results consistently showed bivariate enhancement or nonlinear enhancement effects, indicating that ecological quality was shaped by the combined effects of natural environmental conditions and anthropogenic activities.

(4) This study developed an integrated assessment framework combining RSEI, Sen+MK trend analysis, and OPGD-based driving factor analysis, which provides a comprehensive understanding of the spatiotemporal evolution patterns and driving mechanisms of ecological quality in the Ili grassland. This framework offers scientific support for ecological environmental monitoring, ecotourism planning, and regional sustainable development in arid and semi-arid grassland regions. Moreover, it provides a methodological reference for ecological quality assessment in other ecologically fragile regions.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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