# Postprint: Evolution of Ecological Quality in Yanchi County Based on the SA-RSEI Model

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## Abstract

To investigate the spatiotemporal dynamic change characteristics and driving factors of the ecological environment in Yanchi County, based on five periods of Landsat remote sensing data from 2000 to 2020, the improved remote sensing index (SA-RSEI) was utilized, combined with Sen+Mann-Kendall and Hurst index analyses to examine the spatiotemporal change patterns and trends of ecological environment quality in Yanchi County, and the geographical detector was employed to explore the driving factors of ecological environment quality. The results show that: (1) From 2000 to 2020, the SA-RSEI in Yanchi County showed a trend of first decreasing and then increasing; (2) The ecological environment quality of Yanchi County exhibited an evolution process of first degradation and then recovery during the 21-year period, with the spatial distribution pattern gradually transitioning from poor in the south and good in the north to good in the southeast and poor in the northwest; (3) During the 21-year period, the overall ecological environment quality of Yanchi County showed a slow degradation trend, but the degree of degradation gradually decreased, and the degree of ecological environment improvement will gradually increase after 2020. (4) The sandiness index, precipitation, elevation, and GDP are the main influencing factors of spatial differentiation of regional ecological environment quality. (5) All interactions between factors exhibit enhancement effects, the interactions of sandiness index, temperature, precipitation, and elevation with other detection factors play a dominant role, and the influence of economic factors on SA-RSEI gradually increases.

# The Evolution of Ecological Quality in Yanchi County Based on the SA-RSEI Model

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## Abstract

This study investigates the spatio-temporal dynamic characteristics and driving factors of ecological environmental changes in Yanchi County from 1990 to 2020 using Landsat remote sensing data and an improved remote sensing ecological index (SA-RSEI). The Theil-Sen median trend analysis, Mann-Kendall significance test, and Hurst index were combined to analyze the spatio-temporal variation patterns of ecological quality, while the geographical detector model was employed to identify the underlying driving factors. The results reveal that: (1) The SA-RSEI value exhibited an overall trend of initial decline followed by increase during 2000–2020. (2) The ecological environment quality showed an evolutionary pattern of "degradation first, then recovery," with the spatial distribution shifting from "poor in the south, good in the north" to "good in the southeast, poor in the northwest."(3) Over the 21-year period, the overall ecological quality of Yanchi County showed a slow degradation trend, but the degree of degradation gradually decreased, and the improvement trend is expected to strengthen after 2020. (4) The sandification index (DI), precipitation, elevation, and GDP are the primary factors influencing the spatial differentiation of regional ecological quality. (5) All factor interactions exhibited enhancement effects, with interactions between the sandification index, temperature, precipitation, elevation, and other factors playing a dominant role, while the influence of economic factors on SA-RSEI gradually increased.

**Keywords:** ecological quality assessment; improved ecological index; geographical detector; Hurst index; Yanchi County

## 1. Introduction

Ecological environmental quality serves as a crucial indicator for evaluating regional ecological conditions, integrating theories from ecology, geography, and environmental science to reflect the sustainable coordination between human activities and the ecological environment at specific temporal and spatial scales. The rapid development of remote sensing information technology and open access to multi-source remote sensing data have significantly advanced regional-scale earth observation research. Remote sensing technology offers numerous advantages for environmental quality assessment, including large data volumes, wide data sources, real-time monitoring, convenient acquisition, and high resolution. Consequently, it has been widely applied in monitoring and evaluating ecosystems such as forests, grasslands, urban areas, and river basins, becoming a key technology for environmental monitoring and quality assessment.

In 2006, China' s State Environmental Protection Administration established the Ecological Index (EI) in the "Technical Criterion for Eco-environmental Status Evaluation" (HJ/T 192-2006) for assessing ecological environments at county level and above. However, the EI index relies heavily on various statistical data that are difficult to collect, making real-time evaluation challenging. To address this limitation, Xu Hanqiu proposed the Remote Sensing Ecological Index (RSEI) in 2013, which integrates greenness (NDVI), humidity (WET), dryness (NDBSI), and heat (LST) indicators derived from remote sensing inversion. This model enables rapid and comprehensive environmental quality detection and evaluation through principal component analysis, offering advantages such as fast computation, strong timeliness, minimal auxiliary parameters, convenient data acquisition, and excellent visualization.

While RSEI has been successfully applied in various regions, including urban areas, basins, mining regions, and the Yellow River Basin, most studies have focused on central and eastern China, with relatively limited research in northwestern arid and semi-arid regions. The dryness indicator in RSEI, composed of soil and building indices, is more suitable for areas with high vegetation coverage and urbanization levels. However, Yanchi County, located in an arid/semi-arid transitional zone bordering the Mu Us Desert to the north and the Loess Plateau to the south, presents a unique challenge. The county features vast desert steppe, hills, and sandy land with low vegetation coverage, scattered urban areas, and severe land desertification, making the traditional RSEI model less applicable. Therefore, this study employs an improved remote sensing index model (SA-RSEI) by adjusting certain indicators to better evaluate the ecological environment in semi-arid regions, providing scientific support for ecological conservation and management in Yanchi County.

## 2. Materials and Methods

### 2.1 Study Area

Yanchi County is located in eastern Ningxia (106°30 -107°47 E, 37°04 -38°10 N) at the intersection of four provincial regions (Shaanxi, Gansu, Ningxia, and Inner Mongolia). The terrain slopes from high in the south to low in the north, with the northern region forming the southern edge of the Mu Us Desert characterized by flat, open terrain with mobile and fixed/semi-fixed sand dunes and low vegetation coverage. The southern region features loess hills with crisscrossing gullies and significant slope variations, resulting in low vegetation coverage and poor ecosystem stability. The county has an average elevation of 1561 m, mean annual precipitation of 300 mm, mean annual temperature of 8.3°C, and maximum temperature variation of 28.5°C, classifying it as an arid/semi-arid region with a fragile ecological environment and limited resource carrying capacity. Land use is dominated by grassland, cultivated land, and forest, with 182.27 $hm^2$ of desertified grassland recorded in 2020, making it the county with the largest desert area and most severe desertification in Ningxia.

### 2.2 Data Sources and Processing

The research data primarily include remote sensing imagery and driving factor datasets. Landsat series remote sensing images with low cloud cover from June to September were selected from the Google Earth Engine platform, including LANDSAT/LT05/C01/T1_{SR}, LANDSAT/LE07/C01/T1_{SR}, and LANDSAT/LC08/C01/T1_{SR} datasets, which have undergone geometric and atmospheric correction and are suitable for long-term sequence analysis. Driving factor data include: (1) mean annual temperature and precipitation data obtained from the National Earth System Science Data Center (http://www.geodata.cn) with 1 km resolution; (2) DEM data from the Geographic Spatial Data Cloud (http://www.gscloud.cn) with identifiers ASTGTM_{N37E106}/107 and ASTGTM_{N38E106}/107, from which slope data were derived; (3) settlement aggregation degree calculated using kernel density tools on residential construction land data in ArcGIS 10.6; and (4) nighttime light data from the National Geophysical Data Center.

### 2.3 Research Methods

**2.3.1 SA-RSEI Model Construction** The SA-RSEI model was developed by improving the RSEI model to better suit arid/semi-arid regions. The model comprises four components: greenness index (GDVI), sandification index (DI), wetness index (WET), and salinization index (SI). Principal component analysis was performed on these four indices, with the first principal component extracted to construct the SA-RSEI:

$$SA\text{-}RSEI = f(GDVI, DI, WET, SI)$$

The first principal component was normalized to obtain the final SA-RSEI value, which was then classified into five levels at 0.2 intervals: poor, relatively poor, moderate, good, and excellent.

**Greenness Index (GDVI):** For arid/semi-arid regions with relatively poor vegetation growth and low coverage, GDVI provides more obvious vegetation condition representation than NDVI. It is calculated as:

$$GDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}$$

where $\rho_{Red}$ and $\rho_{NIR}$ represent the reflectance of red and near-infrared bands, respectively.

**Sandification Index (DI):** This index reflects land degradation caused by human activities or other factors, manifested as bare sandy land. Based on the Desertification Difference Index (DDI) proven effective in desertification monitoring:

$$DDI = -K_i \times NDVI - Albedo$$

$$DI = -DDI = Albedo + K_i \times NDVI$$

$$Albedo = 0.356 \times \rho_B + 0.130 \times \rho_R + 0.373 \times \rho_{NIR} + 0.072 \times \rho_{SWIR2}$$

where $\rho_B$, $\rho_R$, $\rho_{NIR}$, and $\rho_{SWIR2}$ represent reflectance of blue, red, near-infrared, and shortwave infrared 2 bands, respectively; $K_i$ is the slope of the linear regression between NDVI and Albedo.

**Wetness Index (WET):** This index effectively reflects regional climate conditions in arid areas. For Landsat TM and OLI data:

$$WET_{TM} = 0.0315 \times \rho_B + 0.202 \times \rho_G + 0.3102 \times \rho_R + 0.1594 \times \rho_{NIR} - 0.6806 \times \rho_{SWIR1} - 0.6109 \times \rho_{SWIR2}$$

$$WET_{OLI} = 0.1511 \times \rho_B + 0.1973 \times \rho_G + 0.3283 \times \rho_R + 0.3407 \times \rho_{NIR} - 0.7117 \times \rho_{SWIR1} - 0.4559 \times \rho_{SWIR2}$$

**Salinization Index (SI):** In arid/semi-arid regions, human activities or other factors cause land degradation and soil salinization. The index is calculated as:

$$SI = \frac{\rho_B - \rho_R}{\rho_B + \rho_R}$$

where $\rho_B$ and $\rho_R$ represent reflectance of blue and red bands.

**2.3.2 Sen+Mann-Kendall Trend Analysis** The Theil-Sen median trend analysis combined with Mann-Kendall significance test is a widely used non-parametric method that does not require data to follow a specific distribution and is insensitive to outliers. The method calculates the median slope ($\beta$) to determine the overall trend:

$$\beta = \text{Median}\left(\frac{SA\text{-}RSEI_j - SA\text{-}RSEI_i}{j-i}\right), \quad \forall i < j$$

where $\beta > 0$ indicates an improving trend and $\beta < 0$ indicates a degrading trend. The Mann-Kendall test statistic $Z$ is calculated to determine significance, with $|Z| > 1.96$ indicating significance at the 95% confidence level.

**2.3.3 Hurst Index** The Hurst index ($H$) is used to predict future trends in long time series data. For $H \in (0, 1)$:

- When $0.5 < H < 1$, the future trend is positively correlated with the past (persistent)
- When $H = 0.5$, the future trend shows no obvious correlation with the past
- When $0 < H < 0.5$, the future trend is negatively correlated with the past (anti-persistent)

**2.3.4 Geographical Detector Model** The geographical detector model examines the consistency between dependent and independent variable spatial distributions.

**Factor Detector:** This analyzes the spatial association and explanatory power between selected factors and ecological quality. The q-statistic is calculated as:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$

where $q$ represents the explanatory power of each factor (0–1), $h$ is the stratum number, $L$ is the total number of strata, $N_h$ and $N$ are the unit numbers in stratum $h$ and the entire region, and $\sigma_h^2$ and $\sigma^2$ are the variances of the dependent variable in stratum $h$ and the entire region.

**Interaction Detector:** This calculates the q-value of interaction between any two factors to determine whether their combined effect enhances or weakens the explanatory power compared to individual factors. Interaction types include non-linear weakening, single-factor non-linear weakening, double-factor enhancement, and non-linear enhancement.

# 3. Results and Analysis

## 3.1 Temporal Variation Characteristics of Ecological Quality

From 2000 to 2020, the SA-RSEI value showed an overall trend of initial decline followed by increase [Figure 2: see original paper]. Specifically, during 2000-2005, SA-RSEI decreased from 0.42 to 0.38, indicating a degradation trend. During 2005-2015, it continued to decline to 0.35, showing persistent degradation. After 2015, SA-RSEI increased continuously to 0.40 by 2020, demonstrating a recovery trend.

Among the four ecological components, GDVI showed an increasing trend, indicating gradual vegetation coverage improvement. The DI trend was opposite to SA-RSEI, decreasing initially then increasing, with a decline from 0.65 in 2000 to 0.58 in 2015 followed by a slight increase. The WET index remained relatively stable with minor fluctuations. The SI index decreased from 0.52 to 0.48, indicating salinization control during this period. Overall, GDVI and WET positively contributed to the ecological environment, while DI and SI had negative effects.

Mean annual precipitation varied from 282.67 mm to 406.82 mm, showing a pattern of initial increase, then decrease, followed by fluctuating increase, similar to the GDVI trend. Mean annual temperature ranged from 8.36°C to 9.41°C, peaking in 2013, with a trend similar to DI [Figure 3: see original paper].

## 3.2 Spatial Variation Characteristics of Ecological Quality

The spatial distribution of SA-RSEI showed distinct patterns across different periods [Figure 4: see original paper]. During 2000-2005, ecological quality was relatively stable, characterized by "poor in the south, good in the north," as the northern area on the Ordos Plateau edge had flat terrain and relatively high vegetation coverage, while the southern loess hills had fragmented terrain with low vegetation coverage.

During 2005-2015, ecological quality gradually degraded. The northern region experienced increased construction land and decreased ecological land, breaking the previous spatial pattern. Areas previously rated as good or excellent degraded to moderate or poor levels, particularly in Huamachi Town, Gaoshawo Town, Wanglejing Township, and Fengjigou Township in the north.

During 2015-2020, ecological quality gradually recovered. The southern region improved from poor and relatively poor levels to moderate or good levels, forming a new pattern of "good in the southeast, poor in the northwest." Poor and relatively poor levels were mainly distributed in the northwest where unused land and construction land were extensive.

The area proportions of different ecological grades varied significantly [Figure 5: see original paper]. In 2000, moderate and relatively poor levels dominated (30.21% and 31.28%, respectively). By 2015, poor and relatively poor areas increased by 29.42%, while excellent and good areas decreased by 9.07%. By 2020, poor and relatively poor areas decreased by 11.44%, while excellent and good areas increased by 3.71%, confirming the overall degradation-recovery pattern.

### 3.3 Spatio-Temporal Change Trends

The Sen+Mann-Kendall trend analysis revealed that stable areas dominated (72.51%), with improvement and degradation areas distributed dispersedly [Figure 6: see original paper]. Improvement areas covered 959.89 km$^2$ (11.44%), mainly in central and south-central Yanchi, while degradation areas covered 1282.50 km$^2$ (15.05%), primarily in central and northern regions. Overall, degradation area exceeded improvement area by 3.61%, indicating a slow degradation trend.

The Hurst index showed that 66.10% of the county will remain stable in the future, while 12.37% will continue degrading and 21.52% will show improvement . Most current degradation areas are projected to improve in the future, suggesting that degradation is being controlled and will gradually reduce. The relatively high proportion of future improvement areas (21.52%) indicates that ecological improvement will accelerate after 2020.

### 3.4 Driving Factor Analysis

**3.4.1 Factor Detection Analysis** The factor detector results showed temporal variations in factor importance [TABLE:4 and TABLE:5]. For remote sensing ecological factors, the ranking of influence on spatial heterogeneity was:

- 2000: SI > DI > WET > GDVI
- 2005: DI > SI > WET > GDVI
- 2010: DI > GDVI > SI > WET
- 2015: DI > SI > WET > GDVI
- 2020: DI > WET > SI > GDVI

The sandification index (DI) consistently showed the strongest influence, indicating that soil sandification is the primary cause of ecological quality changes in Yanchi County.

For natural and social factors, the ranking was:

- 2000: Elevation > Temperature > Precipitation > Slope > GDP > Settlement aggregation > Night light
- 2005: Elevation > Precipitation > Temperature > Settlement aggregation > GDP > Slope > Night light
- 2010: Precipitation > Elevation > Temperature > Settlement aggregation > GDP > Slope > Night light
- 2015: Temperature > Elevation > Precipitation > Settlement aggregation > GDP > Slope > Night light
- 2020: Elevation > Temperature > Precipitation > Settlement aggregation > GDP > Slope > Night light

Elevation, precipitation, and temperature are the main factors influencing spatial differentiation of ecological quality. Settlement aggregation showed gradually increasing influence, while slope and night light had relatively stable but minor impacts.

**3.4.2 Interaction Detection Analysis** All factor interactions showed double-factor enhancement or non-linear enhancement effects, indicating that combined effects are stronger than individual factors [FIGURE:7 and FIGURE:8]. In remote sensing ecological factors, DI × SI was the most influential interaction in most years (q values: 0.82 in 2000, 0.79 in 2005, 0.85 in 2015), while DI × WET ranked first in 2020 ($q = 0.86$). The sandification index' s interactions with other factors consistently showed strong explanatory power.

In natural and social factors, temperature × precipitation and temperature × elevation were the most influential interactions across most years. Economic factors (GDP, settlement aggregation, night light) showed low individual explanatory power but strong interactive effects with natural factors, and their influence increased annually. This indicates that while natural factors directly drive ecological changes, economic development has become an increasingly important indirect factor.

## 4. Discussion

The SA-RSEI model improvement was necessary because the original RSEI' s dryness indicator, composed of soil and building indices, is more suitable for highly vegetated and urbanized areas. For arid/semi-arid regions like Yanchi County with small, scattered urban areas dominated by desert steppe, the traditional RSEI has limited applicability. This study replaced the dryness index with sandification and salinization indices that better reflect land degradation characteristics in northwestern China, providing more scientific monitoring of ecological quality in such regions.

The temporal evolution pattern of ecological quality aligns with policy implementation. During 2005-2015, the Western Development Strategy and increased construction land led to ecological degradation. After 2015, measures including enclosed animal husbandry, the Yanchi-Dingbian water diversion project, and national programs such as the "Three-North" Shelterbelt and Grain for Green significantly increased vegetation coverage and promoted coordinated development among agriculture, animal husbandry, and ecology.

The spatial pattern change from "poor in the south, good in the north" to "good in the southeast, poor in the northwest" reflects comprehensive impacts of grassland degradation, construction land expansion, mining development, and water scarcity in the northwestern region. The southeastern area benefited from increasing precipitation and elevation, reduced construction land, and effective implementation of ecological restoration policies.

The dominant role of the sandification index aligns with Yanchi' s status as the county with the most severe desertification in Ningxia. Higher temperatures correlate with lower soil moisture and vegetation coverage, reducing sand fixation capacity, while higher precipitation promotes vegetation growth and reduces desertification area. The increasing influence of economic factors, particularly through interactions with natural factors, reflects the growing impact of human activities on the ecological environment.

## 5. Conclusions

1. **Temporal trends:** From 2000 to 2020, SA-RSEI showed an overall pattern of initial decline followed by increase. GDVI and WET had positive effects, while DI and SI had negative effects. Precipitation trends aligned with GDVI, and temperature trends aligned with DI.
2. **Spatial patterns:** Ecological quality showed a degradation-recovery evolution during 2000–2020. The spatial pattern shifted from "poor in the south, good in the north" (2000–2005) to "good in the southeast, poor in the northwest" (2015-2020). Degradation area exceeded improvement area by 3.61%, indicating slow overall degradation, but most degradation areas are projected to improve in the future, with improvement accelerating after 2020.
3. **Driving factors:** In remote sensing ecological factors, the sandification index (DI) is the dominant factor influencing spatial distribution. In natural and social factors, elevation, precipitation, and temperature are the main influencing factors. All factor interactions show double-factor or nonlinear enhancement effects, with interactions involving DI, temperature, precipitation, and elevation playing dominant roles. Economic factors' influence on SA-RSEI is gradually increasing.

## References

[1] Liu Jiyuan, Buheaosier. Study on spatial-temporal feature of modern land use change in China: Using remote sensing techniques[J]. Quaternary Sciences, 2000, 20(3): 229-239.

[2] Tian Jialiang. A review of regional ecological environment quality evaluation[J]. Environmental Protection and Circular Economy, 2013, 33(11): 63-66.

[3] Yang Dehu, Meng Dan, Li Yulu, et al. Remote sensing assessment of ecological quality in the surrounding area before and after the construction of large-scale projects: A case study of Beijing Daxing International Airport, China[J]. Journal of Earth Sciences and Environment, 2022, 44(5): 839-849.

[4] Xu D, Yang F, Yu L, et al. Quantization of the coupling mechanism between eco-environmental quality and urbanization from remote sensing data[J]. Journal of Cleaner Production, 2021, 321: 128980.

[5] Jia Haowei, Yan Changzhen, Xing Xuegang, et al. Evaluation of ecological environment in the Dulan County based on the modified remote sensing ecological index model[J]. Journal of Desert Research, 2021, 41(2): 181-190.

[6] Song Huimin, Xue Liang. Dynamic monitoring and analysis of ecological environment in Weinan City, Northwest China based on RSEI model[J]. Chinese Journal of Applied Ecology, 2016, 27(12): 3913-3919.

[7] Ochoa-Gaona S, Kampichler C, de Jong B H J, et al. A multi-criterion index for the evaluation of local tropical forest conditions in Mexico[J]. Forest Ecology and Management, 2010, 260(5): 618-627.

[8] Sullivan C A, Skeffington M S, Gormally M J, et al. The ecological status of grasslands on lowland farmlands in western Ireland and implications for grassland classification and nature value assessment[J]. Biological Conservation, 2010, 143(6): 1529-1539.

[9] Xu H Q, Ding F, Wen X L. Urban expansion and heat island dynamics in the Quanzhou region, China[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2009, 2: 74-79.

[10] Wang Yao, Gong Huili, Li Xiaojuan. The monitoring and analysis of ecological environment quality in Beijing based on GIS[J]. Remote Sensing for Natural Resources, 2008(1): 91-96.

[11] Meng Yan, Zhao Gengxing. Ecological environment condition evaluation of estuarine area based on quantitative remote sensing: A case study in Kenli County[J]. China Environmental Science, 2009, 29(2): 163-167.

[12] Ministry of Ecology and Environment of the People' s Republic of China. Technical Criterion for Eco-environmental Status Evaluation: HJ/T 192-2006[S]. Beijing: China Environmental Science Press, 2006.

[13] Ye Youhua, Liang Yongxian, Shen Yiqing, et al. Some issues related to Technical Criterion for Eco-environmental Status Evaluation (Trial Implementation)[J]. Tropical Geography, 2009, 29(4): 404-406.

[14] Liu Shangqin, Zhang Fuhao, Zhao Xizhi, et al. Improvement of remote sensing ecological index in oasis in arid area[J]. Science of Surveying and Mapping, 2022, 47(6): 143-151, 203.

[15] Zeng Hui, Liu Jianguo. Analysis of regional ecological risk based on landscape structure[J]. China Environmental Science, 1999, 19(5): 454-457.

[16] Ivits E, Cherlet M, Mehl W, et al. Estimating the ecological status and change of riparian zones in Andalusia assessed by multi-temporal AVHRR datasets[J]. Ecological Indicators, 2009, 9(3): 422-436.

[17] Moran M S, Peters-Lidard C D, Watts J M, et al. Estimating soil moisture at the watershed scale with satellite-based radar and land surface models[J]. Canadian Journal of Remote Sensing, 2004, 30(5): 805-826.

[18] Xu Hanqiu. A remote sensing index for assessment of regional ecological changes[J]. China Environmental Science, 2013, 33(5): 889-897.

[19] Wang Lichun, Jiao Li, Lai Fengbing, et al. Evaluation of ecological changes based on a remote sensing ecological index in Manas Lake wetland, Xinjiang[J]. Acta Ecologica Sinica, 2019, 39(8): 2963-2972.

[20] Li Hongxing, Huang Jiejun, Liang Youjia, et al. Evaluating the quality of ecological environment in Wuhan based on remote sensing ecological index[J]. Journal of Yunnan University (Natural Sciences Edition), 2020, 42(1): 81-90.

[21] Wu S P, Gao X, Lei J Q, et al. Ecological environment quality evaluation of the Sahel region in Africa based on remote sensing ecological index[J]. Journal of Arid Land, 2022, 14(1): 14-33.

[22] Shan Dan, Guo Jianying, Abi Yasi, et al. Vegetation spatial-temporal dynamic characteristics and ecological quality assessment in metal mine areas of desert steppe[J]. Bulletin of Soil and Water Conservation, 2023, 43(2): 230-238.

[23] Kong Lingling, Feng Xianfeng, Wu Shuang, et al. Spatio-temporal dynamics and driving factor analysis of ecological quality change in the Lhasa urban circle from 1994 to 2017[J]. Progress in Geography, 2022, 41(3): 437-450.

[24] Yan Geding, Jing Meiling. The influence factors of grassland area change in agro-pastoral transitional zone by STIRPAT model: A case of Yanchi County of Ningxia Hui Autonomous region in China[J]. Chinese Journal of Agricultural Resources and Regional Planning, 2018, 39(3): 48-54.

[25] Wang Bei, Zhong Juntao, Tan Meibao. Spatial pattern analysis of grazing prohibition grassland ecosystem services in Yanchi County from 2000 to 2015[J]. Ecological Science, 2023, 42(1): 30-39.

[26] Lin Yanmin, Nan Xiongxiong, Hu Zhirui, et al. Fractional vegetation cover change and its ecological security evaluation in the typical vulnerable ecological region of Northwest China: Helan Mountains in Ningxia[J]. Journal of Ecology and Rural Environment, 2022, 38(5): 599-608.

[27] Chen Fangmiao, Huang Huiping, Yang Guang, et al. Research on the dynamic change of the ecological environment and its influencing factors in the Yellow River Basin based on Remote Sensing Ecological Index[J]. Journal of Desert Research, 2023, 43(4): 252-262.

[28] Liu Jin, Chen Tianwei, Liu Peng, et al. Monitoring and analyzing driving forces of ecological environmental quality in Taiyuan Urban Agglomeration[J]. Bulletin of Soil and Water Conservation, 2023, 43(4): 154-161, 210.

[29] Wang Yongxiang, Xu Yuanyuan, Yang Jiajia, et al. Dynamic monitoring and spatio-temporal pattern evolution analysis of eco-environmental quality in Chongqing based on remote sensing[J]. Acta Ecologica Sinica, 2023, 43(15): 6278-6292.

[30] Zhou Zhe, Hu Xiasong, Liu Changyi, et al. Dynamic monitoring and evaluation of eco-environmental quality in the upper reaches of the Yellow River based on GEE: A case study of the section from Longyang Gorge to Jishi Gorge[J]. Chinese Journal of Ecology, 2023, 42(10): 2545-2554.

[31] Wang Jin, Diwu Jingwei, Mei Jialong, et al. Change of ecological environment in Turpan and Hami cities based on remote sensing ecology index[J]. Arid Land Geography, 2022, 45(5): 1591-1603.

[32] Cui Yuanzheng, Zha Hui, Wang Lei, et al. Evaluation of ecological environment quality in townships and its influencing factors, exemplified in Jiangsu Province[J]. Resources and Environment in the Yangtze Basin, 2023, 32(9): 1922-1931.

[33] Liu Ying, Yue Hui, Meng Jinxin, et al. Ecological environment assessment for the main cities along the Silk Road Economic Belt (China Section) based on remote sensing[J]. The Administration and Technique of Environmental Monitoring, 2018, 30(5): 35-39, 48.

[34] Su Wanfeng, Han Guangzhao, Ye Deli, et al. Remote sensing evaluation and driving force analysis of ecological environment in Gonghe Basin[J]. Journal of Desert Research, 2023, 43(5): 74-84.

[35] Chang Ming, Meng Shuying, Zhou Jingwei, et al. Analysis of spatio-temporal pattern change characteristics of eco-environmental quality in Heidaigou and Harwusu Mining Area based on RSEI[J]. Science Technology and Engineering, 2023, 23(25): 10701-10712.

[36] Diwu Jingwei, Mei Jialong, Yu Hanming, et al. Construction and application of remote sensing ecological index in semi-arid region[J]. The Administration and Technique of Environmental Monitoring, 2022, 34(4): 21-26.

[37] Li Jianhua, Yang Jinping, Shen Peipei, et al. Interpretation of landforms in place names of rural settlements in Yanchi County, Ningxia[J]. China Place Name, 2019(2): 18-21.

[38] Wang Rong, Wu Hongqi, He Tonghui. The natural factors spatial characteristics in settlement place names in Yanchi County[J]. Journal of Arid Land Resources and Environment, 2012, 26(11): 152-158.

[39] Zhang Juan. The Impact of the Oasis Development on Ecological Environment[D]. Lanzhou: Lanzhou University, 2016.

[40] Zeng Yongnian, Xiang Nanping, Feng Zhaodong, et al. Albedo feature space and remote sensing synthesis index models for desertification monitoring[J]. Scientia Geographica Sinica, 2006, 26(1): 75-81.

[41] Wang Jiaqi, Chen Xingren. Study on the variation trend of desertification in Chifeng, Inner Mongolia and its surrounding area based on the albedo and the characteristic space of the normalized difference vegetation index[J]. Journal of Anhui Agricultural Sciences, 2016, 44(27): 217-219.

[42] Cist E P, Cicone R C. A physically based transformation of the Thematic Mapper data—the TM tasseled cap[J]. IEEE Transactions on Geoscience and Remote Sensing, 1984, GE-22(3): 256-263.

[43] Baig M H A, Zhang L, Shuai T, et al. Derivation of a tasseled cap transformation based on Landsat 8 at-satellite reflectance[J]. Remote Sensing Letters, 2014, 5(5): 423-431.

[44] Khan N M, Sato Y. Monitoring hydro-salinity status and its impact in irrigated semi-arid areas using IRS-IB LISS data[J]. Asian Journal of Geoinformatics, 2001, 1(3): 63-73.

[45] Tian Zhihui, Wang Fang, Li Wenhui, et al. Spatiotemporal pattern and driving force analysis of ecological environmental quality in typical ecological areas of the Yellow River Basin from 1990 to 2020[J]. Environmental Science, 2023, 44(5): 2518-2527.

[46] Huang Jin, Chen Yong, Liang Yaqi, et al. Analysis of spatial-temporal variation and driving factors of ecological quality in typical mining areas of Daye City[J/OL]. Industrial Minerals & Processing: 1-11[2022-12-05].

[47] Li Chen, Wu Yingmei, Gao Binpin, et al. Spatial differentiation and driving factors of rural settlement in plateau lake: A case study of the area around the Erhai[J]. Economic Geography, 2022, 42(4): 220-229.

[48] Huang Yue, Cheng Jing, Wang Peng. Spatio-temporal evolution pattern and driving factors of ecological vulnerability in agro-pastoral region in northern China: A case of Yanchi County in Ningxia[J]. Arid Land Geography, 2021, 44(4): 1175-1185.

[49] Cheng Jing, Wang Peng, Chen Hongxiang, et al. Geographical exploration of the spatial and temporal evolution of ecological risk and its influencing factors in semi-arid regions: A case of Yanchi County in Ningxia[J]. Arid Land Geography, 2022, 45(5): 1637-1648.

[50] Yang Xinguo, Song Naiping, Chen Lin, et al. Ecological causality between vegetation construction and habitat drought in arid areas[J]. Chinese Journal of Applied Ecology, 2023, 34(6): 1713-1720.

[51] Zhang Qiaoxian, Wang Jianmin, Feng Jongting. Achievement and problems of ecological construction in Yanchi County and countermeasures[J]. Journal of Ningxia Agriculture and Forestry Science and Technology, 2012, 53(3): 89-90.

[52] Yue Peng, Ren Jia, Ma Wenjing, et al. Exploration of water resource utilization and land desertification change in Yanchi County[J]. Journal of Ningxia Agriculture and Forestry Science and Technology, 2023, 64(9): 65-68.

[53] Yu Guoliang, Li Jianhua, Sun Jiaxin, et al. Research on BMI influencing factors of urban male adolescents in China based on geographical detector[J]. Geographical Research, 2019, 38(9): 2288-2301.

[54] Wang Junchuan, Lin Zhongxue, Ma Juanli, et al. Analysis of temporal and spatial changes of vegetation cover and climate driving force in Wuzhong in recent 21 years[J]. Journal of Anhui Agricultural Sciences, 2023, 51(2): 90-92, 98.

[55] Liu Shuqing, Bai Cunlin, Bian Zhen, et al. Land use change and its eco-environmental effects on vulnerable desert margin areas: A case study from Yanchi County in Ningxia[J]. Pratacultural Science, 2020, 37(11): 2175-2184.

*Note: Figure translations are in progress. See original paper for figures.*