Remote Sensing-Based Ecological Environment Quality Assessment and Cause Analysis in the Korla Region: Postprint

Authors: Li Shijiao, Zhang Keke, Xie Baoni, Wang Shi-Wen, Li Zhiguang

Date: 2025-02-27T00:00:00+00:00

Abstract

The ecological environment in the Korla region is sensitive and fragile, and accurate cognition of its ecological environment quality constitutes the foundation for local governments to scientifically formulate policies for ecological environmental protection and restoration. Based on the remote sensing ecological index concept, coupled with the ecosystem characteristics of the study area, and integrating seven ecological elements including vegetation coverage, soil moisture, land surface temperature, land surface dryness, desertification degree, salinization degree, and evapotranspiration, the Modified Remote Sensing based Ecology Index (MRSEI) was constructed using principal component analysis to evaluate and analyze the driving factors of ecological environment quality in the Korla region from 1994 to 2021. The results indicate that: (1) MRSEI can reflect the ecological environment quality of the Korla region. (2) From 1994 to 2021, the MRSEI in the Korla region ranged from 0.253~0.346, exhibiting an overall upward trend with general improvement in ecological environment quality; the ecological environment quality grades were predominantly "poor" and "relatively poor," accounting for 70.96% of the total area, and the overall ecological environment quality displayed a spatial pattern of "relatively poor in the west and relatively good in the east." (3) Over the past 27 years, the ecological environment quality remained essentially unchanged across 60.41% of the Korla region, primarily distributed in the western hills and terraces; degraded across 16.47% of the area, mainly located in the northern plains, portions of medium-relief mountains, and low-relief mountains; and improved across 23.12% of the area, predominantly situated in the eastern plains and hills. (4) Climate and socio-economic factors are closely correlated with the ecological environment quality in the Korla region, wherein evaporation exerts a more significant influence than other climatic elements, and year-end total population represents the primary socio-economic factor affecting the region' s ecological environment quality.

ChinaRxiv 中X

Full Text

Ecological Environment Quality Evaluation and Driving Factor Analysis of Korla Region Based on Remote Sensing

LI Shijiao[1], ZHANG Keke[1], XIE Baoni[1,2], WANG Shiwen[1,3], LI Zhiguang[1,3]

[1]School of Urban Geology and Engineering, Hebei GEO University, Shijiazhuang 050031, Hebei, China
[2]Hebei International Joint Research Center for Remote Sensing of Agricultural Drought Monitoring, Hebei GEO University, Shijiazhuang 050031, Hebei, China
[3]Hebei Technology Innovation Center for Intelligent Development and Control of Underground Built Environment, Hebei GEO University, Shijiazhuang 050031, Hebei, China

Abstract

The ecological environment of the Korla region is highly sensitive and fragile, making accurate assessment of its ecological quality essential for formulating scientifically sound environmental protection and restoration policies. Building upon the remote sensing ecological index concept and considering the characteristics of the study area' s ecosystem, this study integrates seven ecological elements—vegetation coverage, soil moisture, land surface temperature, land surface dryness, desertification degree, salinization degree, and evapotranspiration—using principal component analysis to construct a modified remote sensing ecological index (MRSEI). This index effectively reflects the ecological environment quality of the Korla region. The results from evaluating and analyzing the ecological environment quality of Korla from 1994 to 2021 reveal that: (1) The MRSEI values ranged from 0.253 to 0.346, showing an overall upward trend and indicating gradual ecological improvement. (2) The ecological quality grades were predominantly "poor" and "relatively poor," accounting for 70.96% of the total area, with an overall spatial pattern of "relatively poor in the west and relatively good in the east." (3) Approximately 60.41% of the area showed minimal change in ecological quality, mainly distributed in the western hilly regions and tablelands; 16.47% of the area experienced ecological degradation, primarily in the northern plains and some moderately and slightly undulating mountainous areas; and 23.12% of the area showed improvement, mainly in the eastern plains and hilly regions. (4) Climate and socioeconomic factors are closely related to ecological environment quality in Korla, with evaporation having a greater impact than other climatic elements, and year-end total population being the primary socioeconomic factor influencing ecological quality.

Keywords: remote sensing; ecological environment quality evaluation; principal component analysis; Korla region

Introduction

Ecological environmental issues pose significant challenges to human survival and sustainable economic development, attracting widespread attention from governments and academia worldwide. Problems such as land desertification, salinization, lake drying, and biodiversity loss have become increasingly prominent. In 2005, the concept that "lucid waters and lush mountains are invaluable assets" was proposed, profoundly illustrating the importance of ecological environments for human survival and social development. China has repeatedly emphasized in its 14th Five-Year Plan and government work reports the need to unswervingly follow a green development path prioritizing ecology, advocating green and low-carbon production and lifestyles, and actively promoting ecological protection and restoration. A series of ecological construction projects have been implemented, including comprehensive desertification control, the Three-North Shelter Forest Program, and returning farmland to forest and grassland, which have curbed further ecological deterioration. However, natural ecosystems have limited adaptive capacity, and coupled with extremely fragile ecological conditions in some regions, the situation for ecological protection and restoration in China remains severe.

Scientific evaluation of ecological environment quality is fundamental to effective ecological protection and restoration. The former State Environmental Protection Administration proposed the Ecological Index (EI) method in relevant technical specifications, which integrates information on biological abundance, vegetation coverage, water network density, land degradation, and environmental quality based on remote sensing technology for annual comprehensive evaluation of ecological environment quality at county level and above. However, in practical application, the weighting of each evaluation index is heavily influenced by individual experience, and visualization of evaluation results is difficult. To address this limitation, Xu Hanqiu proposed the Remote Sensing Ecological Index (RSEI), which uses principal component analysis to integrate greenness, dryness, wetness, and thermal information from remote sensing images, enabling spatial expression of regional ecological environment quality evaluation results.

In recent years, based on the RSEI concept, scholars have introduced additional ecological element indicators according to regional characteristics and application needs, developing various modified approaches. For example, some studies incorporated landscape diversity indices to evaluate the ecological environment of oases along the Ningxia section of the Yellow River, while others added salinity indicators to assess ecological quality in the Qaidam Basin, achieving good results that reflected temporal and spatial variations in regional ecological environment quality.

The Korla region, a critical passage on the ancient Silk Road and an important birthplace of Western culture, serves as a current logistics hub under the

Belt and Road Initiative. Its ecological environment is extremely fragile. Previous studies have examined Korla' s ecological environment from perspectives including urban expansion, water resource pressure, vegetation coverage, and land use, revealing close relationships between ecological conditions and vegetation cover, water resource utilization, land desertification, and salinization. Therefore, comprehensive evaluation of ecological environment quality in Korla considering multiple ecological elements is crucial for precisely implementing vegetation restoration, water resource management, windbreak and sand fixation, and other ecological protection measures. However, quantitative assessment results reflecting the region' s ecological environment quality using multi-indicator approaches remain scarce. This study utilizes remote sensing imagery from 1994 to 2021 to construct a Modified Remote Sensing Ecological Index (MRSEI) and conducts multi-indicator quantitative evaluation of ecological environment quality in Korla, aiming to reveal spatiotemporal evolution characteristics of ecological quality in this region.

---

1. Study Area Overview

Korla City is located in the Bayingolin Mongol Autonomous Prefecture of Xinjiang Uygur Autonomous Region, geographically positioned between 85°14 10 –86°34 21 E and 41°15 06 –42°16 46 N, in the northeastern part of the Tarim Basin. The terrain slopes from north to south, with a total area of 7,373.530 km^2. The region has a warm temperate continental desert climate, with an average annual temperature of approximately 11.4°C and average annual precipitation of about 61 mm. The area enjoys abundant light and heat resources with large diurnal temperature variations. Water resources are scarce, with the Tarim River and Kongque River as the main water systems. Vegetation is sparse, dominated by shrubs and grasslands. The geomorphology of the Korla region includes five types: hills, plains, tablelands, small undulating mountains, and moderately undulating mountains [Figure 1: see original paper].

---

2. Data and Methods

2.1 Data Sources and Preprocessing Remote sensing data were obtained from the United States Geological Survey (USGS), using multi-temporal Landsat satellite imagery (Table 1). The dataset includes Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI/TIRS images with a spatial resolution of 30 m. Original images were preprocessed through radiometric calibration, atmospheric correction, image mosaicking, and clipping. Meteorological data were downloaded from the China Meteorological Data Network using the Korla weather station. Socioeconomic data were sourced from the Xinjiang Statistical Yearbook and China County Statistical Yearbook. Geomorphology and land use data were obtained from the Resources and Environmental Science Data Center of the

Chinese Academy of Sciences.

2.2 Construction of MRSEI

2.2.1 Calculation of Ecological Factors Based on the ENVI 5.3 platform, this study integrates seven ecological elements from remote sensing imagery: vegetation coverage, soil moisture, land surface temperature, land surface dryness, desertification degree, salinization degree, and evapotranspiration. The selected indicators and calculation formulas are as follows:

(1) Vegetation Coverage

The Generalized Difference Vegetation Index (GDVI) was selected as the vegetation coverage indicator, which effectively reflects vegetation cover in low-coverage areas and is suitable for desert vegetation monitoring:

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

where ρ_{NIR} and ρ_{Red} are reflectance values in the near-infrared and red bands, respectively.

(2) Soil Moisture

Soil moisture is represented by the wetness component obtained from Tasseled Cap Transformation, which effectively reveals moisture information in soil and vegetation:

For Landsat 5:

$$\mathrm{Wet}_5 = 0.0315\rho_{\mathrm{Blue}} + 0.2021\rho_{\mathrm{Green}} + 0.3102\rho_{\mathrm{Red}} + 0.1594\rho_{\mathrm{NIR}} - 0.6806\rho_{\mathrm{SWIR1}} - 0.6109\rho_{\mathrm{SWIR2}}$$

For Landsat 7:

$$\mathrm{Wet}_7 = 0.2626\rho_{\mathrm{Blue}} + 0.2141\rho_{\mathrm{Green}} + 0.0926\rho_{\mathrm{Red}} + 0.0656\rho_{\mathrm{NIR}} - 0.7629\rho_{\mathrm{SWIR1}} - 0.5388\rho_{\mathrm{SWIR2}}$$

For Landsat 8:

$$\mathrm{Wet}_8 = 0.1511\rho_{\mathrm{Blue}} + 0.1972\rho_{\mathrm{Green}} + 0.3283\rho_{\mathrm{Red}} + 0.3407\rho_{\mathrm{NIR}} - 0.7117\rho_{\mathrm{SWIR1}} - 0.4559\rho_{\mathrm{SWIR2}}$$

where ρ_{Blue}, ρ_{Green}, ρ_{Red}, ρ_{NIR}, ρ_{SWIR1}, and ρ_{SWIR2} are reflectance values in the corresponding bands.

(3) Land Surface Temperature

Land Surface Temperature (LST) was retrieved using the parameter model provided in the Landsat User Manual:

$$\mathrm{LST} = \frac{T_\lambda}{1 + (\lambda T_\lambda/\rho)\ln\varepsilon}$$

where $T_\lambda = \frac{K_2}{\ln(K_1/L_\lambda+1)}$, $L_\lambda = \mathrm{gain} \times \mathrm{DN} + \mathrm{bias}$, λ is the central wavelength of the thermal infrared band, $\rho = 1.438 \times 10^{-2}$ m · K, $\varepsilon = 0.986v + 0.084$, v is vegetation coverage, and K_1 and K_2 are parameters obtained from image metadata.

(4) Land Surface Dryness

Land surface dryness is represented by the Normalized Difference Built-up and Soil Index (NDBSI):

$$\mathrm{NDBSI} = \frac{\mathrm{IBI} + \mathrm{SI}}{2}$$

where IBI is the Index of Built-up Information and SI is the Bare Soil Index:

$$\mathrm{IBI} = \frac{2\mathrm{SWIR1}}{\mathrm{SWIR1} + \mathrm{NIR}} - \frac{\mathrm{NIR}}{\mathrm{NIR} + \mathrm{Red}} + \frac{\mathrm{Green}}{\mathrm{Green} + \mathrm{SWIR1}}$$

$$\mathrm{SI} = \frac{(\mathrm{SWIR1} + \mathrm{Red}) - (\mathrm{NIR} + \mathrm{Blue})}{(\mathrm{SWIR1} + \mathrm{Red}) + (\mathrm{NIR} + \mathrm{Blue})}$$

(5) Desertification Degree

The Desertification Index (DI) was selected to represent desertification degree, which effectively extracts soil desertification information in arid regions:

$$\mathrm{DDI} = -\frac{1}{K_i} \times \mathrm{NDVI}_{\mathrm{std}} - \mathrm{Albedo}_{\mathrm{std}}$$

where:

$$\mathrm{NDVI}_{\mathrm{std}} = \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}} \times 100\%$$

$$\mathrm{Albedo}_{\mathrm{std}} = \frac{\mathrm{Albedo} - \mathrm{Albedo}_{\mathrm{min}}}{\mathrm{Albedo}_{\mathrm{max}} - \mathrm{Albedo}_{\mathrm{min}}} \times 100\%$$

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{Red}}}$$

$$\mathrm{Albedo} = 0.356\rho_{\mathrm{Blue}} + 0.130\rho_{\mathrm{Red}} + 0.373\rho_{\mathrm{NIR}} + 0.072\rho_{\mathrm{SWIR1}} + 0.0018\rho_{\mathrm{SWIR2}} - 0.0018$$

K_i is the slope of the characteristic equation, and $\mathrm{NDVI}_{\min}$, $\mathrm{NDVI}_{\max}$, $\mathrm{Albedo}_{\min}$, $\mathrm{Albedo}_{\max}$ are the minimum and maximum values of NDVI and Albedo, respectively.

(6) Salinization Degree

The Modified Salinity Index (MSI) was selected as the salinization indicator:

$$\mathrm{MSI} = \mathrm{SI}_{\mathrm{std}} - \mathrm{MSAVI}_{\mathrm{std}}$$

where:

$$\mathrm{MSAVI}_{\mathrm{std}} = \frac{\mathrm{MSAVI} - \mathrm{MSAVI}_{\min}}{\mathrm{MSAVI}_{\max} - \mathrm{MSAVI}_{\min}} \times 100\%$$

$$\mathrm{SI}_{\mathrm{std}} = \frac{\mathrm{SI} - \mathrm{SI}_{\min}}{\mathrm{SI}_{\max} - \mathrm{SI}_{\min}} \times 100\%$$

$$\mathrm{MSAVI} = \frac{2\rho_{\mathrm{NIR}} + 1 - \sqrt{(2\rho_{\mathrm{NIR}} + 1)^2 - 8(\rho_{\mathrm{NIR}} - \rho_{\mathrm{Red}})}}{2}$$

$\mathrm{MSAVI}_{\min}$ and $\mathrm{MSAVI}_{\max}$ are the minimum and maximum values of MSAVI, while $\mathrm{SI}_{\min}$ and $\mathrm{SI}_{\max}$ are the minimum and maximum values of the Salinity Index.

(7) Evapotranspiration

Evapotranspiration is represented by Potential Evapotranspiration (PET), a crucial component of the water cycle. Monthly PET data were derived from the China monthly PET dataset provided by the National Earth System Science Data Center.

2.2.2 Construction of MRSEI The seven indicators were coupled through principal component analysis (PCA) to construct the MRSEI. PCA transforms a set of correlated variables into uncorrelated principal components through orthogonal transformation. To facilitate comparison, the MRSEI was normalized:

$$\mathrm{MRSEI} = \frac{\mathrm{MRSEI}_0 - \mathrm{MRSEI}_{\min}}{\mathrm{MRSEI}_{\max} - \mathrm{MRSEI}_{\min}}$$

where MRSEI_0 is the initial value of the modified remote sensing ecological index, and $\mathrm{MRSEI}_{\min}$ and $\mathrm{MRSEI}_{\max}$ are its minimum and maximum values, respectively.

Using 0.2 intervals, MRSEI values were classified into five ecological environment quality levels: [0.0, 0.2) = poor, [0.2, 0.4) = relatively poor, [0.4, 0.6) = moderate, [0.6, 0.8) = good, and [0.8, 1.0] = excellent.

3. Results

3.1 Reasonableness Analysis of MRSEI The first principal component (PC1) contributed 77.08% of the information, integrating most of the information from the seven ecological factors with contribution rates ranging from 68.41% to 77.08%. The loadings of GDVI, Wet, and PET were positive, positively contributing to ecological environment quality, while the loadings of NDBSI, DI, and MSI were negative, negatively affecting ecological environment quality—consistent with ecological understanding. In contrast, the loadings of LST showed unstable signs without clear patterns, making ecological interpretation difficult. Therefore, using MRSEI based on PC1 is reasonable and scientifically sound.

3.2 Spatial-Temporal Distribution Characteristics of Ecological Environment Quality The mean MRSEI change curve (Figure 2) shows that ecological environment quality in Korla was generally poor from 1994 to 2021, with MRSEI values ranging from 0.253 to 0.346. However, the overall trend was upward at a rate of $R^2 = 0.4929$, indicating gradual improvement. Statistical analysis of different ecological quality levels (Table 3) reveals that "poor" and "relatively poor" grades dominated, jointly accounting for 70.96% of the area. Specifically, "poor" grade covered approximately 4,043.44 km^2 (54.84%), while "relatively poor" grade covered about 1,188.75 km^2 (16.12%). The areas of "excellent," "moderate," and "good" grades followed in descending order.

Significant spatial variations existed in ecological quality grades (Figure 4). Moderately undulating mountains were primarily "relatively poor" and "moderate," with some "good" areas. Slightly undulating mountains were mainly "relatively poor" and "poor," with minor "moderate" and "good" areas. Tablelands were predominantly "poor," with some "relatively poor" areas. Plains showed a mix of "poor" and "excellent" grades, with portions of "relatively poor," "good," and minor "moderate" areas. Hills were mainly "poor," partially "relatively poor," with minor "excellent" and "good" areas. The overall ecological quality pattern was "relatively poor in the west and relatively good in the east."

3.3 Dynamic Changes in Ecological Environment Quality Based on MRSEI classification, differential calculations were performed on MRSEI images from adjacent years and the start/end years to analyze spatial distribution of ecological quality changes. Results show that 60.41% of the area experienced minimal change, mainly in western hilly areas and tablelands. Approximately 16.47% of the area showed degradation, primarily distributed in northern plains and some moderately and slightly undulating mountains. About 23.12% of the area demonstrated improvement, mainly in eastern plains and hills (Figure 5).

Examining different periods, from 1994-2003, improved areas accounted for 9.31%, mainly at the eastern edge of plains, with change pathways primarily from "poor to relatively poor" and "good to excellent." Degraded areas accounted for 11.47%, distributed in plains and slightly undulating mountains, with pathways mainly "relatively poor to poor" and "excellent to good." From 2003–2012, improved areas represented 22.88%, mainly in eastern plains and hills, with pathways "poor to relatively poor" and "good to excellent." Degraded areas accounted for 8.78%, mainly in northern moderately and slightly undulating mountains, with pathways "moderate to relatively poor" and "excellent to good." From 2012–2021, improved areas comprised 14.89%, distributed in plains, eastern hills, and northern mountainous areas, with pathways "good to excellent," "relatively poor to good," and "poor to relatively poor." Degraded areas represented 7.22%, scattered in southern plains, with pathways "relatively poor to poor" and "excellent to good."

3.4 Analysis of Driving Factors Using MRSEI as the reference sequence and corresponding annual climatic and socioeconomic elements as comparative sequences, grey correlation analysis was performed (Figure 6). Climatic factors included evaporation, sunshine hours, average temperature, relative humidity, wind speed, and precipitation. Socioeconomic factors included year-end total population, grain yield, per capita GDP, urban construction land area, and GDP values for primary, secondary, and tertiary industries. Land use types included cultivated land, forest land, grassland, water bodies, glaciers and permanent snow, and unused land.

The average correlation coefficient between climatic factors and MRSEI was 0.71, with evaporation showing the strongest correlation (0.78). Korla' s annual evaporation is approximately 2,772.8 mm, and high evaporation rates intensify water loss, affecting vegetation water supply and negatively impacting ecological quality. Among socioeconomic factors, the average correlation coefficient was 0.69, with year-end total population showing the highest correlation (0.73). In early stages, sparse population and insufficient labor resulted in poor ecological quality. As population gradually increased, reclamation of wasteland and afforestation expanded vegetation coverage, improving ecological conditions. Agricultural development and tourism-based tertiary industry growth have also positively contributed to ecological quality improvement.

Ecological quality is closely related to land use types. Statistical analysis of average MRSEI values for different land use types shows that cultivated land and forest land had values of 0.42 and 0.45, respectively, indicating relatively good ecological quality, while unused land had a value of 0.18, showing the poorest quality.

---

4. Conclusions

This study evaluated the ecological environment quality of Korla region from 1994 to 2021 using the modified remote sensing ecological index (MRSEI). Key findings include:

1. The MRSEI effectively characterizes ecological environment quality in Korla, with values ranging from 0.253 to 0.346 and an overall upward trend ($R^2 = 0.4929$), indicating gradual ecological improvement.
2. Ecological quality grades were dominated by "poor" and "relatively poor," accounting for 70.96% of the area. The spatial pattern showed "relatively poor in the west and relatively good in the east."
3. Over the 27-year period, 60.41% of the area remained stable (mainly western hills and tablelands), 16.47% experienced degradation (northern plains and some mountainous areas), and 23.12% showed improvement (eastern plains and hills).
4. Climate and socioeconomic factors significantly influence ecological quality, with evaporation being the most impactful climatic factor and year-end total population the primary socioeconomic driver.

References

[1] Yang Yu, Li Xiaoyun, Dong Wen, et al. Comprehensive evaluation on China's man-land relationship: Theoretical model and empirical study[J]. Acta Geographica Sinica, 2019, 74(6): 1063-1078.

[2] Li Guihua, Du Ying. On the conviction that "lucid waters and lush mountains are invaluable assets"[J]. Journal of Xinjiang Normal University (Philosophy and Social Sciences Edition), 2019, 40(4): 43-51.

[3] Liu Jiyuan, Shao Quanqin, Fan Jiangwen, et al. Exploration on the path of ecological protection and construction in western China[J]. China Population, Resources and Environment, 2013, 23(10): 38-43.

[4] Zhang Zhaohui, Yu Shiqi. Spatio-temporal characteristics and interaction drivers of ecosystem service value in Hotan region based on land use scenario simulation[J]. Journal of Agriculture Resources and Environment, 2024, 41(4): 780-793.

[5] Wei Xing, Zhou Jinlong, Zeng Yanyan, et al. Evaluation of water resources pressure in Korla City of Xinjiang[J]. Water Resources and Power, 2021, 39(4): 44-47.

[6] Song Ge, Wang Jinshuo, He Liheng, et al. Simulation of land use change in western arid region under different scenarios based on the CLUE-S model[J]. Journal of Nanjing Forest University (Natural Science Edition), 2013, 37(3): 135-139.

[7] Lu Zhongqi, Zhao Zhujun, He Qing. Concentrations characteristics and sources of particulate matter in Korla, Xinjiang, China[J]. Journal of Desert Research, 2022, 42(6): 74-84.

[8] Jing Y Q, Zhang F, He Y F, et al. Assessment of spatial and temporal variation of ecological environment quality in Ebinur Lake Wetland National Nature Reserve, Xinjiang, China[J]. Ecological Indicators, 2020, 110(1): 105874, doi: 10.1016/j.ecolind.2019.105874.

[9] Wu W C. The generalized difference vegetation index (GDVI) for dry land characterization[J]. Remote Sensing, 2014, 6(2): 1211-1233.

[10] Xu Hanqiu. A remote sensing urban ecological index and its application[J]. Acta Ecologica Sinica, 2013, 33(24): 7853-7862.

[11] Xu Hanqiu. Assessment of ecological change in soil loss area using remote sensing technology[J]. Transactions of the Chinese Society of Agricultural Engineering, 2013, 29(7): 91-97, 294.

[12] Dong C Y, Qiao R R, Yang Z C, et al. Eco-environmental quality assessment of the artificial oasis of Ningxia section of the Yellow River with the MRSEI approach[J]. Frontiers in Environmental Science, 2023, 10: 1071631, doi: 10.3389/fenvs.2022.1071631.

[13] Li Qianlin, Sha Zhanjiang. Remote sensing monitoring of ecological environment quality in Qaidam Basin under the background of climate warming[J]. Ecological Science, 2022, 41(6): 92-99.

[14] Tan Xin. Mechanism analysis and expansion simulation of urban spatial evolution in Korla[D]. Chengdu: Southwest Jiaotong University, 2020.

[15] Mu Jiawei, Qiao Baorong, Yu Guoxin. Spatial and temporal patterns of agricultural low-carbon productivity and its influence effects in the counties of Tarim River Basin, Xinjiang[J]. Arid Land Geography, 2023, 46(6): 968-981.

[16] Cai Zhaozhao, An Shazhou, Pu Zhi, et al. A study on vegetation coverage change in Korla City based on the TM NDVI[J]. Pratacultural Science, 2015, 32(7): 1069-1078.

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

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

[19] Nichol J. Remote sensing of urban heat islands by day and night[J]. Photogrammetric Engineering and Remote Sensing, 2005, 71(5): 613-621.

[20] Chander G, Markham B L, Helder D L. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors[J]. Remote Sensing of Environment, 2009, 113(5): 893-903.

[21] Yang X D, Bai Y P, Che L, et al. Incorporating ecological constraints into urban growth boundaries: A case study of ecologically fragile areas in

the Upper Yellow River[J]. Ecological Indicators, 2021, 124: 107436, doi: 10.1016/j.ecolind.2021.107436.

[22] Zhang M M, Kafy A A, Ren B, et al. Application of the optimal parameter geographic detector model in the identification of influencing factors of ecological quality in Guangzhou, China[J]. Land, 2022, 11(8): 1303, doi: 10.3390/land11081303.

[23] Zou Mingliang, Han Yamin, Zeng Jianjun, et al. Temporal and spatial evolution of eco-environmental quality in the oasis of Shiyang River Basin based on RSEDI[J]. Chinese Journal of Ecology, 2018, 37(4): 1152-1163.

[24] Shi Sane, Wei Wei, Yang Dong, et al. Spatial and temporal dynamic monitoring of desertification in Maqu County based on Albedo-NDVI feature space[J]. Journal of Glaciology and Geocryology, 2019, 41(1): 45-53.

[25] Wei Wei, Yu Xiao, Zhang Mengzhen, et al. Dynamics of desertification in the lower reaches of Shiyang River Basin, northwest China during 1995–2018[J]. Chinese Journal of Applied Ecology, 2021, 32(6): 2098-2106.

[26] Li Hongyang, Chen Tianyu, Wang Shengjie, et al. Spatial and temporal variations of potential evapotranspiration on the northern slope of the Kunlun Mountains in Xinjiang from 1979 to 2021[J]. Arid Land Geography, 2024, 47(9): 1443-1450.

[27] Peng S Z, Ding Y X, Liu W Z, et al. 1 km monthly temperature and precipitation dataset for China from 1901 to 2017[J]. Earth System Science Data, 2019, 11(4): 1931-1946.

[28] Dai Yunhao, Guan Yao, Zhang Qinkai, et al. Remote sensing monitoring and temporal and spatial characteristics of soil salinization in Aral Reclamation Area[J]. Arid Land Geography, 2022, 45(4): 1176-1185.

[29] Feng Shangrong, Chen Qingtao. Application of principal component analysis in remote sensing processing[J]. World Nonferrous Metals, 2019(11): 255-256.

[30] Wang Miao, Liu Puxing, Qiao Xuemei, et al. Analysis of the spatiotemporal evolution of ecological environmental quality in Ningxia and its driving force contribution based on RSEDI[J]. Chinese Journal of Ecology, 2021, 40(10): 3278-3289.

[31] Pan Ting, Wang Yixiang, Liu Xianzhao, et al. Land use change and its impact on ecological quality in Xiong' an New Area[J]. Journal of Zhejiang A & F University, 2023, 40(5): 1102-1110.

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