Land degradation sensitivity assessment and convergence analysis in Korla of Xinjiang, China (Postprint)

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Abstract

Land degradation has a major impact on environmental and socio-economic sustainability. Scientific methods are necessary to monitor the risk of land degradation. In this study, the environmental sensitive area index (ESAI) was utilized to assess land degradation sensitivity and convergence analysis in Korla, a typical oasis city in Xinjiang of China, which is located on the northeast border of the Tarim Basin. A total of 18 indicators depicting soil, climate, vegetation, and management qualities were used to illustrate spatial-temporal patterns of land degradation sensitivity from 1994 to 2018. We investigated the causes of spatial convergence and divergence based on the Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models. The results show that the branch of the Tianshan Mountains and oasis plain had a low sensitivity to land degradation, while the Tarim Basin had a high risk of land degradation. More than two-thirds of the study area can be categorized as "critical" sensitivity classes. The largest percentage (32.6%) of fragile classes was observed for 2006. There was no significant change in insensitive or low-sensitivity areas, which accounted for less than 0.4% of the entire observation period. The ESAI of the four time periods (1994–1998, 1998–2006, 2006–2010, and 2010–2018) formed a series of convergence patterns. The convergence patterns of 1994–1998 and 1998–2006 can be explained by the government's efforts to "Returning Farmland to Forests" and other governance projects. In 2006–2010, the construction of afforested work intensified, but industrial development and human activities affected the convergence pattern. The pattern of convergence in most regions between 2010 and 2018 can be attributed to the government's implementation of a series of key ecological protection projects, which led to a decrease in sensitivity to land degradation. The results of this study altogether suggest that the ESAI convergence analysis is an effective early warning method for land degradation sensitivity.

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Full Text

Preamble

Land degradation significantly impacts environmental and socio-economic sustainability, necessitating scientific methods to monitor degradation risk. This study employs the Environmental Sensitive Area Index (ESAI) to assess land degradation sensitivity and conduct convergence analysis in Korla, a typical oasis city in Xinjiang, China, located on the northeastern border of the Tarim Basin. A total of 18 indicators depicting soil, climate, vegetation, and management qualities were used to characterize spatiotemporal patterns of land degradation sensitivity from 1994 to 2018. We investigated the causes of spatial convergence and divergence using Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR) models. The results show that the Tianshan Mountain branch and oasis plain exhibited low sensitivity to land degradation, while the Tarim Basin faced high degradation risk. More than two-thirds of the study area fell into "critical" sensitivity classes, with fragile classes peaking at 32.6% in 2006. Insensitive or low-sensitivity areas showed no significant change, accounting for less than 0.4% throughout the observation period.

The ESAI values for four time periods (1994-1998, 1998-2006, 2006-2010, and 2010-2018) formed distinct convergence patterns. The convergence patterns of 1994-1998 and 1998-2006 reflect government efforts through the "Returning Farmland to Forests" program and other governance projects. During 2006-2010, afforestation construction intensified, but industrial development and human activities affected the convergence pattern. The convergence pattern observed across most regions between 2010 and 2018 can be attributed to the government' s implementation of key ecological protection projects, which reduced land degradation sensitivity. Overall, these results suggest that ESAI convergence analysis serves as an effective early warning method for land degradation sensitivity.

Keywords: land degradation; quality index; convergence analysis; remote sensing; environmental sensitive area index; Korla

1 Introduction

Land degradation, driven by extreme climate events, rapid population growth, and unsustainable land management practices, poses a global environmental threat and represents a major challenge to worldwide survival and sustainable development [**?**, **?**, **?**, **?**, **?**, **?**]. Severe land degradation has occurred in 10%-20% of the world' s drylands, directly affecting approximately 250$×10^{6}$ people in the developing world [**?**, **?**]. The Xinjiang Uygur Autonomous Region contains China' s widest distribution and largest area of desert lands [**?**, **?**, **?**]. Korla, a typical oasis city in Xinjiang, has experienced rapid economic development accompanied by urban expansion and industrial production, creating complex challenges for land supply and carrying capacity [**?**, **?**]. Interactions among the Tarim River, Taklimakan Desert, and other systems further render Korla' s ecological environment fragile and increase land degradation risk [?, ?].

Land degradation is a complex and continuous dynamic process [?, ?]. Monitoring requires consideration of multiple factors. Using remote sensing and GIS technologies, researchers have employed various indicators to identify degraded areas, including spectral biophysical indicators, environmental indicators, and socio-economic indicators [?, ?, ?]. However, previous studies have generally lacked standardized methodology or focused on limited indicators [?, ?, ?, ?]. To comprehensively and straightforwardly describe degradation processes, quantitative and qualitative methods can be combined with specific indicators [?, ?, ?].

The Environmental Sensitive Area Index (ESAI) approach was developed to identify and assess potentially degraded Mediterranean regions [?, ?]. It considers key factors driving land degradation: soil, climate, vegetation, and management indicators, which facilitate deeper understanding of land degradation sensitivity. The ESAI approach offers simplicity, flexibility, and rapid implementation, and can be adapted to different scales according to study area conditions [?, ?]. As a widely recognized method, ESAI has been successfully applied across Europe, the Mediterranean Basin, and Central Asia [?, ?, ?, ?, ?, ?, ?]. However, few previous studies have examined land degradation sensitivity in oasis cities such as Korla.

Combining land degradation sensitivity with convergence analysis extends previous research. The "convergence" concept originates from economists' measurements of development gaps among countries and is widely used in economic and industrial development studies [?, ?, ?, ?], but rarely in environmental quality convergence analysis. In environmental research, convergence analysis was first used to monitor land degradation sensitivity in Italy, providing empirical evidence for spatial convergence at the country scale [?, ?]. In this study, convergence indicates a negative correlation between ESAI differences over a particular time interval and initial observation values. Regions with the lowest ESAI values converge toward the mean faster than others [?, ?]. Spatial convergence and divergence are applicable for regional land degradation assessments and can inform government management of degraded areas. Therefore, convergence analysis incorporating environmental indicators may provide evidence of land degradation drivers and serve as an early warning signal for land degradation sensitivity [?, ?].

This study calculates Korla' s ESAI from 1994 to 2018 using time-series, multisource spatial data to determine regional degradation sensitivity across different years. Convergence of time-series ESAI was used to identify "hotspots" requiring attention and analyze the effects of land management measures. This work' s novelty lies in its focus on typical oasis areas, validation of ESAI approach feasibility, and establishment of suitable methods for evaluating land degradation sensitivity in areas significantly impacted by human activities and natural factors. Most importantly, spatiotemporal ESAI analysis identified areas requiring close attention.

The study aims to: (1) monitor the quality index and spatiotemporal pattern of ESAI; (2) analyze spatial convergence of ESAI at time intervals on a grid scale; and (3) determine underlying mechanisms of ESAI convergence and divergence patterns. These results may provide a scientific reference for optimizing land management and preventing land degradation in Korla and similar regions worldwide.

2.1 Study Area

Korla City (41°10 48 -42°21 36 N, 85°14 10 -86°34 21 E) is located in central Xinjiang Uygur Autonomous Region, China, at the northeastern border of the Tarim Basin and across the southern reaches of the Tarim River alluvial fan [Figure 1: see original paper]. Situated in the Konqi River Delta, it forms a vast, fan-shaped oasis plain. Korla' s northern region comprises a Tianshan Mountains branch forming a mountain-front alluvial fan. The city covers 7,268 km^2 with a length of 127 km and width of 105 km [?, ?]. Korla has a temperate continental arid climate with an annual mean temperature of 11°C, mean annual precipitation of 59 mm, total annual solar irradiance of 2,990 h, and mean annual evaporation of 2,778 mm. The favorable water, soil, light, and heat resources are highly suitable for cash crops such as pear, cotton, and tomato [?, ?].

At the end of 2018, Korla's total population was 4.73$\times$10^{5}$ and its regional gross domestic product (GDP) was 6.16$\times$10^{10}$ CNY [?, ?]. Korla has gradually become an important modern city in Xinjiang. However, land degradation caused by desertification, salinization, over-exploitation of cultivated land, and drought significantly impacts the ecological environment, threatening coordinated economic, social, and environmental development in the city and surrounding regions [?, ?]. Effective monitoring of land degradation sensitivity is urgently needed.

Fig. 1 Landsat TM imagery of the study area (Bands 5-4-3)

2.2 Data and Indicators

The United Kingdom's Ministry of Agriculture, Fisheries, and Food launched the ESAI approach in 1987 to encourage farmers and landowners to adopt environmentally friendly land management measures [?, ?]. Through field surveys and general and local knowledge of environmental processes, Kosmas et al. (1999) improved the ESAI approach and successfully applied it in the Mediterranean Desertification and Land Use Project (MEDALUS).

Following the ESAI approach, this study selected 18 indicators across four quality domains: soil, climate, vegetation, and management. Each quality indicator was calculated as the geometric mean of relevant sub-indicators. Sub-indicator values were divided into classes with assigned scores. Score thresholds were determined based on extensive MEDALUS fieldwork and the study area' s actual conditions [?, ?]. Sensitivity scores between 1 (lowest sensitivity) and 2 (highest sensitivity) were assigned to each class based on their importance in land degradation sensitivity and relationship to degradation onset [?, ?].

To ensure strong spatial consistency across indicators, all sub-indicator data were resampled to 300 m spatial resolution using the nearest neighbor method and the same projection system. Land degradation sensitivity was assessed across a 24-year period at five specific time points: 1994, 1998, 2006, 2010, and 2018. A field survey of local land conditions was conducted in August 2018, selecting sites representing sparse vegetation conditions to further analyze degradation sensitivity.

2.2.1 Soil Quality Index (SQI)

Soil maintains biological productivity and environmental quality while supporting plant and animal health across ecosystems [?, ?]. Following the ESAI approach, we assessed SQI using six parameters: texture, slope, surface albedo, dryness, salinity, and moisture . Soil texture data were obtained from the Chinese Resource and Environment Data Cloud Platform (http://www.resdc.cn), compiled from a 1:1,000,000 soil type map. Soil profile data from the Second Soil Census [?, ?] classified texture by sand, silt, and clay contents.

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model Version 2 with 30 m spatial resolution was used to derive slope. Landsat image acquisition dates were 24 August 1994, 4 September 1998, 10 September 2006, 20 August 2010, and 26 August 2018. These scenes were selected for minimal cloud cover and similar acquisition dates. All Landsat imagery was radiometrically calibrated and atmospherically corrected. Surface albedo (Eq. 1), dryness (Eq. 2), salinity (Eq. 3), and moisture (Eq. 4) data were retrieved from 30 m resolution Landsat images. The band calculation formulas are as follows:

Surface albedo 0.356 B 0.130 R 0.373 NIR 0.085 SWIR 0.072 SWIR 0.0018, SWIR R SWIR R Dryness NIR B NIR B

SWIR NIR

SWIR NIR Salinity= B R ,× NIR R G SWIR NIR R G SWIR Moisture

0.0315 B 0.2021 G 0.3102 R 0.1594 NIR 0.6806 SWIR 0.6109 SWIR,

where B is the blue band; R is the red band; NIR is the near-infrared band; SWIR1 is the short-wave infrared band 1 (1550–1750 nm); SWIR2 is the short-wave infrared band 2 (2090–2350 nm); SI is the bare soil index; IBI is the index-based built-up index; and G is the green band.

SQI was calculated as follows [?, ?]:

$$SQI = \sqrt[6]{\text{Texture} \times \text{Slope} \times \text{Surface albedo} \times \text{Soil dryness} \times \text{Soil salinity} \times \text{Soil moisture}}$$

Table 1 Calculation parameters of soil quality index (SQI)

2.2.2 Climate Quality Index (CQI)

Severe climatic conditions such as low precipitation, gusty winds, and extreme temperatures can exacerbate land degradation. This study assessed CQI using four parameters: precipitation, aridity index, aspect, and wind speed . Precipitation and wind speed data were obtained from annual datasets of the National Meteorological Information Center (http://data.cma.cn). The Australian National University Spline (ANUSPLINE) meteorological interpolation model [**?**, **?**] interpolated precipitation and wind speed data from meteorological stations of varying altitudes and locations during 1994–2018 at 300 m spatial resolution.

The aridity index (AI) at 1 km^2 spatial resolution was obtained from the Consortium for Spatial Information (CSI) at http://www.cgiar-csi.org. AI was calculated using AI = P/PET, where P is annual precipitation (mm) and PET is annual potential evapotranspiration (mm). Aspect affects the angle and duration of sunlight striking the soil surface, influencing vegetation humidity [**?**, **?**]. The ASTER Global Digital Elevation Model Version 2 (https://search.earthdata.nasa.gov) was used to calculate aspect.

CQI was calculated as follows [**?**, **?**]:

$$CQI = \sqrt[4]{\text{Precipitation} \times \text{Aridity index} \times \text{Aspect} \times \text{Wind speed}}$$

Table 2 Calculation parameters of climate quality index (CQI)

2.2.3 Vegetation Quality Index (VQI)

Vegetation regulates climate, conserves water and soil, reduces wind and sand effects, and protects farmlands, particularly in arid and semi-arid regions. This study assessed VQI through four indicators: fire risk, erosion protection, drought resistance, and vegetation coverage . Land use/cover maps were provided by the European Space Agency Climate Change Initiative-Land Cover (ESACCI-LC) project, which delivers consistent global land use/cover maps at 300 m spatial resolution annually (http://maps.elie.ucl.ac.be/CCI/viewer/). Maps for 1994–2018 were used to derive detailed fire risk, erosion protection, and drought resistance information for VQI, with results divided into different classes based on land use/cover type.

The dimidiate pixel model calculated vegetation coverage for each period (Eq. 7) via the normalized difference vegetation index (NDVI) (Eq. 8) to determine vegetation status:

$$FVC = \frac{NDVI - NDVI_{soil}}{NDVI_{veg} - NDVI_{soil}} \times 100\%$$

$$NDVI = \frac{NIR - R}{NIR + R}$$

where FVC is vegetation coverage (%); NDVI_{soil} is the NDVI value of pure soil cover pixels; NDVI_{veg} is the NDVI value of pure vegetation cover pixels; NIR is the near-infrared band; and R is the red band.

VQI was calculated as follows [**?**, **?**]:

$$VQI = \sqrt[4]{\text{Fire risk} \times \text{Erosion protection} \times \text{Drought resistance} \times \text{Vegetation coverage}}$$

Table 3 Calculation parameters of vegetation quality index (VQI)

2.2.4 Management Quality Index (MQI)

Anthropogenic environmental pressures and different land use and management practices affect land degradation sensitivity. This study calculated MQI using GDP, population density, agricultural intensity, and policy enforcement information . GDP and population density data were obtained from the Chinese Resource and Environment Data Cloud Platform (http://www.resdc.cn). This dataset uses administrative areas as basic statistical units to spatially distribute population and GDP information onto kilometer-level grid cells, which can then be re-projected, re-sampled, and clipped as needed.

Agricultural intensity and policy enforcement information were derived from ESACCI-LC land use/cover maps at 300 m spatial resolution. Based on local agricultural systems, agricultural intensity depended on plant variety types, irrigation modes, mechanization degrees, and related factors. Policy enforcement was classified into three categories according to land protection degree .

MQI was calculated as follows [**?**, **?**]:

$$MQI = \sqrt[4]{\text{GDP} \times \text{Population density} \times \text{Agricultural intensity} \times \text{Policy enforcement}}$$

Table 4 Calculation parameters of management quality index (MQI)

2.2.5 Environmental Sensitive Area Index (ESAI)

ESAI is calculated as the geometric mean of the four quality indices described above [**?**, **?**]:

$$ESAI = \sqrt[4]{SQI \times CQI \times VQI \times MQI}$$

Following the MEDALUS scoring system, ESAI values range from 1 (lowest sensitivity) to 2 (highest sensitivity), covering diverse land sensitivity levels. **Table 5** shows ESAI values divided into eight classes reflecting commonly used classification thresholds [?, ?, ?, ?, ?].

Table 5 Classes and corresponding ranges of environmental sensitive area index (ESAI)

2.3 Methodology

2.3.1 Spatial-Temporal Variation Trend Surface Analysis

Trend surface analysis reveals spatial variation trends in different directions and provides optimal trend surfaces through function fitting, reflecting overall spatial object variation [?, ?]. This study used trend surface analysis to project ESAI values onto east-west and north-south planes, performing function fitting to obtain optimal curves representing overall spatiotemporal variation trends. The final quadratic trend surface model provides sufficient fitting accuracy, with its binary regression function described as [?, ?]:

$$Z = a_0 + a_{1x} + a_{2y} + a_{3x}^2 + a_{4xy} + a_{5y}^2 + \varepsilon$$

where spatial coordinates (x, y) of sample points are independent variables; Z is the dependent variable; a_0, a_1, a_2, a_3, a_4, and a_5 are polynomial coefficients; and   is the error term.

2.3.2 Convergence Analysis

In this context, "convergence" refers to a negative correlation between the ESAI change rate and the initial year ESAI value during a particular time interval. Different regions have different initial ESAI values, and low-value regions may exhibit faster growth rates. Over time, all regions converge toward the mean ESAI value ("reaching convergence"). The average ESAI value and annual average rate for different intervals were calculated as detailed below.

The following ordinary least squares (OLS) model [?, ?, ?, ?] measured overall spatial convergence of ESAI in Korla:

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + \varepsilon_i$$

where y represents the ESAI change rate at the corresponding time interval; β_0 is a constant term; β is a regression coefficient; i is the number of observations; x   (j = 1, 2, ···, k) represents the ESAI value of the ith spatial domain in the jth year; and   is a random error term conforming to a normal distribution. The coefficient β is statistically significant (P < 0.01) based on F-tests. A positive coefficient indicates divergent ESAI trends, while a negative coefficient indicates convergent trends [?, ?].

The geographically weighted regression (GWR) model [?, ?] identified local spatial convergence of ESAI in Korla. A fixed-weight Gaussian function served as the spatial weight function, and the AIC (Akaike Information Criterion) method determined the weight function bandwidth [?, ?]. The ESAI regression coefficient was obtained through local regression using adjacent observation point data, varying with geographic location. Convergence analysis was estimated as follows [?, ?, ?, ?, ?]:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{k} \beta_j(u_i, v_i)x_{ij} + \varepsilon_i$$

where y represents the ESAI change rate at the corresponding time interval; β_0 is a constant term; (u , v) is the geographic center coordinate of the ith spatial domain; β_0(u , v) is a constant term; β (u , v) is the jth regression coefficient of the ith spatial domain; x   (j = 1, 2, ···, k) represents the ESAI value of the ith spatial domain in the jth year; and   is an error term obeying an independent normal distribution with zero mean. A positive ESAI regression coefficient indicates divergent trends in the corresponding region, while a negative coefficient indicates convergent trends [?, ?].

3.1 Spatial Assessment of ESAI from 1994 to 2018

Figure 2 shows the spatial distribution of ESAI in Korla. Degradation-susceptible regions were scattered throughout the study area. Generally, low ESAI values concentrated in the Tianshan Mountains branch and oasis plains, while high ESAI values concentrated in the Tarim Basin, alluvial fan, and Tarim River alluvial plain—the regions most susceptible to land degradation in Korla. As expected, desert areas showed higher degradation sensitivity than mountains and oasis plains. Anthropogenic activity had minimal impact on grasslands in the Tianshan Mountains branch, so slight changes likely responded to climatic factors.

Fig. 2 Spatial distributions of ESAI (environmental sensitive area index) in 1994 (a), 1998 (b), 2006 (c), 2010 (d), and 2018 (e), and spatial distribution of mean ESAI from 1994 to 2018 (f), as represented by different sensitivity classes of ESAI. The description of sensitivity classes is shown in Table 5.

Table 6 shows the area percentage of each ESAI sensitivity class. Throughout the observation period, most of the study area fell into critical classes. Critical classes accounted for 85.42% of the total area in 1994, dropped sharply to 66.98% in 2006, then increased to 76.33% in 2018. Fragile classes concentrated mainly in the Tianshan Mountains branch and oasis plains, representing 14.39% of the total area in 1994 and remaining above 20.00% from 1998 to 2018. Non-affected and potential classes showed no significant changes, accounting for less than 0.40% of the total area. Overall, land degradation sensitivity in Korla declined during the study period.

Table 6 Area percentages of ESAI sensitivity classes in different years

Overall, land degradation sensitivity in western Korla was substantially higher than in the east (**Fig. 3**). Four land conditions from the field survey—sparse *Tamarix ramosissima* vegetation (**Fig. 3a**), cotton intensive agricultural areas (**Fig. 3b**), severely saline-alkali soils (**Fig. 3c**), and extensive desert areas (**Fig. 3d**)—corresponded to fragile 3, fragile 1, critical 2, and critical 3 classes, respectively. The ESAI accurately reflects these conditions: high ESAI values relate to harsh environmental conditions. Land degradation differences among field survey locations were consistent with corresponding ESAI classification results.

Figure 4 shows the land degradation sensitivity trend line from spatial statistical analysis in ArcGIS. The blue line indicates the east-west trend, while the green line represents the north-south trend. North-south trend lines formed convex curves in certain periods, indicating high ESAI values in the middle and low values on both sides. The east-west trend showed the opposite pattern: low values in the middle and high values on both sides. The land degradation sensitivity trend line was steeper in 2006 and 2010 (**Figs. 4c and d**), indicating that sensitivity not only shows spatial differences across Korla but also changes in state and speed across years.

Fig. 3 Spatial distribution of ESAI in 2018 (represented by different sensitivity classes; a) and field survey photos of land degradation sensitivity areas (b, *Tamarix ramosissima*; c, cotton plantations; d, extensive desert areas; and e, saline-alkali soil)

Fig. 4 Spatial trend surface analysis of land degradation sensitivity in 1994 (a), 1998 (b), 2006 (c), 2010 (d), and 2018 (e)

3.2 Convergence Analysis of ESAI

Convergence patterns examined the relationship between initial ESAI values (at 1994, 1998, 2006, and 2010) and differences over four respective intervals (1994–1998, 1998–2006, 2006–2010, and 2010–2018). OLS model coefficients for the four periods were -0.0095, -0.0102, -0.0114, and -0.0081, respectively, indicating convergence trends in each period and stabilizing land conditions in Korla over time.

Figure 5 shows GWR model coefficients and local R^2 values for ESAI spatial convergence analysis across four time intervals. From 1994 to 1998, 96.93% of the study area showed convergence, with stronger convergence effects in oasis plains than other regions (**Figs. 5a1 and a2**). During 1998–2006, highly convergent regions concentrated in the southeast with high local R^2 values, suggesting ESAI convergence tendencies there (**Figs. 5b1 and b2**). From 2006 to

2010, positive ESAI coefficients indicating divergence concentrated in the Tianshan Mountains branch and oasis-desert ecotone with low local R^2 values, while convergent regions increased compared to the previous period and 主要分布在绿洲平原 with high local R^2 values (**Figs. 5c1 and c2**). Up to 18.95% of regions showed divergence in the oasis-desert ecotone, alluvial fan, and Tarim River alluvial plain, while convergent regions concentrated in oasis plains with high local R^2 values during 2010–2018 (**Figs. 5d1 and d2**). Overall, land degradation sensitivity tended to converge between 1994 and 2018. ESAI converged or diverged faster in high land quality regions than in low quality regions.

Fig. 5 Spatial distributions of coefficients and local R^2 values of the ESAI spatial convergence analysis from the geographically weighted regression (GWR) model over the time intervals of 1994–1998 (a1 and a2), 1998–2006 (b1 and b2), 2006–2010 (c1 and c2), and 2010–2018 (d1 and d2)

4 Discussion

This study assessed 18 indicators depicting soil, climate, vegetation, and management qualities using the ESAI approach. Land degradation sensitivity and spatial convergence analysis of ESAI information determined potential land degradation in Korla from 1994 to 2018. Spatial convergence analysis reflects complex interactions between ecological conditions and socio-economic backgrounds across different time intervals. Convergence patterns appeared in most regions over sequential intervals, gradually consolidating gaps between vulnerable regions. Korla' s oasis plains, exhibiting high land quality, experienced relatively high anthropogenic environmental pressures (e.g., population growth, urban expansion, crop intensification). The Taklimakan Desert in western Korla showed low-quality natural capital due to harsh ecological conditions and high land degradation sensitivity [**?**, **?**].

The 1994–1998 ESAI convergence pattern reflected impacts of macro-control measures such as city planning and industrial development. To strengthen the ecological environment, Korla' s local government implemented the "Returning Farmland to Forest" Program, encouraging farmers to plant fruit trees such as pears and red dates while increasing subsidies for releasing farmland to forests [**?**, **?**]. Additionally, Korla launched the "Three-North" Shelterbelt Project, achieving remarkable forestry development [**?**, **?**].

During 1998–2006, China' s "Western Development Strategy" significantly accelerated Korla' s development. Population shifted from rural to urban areas as urbanization grew rapidly, gradually increasing land bearing capacity [**?**, **?**]. Promotion of advanced agricultural irrigation technology considerably strengthened Korla' s agricultural sector. These measures indirectly protected ecosystems and continuously adjusted land use structures, significantly changing major land use type areas (**Figs. 2b and c**). Cultivated land, garden, forest, and under-construction land areas showed overall upward trends while unused land decreased [**?**, **?**]. The ESAI convergence pattern during this observation period appears influenced by urban development and governance project plans.

During 2006–2010, afforestation construction intensified, particularly the Kongqi River Tourism Scenic Belt Project, which greatly improved urban public green space. As shown in **Figure 5c1**, convergence emerged near the Kongqi River Basin. Rapid industrial development brought environmental loads, with building sites increasingly occupying large land areas and reducing available green space. Divergence patterns in partial regions (**Fig. 5c1**) reflect anthropogenic activity impacts [**?**, **?**].

From 2010 to 2018, land urbanization and population growth drove Korla' s development [**?**, **?**]. Divergence patterns were significantly affected by anthropogenic activity scale. The government adopted effective farmland protection measures and scientific urban planning layouts, increased land development and rectification efforts, and achieved balanced cultivated land occupation and compensation [**?**, **?**]. City structure was continuously optimized and adjusted alongside industrialization breakthroughs. Advanced urbanization increased public awareness of cultivated land protection. In 2018, the government continued implementing key ecological projects such as the northern ecological protection corridor, natural forest protection, sand control, and soil and water conservation to improve protection of natural *Populus euphratica* forests (regarded as an ecological security barrier system) on the lower Kongqi River reaches, reducing Korla' s land degradation sensitivity.

5 Conclusions

This study used the ESAI approach to assess land degradation sensitivity in Korla from 1994 to 2018 and performed convergence analysis across different time intervals. Korla' s land degradation sensitivity shows not only spatial differences but also changes in state and speed across years. Overall, land degradation sensitivity in Korla declined during the study period. ESAI values across four time periods showed convergence patterns, suggesting increasingly stable land conditions in Korla. ESAI converged or diverged faster in high land quality areas than in low quality areas.

Limited data availability and spatial resolution restricted sensitivity analysis to five time nodes. Future research with expanded data acquisition could analyze longer-term series with finer temporal resolution. The precise land degradation mechanism also merits further research to elucidate various indicators' impacts on degradation sensitivity. Additional work is needed to establish a workable reference for dynamic changes and convergence of land degradation sensitivity in arid areas.

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