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Assessment of ecological quality in Northwest China (2000–2020) using the Google Earth Engine platform: Climate factors and land use/land cover contribute to ecological quality Postprint

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Abstract

The ecological quality of inland areas represents a critical dimension of the United Nations Sustainable Development Goals (UN SDGs). The ecological environment of Northwest China is particularly vulnerable to climate change and land use/land cover dynamics, yet the evolution of ecological quality in this arid region over the past two decades remains poorly understood. This knowledge gap complicates efforts to advance the UN SDGs and formulate appropriate regional interventions. In this study, we utilized Moderate Resolution Imaging Spectroradiometer (MODIS) products to generate a Remote Sensing Ecological Index (RSEI) on the Google Earth Engine (GEE) platform, examining the relationship between ecological quality and environmental factors in Xinjiang from 2000 to 2020. We analyzed 21-year time series data to characterize trends and spatial patterns of ecological quality, and further assessed the relative importance of different environmental drivers using the random forest algorithm with data from statistical yearbooks and land use products. Our results demonstrate that RSEI constructed via the GEE platform accurately captures ecological quality information in Xinjiang, as the first principal component contribution exceeded 90.00%. Ecological quality in Xinjiang improved significantly over the study period, with northern Xinjiang exhibiting better conditions than southern Xinjiang. Areas showing slight improvement accounted for 31.26% of Xinjiang's total land area, while only 3.55% experienced slight deterioration (3.16%) or worsening (0.39%). The vast majority of degradation occurred in barren areas. Temperature, precipitation, closed shrublands, grasslands, and savannas emerged as the top five environmental factors influencing RSEI changes. Environmental factors carried different weights across RSEI categories. Overall, ecological recovery in Xinjiang over the past two decades has been driven by climate and land use/land cover dynamics, underscoring the importanc

Full Text

Preamble

Assessment of Ecological Quality in Northwest China (2000–2020) Using the Google Earth Engine Platform: Climate Factors and Land Use/Land Cover Contribute to Ecological Quality

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Abstract: The ecological quality of inland areas represents a critical dimension of the United Nations Sustainable Development Goals (UN SDGs). The ecological environment of Northwest China is particularly vulnerable to climate change and land use/land cover dynamics, yet the evolution of ecological quality in this arid region over the past two decades remains poorly understood. This knowledge gap complicates efforts to advance the UN SDGs and formulate appropriate regional interventions. In this study, we utilized Moderate Resolution Imaging Spectroradiometer (MODIS) products to generate a Remote Sensing Ecological Index (RSEI) on the Google Earth Engine (GEE) platform, examining the relationship between ecological quality and environmental factors in Xinjiang from 2000 to 2020. We analyzed 21-year time series data to characterize trends and spatial patterns of ecological quality, and further assessed the relative importance of different environmental drivers using the random forest algorithm with data from statistical yearbooks and land use products. Our results demonstrate that RSEI constructed via the GEE platform accurately captures ecological quality information in Xinjiang, as the first principal component contribution exceeded 90.00%. Ecological quality in Xinjiang improved significantly over the study period, with northern Xinjiang exhibiting better conditions than southern Xinjiang. Areas showing slight improvement accounted for 31.26% of Xinjiang's total land area, while only 3.55% experienced slight deterioration (3.16%) or worsening (0.39%). The vast majority of degradation occurred in barren areas. Temperature, precipitation, closed shrublands, grasslands, and savannas emerged as the top five environmental factors influencing RSEI changes. Environmental factors carried different weights across RSEI categories. Overall, ecological recovery in Xinjiang over the past two decades has been driven by climate and land use/land cover dynamics, underscoring the importance of policy-driven ecological restoration. Rapid monitoring of inland ecological quality using the GEE platform is expected to support comprehensive assessment of the UN SDGs.

Keywords: ecological quality; land use/land cover; spatiotemporal change; remote sensing ecological index (RSEI); Google Earth Engine; Xinjiang

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1 Introduction

Ecological sustainability constitutes a critical component of high-quality sustainable development worldwide. The global ecological environment is increasingly vulnerable to climate change and intensified anthropogenic activities (Malhi et al., 2020). The widespread emergence of land degradation, characterized by reduced vegetation cover and drought stress, poses significant challenges to achieving the United Nations Sustainable Development Goals (UN SDGs). In response to these global challenges, China has progressively implemented policies to improve ecological quality (Bryan et al., 2018). However, Northwest China—a typical arid region (Li et al., 2017)—faces particularly severe constraints on ecological quality. Beyond poor natural conditions such as water scarcity, arid climate, and drought stress, water and land resources are being exploited unsustainably (Zuo et al., 2018). When assessing China's progress toward sustainable development, Northwest China ranks among the lowest in UN SDG index scores (Xu et al., 2020). Consequently, evaluating ecological quality in reference to the UN SDGs in Northwest China is essential for balancing regional disparities in sustainable development.

Traditional ecological quality assessments have been limited to small-scale areas, requiring substantial time and labor investments (Li et al., 2020a). In contrast, remote sensing technology enables rapid monitoring of ecological environments across large scales (Ge et al., 2022a). Numerous remote sensing products have been developed to effectively monitor eco-environmental changes. Regional ecosystems can be directly monitored through spectral indices such as the Normalized Difference Vegetation Index (NDVI) (Pettorelli et al., 2005; Jiang et al., 2021) and Leaf Area Index (Hill et al., 2006; Xie et al., 2019). Remote sensing technology can also indirectly monitor ecosystems using physical model-driven products such as Land Surface Temperature (LST) (Vlassova et al., 2014; Peng et al., 2018) and soil moisture content (Deng et al., 2016; Bradford et al., 2020). However, ecological quality cannot be comprehensively interpreted using a single indicator, even if it reflects environmental changes.

To address the integrated and complex nature of ecological environments, multiple indices and products should be considered in synergistic calculations (Zheng et al., 2022). Synergistic indices can leverage the strengths of individual indicators to better approximate true surface ecological quality. The disturbance index can detect forest disturbance using tasseled cap transformation indices (Healey et al., 2005). Ecosystem disturbance can be systematically evaluated by combining LST and Enhanced Vegetation Index (EVI) (Mildrexler et al., 2009). The ecological quality index can assess urban green space through several landscape metrics (Tian et al., 2011). The relative importance of individual indicators is key to integrating different metrics into a comprehensive ecological index.

In recent years, the Remote Sensing Ecological Index (RSEI) has been effectively used to assess ecological quality through an aggregated approach incorporating greenness, humidity, dryness, and heat indicators (Xu et al., 2018, 2019). These four indicators reflect the influence of human activity expansion, environmental suitability, and climate at various scales (Xu et al., 2018; Wu et al., 2021). RSEI accuracy has been verified at both local and regional scales (Yue et al., 2019; Xiong et al., 2021; Xu et al., 2021), making it suitable for spatial evaluation of regional-scale, long-term ecological quality. However, vegetation characteristics vary significantly across regions, and traditional NDVI, as a covariate of RSEI, may not accurately reflect ecological quality in arid areas.

The construction process of RSEI is computationally intensive, particularly for large-scale evaluations. To address this challenge, researchers have utilized the Google Earth Engine (GEE) platform to handle large-volume data analysis (Gorelick et al., 2017; Tamiminia et al., 2020). Leveraging cloud computing services rather than local systems enables rapid and straightforward large-scale RSEI construction. Ecological quality at local scales has been explored using the GEE platform (Xiong et al., 2021; Zheng et al., 2022). These studies suggest that GEE's computational efficiency could support high-temporal-resolution ecological quality assessments (Yang et al., 2019), avoiding intensive computation and efficiency issues. Xinjiang Uygur Autonomous Region, located in the arid regions of Northwest China, faces frequent ecological issues across its vast territory, yet its long-term ecological quality has not been quantitatively assessed.

To fill this gap, this study aimed to: (1) assess ecological quality in Xinjiang from 2000 to 2020 based on RSEI; (2) monitor spatial and temporal changes in ecological quality; and (3) discuss the environmental factors influencing these changes. Rapid monitoring of inland ecological quality using the GEE platform is expected to advance comprehensive UN SDG assessments in arid regions.

2.1 Study Area

Xinjiang, situated in Northwest China, covers approximately 1.66×10^{6} km^2—one-sixth of China's total land area. The region features a complex mountain–oasis–desert landscape system (Fig. 1 [Figure 1: see original paper]).

Three major mountain ranges run from north to south (the Altay, Tianshan, and Kunlun Mountains), framing two basins (the Junggar and Tarim basins). Geographically, the Tianshan Mountains divide Xinjiang into northern Xinjiang and southern Xinjiang. The region experiences a continental arid climate with low precipitation and high evaporation rates. The annual average temperature is 7.6°C, with average annual precipitation of 158.0 mm and average annual evapotranspiration of 365.7 mm (Yao et al., 2019). Evaporation exceeds precipitation, making groundwater and seasonal glacier melt the primary freshwater sources, though these are largely lost to evapotranspiration (Rodell et al., 2018). Vegetation is sparse, dominated by farmland and grassland, though all vegetation types show a greening trend, particularly farmland (Ge et al., 2021; Guan et al., 2021). Cotton is the main cultivated crop, with Xinjiang being China's largest producer.

2.2 Data Acquisition and Processing

We used MODIS products including Terra Land Surface Reflectance (MOD19A1), Terra Land Surface Temperature and Emissivity (MOD11A2), and Terra Vegetation Indices (MOD13A1). Data stitching, cropping, resampling, and projection were performed on the GEE platform using the World Geodetic System 84 (WGS84, EPSG:4326) projection and nearest neighbor resampling. We selected data for 2000–2020 and calculated annual averages for each year.

Population and Gross Domestic Product (GDP) represented overall socioeconomic development. We also included representative energy production and consumption data, given Xinjiang's role as China's energy base. Total water resources were considered central to Xinjiang's socioeconomic development. Temperature and precipitation served as meteorological factors, while aerosol optical depth was included as a driver because Xinjiang lies in the direct path of prevailing westerly winds, receiving hazardous aerosols year-round. Land use area represents the outcome of human–nature interactions. We considered the following factors affecting the ecological environment: population, GDP, total energy production, total energy consumption, total water resources, temperature, precipitation, aerosol optical depth, and land use/land cover area.

Aerosol optical depth data and land use type areas were derived from Terra+Aqua MAIAC Land Aerosol Optical Depth (MCD19A2) and Land Cover Type products, respectively. The land use data comprised 17 classes from the International Geosphere–Biosphere Programme (https://developers.google.com/earth-engine/datasets/catalog/MODIS_{006}MCD12Q1): evergreen needleleaf, evergreen broadleaf, deciduous needleleaf, deciduous broadleaf, and mixed broadleaf forests; closed and open shrublands; woody savannas; savannas; grasslands; permanent wetlands; croplands; urban and built-up lands; cropland/natural vegetation mosaics; permanent snow and ice; barren areas; and water bodies. Land use/land cover areas were calculated in ArcGIS 10.3 software (Esri, Redlands, CA, USA). Aerosol optical depth data used the Optical_{{{Depth}}_{{055}}} band from MCD19A2 products, calculated as the annual mean for the study area. Other data (population, GDP, total energy production, total energy consumption, total water resources, temperature, and precipitation) were obtained from the Xinjiang Statistical Yearbook (Statistic Bureau of Xinjiang Uygur Autonomous Region, 2001–2020). Data preprocessing was conducted on the GEE platform (https://code.earthengine.google.com/).

2.3 Remote Sensing Ecological Index (RSEI)

RSEI comprehensively reflects regional ecological quality through four indicators: greenness, dryness, wetness, and heat (Xu et al., 2018). We used EVI from MOD13A1 products to represent greenness (Zheng et al., 2020). Normalized Difference Impervious Surface Index (NDBSI) expressed dryness, while the wet component (Wet) derived from tasseled cap transformation of MODIS represented wetness (Zheng et al., 2020). LST from the LST_{Day}1km band of MOD11A2 products reflected heat. Detailed information about the four indicators appears in Table 1 .

The RSEI calculation process involves: (1) standardizing the four indicators; (2) calculating principal components and selecting the first principal component (PC1) as the initial RSEI ($RSEI_0$); and (3) standardizing $RSEI_0$. RSEI was calculated according to Equations 1 and 2:

$$0RSEI1RSEI = -0RSEIPC1[(EVI, NDBSI, Wet, LST)]f =$$

where f represents the functional relationship.

Following previous studies (Xu et al., 2018; Yue et al., 2019; Xiong et al., 2021), RSEI can be classified into five categories: excellent (0.8<RSEI$ 1.0), $good(0.6 < RSEI$ 0.8), $moderate(0.4 < RSEI$ 0.6), $fair(0.2 < RSEI$ 0.4), $andpoor(0.0 < RSEI$ \$0.2).

2.4 Change Trend Analysis of RSEI

We used the RSEI assessment time points as nodes for change analysis following Yuan et al. (2021) (Fig. 2 [Figure 2: see original paper]). This method determines RSEI change trends using differences between two time points, identifying three trend types: improved, stable, and worsen. We calculated RSEI trends from differences between 2020 and 2000 results using ArcGIS 10.3. The RSEI change trend classification appears in Table 2 .

2.5 Importance of Influencing Factors

The significance of factors affecting RSEI varies. We employed the random forest algorithm to determine factor importance and clarify the role of socioenvironmental drivers. This ensemble tree model combines multiple weak learners into a strong learner, handling numerous input variables while providing a characteristic importance index for each variable. Importance is assessed by adding noise interference to out-of-bag samples and recalculating prediction errors. Variables causing significant error changes are deemed more important. Variable importance is quantified by dividing the difference between out-of-bag errors by the number of regression trees. We implemented this method using the randomForest package in R (version 4.0.2).

3.1 Ecological Quality of Xinjiang from 2000 to 2020

Figure 3 [Figure 3: see original paper] illustrates spatial variations in Xinjiang's ecological quality from 2000 to 2020. Overall, northern Xinjiang exhibited better ecological quality than southern Xinjiang. Areas with excellent RSEI were concentrated in northern Xinjiang, including the Altay Mountains, oases on the northern Tianshan slopes, and the central Tianshan Mountains. Areas south of the Tianshan Mountains, such as the Taklimakan Desert, showed ecological quality at risk. Moderate RSEI areas were distributed in oases and mountains surrounding the Taklimakan Desert. Eastern Xinjiang's ecological quality showed high variability over the two decades, indicating sensitivity to environmental factors.

RSEI values in Xinjiang generally increased from 2000 to 2020 (Fig. 4a [Figure 4: see original paper]), rising by 7.00% over the study period. The worst and best RSEI years were 2000 and 2012, respectively. Higher percentages of fair and poor RSEI areas indicate greater ecological degradation risk. The proportion of low ecological quality areas (poor and fair RSEI) decreased from 52.41% in 2000 to 37.35% in 2020 (Fig. 4b). Fair RSEI areas declined notably in 2011 and 2018, transitioning primarily to moderate RSEI in the southern Tianshan Mountains. Xinjiang's mean RSEI value was proportional to the percentage of moderate RSEI areas. The ecological quality improvement in southern Xinjiang contributed substantially to the region's overall enhancement.

3.2 Spatial Distribution of the Change Trend of Environmental Quality in Xinjiang from 2000 to 2020

Xinjiang's overall ecological quality remained stable with slight improvement in spatial distribution over the study period (Fig. 5 [Figure 5: see original paper]). Areas with slightly improved ecological quality accounted for 31.26% of Xinjiang's land area, with northern Xinjiang showing a higher percentage than southern Xinjiang. Improved ecological quality areas were concentrated in oases and foothills. Stable ecological quality areas comprised 64.32% of Xinjiang's land area. Slightly deteriorated areas constituted only 3.16%, primarily in deserts with minor portions in high mountains, while only 0.39% of land area showed deterioration. Poor ecological quality land was concentrated mainly in the Taklimakan Desert, with very few areas classified as significantly improved or significantly deteriorated.

We assessed land use/land cover changes in areas with decreasing ecological quality. Most degradation occurred in locations that remained barren during 2000–2020. Over 60.00% of Xinjiang was covered by non-vegetated barren areas (<10.00% vegetation cover) (Fig. 6 [Figure 6: see original paper]). Changes within barren areas accounted for 92.50% and 84.25% of worsen and slightly worsen ecological quality areas, respectively. More than half of improved and slightly improved areas also occurred in barren areas, representing 74.40% and 58.75%, respectively (Fig. 6). These results indicate that although few areas experienced ecological quality deterioration, most were in barren areas. Nevertheless, overall ecological quality improved in the barren portions of eastern and mountainous regions.

3.3 Analysis of the Importance of Factors Influencing Ecological Quality

RSEI in Xinjiang was primarily controlled by climatic conditions, though different RSEI levels showed differential responses to environmental factors (Fig. 7 [Figure 7: see original paper]). Temperature and precipitation not only dominated average RSEI but also significantly influenced fair RSEI areas. Aerosol optical depth ranked second in importance for good RSEI areas, in addition to the two meteorological factors, indicating that northern Xinjiang oases face aerosol optical depth stress.

Permanent wetlands, grasslands, and mixed forests significantly influenced excellent, moderate, and poor RSEI, respectively, demonstrating that the best and worst ecological quality levels were affected by land use/land cover types. Closed shrublands ranked among the top five influencing factors for nearly all ecological quality levels. Permanent wetlands, closed shrublands, and total water resources showed similar importance for excellent RSEI areas, suggesting water resource-centered influences. Grasslands, closed shrublands, savannas, and vegetation mosaics emerged as top influencing factors for moderate RSEI areas, indicating that vegetation factors are key to regional ecological quality. Temperature, precipitation, water resources, and vegetation all contributed to Xinjiang's ecological quality.

4 Discussion

A single land surface factor is inadequate for assessing complex land surface ecosystem quality. The interactions among ecological factors necessitate multifactor evaluation. RSEI can effectively assess land surface ecological quality (Yang et al., 2021). In this study, we calculated eigenvalues and principal component contributions to verify RSEI applicability. PC1 contributions exceeded 90.00%, indicating that RSEI could reflect Xinjiang's ecological quality over the past two decades (Boori et al., 2021). The GEE platform, as a remote sensing big data processing platform, can rapidly and easily acquire surface ecological quality results (Gao et al., 2021). Large-scale regional ecological quality assessments based on GEE offer advantages over conventional local processing. The UN SDGs have been highlighted by numerous countries, and GEE has been applied in large-scale ecological monitoring and evaluation (Bian et al., 2020; Wu et al., 2020; Deng et al., 2022), which will help achieve the UN SDGs more rapidly.

Xinjiang's overall ecological quality improved from 2000 to 2020. Improved areas were located not only in oases but also in desert–oasis ecotones and deserts. The primary driver was Xinjiang's warming and humidifying climate; increased precipitation substantially improved soil moisture and habitats, leading to vegetation recovery (Guan et al., 2021). Warmer temperatures also accelerated glacier melting, with glacial snowmelt being the main water recharge source in arid areas. Adequate meltwater greatly replenishes ecological water needs and improves ecological quality. Xinjiang's dryland ecosystems are extremely sensitive to climate change due to their inherently fragile ecology.

The recent trend toward a warmer, more humid climate will help improve Xinjiang's ecological quality (Yao et al., 2021), consistent with our finding that temperature and precipitation control ecological quality. A warmer, more humid climate ultimately manifests as increased water availability (Luo et al., 2019). Water resources are key to sustainable land surface ecology in arid regions and are relatively important in excellent and good RSEI areas (Fig. 7b and c). Spatial and temporal differences in water resources contribute to heterogeneity in ecological quality. We therefore recommend developing ecological restoration policies that account for climate change complexity and water resources.

Southern Xinjiang's ecological quality was lower than northern Xinjiang's almost annually, while eastern Xinjiang's ecological quality proved vulnerable. This may stem from climatic differences affecting natural vegetation distribution and thus ecological quality (Ma et al., 2021). Northern Xinjiang has been reported to be more precipitation-sensitive than southern Xinjiang (Luo et al., 2019), consistent with our findings. Eastern Xinjiang's ecological quality is easily impacted due to scant vegetation resulting from the dry climate, as environmental conditions favor desertification (Jiang et al., 2019). Dust aerosols are regional factors affecting ecological quality. Previous studies show that the Ebinur Lake region (northern Xinjiang) and Taklimakan Desert (southern Xinjiang), as major dust sources, transport substantial atmospheric pollutants to surrounding areas, degrading the ecological environment (Ge et al., 2016; Liu et al., 2021). Dust transport is climate-controlled, with higher temperatures favoring dust transport and movement, while precipitation suppresses dust concentration and activity.

Land use/land cover proved relatively important in Xinjiang's ecological quality assessment (Fig. 7). Land use/land cover types with higher vegetation density have higher RSEI values (Zheng et al., 2022). Most of Xinjiang is barren, with unchanged barren areas over the past two decades accounting for 68.31% of Xinjiang's total area. RSEI in barren areas has been rated as poor or fair (Zheng et al., 2022), consistent with our results. However, our findings suggest that ecological quality in these unchanged barren areas also improved, likely due to the warmer, more humid climate. Human activity-driven improvements occurred in oases or oasis–desert ecotones (grasslands), though the warmer, more humid climate trend transformed these barren areas into grasslands (Gang et al., 2019). Grasslands, dominated by natural vegetation in Northwest China's arid regions, are influenced by climate, water resources, and human activities. Our results indicate grasslands are important for Xinjiang's ecological quality, though grassland restoration may approach water resource sustainability limits (Feng et al., 2016).

Xinjiang grasslands have also been converted to croplands, a transformation accounting for 1.60% of Xinjiang's area and ranking second in land use/land cover change. Notably, >60.00% conversion from grasslands to croplands can cause slight soil salinization (Zhuang et al., 2021). Cropland expansion also exacerbates natural habitat degradation (Tang et al., 2021). Fortunately, the area converted from grasslands to croplands (1.62%) was balanced by increased grassland area (2.67%). Planned cropland expansion can reduce ecosystem stress through such balanced approaches. The Chinese government aims to achieve ecological and rural rejuvenation by coordinating and balancing agricultural output with ecological conservation in rural areas (Liu and Li, 2017; Liu et al., 2020). Intensive (Zhang et al., 2020; Feng et al., 2022) and precision (Wu et al., 2005; Xu et al., 2020) agriculture serves croplands and generates economic benefits, further contributing to Xinjiang's ecological quality improvement. The Chinese government focuses on rural ecological revitalization in Xinjiang through geographical indications of agricultural products, ecological certification, and rural ecological revitalization (Chen et al., 2021). These policies and measures help mitigate cropland expansion impacts on ecosystems.

Xinjiang's ecological quality improvement cannot be achieved without Chinese government policy support, which has implemented a series of scientifically-based ecological restoration policies. The Three-North Shelterbelt Program (Li et al., 2012; Zhang et al., 2016; Guo et al., 2022a) and the Tarim River Basin comprehensive management project (Xue et al., 2019) serve as excellent examples. Over the past four decades, Xinjiang's vegetation has recovered, regional desertification has improved, and human activities have positively affected regional greening (Guan et al., 2021). Soils have improved in some areas with native salinity due to vegetation improvements (Ge et al., 2022b). The Tarim River Basin shows sustainable ecological development trends, with natural vegetation improvement and halted conversion of natural vegetation to agricultural land (Xue et al., 2019; Guo et al., 2020). Although local ecological quality deterioration has occurred in Xinjiang, it has not been caused by human activities, with the vast majority happening in unused barren areas. While policy drivers have led global greening (Chen et al., 2019; Guo et al., 2022b), as demonstrated by Tarim River Basin ecological restoration, we must also consider reducing natural vegetation conversion to agricultural land. Additionally, afforestation must consider water resource carrying capacity, as afforestation may lower groundwater levels in arid regions (Lu et al., 2018).

The Chinese government has established nine national nature reserves in Xinjiang to demonstrate policy-driven action effectiveness (Fig. 8 [Figure 8: see original paper]) (Wu et al., 2011). These reserves include wetlands, shrublands, and forests. Wetlands are the most crucial factor for excellent RSEI (Fig. 7b) because they regulate water resources and serve as ecological barriers. Statistics show ecological quality improved in 21.03% of these national nature reserves, with slight improvement in 1.04% of the area, stability in 73.77%, and slight deterioration in only 4.15%. Deteriorating areas were concentrated in the Lop Nur Wild Camel National Nature Reserve, possibly due to climate-driven water resource shortages increasing vulnerability (Xue et al., 2021). Wetlands, shrublands, forests, and grasslands all play vital roles across distinct RSEI levels. These positive improvements likely reflect national policy drivers. China's River Chief System, Lake Chief System, and Forest Chief System policies (Li et al., 2020b) have been implemented, promising more precise ecological quality management in Xinjiang.

5 Conclusions

In this study, we constructed RSEI through the GEE platform to assess Xinjiang's ecological quality from 2000 to 2020. We found that ecological quality in this arid region improved due to both climate factors and human activities (land use/land cover changes). GEE's computational power supports large-scale ecological assessments. RSEI adequately indicated Xinjiang's ecological quality, as the first principal component contribution exceeded 90.00%. Xinjiang's ecological quality improved, with average RSEI values increasing by 7.00%. Ecological quality slightly improved in 31.26% of Xinjiang's area and remained stable in 64.32%. Approximately 3.16% of land area deteriorated slightly, with only 0.39% showing deterioration. Slightly deteriorated or deteriorated areas were distributed in unused barren lands. Xinjiang's ecological quality improvement was driven by the warmer, more humid climate, land use/land cover changes, and government policies. Temperature, precipitation, closed shrublands, grasslands, and savannas had the greatest effects on RSEI. Among areas with slightly improved and slightly deteriorated ecological quality in Xinjiang, 84.25% and 74.40%, respectively, were in barren areas. For the nine national nature reserves, 22.07% of protected areas were restored (improved and slightly improved) and 73.77% remained stable. The Chinese government achieves ecological and rural rejuvenation by coordinating agricultural output with ecological conservation in rural areas. Our results will contribute to advancing UN SDGs in Central Asian inland drylands.

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