



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 is an important aspect of the United Nations Sustainable Development Goals (UN SDGs). The ecological environment of Northwest China is vulnerable to changes in climate and land use/land cover, and the changes in ecological quality in this arid region over the last two decades are not well understood. This makes it more difficult to advance the UN SDGs and develop appropriate measures at the regional level. In this study, we used the Moderate Resolution Imaging Spectroradiometer (MODIS) products to generate remote sensing ecological index (RSEI) on the Google Earth Engine (GEE) platform to examine the relationship between ecological quality and environment in Xinjiang during the last two decades (from 2000 to 2020). We analyzed a 21-year time series of the trends and spatial characteristics of ecological quality. We further assessed the importance of different environmental factors affecting ecological quality through the random forest algorithm using data from statistical yearbooks and land use products. Our results show that the RSEI constructed using the GEE platform can accurately reflect the ecological quality information in Xinjiang because the contribution of the first principal component was higher than 90.00%. The ecological quality in Xinjiang has increased significantly over the last two decades, with the northern part of this region having a better ecological quality than the southern part. The areas with slightly improved ecological quality accounted for 31.26% of the total land area of Xinjiang, whereas only 3.55% of the land area was classified as having a slightly worsen (3.16%) or worsen (0.39%) ecological quality. The vast majority of the deterioration in ecological quality mainly occurred in the barren areas. Temperature, precipitation, closed shrublands, grasslands and savannas were the top five environmental factors affecting the changes in RSEI. Environmental factors were allocated different weights for different RSEI categories. In general, the recovery of ecological quality in Xinjiang has been controlled by climate and land use/land cover during the last two decades and policy-driven ecological restoration is therefore crucial. Rapid monitoring of inland ecological quality using the GEE platform is projected to aid in the advancement of the 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 is an important part of high-quality sustainable development worldwide. The ecological environment is becoming increasingly vulnerable to climate change and increased anthropogenic activities (Malhi et al., 2020). The global emergence of land degradation, with reduced vegetation cover and drought stress, challenges the advancement of the United Nations Sustainable Development Goals (UN SDGs). In response to global challenges, China has progressively implemented policies to improve ecological quality (Bryan et al., 2018), but the ecological quality in Northwest China, a typical arid region (Li et al., 2017), is more restricted. In addition to poor natural conditions (e.g., insufficient water resources, arid climate and drought conditions), water and land resources are unsustainably exploited (Zuo et al., 2018). When assessing China's progress in sustainable development, Northwest China was found to be in the lower part of the UN SDG index scores (Xu et al., 2020). It is therefore necessary to assess ecological quality with reference to the UN SDGs in Northwest China to balance regional differences in sustainable development.

Traditional assessments of ecological quality are limited to small-scale areas, which are both time consuming and labor intensive (Li et al., 2020a). By contrast, remote sensing technology can be used to rapidly monitor the ecological environment on large scales (Ge et al., 2022a). Many remote sensing products have been developed and designed to effectively monitor changes in the eco-environment. Regional ecosystems are directly monitored through the normalized difference vegetation index (NDVI) (Pettorelli et al., 2005; Jiang et al., 2021) and the leaf area index (Hill et al., 2006; Xie et al., 2019), among others; these products are driven by spectral indices. Remote sensing technology can also monitor ecosystems indirectly using products such as the land surface temperature (LST) (Vlassova et al., 2014; Peng et al., 2018) and soil moisture content (Deng et al., 2016; Bradford et al., 2020), which are driven by physical models. However, ecological quality cannot be broadly interpreted using a single indicator, even if this reflects the results of a changing environment.

To overcome the integrated and complex nature of ecological environments, various indices and products should be considered in synergistic calculations (Zheng et al., 2022). Synergistic indices can leverage the strengths of each indicator to maximize the approximation to the true ecological quality of the surface. The disturbance index can detect forest disturbance using the tasseled cap transformation indices (Healey et al., 2005). Ecosystem disturbance can be systematically evaluated by leveraging the strengths of the LST and enhanced vegetation index (EVI) (Mildrexler et al., 2009). The ecological quality index can be used to assess urban green space through several landscape indices (Tian et al., 2011). The relative importance of these individual indicators is the key to synergizing different indicators for integration into a comprehensive ecological index.

In recent years, remote sensing ecological index (RSEI) has been effectively used to assess ecological quality by an aggregated approach, including greenness, humidity, dryness and heat indicators (Xu et al., 2018, 2019). These four indicators reflect the influence of the expansion of human activities, environmental suitability and the climate on different scales (Xu et al., 2018; Wu et al., 2021). The accuracy of RSEI has been verified on both local and regional scales (Yue et al., 2019; Xiong et al., 2021; Xu et al., 2021) and this index is therefore suitable for spatially evaluating regional-scale, long-term ecological quality. However, the characteristics of vegetation are clearly different in different regions and the traditional NDVI, as a covariate of RSEI, may not accurately reflect ecological quality in arid areas.

The construction process of RSEI is computationally intensive, especially with large-scale evaluations. To solve this problem, researchers used the Google Earth Engine (GEE) platform to handle the analysis of large amounts of data (Gorelick et al., 2017; Tamiminia et al., 2020). It is both rapid and easy to build large-scale RSEI using the power of cloud computing services rather than local computing systems. Ecological quality at the local scale has been explored using the GEE platform (Xiong et al., 2021; Zheng et al., 2022). These studies suggested that the

computational efficiency of the GEE platform might provide support for assessing ecological quality at high temporal resolutions (Yang et al., 2019). This could avoid intensive computation and efficiency issues. Xinjiang Uygur Autonomous Region (abbreviated as Xinjiang) is located in arid regions of Northwest China. Several ecological issues are frequently present in this vast region, but the long-term ecological quality has not yet been quantitatively assessed.

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

2 Materials and methods

2.1 Study area

Xinjiang, located in Northwest China, has an area of about 1.66×10^6 km², accounting for one-sixth of the total land area of China. It has a complex landscape system with a mountain–oasis–desert landscape (Fig. 1). It is composed of three main mountain ranges from north to south (the Altay, Tianshan and Kunlun mountains) and two basins from north to south (the Junggar and Tarim basins). Geographically, Xinjiang is divided by the Tianshan Mountains into the northern part (northern Xinjiang) and the southern part (southern Xinjiang). It has a continental arid climate with little precipitation and high rates of evaporation. The annual average temperature is 7.6°C and the average annual precipitation is 158.0 mm. The average annual evapotranspiration is 365.7 mm (Yao et al., 2019). Evaporation exceeds precipitation and therefore groundwater and the seasonal melting of glaciers serve as the primary sources of freshwater recharge, although they are lost to evapotranspiration (Rodell et al., 2018). The vegetation is sparse and consists mainly of farmland and grassland, although the overall trend is toward greening for all vegetation types, particularly farmland (Ge et al., 2021; Guan et al., 2021). The main cultivated crop is cotton, of which Xinjiang is the largest producer in China.

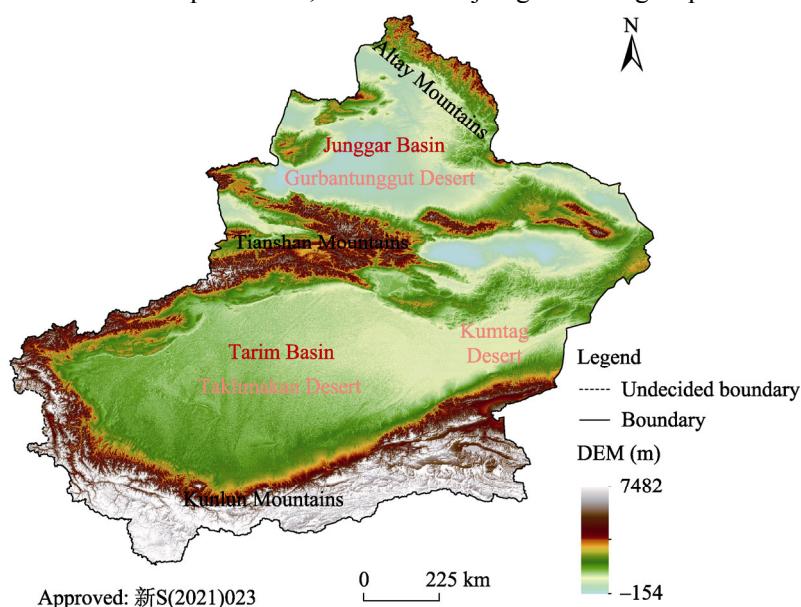


Fig. 1 Overview of Xinjiang Uygur Autonomous Region (Xinjiang) in Northwest China. Note that the figure is based on the standard map (新 S(2021)023) of the Map Service System (<https://xinjiang.tianditu.gov.cn/main/bzdt.html>) marked by the Xinjiang Uygur Autonomous Region Platform for Common Geospatial Information Services, and the standard map has not been modified. DEM, digital elevation model.

2.2 Data acquisition and processing

We used products from the Moderate Resolution Imaging Spectroradiometer (MODIS), including the Terra Land Surface Reflectance (MOD19A1), the Terra Land Surface Temperature and Emissivity (MOD11A2) and the Terra Vegetation Indices (MOD13A1). We conducted the stitching, cropping, resampling and projection of these data in the GEE platform. We used the World Geodetic System 84 (WGS84, EPSG:4326) projection and the nearest neighbor method for resampling. We selected data for the time period 2000–2020 and calculated the annual averages for each year.

We used the population and gross domestic product (GDP) to represent the overall socioeconomic development. We also used representative energy production and consumption data because Xinjiang is the energy base of China. Furthermore, we also used the total water resources because these are at the core of Xinjiang's socioeconomic development. We considered temperature and precipitation as the meteorological factors and the aerosol optical depth as a driver because Xinjiang is in the direct path of the prevailing westerly winds and therefore receives hazardous aerosols throughout the year. The area of land use represents the result of human–nature interactions. We considered the following factors affecting the ecological environment, including population, GDP, total energy production, total energy consumption, total water resources, temperature, precipitation, aerosol optical depth and the area of land use/land cover types. The aerosol optical depth data and the area of land use types used the Terra+Aqua MAIAC Land Aerosol Optical Depth (MCD19A2) and the Land Cover Type products, respectively.

The land use data consisted of 17 classes of land use/land cover types from the International Geosphere–Biosphere Programme (https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MCD12Q1), including forests (evergreen needleleaf, evergreen broadleaf, deciduous needleleaf, deciduous broadleaf and mixed broadleaf), 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. The area of land use/land cover types was counted in ArcGIS 10.3 software (Esri, Redlands, CA, USA). The aerosol optical depth data were the Optical_Depth_055 of the MCD19A2 products and these data were calculated as the annual mean of the study area. Other data (including population, GDP, total energy production, total energy consumption, total water resources, temperature and precipitation) were collected from the Xinjiang Statistical Yearbook (Statistic Bureau of Xinjiang Uygur Autonomous Region, 2001–2020). Data preprocessing was conducted in the GEE platform (<https://code.earthengine.google.com/>).

2.3 Remote sensing ecological index (RSEI)

RSEI comprehensively reflect a region's ecological quality because it consists of four indicators: greenness, dryness, wetness and heat (Xu et al., 2018). We used the EVI of the MOD13A1 products to represent greenness (Zheng et al., 2020). We calculated the normalized difference impervious surface index (NDBSI) to express dryness and the wet component (Wet) driven by the tasseled cap transformation of MODIS to represent wetness (Zheng et al., 2020). We also used the LST from the LST_Day_1km of the MOD11A2 products to reflect heat. The calculation processes of NDBSI and the wet component have been reported previously (Zheng et al., 2020). The detailed information about the four indicators are shown in Table 1.

The calculation process for RSEI is as follows: (1) standardization of the four indicators; (2) calculation of the principal components of the four indicators and the selection of the first principal component (PC1) as the initial RSEI ($RSEI_0$); and (3) standardization of $RSEI_0$. RSEI was calculated according to the Equations 1 and 2:

$$RSEI = 1 - RSEI_0, \quad (1)$$

$$RSEI_0 = PCI[f(EVI, NDBSI, Wet, LST)], \quad (2)$$

where f represents the functional relationship.

Table 1 Main information of the selected four indicators for the construction of remote sensing ecological index (RSEI)

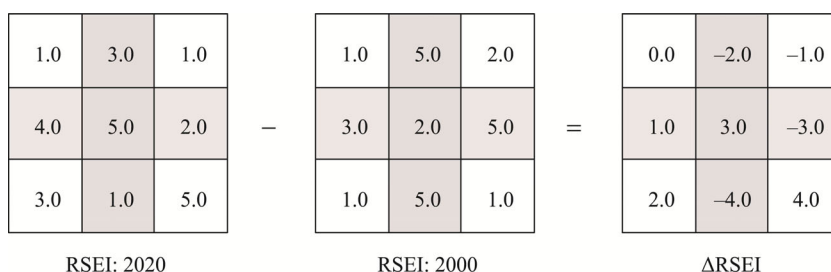
Indicator	Source	Product	Spatial resolution	Temporal resolution
Greenness	EVI	MOD13A1	0.5 km	16 d
Dryness	NDBSI	MOD09A1	0.5 km	8 d
Wetness	Wet	MOD09A1	0.5 km	8 d
Heat	LST	MOD11A2	1.0 km	8 d

Note: EVI, enhanced vegetation index; LST, land surface temperature, NDBSI, normalized difference impervious surface indices; Wet, wet component.

According to previous studies (Xu et al., 2018; Yue et al., 2019; Xiong et al., 2021), RSEI can be classified into five categories: excellent ($0.8 < \text{RSEI} \leq 1.0$), good ($0.6 < \text{RSEI} \leq 0.8$), moderate ($0.4 < \text{RSEI} \leq 0.6$), fair ($0.2 < \text{RSEI} \leq 0.4$) and poor ($0.0 < \text{RSEI} \leq 0.2$).

2.4 Change trend analysis of RSEI

We used the time of the assessment of RSEI as a node to perform change analysis using the calculation reported by Yuan et al. (2021) (Fig. 2). This calculation determines the change trend of RSEI using the difference in RSEI at two different time points. There are three types of change trend: improved, stable and worsen. We calculated the trend of RSEI from the difference between the results in 2020 and 2000 using ArcGIS 10.3. The classification of the change trend of RSEI is shown in Table 2.

**Fig. 2** Schematic diagram of the change trend analysis of remote sensing ecological index (RSEI). ΔRSEI , difference of RSEI between 2020 and 2000.**Table 2** Classification of the change trend of RSEI

ΔRSEI	Change trend	ΔRSEI	Change trend
3.0	Significantly improved	-1.0	Slightly worsen
2.0	Improved	-2.0	Worsen
1.0	Slightly improved	-3.0	Significantly worsen
0.0	Stable		

Note: ΔRSEI , difference of RSEI between 2020 and 2000.

2.5 Importance of influencing factors

There are differences in the importance of the factors affecting RSEI. We determined the significance of the influencing factors using the random forest algorithm to clarify the importance of socioenvironmental factors. This algorithm is an integrated tree model that sets multiple weak learners into a single strong learner. It can manage a high number of input variables and provide a characteristic importance index for each variable to judge its importance in the model. In doing so, a variable is randomly re-predicted by adding noise interference to all the samples of out-of-bag data and this error is then re-calculated. If it changes significantly, then the variable is more important. The importance of the variable can be quantified by dividing the difference between the out-of-bag errors, and calculated twice by the number of regression trees. We conducted this method using the randomForest package within R (version 4.0.2).

3 Results

3.1 Ecological quality of Xinjiang from 2000 to 2020

Figure 3 shows the spatial variations in ecological quality in Xinjiang from 2000 to 2020. Overall, the ecological quality of northern Xinjiang was better than that of southern Xinjiang. Areas with excellent RSEI were often found in northern Xinjiang; for example, the Altay Mountains, the oases on the northern slopes of the Tianshan Mountains and the central Tianshan Mountains. The ecological quality of the areas south of the Tianshan Mountains (e.g., the Taklimakan Desert) was at risk. Areas with moderate RSEI were distributed in the oases and mountains surrounding the Taklimakan Desert. The ecological quality of eastern Xinjiang has been highly variable over the last two decades, which indicates that it is affected by environmental factors.

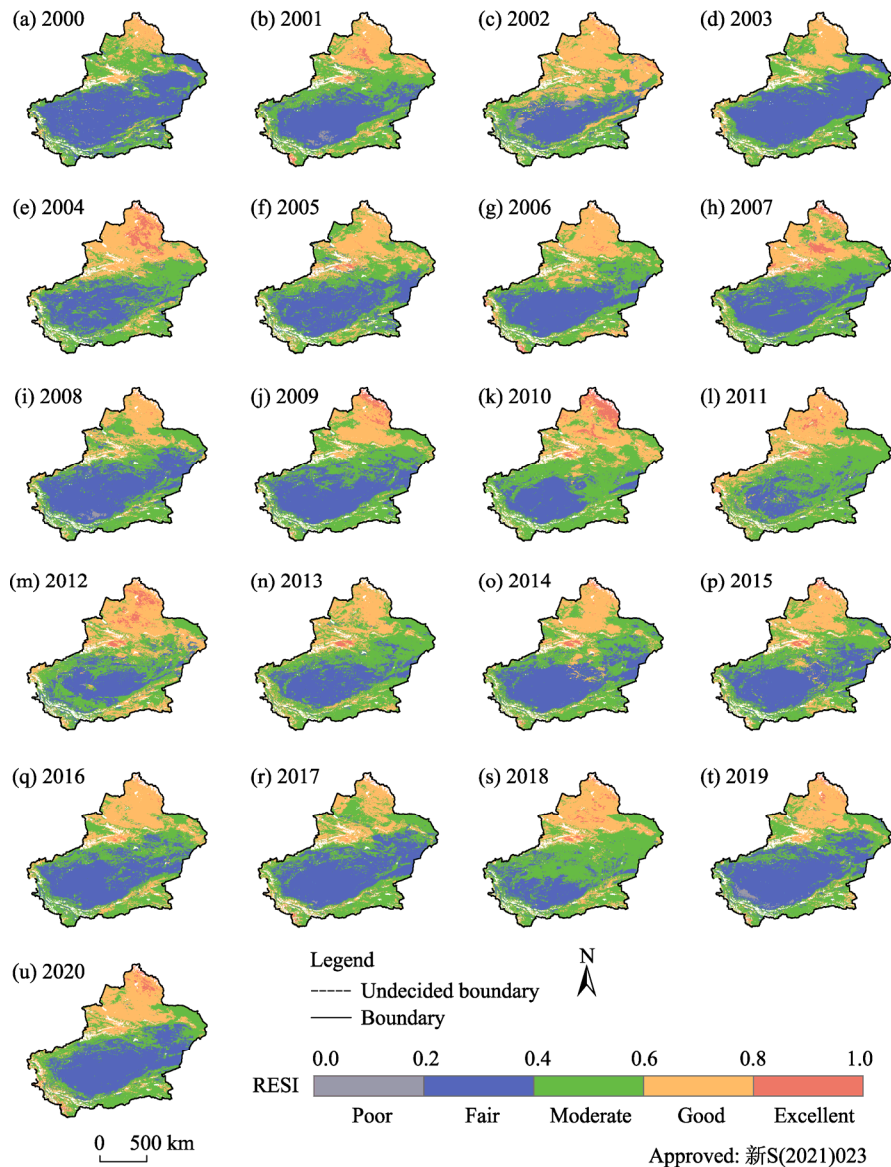


Fig. 3 Spatial and temporal distribution of ecological quality in Xinjiang from 2000 to 2020 (a–u). Note that the figures are based on the standard map (新S(2021)023) of the Map Service System (<https://xinjiang.tianditu.gov.cn/main/bzdt.html>) marked by the Xinjiang Uygur Autonomous Region Platform for Common Geospatial Information Services, and the standard map has not been modified.

The values of RSEI in Xinjiang generally increased from 2000 to 2020 (Fig. 4a), with an increase of 7.00% over the study period. The worst and best years of RSEI were in 2000 and 2012, respectively. The higher the percentage of areas with fair and poor RSEI, the greater the risk of ecological degradation. The results show that the percentage of areas with low ecological quality (poor and fair RSEI) decreased from 52.41% in 2000 to 37.35% in 2020 (Fig. 4b). The areas with fair RSEI noticeably decreased in 2011 and 2018. These reduced areas later transitioned to areas with moderate RSEI, primarily in the southern Tianshan Mountains. The mean value of RSEI in Xinjiang was proportional to the percentage of areas with moderate RSEI. The increase in ecological quality in southern Xinjiang contributed to the overall ecological quality of the whole region.

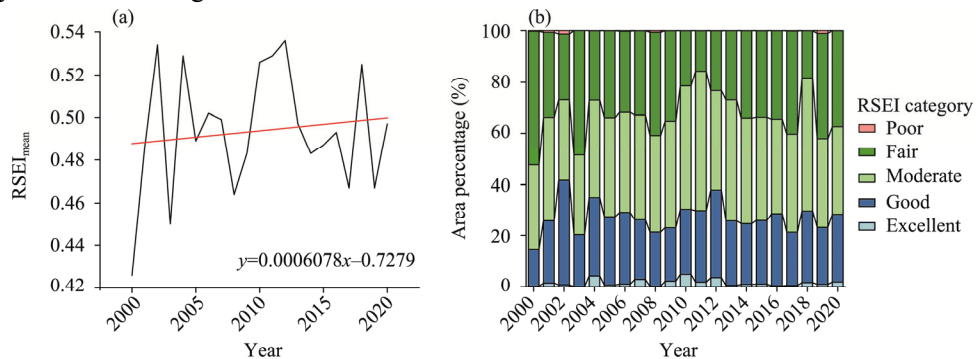


Fig. 4 Change of ecological quality in Xinjiang from 2000 to 2020. (a), change trend of mean RSEI (RSEI_{mean}); (b), area statistics under the five categories of RSEI (excellent, good, moderate, fair and poor).

3.2 Spatial distribution of the change trend of environment quality in Xinjiang from 2000 to 2020

The overall ecological quality in Xinjiang was stable and improved slightly in terms of spatial distribution over the study period (Fig. 5). The areas with a slightly improved ecological quality accounted for 31.26% of the land in Xinjiang, with northern Xinjiang having a higher percentage than southern Xinjiang. The areas with improved ecological quality were mainly in the oases and foothills. The areas with a stable ecological quality accounted for 64.32% of the land in Xinjiang. The areas with a slightly worsen ecological quality made up only 3.16% of the land, mainly in the deserts, with a very minor fraction in the high mountains, and only 0.39% of the land area deteriorated. The land with a poor ecological quality was primarily concentrated in the Taklimakan Desert. Very few areas were classified as having significantly improved or significantly worsen ecological quality.

We assessed the changes in land use/land cover in the areas with decreasing ecological quality. Most of the degradation in ecological quality occurred in places that were barren during 2000 and 2020. More than 60.00% of the region (Xinjiang) was covered by non-vegetated barren areas (<10.00% vegetation cover) (Fig. 6). Changes within the barren areas accounted for 92.50% and 84.25% of the areas with worsen and slightly worsen ecological quality, respectively. More than half of the areas with improved and slightly improved ecological quality also occurred in the barren areas, accounting for 74.40% and 58.75%, respectively (Fig. 6). These results indicate that, although there are few areas where the ecological quality has deteriorated, most of these areas were in the barren areas. However, ecological quality was still improved overall in the barren part of the eastern and mountainous regions of the study area.

3.3 Analysis of the importance of factors influencing ecological quality

RSEI in Xinjiang was mainly controlled by climatic conditions, but distinct levels of RSEI had differential responses to environmental factors (Fig. 7). Temperature and precipitation not only had a dominant role in average RSEI, but also had an important influence on the areas with fair RSEI. The aerosol optical depth ranked second in the importance in the areas with good RSEI, in addition to the two meteorological factors of temperature and precipitation. This indicates that the oases in northern Xinjiang were under stress in terms of the aerosol optical depth.

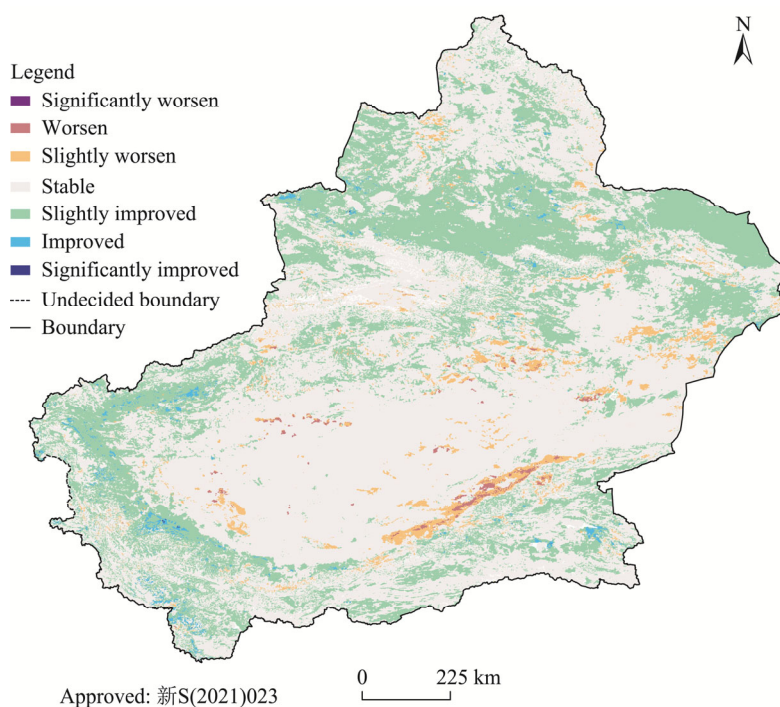


Fig. 5 Spatial distribution of changes in ecological quality in Xinjiang during 2000–2020. Note that the figure is based on the standard map (新 S(2021)023) of the Map Service System (<https://xinjiang.tianditu.gov.cn/main/bzdt.html>) marked by the Xinjiang Uygur Autonomous Region Platform for Common Geospatial Information Services, and the standard map has not been modified.

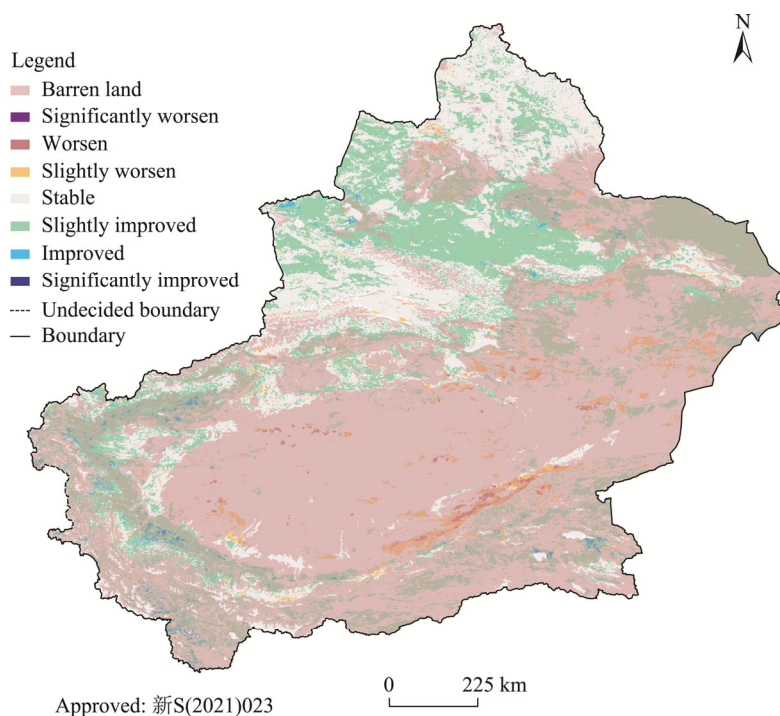


Fig. 6 Spatial distribution of the changes in ecological quality within barren and non-barren areas in Xinjiang during 2000–2020. Note that the figure is based on the standard map (新 S(2021)023) of the Map Service System (<https://xinjiang.tianditu.gov.cn/main/bzdt.html>) marked by the Xinjiang Uygur Autonomous Region Platform for Common Geospatial Information Services, and the standard map has not been modified.

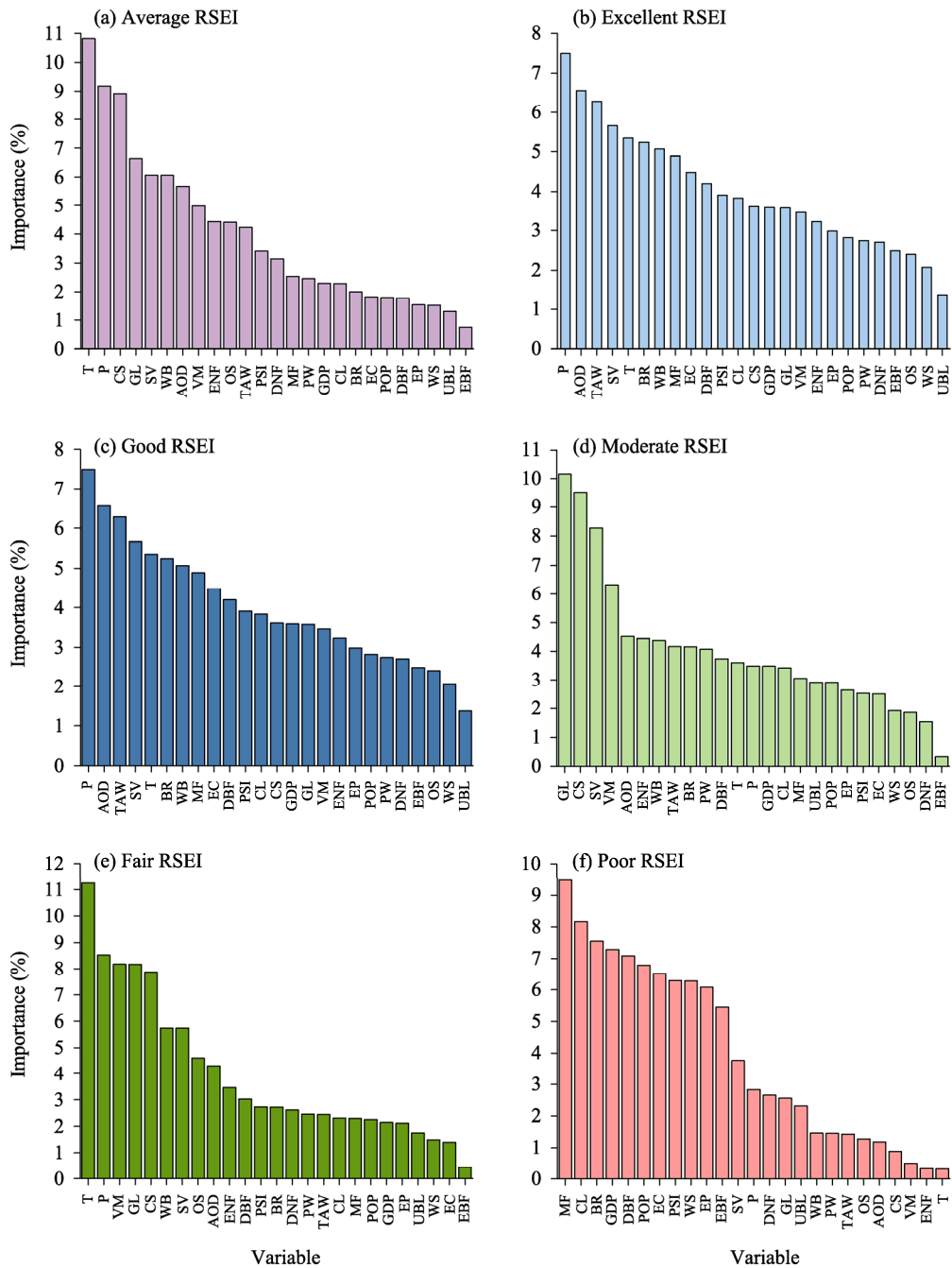


Fig. 7 Importance of factors influencing the level of ecological quality in Xinjiang during 2000–2020. (a)–(f) are the importance of different influencing factors on average, excellent, good, moderate, fair and poor RSEI, respectively. T, temperature; P, precipitation; CS, closed shrublands; GL, grasslands; SV, savannas; WB, water bodies; AOD, aerosol optical depth; VM, vegetation mosaics; ENF, evergreen needleleaf forest; OS, open shrublands; TAW, total water resources; PSI, permanent snow and ice; DNF, deciduous needleleaf forest; MF, mixed forests; PW, permanent wetlands; GDP, gross domestic product; CL, croplands; BR, barren; EC, energy consumption; POP, population; DBF, deciduous broadleaf forest; EP, energy production; WS, woody savannas; UBL, urban and built-up lands.

The permanent wetlands, grasslands and mixed forests significantly influenced the excellent, moderate and poor RSEI, respectively, indicating that the best and worst ecological quality levels were affected by the land use/land cover types. Closed shrublands ranked in the top five

influencing factors for almost all the ecological quality levels. Permanent wetlands, closed shrublands and total water resources had a similar importance for the areas with excellent RSEI, which suggests that these areas are influenced by variables centered on water resources. Grasslands, closed shrublands, savannas and vegetation mosaics emerged as the top influencing factors for the areas with moderate RSEI, which suggests that vegetation factors are key to the ecological quality of the region. Temperature, precipitation, water resources and vegetation all contributed to the ecological quality of Xinjiang.

4 Discussion

A single land surface factor is not a good indicator for assessing the quality of complex land surface ecosystems. The interactions between ecological factors require us to evaluate ecological quality using multiple factors. RSEI can effectively assess the ecological quality of the land surface (Yang et al., 2021). In this study, we calculated the eigenvalues and contributions of the principal components to prove the applicability of RSEI. The contributions of PC1 were all higher than 90.00%, indicating that RSEI could reflect the ecological quality of Xinjiang over the last two decades (Boori et al., 2021). The GEE platform, as a remote sensing big data processing platform, can rapidly and easily acquire the results of surface ecological quality (Gao et al., 2021). Assessments of large-scale regional ecological quality based on the GEE platform have advantages over typical locally processed assessments. The UN SDGs have been highlighted by a number of countries and the GEE platform has been applied in large-scale ecological monitoring and evaluation (Bian et al., 2020; Wu et al., 2020; Deng et al., 2022). This will help to achieve the UN SDGs as soon as possible.

The overall ecological quality in Xinjiang was improved from 2000 to 2020. The improved areas were not only in the oases, but also in the desert–oasis ecotone and deserts. The main reason for this change is that the climate in Xinjiang has become warmer and more humid; the increased precipitation has greatly improved the soil moisture content and habitats, leading to the recovery of vegetation (Guan et al., 2021). Warmer temperatures have also accelerated the melting of glaciers and glacial snowmelt is the main means of water recharge in arid areas. Adequate meltwater greatly replenishes ecological water needs and improves ecological quality. The dryland ecosystems of Xinjiang are extremely sensitive to climate change as a result of their inherently fragile ecology.

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

We observed that the ecological quality of southern Xinjiang was lower than that of northern Xinjiang almost every year and the ecological quality of eastern Xinjiang was vulnerable. This might be due to differences in climate, where climate change affects the distribution of natural vegetation and thus ecological quality (Ma et al., 2021). Northern Xinjiang has been reported to be more sensitive to precipitation than southern Xinjiang (Luo et al., 2019), consistent with our findings. The ecological quality of eastern Xinjiang, where the environmental conditions favor desertification, is easily impacted due to the scant vegetation generated by the dry climate (Jiang et al., 2019). Dust aerosols are also regional factors that affect ecological quality. Previous studies have shown that the Ebinur Lake region (in northern Xinjiang) and the Taklimakan Desert (in southern Xinjiang), which are major sources of dust, transport substantial amounts of atmospheric pollutants to the surrounding areas and degrade the ecological environment (Ge et al., 2016; Liu

et al., 2021). The transport of dust is controlled by the climate, with higher temperatures favoring the transport and movement of dust and precipitation suppressing the concentration and activity of dust.

Land use/land cover was found to be relatively important in the assessment of ecological quality in Xinjiang (Fig. 7) and land use/land cover types with a higher density of vegetation cover have higher RSEI values (Zheng et al., 2022). Most of Xinjiang is barren and the barren areas that have not changed during the last two decades accounted for 68.31% of the total area of Xinjiang. The RSEI of the barren areas has been rated as poor or fair (Zheng et al., 2022), which is consistent with our results. However, our findings suggest that the ecological quality of these unchanged barren areas has also improved, which may be caused by a warmer and more humid climate. Improvements of ecological quality resulting from human activities were found in oases or the oasis–desert ecotone (grasslands); however, it is the trend of a warmer and more humid climate that has transformed these barren areas into grasslands (Gang et al., 2019). Grasslands, which are dominated by natural vegetation in arid regions of Northwest China, are influenced by the climate, water resources and human activities. Our results indicate that grasslands are important for the ecological quality in Xinjiang, although grassland restoration may reach the limits of sustainability in terms of water resources (Feng et al., 2016).

Grasslands in Xinjiang have also been transformed to croplands, a transformation that accounted for 1.60% of the area of Xinjiang and ranked the second for land use/land cover change. Notably, a conversion from grasslands to croplands of >60.00% can result in slight soil salinization (Zhuang et al., 2021). The expansion of croplands also exacerbates the degradation of natural habitats (Tang et al., 2021). Fortunately, the area converted from grasslands to croplands (1.62%) was balanced by the increased area of grasslands (2.67%). The planned expansion of croplands can reduce ecosystem stress through such a balanced perspective. The Chinese government's objective is to achieve ecological and rural rejuvenation through coordinating and balancing agricultural output and 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 brings economic benefits, which will further contribute to the improvement of ecological quality in Xinjiang. 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). All these policies and measures help to mitigate the impact of cropland expansion on ecosystems.

The improvement of ecological quality in Xinjiang cannot be achieved without policy encouragement from the Chinese government, which has been implementing a series of ecological restoration policies in a scientific manner. For instance, the Three-North Shelterbelt Program (Li et al., 2012; Zhang et al., 2016; Guo et al., 2022a) and the comprehensive management project in the Tarim River Basin (Xue et al., 2019) serve as good examples in China. In the last four decades, vegetation in Xinjiang has recovered, regional desertification has been improved and human activities have had a positive effect on the greening of the region's vegetation (Guan et al., 2021). Soils have been improved in some areas with native soil salinity due to the improvements in vegetation (Ge et al., 2022b). There is a trend of sustainable ecological development in the Tarim River Basin, where natural vegetation has improved and the conversion of natural vegetation to agricultural land has been halted (Xue et al., 2019; Guo et al., 2020). Although there has been a deterioration in ecological quality locally in Xinjiang, this has not been caused by human activities and the vast majority of the deterioration has occurred in the unused barren areas. Although policy drivers have led the way to global greening (Chen et al., 2019; Guo et al., 2022b), as shown by the ecological restoration in the Tarim River Basin, we also need to consider reducing the conversion of natural vegetation to agricultural lands. In addition, afforestation needs to consider the carrying capacity of the water resources because afforestation may lower the groundwater level in arid regions (Lu et al., 2018).

The Chinese government has established nine national nature reserves in Xinjiang to demonstrate the effect of policy-driven actions (Fig. 8) (Wu et al., 2011). These reserves include

wetlands, shrublands and forests. Wetlands are the most crucial factor required for excellent RSEI (Fig. 7b) because they regulate water resources and serve as ecological barriers. According to statistics, ecological quality was improved in 21.03% of these national nature reserves, 1.04% of the area showed only slight improvement in ecological quality, 73.77% of area was stable and only 4.15% of the area had a slight deterioration. These deteriorating areas were concentrated in the Lop Nur Wild Camel National Nature Reserve and may have been caused by a shortage of water resources in the reserve due to the climate, which would increase its vulnerability (Xue et al., 2021). Wetlands, shrublands, forests and grasslands all have vital roles in the distinct levels of RSEI. These positive improvements may be the effects of national policy drivers. Policies of the River Chief System, Lake Chief System and Forest Chief Systems proposed in China (Li et al., 2020b) have also been implemented and the management of ecological quality in Xinjiang will become more precise in the future.

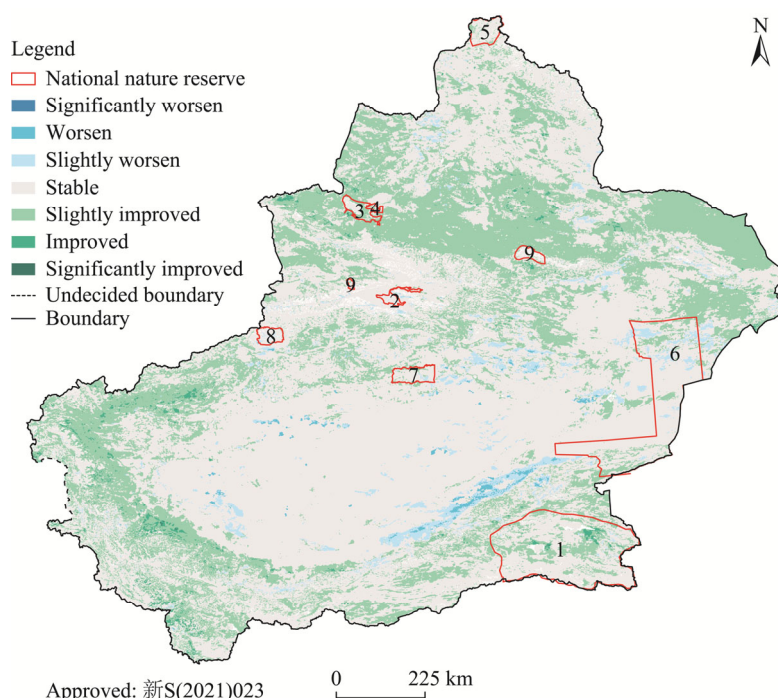


Fig. 8 Changes in ecological quality in national nature reserves in Xinjiang during 2000–2020. 1, Altun Mountains National Nature Reserve; 2, Bayanbulak National Nature Reserve; 3, Ebinur Lake Wetland National Nature Reserve; 4, Ganjiahu *Haloxylon* Forest National Nature Reserve; 5, Hanas National Nature Reserve; 6, Lop Nur Wild Camel National Nature Reserve; 7, Tarim *Populus euphratica* Forest National Nature Reserve; 8, Tomur National Nature Reserve; 9, West Tianshan Mountains National Nature Reserve. The data were from the China Nature Reserve Specimen Resource Sharing Platform (<http://www.papc.cn/>).

5 Conclusions

In this study, we constructed RSEI through the GEE platform to assess the ecological quality of Xinjiang from 2000 to 2020. We found that ecological quality in this arid region has improved due to both climate factors and human activities (changes in land use/land cover). The arithmetic power of the GEE platform supports large-scale ecological assessments. RSEI was sufficient to indicate the ecological quality in Xinjiang because the contribution of the first principal component was higher than 90.00%. The ecological quality of Xinjiang has improved and the average values of RSEI were increased by 7.00%. Ecological quality was slightly improved in 31.26% of the area in Xinjiang and remained stable at 64.32% of the land area. About 3.16% of the land area deteriorated slightly and only 0.39% of the land area deteriorated. In particular, the slightly deteriorated or deteriorated areas were distributed in the unused barren lands. The

improvement in the ecological quality of Xinjiang was driven by the warmer and more humid climate, changes in land use/land cover and government policies. Changes in temperature, precipitation, closed shrublands, grasslands and savannas had the greatest effects on the RSEI. Among the areas with slightly improved and slightly worsen ecological quality in Xinjiang, 84.25% and 74.40% of the areas, respectively, were in the barren areas. For the nine national nature reserves, 22.07% of the protected areas were restored (improved and slightly improved) and 73.77% were stable. The Chinese government achieves ecological and rural rejuvenation through coordinating and balancing agricultural output and ecological conservation in rural areas. Our results will contribute to the promotion of the UN SDGs in the inland drylands in Central Asia.

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