



Article

Spatiotemporal Analysis of the Interactions between Ecosystem Services in Arid Areas and Their Responses to Urbanization and Various Driving Factors

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Abstract: In recent years, rapid urban expansion and increasing ecological sensitivity in arid zones have led to extreme imbalances in ecosystem development. Therefore, there is an urgent need to balance the dual goals of synergistic development of ecosystem services (ESs) and increased urbanization. Previous studies have analyzed the impacts of urbanization on ESs but have selected a limited number of indicators and have not focused on the impacts of urbanization on ES pair interactions. In this study, six key ESs (water yield, habitat quality, soil conservation, carbon storage, carbon sequestration and oxygen production, and food production) and total ecosystem services (TESs) were selected, and trends in the temporal and spatial relationship between trade-offs and synergies were analyzed over 20 years. This study refined the living standards urbanization indicator and evaluated the impact of urbanization and multiple drivers on ESs and ES pair interrelationships based on geo-detectors and segmented linear regression. The results show that there is heterogeneity in the overall and regional ES trade-offs and synergistic relationships, and water yield (WY)-related ES pairs generally exhibit synergistic relationships at the overall level. Spatially, however, the trade-off ratio exceeds the synergy ratio. Segmented linear regression results show that the relationship between all the urbanization indicators and TESs demonstrates an upward trend followed by a downward trend. Measures such as the increase in man-made oases in the early stages of urbanization did have some positive effects on TESs. However, as urbanization increased, these positive effects were quickly offset by the negative effects of overdevelopment and environmental degradation, leading to an overall decline in TESs. Urbanization of construction land (CL) had the most direct impact on ecosystem services. In summary, due to special climatic constraints, arid zones are more sensitive than other ecosystems, and urban development is strictly limited by oasis capacity. As cities expand, attention needs to be focused on protecting ecological land and limiting the expansion of CL to promote the synergistic development of urbanization and ecosystem services in arid zones.



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Keywords: ecosystem services (ES); trade-offs; comprehensive urbanization level (CUL); arid zones; multiscale geographically weighted regression (MGWR)

1. Introduction

Arid zones occupy one-third of the global land area, and more than 38% of the global population is settled in these arid regions [1]. This makes drylands not only an important

part of the global ecosystem but also one of the key challenges to global socioeconomic development. With the constant progress of society and the changing climate [2], the problem of desertification is becoming increasingly serious [3,4]. At the same time, it is worth noting that arid zones are usually located in the least developed regions of the world [5]. This phenomenon triggers a complex interaction between ecology and the socioeconomy.

Ecosystems provide not only a variety of important productive resources but also indispensable ecological services in a variety of areas, such as climate regulation, air purification, soil conservation (SC), and recreation [6]. These ecological services not only support human development and well-being but also contribute to the synergistic stability between regional ecological security and socioeconomics [7–10]. However, the ecological environment of arid zones is extremely sensitive and faces the challenges of environmental degradation and fragile socioeconomic adaptation. Local urban development and human activities are highly dependent on oases, which are terrestrial ecosystems with some of the most intense human–nature interactions within arid zones. The livelihoods of local residents depend heavily on the services provided by these ecosystems [5]. However, research targeting ecosystem services (ESs) in arid zones is still insufficient compared to that targeting other regions [11].

Different ESs are often closely linked to each other and influenced by factors such as resources and the environment [12]. Measures implemented to maximize one ecosystem service often have adverse effects on other ESs [13]. Therefore, an understanding of the relationships among these ESs is essential for the effective development of sustainable ecosystem management strategies that improve human well-being [14–17].

To address the diverse ecosystem service types, spatial heterogeneity and complex interrelationships among ESs induced by human activity [18–20], an increasing number of scholars have introduced the concept of “trade-offs and synergies” to measure the interrelationships among these ESs. Trade-offs and synergistic relationships refer to the mutual constraints or mutual reinforcement between two or more objectives [21]. Although scholars have conducted many studies globally on ecosystem service trade-off relationships via a variety of methods, such as the root mean square deviation (RMSD) method [22], Pearson correlation analysis [21,23], the difference-in-difference comparison method [24], and Spearman’s correlation coefficient method, to assess the relationships among ESs, the spatial heterogeneity and trend analysis of different ecosystem service trade-offs and synergistic relationships across time and space, as well as the study of driving factors behind these balancing relationships between ESs, remain underexplored.

With rapid global urbanization, the global urban land area will triple by 2030 [25]. It is estimated that approximately 60% of the global population will live in cities [26]. Rapid expansion of urban land and rapid growth of the urban population will further increase the demand for resources, leading to ecological and environmental problems such as soil erosion, extreme weather, and global warming [27]. However, studies have shown that approximately 60% of global ESs are already degraded, with urbanization being one of the most important drivers [28]. For this reason, it is necessary to thoroughly assess the impacts of urbanization on ESs, rationally manage the rate of urban growth to prevent or reduce the ecological crises that may result, and achieve the 2030 Sustainable Development Goals [29,30].

Some studies have shown that there may be a nonlinear relationship between urbanization and ESs, implying that there are critical thresholds between urbanization and ESs [31]. Segmented linear regression is an effective analytical method for identifying the turning point at which two trends intersect [32], and it is widely used in ecosystem studies. It has been successfully used in past studies to assess the response of total ESs (TESs) and their thresholds to demographic, economic, and land urbanization [33]. However, few studies have considered the effects of living standard urbanization on TESs, which is an important addition to this study. To obtain a more comprehensive understanding of the impacts of urbanization on ESs and thresholds, a segmented linear

regression approach was chosen in this paper. In addition, geo-detector models are widely used to identify the spatial impacts of urbanization on ESs [34]. In this study, segmented linear regression and geo-detector models will be applied in combination to characterize the thresholds, patterns, and intensity of the impacts of urbanization indicators on ESs more accurately.

Located in the center of Asia and Europe, Xinjiang is the largest oasis area in China and the fastest-growing oasis in the world, comprising the core area of the Silk Road Economic Belt and a major area for the development of new energy sources. However, it is also an extremely fragile ecological environment, with serious desertification. More than 80 counties and cities in the region suffer from the hazards of land desertification and a fragile ecological environment [35]. Over the past 40 years, the area of oasis in Xinjiang has expanded by approximately 20%, while urban land use has increased by more than 200% [36], and the contradiction between the carrying capacity of the ecological environment and economic development has become increasingly prominent. Rapid social and economic development will lead to the degradation of ES and, in turn, will limit human socioeconomic development.

In light of the aforementioned issues, this study evaluated six ESs, namely water yield (WY), habitat quality (HQ), soil conservation (SC), carbon storage (CS), carbon sequestration and oxygen production (CSOP), and food production (FP) according to the actual situation of Xinjiang and obtained the total ecosystem services (TESs). This study aims to: (1) clarify the relationship between ESs based on a multiscale geographically weighted regression (MGWR) [37] model and a Pearson correlation analysis, and at the same time, evaluate the spatial and temporal dynamic trends to assess the trade-offs and synergistic relationships in the spatial distribution of ESs in Xinjiang from 2000 to 2020; (2) analyze the changes in urban construction in Xinjiang over the past 20 years based on the shift in the center of gravity of core urban construction land (CL) in the top ten GDP regions; (3) detect the level of urbanization in Xinjiang based on the indicators of population, economy, land, and standard of living and refine the comprehensive urbanization level indicator (CUL); (4) combine the results with segmented linear regression and geo-detector model to quantify the impacts and thresholds of urbanization indicators on TESs and discern the main drivers affecting ecosystem service interactions. The objective of this study is to comprehensively and quantitatively assess the interaction mechanisms between TESs and urbanization and to provide references and suggestions for the coordination between ecosystems and urbanization in arid zones.

2. Materials and Methods

2.1. Study Area

The Xinjiang Uygur Autonomous Region is located in the central part of Eurasia in Northwestern China, with a geographical location of 73°40′~96°23′E, 34°25′~49°10′N; a vast area that is rich in mineral resources and tourism resources with a complex topography and geomorphology, low vegetation cover, low precipitation, high evaporation, and uneven distribution of water resources. The vertical distribution of natural resources ranges from −159 m to 8234 m in the mountains, forming a complex and diversified ecosystem of natural resources in the inland arid zone, which is unique (Figure 1).

2.2. Data

This study used remote sensing data, land use data, basic geographic data, climate data, POI data, and social statistical data. The detailed information is listed in Table 1.

- (1) Land use data from the Chinese Academy of Sciences Resource and Environment Science and Data Center (RESDC) (<https://www.resdc.cn/> (accessed on 13 April 2023)) from 2000 to 2020 are issued every five years. According to the actual situation of the research area, the secondary classification data will be reclassified into the following nine categories: cultivated land (CR), forestry land (FR), high-coverage

- grassland (HGS), medium-coverage grassland (MGS), low-coverage grassland (LGS), water area (WA), glacier (GL), CL, and unused land (UL).
- (2) GDP and population (POP) data are from the Chinese Academy of Sciences (RESDC) (<https://www.resdc.cn/> (accessed on 9 June 2023)).
 - (3) The temperature and precipitation grid data are sourced from the National Earth System Science Data Center and are in a NetCDF (.nc) format with a spatial resolution of 1 km. These data need to be converted into grid data in ArcGIS (ArcGIS Pro 3.0.0).
 - (4) The digital elevation model (DEM) data are from a geospatial data cloud platform with a spatial resolution of 1 km.
 - (5) The NDVI data include a MODIS13Q1 dataset synthesized and downloaded through the GEE platform with a spatial resolution of 1 km.
 - (6) Soil data (<https://www.fao.org/> (accessed on 19 April 2023)), including soil texture, soil sand content, silt content, clay content, organic carbon content, and root depth, were collected using the World Soil Database (HWSD)-based World Soil Dataset (v1.2) with a resolution of 1 km.
 - (7) The evapotranspiration and net primary productivity (NPP) data were taken from the MOD17A1 dataset on NASA with a resolution of 500 m.
 - (8) POI data were sourced from Baidu and Gaode.

All the above data are based on ArcGIS software and converted into a unified projection coordinate system (WGS1984).

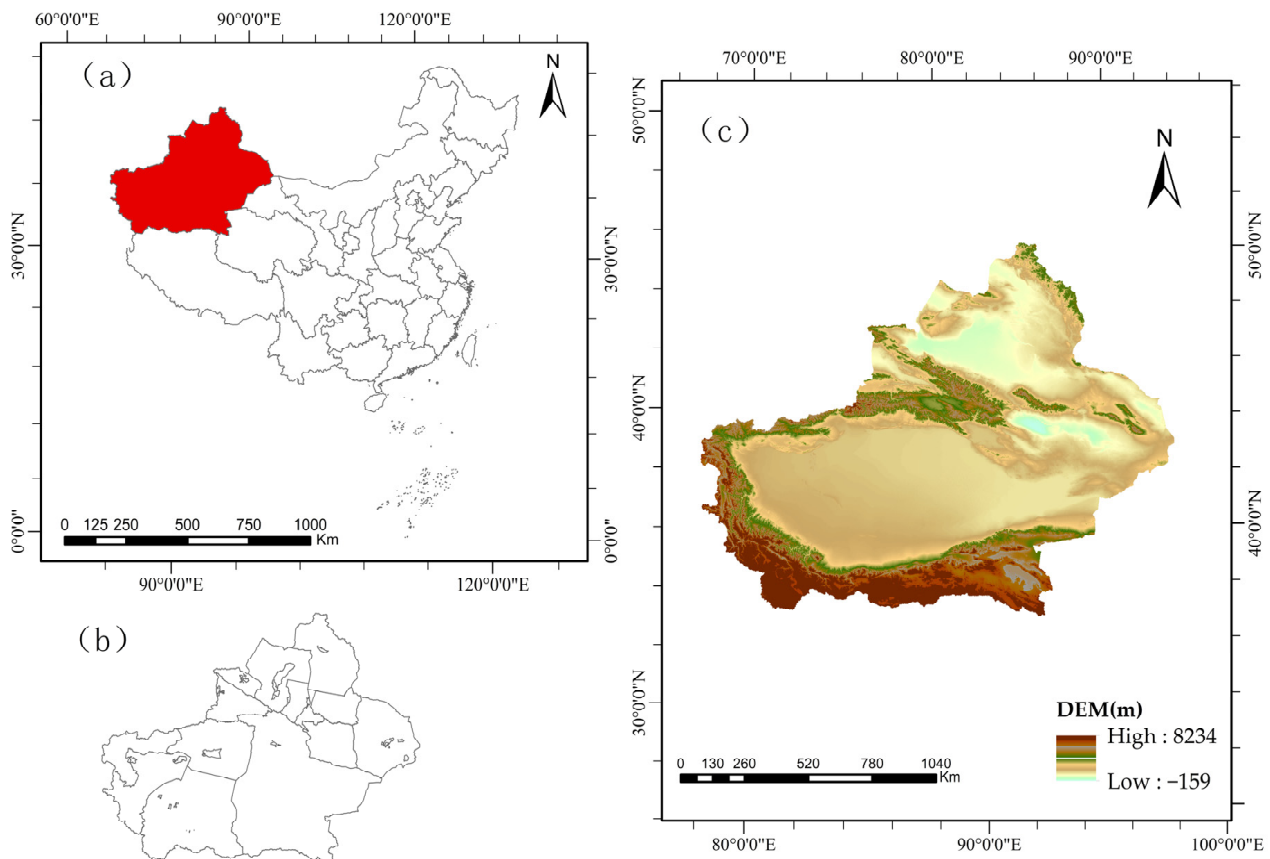


Figure 1. Location of the study area. (a) location of XinJiang in China; (b) administrative divisions; (c) DEM.

Table 1. Data sources.

Data	Time	Resolution	Data Sources
Land use/land cover (LULC) data	2000~2020	1 km	Resource and Environment Science and Data Center (http://www.resdc.cn/ , accessed on 13 April 2023)
DEM	2020	1 km	Geospatial Data Cloud (http://www.gscloud.cn , accessed on 24 April 2023)
Normalized difference vegetation index (NDVI)	2000~2020	1 km	GEE
NPP	2000~2020	500 m	NASA
Temperature	2000~2020	1 km	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn/ , accessed on 23 April 2022)
Precipitation	2000~2020	1 km	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn/ , accessed on 23 April 2023)
Evapotranspiration	2000~2020	500 m	NASA
Soil data	2020	1 km	Harmonized World Soil Database (HWSD) (https://www.fao.org/ , accessed on 19 April 2023)
GDP	2000~2019	1 km	Resource and Environment Science and Data Center (http://www.resdc.cn/ , accessed on 9 June 2023)
POP	2000~2019	1 km	Resource and Environment Science and Data Center (http://www.resdc.cn/ , accessed on 9 June 2023)
POI	2012~2022	\	Baidu, GaoDe
Social statistical data	2000~2020	\	https://tjj.xinjiang.gov.cn/ , accessed on 24 April 2023

2.3. ES Evaluation

In the past 60 years, rapid population increases, oasis expansion, and urbanization in Xinjiang have broken the original ecological stability and posed a serious threat to local sustainable development. Therefore, the InVEST model was used to quantitatively assess four typical ESs, namely carbon storage, HQ, water production, and SC, in accordance with the actual situation in Xinjiang. CSOP and food production (FP) services were also added for a more comprehensive assessment of local Ess (Table 2). The six ES were standardized and integrated into TESSs, and the InVEST model was able to select targeted algorithms and data according to the assessment requirements of different ecosystem service types with multimodule and multilevel characteristics. Moreover, the data input is relatively simple and easy to obtain, and the operation efficiency is high. At the same time, it is easy to combine with other specialized software to spatially display the results of ecosystem service function assessments, which helps decision makers to better understand the characteristics and spatial distribution of ESs.

Table 2. Ecosystem services evaluated in this study.

Ecosystem Service	Description	Methodology	Abbreviation
Soil conservation [38]	Soil conservation capacity of ecosystems	Sediment retention model of InVEST	SC
Water yield [39,40]	The yield of annual water	Water yield model of InVEST	WY
Habitat quality [41]	Measuring the rank of biodiversity under ecosystem services	Habitat quality model of InVEST	HQ
Carbon storage [42]	Carbon storage in ecosystems	Carbon storage and sequestration of InVEST	CS
Carbon sequestration and oxygen production [43]	Oxygen production capacity of ecosystems	Photosynthesis equation	CSOP
Food production [44,45]	Production of major food crops	Linear relationship between grain output and NDVI	FP

2.4. Trade-Offs and Synergy Analysis among Ecosystem Services

A correlation analysis is usually used to study the correlation between variables. In this paper, Pearson's correlation analysis was used to study the trends in the relationships among six ESs, namely water production, SC, CS, HQ, CSOP, and FP, from 2000 to 2020 at the global scale. The magnitude of the value indicates the strength of the correlation, with a positive value indicating that one ecosystem service will be enhanced with the enhancement of another, i.e., a synergistic relationship, and vice versa for a trade-off relationship. The formula is as follows:

$$R_{ab} = \frac{\sum_{i=1}^n (ES1_i - \overline{ES1})(ES2_i - \overline{ES2})}{\sqrt{\sum_{i=1}^n (ES1_i - \overline{ES1})^2 \sum_{i=1}^n (ES2_i - \overline{ES2})^2}} \quad (1)$$

where R_{ab} represents the correlation coefficient between ecosystem services; $R_{ab} \in [-1, 1]$. $R > 0$ indicates a positive correlation, and $R < 0$ indicates a negative correlation. The closer R is to 1, the stronger the correlation between ES. $ES1_i$, $ES2_i$ represents the variable values; $\overline{ES1}$, $\overline{ES2}$ denotes their respective means; and n represents the sample size.

2.5. MGWR Model Trade-Offs and Synergistic Spatial Analysis

To explore the spatial interaction correlation among ESs, previous studies have mostly used the geographically weighted regression (GWR) model [46]. The multiscale geographically weighted regression (MGWR) model is an upgraded version of GWR that accounts for the spatial scale differences between different variables, with each selected variable presenting different scale characteristics, which is more in line with the spatial heterogeneity of geographic processes. In this paper, ArcGIS PRO is used to implement the calculation and visualization of the MGWR model. The calculation formula is as follows:

$$y_i = \beta_{bw0}(u_i, v_i) + \sum \beta_{bwk}(u_i, v_i)x_{ik} + \varepsilon_i \quad (2)$$

where y_i represents the dependent variable value at point i , (u_i, v_i) represents the spatial coordinates of point i , $\beta_{bw0}(u_i, v_i)$ represents the intercept at point i , $\beta_{bwk}(u_i, v_i)$ represents the optimal local regression coefficient at point i , x_{ik} represents the independent variable value, and ε_i represents the random error term.

2.6. Geographical Detector Model Spatial Analysis

Geographic phenomena have spatial heterogeneity. In this paper, we use the geographical detector model (Geo-Detector) to explore the spatial heterogeneity of drivers affecting ecosystem service trade-offs in Xinjiang, which can reveal the driving relationships behind geographic phenomena [47,48]. The formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (3)$$

where q represents the explanatory power of the factor and N_h and N denote the number of units in layer h and the total number of units, respectively. σ_h^2 and σ^2 represent the variances in layer h and the overall variance, respectively, L represents the number of divided regions, and a larger q value indicates a more pronounced influence of the independent variable on the dependent variable.

2.7. Comprehensive Evaluation of the Urbanization Level

The multifaceted manifestation of urbanization includes population growth, economic development, CL expansion, and living standards improvements [49]. Economic prosperity is regarded as the fundamental basis of urbanization; continuous population growth and urban CL expansion specifically reflect this trend, and continuous improvements in living standards are regarded as the ultimate goal [50]. Previous studies have tended to focus on only three aspects: population, economy and urban built-up land [51]. To measure the CUL

more comprehensively, this study adds four indicators of improved living standards based on POI data: resident savings (RES), accessibility of medical beds, accessibility of transport facilities (TF), and accessibility of living services (LF). Together, these four indicators consider the degree of convenience of medical, transportation, economic, shopping, and leisure needs, essentially covering multiple aspects of residents' daily lives. Specifically, population urbanization is measured by population density, economic urbanization based on GDP, and building land expansion based on the building land ratio. Living standard urbanization is measured based on a combination of four new indicators. These seven indicators are standardized and combined into a CUL.

2.8. Threshold Analysis of the Impact of Urbanization on Ecosystem Services

To accurately delineate the thresholds of the impact of urbanization indicators on ESs and to identify critical nodes in the relationship shift, in this study, not only is the geo-detector adopted, but segmented linear regression is also applied using the R language to identify the thresholds of the impact of ESs on TESs. Segmented linear regression methods are widely used to identify critical thresholds in relationship shifts, and the model actually combines two regression lines before and after the fold point. Segmented linear regression allows for simultaneous fitting of segments (different ranges) of data at the same time, as summarized in the following calculations [32]:

$$y = \begin{cases} \beta_0 + \beta_1 x + \varepsilon, & x \leq a \\ \beta_0 + \beta_1(x - a) + \varepsilon, & x > a \end{cases} \quad (4)$$

where y represents TES, x represents the level of urbanization, a represents the urbanization level at the inflection point, β_0 and β_1 are coefficients, and ε represents the error term.

In this study, the seven urbanization indicators and the comprehensive indicator CUL will be used as independent variables in segmented linear regression, aiming to clarify the changing trends in the impact of the urbanization process on ecosystems.

3. Results

3.1. Land Use Changes

Figure 2 shows the changes in different land use types in Xinjiang between 2000 and 2020. Xinjiang has a total area of 1.66 million square kilometers, and land use is dominated by unused land, which accounts for 61% of the total area, followed by grassland, which accounts for 29% of the total area. CL, FR, and WA account for less than 7% of the total area. The change from 2000 to 2010 was relatively small, with mainly grassland and unused land converted to CL. From 2010 to 2020, with the country's vigorous development of Xinjiang, its land-use pattern changed dramatically. Grassland and unused land were converted in large quantities. CR, FR, WA, and CL all increased, with CL increasing the most, over 90,000 square kilometers, followed by CR, which increased by approximately 51% compared to 2000, reaching 89,000 square kilometers.

During the period from 2000 to 2020, the different land use types are transformed by area as follows: CR > grassland > CL > WA > FR > unused land > glacier.

3.2. Relocation of Construction Land Center in Xinjiang

Changes in CL often reflect changes in the center of gravity of urban development and construction; thus, this study chose core cities in the top ten regions of Xinjiang in terms of GDP to explore the migration of the center of gravity of their CL (Figure 3). The results show that the largest amount of migration in the direction of urban development is Tulumfan, followed by Kashgar, and the smallest change in the direction of urban development during this 20-year period is Tacheng City, followed by Yining City.

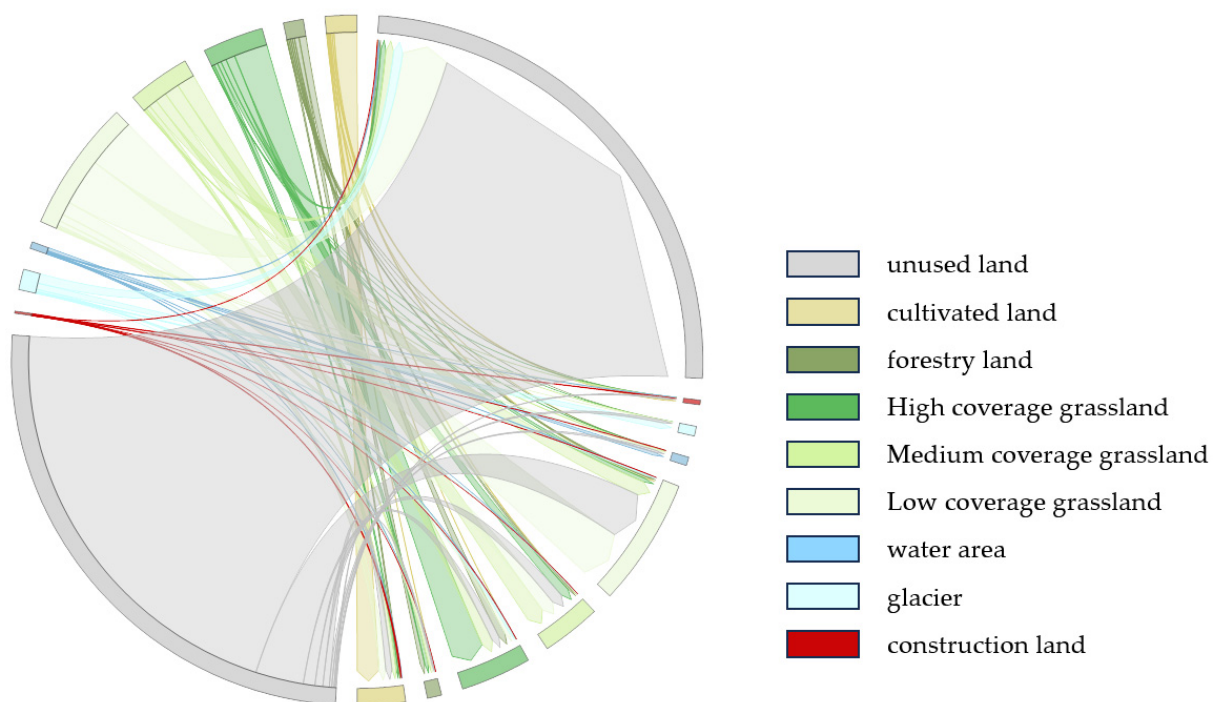


Figure 2. Land use conversion changes in Xinjiang from 2000 to 2020.

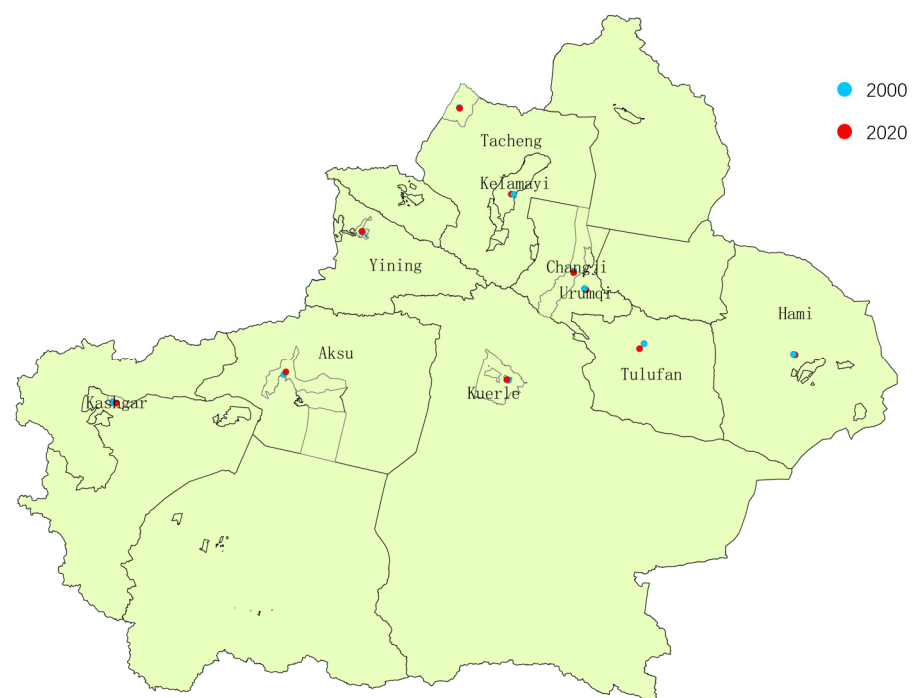


Figure 3. Relocation of construction land centers in the top ten regions based on GDP.

3.3. Spatial Patterns and Temporal Changes in Ecosystem Services in Xinjiang

To assess the changes in ESs in Xinjiang, six typical ESs were selected, namely CS, HQ, water production, soil retention, CSOP, and FP, in combination with the characteristics of the study area. Then, the changes in these six ESs were quantified and analyzed for the period of 2000–2020.

(1) Carbon storage

In the context of climate warming and carbon neutrality, the study of spatial and temporal changes in CS in ecosystems is helpful for relevant departments to make decisions on carbon neutrality. From 2000–2020, the CS in Xinjiang increased continuously (Figure 4); the total amount of CS in 2020 was 8.4×10^9 t. The increase was small, in the range of 0.3~0.5%, from 2000 to 2015, and the increase was larger from 2015 to 2020, reaching 2%. According to the land use change, a large amount of unused land was converted to grassland, which provided a higher carbon source.

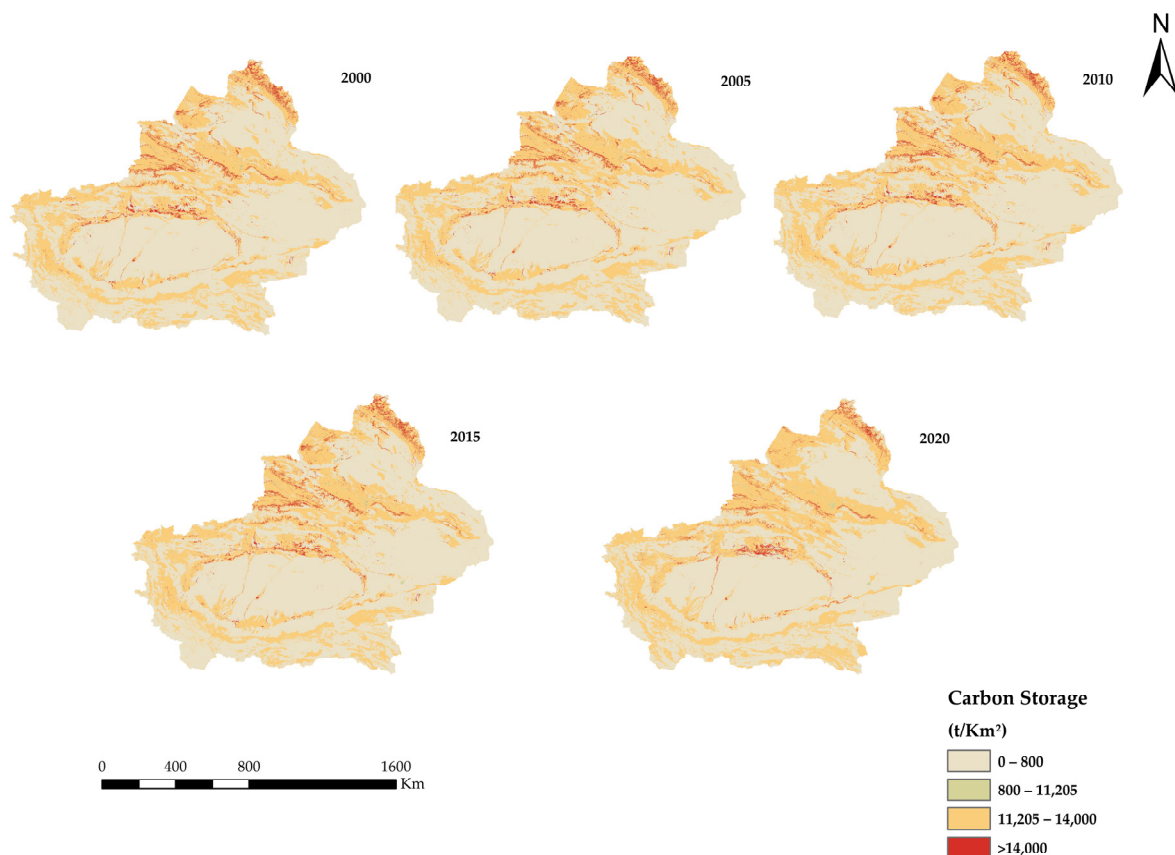


Figure 4. Spatial distribution of carbon storage from 2000 to 2020.

(2) Habitat quality

HQ, which represents the ability of an area to provide living conditions for organisms, is relatively average in Xinjiang as a whole. The areas with slightly higher HQs are mainly near the Yili and Bortala Mongol Autonomous Prefectures; a large proportion of the desert in the southern part of the country is of low quality (Figure 5). In southern Xinjiang, where deserts account for a large proportion of the area, HQ is generally low; furthermore, HQ declined steadily from 2000 to 2020. Since 2000, the low-value areas have been expanding uniformly, centered on the economic zone on the northern slopes of the Tianshan Mountains. HQ is highly influenced by human activities [52,53]. Section 3.5, “Analysis of Driving Factors”, provides a detailed examination of the factors affecting HQ. Among these factors, POP exerted the greatest impact. The noticeable degradation of HQ in the Tianshan Northern Slope is predominantly attributed to the economic development in Xinjiang and the increase in human activities.

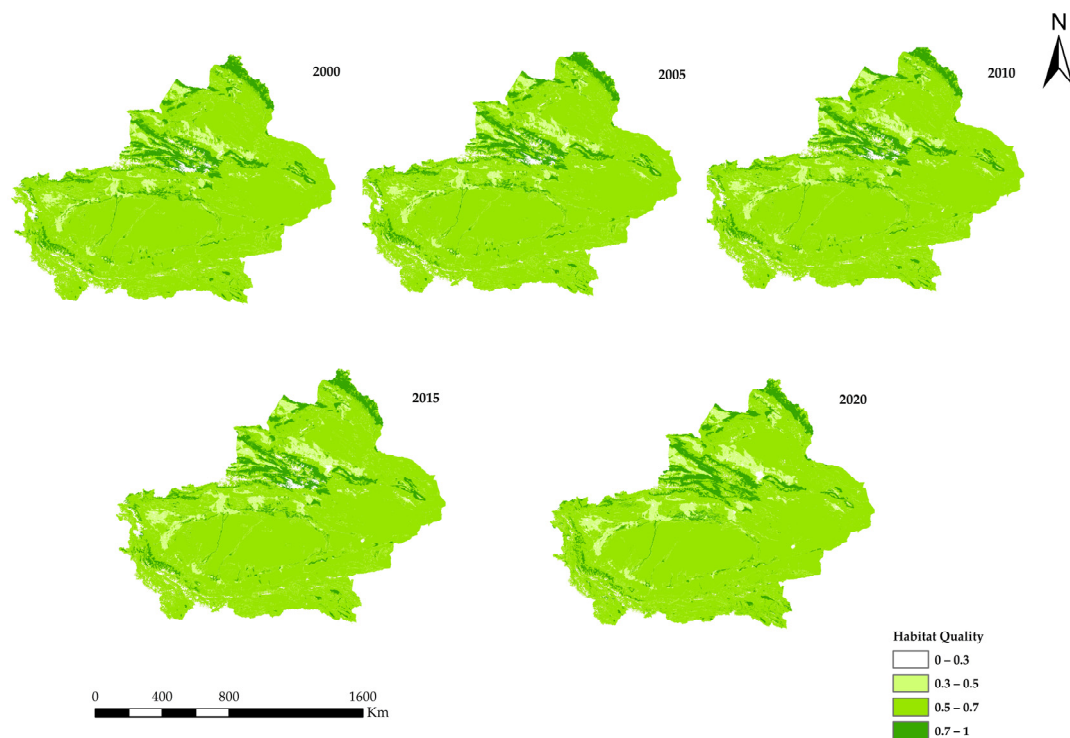


Figure 5. Spatial distribution of habitat quality from 2000 to 2020.

(3) Water yield

Changes in WY are of great significance to surface runoff, soil properties, and vegetation growth. The results show that the WY in Xinjiang had a varying trend from 2000 to 2020. The year 2010 had the highest WY, with an average of 1123 mm. The WY in Xinjiang increased from 946.51 mm to 1123.1 mm from 2000 to 2010, then decreased to 923.18 mm in 2015, and then rebounded to 991.93 mm in 2020. The simulation results for WY include surface water and groundwater; therefore, it is more appropriate to compare them with the total water resource data in the water resources bulletin of that year. A comparison with the data in the water resources bulletins of Xinjiang from 2000 to 2020 shows that the differences are not large, thus indicating that the simulation results of this study are accurate. As shown in Figure 6, the WY region in Xinjiang is divided by the Tianshan Mountains, and the high-value areas of WY are distributed in the Erqis River basin in Northern Xinjiang, spanning the Tacheng and Altay regions, except for the southern part of the Bayin'guoleng Mongol Autonomous Prefecture, which provides a higher WY. The Altay region is a water-abundant area in Xinjiang, which is recognized by the State Council as a water-containing mountain and grassland ecological functional area. According to the statistics of Xinjiang Water Resources Bulletin in 2020, the total water resources of Yili Prefecture alone accounted for 37% of the total water resources of the entire Xinjiang Province, again confirming the accuracy of the spatial simulation.

(4) Soil conservation

Soil erosion can be understood more intuitively and clearly by simulating the soil retention capacity [37], which is important for protecting and improving soil and water resources and helps determine the economic and social benefits of soil and water resources. Figure 7 shows that the region with better SC capacity is located in the northern part of the Tianshan Mountains, with many ecological and environmental protection zones and high vegetation cover, which reduce soil erosion. The Taklamakan and Gurbantunguqi Desert regions have very low soil retention capacities because they all comprise sandy soils. Over the past 20 years, the soil conservation capacity in Xinjiang has shown a trend of an initial increase followed by a subsequent decline. The overall soil retention level was higher in

2015; however, considering the distribution of WY in Figure 6, we can conclude that this was due to the low WY in the Tarim Basin in 2015, which resulted in less soil loss.

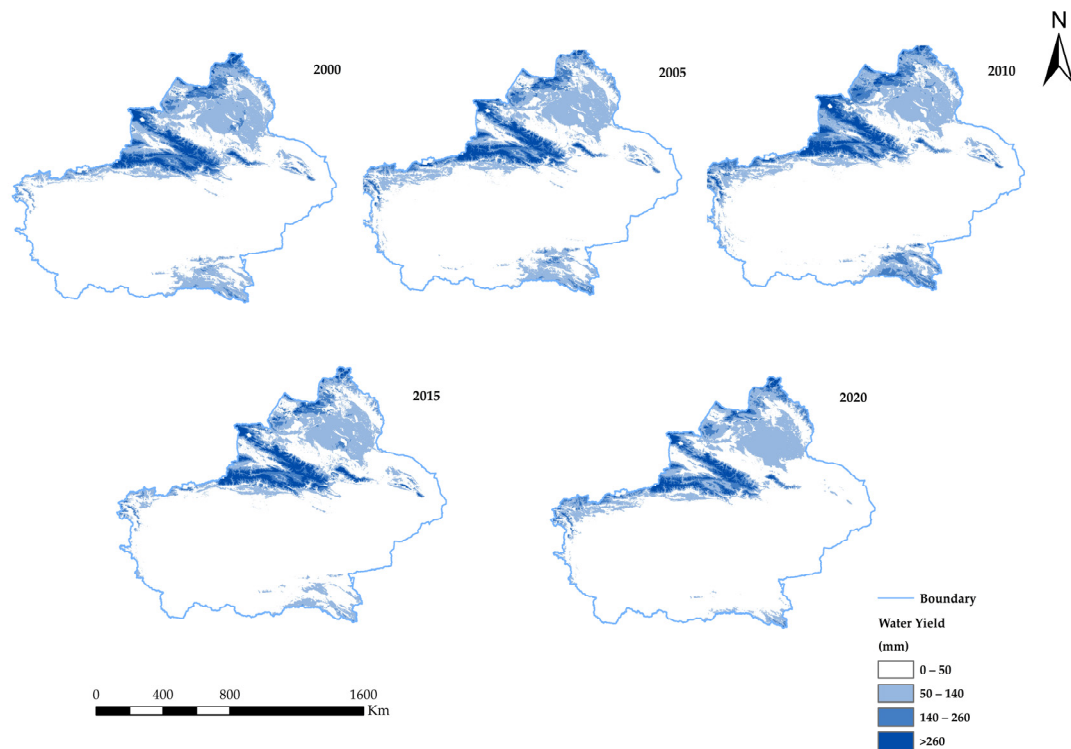


Figure 6. Spatial distribution of water yield from 2000 to 2020.

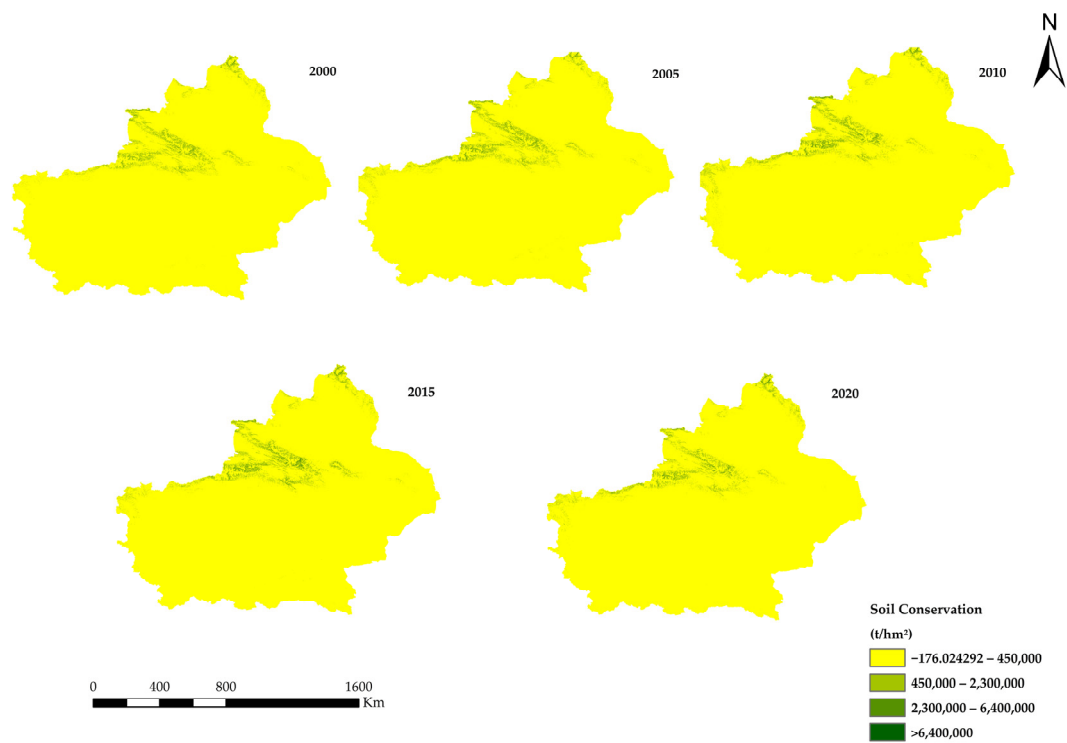


Figure 7. Spatial distribution of soil conservation from 2000 to 2020.

(5) Carbon sequestration and oxygen production

CSOP services can improve the living environment of residents and reduce the greenhouse effect. These services are calculated from NPP data based on the photosynthesis of vegetation. Because the desert area has no NPP value due to its lack of vegetation cover and thus cannot provide these services, they are not included in calculations of the CSOP service (Figure 8). Oxygen production in Xinjiang increased from 2000 to 2010, with figures rising from $2.32 \times 10^8 \text{ g/m}^2$ to $2.6 \times 10^8 \text{ g/m}^2$. CSOP decreased in 2015 and then increased to its highest value in 2020, reaching $2.75 \times 10^8 \text{ g/m}^2$, which, combined with the change in land use, was attributed to the large increase in grassland. The high values of CSOP were mainly distributed in areas with a high vegetation cover, such as Yili and Bortala Mongol Autonomous Prefecture.

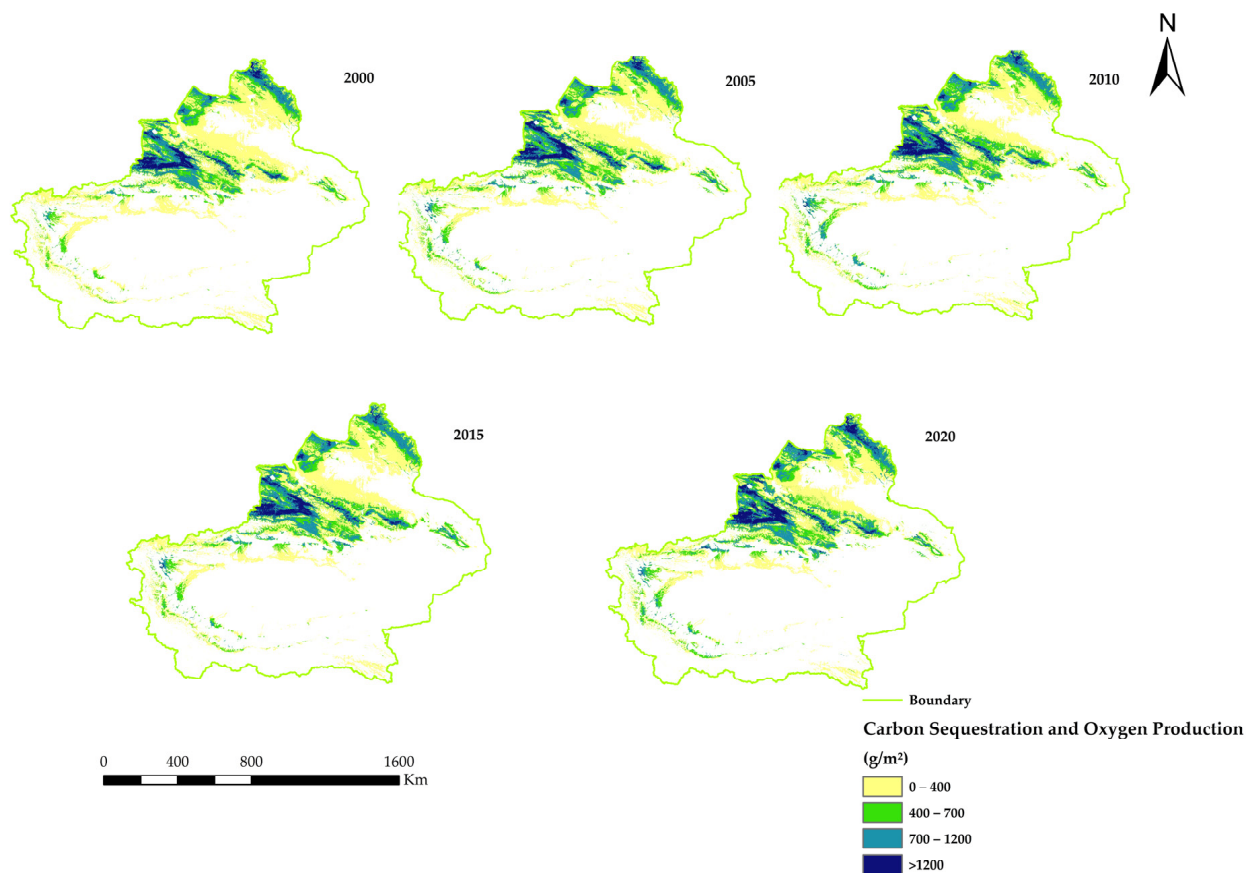


Figure 8. Spatial distribution of carbon sequestration and oxygen production from 2000 to 2020.

(6) Food production

FP capacity is linked to the basic survival of people; therefore, only basic food crops are accounted for in the calculation and not cash crops such as fruits and livestock. The trend of change in FP is similar to that of CSOP and WY, as it also shows a trend of increase and decrease (Figure 9). From 8.214 million tons in 2000, it rose continuously to a peak of 18.9533 million tons in 2015 and then fell to 15.834 million tons in 2020. Grain production is affected by the natural environment, local policies, and other multiple influences. High values are also distributed in Yili, Bortala Mongol Autonomous Prefecture, etc.

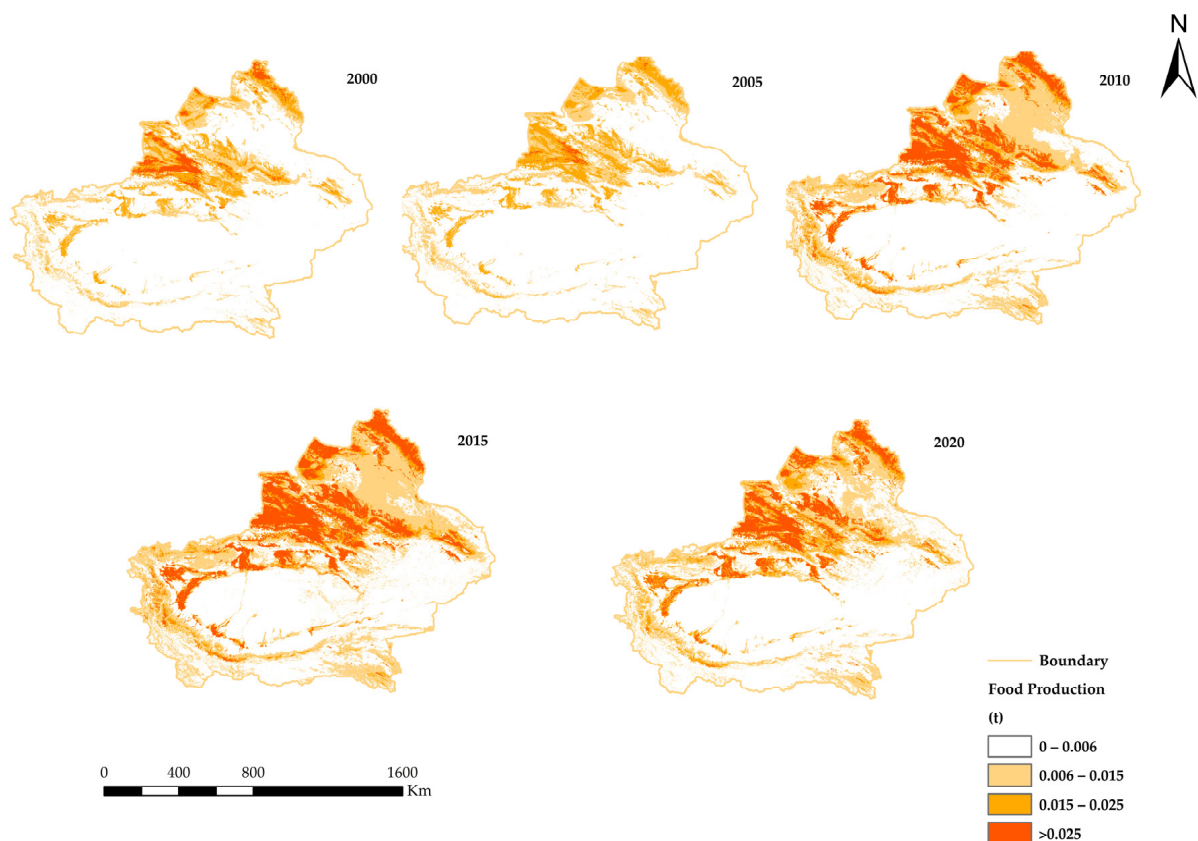


Figure 9. Spatial distribution of food production from 2000 to 2020.

3.4. Spatial and Temporal Analysis of Ecosystem Service Trade-Offs and Synergies in Xinjiang

3.4.1. Spatial Distribution of Ecosystem Service Trade-Offs and Synergies in Xinjiang in 2000 and 2020

Due to the wide area of Xinjiang and the great difference in topography and climate between the northern and southern borders, a spatial representation can more intuitively show the actual ecosystem service relationship changes in Xinjiang. The spatial correlation of ES was identified by a GWR model, and the results are shown in Figure 10. The proportions of spatial synergies of CS-SC, HQ-SC, CSOP-HQ, FP-SC, FP-HQ, and FP-CSOP were higher than those of the spatial trade-offs, indicating that spatial synergies predominated in these ES pairs. The high spatial synergies of these ES pairs were mainly in Bayin'guoleng Mongol Autonomous Prefecture. In contrast, the proportions of CS-WY, CSOP-SC, CSOP-WY, CSOP-CS, and FP-WY spatial trade-offs were higher than the proportions of spatial synergisms, suggesting that these ES pairs were characterized by spatial trade-offs. The high spatial trade-offs of the CSOP-associated ES pairs were mainly distributed in the Tianshan Mountains close to the Tarim Basin, whereas the areas of high spatial trade-offs of the WY-associated ES pairs were mainly in East Xinjiang and partly distributed in the Tarim Basin (CS-WY, FP-WY). The spatial synergies and trade-off ratios of the remaining ES pairs varied only slightly. A comparison of the two figures shows that the spatial trade-offs between ESs in Xinjiang increased significantly over the past 20 years, consistent with the results in Figure 10. Meanwhile, the spatial pattern of ES in Xinjiang remained relatively stable during these 20 years, and there was no significant shift in the relationships between ESs, except for the decrease in the overall synergistic relationship.

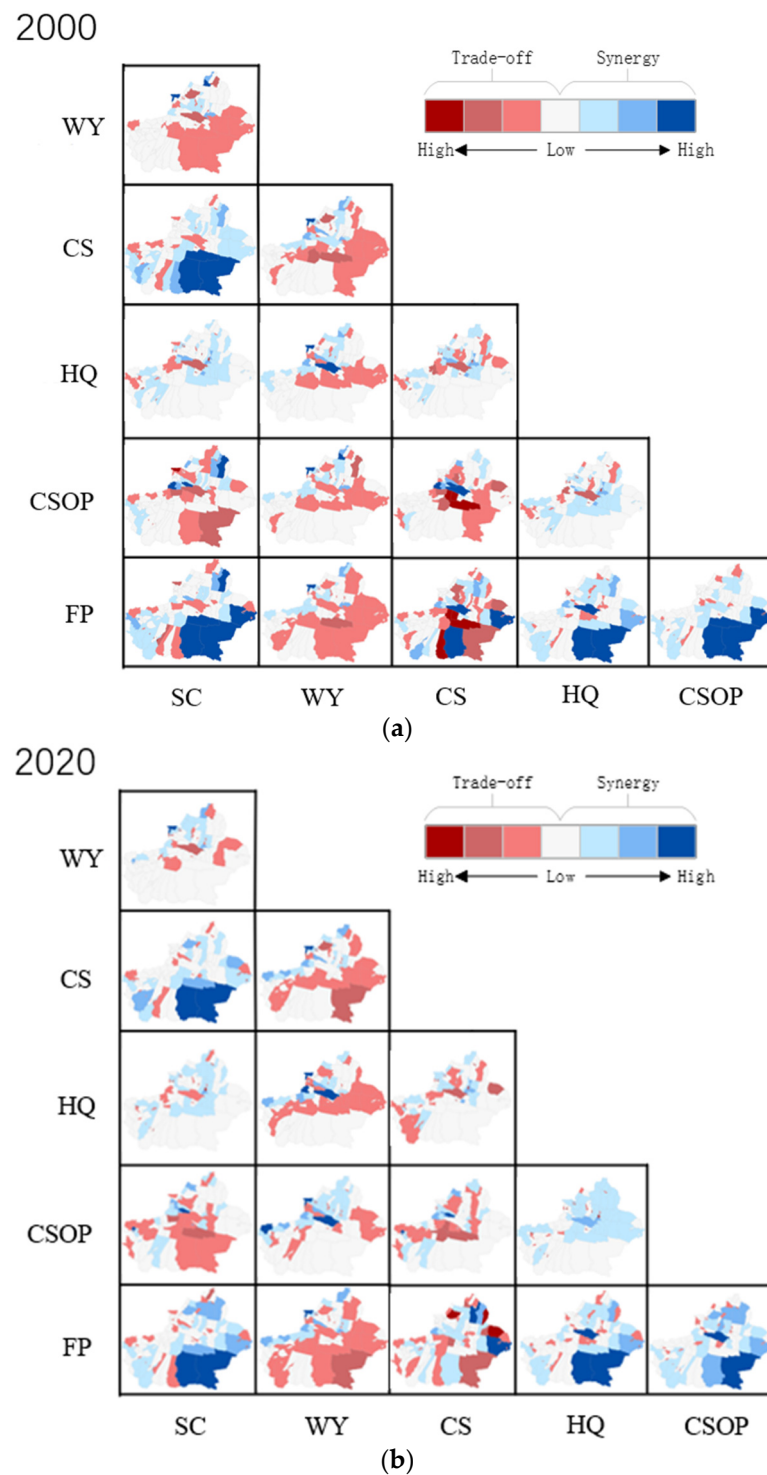


Figure 10. Spatial distribution of ES pair trade-offs in Xinjiang in 2000 (a) and 2020 (b).

3.4.2. Temporal Changes in Ecosystem Service Trade-Offs and Synergies in Xinjiang from 2000 to 2020

The trends in the dynamics of these six ESs were assessed using a time series from 2000 to 2020, as shown in Figure 11a. The increase in trade-offs between ESs in Xinjiang mainly occurred between CS and WY, HQ, CSOP; HQ and SC, FP; FP and CSOP; and SC and CSOP, and the trend of increase was obvious. The strongest synergistic trend was between HQ and WY and CSOP, as well as FP and SC. The relationship between WY and SC, FP, and CSOP has remained stable over the past two decades.

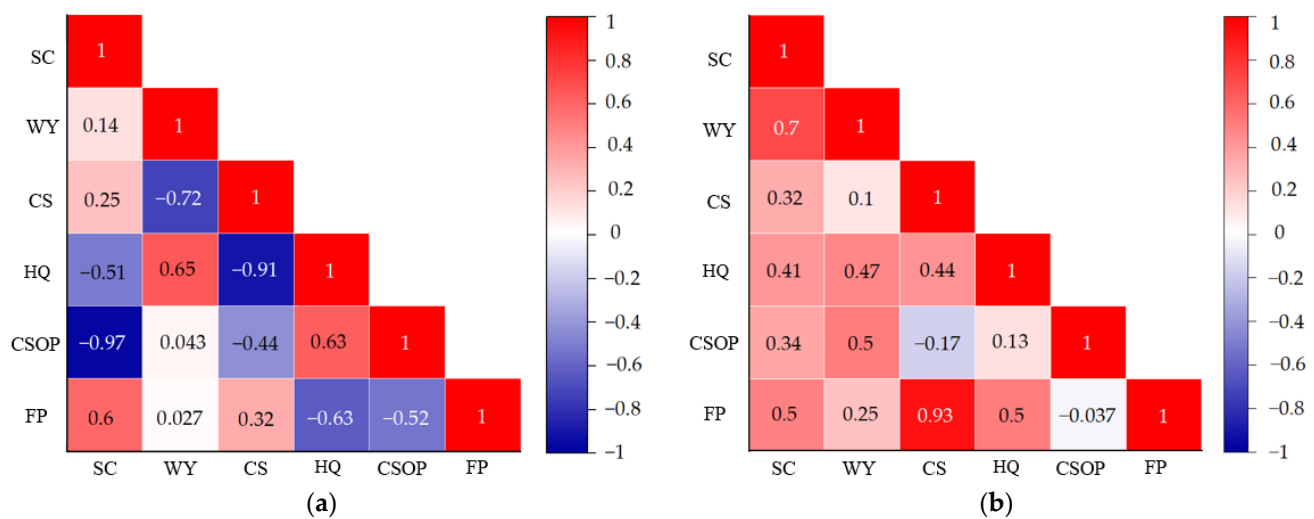


Figure 11. (a) ES pair trade-off and synergy variation in XinJiang for the years 2000–2020; (b) ES pair trade-off and synergy variation in XinJiang in 2020.

The interrelationships and the spatial distribution of trade-offs and synergies for the overall ES pairs in the region in 2020 were compared (Figures 10b and 11b). In 2020 alone (Figure 11b), all the ecosystems were synergistic, except for the weak trade-offs between CSOP and CS and FP. Spatially, the area where the trade-off between CSOP and CS remained was greater, but the area where CSOP and FP were synergized was substantially higher. Meanwhile, although the overall area remained synergistic, the proportions of the trade-off area were also higher than those of the synergistic area for CSOP-SC, CSOP-WY, and FP-WY. This indicates that there is heterogeneity between the spatial distribution of ES and the trade-offs and synergies derived from the overall numerical statistics. Furthermore, spatial trade-offs and synergies should be accounted for not only in the overall scope of the trade-offs and synergies but also in the planning of ecological protection or regional development.

3.5. Analysis of Driving Factors

Changes in ESs and their related relationships are driven by a combination of natural and anthropogenic factors. To address the complex interactions between multiple ESs in time and space, fifteen drivers, namely DEM, fractional vegetation cover (FVC), grasslands proportion (GP), cultivated land proportion (CUP), forestry land proportion (FP), precipitation, temperature, evaporation, construction land proportion (CLP), gross domestic product (GDP), POP, RES, TF, LS, and medical convenience (MC), were selected to identify the main ES and trade-off relationships based on the geo-detector model. The results, as shown in Table 3, showed that the most significant factors affecting SC were temperature and evapotranspiration. WY, on the other hand, was significantly influenced by precipitation and evapotranspiration. CS was mainly influenced by CLP, GDP, and TF. HQ was mainly influenced by CUP, GDP, and POP. The main drivers of CSOP processes included FVC and precipitation. In addition, the effects of urban drivers on FP were quite significant.

The magnitude of the effects of the drivers on the ecosystem service pair correlations is shown in Figure 12. Among all the drivers, temperature, precipitation, evapotranspiration, CLP, POP, and FVC had the greatest influence on the interactions between all ES pairs. Among them, CS-HQ, CS-CSOP, CS-FP, HQ-FP, and CSOP-FP were more affected by urbanization, while the remaining ESs were mainly driven by natural factors such as temperature, precipitation, and evapotranspiration.

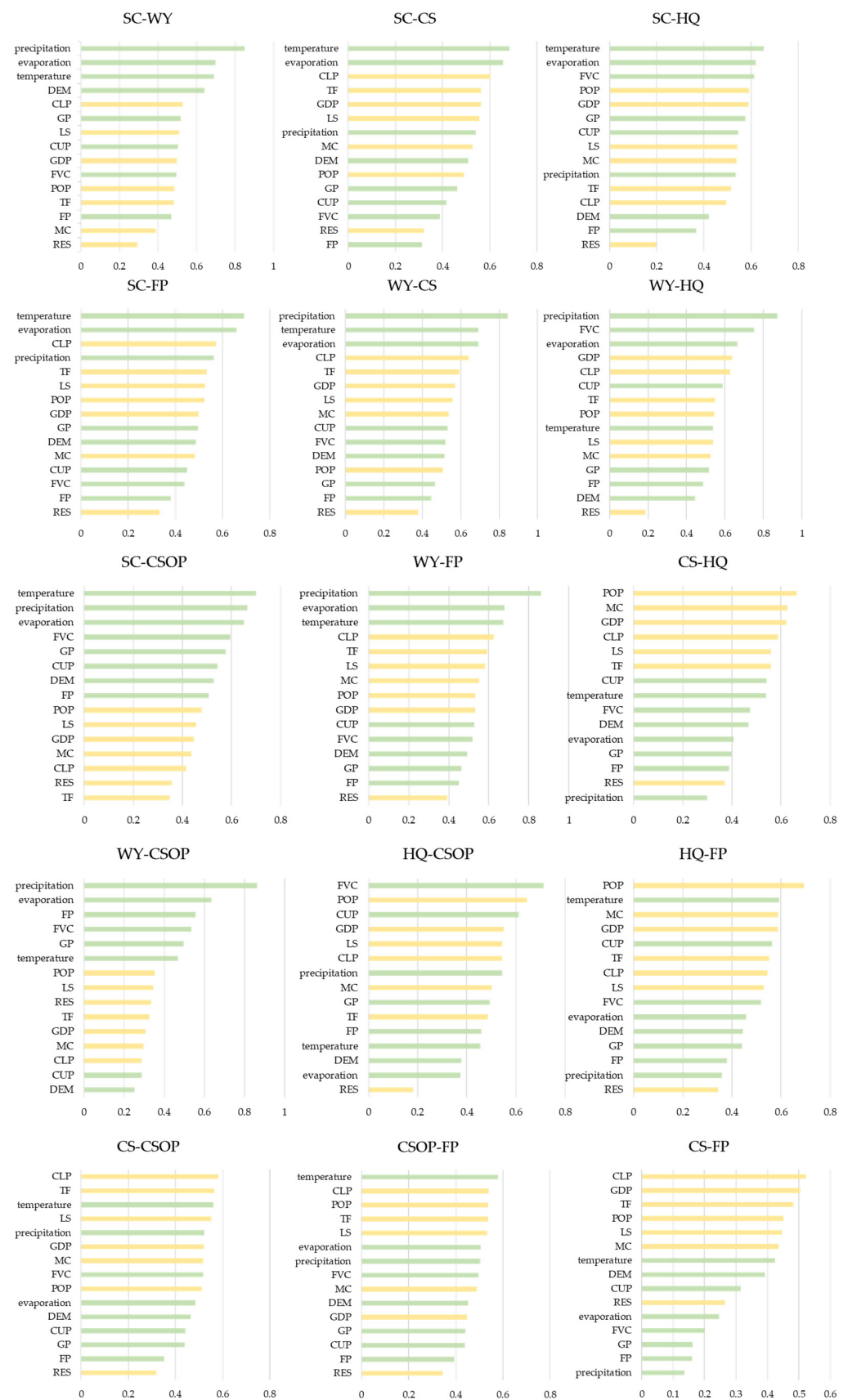
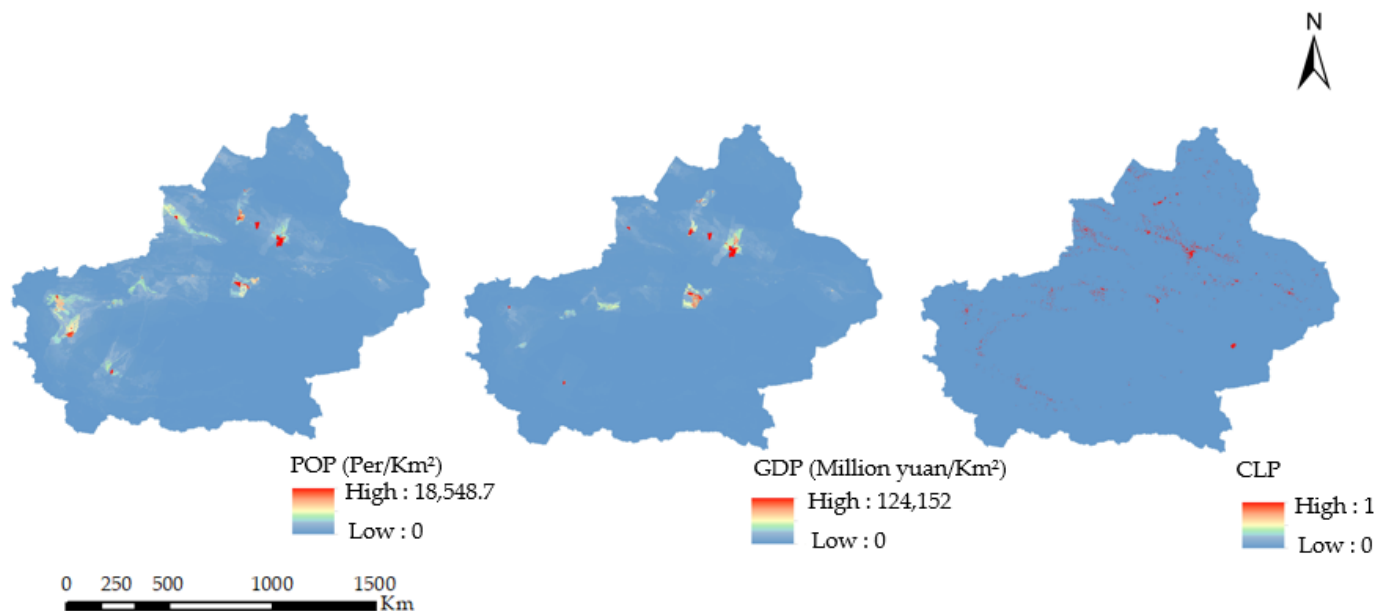


Table 3. Impact of natural and urbanization factors on ecosystem services.

	SC	WY	CS	HQ	CSOP	FP
DEM	0.29227093	0.09805016	0.30521217	0.16274507	0.03629018	0.25955970
FVC	0.11420168	0.20083537	0.10395276	0.38963397	0.31083433	0.09009719
GP	0.38886371	0.34621870	0.11161103	0.28184590	0.17174145	0.10766714
CUP	0.20728609	0.03905918	0.28282993	0.43934529	0.07684186	0.25121471
FP	0.17997718	0.36477716	0.10283935	0.22964929	0.19541321	0.07579300
Precipitation	0.32343631	0.78952211	0.03339138	0.15918269	0.35250877	0.05520211
Temperature	0.60696058	0.38043973	0.36547877	0.21161995	0.09277204	0.35984316
Evaporation	0.51831635	0.56665973	0.16431279	0.17129962	0.14807312	0.16392041
CLP	0.16854432	0.06561134	0.49980733	0.37356051	0.03295991	0.42997689
GDP	0.17806914	0.04164061	0.46716935	0.44373716	0.03002953	0.38099433
POP	0.21310473	0.06412670	0.42374081	0.47789360	0.06145802	0.40439412
RES	0.06549166	0.02550635	0.23813468	0.02312526	0.06067181	0.21536051
TF	0.12750583	0.07104539	0.46016631	0.34070411	0.03854383	0.44465324
LS	0.12271040	0.0692059	0.42371470	0.36571853	0.07013113	0.3975418
MC	0.12406081	0.0202449	0.41971044	0.39918103	0.04997951	0.38226244

3.6. Comprehensive Evaluation of the Spatial Patterns of Urbanization Levels

The spatial patterns between land urbanization, population urbanization, economic urbanization, and living standard urbanization are all largely consistent (Figures 13 and 14). As the center of Xinjiang's economic development, the economic zone on the northern slope of the Tianshan Mountains is also the main core area of high-value urbanization in Xinjiang. As a typical arid region, the high urbanization value area in Xinjiang shows a significant distribution along rivers. The distribution of the urbanization level is centered on the highest value and gradually decreases from the center outward [54]. This is also in line with the general law of urban development, which states that urban development is centered on the core area of the urban economy, characterized by large crowds and various kinds of living facilities. The level of development and quality of both the economy and living facilities decrease with increasing distances from the center of the city.

**Figure 13.** Population urbanization, economic urbanization, and land urbanization.

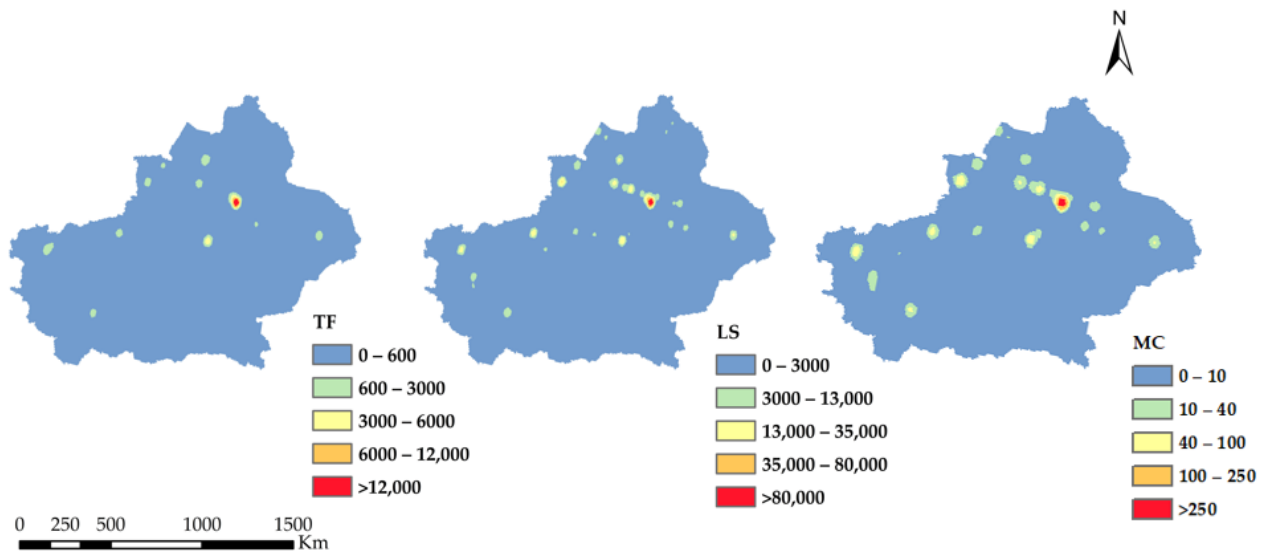


Figure 14. Living standard urbanization.

3.7. Thresholds for the Impact of Urbanization on Ecosystem Services

The results of the segmented linear regression of the urbanization indicators and TESs are shown in Figure 15. The impact thresholds of all the urbanization indicators on the TESs vary significantly. Except for the living standard indicator, TESs increase significantly with increases in all urbanization indicators, but as the urbanization level continues to increase, TESs decrease sharply and slows after reaching the threshold. Considering that Xinjiang is located in an arid region, early moderate urban development will have some positive impacts on the surrounding ESs due to expansions in arable land and artificial increases in greening. However, as the demand for ESs for human life increases, the ecosystems in the arid zone again become more fragile. Therefore, after a short period of positive impact, the ecology declines sharply. When urban development reaches a certain level, the change decreases, and the rate of ecosystem decline also decreases. The impacts of POP, GDP, CLP, TF, and MC on TESs all show a tendency of increasing and then decreasing, while TESs continue to rapidly decrease with the development of living services, with only a very small period of increase. This indicates that the relationship between the two is a very strong negative relationship. The RES indicator shows a different trend from the remaining indicators due to the influence of the lifestyle and psychology of the local people. The trend in the relationship between CUL and TESs, which is a combination of all the indicators, is similar to that of the remaining indicators. TESs as a whole increase during the early stages of urban development, though only for a very small area, and thereafter decline.

Urbanization indicators are related to each other. For example, the population concentration inevitably requires CL, which in turn drives the improvement of all kinds of amenities. The sequence of TES decline can be derived from the order in which the indicators affect the ecology. In terms of the threshold, of the four levels of urbanization, increases in land urbanization or CL lead to the most direct and rapid deterioration of the ecology. This is followed by living standard urbanization. Furthermore, since all types of amenities require CL as a base, the impact of the living standard indicator on TESs is actually driven by CL. This is followed by GDP, where the construction of various types of living and consumption places drives the economy, and POP has the slowest relative impact on TESs. While CL has the most direct impact on TESs, the relative lag of other indicators is also consistent with previous research [33].

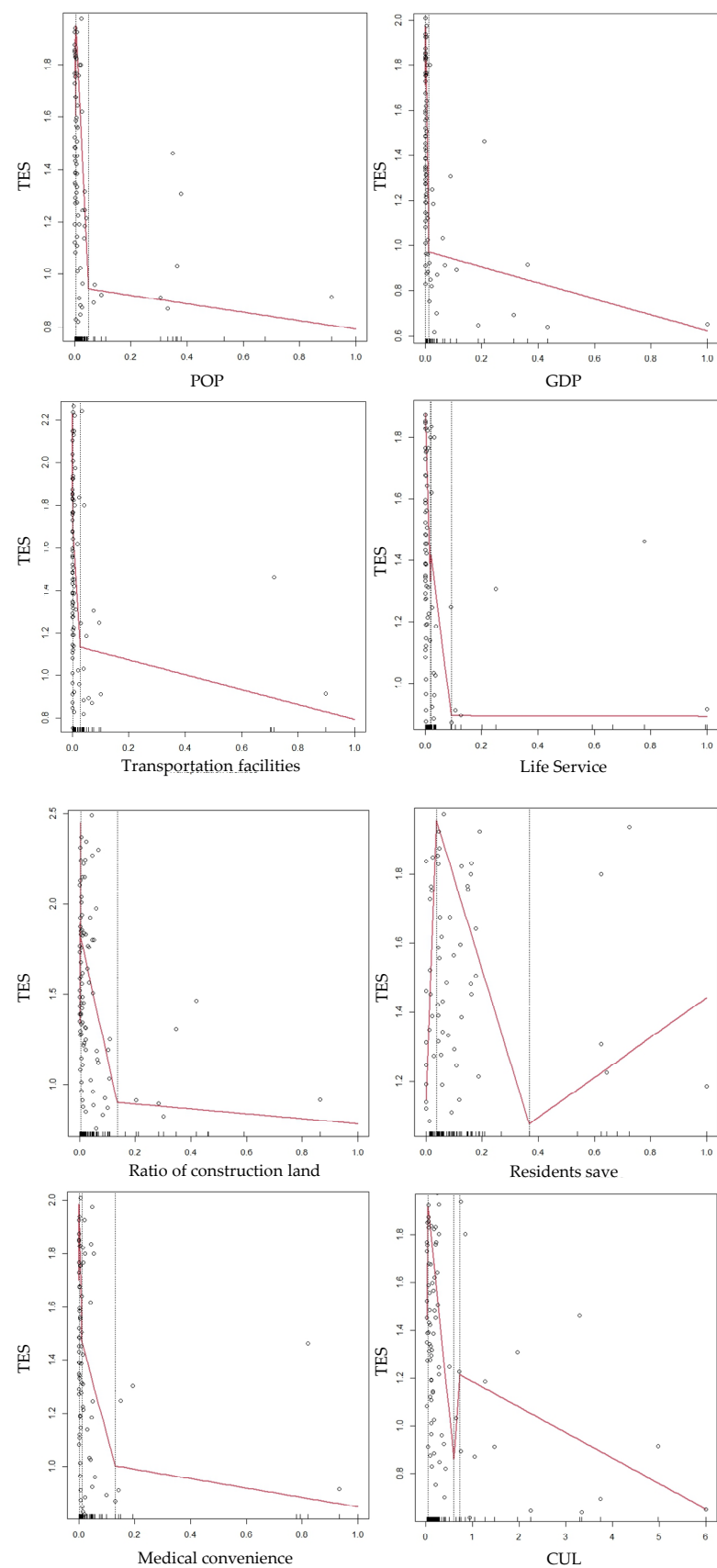


Figure 15. Correlations between total ecosystem services and urbanization levels in Xinjiang.

4. Discussion

4.1. Spatiotemporal Analysis of ES and ES Pair Trade-Offs and Synergies

This study provides an in-depth analysis of the evolution of ESs and the mechanisms of trade-offs and synergies in Xinjiang from 2000 to 2020. Over the past 20 years, ESs in Xinjiang as a whole have shown high levels in the Yili Valley and the Tien Shan Mountains and extremely low levels in the two major desert basins and their neighboring desert zones. The high WY areas are mainly located in the Tianshan Mountains, which have better environmental conditions, while the high-value areas for other ESs are mainly located in the Yili and Bortala Mongol Autonomous Prefecture. The lower rainfall and higher evapotranspiration in the desert and Gobi regions result in generally low values for all types of ESs. The extensive desert areas in the Xinjiang region also contribute to the overall reduced level of SC.

The evolutionary trends of trade-offs and synergistic relationships among ES pairs in time and space over 20 years were comprehensively analyzed. In this paper, the changes in ES single-year interrelationships, the changes in the trend of trade-offs and synergies over the past 20 years, and the spatial trade-offs and synergies among ES pairs were explored on the county scale. First, it is obvious from both the trend change (Figure 11a) and the spatial relationship comparison (Figure 10b vs. Figure 11b) results that the trade-off trend has increased dramatically over the past 20 years. At the same time, some ES pairs are highly spatially homogeneous (e.g., WY-SC, CS, CSOP; CS-SC; FP-SC; FP-HQ; CSOP-FP), whereas other ES pairs are almost opposite (e.g., SC-WY; SC-CS). FP-related ES pairs, unlike the rest, were synergistic with other ESs in the arid basin, likely because the demand for FP increased the vegetation cover of cropland, which played a positive role in ESs. Over the past 20 years, ES pairs related to HQ and CSOP shifted the most toward the trade-off trend, indicating that the ecological environment has been deteriorating along with human activities and urban development. Thus, it is necessary to focus on the ecological environment in Xinjiang. Additionally, it is necessary to focus on the level of biodiversity and the coordinated and common development of various ESs in Xinjiang.

Finally, when comparing and analyzing the trade-offs and synergistic relationships among ES pairs in 2020, significant heterogeneity was found among ES pairs. Specifically, the proportion of trade-offs and synergistic relationships between ES pairs was compared both overall and spatially. The results showed that synergistic relationships still dominated between ES pairs in the Xinjiang region overall, but many regions demonstrated strong trade-offs when accounting for spatial distribution. This finding highlights the diversity and complexity within the ecosystems of the Xinjiang region, as well as ecosystem differences across geographic regions. An understanding of this heterogeneity is crucial for ecosystem management and conservation, as it can guide us to adopt different strategies and measures to maintain and restore the ecological balance and provide useful references and guidance for future ecological conservation efforts.

4.2. ES and ES Analysis of Trade-Offs, Synergistic Urbanization, and Multiple Drivers

In the analysis of the driving factors of ESs and their mutual relationships, a geodetector was employed in this study to assess the responses of ESs and their interactions with 15 natural and social factors. To determine the changes in the impacts of the urbanization process on ESs, the thresholds of urbanization factors on TESs were clarified through segmented linear regression to explore the model of coordinated ecological and social development.

SC, WY, and CSOP were the most responsive to the natural factors of temperature, precipitation, and evapotranspiration [39], while CSOP was influenced by FVC. CS, HQ, and FP were more driven by urbanization factors. Only one-third of all ES pairs were more influenced by urbanization indicators, and the rest were mainly driven by natural factors. There was homogeneity in the responses of ES and ES pair interactions to natural and urbanization indicators, which were all more influenced by natural factors, while those that were more influenced by the urbanization indicators were mainly concentrated in CS and

FP and related ES pairs. This result is largely consistent with the characteristics of dryland ecosystems, where climatic factors such as precipitation and evapotranspiration usually play a decisive role in the generation and maintenance of ESs in this particular climatic environment. Therefore, we observed a high degree of influence of these natural factors on services such as SC, WY, and CSOP. Changes in these natural factors can directly affect water cycling, vegetation growth, and carbon cycling processes in ecosystems and thus have a significant impact on these ESs. In contrast, ESs such as CS, HQ, and FP are more likely to be driven by urbanization factors [55]. This reflects the impacts of urbanization on land use, HQ, and agricultural activities, thereby altering the supply and quality of these services. Urbanization factors such as the expansion of built-up land, population growth, and economic development can lead to declines in HQ, reductions in CS, and changes in FP.

The results of the segmented linear regression analysis further revealed the mechanisms through which urbanization affects ESs. Among them, the increase in CL was found to be one of the most direct and fundamental influences of urbanization on ESs. In addition, other indicators of urbanization were potentially affected by CL. The indicator of living standard urbanization had the strongest negative impact on TESs, followed by economic urbanization and demographic urbanization. The range of TESs increased with the development of demographic urbanization. Although it was difficult to obtain the key nodes where all the indicators were coordinated with TESs based on the results, it was found through the stage change in CUL that the total aggregate factor integrating all the urbanization indicators could coordinate with TESs relatively easily. This suggests that the integration of the different urbanization factors may help coordinate and balance urbanization and ESs and promote sustainable urban development.

5. Conclusions

In this paper, six ESs, namely, SC, CS, HQ, FP, WY, and CSOP, were quantitatively measured from 2000 to 2020 based on multisource data in the Xinjiang region. This study aimed to assess the synergistic relationship between trade-offs and the trend of the dynamic changes among the ESs during this 20-year period in both the spatial and temporal dimensions and to deeply explore the intrinsic driving force of these ESs and their interrelationships. The core objective of this study was to provide a strong scientific basis for future urban planning and construction in arid zones.

The interrelationships between ESs showed some heterogeneity in terms of overall and spatial distribution. At the same time, different ESs show some spatial homogeneity, which suggests that when planning urban development, we must also consider the impacts on different ESs and their spatial distribution, thus preventing situations in which there is no obvious problem with ESs in general, but there is an extreme imbalance of ES in certain areas.

This study also revealed that natural and urban factors play a major role in driving different ESs. While natural factors play a dominant role in shaping ESs in drylands, the impact of urbanization on ESs cannot be ignored. Interestingly, among all urbanization indicators, the growth of CL has the most direct impact on TESs. This finding emphasizes the importance of strict adherence to the ecological red line policy in future urban planning and construction and of not developing land on a large scale for urban development to avoid irreversible damage to the ecosystem.

In future studies, it is necessary to further introduce more socioeconomic and natural factors to comprehensively explore the causes of ES trade-offs in Xinjiang, which covers a vast area and has a complex spatial distribution. In addition, the introduction of more urbanization indicators should be considered to deepen the detailed study of the thresholds and trends of urbanization's impact on the ecosystem. These efforts will contribute to a better understanding of the complex relationship between urbanization and ecological balance and provide more scientific and effective guidance for sustainable urban development.

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Data Availability Statement: Land use, GDP and POP data that supports the findings of this study are openly available in Chinese Academy of Sciences Resource and Environment Science and Data Center (RESDC) (<https://www.resdc.cn/>, accessed on 13 April 2023, 9 June 2023). Temperature and Precipitation data that supports the findings of this study are openly available in National Earth System Science Data Center, National Science & Technology Infrastructure of China (<http://www.geodata.cn>, accessed on 23 April 2023). Soil Data that supports the findings of this study are openly available in Harmonized World Soil Database (HWSD) (<https://www.fao.org/>, accessed on 19 April 2023). DEM data that supports the findings of this study are openly available in Geospatial Data Cloud (<http://www.gscloud.cn>, accessed on 24 April 2023).

Conflicts of Interest: The authors declare no conflicts of interest.

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