land

MDPI

Article

Assessment of Carbon Storage in a Multifunctional Landscape: A Case Study of Central Asia

Xinyue Dong, Zeyu Cao, Yi Guo, Jingyuan Lin, Hanze Yan, Mengyu Li and Peng Yao *

School of Landscape Architecture, Beijing Forestry University, Beijing 100083, China; dongxyue@bjfu.edu.cn (X.D.); czy450471282@bjfu.edu.cn (Z.C.); guoyoii@bjfu.edu.cn (Y.G.); jingyuan_lin@bjfu.edu.cn (J.L.); yanhanze0118@bjfu.edu.cn (H.Y.); limengyu0320@bjfu.edu.cn (M.L.)
* Correspondence: chinayp@bjfu.edu.cn

Abstract: The robust carbon storage (CS) capacity of terrestrial ecosystems is crucial in mitigating climate change and holds indispensable significance for global sustainable development. The diverse topography of Central Asia (CA), comprising oases, grasslands, forests, deserts, and glaciers, has fostered industries like animal husbandry, irrigation agriculture, and mining. However, the fragile arid ecosystems of CA render it highly sensitive to climate change and human activities, with their impact on the sustainable development of multifunctional landscapes in this region remaining ambiguous in the future. This study linked land use changes with multiple socio-economic and ecological indicators to predict the dynamics of land use and changes in CS in CA. The findings reveal a significant spatial heterogeneity in CS, with considerable variations among five countries driven by differences in landscape composition. Kyrgyzstan and Kazakhstan, characterized by grasslands, demonstrate higher CS per unit area, whereas Turkmenistan, dominated by barren land, exhibits the lowest CS per unit area. Strategies involving innovative development and improved biodiversity conservation have proven effective in augmenting CS. Meanwhile, high economic and population growth stimulates the expansion of cropland and urban land, reducing the CS capacity of ecosystems. This study contributes to a more precise assessment of CS dynamics in CA. Furthermore, by elucidating the interrelationships between future socio-economic development and environmental conservation in CA, it offers solutions for enhancing the conservation of multifunctional landscapes in CA.

Keywords: carbon storage; sustainable development; climate change; land use change; scenarios simulation

check for updates

Citation: Dong, X.; Cao, Z.; Guo, Y.; Lin, J.; Yan, H.; Li, M.; Yao, P. Assessment of Carbon Storage in a Multifunctional Landscape: A Case Study of Central Asia. *Land* **2024**, *13*, 801. https://doi.org/10.3390/land13060801

Academic Editor: Dietrich Schmidt-Vogt

Received: 6 April 2024
Revised: 27 May 2024
Accepted: 2 June 2024
Published: 5 June 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

With human activities accelerating the exploitation and utilization of land resources, improper land use practices have altered the structure and function of terrestrial ecosystems [1,2]. This alteration has resulted in various issues, including global warming, decreased biodiversity, heightened probability of disasters and diseases [3], and carbon loss [4]. By 2030, urban areas worldwide are projected to expand to three times their size in 2000, which will result in a loss of 1.38 Pg C of vegetation biomass [5]. Additionally, by 2050, the expansion of croplands is expected to cause a carbon loss equivalent to 2.9 times the annual global carbon emissions [6]. These significant changes have brought formidable challenges to achieving sustainable development worldwide.

Multifunctional landscapes represent complex and diverse systems influenced by both human and natural factors [7]. Due to their capacity to provide various benefits including regulating, provisioning, and cultural services [8], they have emerged as crucial agents for achieving global sustainable development, thereby attracting widespread attention. Carbon storage (CS), as one of the crucial regulating functions of multifunctional landscapes, plays an indispensable role in maintaining ecological equilibrium since the ecosystems absorb

and store carbon from the atmosphere, making a significant contribution to mitigating climate change and other related issues [9]. Drylands, including arid, semiarid, and dry sub-humid areas [10], cover 45% of the global land area [11], are a vital part of terrestrial ecosystems, and govern the global land carbon sink [12]. Soil organic carbon (SOC) at a 2 m depth accounts for approximately 32% of global SOC [13]. The more active surface SOC that is 0–30 cm deep accounts for 44% of global SOC. The overall CS, which includes the aboveground and belowground plant CS and surface soil CS, constitutes about 30% of the global carbon reservoir [14].

However, long-term water scarcity and intense solar radiation render dryland ecosystems particularly vulnerable, making them more sensitive to environmental changes [15,16]. Precipitation has been demonstrated as a primary driving factor for vegetation growth in arid regions [17,18], and meanwhile, the effect of temperature on CS in drylands remains uncertain [18]. Drylands not only sustain over 30% of the global population, but 70% of it is located in developing countries [13]. Given the projected exacerbation of global aridity in the future and the estimated expansion of drylands from 45% to 50–56% of the global land area by 2100 [11,19], there is a need to study the role of dryland ecosystems in maintaining carbon balance. Additionally, further exploration is required to understand the response of dryland ecosystems to climate change. The ecological processes of CS interact with the evolving irrigation agriculture, animal husbandry, and mining industries, as well as the dramatic shifts in climate conditions, underscoring their significant role in the global carbon cycle.

Central Asia (CA) encompasses 80–90% of the world's cold/temperate deserts, positioning it as a prominent arid region globally. Since its CS accounts for 18–24% of the total CS of deserts and arid shrublands worldwide [20], CA plays a significant role in the global carbon cycle. However, the strong heterogeneity in its vegetation and soil and the lack of observational data have made it challenging to estimate its CS. The combined usage of land use models and the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model has shown wide applicability in CS estimation studies. Remote sensing methods offer extensive high-resolution surface information, thus aiding in providing a comprehensive understanding of the spatial distribution and variations in CS from global to local scales. Land use and land cover change (LUCC) is an intricate and dynamic mechanism closely related to multiple factors such as socio-economic development and ecological environment [21,22]. The Patch-generating Land Use Simulation (PLUS) model integrates human and natural driving forces for land use simulation [23], thus offering a foundation for novel approaches that can be used to study future land use and CS dynamics. Previous studies have highlighted the impact of economic development and population growth on CS as a key research focus. Recently, with increasing attention on climate issues, numerous studies have utilized land use models and the InVEST model to predict changes in CS under various climate scenarios [24]. While these studies provide valuable insights for developing strategies to protect and enhance CS, CS dynamics are influenced by the interplay between socio-economic development and natural environmental factors. Given the complexity of these influences, the precise changes in CS remain uncertain. To promote harmonious development of the society, economy, and environment, the United Nations General Assembly established 17 Sustainable Development Goals (SDGs) and provided 169 specific targets in 2015 [25], while stipulating explicit indicators for the simulations of complex land use system changes. The System Dynamics (SD) model enables the integration of multiple dimensions within a land use system [26] while exhibiting a higher simulation accuracy than other models [27].

In response to future climate change, the Intergovernmental Panel on Climate Change has introduced a range of scenarios to predict the development of human societies. The Coupled Model Intercomparison Project Phase 6 (CMIP6) combines Representative Concentration Pathways (RCPs) with shared socio-economic pathways (SSPs) [28,29], providing diverse scenarios for climate change and socio-economic impacts [30]. Researchers have utilized these scenarios to simulate changes in CS, revealing substantial differences in

CS dynamics across different scenarios [24,31]. Given the escalating environmental concerns, these scenarios hold significant implications for achieving carbon neutrality and global sustainable development. Accordingly, this study proposes a framework that integrates population–economic–social–environmental indicators for land use forecasting while elucidating the future patterns of CS in CA under varying socio-economic and climatic contexts. This framework will enable the formulation of development strategies for CA and contribute to sustainable development in the region.

2. Materials and Methods

2.1. Study Area Description

In this study, CA includes Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan (Figure 1). It spans an area of about 4×10^6 km^2 and is located at the center of the Eurasian continent, implying that it is positioned far from any ocean. The vast mountain ranges in the western part of CA obstruct the moist air currents from the Atlantic Ocean [32]. The region exhibits a typical continental climate, with hot and dry summers as well as cold and humid winters. The geographical landscape of CA is intricate since it spans from the Caspian Sea to the Altai Mountains and the Tien Shan Mountains, with elevations gradually increasing from −134 to 6918 m. It encompasses various terrain types including deserts, basins, oases, and mountainous regions.



Figure 1. Topography map of CA.

2.2. Methods

2.2.1. Establishing a Framework for Population–Economy–Society–Environment Indicators

The introduction of shared socio-economic pathways (SSPs) has provided a new developmental context for land use and land cover change (LUCC). These pathways, which involve various aspects such as economy, population, energy, technology, education, and environment, are closely related to LUCC. Based on the descriptions of SSP scenarios and land use under these scenarios by Popp et al. [33] and O'Neil et al. [34], the related SDGs are categorized into four primary groups: population, economy, society, and environment. Specifically, population and economy are crucial factors in land system modeling [35]. Economic development encompasses various industries such as agriculture, fisheries,

livestock, and forestry, with their outputs and values (SDGs 2, 8; for detailed definitions of the specific goals, see Table S1 in Supplementary File S1) closely linked to the intensity of land development [36].

Food security, infrastructure development, education, and innovation are key aspects of social progress. The future food demand (SDG 2) is expected to continue increasing [37], placing higher demands on the intensity of agricultural land use and agricultural technological innovation, which in turn leads to changes in cropland and forestland [38,39]. Infrastructure development (SDGs 7, 9) is a significant indicator of urbanization and technological progress, influencing both urban and rural development and indirectly affecting other land types [40]. Education levels (SDGs 1, 4) impact population size and structure [40], indirectly affecting land use changes. Innovation is primarily reflected in resource use efficiency (SDGs 6, 7) and technological advancements (SDGs 8, 9). In terms of resource efficiency, improving water use efficiency is crucial for maintaining sustainable ecosystems [41], while land use and related human activities influence water resource distribution [42]. Regarding energy efficiency, promoting clean energy and enhancing energy use efficiency can reduce reliance on fossil fuels, thereby mitigating the dramatic LUCC caused by energy extraction and contributing to achieving negative emissions [39,43].

In terms of the environment, greenhouse gas (GHG) emissions (SDG 13) are one of the core indicators of SSP scenarios, closely linked to climate change and land use changes [44]. Additionally, biodiversity (SDG 15) is a critical environmental issue. With increasing urbanization, habitats for various species have faced significant reduction and fragmentation [45]. SDG 15 provides specific quantitative targets for habitat protection, reflecting changes in forests, water bodies, and other habitats.

Accordingly, we have categorized the relevant indicators from SDGs into four primary groups (population, economy, society, and environment), which are further subdivided into six secondary indicators; overall, there are twenty-two specific indicators (Table S1). To assess the development level of CA across different population, economic, social, and environmental dimensions, we have normalized the abovementioned indicators. The calculation method follows the guidelines presented in the SDG Index and Dashboards Detailed Methodological Paper [46].

This intricate model was constructed as a System Dynamics (SD) model using Vensim PLE 9.4.0 (https://vensim.com, accessed on 7 June 2023) and encompasses four subsystems: population, economy, society, and environment. Historical data from 2001 to 2015 were processed using ridge regression methods to eliminate collinearity and determine the relationships between various variables (Figure S1). Owing to the different development levels and development patterns among the five countries, the regression equations used for the indicators within the model exhibit variations (Table S2). During Uzbekistan's economic development from 2001 to 2015, the protection of aquatic areas was overlooked, leading to a drastic reduction in these areas at a rate of 47.2%. This led to negative values for the projected aquatic area under SSP245 and SSP585 scenarios. To address this issue, the projected aquatic area for 2015 was treated as a constant to represent the aquatic area for the SSP245 and SSP585 scenarios from 2015 to 2030.

2.2.2. Evaluation of the SD Model

Accuracy Test

To test the model, accuracy verification was conducted by comparing simulated data with actual area measurements from 2001 to 2015 for all five countries [47].

Global Sensitivity and Uncertainty Analysis

Sensitivity analysis identifies the contribution of each parameter to the output, while uncertainty analysis assesses the range of output uncertainty, both of which are crucial for model validation and confirmation [48]. Sensitivity analysis includes both local sensitivity analysis and global sensitivity analysis [49,50]. While local sensitivity analysis involves changing one parameter at a time, global sensitivity analysis allows multiple parameters

to vary simultaneously, comprehensively assessing the impact of individual parameters and their combinations on the output [51]. Therefore, this study employs Sobol sensitivity analysis to examine the sensitivity of different factors to the output [52].

In terms of uncertainty analysis, Monte Carlo simulation is commonly used to calculate cumulative distribution functions for assessing output uncertainty [51,53].

2.2.3. Assessment of Future Development under Various Scenarios in CA

For 2023 to 2030, future land use quantities have been projected based on the different scenarios of SSPs by taking into account each country's development level. SSPs, which describe the future changes in population trends, human development, economy and lifestyles, policies and institutions, technology, environment, and natural resources [34], align closely with the framework of population–economy–society–environment established in this study. CMIP6 combines SSPs with Representative Concentration Pathways (RCPs), with SSP126, SSP245, and SSP585 scenarios representing sustainable development, the continuation of historical trends, and high-speed development, respectively, each embodying typical characteristics [47,54]. Therefore, this study selects these three scenarios for simulation purposes.

The SSP126 scenario outlines a sustainable pathway with low GHG emissions [29,43]. Its core features involve a commitment to achieving SDGs with a strong focus on human well-being. This scenario emphasizes infrastructure development and investments in education and healthcare, thus aiming to achieve a slowdown in population growth. It also places an emphasis on technological advancements and the utilization of renewable energy sources. Consequently, economic development gradually accelerates and resource efficiency improves. Additionally, an increased environmental consciousness leads to enhanced air quality and biodiversity [34].

In the SSP245 scenario, which represents the "middle of the road" pathway, there are no significant departures from the historical trends of social, economic, and technological factors [34]. Consequently, the indicators for this period are set to at least reach the maximum levels of the current era. If a given indicator has already reached its maximum level or is near it, the historical trend is continued. The process of achieving SDGs is slower in this scenario, which is reflected in areas such as education and infrastructure development. Technological advancements are not radical and only moderately improve resource efficiency while lacking any significant technological innovation. The required demographic transition is successfully achieved, resulting in moderate population growth. However, insufficient progress in education levels contributes to the persistence of population growth [34]. The moderate development trend leads to a continuous decline in pollution control and biodiversity enhancement. Environmental indicators in this scenario are set to be slightly higher than SSP585 if historical trends are positive; however, if they are negative, the indicators continue to exhibit historical trends [29,43].

The SSP585 scenario portrays a pathway of rapid development and high GHG emissions. In this scenario, countries heavily invest in education and infrastructure development [34], and these indicators are set higher than those in the SSP1 scenario due to rapid economic growth. Economic growth is driven by energy-intensive industries and heavily relies on fossil fuels. Therefore, resource efficiency improvements are relatively slow, positioned between the first two scenarios. Given that SSP5 exhibits a higher economic growth rate than SSP1 and emphasizes competitive markets and sustainable development innovation, technological advancements are rapid and exceed those achieved under the SSP1 scenario. Fertility rates drop rapidly in developing countries, and the lowest population growth rate is observed in this scenario. While technology development alleviates local environmental issues, global environmental concerns are less prioritized, leading to a lower habitat quality [54,55]. Greenhouse gas emissions are significantly higher in SSP5 compared to those in other scenarios [29], resulting in two environmental indicators being lower than the current levels.

Based on the development levels and various scenarios in the SD model, scores are assigned to each indicator to determine the future land usage quantities for the five Central Asian countries (Figure 2).

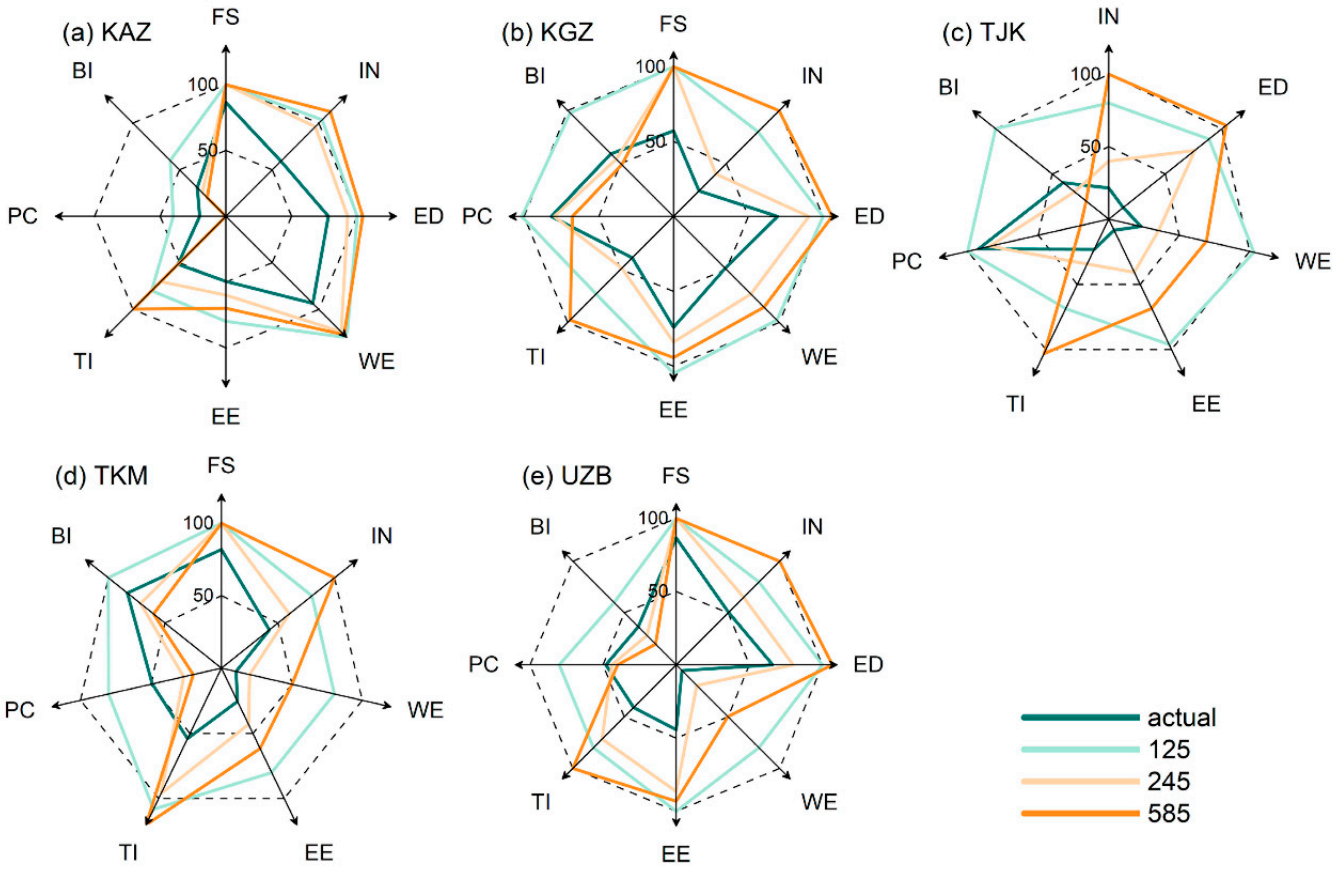


Figure 2. Indicator scores under different scenarios in five Central Asian countries. FS: food security; IN: infrastructure; ED: education; WE: water efficiency; EE: energy efficiency; TI: technology innovation; PC: pollution control; BI: biodiversity. Due to the absence of statistical data, the impact of education indicators was not considered for Turkmenistan.

2.2.4. Spatial Simulation of LUCC and Validation

The spatial simulation of land use was performed in the PLUS model V1.4 by using multi-year land use, natural, and socio-economic data (Table 1). After undergoing projection transformation and clipping in ArcGIS 10.8, the aforementioned data were uniformly transformed into raster data at a spatial resolution of 1 km × 1 km (Figure 3). Initially, the relationship between LUCC and various driving factors was explored using historical land use data from two periods, which yielded development probabilities for different land use types and unveiled the contributions of different driving factors. Subsequently, using the multi-type random patch seeds, simulation patches were autonomously generated based on the abovementioned development probabilities and neighborhood weights for each land use type by adhering to the constraints imposed by these probabilities [23].

To explore the influence of future climate change on CS dynamics, future precipitation and temperature data were obtained by the CMIP6 project (SSP126 SSP245 SSP585) by using 100 km of climate datasets (https://esgf-node.llnl.gov/search/cmip6/, accessed on 28 June 2023). To unify data accuracy, the results were resampled for a 1 km × 1 km area, which ensures consistency with the resolution of the 2015 dataset.

Table 1. Data used in the PLUS model and their sources.

Category	Data/Maps	Year	Description	Data Source
Land use	Land cover data	2015	300 m	European Space Agency Climate Change Initiative https://www.esa-landcover-cci.org/ (accessed on 21 June 2023)
Natural environmental data	Elevation	2000	30″	WorldClim version 2.1 http://www.worldclim.org/ (accessed on 11 June 2023)
	Slope	2000	30″	Calculated from DEM
	Aspect	2000	30″	Calculated from DEM
	Annual average temperature Annual Precipitation	1979–2013	30″	Climatologies at high resolution for the earth's land surface areas https://chelsa-climate.org/ (accessed on 21 June 2023)
	Topsoil pH Topsoil sand fraction Topsoil clay fraction	2008	30″	FAO, Harmonized World Soil Database v 1.2 https://www.fao.org/soils-portal/ (accessed on 21 June 2023)
	River	2005		Institute of Geographic Sciences and Natural Resources Research, CAS https://www.resdc.cn/ (accessed on 21 June 2023)
Socio-economic data	Nighttime lights	2015	15″	Earth Observation Group Annual VIIRS nighttime lights V2.1 https://eogdata.mines.edu/products/vnl/ (accessed on 21 June 2023)
	GDP	2015	30″	Kummu, Matti; Taka, Maija; Guillaume, Joseph H. A. (2020). Data from: Gridded global datasets for Gross Domestic Product and Human Development Index over 1990–2015 [Dataset]. Dryad. https://doi.org/10.5061/dryad.dk1j0 (accessed on 21 June 2023)
	Population	2015	30″	NASA, Gridded Population of the World, v4 https://sedac.ciesin.columbia.edu/ (accessed on 21 June 2023)
	Road Railway	2005 2005		CAS https://www.resdc.cn/ (accessed on 21 June 2023)

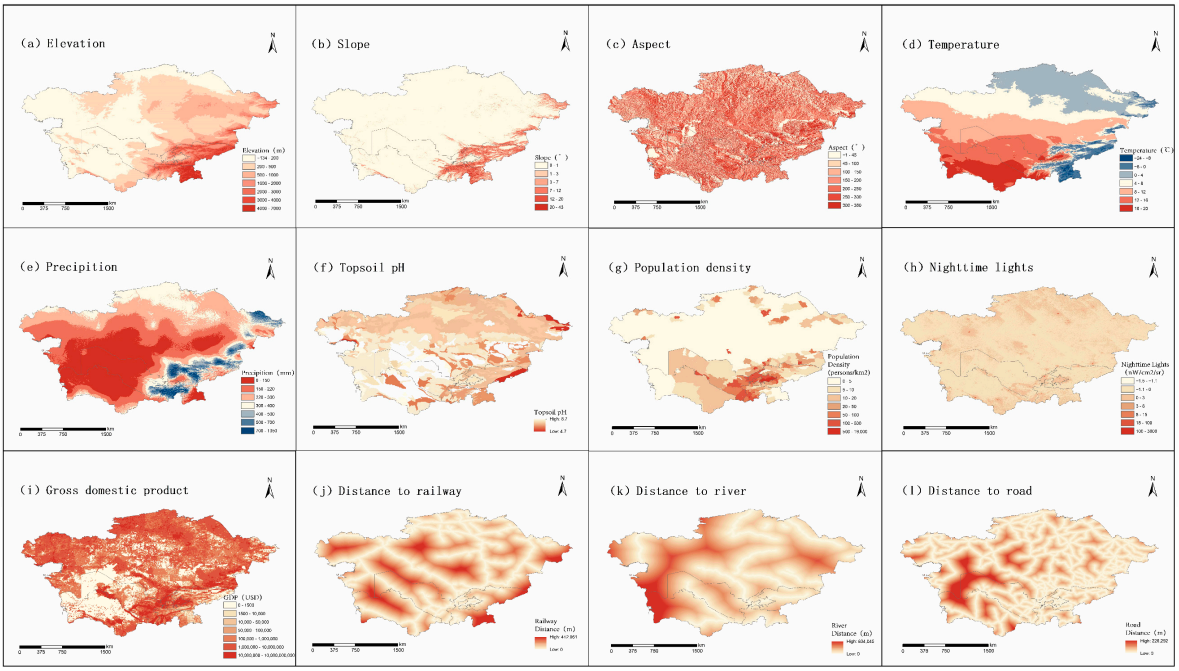


Figure 3. Driving factors.

2.2.5. Assessment of CS

The CS and sequestration module of the InVEST 3.1.3.0 model was used to estimate and analyze the CS in all five countries under multiple scenarios. The carbon sink estimates determined using the InVEST model included four basic carbon pools [56]. Meanwhile, CS values were calculated by formulas given in Supplementary File S2.

2.2.6. Identification of Spatial Patterns of CS

In ArcGIS, the Getis-Ord Gi* statistic is used to identify cold spots (low-value clustering) and hot spots (high-value clustering), which in turn elucidate the spatial distribution characteristics and time variation rules of CS.

Furthermore, the factor detector in the GeoDetector model system is used to analyze the relationship between climate factors and CS as follows:

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

$$SSW = \sum_{h=1}^{L} N_h \sigma_h^2,\ SST = N\sigma^2 \quad (2)$$

where $h = 1, \ldots, L$ represents the classification of variables; N_h and N are the number of units in layer h and the entire area, respectively. σ_h^2 and σ^2 are the variances of layer h and CS, respectively. SSW and SST represent the sum of squares and the total sum of squares, respectively. The range of q is [0, 1]; the larger the value, the stronger the explanatory power of climate factors for CS.

3. Results

3.1. LUCC from 2001 to 2030 under Various Scenarios

Comparing the actual value from 2001 to 2015 with the predicted results of the SD model reveals that the errors are mostly within 5% (Table S3 in Supplementary File S1). Owing to the smaller construction land area in Turkmenistan (128.7 km^2) in 2001, an error of 6.19% is observed, which is still reasonable. Meanwhile, the simulation accuracy is relatively high, which demonstrates the reliability of the SD model.

The results of the global sensitivity analysis indicate significant differences in the factors influencing LUCC among different land use types and across the five countries (Figure S2 in Supplementary File S1). Total sensitivity index (ST_i) and the first order sensitivity index (S_i) were closely aligned, showcasing the degree of sensitivity of the output to different parameters. Overall, croplands exhibited a heightened sensitivity to factors such as food demand, food security, biodiversity, and water efficiency. Meanwhile, forested areas demonstrated a high sensitivity to infrastructure development, cropland, energy efficiency, and biodiversity. Grasslands were particularly sensitive to population dynamics, the gross output value of livestock, and biodiversity. Urban areas showed primary sensitivity to GDP, infrastructure development, and pollution control. Additionally, water exhibited sensitivity to resource efficiency and biodiversity. Uncertainty analysis demonstrated the output ranges and the probability of output for different land use types from 2001 to 2015 (Table S4, Figure S3 in Supplementary File S1).

The combined area of each land type from the five countries indicates significant differences in future land use changes under different scenarios in CA (Figure 4). Rapid growth in population and economy leads to the fastest increase in cropland with a growth rate of 6.89% (Figure 4a) and urban land with a growth rate of 336.73% (Figure 4d) under the SSP585 scenario. Meanwhile, due to the significance of livestock husbandry as a major economic source in CA, the growth rate of grasslands (2.31%) also reached its peak under SSP585. Forested areas are effectively protected under the SSP126 scenario (Figure 4b), exhibiting a growth rate of 17.37% and providing a 0.34% increase in the proportion of land area for SDG15.1.1. However, forestlands suffer varying degrees of loss, with rates of −3.21% (SSP245) and −8.8%(SSP585), respectively, in the other two scenarios

(Figure 4b). Despite a continuous increase in water areas from 2015 to 2030 in the SSP126, there remains a declining trend compared to the 2000s (−7.21%), with a more severe reduction in water areas (−17.07% to −17.4%) under other scenarios (Figure 4f). Owing to ongoing urban development and different degrees of land use conversion, the area of bare lands consistently decreases (−9.6% to −6.19%) across all three scenarios (Figure 4e).

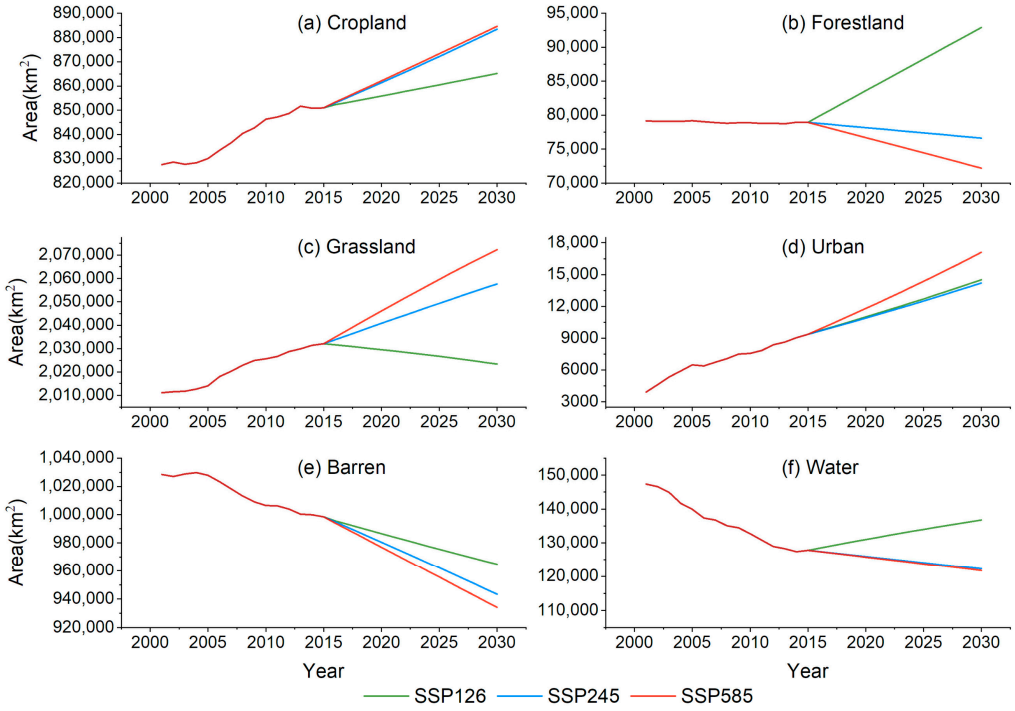


Figure 4. Predictions of various land use types in multiple scenarios.

Based on the land use areas predicted above, the PLUS model simulated the future distribution of land use (Figure 5). After verification, the kappa coefficients and overall accuracy of LUCC in all five countries exceeded 90%, indicating the excellent applicability of the model. From a spatial perspective, grasslands dominate the central and southeastern regions of CA, while barren land is concentrated primarily in the southwest. Forestland is mainly located in the Altai Mountains, Tian Shan Mountains, and Pamir Plateau areas. Cropland is predominantly distributed in the northern and southern parts of CA. Water bodies and urban land are scattered throughout the region.

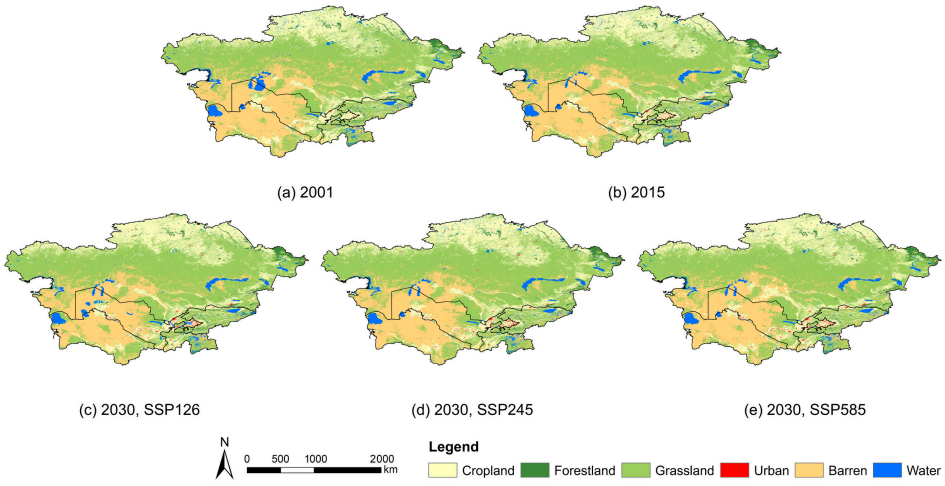


Figure 5. Actual spatial land use patterns: (**a**) 2001, (**b**) 2015; simulated spatial land use patterns: (**c**) SSP126, (**d**) SSP245, (**e**) SSP585.

3.2. Simulated Carbon Storage in CA

By adopting the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model, CS and its spatial distribution for the year 2030 were calculated under three different scenarios. Overall, CS in CA shows an increasing trend. CS exhibits the highest growth in the SSP126 scenario (1033.5 Tg), which is followed by that in SSP245 (700.7 Tg) and SSP585 (617.2 Tg). According to the land use conversion matrix between 2001 and 2030 in CA (Figure 6), various scenarios of land use conversion have shown differing intensities and characteristics. Notably, urban expansion has encroached upon over half of cultivated lands, with proportions of 57.6% in SSP126, 51.1% in SSP245, and 67.6% in SSP585, leading to a significant decrease in SOC. In the SSP126 scenario, 11.34% of grasslands are converted to urban land, with 4.57% converted to cropland. This is followed by the SSP245 scenario, where grasslands are encroached upon by urban areas (17.35%) and cropland (7.36%). The rapid economic growth depicted in SSP585 leads to better preservation of grasslands, with only 5.66% and 4.46% being converted to urban and cropland, respectively. Additionally, barren land partially compensates for the loss of grasslands, contributing to the restoration of carbon storage. Forested areas suffer the most severe losses in the SSP585 scenario (0.77%), followed by SSP245 (0.56%) and SSP126 (0.46%), making them significant contributors to carbon loss in CA. Moreover, restored barren lands represent substantial proportions, accounting for 21.71%, 10.92%, and 12.85% of the total area in SSP126, SSP245, and SSP585, respectively. The recovery of forests and grasslands facilitates an increase in CS, with this effect particularly pronounced in the SSP126 scenario.

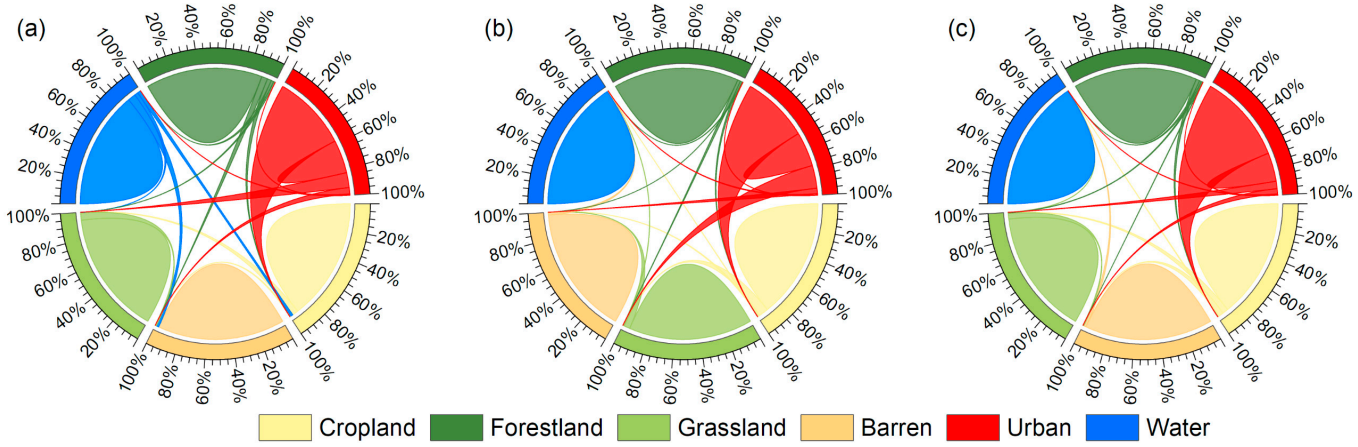


Figure 6. Chord diagrams representing the conversion rates of different land use types and land covers during 2001–2030: (**a**) SSP126, (**b**) SSP245, and (**c**) SSP585.

There are notable differences in CS changes among the states or regions of the five countries (Figure 7). The main country contributing to the increase in CS in CA is Kazakhstan. In all scenarios, CS in all regions of Kazakhstan demonstrates a positive growth trend. Based on the land use transition matrix and global sensitivity analysis results (Figure S2 in Supplementary S1), it is projected that, driven by future economic growth, 18.92% to 28.54% of barren land in Kazakhstan will be converted to grassland, thereby increasing CS. Forestland shows high sensitivity to changes in energy efficiency and urban land use, with 0.15% to 0.37% of cropland being restored to forest. Karaganda, Qyzylorda, and Mangghystau stand out with the most pronounced increases in CS. The substantial expansion of cropland in Qyzylorda, driven by rapid economic growth, has led to a remarkable surge in CS, surpassing the SSP126 scenario (35.8 Tg) in SSP585 (53.8 Tg), while in most regions, the CS increase in the SSP126 scenario exceeds that in other scenarios.

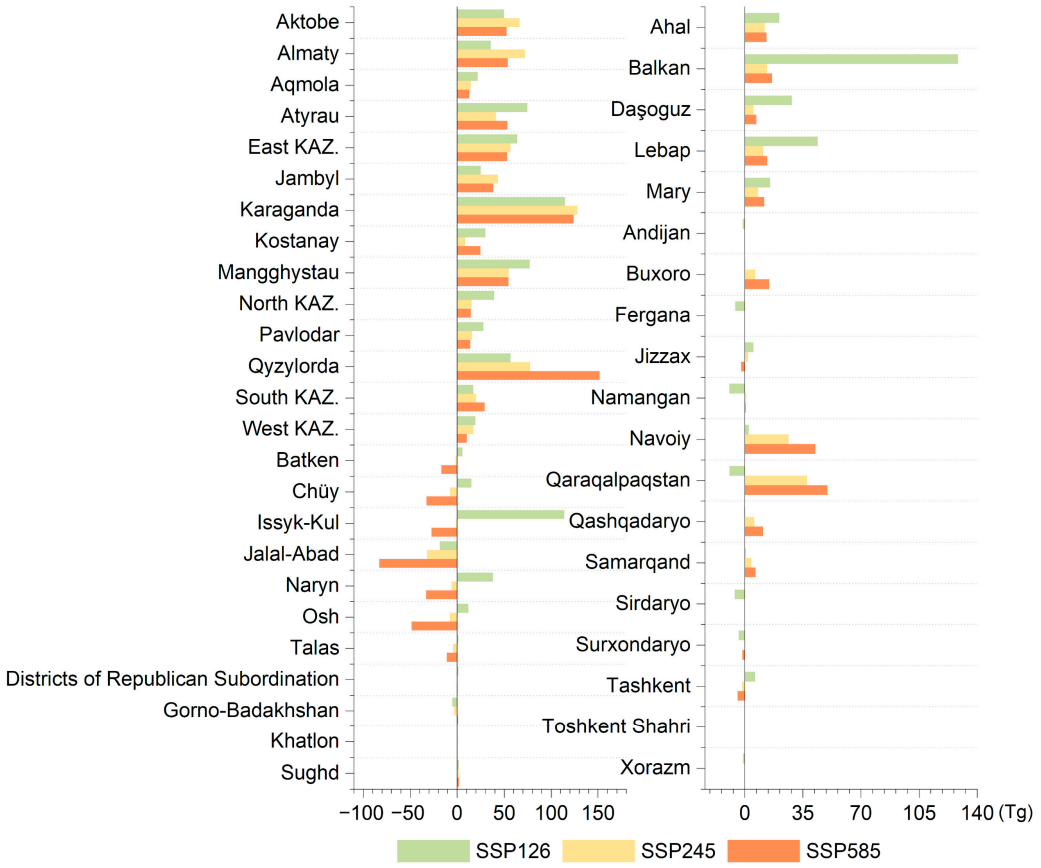


Figure 7. CS change in the states, provinces, or regions of five countries under different scenarios, excluding those with unchanged CS.

Kyrgyzstan is responsible for the highest carbon losses in the SSP245 and SSP585 scenarios, which lead to the largest reductions in CS in CA. Influenced by infrastructure development, biodiversity, and resource efficiency, 4.37% to 7.44% of forestland is projected to be converted to cropland. Additionally, under the SSP126 scenario, 36.45% of barren land is expected to be restored to forest, particularly in the Naryn (37.9%). Driven by biodiversity and pollution control, cropland is anticipated to expand by 0.6% to 2.23%, resulting in some carbon loss, especially in Jalal-Abad under the SSP585 scenario (−83.01 Tg).

In all regions of Turkmenistan, significant positive growth is observed across different scenarios. Biodiversity and resource efficiency primarily drive the restoration of 4.17% to 14.13% of grassland, particularly under the SSP126 scenario, where 12.38% of barren land is restored to grassland, increasing CS. The most significant increases are seen in the Balkan (128.5 Tg) and Lebap (43.86 Tg). Urban expansion is mainly influenced by energy efficiency, with the least expansion under the SSP126 scenario (1.51%). Under the SSP585 scenario, 2.29% of other land is projected to be converted to urban land, resulting in some carbon loss. All regions of Turkmenistan are experiencing significant positive growth, with Balkan (128.5 Tg) and Lebaq (43.86 Tg) showing a particularly notable increase in CS due to rapid grassland expansion in SSP126. Similar situations are observed in regions such as Lebap (43.9 Tg) and Mary (15.3 Tg). The changes in CS are not significant in most regions of Tajikistan and Uzbekistan, while Qaraqalpaqstan and Navoiy experienced some increase under SSP245 and SSP585 due to the conversion of water to barren land and the expansion of cropland.

3.3. Spatial Patterns and Climate Change Response of CS

From a spatial perspective, the overall distribution of CS is similar across the three scenarios; that is, a lower CS is observed in the southwest region, and a higher CS is observed in the northern and northeastern regions (Figure 8).

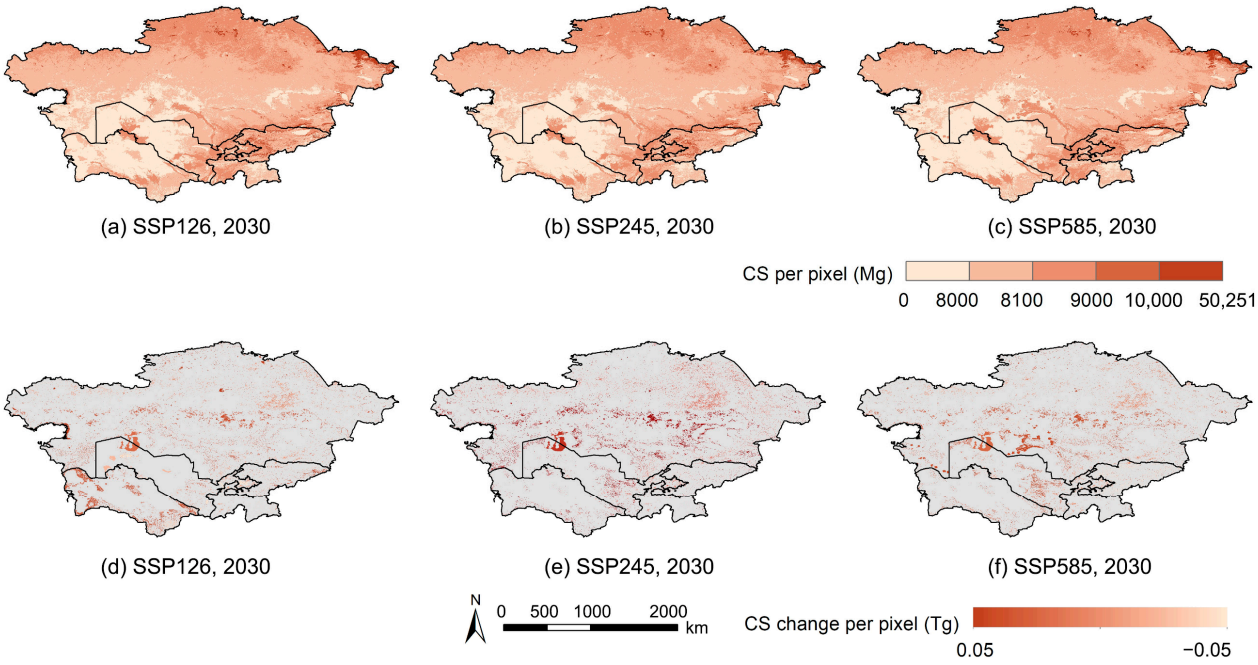


Figure 8. Spatial distribution of CS (**a**–**c**) and CS change (**d**–**f**) in CA under three scenarios.

To further explore the spatial distribution characteristics of CS, the Getis-Ord Gi statistic was employed to assess the spatial variation of CS from 2001 to 2030 (Figure 9). Over the past 30 years, cold spots have consistently clustered in the southwestern region of CA, including Mangghystau and Qyzylorda in Kazakhstan, the northwestern region of Uzbekistan, and the entire territory of Turkmenistan. Apart from the confidence level of Mangghystau increasing from 95% to 99% in the SSP585 scenario, these cold spots remained stable throughout the 30-year period.

Hot spots are mainly gathered in the southeastern region of CA, encompassing southeastern parts of Kazakhstan, Kyrgyzstan, and a significant portion of Tajikistan. Within these hot spots, South Kazakhstan exhibits an unstable hot spot pattern. The changes in CS hot spots are comparable in the SSP126 and SSP245 scenarios. In Almaty, the confidence level transitions from 95% to 99%. The hot spot confidence levels associated with the Districts of Republican Subordination and Khatlon in Tajikistan shift from 95% to an insignificant value. In the SSP585 scenario, the hot spot confidence level of East Kazakhstan increases from 90% to 95%.

Overall, the spatial distribution of CS exhibits relatively stable cold and hot spot patterns from 2001 to 2030. There is a strong spatial heterogeneity, and the spatiotemporal changes in CS vary across different scenarios.

The CS patterns are closely related to climate change [57,58]. By using the GeoDetector model system to explore the factors influencing the average CS values from 2001 to 2030, it was found that temperature and precipitation passed the significance tests ($p < 0.05$) across all three scenarios. Moreover, these climate factors exhibited strong explanatory powers ($q\ value$) for the spatial distribution of CS (Table 2).

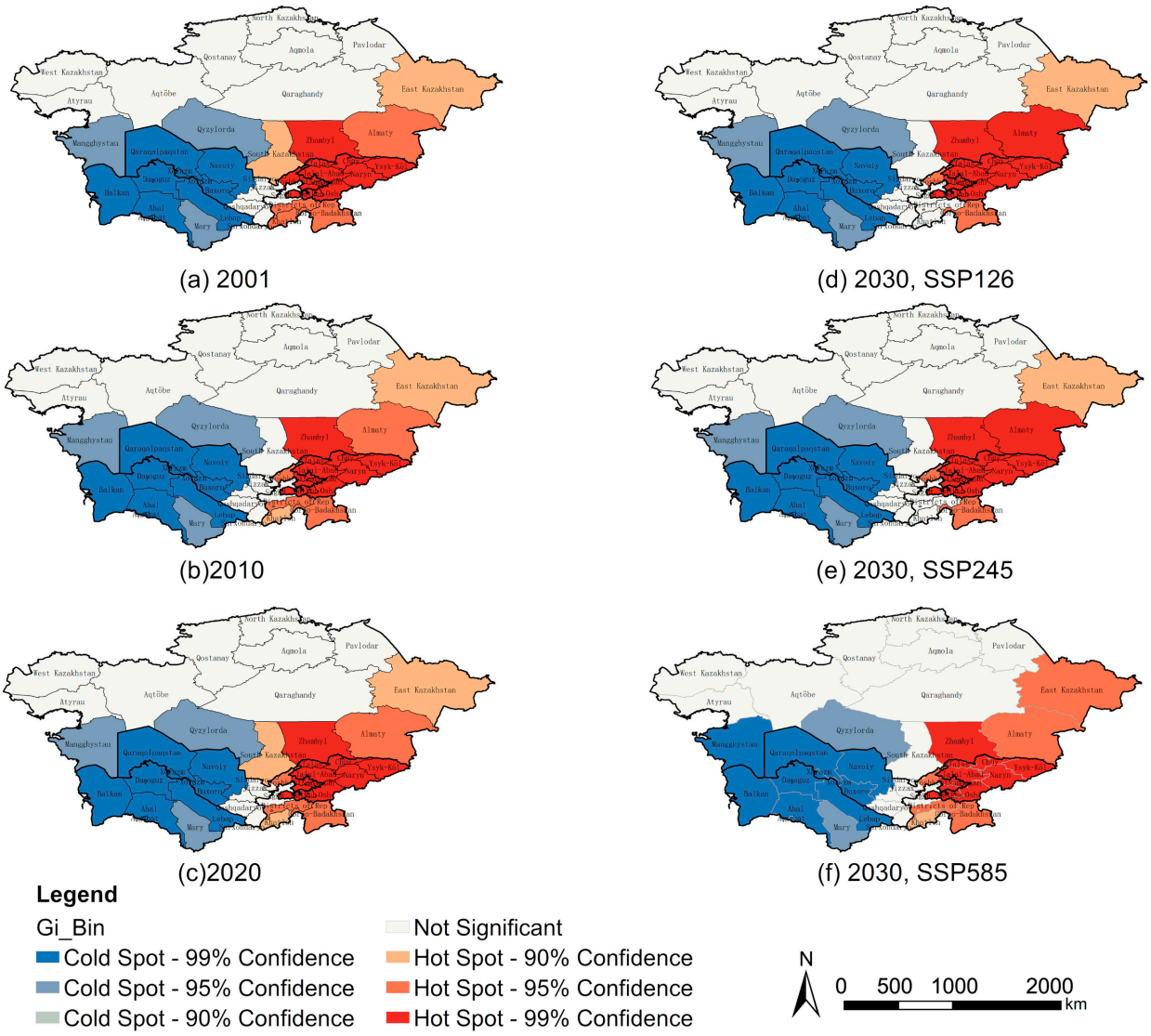


Figure 9. Distribution of cold and hot spots for CS in 2001, 2010, 2020, and 2030 (for three scenarios).

Table 2. *q* values of climate factors influencing CS.

Scenario	Temperature		Precipitation	
	q Statistic	*p* Value	*q* Statistic	*p* Value
SSP126	0.491	0.000	0.528	0.000
SSP245	0.324	0.028	0.490	0.000
SSP585	0.505	0.000	0.439	0.000

Comparing the temperature and precipitation data revealed that the spatial distribution of hot and cold spots associated with CS aligns with the distribution of temperature hot spots and precipitation cold spots. Temperature hot spots roughly coincide with the CS cold spots, while temperature cold spots and precipitation hot spots generally overlap with the CS hot spots (Figure 10).

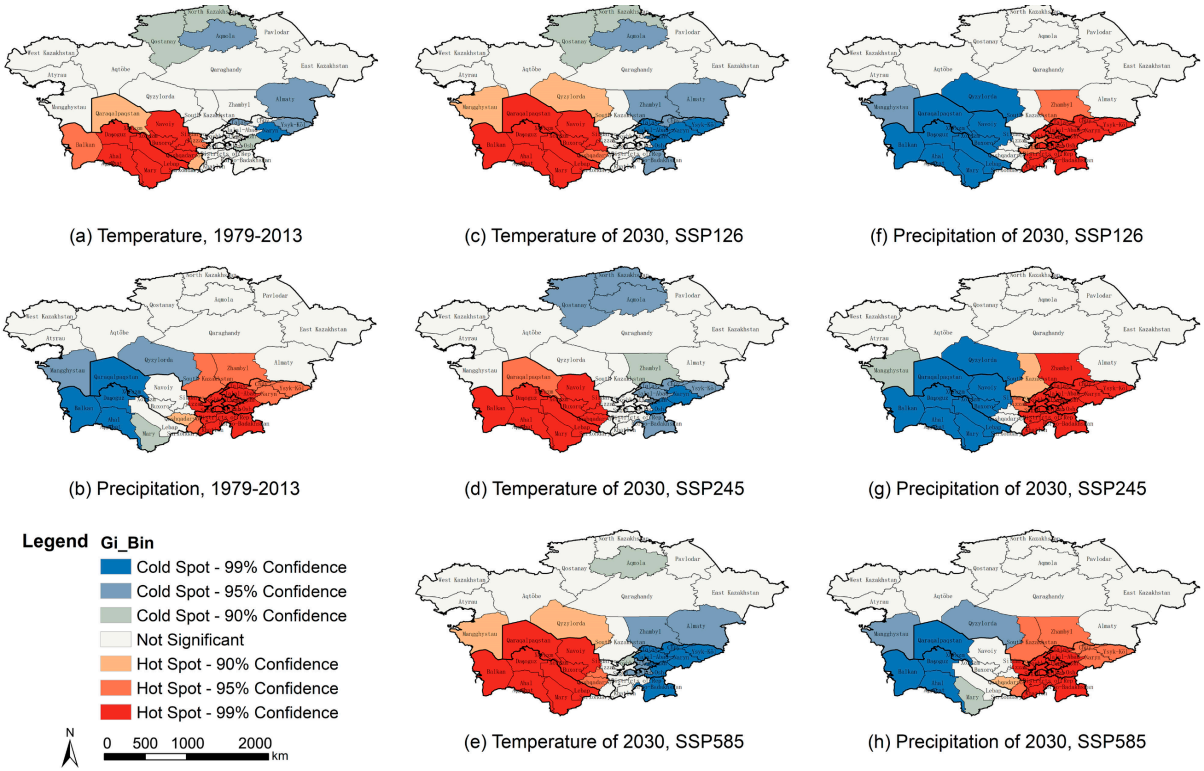


Figure 10. Distribution of the cold–hot spots for climate factors in CA.

4. Discussion

Remote sensing methods are commonly used to assess the CS of an ecosystem. Previous studies have mainly focused on either LUCC [59] or the changes in CS that occur due to LUCC under different population and economic influences [47,60]. However, LUCC combines complex interactions among population, economy, society, and environment; thus, the mechanisms that govern CS changes are highly intricate and have not been adequately considered in previous studies. In this study, based on the actual development status of the five Central Asian countries and by taking into account the high uncertainty of the future climate in CA [61], we utilized SDGs to quantify multiple indicators such as technical innovation, education, and pollution control, which are involved in SSPs and RCPs. In different scenarios, CS in CA is expected to undergo varying changes, providing crucial references for future development.

4.1. Progress in Socio-Economy and Environment Influences on CS in CA

High GDP growth rates often lead to ecological degradation and reduced CS [62,63]. In this study, the economic growth rate of SSP126 is higher than that of SSP245; however, the CS of SSP126 is 1.71 times that of SSP245. This result has also been observed in recent studies: Wang et al. (2022) [47] utilized the PLUS model to predict the CS changes in Bortala, Xinjiang, demonstrating that a moderate GDP growth rate and a low population growth rate favor an increase in CS based on LUCC. Similar views were proposed by Yang et al. (2020) [26], who concluded this result as an outcome of moderate urbanization and technological development. Building upon previous research findings, we substantiate that innovative development indeed promotes CS growth. Furthermore, education and environmental factors also play significant roles in this regard.

1. Innovative development, which is one of the driving forces behind LUCC [64], influences energy efficiency, industrial structure, consumption patterns, etc. Central Asian countries are rich in natural resources such as oil, coal, and natural gas [65]; however, extraction processes involving heavy equipment such as vehicles have caused surface disruption, leading to the replacement of vegetation and soil with impermeable surfaces.

Such replacements damage the carbon sequestration function of the vegetation and result in water resource losses, thereby contributing to artificial carbon emissions [66]. Technological innovations and energy transitions can reduce dependence on fossil fuels and alleviate the ecological footprint [67]. However, the current progress of energy transition in the five Central Asian countries is sluggish [68], and active transitions can aid in ecosystem restoration and enhance carbon sequestration.

2. Education, a crucial determinant of population structure and size [69], is a necessary prerequisite for economic growth [70] since it drives social innovation, development, and progress [71]. Simultaneously, educational attainment also shapes people's understanding of forestry production [72,73], thereby preventing forest resource degradation or deforestation to some extent [74]. This contributes positively to the sustainable management of forest resources and can have profound indirect impacts on CS.

3. The relationship of environmental factors and land use with carbon is intricate and complex [75]. On one hand, anthropogenic activities such as fossil fuel combustion and agricultural practices have led to climate warming since the advent of the Anthropocene, while significantly reducing soil organic matter globally and decreasing NPP in arid forest regions due to water limitations [76]. Reducing greenhouse gas emissions not only controls urban expansion resulting from industrial activities but also enhances the CS capacity of ecosystems. On the other hand, biodiversity is a crucial component of global sustainable development. Plant diversity influences the balance between gross primary productivity and respiration, thus impacting the overall productivity of ecosystems [77]. Strong correlations have also been observed between biomass carbon and amphibian, avian, and mammalian diversities ($r_s = 0.82$) [78], highlighting the connection of biodiversity conservation with CS enhancement. In many developing countries, economic growth takes precedence over everything else. However, our research indicates that improving education levels, increasing energy efficiency, focusing on technological innovation, and pursuing environmental sustainability can incentivize economic growth and realize ecological preservation, thereby promoting the increase in CS.

4.2. Enhance Water Resource Management to Better Address the Challenges of Complex Climate Change

Temperature and precipitation, which are key factors influencing vegetation growth, tend to promote CS accumulation [75,79]. However, between 1979 and 2011, the warming rate in CA (0.4 °C decade^{-1}) was significantly higher than the global warming rate (0.29 °C decade^{-1}) and precipitation sharply decreased (5.8 mm a^{-1}) [20,80]. By the end of this century, more frequent extreme heat events and intensified droughts are projected [81]. These adverse factors collectively impact the stability of arid ecosystems, leading to issues such as vegetation degradation and soil quality decline [82]. Yan and Li (2023) [83] demonstrated that among climate variables, precipitation has a stronger impact on the NPP of arid land vegetation than temperature. Using a geographic detector, we found that under the SSP126 ($q_{prec} = 0.52, q_{temp} = 0.49$) and SSP245 ($q_{prec} = 0.49, q_{temp} = 0.32$) scenarios, precipitation has a greater influence on CS; this is unanimous with the results of previous studies. Additionally, Li et al. (2013) [84] indicated that climate has a positive impact on the vegetable organic carbon (VEGC) content in temperate coniferous forests of the mountain belt in northern Xinjiang, while reducing the VEGC content in lowland temperate broadleaf forests. This suggests that climate has complex impacts on regional carbon dynamics in arid areas. However, given the intricate climatic context of CA, the response of CS to climate remains uncertain.

Water resources, which are a critical limiting factor for vegetation growth in arid lands [85–87], directly govern the productivity of plants by influencing their photosynthetic characteristics and rates [88,89]. Meanwhile, increased precipitation can affect microbial activity, accelerate soil chemical reactions, reduce soil respiration rates, and increase SOC content [90]. Between 2001 and 2030, the cold spots of CS in CA radiate outward from the core regions of the Karakum Desert and the Kyzylkum Desert. These areas are the

hottest and driest regions in CA, where inadequate precipitation has led to substantial biomass loss in the deserts [91]. The Amu Darya and Syr Darya rivers, which are crucial water sources for these deserts, have been excessively exploited since as early as 1960. The reduced flow of these rivers due to climate change and the shrinking of the Aral Sea have transformed the delta regions of these rivers into unproductive deserts [92]. The delta soils of Amu Darya are heavily salinized, exacerbating desertification problems and significantly reducing ecosystem productivity [93,94].

CS hot spots are notably concentrated in the Altay Mountains, Tien Shan Mountains, and Pamir Plateau. Abundant water from glaciers, suitable climate, and vertical zonation have fostered rich grassland and forest resources in this region [95]. CS is significantly higher in this area than in other regions. However, regions such as Almaty, East Kazakhstan, Khatlon, and the Districts of Republican Subordination are unstable high-CS areas and are more susceptible to the impacts of climate change and human activities in the future. Although Kyrgyzstan is a CS hot spot, it exhibits the most severe carbon loss within the studied 30-year period under the SSP245 and SSP585 scenarios primarily due to intense human activities such as agriculture and energy extraction.

Interestingly, results for the SSP585 scenario differ from the findings of previous studies; that is, temperature has a greater impact on CS than precipitation ($q_{prec} = 0.43$, $q_{temp} = 0.50$), which indicates that there may be a tipping point for the impact of climate on dryland CS. Although plants can obtain some limited relief through rainfall when subjected to high temperature stress [96], excessive temperatures can injure plants and lead to other irreversible effects [97,98]. Meanwhile, Albaladejo et al. (2013) [99] revealed that there is no significant relationship between the SOC content in farmlands and precipitation, while concluding that the impact of precipitation on shrubs is unknown. However, they did confirm that an increase in temperature reduces the SOC content of farmland and shrubs; thus, our result is reasonable.

The climate and CS in CA are highly heterogeneous; thus, targeted measures are needed to protect and restore the ecosystems in these regions and mitigate the adverse effects of climate change. Strengthening water resource management is bound to be a key strategy, while appropriate land management and conservation measures also need to be implemented to maintain the stability of CS and promote the health of ecosystems. Agriculture in CA is primarily focused on irrigated farming and animal husbandry. Water resources are crucial for the development of irrigation farming. In order to address the challenges posed by future climate change and the scarcity of water resources in arid areas, it is essential to enhance water utilization efficiency to reduce the risk to food security in CA. On the other hand, the expansion of croplands releases a significant amount of carbon [6]. Additionally, the extra fertilizer production, transportation, and electricity consumption generated by irrigation agriculture also contribute to carbon emissions [100]. Therefore, sustainable agricultural practices such as straw recycling and regulated fertilization need to be adopted to mitigate the negative environmental impacts of irrigated agriculture [101].

Furthermore, since grassland ecosystems are highly fragile and water resources in CA are scarce, intensive grazing can reduce NPP of plants and generate an unknown amount of carbon emissions [102,103]. Thus, despite their excellent CS capacity, grasslands can still become carbon sources [104]. Livestock husbandry is one of the key industries in CA because its vast grasslands encompass the world's largest continuous pastureland [103]. Although rapid economic growth has prompted the sustained expansion of grasslands, over the past 12,000 years, degraded pastures in arid lands have been a major hot spot for global carbon loss [105]. Therefore, in addition to controlling the grazing intensity, avoiding overgrazing, and regular rotation of grazing areas, enhancing water resource efficiency through proper irrigation management and water conservation to maintain adequate water supply for grasslands is also crucial for reducing grassland degradation and carbon emissions.

There are many transnational water bodies distributed in CA; thus, future research and policy development will need to strengthen transnational and interdisciplinary cooperation to address these complex issues, enhance CS, and achieve SDGs.

4.3. Limitations and Future Prospects

Although the seasonal variability of climate significantly impacts the CS of any ecosystem, the InVEST model does not account for the influence of seasonal changes on carbon density, and diverse climate conditions across different seasons introduce considerable variation. This limitation restricts the accuracy of predictive outcomes. In the future, a more comprehensive integration of process-based modeling methods is necessary to simulate CS and its dynamics in drylands. Furthermore, investigating the response mechanisms of CS in arid land toward climate change requires additional research.

5. Conclusions

This study established a comprehensive framework integrating population, economy, society, and environment to predict LUCC and future CS dynamics under three typical scenarios in CA. The results indicate that population and economic growth, social development, and environmental protection influence future CS changes. Unrestricted growth in economy and population would decrease CS; however, promoting CS enhancement through innovative development, education, and environmental protection, while simultaneously considering economic development, is essential for achieving sustainable development.

Under the backdrop of future climate and socio-economic changes, drylands will face sustained challenges, necessitating enhanced water resource management and human-induced activities such as agriculture and mining to strengthen the ecological stability and service capacity of multifunctional landscapes. The CS prediction framework established in this study provides a comprehensive reference for the future development direction of CA, contributing to the enhancement of CS in multifunctional landscapes and the realization of sustainable development in CA.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/land13060801/s1, Supplementary File S1: Table S1. Population–economy–society–environment indicators; Table S2. Formulas for land use types utilized in the SD model; Table S3. Accuracy test of land use demand modeling by the SD model; Table S4. Uncertainty analysis statistics for various land use types in five countries; Figure S1. The interactions and feedback among different variables; Figure S2. Total sensitivity index (ST_i), the first order sensitivity index (S_i), and their confidence intervals; Figure S3. Uncertainty analysis cumulative distribution functions. Supplementary File S2: Formulas for calculating carbon storage.

Author Contributions: X.D.: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data Curation, Writing—Original Draft Preparation, Visualization. Z.C.: Resources, Investigation, Data curation. Y.G.: Software, Data curation. J.L.: Data curation. H.Y.: Data curation. M.L.: Resources. P.Y.: Conceptualization, Writing—Review and Editing, Supervision, Funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Natural Science Foundation of Beijing Province (Grant No. 8222022); the Beijing Forestry University Science and Technology Innovation Plan Project (Grant No. 2019JQ03010); and the Hot Spot Tracking Project of Beijing Forestry University (Grant No. 2022BLRD08).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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

References

1. Martinez-Harms, M.J.; Bryan, B.A.; Figueroa, E.; Pliscoff, P.; Runting, R.K.; Wilson, K.A. Scenarios for Land Use and Ecosystem Services under Global Change. *Ecosyst. Serv.* **2017**, *25*, 56–68. [CrossRef]
2. Eigenbrod, F.; Bell, V.A.; Davies, H.N.; Heinemeyer, A.; Armsworth, P.R.; Gaston, K.J. The Impact of Projected Increases in Urbanization on Ecosystem Services. *Proc. R. Soc. B Biol. Sci.* **2011**, *278*, 3201–3208. [CrossRef] [PubMed]
3. Foley, J.A.; DeFries, R.; Asner, G.P.; Barford, C.; Bonan, G.; Carpenter, S.R.; Chapin, F.S.; Coe, M.T.; Daily, G.C.; Gibbs, H.K.; et al. Global Consequences of Land Use. *Science* **2005**, *309*, 570–574. [CrossRef] [PubMed]
4. Mahowald, N.M.; Randerson, J.T.; Lindsay, K.; Munoz, E.; Doney, S.C.; Lawrence, P.; Schlunegger, S.; Ward, D.S.; Lawrence, D.; Hoffman, F.M. Interactions between Land Use Change and Carbon Cycle Feedbacks. *Glob. Biogeochem. Cycles* **2017**, *31*, 96–113. [CrossRef]
5. Seto, K.C.; Güneralp, B.; Hutyra, L.R. Global Forecasts of Urban Expansion to 2030 and Direct Impacts on Biodiversity and Carbon Pools. *Proc. Natl. Acad. Sci. USA* **2012**, *109*, 16083–16088. [CrossRef]
6. Molotoks, A.; Stehfest, E.; Doelman, J.; Albanito, F.; Fitton, N.; Dawson, T.P.; Smith, P. Global Projections of Future Cropland Expansion to 2050 and Direct Impacts on Biodiversity and Carbon Storage. *Glob. Chang. Biol.* **2018**, *24*, 5895–5908. [CrossRef] [PubMed]
7. Hölting, L.; Jacobs, S.; Felipe-Lucia, M.R.; Maes, J.; Norström, A.V.; Plieninger, T.; Cord, A.F. Measuring Ecosystem Multifunctionality across Scales. *Environ. Res. Lett.* **2019**, *14*, 124083. [CrossRef]
8. Bennett, E.M.; Peterson, G.D.; Gordon, L.J. Understanding Relationships among Multiple Ecosystem Services. *Ecol. Lett.* **2009**, *12*, 1394–1404. [CrossRef]
9. IPCC. *Climate Change 2013: The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2014; ISBN 1-107-05799-X.
10. Reynolds, J.F.; Smith, D.M.S.; Lambin, E.F.; Turner, B.L.; Mortimore, M.; Batterbury, S.P.J.; Downing, T.E.; Dowlatabadi, H.; Fernández, R.J.; Herrick, J.E.; et al. Global Desertification: Building a Science for Dryland Development. *Science* **2007**, *316*, 847–851. [CrossRef]
11. Prăvălie, R. Drylands Extent and Environmental Issues. A Global Approach. *Earth-Sci. Rev.* **2016**, *161*, 259–278. [CrossRef]
12. Ahlström, A.; Raupach, M.R.; Schurgers, G.; Smith, B.; Arneth, A.; Jung, M.; Reichstein, M.; Canadell, J.G.; Friedlingstein, P.; Jain, A.K.; et al. The Dominant Role of Semi-Arid Ecosystems in the Trend and Variability of the Land CO_2 Sink. *Science* **2015**, *348*, 895–899. [CrossRef] [PubMed]
13. Plaza, C.; Zaccone, C.; Sawicka, K.; Méndez, A.M.; Tarquis, A.; Gascó, G.; Heuvelink, G.B.M.; Schuur, E.A.G.; Maestre, F.T. Soil Resources and Element Stocks in Drylands to Face Global Issues. *Sci. Rep.* **2018**, *8*, 13788. [CrossRef] [PubMed]
14. Hanan, N.P.; Milne, E.; Aynekulu, E.; Yu, Q.; Anchang, J. A Role for Drylands in a Carbon Neutral World? *Front. Environ. Sci.* **2021**, *9*, 786087. [CrossRef]
15. Schimel, D.S. Drylands in the Earth System. *Science* **2010**, *327*, 418–419. [CrossRef] [PubMed]
16. Zhu, S.; Li, C.; Shao, H.; Ju, W.; Lv, N. The Response of Carbon Stocks of Drylands in Central Asia to Changes of CO_2 and Climate during Past 35 years. *Sci. Total Environ.* **2019**, *687*, 330–340. [CrossRef] [PubMed]
17. He, L.; Guo, J.; Yang, W.; Jiang, Q.; Chen, L.; Tang, K. Multifaceted Responses of Vegetation to Average and Extreme Climate Change over Global Drylands. *Sci. Total Environ.* **2023**, *858*, 159942. [CrossRef] [PubMed]
18. Zhang, C.; Ren, W. Complex Climatic and CO_2 Controls on Net Primary Productivity of Temperate Dryland Ecosystems over Central Asia during 1980–2014. *J. Geophys. Res. Biogeosci.* **2017**, *122*, 2356–2374. [CrossRef]
19. Huang, J.; Yu, H.; Guan, X.; Wang, G.; Guo, R. Accelerated Dryland Expansion under Climate Change. *Nat. Clim. Change* **2016**, *6*, 166–171. [CrossRef]
20. Li, C.; Zhang, C.; Luo, G.; Chen, X.; Maisupova, B.; Madaminov, A.A.; Han, Q.; Djenbaev, B.M. Carbon Stock and Its Responses to Climate Change in Central Asia. *Glob. Chang. Biol.* **2015**, *21*, 1951–1967. [CrossRef]
21. Lambin, E.F.; Meyfroidt, P. Land Use Transitions: Socio-Ecological Feedback versus Socio-Economic Change. *Land Use Policy* **2010**, *27*, 108–118. [CrossRef]
22. Zhou, M. An Interval Fuzzy Chance-Constrained Programming Model for Sustainable Urban Land-Use Planning and Land Use Policy Analysis. *Land Use Policy* **2015**, *42*, 479–491. [CrossRef]
23. Liang, X.; Guan, Q.; Clarke, K.C.; Liu, S.; Wang, B.; Yao, Y. Understanding the Drivers of Sustainable Land Expansion Using a Patch-Generating Land Use Simulation (PLUS) Model: A Case Study in Wuhan, China. *Comput. Environ. Urban Syst.* **2021**, *85*, 101569. [CrossRef]
24. Pechanec, V.; Purkyt, J.; Benc, A.; Nwaogu, C.; Štěrbová, L.; Cudlín, P. Modelling of the Carbon Sequestration and Its Prediction under Climate Change. *Ecol. Inform.* **2018**, *47*, 50–54. [CrossRef]
25. *Transforming Our World: The 2030 Agenda for Sustainable Development*; United Nations: New York, NY, USA, 2015.
26. Yang, H.; Huang, J.; Liu, D. Linking Climate Change and Socioeconomic Development to Urban Land Use Simulation: Analysis of Their Concurrent Effects on Carbon Storage. *Appl. Geogr.* **2020**, *115*, 102135. [CrossRef]
27. Jiao, M.; Hu, M.; Xia, B. Spatiotemporal Dynamic Simulation of Land-Use and Landscape-Pattern in the Pearl River Delta, China. *Sustain. Cities Soc.* **2019**, *49*, 101581. [CrossRef]
28. Eyring, V.; Bony, S.; Meehl, G.A.; Senior, C.A.; Stevens, B.; Stouffer, R.J.; Taylor, K.E. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) Experimental Design and Organization. *Geosci. Model Dev.* **2016**, *9*, 1937–1958. [CrossRef]

29. O'Neill, B.C.; Tebaldi, C.; van Vuuren, D.P.; Eyring, V.; Friedlingstein, P.; Hurtt, G.; Knutti, R.; Kriegler, E.; Lamarque, J.-F.; Lowe, J.; et al. The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geosci. Model Dev.* **2016**, *9*, 3461–3482. [CrossRef]
30. van Vuuren, D.P.; Kriegler, E.; O'Neill, B.C.; Ebi, K.L.; Riahi, K.; Carter, T.R.; Edmonds, J.; Hallegatte, S.; Kram, T.; Mathur, R.; et al. A New Scenario Framework for Climate Change Research: Scenario Matrix Architecture. *Clim. Chang.* **2014**, *122*, 373–386. [CrossRef]
31. Li, J.; Chen, X.; Kurban, A.; Van de Voorde, T.; De Maeyer, P.; Zhang, C. Coupled SSPs-RCPs Scenarios to Project the Future Dynamic Variations of Water-Soil-Carbon-Biodiversity Services in Central Asia. *Ecol. Indic.* **2021**, *129*, 107936. [CrossRef]
32. Schiemann, R.; Lüthi, D.; Vidale, P.L.; Schär, C. The Precipitation Climate of Central Asia—Intercomparison of Observational and Numerical Data Sources in a Remote Semiarid Region. *Int. J. Climatol.* **2008**, *28*, 295–314. [CrossRef]
33. Popp, A.; Calvin, K.; Fujimori, S.; Havlik, P.; Humpenöder, F.; Stehfest, E.; Bodirsky, B.L.; Dietrich, J.P.; Doelmann, J.C.; Gusti, M.; et al. Land-Use Futures in the Shared Socio-Economic Pathways. *Glob. Environ. Chang.* **2017**, *42*, 331–345. [CrossRef]
34. O'Neill, B.C.; Kriegler, E.; Ebi, K.L.; Kemp-Benedict, E.; Riahi, K.; Rothman, D.S.; van Ruijven, B.J.; van Vuuren, D.P.; Birkmann, J.; Kok, K.; et al. The Roads Ahead: Narratives for Shared Socioeconomic Pathways Describing World Futures in the 21st Century. *Glob. Environ. Chang.* **2017**, *42*, 169–180. [CrossRef]
35. Lambin, E.F.; Meyfroidt, P. Global Land Use Change, Economic Globalization, and the Looming Land Scarcity. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 3465–3472. [CrossRef]
36. Yin, G.; Liu, L.; Jiang, X. The Sustainable Arable Land Use Pattern under the Tradeoff of Agricultural Production, Economic Development, and Ecological Protection—An Analysis of Dongting Lake Basin, China. *Environ. Sci. Pollut. Res.* **2017**, *24*, 25329–25345. [CrossRef] [PubMed]
37. Bodirsky, B.L.; Rolinski, S.; Biewald, A.; Weindl, I.; Popp, A.; Lotze-Campen, H. Global Food Demand Scenarios for the 21st Century. *PLoS ONE* **2015**, *10*, e0139201. [CrossRef] [PubMed]
38. Dietrich, J.P.; Schmitz, C.; Lotze-Campen, H.; Popp, A.; Müller, C. Forecasting Technological Change in Agriculture—An Endogenous Implementation in a Global Land Use Model. *Technol. Forecast. Soc.* **2014**, *81*, 236–249. [CrossRef]
39. Doelman, J.C.; Stehfest, E.; Tabeau, A.; Van Meijl, H.; Lassaletta, L.; Gernaat, D.E.H.J.; Hermans, K.; Harmsen, M.; Daioglou, V.; Biemans, H.; et al. Exploring SSP Land-Use Dynamics Using the IMAGE Model: Regional and Gridded Scenarios of Land-Use Change and Land-Based Climate Change Mitigation. *Glob. Environ. Chang.* **2018**, *48*, 119–135. [CrossRef]
40. Jiang, L.; O'Neill, B.C. Global Urbanization Projections for the Shared Socioeconomic Pathways. *Glob. Environ. Chang.* **2017**, *42*, 193–199. [CrossRef]
41. Tian, H.; Lu, C.; Chen, G.; Xu, X.; Liu, M.; Ren, W.; Tao, B.; Sun, G.; Pan, S.; Liu, J. Climate and Land Use Controls over Terrestrial Water Use Efficiency in Monsoon Asia. *Ecohydrology* **2011**, *4*, 322–340. [CrossRef]
42. Rafiei-Sardooi, E.; Azareh, A.; Joorabian Shooshtari, S.; Parteli, E.J.R. Long-Term Assessment of Land-Use and Climate Change on Water Scarcity in an Arid Basin in Iran. *Ecol. Model.* **2022**, *467*, 109934. [CrossRef]
43. Riahi, K.; van Vuuren, D.P.; Kriegler, E.; Edmonds, J.; O'Neill, B.C.; Fujimori, S.; Bauer, N.; Calvin, K.; Dellink, R.; Fricko, O.; et al. The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview. *Glob. Environ. Chang.* **2017**, *42*, 153–168. [CrossRef]
44. Cao, M.; Tian, Y.; Wu, K.; Chen, M.; Chen, Y.; Hu, X.; Sun, Z.; Zuo, L.; Lin, J.; Luo, L.; et al. Future Land-Use Change and Its Impact on Terrestrial Ecosystem Carbon Pool Evolution along the Silk Road under SDG Scenarios. *Sci. Bull.* **2023**, *68*, 740–749. [CrossRef] [PubMed]
45. Pu, J.; Shen, A.; Liu, C.; Wen, B. Impacts of Ecological Land Fragmentation on Habitat Quality in the Taihu Lake Basin in Jiangsu Province, China. *Ecol. Indic.* **2024**, *158*, 111611. [CrossRef]
46. Lafortune, G.; Fuller, G.; Moreno, J.; Schmidt-Traub, G.; Kroll, C. SDG Index and Dashboards Detailed Methodological Paper. *Sustain. Dev. Solut. Netw.* **2018**, *9*, 1–56.
47. Wang, Z.; Li, X.; Mao, Y.; Li, L.; Wang, X.; Lin, Q. Dynamic Simulation of Land Use Change and Assessment of Carbon Storage Based on Climate Change Scenarios at the City Level: A Case Study of Bortala, China. *Ecol. Indic.* **2022**, *134*, 108499. [CrossRef]
48. Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M.; Tarantola, S. *2004 Global Sensitivity Analysis: The Primer*; John Wiley & Sons: Hoboken, NJ, USA, 2008; ISBN 978-0-470-05997-5.
49. Servadio, J.L.; Convertino, M. Optimal Information Networks: Application for Data-Driven Integrated Health in Populations. *Sci. Adv.* **2018**, *4*, e1701088. [CrossRef] [PubMed]
50. Christopher Frey, H.; Patil, S.R. Identification and Review of Sensitivity Analysis Methods. *Risk Anal.* **2002**, *22*, 553–578. [CrossRef]
51. DeJonge, K.C.; Ascough, J.C.; Ahmadi, M.; Andales, A.A.; Arabi, M. Global Sensitivity and Uncertainty Analysis of a Dynamic Agroecosystem Model under Different Irrigation Treatments. *Ecol. Model.* **2012**, *231*, 113–125. [CrossRef]
52. Chu-Agor, M.L.; Muñoz-Carpena, R.; Kiker, G.; Emanuelsson, A.; Linkov, I. Exploring Vulnerability of Coastal Habitats to Sea Level Rise through Global Sensitivity and Uncertainty Analyses. *Environ. Model. Softw.* **2011**, *26*, 593–604. [CrossRef]
53. Baraldi, P.; Zio, E. A Combined Monte Carlo and Possibilistic Approach to Uncertainty Propagation in Event Tree Analysis. *Risk Anal.* **2008**, *28*, 1309–1326. [CrossRef]
54. Wu, J.; Luo, J.; Zhang, H.; Qin, S.; Yu, M. Projections of Land Use Change and Habitat Quality Assessment by Coupling Climate Change and Development Patterns. *Sci. Total Environ.* **2022**, *847*, 157491. [CrossRef] [PubMed]

55. Huang, J.; Tang, Z.; Liu, D.; He, J. Ecological Response to Urban Development in a Changing Socio-Economic and Climate Context: Policy Implications for Balancing Regional Development and Habitat Conservation. *Land Use Policy* **2020**, *97*, 104772. [CrossRef]
56. Zhu, W.; Zhang, J.; Cui, Y.; Zhu, L. Ecosystem Carbon Storage under Different Scenarios of Land Use Change in Qihe Catchment, China. *J. Geogr. Sci.* **2020**, *30*, 1507–1522. [CrossRef]
57. Li, Z.; Chen, Y.; Zhang, Q.; Li, Y. Spatial Patterns of Vegetation Carbon Sinks and Sources under Water Constraint in Central Asia. *J. Hydrol.* **2020**, *590*, 125355. [CrossRef]
58. Zeng, Z.; Wu, W.; Li, Y.; Huang, C.; Zhang, X.; Peñuelas, J.; Zhang, Y.; Gentine, P.; Li, Z.; Wang, X.; et al. Increasing Meteorological Drought under Climate Change Reduces Terrestrial Ecosystem Productivity and Carbon Storage. *One Earth* **2023**, *6*, 1326–1339. [CrossRef]
59. Li, J.; Chen, H.; Zhang, C.; Pan, T. Variations in Ecosystem Service Value in Response to Land Use/Land Cover Changes in Central Asia from 1995–2035. *PeerJ* **2019**, *7*, e7665. [CrossRef] [PubMed]
60. He, C.; Zhang, D.; Huang, Q.; Zhao, Y. Assessing the Potential Impacts of Urban Expansion on Regional Carbon Storage by Linking the LUSD-Urban and InVEST Models. *Environ. Model. Softw.* **2016**, *75*, 44–58. [CrossRef]
61. Lioubimtseva, E.; Henebry, G.M. Climate and Environmental Change in Arid Central Asia: Impacts, Vulnerability, and Adaptations. *J. Arid Environ.* **2009**, *73*, 963–977. [CrossRef]
62. Luo, Y.; Shen, J.; Chen, A.; Tao, Q.; Li, Q.; White, P.J.; Li, T.; Li, B.; Chen, L.; Li, H.; et al. Loss of Organic Carbon in Suburban Soil upon Urbanization of Chengdu Megacity, China. *Sci. Total Environ.* **2021**, *785*, 147209. [CrossRef]
63. Wang, Z.; Gao, Y.; Wang, X.; Lin, Q.; Li, L. A New Approach to Land Use Optimization and Simulation Considering Urban Development Sustainability: A Case Study of Bortala, China. *Sustain. Cities Soc.* **2022**, *87*, 104135. [CrossRef]
64. Moss, R.H.; Edmonds, J.A.; Hibbard, K.A.; Manning, M.R.; Rose, S.K.; van Vuuren, D.P.; Carter, T.R.; Emori, S.; Kainuma, M.; Kram, T.; et al. The next Generation of Scenarios for Climate Change Research and Assessment. *Nature* **2010**, *463*, 747–756. [CrossRef] [PubMed]
65. Dorian, J.P. Central Asia: A Major Emerging Energy Player in the 21st Century. *Energy Policy* **2006**, *34*, 544–555. [CrossRef]
66. Jones, N.F.; Pejchar, L.; Kiesecker, J.M. The Energy Footprint: How Oil, Natural Gas, and Wind Energy Affect Land for Biodiversity and the Flow of Ecosystem Services. *BioScience* **2015**, *65*, 290–301. [CrossRef]
67. Bashir, M.F.; Pan, Y.; Shahbaz, M.; Ghosh, S. How Energy Transition and Environmental Innovation Ensure Environmental Sustainability? Contextual Evidence from Top-10 Manufacturing Countries. *Renew. Energy* **2023**, *204*, 697–709. [CrossRef]
68. Radovanović, M.; Filipović, S.; Andrejević Panić, A. Sustainable Energy Transition in Central Asia: Status and Challenges. *Energy Sustain. Soc.* **2021**, *11*, 49. [CrossRef]
69. Kc, S.; Lutz, W. The Human Core of the Shared Socioeconomic Pathways: Population Scenarios by Age, Sex and Level of Education for All Countries to 2100. *Glob. Environ. Chang.* **2017**, *42*, 181–192. [CrossRef] [PubMed]
70. Lutz, W.; Cuaresma, J.C.; Sanderson, W. The Demography of Educational Attainment and Economic Growth. *Science* **2008**, *319*, 1047–1048. [CrossRef] [PubMed]
71. Wu, N.; Liu, Z. Higher Education Development, Technological Innovation and Industrial Structure Upgrade. *Technol. Forecast. Soc. Chang.* **2021**, *162*, 120400. [CrossRef]
72. Bardsley, D.K.; Cedamon, E.; Paudel, N.S.; Nuberg, I. Education and Sustainable Forest Management in the Mid-Hills of Nepal. *J. Environ. Manag.* **2022**, *319*, 115698. [CrossRef]
73. Godoy, R.; Groff, S.; O'Neill, K. The Role of Education in Neotropical Deforestation: Household Evidence from Amerindians in Honduras. *Hum. Ecol.* **1998**, *26*, 649–675. [CrossRef]
74. Handavu, F.; Chirwa, P.W.C.; Syampungani, S. Socio-Economic Factors Influencing Land-Use and Land-Cover Changes in the Miombo Woodlands of the Copperbelt Province in Zambia. *For. Policy Econ.* **2019**, *100*, 75–94. [CrossRef]
75. Wani, O.A.; Kumar, S.S.; Hussain, N.; Wani, A.I.A.; Babu, S.; Alam, P.; Rashid, M.; Popescu, S.M.; Mansoor, S. Multi-Scale Processes Influencing Global Carbon Storage and Land-Carbon-Climate Nexus: A Critical Review. *Pedosphere* **2023**, *33*, 250–267. [CrossRef]
76. Saxe, H.; Cannell, M.G.R.; Johnsen, Ø.; Ryan, M.G.; Vourlitis, G. Tree and Forest Functioning in Response to Global Warming. *New Phytol.* **2001**, *149*, 369–399. [CrossRef] [PubMed]
77. Catovsky, S.; Bradford, M.A.; Hector, A. Biodiversity and Ecosystem Productivity: Implications for Carbon Storage. *Oikos* **2002**, *97*, 443–448. [CrossRef]
78. Strassburg, B.B.N.; Kelly, A.; Balmford, A.; Davies, R.G.; Gibbs, H.K.; Lovett, A.; Miles, L.; Orme, C.D.L.; Price, J.; Turner, R.K.; et al. Global Congruence of Carbon Storage and Biodiversity in Terrestrial Ecosystems. *Conserv. Lett.* **2010**, *3*, 98–105. [CrossRef]
79. Tian, H.; Melillo, J.M.; Kicklighter, D.W.; McGuire, A.D.; Helfrich, J. The Sensitivity of Terrestrial Carbon Storage to Historical Climate Variability and Atmospheric CO_2 in the United States. *Tellus B Chem. Phys. Meteorol.* **1999**, *51*, 414–452. [CrossRef]
80. Hu, Z.; Zhang, C.; Hu, Q.; Tian, H. Temperature Changes in Central Asia from 1979 to 2011 Based on Multiple Datasets. *J. Clim.* **2014**, *27*, 1143–1167. [CrossRef]
81. Reyer, C.P.O.; Otto, I.M.; Adams, S.; Albrecht, T.; Baarsch, F.; Cartsburg, M.; Coumou, D.; Eden, A.; Ludi, E.; Marcus, R.; et al. Climate Change Impacts in Central Asia and Their Implications for Development. *Reg. Environ. Change* **2017**, *17*, 1639–1650. [CrossRef]

82. Gong, H.; Meng, D.; Li, X.; Zhu, F. Soil Degradation and Food Security Coupled with Global Climate Change in Northeastern China. *Chin. Geogr. Sci.* **2013**, *23*, 562–573. [CrossRef]
83. Yan, X.; Li, L. Spatiotemporal Characteristics and Influencing Factors of Ecosystem Services in Central Asia. *J. Arid Land* **2023**, *15*, 1–19. [CrossRef]
84. Li, C.; Zhang, C.; Luo, G.; Chen, X. Modeling the Carbon Dynamics of the Dryland Ecosystems in Xinjiang, China from 1981 to 2007—The Spatiotemporal Patterns and Climate Controls. *Ecol. Model.* **2013**, *267*, 148–157. [CrossRef]
85. He, B.; Wang, S.; Guo, L.; Wu, X. Aridity Change and Its Correlation with Greening over Drylands. *Agric. For. Meteorol.* **2019**, *278*, 107663. [CrossRef]
86. Wu, Z.; Dijkstra, P.; Koch, G.W.; Peñuelas, J.; Hungate, B.A. Responses of Terrestrial Ecosystems to Temperature and Precipitation Change: A Meta-Analysis of Experimental Manipulation. *Glob. Change Biol.* **2011**, *17*, 927–942. [CrossRef]
87. Zhao, M.; Running, S.W. Drought-Induced Reduction in Global Terrestrial Net Primary Production from 2000 through 2009. *Science* **2010**, *329*, 940–943. [CrossRef]
88. Pinheiro, C.; Chaves, M.M. Photosynthesis and Drought: Can We Make Metabolic Connections from Available Data? *J. Exp. Bot.* **2011**, *62*, 869–882. [CrossRef] [PubMed]
89. Quick, W.P.; Chaves, M.M.; Wendler, R.; David, M.; Rodrigues, M.L.; Passaharinho, J.A.; Pereira, J.S.; Adcock, M.D.; Leegood, R.C.; Stitt, M. The Effect of Water Stress on Photosynthetic Carbon Metabolism in Four Species Grown under Field Conditions. *Plant Cell Environ.* **1992**, *15*, 25–35. [CrossRef]
90. Wei, G.; Zhang, C.; Li, Q.; Wang, H.; Wang, R.; Zhang, Y.; Yuan, Y. An Evaluation of Topsoil Carbon Storage in Chinese Deserts. *Sci. Total Environ.* **2023**, *872*, 162284. [CrossRef] [PubMed]
91. Zhang, C.; Lu, D.; Chen, X.; Zhang, Y.; Maisupova, B.; Tao, Y. The Spatiotemporal Patterns of Vegetation Coverage and Biomass of the Temperate Deserts in Central Asia and Their Relationships with Climate Controls. *Remote Sens. Environ.* **2016**, *175*, 271–281. [CrossRef]
92. Saiko, T.A.; Zonn, I.S. Irrigation Expansion and Dynamics of Desertification in the Circum-Aral Region of Central Asia. *Appl. Geogr.* **2000**, *20*, 349–367. [CrossRef]
93. Jiang, L.; Jiapaer, G.; Bao, A.; Kurban, A.; Guo, H.; Zheng, G.; De Maeyer, P. Monitoring the Long-Term Desertification Process and Assessing the Relative Roles of Its Drivers in Central Asia. *Ecol. Indic.* **2019**, *104*, 195–208. [CrossRef]
94. Jiang, L.; Jiapaer, G.; Bao, A.; Guo, H.; Ndayisaba, F. Vegetation Dynamics and Responses to Climate Change and Human Activities in Central Asia. *Sci. Total Environ.* **2017**, *599–600*, 967–980. [CrossRef] [PubMed]
95. Yin, H.; Khamzina, A.; Pflugmacher, D.; Martius, C. Forest Cover Mapping in Post-Soviet Central Asia Using Multi-Resolution Remote Sensing Imagery. *Sci. Rep.* **2017**, *7*, 1375. [CrossRef] [PubMed]
96. Fahad, S.; Bajwa, A.A.; Nazir, U.; Anjum, S.A.; Farooq, A.; Zohaib, A.; Sadia, S.; Nasim, W.; Adkins, S.; Saud, S.; et al. Crop Production under Drought and Heat Stress: Plant Responses and Management Options. *Front. Plant Sci.* **2017**, *8*, 1147. [CrossRef] [PubMed]
97. Chaudhry, S.; Sidhu, G.P.S. Climate Change Regulated Abiotic Stress Mechanisms in Plants: A Comprehensive Review. *Plant Cell Rep.* **2022**, *41*, 1–31. [CrossRef] [PubMed]
98. Niu, S.; Luo, Y.; Li, D.; Cao, S.; Xia, J.; Li, J.; Smith, M.D. Plant Growth and Mortality under Climatic Extremes: An Overview. *Environ. Exp. Bot.* **2014**, *98*, 13–19. [CrossRef]
99. Albaladejo, J.; Ortiz, R.; Garcia-Franco, N.; Navarro, A.R.; Almagro, M.; Pintado, J.G.; Martínez-Mena, M. Land Use and Climate Change Impacts on Soil Organic Carbon Stocks in Semi-Arid Spain. *J. Soils Sediments* **2013**, *13*, 265–277. [CrossRef]
100. Zhang, W.; He, X.; Zhang, Z.; Gong, S.; Zhang, Q.; Zhang, W.; Liu, D.; Zou, C.; Chen, X. Carbon Footprint Assessment for Irrigated and Rainfed Maize (*Zea mays* L.) Production on the Loess Plateau of China. *Biosyst. Eng.* **2018**, *167*, 75–86. [CrossRef]
101. Yu, C.; Xu, G.; Cai, M.; Li, Y.; Wang, L.; Zhang, Y.; Lin, H. Predicting Environmental Impacts of Smallholder Wheat Production by Coupling Life Cycle Assessment and Machine Learning. *Sci. Total Environ.* **2024**, *921*, 171097. [CrossRef] [PubMed]
102. Chang, J.; Ciais, P.; Gasser, T.; Smith, P.; Herrero, M.; Havlík, P.; Obersteiner, M.; Guenet, B.; Goll, D.S.; Li, W.; et al. Climate Warming from Managed Grasslands Cancels the Cooling Effect of Carbon Sinks in Sparsely Grazed and Natural Grasslands. *Nat. Commun.* **2021**, *12*, 118. [CrossRef]
103. Mirzabaev, A.; Ahmed, M.; Werner, J.; Pender, J.; Louhaichi, M. Rangelands of Central Asia: Challenges and Opportunities. *J. Arid Land* **2016**, *8*, 93–108. [CrossRef]
104. Jones, M.B.; Donnelly, A. Carbon Sequestration in Temperate Grassland Ecosystems and the Influence of Management, Climate and Elevated CO_2. *New Phytol.* **2004**, *164*, 423–439. [CrossRef]
105. Sanderman, J.; Hengl, T.; Fiske, G.J. Soil Carbon Debt of 12,000 Years of Human Land Use. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 9575–9580. [CrossRef] [PubMed]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.