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Abstract

As a critical ecological barrier and carbon reservoir on the eastern Qinghai-Xizang Plateau, the Qilian Mountains (QLMs) play a vital role in maintaining regional ecological security. This study employed an enhanced Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model with dynamic interannual carbon density parameterization to evaluate carbon storage (CS) variations in the QLMs during the historical period of 1990–2020 and future period of 2030–2100 under climate scenarios (SSP126, SSP245, and SSP585, where SSP is the Shared Socio-economic Pathway). By integrating GeoDetector analysis, random forest modeling, and scenario simulations, we further assessed climate-human interactions and their impacts on CS. The QLMs had a multi-year average CS of 1.49×10^9 t during 1990–2020, with higher values in the southeast and lower values in the northwest. The spatial heterogeneity of CS was primarily driven by warming–wetting climatic gradients. Multi-scenario projections revealed divergent trajectories: under the SSP126 scenario, ecological restoration measures (e.g., mountain closure and afforestation) increased CS, whereas CS under SSP245 and SSP585 scenarios exhibited inverted U-shaped patterns. Notably, SSP585 resulted in 8.00×10^7 t losses due to extensive conversions from grassland to urban area during 2050–2100. Grassland and cropland CS, together with precipitation, emerged as the key determinants of regional CS dynamics, with a synergistic interaction between precipitation and temperature. This study introduced a century-scale, multi-scenario framework that captures temporal interactions and dynamically parameterizes carbon density coefficients for era-specific accuracy. The findings suggest optimizing vegetation coverage, managing urban expansion, and implementing climate adaptation strategies to enhance the total CS of this ecologically sensitive region.

Full Text

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Enhanced InVEST modeling reveals divergent trajectories of carbon storage in the eastern Qinghai-Xizang Plateau during 1990–2100

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Abstract: As a critical ecological barrier and carbon reservoir on the eastern Qinghai-Xizang Plateau, the Qilian Mountains (QLMs) play a vital role in maintaining regional ecological security. This study employed an enhanced Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model with dynamic interannual carbon density parameterization to evaluate carbon storage (CS) variations in the QLMs during the historical period of 1990–2020 and future period of 2030–2100 under climate scenarios (SSP126, SSP245, and SSP585, where SSP is the Shared Socio-economic Pathway). By integrating GeoDetector analysis, random forest modeling, and scenario simulations, we further assessed climate-human interactions and their impacts on CS. The QLMs had a multi-year average CS of 1.49×10^9 t during 1990–2020, with higher values in the southeast and lower values in the northwest. The spatial heterogeneity of CS was primarily driven by warming–wetting climatic gradients. Multi-scenario projections revealed divergent trajectories: under the SSP126 scenario, ecological restoration measures (e.g., mountain closure and afforestation) increased CS, whereas CS under SSP245 and SSP585 scenarios exhibited inverted U-shaped patterns. Notably, SSP585 resulted in 8.00×10^7 t losses due to extensive conversions from grassland to urban area during 2050–2100. Grassland and cropland CS, together with precipitation, emerged as the key determinants of regional CS dynamics, with a synergistic interaction between precipitation and temperature. This study introduced a century-scale, multi-scenario framework that captures temporal interactions and dynamically parameterizes carbon density coefficients for era-specific accuracy. The findings suggest optimizing vegetation coverage, managing urban expansion, and implementing climate adaptation strategies to enhance the total CS of this ecologically sensitive region.

Keywords: carbon storage (CS); land use and land cover (LULC); GeoDetector analysis; scenario simulations; climate change; Qilian Mountains

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1 Introduction

Global climate change is profoundly affecting ecosystem structure and function, posing severe

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challenges to regional sustainable development (Liu et al., 2019). In this context, enhancing the carbon storage (CS) of terrestrial ecosystems has become an important pathway toward achieving the "dual-carbon" strategy. As a pivotal component of the Earth' s carbon cycle, terrestrial ecosystems regulate atmospheric carbon dioxide (CO_2) concentrations through vegetation photosynthesis, soil organic matter storage, and detritus carbon fixation (Ito et al., 2016; Xu et al., 2018). The spatiotemporal patterns of carbon sources or sinks exhibit significant associations with land use and land cover (LULC) change (Ma and Wang, 2015). Previous studies have demonstrated that LULC, as a direct manifestation of human impacts on terrestrial ecosystems, alters surface biogeochemical processes and material-energy cycles (Li et al., 2014). These changes not only drive vegetation redistribution but also amplify spatial heterogeneity in CS (Pongratz et al., 2008). Since the Industrial Revolution, human activities such as fossil fuel consumption and deforestation have dramatically transformed LULC patterns (Fang et al., 2018), generating approximately 4.30×10^9 t of annual carbon emissions (deB Richter and Houghton, 2011). This unequivocally underscores LULC' s profound regulatory role in the global carbon cycle equilibrium.

In light of China' s strategic goals of achieving carbon peaking by 2030 and carbon neutrality by 2060, there is an urgent need to investigate the dynamic response mechanisms between LULC and CS (Zeng et al., 2022). First, different LULC types directly regulate ecosystem CS by altering vegetation coverage and soil physicochemical properties (Rimal et al., 2019). Second, LULC-induced alterations in energy budgets and biogeochemical processes indirectly influence regional carbon fluxes by modifying microclimatic conditions (Chang et al., 2022). In this context, constructing multi-scale LULC–CS coupling models becomes essential to elucidate the interactions between climatic drivers (e.g., temperature and precipitation) and anthropogenic factors (e.g., urbanization and grazing intensity). Such research is of critical significance for maintaining the balance and stability of regional carbon cycles.

Methodologically, CS assessment systems have evolved from traditional observations to model-based simulations. Conventional approaches such as flux measurements and plot inventories ensure accuracy but are limited by spatial coverage and temporal costs (Liang et al., 2021; Yan et al., 2022). Biogeochemical models including Carbon Exchange between Vegetation, Soil, and Atmosphere (CEVSA) (Zhang et al., 2025b), BIOME-BioGeochemical Cycles (BIOME-BGC) (Yan et al., 2016; Fang et al., 2024), and CENTURY (Berardi et al., 2020) have advanced dynamic CS assessments. However, the complex parameterization of these models restricts their application in multi-scenario studies. The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model has become a widely used tool for LULC–CS analyses due to its simplicity, spatial visualization, and integration of climatic and anthropogenic factors (Mukhopadhyay et al., 2025). It enables large-scale assessments with user-friendly outputs, making it applicable to diverse LULC studies (Wang et al., 2022). Representative studies include Zhu et al. (2021), who detected gradient carbon loss patterns from construction land expansion in arid Northwest China using the Cellular Automata-Markov (CA-Markov) model combined with the InVEST; Wang et al. (2022), who identified cropland-to-urban conversion as the dominant driver of carbon loss in Changchun City, Jilin Province, China; and collaborative research by Jiang et al. (2017) and Liu et al. (2023), who assessed urbanization' s system-wide carbon impacts. However, the model' s simplified treatment of biogeochemical processes in its CS component can limit its accuracy in regions characterized by complex ecological dynamics and varying carbon fluxes. These limitations arise from the model's reliance on static carbon density values and its inability to account for annual fluctuations in CS across diverse LULC types and scenarios (Zhang et al., 2025a). Therefore, applying dynamic InVEST carbon density parameters is critical for improving the model' s capacity to simulate CS under evolving natural and socio-economic conditions, thereby ensuring more accurate predictions of carbon dynamics.

As a key ecological barrier in the Qinghai-Xizang Plateau of China, the Qilian Mountains (QLMs) play a crucial role in maintaining regional ecological balance, safeguarding inland water

resources, and ensuring watershed security (Qian et al., 2019). The region possesses significant CS potential through its forest, grassland, and wetland ecosystems. However, intensive human activities since the 1950s, including overgrazing and mining, have severely degraded its ecological functions (Shan et al., 2023). Although policies such as the Grain for Green Program and the Natural Forest Protection Project have facilitated localized recovery, population growth and economic pressures continue to drive LULC transformations (Li et al., 2021). Current research on CS in the QLMs has insufficiently investigated long-term temporal variations (Su et al., 2024; Yuan et al., 2024). In addition to human activities, the QLMs face unique challenges due to permafrost degradation. The acceleration of permafrost thaw and LULC driven by climate warming leads to the destabilization of vegetation and soil carbon pools, compounding concerns regarding CS in these regions (Schuur et al., 2015; Deng et al., 2024). Understanding how LULC interacts with climate change to affect CS in the QLMs is vital for formulating effective land management and climate-adaptive strategies to protect permafrost soils and alpine vegetation.

This study applied dynamic annual adjustments to the InVEST carbon density parameters to simulate CS in the QLMs and quantified the interactions between LULC and CS during the historical period (1990–2020) and future period (2030-2100) under climate scenarios (SSP126, SSP245, and SSP585, where SSP is the

Fig. 1 Elevation distribution of the Qilian Mountains (QLMs).

Figure 1: Fig. 1 Elevation distribution of the Qilian Mountains (QLMs).

Shared Socio-economic Pathway). The findings provide new insights into CS dynamics in the QLMs, contributing to the stability of CS in vulnerable regions facing permafrost and vegetation degradation.

2 Materials and methods

2.1 Study area

Situated along the margin of the Qinghai-Xizang Plateau, the QLMs span 33 counties across Gansu and Qinghai provinces in northwestern China, covering approximately 2.0×10^5 km^2 (93°31′–103°54′E, 35°50′–39°59′N; Fig. 1). Bordered by the Hexi Corridor to the north and the Qaidam Basin to the south, this region serves as a transitional zone connecting the Qinghai-Xizang Plateau, Inner Mongolian Plateau, and Loess Plateau. Elevations range from 2156 to 5674 m, and the topography shows higher in the northwest and lower in the southeast. The QLMs feature diverse landforms, including alpine ranges, permanent snowfields, glaciers, deep canyons, and intermontane basins shaped by tectonic fault zones. Climatically, the region exhibits a plateau continental regime characterized by intense solar radiation (annual average 5800 MJ/m^2), significant annual temperature variations (from -5.6°C to 14.5°C), and uneven precipitation (370 mm/a), with most precipitation concentrated between May and September (Xu et al., 2020). The QLMs serve as the headwater source for major rivers (e.g., the Datong River, Heihe River, Shule River, and Shiyang River) and host Qinghai Lake, China' s largest inland lake, earning the region the designation of a "solid water tower". Vegetation shows distinct horizontal and vertical zonation, dominated by grassland and desert ecosystems that reflect unique eco-geographic patterns.

Fig. 1 Elevation distribution of the Qilian Mountains (QLMs). The elevation data are sourced from the Resource and Environmental Science Data Platform (https://www.resdc.cn/data.aspx?DATAID=123).

2.2 Data sources

The datasets employed in this study included historical and future LULC, net primary productivity (NPP; g C/m^2), forest aboveground biomass (AGB; Mg/hm^2), 0–30 cm soil organic carbon density (SOCD; kg C/m^2), historical and future mean annual temperature (MAT; °C), historical and future precipitation (PRE; mm), sunshine duration (SSD; h), population density (PD; persons/km^2), gross domestic product (GDP; 10^4 CNY/km^2), and grazing intensity (GI; SU/hm^2) datasets. Future LULC data from 2030 to 2100 were obtained from the study of Zhang et al. (2023), which incorporated variations in climatic and socio-economic factors. This dataset demonstrates robust applicability in mountainous ecosystems, evidenced by an averaged Pearson correlation coefficient of 0.88 against regional validation samples. LULC classification was standardized into six categories (cropland, woodland, grassland, water body, urban area, and bareland) using ArcGIS 10.8 for reclassification. Future temperature and precipitation data were based on SSP126 (sustainability pathway), SSP245 (intermediate pathway), and SSP585 (fossil-fueled development pathway) scenarios. Details of all datasets are shown in Table 1.

Table 1 Description of the data used in this study

Data type	Unit	Spatial resolution	Time period	Data source
Land use and land cover (LULC)	-	300 m	1990–2020	ESA CCI Land Cover (http://www.esa-landcover-cci.org/)
Land use and land cover (LULC)	-	1 km	2030–2100	Zhang et al. (2023) (https://doi.org/10.6084/m9.figshare.2354
Net primary productivity (NPP)	g C/m^2	5 km	1982–2018	National Earth System Science Data Center (https://www.glass.hku.hk/download.html
Forest above-ground biomass (AGB)	Mg/hm^2	30 m	1985–2023	Cai et al. (2025) (https://code.earthengine.google.com/4f8a
Soil organic carbon density (SOCD)	kg C/m^2	250 m	2010–2018	National Tibetan Plateau Scientific Data Center (https://cstr.cn/18406.11.Terre.tpdc.27248

Data type	Unit	Spatial resolution	Time period	Data source
Precipitation (PRE)	mm	1 km	1990–2020	Resource and Environmental Science Data Platform (https://www.resdc.cn/data.aspx?DATAII
Precipitation (PRE)	mm	1 km	2030–2100	National Tibetan Plateau Scientific Data Center (https://data.tpdc.ac.cn/zh-hans/data/90a7b4b6-4009-463a-b34f-e8ebd0238617)
Mean annual temperature (MAT)	°C	1 km	1990–2020	Resource and Environmental Science Data Platform (https://www.resdc.cn/data.aspx?DATAII
Mean annual temperature (MAT)	°C	1 km	2030–2100	National Tibetan Plateau Scientific Data Center (https://data.tpdc.ac.cn/zh-hans/data/169d91c0-c38f-4253-84ae-03f3e18ba643)
Sunshine duration (SSD)	h	1 km	1990–2020	Resource and Environmental Science Data Platform (https://www.resdc.cn/data.aspx?DATAII

Data type	Unit	Spatial resolution	Time period	Data source
Population density (PD)	persons/km^2	1 km	1990–2020	Resource and Environmental Science Data Platform (https://www.resdc.cn/DOI/DOI.aspx?DI
Gross domestic product (GDP)	10^4 CNY/km^2	1 km	1990–2020	Resource and Environmental Science Data Platform (https://www.resdc.cn/DOI/DOI.aspx?DO
Grazing intensity (GI)	SU/hm^2	250 m	1990–2020	National Ecosystem Science Data Center (https://www.nesdc.org.cn/sdo/detail?id=

Note: "-" means no unit. ESA, European Space Agency; CCI, Climate Change Initiative.

Given that these datasets originated from diverse sources and had different spatial resolutions, their direct integration may lead to spatial mismatches and scale inconsistency. This issue would compromise the accuracy and comparability of subsequent spatial statistics and modeling results. To ensure spatial consistency and analytical validity, all raster layers were uniformly resampled to a spatial resolution of 1 km(×)1 km using the nearest neighbor algorithm and projected to the WGS_1984_World_Mercator coordinate system.

2.3 Methods

2.3.1 InVEST model

The InVEST model, a free and open-source tool developed by the Natural Capital Project, enables quantitative assessments of multiple ecosystem services. Its CS module categorizes ecosystem CS into four distinct pools (aboveground biomass, belowground biomass, soil, and dead organic matter). Based on LULC classifications, the model calculated the total CS values for each LULC class across these pools. Total regional CS was computed by multiplying the area of each LULC class by its corresponding carbon density and summing the results.

2.3.2 Construction of dynamic carbon density table

This study developed a historical carbon density table by integrating data on NPP, AGB, and SOCD within the 0–30 cm soil layer. For cropland, grassland, and bareland, we estimated the total vegetation CS comprising both aboveground carbon density (C_{above}) and belowground carbon density (C_{below}) using multi-year mean NPP. These two carbon pools were further partitioned based on root-to-shoot ratios reported by Tang et al. (2018). In woodland, multi-year average AGB directly represented C_{above}, while C_{below} was derived using root-to-shoot ratios from the same study (Tang et al., 2018). Soil carbon density (C_{soil}) across all LULC types was estimated using multi-year average SOCD values. Additionally, dead organic carbon density (C_{dead}) data were incorporated based on existing studies conducted in the QLMs, specifically Su et al. (2024) and Yuan et al. (2024).

Moreover, we employed a dynamic parameterization approach to generate carbon density parameters for future climate scenarios. First, we developed a random forest (RF) model using historical MAT, PRE, and their interaction (MAT PRE) to predict NPP and AGB, achieving an average determination of coefficient (R^2) of 0.75. Then, we applied this model to future climate projections under multiple SSP scenarios to obtain spatially explicit predictions of NPP and AGB for each time period and LULC type (Peng et al., 2022). Assuming a constant proportional composition of the four carbon pools over time, the predicted NPP and AGB were allocated to each pool based on historical ratios, with adjustments for LULC type and time period. By integrating these predictions with future climate scenarios, we constructed a dynamic carbon density table, reflecting projected CS from 1990 to 2100 across different LULC types (Table S1).

2.3.3 Landscape pattern analysis

Landscape pattern analysis was conducted using Fragstats 4.2 to establish a multi-scale quantification framework. Metrics were selected based on their direct relevance to key landscape processes influencing carbon dynamics: spatial aggregation (modulating habitat connectivity and edge effects), patch morphology (affecting microclimate and biogeochemical exchanges), and patch-type adjacency (shaping material flows and ecological interactions) (Turner, 1989). At the class level, we calculated two landscape metrics: the Aggregation Index (AI), which ranges from 0 to 100, and the Mean Shape Index (SHAPE_MN), which has a minimum value of 1. AI was used to quantify the spatial clustering of homogeneous patches, with lower values serving as an indicator of habitat fragmentation. This fragmentation reduces connectivity, increases edge effects that promote carbon loss, and ultimately diminishes CS. SHAPE_MN acts as a morphological benchmark by normalizing the ratio of patch perimeter to that of an equivalent circle, thus reflecting the geometric complexity of LULC class boundaries. Increased shape irregularity typically amplifies edge effects and microclimatic variation, potentially accelerating soil respiration and carbon exchange between vegetation and the atmosphere. At the landscape level, we incorporated the Interspersion and Juxtaposition Index (IJI) with a range of 0-100 to assess adjacency relationships among heterogeneous patches. IJI quantifies the intermixing and connectivity of different patch types, serving as a metric of adjacent patch diversity. While higher values can enhance landscape complementarity and stabilize carbon accumulation, they may also indicate a fragmented configuration that disrupts nutrient cycling and CS continuity.

Consequently, we constructed an analytical framework based on three core components linked

to key carbon-influencing mechanisms: (1) a dual-scale AI approach to assess the effects of fragmentation on CS by evaluating patch integrity at the class level and overall connectivity at the landscape level; (2) the shape normalization function of SHAPE_MN to assess edge- and morphology-mediated carbon dynamics; and (3) the unique capacity of IJI to elucidate how landscape configuration modulates carbon fluxes across mosaic surfaces. Collectively, these indices provided a structured framework for linking landscape pattern changes to carbon-related ecological processes.

2.3.4 Parametric optimal GeoDetector model

The GeoDetector model functions as a global parameter optimization framework for identifying drivers of spatial heterogeneity (Wang et al., 2016). Its core principle involves exploring all possible discretization schemes (defined by class breakpoints) for each continuous explanatory factor under the constraint of a fixed number of classes, in order to discover the scheme that maximizes the factor' s explanatory power (q-statistic) for the target variable. The q-statistic is computed as:

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

where h denotes a specific class of factor X (or Y); L is the total number of classes; N_h is the number of sample points (or pixels) in class h; N is the total number of samples; σ_h^2 is the variance within class h; and σ^2 is the variance over the entire region.

Crucially, the optimal q-value for a factor represents the maximum explanatory power achievable under any class discretization scheme. This optimum is found by systematically testing candidate breakpoints to minimize the pooled within-stratum variance, revealing the factor' s intrinsic association with spatial heterogeneity when expressed in its optimally categorized form.

Interaction detection extends this global optimization paradigm by comparing the q-value derived from the optimal joint discretization of a two-factor combination, denoted $q(X_1 \cap X_2)$, with the sum of the individually optimal q-values of each single factor, $q(X_1)+q(X_2)$. For instance, if $q(X_1+X_2) > q(X_1)+q(X_2)$, a bilinear enhancement is indicated, quantifying synergistic effects between factors under their respective optimal representations. To implement this global parameter search, we normalized all continuous drivers (MAT, PRE, SSD, GDP, PD, and GI). No predetermined classification method (e.g., quantiles or equal intervals) was imposed; instead, GeoDetector' s intrinsic optimization algorithm systematically explored the parameter space of breakpoints to identify the scheme that maximizes q for each factor independently and for factor combinations. Consequently, the factor detector quantified the globally optimized, independent explanatory power of climatic and anthropogenic drivers, while the interaction detector investigated synergies based on comparisons of these globally optimized q-values.

2.3.5 RF model

This study employed the RF model to explore the importance ranking of different LULC types and climatic factors in influencing total CS in the OLMs, in order to evaluate the relative influence of various drivers. The RF model is an ensemble learning method that constructs multiple decision trees through bootstrap sampling and random feature selection during training, aggregating their predictions to improve accuracy and reduce overfitting (Breiman, 2001). We used the model' s intrinsic feature importance measures to evaluate variable contributions. The feature importance analysis incorporated two established metrics: (1) the mean decrease in impurity, quantified as the average reduction in Gini impurity or information entropy attributable to each feature across all trees; and (2) permutation importance, a robust alternative measured by randomly shuffling a feature' s values in out-of-bag samples and observing the corresponding decline in predictive accuracy. Based on these metrics, we computed and ranked the importance scores for all predictors to identify the most influential drivers. In this study, we configured the model with 200 trees (each allowing a maximum of 2 leaves) and employed 5-fold cross-validation during training.

3 Results

3.1 Spatiotemporal evolution of LULC

Grassland, dominated by alpine meadow, served as the basal landscape across the region (Fig. 2). Woodland formed patchy clusters along mid-eastern foothills, with spatial expansion trends, while cropland was concentrated in eastern alluvial valleys and bareland predominated in the western arid zones. During 1990–2020, intensified human disturbances, including grassland overgrazing, excessive tourism, mineral resource exploitation, and dense hydropower construction, caused the contraction of woodland and grassland, resulting in increasingly fragmented landscape patterns. Concurrently, drastic climatic shifts and rapid economic growth in the western areas accelerated the expansion of urban area and bareland. Future scenario simulations indicated consistent yet gradient-differentiated spatial patterns across SSP pathways:

Fig. 2 Spatial distribution of land use and land cover (LULC) types during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios.

Figure 2: Fig. 2 Spatial distribution of land use and land cover (LULC) types during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios.

Fig. 3 String plot of LULC types transfer during the historical period of 1990-2020 (a) and future period of 2030-2100 under SSP126 (b), SSP245 (c), and SSP585 (d) scenarios

Figure 3: Fig. 3 String plot of LULC types transfer during the historical period of 1990-2020 (a) and future period of 2030-2100 under SSP126 (b), SSP245 (c), and SSP585 (d) scenarios

under the SSP126 scenario, grassland and woodland expanded while cropland contracted; under the SSP245 scenario, grassland growth slowed, woodland declined, and bareland expanded once again; SSP585 featured comprehensive degradation of cropland, woodland, and grassland, along with a surge in urban area, where high intensity urbanization-driven contraction of grassland became prominent.

Fig. 2 Spatial distribution of land use and land cover (LULC) types during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios. SSP, Shared Socio-economic Pathway.

The LULC transition chord diagram illustrated distinct conversion patterns across time periods (Fig. 3). In the historical phase, grassland showed a net increase of 3.52 × 10^5 hm^2, with inflow contributions from cropland (29.87%) and bareland (68.98%). Cropland experienced a net loss of 1.59 × 10^5 hm^2, of which 93.01% was converted to grassland. Bareland decreased by 2.38 × 10^5 hm^2 through ecological restoration, with 99.54% of this area transitioning to grassland. Under future scenarios, land conversion complexity intensified. Under the SSP126 scenario, cropland transferred out 1.24 × 10^5 hm^2, while grassland gained 9.61 × 10^4 hm^2 (jointly sourced from cropland and bareland). SSP245 exhibited losses of cropland and woodland (7.35 × 10^5 and 8.13 × 10^5 hm^2, respectively), offset by an inflow of 1.03 × 10^5 hm^2 into grassland (35.02% from

cropland and 53.63% from woodland degradation). SSP585 demonstrated widespread contraction of cropland, woodland, and grassland alongside an expansion of urban area (9.91×10^5 hm^2), with 97.48% of this urban area increase resulting from grassland conversion, confirming grassland as the primary reservoir for urban sprawl.

Fig. 3 String plot of LULC types transfer during the historical period of 1990-

Fig. 4. Spatial distribution of carbon density (CD) during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios

Figure 4: Fig. 4. Spatial distribution of carbon density (CD) during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios

2020 (a) and future period of 2030-2100 under SSP126 (b), SSP245 (c), and SSP585 (d) scenarios

3.2 Spatiotemporal evolution of CS

Spatial distribution patterns demonstrated significant CS heterogeneity across four distinct time periods in the QLMs, displaying a characteristic "low in the west and high in the east" gradient along the southeastern mountain ranges (Fig. 4). Specifically, high CS zones were mainly clustered in the eastern mountainous regions, while low CS zones predominated in the western and central-western sectors. The latter areas, rich in mineral resources and subject to intensive human activities (e.g., transportation networks and infrastructure development), experienced significant degradation of woodland and cropland into bareland and urban area, therefore reducing CS. Conversely, the eastern and central-eastern regions maintained higher CS due to their dense woodland coverage, stronger soil water conservation capacity, and higher elevations that naturally restricted land degradation and urban area expansion.

CS showed both significant spatial heterogeneity and complex temporal dynamics, driven by regional geographic patterns, climatic fluctuations, and human activity intensity. Through comparative analysis of the historical baseline and future scenario simulations, this study constructed a multi-scenario, three phase CS evolution framework. Spatial pattern maps visualized the spatial heterogeneity of carbon gain or loss, while Sankey diagrams dissected transition flux structures (defining ($\pm$)1.00% inter-period variation as stable states). A nine-category state transition matrix showed that stable to stable transitions dominated (91.00%-99.00%) (Fig. 5). To avoid obscuring minor transition types in visual interpretation, the Sankey diagrams were filtered to

Fig. 4 Spatial distribution of carbon density (CD) during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios

emphasize dominant transitions. From 1990 to 2020, CS steadily increased, rising from $1.48 \times 10\hat{}9$ t to $1.49 \times 10\hat{}9$ t, with cumulative CS reaching $1.40 \times 10\hat{}7$ t at an annual rate of $4.67 \times 10\hat{}5$ t/a (Fig. 5). During 1990-2010, systematic conversion of bareland to grassland in the western and central-western regions driven by climate warming and ecological policies created significant carbon sinks, while human-induced grassland degradation and bareland expansion formed localized carbon source zones in the eastern areas. The period 2010–2020 witnessed spatially fragmented CS variations across the study area, attributed to intensive LULC conversions, pronounced climate fluctuations, and policy interventions.

Scenario simulations revealed distinct trajectories across all scenarios (Fig. 5). Under the SSP126 scenario, CS exhibited significant growth, albeit at a slowing rate from 2030 to 2100. Climate-driven grassland expansion from bareland contributed to major carbon gains in the western region during 2030–2050, followed by eastern ecological restoration projects that facilitated woodland expansion, turning these woodlands into the primary carbon sink area (2050–2070). Post-2070, sustained grassland and woodland extension further enhanced regional CS, with Sankey diagram analysis confirming an accumulation pattern that varied significantly across policy stages. CS under the SSP245 scenario displayed an inverted U-shaped trajectory, characterized by initial carbon gains driven by climate-induced increases in carbon density during 2030–2070 and followed by a decline after 2070 primarily attributable to substantial woodland losses. Overall, total CS increased by $5.30 \times 10\hat{}7$ t at an average rate of $7.57 \times 10\hat{}5$ t/a, despite the decline in the later stage. CS under the SSP585 scenario manifested a similar initial increase driven by climate-induced carbon density gains (2030–2050), but experienced an earlier

and steeper decline starting around 2050. The accelerated depletion after 2050 resulted from substantial conversion of woodland and grassland to lower-carbon urban area, with carbon loss rising from 2.50×10^7 t during 2050–2070 to 5.50×10^7 t during 2070–2100. Notably, SSP585 resulted in 8.00×10^7 t losses due to extensive conversions from grassland to urban area during 2050–2100. Spatially, from 2050 onwards, the principal carbon depletion zones emerged from grassland degradation in the western sectors and accelerated urbanization along the southern-central foothills (the proportion of urban area surged from 0.16% in 2050 to 5.10% in 2100). These processes collectively shaped fragmented carbon loss patterns stemming from intensified human interventions under high emission scenarios.

Figure 6 illustrates temporal variations of three landscape indices that characterize the spatial configurations of carbon depletion and accumulation zones. For carbon depletion zones, the SSP126 and SSP245 scenarios exhibited reduced AI values compared to the historical period, reflecting intensified patch fragmentation. Conversely, SSP585 demonstrated progressive AI recovery approaching historical levels, suggesting enhanced connectivity through concentrated urban area expansion that consolidated artificial surfaces while fragmenting natural habitats. Carbon accumulation zones maintained consistently low AI values across all scenarios, confirming their dispersed spatial distribution. Both carbon depletion and accumulation areas showed subdued SHAPE_MN values throughout the study period, consistent with the intensive human disturbance regime. The IJI analysis revealed limited intermixing between CS change zones (gain or loss) and stable areas, as evidenced by consistently low index values across

Fig. 5. Spatial variations and transfer matrices of terrestrial carbon storage (CS) during the historical period of 1990-2020 and future period of 2030-2100 under SSP126, SSP245, and SSP585 scenarios.

Figure 5: Fig. 5. Spatial variations and transfer matrices of terrestrial carbon storage (CS) during the historical period of 1990-2020 and future period of 2030-2100 under SSP126, SSP245, and SSP585 scenarios.

Fig. 6

Figure 6: Fig. 6

all scenarios. This spatial segregation pattern corresponded with extensive unchanged carbon reservoir regions, demonstrating discrete spatial partitioning between dynamic and static landscape units. Collectively, these metrics systematically captured how varying anthropogenic pressures under different scenarios reshaped the spatial architecture of CS dynamics.

Fig. 5 Spatial variations and transfer matrices of terrestrial carbon storage (CS) during the historical period of 1990-2020 (a1-a4) and future period of 2030-2100 under SSP126 (b1-b4), SSP245 (c1-c4), and SSP585 (d1-d4) scenarios. The historical period is subdivided into three phases: 1990-2000, 2000-2010, and 2010-2020. The future period is subdivided into three phases: 2030-2050, 2050-2070, and 2070-2100.

Fig. 6 Landscape indices of the Aggregation Index (AI), Mean Shape Index (SHAPE_MN), and Interspersion and Juxtaposition Index (IJI) for areas showing decreased CS (a-c) and increased CS (d-f) during the historical period of 1990-2020 and future period of 2030-2100 under SSP126, SSP245, and SSP585 scenarios. The future period is subdivided into three phases: 2030-2050, 2050-2070, and 2070-2100.

3.3 Driver analysis of CS

Our spatial analysis revealed that factor interactions showed dual-enhancement effects that consistently outweighed single-factor influences. The factor detector analysis demonstrated the hierarchy of explanatory power during 1990-2020 as: PRE>SSD>PD>GI>GDP>MAT (Fig. 7). Interaction detector identified MAT PRE as the strongest synergistic combination, while GDP PD remained the weakest. Given the dominance of this interaction, we specifically incorporated MAT PRE into the simulation and prediction of NPP and AGB. This pattern was attributable to the humid climate that sustained dense vegetation, rendering climatic factors more influential than anthropogenic drivers. The PRE SSD interaction effectively elucidated CS mechanisms within the dominant framework of PRE. Although GI, PD, and GDP showed varying degrees of intrinsic explanatory power (with q-values greater than 0.100), they remained statistically significant, indicating that these anthropogenic drivers play sec-

Fig. 7

Figure 7: Fig. 7

ondary roles. These spatial interaction patterns, when combined with preceding temporal analyses, demonstrated that climate-vegetation couplings were the primary regulators of CS in this alpine ecosystem.

Fig. 7 Results of factor detection (a) and interaction detection (b) of factors influencing terrestrial CS. PRE, precipitation; SSD, sunshine duration; PD, population density; GI, grazing intensity; GDP, gross domestic product; MAT, mean annual temperature. The q value indicates the factor' s explanatory power for terrestrial CS. * and ** denote the statistical significance at the 95.00% and 99.00% confidence levels, respectively.

PRE was positively correlated with CS distribution, and this was accompanied by a 216.00% increase in mean annual PRE from bareland to woodland that confirmed the spatial coupling between high carbon areas and humid climatic belts (Fig. 8). It was noteworthy that although grassland ecosystems had relatively high CS, their average PRE was lower than that of cropland. This phenomenon could be attributed to differences in spatial distribution: grassland and mosaic cropland were widely distributed in the western arid regions, while cropland was concentrated in river valley areas with favorable water and thermal conditions. Grassland received higher SSD due to their higher elevations, in contrast to cropland, which was often shaded by topography. The correlations of GI, PD, and GDP with CS gradients were minimal, further emphasizing the primary influence of PRE and SSD on spatial CS heterogeneity, a finding consistent with the results of the GeoDetector factor analysis. This mechanistic evidence confirmed that climate parameters were critical regulators of CS in arid mountain ecosystems.

Under the SSP126 scenario, CS exhibited a sustained increase with decelerating growth (Fig. 9). Conversely, CS under both SSP245 and SSP585 scenarios manifested inverted U-shaped trajectories, characterized by initial increases followed by declines. The decline phase commenced earlier in 2050 and proceeded at a higher rate under the SSP585 scenario relative to the SSP245 scenario (which initiated post-2070). Driver analysis revealed divergent LULC dynamics: woodland area under the SSP126 scenario displayed progressive growth driven by effective mountain closure afforestation policies, whereas after 2030, woodland area underwent continuous decline under both SSP245 and SSP585 scenarios, with markedly greater reductions under the SSP585 scenario. Grassland carbon pools experienced sustained increases throughout the study period under SSP126 and SSP245 scenarios, but declined persistently under the SSP585 scenario. Urban expansion occurred across all scenarios, most substantially under the SSP585 scenario, where land conversion rates accelerated.

All scenarios exhibited sustained increases in MAT and fluctuating but over-

Fig. 8 Multi-year average values of climatic (a–c) and anthropogenic (d–f) factors during 1990-2020 under different LULC types

Figure 8: Fig. 8 Multi-year average values of climatic (a–c) and anthropogenic (d–f) factors during 1990-2020 under different LULC types

all increasing PRE, resulting in a net warming–wetting trend (Fig. 9). This climatic shift generally enhanced CS relative to the historical baseline across all three future periods. However, under the SSP245 scenario, substantial woodland degradation after 2070 reversed the accumulated gains. Under the SSP585 scenario, extensive conversion to urban area drove accelerated losses in both woodland and grassland (with severe grassland degradation), causing a significant decline in CS beginning around 2050. Particularly in middle- to low-elevation transition zones, the synergistic effects of this climatic shift and intensive land conversion exceeded ecosystem resilience thresholds, leading to critical degradation of CS. These complex "climate–ecosystem–land use" interactions constituted the primary regulatory mechanisms governing CS evolution, highlighting scenario-dependent thresholds in ecological resilience.

Fig. 8 Multi-year average values of climatic (a–c) and anthropogenic (d–f) factors during 1990-2020 under different LULC types

Figure 10 delineates relationships between total CS in the QLMs and its key influencing factors, contextualized by variable importance ranking: cropland CS > urban area CS > grassland CS > PRE > MAT > bareland CS > woodland CS. Scatter plots retained only statistically significant variables: cropland CS, grassland CS, PRE, and MAT—excluding urban area CS due to its lack of significant global relationship, although it showed scenario-specific significance under the SSP585 scenario. Total CS showed significant positive correlations with grassland CS ($R^2 = 0.57$), PRE ($R^2 = 0.45$), and MAT ($R^2 = 0.22$), while it exhibited significant negative correlation with cropland CS ($R^2 = 0.80$). This inverse relationship reflected carbon gains when cropland converted to grassland, despite cropland' s substantial carbon pool. Among climatic factors, PRE explained 44.50% of the variation, exceeding MAT' s influence. These patterns confirmed grassland dynamics, cropland conversion, and hydroclimatic factors as primary temporal regulators of CS.

4 Discussion

4.1 Spatiotemporal dynamics of CS in response to LULC change

Human activities, particularly LULC change, significantly affected carbon source-sink dynamics in the QLMs. Our study revealed that LULC transformations, such as deforestation and

Fig. 9 Temporal variations in terrestrial CS (a), area proportions of different LULC types (b–f), MAT (g), and PRE (h) from 1990 to 2100

Fig. 9

Figure 9: Fig. 9

Fig. 10

Figure 10: Fig. 10

urbanization, typically reduced CS by disrupting natural carbon pools in biomass and soil. The conversion of woodland to cropland or urban area led to the release of stored carbon, thus increasing emissions (Houghton, 2003). This aligns with Li et al. (2021), who observed similar trends in CS reductions in the QLMs. However, the present study introduced an innovation: a dynamic carbon density table that adjusted carbon densities according to different climate scenarios and time periods, thereby providing more refined projections compared to previous static models.

The shift from carbon sinks to sources driven by LULC change was pronounced in the western QLMs, where land degradation accelerated carbon losses due to overgrazing and unsustainable farming (Fu et al., 2017). This supports the findings of Yuan et al. (2024), but we extended this work by employing landscape metrics such as the AI to demonstrate how fragmentation increased carbon losses in urban area. Fragmentation led to a decrease in habitat continuity, which reduced the capacity of ecosystems to store carbon. As landscape fragmentation intensified, edge effects (e.g., increased soil erosion, temperature fluctuations, and altered water cycles) exacerbated carbon losses in degraded area. Additionally, reduced vegetation cover and soil disturbance resulting from unsustainable land use practices further released stored carbon from soil and biomass and decreased CS.

This study underscored the importance of ecological restoration by identifying woodland as the most efficient CS in the QLMs. Their CS capacity exceeded that of grassland by 3.27 times and that of cropland by 2.34 times, highlighting the need to prioritize ecosystem protection and restoration to sustain CS. The restoration of degraded grassland and woodland can restore CS and mitigate the negative impacts of human disturbances by enhancing soil organic matter content, improving vegetation cover, and increasing soil CS through root expansion and biomass accumulation.

Fig. 10 Importance of seven driving factors for explaining the temporal dynamics of terrestrial CS (a) in the study area and dependence of the interannual variation in terrestrial CS on grassland and cropland components (b and c), MAT (d), and PRE (e)

4.2 Mechanisms behind CS variations and scenario-based management implications

The temporal dynamics of CS in the QLMs were driven by both climatic and anthropogenic factors. Historical data showed that CS initially increased before declining, consistent with Zhu et al. (2021) and Yuan et al. (2024). However, the present study diverged from previous studies by integrating dynamic carbon density values across time, offering a more nuanced understanding of CS variations. Future projections also diverged: under the SSP126 scenario, CS exhibited continued growth, whereas CS under SSP245 and SSP585 scenarios displayed inverted U-shaped trajectories, in which initial carbon gains were followed by significant declines under the high emission scenario (SSP585). This decline was largely driven by the transformation of grassland to

urban area, which resulted in substantial carbon losses (Wang et al., 2022). These findings align with broader assessments showing that both climate change and human activities jointly regulated terrestrial carbon dynamics (Fang et al., 2018). Notably, this study' s incorporation of scenario- and period-specific dynamic adjustments to carbon densities provides more accurate projections than traditional models.

The primary mechanism behind carbon depletion under the high emission scenario was the conversion of grassland to urban area. This process reduced vegetation cover, disrupted the soil carbon pool, and led to significant carbon release. We also demonstrated how landscape fragmentation exacerbated this process by decreasing patch connectivity, which weakened the synergistic effect between vegetation and soil on CS. These dynamics are consistent with the findings of Shang et al. (2013) but provide a more detailed explanation of the spatial mechanisms at play.

CS variations have important implications for ecosystem services. Enhanced CS improves habitat quality for species such as the snow leopard and mitigates soil erosion, whereas carbon depletion phases reduce water retention, exacerbating water scarcity and disrupting migration corridors. These findings underscore the need for differentiated management strategies based on spatiotemporal heterogeneity of CS across the QLMs. For example, the eastern QLMs, characterized by higher CS, should prioritize conservation, while the western QLMs, which face more severe degradation, require targeted ecological restoration efforts.

4.3 Uncertainty and limitations

This study has several uncertainties that primarily arise from four key aspects: the omission of deep soil carbon, the use of fixed allocation ratios among carbon pools, reliance on the accuracy of LULC classification, and the exclusion of extreme climatic disturbances. These limitations should be addressed in future research to improve CS predictions.

First, the omission of deep soil carbon (beyond 30 cm) in the dynamic carbon density table is a significant limitation. Deep soil carbon is crucial for long-term CS, and its exclusion, especially in regions with substantial deep carbon pools, may lead to an underestimation of overall CS. Second, the model' s reliance on fixed allocation ratios among carbon pools does not account for climate-induced carbon redistribution, potentially resulting in inaccurate carbon estimates. Additionally, the assumption of constant root-to-shoot ratios overlooks biome-specific adaptations to climate trends such as warming and wetting. These assumptions, coupled with insufficient sensitivity assessments, may propagate uncertainties in projections. Third, uncertainties also arise from LULC classification in ecologically transitional zones where remote sensing accuracy is critical. Misclassification of vegetation types or LULC types in heterogeneous ecosystems like the QLMs, can significantly affect CS estimates. As noted by Ma et al. (2022) and Wu et al. (2024), the accuracy of NPP data derived from remote sensing is highly sensitive to classification errors, sensor resolution, and temporal coverage, all of which influence CS. Finally, this study does not incorporate the impacts of extreme climatic events, such as droughts and extreme rainfall, which can drastically alter carbon fluxes in the QLMs where climatic variability is high. Future studies should include the effects of such events to better capture vegetation responses and refine long-term CS simulations.

In comparison with previous studies that assessed the CS of the QLMs (Ding et al., 2019; Xu et al., 2020; Liang et al., 2021; Qin et al., 2021; Deng et al., 2022; Li et al., 2022; Hou et al., 2023; Yang et al., 2023; Dong et al., 2024; Qi et al., 2024; Su et al., 2024; Wang et al., 2024; Yuan et al., 2024), we found that discrepancies in InVEST-based CS primarily arose from differences in carbon pool composition and variations in soil carbon pools across studies. However, our estimate of $1.49 \times 10\hat{}9$ t fell within the statistical confidence interval (±standard deviation) of the multi-study mean (Fig. 11), confirming the validity of our parameterization and dynamic carbon density tables through cross-study verification. This comparison highlights the importance of standardized protocols in regional carbon accounting to reduce uncertainties and improve the robustness of CS assessments.

Fig. 11 Uncertainty analysis of the CS modelling result. Error bars represent standard deviations.

5 Conclusions

This study presented a century-scale framework (1990–2100) to explore climate-human synergies in CS dynamics in the QLMs. Two key advances included multi-scenario projections over a centennial timeline and era-specific parameterization of carbon density coefficients. Key findings showed that sustained warming and wetting enhanced CS, while conservation policies such as grazing control and afforestation fostered carbon gains. In contrast, grassland-to-urban transitions resulted in substantial carbon losses. The dynamic parameterization improved projection accuracy, with SSP126 supporting carbon recovery and SSP585 accelerating carbon depletion caused by rapid urbanization. These insights highlight the need for strategies that prioritize the protection of grassland and woodland while balancing urbanization with CS. This framework offers a transferable model for mountain ecosystem assessments and climate-smart conservation planning.

Conflict of interest

XU Haojie is a Young Editorial Board member of Journal of Arid Land and was not involved in the editorial review or the decision to publish this article. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

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Appendix

Table S1 Carbon density of different land use and land cover (LULC) types in the Qilian Mountains

Scenario	Period	LULC type	C_{above} (t/hm^2)	C_{below} (t/hm^2)	C_{soil} (t/hm^2)	C_{dead} (t/hm^2)
History	1990–2020	Cropland	2.28	0.46	109.74	2.84
History	1990–2020	Woodland	99.14	25.71	142.64	2.00
History	1990–2020	Grassland	0.55	0.99	79.93	0.95
History	1990–2020	Urban area	0.00	0.00	36.01	0.00
History	1990–2020	Bareland	0.10	0.21	23.23	0.10
History	1990–2020	Water body	0.00	0.00	0.00	0.00
SSP126	2030	Cropland	2.46	0.49	118.58	3.07
SSP126	2030	Woodland	100.40	26.04	144.45	2.03
SSP126	2030	Grassland	0.60	1.10	88.23	1.05
SSP126	2030	Urban area	0.00	0.00	36.01	0.00
SSP126	2030	Bareland	0.12	0.23	26.23	0.11
SSP126	2030	Water body	0.00	0.00	0.00	0.00
SSP126	2050	Cropland	2.54	0.51	122.60	3.17
SSP126	2050	Woodland	101.51	26.33	146.05	2.05
SSP126	2050	Grassland	0.62	1.13	90.83	1.08
SSP126	2050	Urban area	0.00	0.00	36.01	0.00
SSP126	2050	Bareland	0.13	0.26	29.22	0.13
SSP126	2050	Water body	0.00	0.00	0.00	0.00
SSP126	2070	Cropland	2.51	0.50	121.00	3.13
SSP126	2070	Woodland	101.05	26.21	145.39	2.04
SSP126	2070	Grassland	0.62	1.14	91.35	1.09
SSP126	2070	Urban area	0.00	0.00	36.01	0.00
SSP126	2070	Bareland	0.13	0.26	29.22	0.13
SSP126	2070	Water body	0.00	0.00	0.00	0.00
SSP126	2100	Cropland	2.53	0.51	121.80	3.15
SSP126	2100	Woodland	101.38	26.29	145.86	2.05
SSP126	2100	Grassland	0.62	1.14	91.35	1.09
SSP126	2100	Urban area	0.00	0.00	36.01	0.00
SSP126	2100	Bareland	0.13	0.27	29.97	0.13

Scenario	Period	LULC type	C_{above} (t/hm^2)	C_{below} (t/hm^2)	C_{soil} (t/hm^2)	C_{dead} (t/hm^2)
SSP126	2100	Water body	0.00	0.00	0.00	0.00
SSP245	2030	Cropland	2.38	0.48	114.96	2.98
SSP245	2030	Woodland	99.42	25.78	143.04	2.01
SSP245	2030	Grassland	0.60	1.09	87.72	1.04
SSP245	2030	Urban area	0.00	0.00	36.01	0.00
SSP245	2030	Bareland	0.12	0.25	27.73	0.12
SSP245	2030	Water body	0.00	0.00	0.00	0.00
SSP245	2050	Cropland	2.45	0.49	118.18	3.06
SSP245	2050	Woodland	100.41	26.04	144.47	2.03
SSP245	2050	Grassland	0.61	1.12	89.79	1.07
SSP245	2050	Urban area	0.00	0.00	36.01	0.00
SSP245	2050	Bareland	0.13	0.25	28.48	0.12
SSP245	2050	Water body	0.00	0.00	0.00	0.00
SSP245	2070	Cropland	2.52	0.50	121.40	3.14
SSP245	2070	Woodland	101.22	26.25	145.63	2.04
SSP245	2070	Grassland	0.62	1.14	91.35	1.09
SSP245	2070	Urban area	0.00	0.00	36.01	0.00
SSP245	2070	Bareland	0.13	0.27	29.97	0.13
SSP245	2070	Water body	0.00	0.00	0.00	0.00

To be continued

Continued

Scenario	Period	LULC type	C_{above} (t/hm^2)	C_{below} (t/hm^2)	C_{soil} (t/hm^2)	C_{dead} (t/hm^2)
SSP245	2100	Cropland	2.53	0.51	122.20	3.16
SSP245	2100	Woodland	101.58	26.34	146.15	2.05
SSP245	2100	Grassland	0.62	1.14	91.35	1.09
SSP245	2100	Urban area	0.00	0.00	36.01	0.00
SSP245	2100	Bareland	0.13	0.27	29.97	0.13
SSP245	2100	Water body	0.00	0.00	0.00	0.00
SSP585	2030	Cropland	2.51	0.50	123.41	3.13

Scenario	Period	LULC type	C_{above} (t/hm^2)	C_{below} (t/hm^2)	C_{soil} (t/hm^2)	C_{dead} (t/hm^2)
SSP585	2030	Woodland	100.90	26.17	145.17	2.04
SSP585	2030	Grassland	0.60	1.10	88.23	1.05
SSP585	2030	Urban area	0.00	0.00	36.01	0.00
SSP585	2030	Bareland	0.12	0.23	26.23	0.11
SSP585	2030	Water body	0.00	0.00	0.00	0.00
SSP585	2050	Cropland	2.49	0.50	120.19	3.11
SSP585	2050	Woodland	100.91	26.17	145.19	2.04
SSP585	2050	Grassland	0.62	1.14	91.35	1.09
SSP585	2050	Urban area	0.00	0.00	36.01	0.00
SSP585	2050	Bareland	0.13	0.27	29.97	0.13
SSP585	2050	Water body	0.00	0.00	0.00	0.00
SSP585	2070	Cropland	2.52	0.50	121.40	3.14
SSP585	2070	Woodland	101.44	26.31	145.95	2.05
SSP585	2070	Grassland	0.62	1.14	91.35	1.09
SSP585	2070	Urban area	0.00	0.00	36.01	0.00
SSP585	2070	Bareland	0.13	0.27	29.97	0.13
SSP585	2070	Water body	0.00	0.00	0.00	0.00
SSP585	2100	Cropland	2.56	0.51	123.41	3.19
SSP585	2100	Woodland	101.69	26.37	146.31	2.05
SSP585	2100	Grassland	0.62	1.14	91.35	1.09
SSP585	2100	Urban area	0.00	0.00	36.01	0.00
SSP585	2100	Bareland	0.13	0.27	29.97	0.13
SSP585	2100	Water body	0.00	0.00	0.00	0.00

Note: C_{above} is the aboveground carbon density; C_{below} is the belowground carbon density; C_{soil} is the soil carbon density; C_{dead} is the dead organic carbon density. SSP, Shared Socio-economic Pathway.

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