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Spatiotemporal Variation and Multi-Scenario Simulation of Terrestrial Ecosystem Carbon Storage in the Turpan-Hami Basin Using the PLUS-InVEST Model: A Postprint

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Abstract

Land cover change can alter regional carbon storage capacity, thereby causing global climate change. Investigating the impacts of land cover change on carbon storage and predicting carbon storage under different future land cover scenarios are of great significance for achieving regional "carbon neutrality" strategic goals; however, research on ecologically fragile areas in western China remains to be explored. Taking the Tuha Basin in Xinjiang as the study area, based on land cover product data and combined with the PLUS model and InVEST model, this study explores the spatiotemporal relationship between land cover change and regional carbon storage, and predicts and evaluates the spatiotemporal dynamic characteristics of land cover and carbon storage under sustainable development scenario, status quo development scenario, and economy-prioritized development scenario for 2025 and 2030. The results show that: (1) Over the past 20 years, cropland and bare land in the Tuha Basin have experienced the largest area increases, followed by construction land, while grassland showed the greatest decreasing trend, with conversion from grassland to cropland and construction land being the primary transition type. (2) The average carbon storage in the Tuha Basin was 26.01 $t \cdot hm^{-2}$, 25.68 $t \cdot hm^{-2}$, and 25.73 $t \cdot hm^{-2}$ in 2000, 2010, and 2020, respectively, showing a trend of first decreasing then increasing, with a cumulative reduction of 0.28 $t \cdot hm^{-2}$ in average carbon storage; soil organic carbon storage accounted for the highest proportion, approximately 94% of total carbon storage, with bare land and grassland contributing the most carbon storage. (3) Under the three scenarios for 2030, forest, shrubland, and wetland show almost no significant changes, bare land exhibits a decreasing trend, while construction land shows an increasing trend. (4) By 2030, under the sustainable development scenario, the total carbon storage in the Tuha Basin increases by 0.18$×10^{6}$ t compared to 2020, while under the status quo development scenario and economy-prioritized development scenario, it decreases by 0.30$\times10^{6}$ t and 1.01$\times10^{6}$ t, respectively, with the largest carbon storage loss occurring under the economy-prioritized development scenario. The research results can provide a basis for land use optimization in the Tuha Basin and for formulating ecosystem sustainable development measures.

Full Text

Spatiotemporal Variation and Multi-scenario Simulation of Terrestrial Ecosystem Carbon Storage in the Turpan-Hami Basin Based on the PLUS-InVEST Model

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Abstract

Land cover change can alter regional carbon storage capacity, thereby influencing global climate change. Investigating the impacts of land cover change on carbon storage and predicting future carbon stocks under different land cover scenarios are crucial for achieving regional "carbon neutrality" strategic goals. However, research on ecologically fragile areas in western China remains insufficient. This study takes the Turpan-Hami Basin in Xinjiang as the study area, utilizing land cover product data coupled with the PLUS and InVEST models to explore the spatiotemporal relationship between land cover change and regional carbon storage. The study predicts and evaluates the spatiotemporal dynamic characteristics of land cover and carbon storage under three scenarios: sustainable development, status quo maintenance, and economic priority development for 2025 and 2030.

The results indicate that: (1) From 2000 to 2020, cultivated land and bare land experienced the largest area increases in the Turpan-Hami Basin, followed by construction land, while grassland showed the most significant decreasing trend. The conversion of grassland to cultivated land and construction land represented the primary transfer type. (2) The average carbon storage in the Turpan-Hami Basin was 26.01 $t\cdot hm^{-2}$, 25.68 $t\cdot hm^{-2}$, and 25.73 $t\cdot hm^{-2}$ in 2000, 2010, and 2020, respectively, exhibiting a trend of initial decline followed by increase, with a cumulative average reduction of 0.28 $t\cdot hm^{-2}$. Soil organic carbon storage accounted for the highest proportion, approximately 94% of total carbon storage, with bare land and grassland contributing the most to carbon stocks. (3) Under the three scenarios for 2030, forests, shrubland, and wetlands show almost no significant change, while bare land exhibits a decreasing trend and construction land shows an increasing trend. (4) By 2030, total carbon storage in the

Turpan-Hami Basin increases by 0.18$×10^{6}$ t under the sustainable development scenario compared to 2020, while decreasing by 0.30$×10^{6}$ t and 1.01$×10^{6}$ t under the status quo and economic priority scenarios, respectively. The economic priority scenario results in the greatest carbon storage loss. These findings provide a basis for land use optimization and sustainable ecosystem development measures in the Turpan-Hami Basin.

Keywords: land cover change; scenario simulation; carbon storage; Turpan-Hami Basin

1. Introduction

Terrestrial ecosystem carbon storage plays a significant role in the global carbon cycle, serving as a critical component in mitigating climate change and achieving "carbon neutrality" strategic goals [1-3]. It can absorb carbon from the atmosphere, thereby increasing ecosystem carbon storage and alleviating global warming, which represents an essential step in the global carbon cycle [4-5]. Land use/land cover change (LUCC) constitutes the primary way humans alter terrestrial ecosystems [6], with studies demonstrating that land cover change is a key driver of regional carbon storage variation due to significant differences in carbon storage capacity among different land use types [7-8]. Furthermore, land cover change can alter vegetation distribution and soil types, consequently causing changes in carbon storage [9].

Constructing land use/cover models is a primary method for understanding land cover change [10]. Existing land use models such as Markov [11] and others struggle to identify the underlying drivers of land use change. In contrast, the Patch-generating Land Use Simulation (PLUS) model can deeply explore the driving factors of land cover change, yielding more accurate simulation results [12]. Reliable land use prediction models are essential for formulating scientifically sound land management policies. Under the backdrop of global climate change, assessing the impacts of land cover change on carbon storage is crucial for sustainable carbon cycling and achieving "dual carbon" goals.

Currently, scholars estimate ecosystem carbon storage using two main approaches: first, through the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model based on carbon densities of different land cover types; and second, through field surveys. While field measurements provide reliable accuracy, they require substantial human and material resources and are suitable only for small-scale studies [13]. The InVEST model offers advantages including simple input parameters, strong visualization, and high stability [14], making it widely applicable. Researchers have used the InVEST model to evaluate spatiotemporal trends and driving factors of regional carbon storage [15-16], explore impacts of different ecological projects on terrestrial ecosystem carbon storage [17], and assess land cover change effects on carbon storage in various regions [18-20]. However, existing research has primarily focused on historical land cover change impacts on carbon storage, with relatively few studies examining future regional carbon storage changes under different scenarios, particularly in ecologically fragile areas of western China.

This study addresses this gap by examining the Turpan-Hami Basin in Xinjiang —a key construction area for China' s "Three Bases and One Channel" initiative. Based on land cover data and considering natural, socioeconomic, and transportation factors, we coupled the PLUS and InVEST models to analyze land cover change from 2000 to 2020 and its impact on carbon storage. Additionally, we established three development scenarios to predict spatiotemporal changes in land cover and carbon storage, providing references for regional green, low-carbon development and sustainable land management.

1.1 Study Area Overview

The Turpan-Hami Basin is located in eastern Xinjiang (87°16 -96°23 E, 40°52 - 45°05 N), comprising the Turpan and Hami Basins with a total area of approximately 21$×10^{4}$ km^2, accounting for 12.6% of Xinjiang' s total area. The basin includes six districts and counties: Gaochang District, Shanshan County, Toksun County, Yizhou District, Barkol Kazakh Autonomous County, and Yiwu County [Figure 1: see original paper]. The region features a typical continental arid climate with large diurnal temperature variations, low precipitation, and high evaporation. The average annual precipitation is approximately 10–30 mm, while average annual evaporation reaches 3000–4000 mm. Extreme climate events such as strong winds and high temperatures occur frequently, making the ecological environment extremely fragile.

1.2 Data Sources

This study utilized land use data at 30 m spatial resolution from the China Annual Land Cover Dataset, which is based on Landsat imagery and shows good consistency with global forest change, global surface water, and impervious surface products [21], making it one of China' s most reliable land use data sources. According to the actual conditions of the study area, the data were reclassified into eight types: cultivated land, forest, shrubland, grassland, water body, bare land, construction land, and wetland.

We selected eight types of data as driving factors influencing land use change, including topographic data (elevation, slope), meteorological data (temperature, precipitation), road network data (distance to roads), and socioeconomic data (GDP, population). Detailed data sources are provided in .

1.3 Methods

1.3.1 PLUS Model for Land Use Change Simulation The PLUS model, developed by China University of Geosciences, includes two modules: Land Expansion Analysis Strategy (LEAS) and Cellular Automata (CA) based on Multiple Random Seeds (CARS). The LEAS module requires two periods of land use data as input, uses random forest algorithms to calculate the influence of driving factors on the expansion of various land use types, and determines regional development potential. The CARS module simulates local land use competition based on CA, enabling total land use quantity to meet future demands according to adaptive coefficients, neighborhood effects, and development probabilities at larger scales [22].

We used overall accuracy and Kappa coefficient to evaluate the simulation performance of the PLUS model. The Kappa coefficient reveals modeling accuracy; generally, a Kappa coefficient greater than 0.75 indicates good consistency and reliable simulation results. The formula is:

$$Kappa = \frac{P_o - P_e}{1 - P_e}$$

where P_o is the actual simulation accuracy and P_e is the expected simulation accuracy under random conditions. The simulated results for 2020 showed a Kappa coefficient of 0.82 and overall accuracy of 91.3%, indicating that the PLUS model can effectively simulate land cover conditions in the Turpan-Hami Basin and can be used for future land cover prediction.

1.3.2 Carbon Storage Estimation The InVEST model (Integrated Valuation of Ecosystem Services and Tradeoffs) comprises a series of sub-models, among which the carbon storage and sequestration model assesses terrestrial ecosystem carbon storage [23]. This module includes four carbon pools: aboveground biomass, belowground biomass, soil organic matter, and dead organic matter. The calculation formula is:

$$C_{total} = \sum_{i=1}^{n} (C_{i-above} + C_{i-below} + C_{i-soil} + C_{i-dead}) \times A_i$$

where i represents land cover type; $C_{i-above}$, $C_{i-below}$, C_{i-soil}, and C_{i-dead} are the aboveground biomass carbon density, belowground biomass carbon density, soil carbon density, and dead organic matter carbon density of land cover type i, respectively; C_{total} is the total terrestrial ecosystem carbon storage; and A_i is the area of land cover type i. Due to the low content of dead organic matter carbon storage and difficulty in data acquisition [24], this study only considered the first three carbon pools.

1.3.3 Carbon Density Determination and Correction Carbon density data for each land cover type in the study area were primarily sourced from local or nearby field measurements, supplemented by findings from adjacent regions [23,35-40], and corrected using relationship models between temperature, precipitation, and carbon density [41]. The correction formulas are:

$$BP = 6.789 \times e^{0.0054 \times MAP}$$

$$BT = 28 \times MAT + 398$$

$$SP = 3.3968 \times MAP + 3996.1$$

where BP and SP are the biomass carbon density and soil carbon density corrected based on mean annual precipitation (MAP), respectively; BT is the biomass carbon density corrected based on mean annual temperature (MAT); K_{BP} and K_{SP} are the correction coefficients for biomass and soil carbon densities, respectively; C_{above}, C_{below}, and C_{soil} are the corrected carbon densities for aboveground biomass, belowground biomass, and soil organic matter in the Turpan-Hami Basin; and $C_{above-nation}$, $C_{below-nation}$, and $C_{soil-nation}$ are the corresponding national carbon densities. The corrected carbon densities for different land cover types in the Turpan-Hami Basin are shown in .

1.3.4 Scenario Settings Based on different socioeconomic development goals and regional land use policy preferences, we established and simulated three scenarios [42]: sustainable development scenario, status quo scenario, and economic priority development scenario.

Sustainable Development Scenario: Under this scenario, ecological protection is strengthened, economic growth is moderated, and transitions from forest, grassland, and wetland to other land types are restricted.

Status Quo Scenario: This baseline scenario maintains historical land use development trends and simulates future land use accordingly.

Economic Priority Development Scenario: This scenario prioritizes economic growth while neglecting resource and environmental protection. It restricts conversion of construction land to other types while increasing the probability of other land types converting to construction land.

2. Results

2.1 Spatiotemporal Characteristics of Land Cover and Carbon Storage

Land cover change in the Turpan-Hami Basin from 2000 to 2020 primarily manifested as grassland converting to cultivated land, construction land, and bare land. Bare land is the dominant land cover type, accounting for over 65% of the total area and distributed throughout the region. Grassland is the second largest type, accounting for approximately 21% of the area and distributed in the central and western parts at higher elevations. Forest and shrubland together account for about 7% of the area, mainly in the central and western regions. Construction land is distributed in the central parts of various counties, accounting for 0.1%-0.2% of the region. Cultivated land is distributed in patches near water sources with gentle slopes, accounting for 0.19% of the area. The remaining land cover types, shrubland and wetland, together account for 0.21%.

From 2000 to 2020, cultivated land and bare land areas increased by 17.1$\times10^{3}$ hm^2 and 40.1$\times10^{3}$ hm^2, respectively, while construction land area increased from 64.3$\times10^{3}$ hm^2 to 65.7$\times10^{3}$ hm^2. Grassland showed the largest decreasing trend, with a total reduction of 156.2$\times10^{3}$ hm^2. The conversion of grassland to cultivated land and construction land was the primary transfer type. The spatial distributions of land cover in 2000, 2010, and 2020 are shown in [Figure 2: see original paper].

The average carbon storage in the Turpan-Hami Basin was 26.01 $t \cdot hm^{-2}$, 25.68 $t \cdot hm^{-2}$, and 25.73 $t \cdot hm^{-2}$ in 2000, 2010, and 2020, respectively, showing a trend of initial decline followed by increase, with an overall cumulative reduction of 0.28 $t \cdot hm^{-2}$. Spatially, medium-value carbon storage areas are distributed throughout the region, primarily covered by bare land. High-value areas are concentrated in the central and western parts, coinciding with cultivated land, forest, and grassland distributions. Low-value areas are mainly distributed near high-value regions in flat terrain dominated by water bodies and construction land, where human activities are intensive and carbon storage capacity is relatively weak.

The contribution of different land cover types to total carbon storage, from largest to smallest, is: bare land, grassland, cultivated land, forest, wetland, and shrubland . In recent years, increases in cultivated land, forest, and bare land areas have increased carbon storage by 1.23$\times10^{6}$ t, 0.018$\times10^{6}$ t, and 6.03$\times10^{6}$ t, respectively, while grassland reduction has caused 14.21$\times10^{6}$ t of carbon storage loss. Overall, high-carbon-density grassland has been encroached upon by construction land or degraded to bare land, leading to gradual ecosystem deterioration and reduced total carbon storage.

Analysis of different carbon pools from 2000 to 2020 reveals that soil organic carbon storage accounts for approximately 94% of total carbon storage, showing a slow decline from 24.56 $t \cdot hm^{-2}$ to 24.28 $t \cdot hm^{-2}$. Belowground biomass carbon storage also decreased significantly by 0.017$\times10^{6}$ t, while aboveground biomass carbon storage showed an increasing trend, growing by 0.018$\times10^{6}$ t. However, due to its small proportion (about 6%), its impact on total carbon storage variation is limited. The spatial distribution of carbon storage changes shows clustered and contiguous patterns [Figure 4: see original paper]. Carbon storage decreased significantly in Yiwu County and Barkol Kazakh Autonomous County from 2000 to 2010 due to extensive grassland degradation to bare land. Carbon storage increased notably in Yizhou District and Gaochang District from 2010 to 2020, as population growth and cultivated land expansion increased soil organic carbon storage.

2.2 Future Land Cover Changes Under Different Scenarios

The PLUS model simulated land cover in 2025 and 2030 under the three scenarios. Compared with 2020, forests, shrubland, and wetlands show almost no change across all scenarios, while bare land exhibits a decreasing trend and construction land shows an increasing trend .

Under the sustainable development scenario, cultivated land shows a 逐年 decreasing trend, grassland increases rapidly, and construction land expands quickly initially then slows. By 2030, cultivated land, grassland, and construction land change by -0.33$\times10^{3}$ hm^2, +26.53$\times10^{3}$ hm^2, and +2.41$\times10^{3}$ hm^2, respectively, compared to 2020. Due to ecological protection measures, grassland ecosystems gradually recover and some bare land converts to grassland.

Under the status quo scenario, cultivated land and construction land show increasing trends, while grassland decreases to some extent. By 2030, cultivated land, construction land, and grassland change by +23.23$\times10^{3}$ hm^2, +11.47$\times10^{3}$ hm^2, and -21.80$\times10^{3}$ hm^2, respectively. Cultivated land expansion increases carbon storage by 1.78$\times10^{6}$ t, but grassland reduction causes 2.69$\times10^{6}$ t of carbon loss, resulting in a net decrease in regional carbon sequestration capacity.

Under the economic priority scenario, cultivated land area continues to decrease, causing 2.78$\times10^{6}$ t of carbon storage loss, while grassland expansion compensates for some losses. However, due to rapid economic growth and infrastructure demand, construction land area increases substantially, reaching 29.61$\times10^{3}$ hm^2 by 2030—an increase of 12.50$\times10^{3}$ hm^2 compared to 2020. The increase in carbon storage is still smaller than the decrease, and regional carbon sequestration capacity continues declining.

2.3 Future Carbon Storage Predictions Under Different Scenarios

We estimated carbon storage in the Turpan-Hami Basin for 2025 and 2030 under the three scenarios . By 2030, total carbon storage shows an initial decrease followed by an increase under the sustainable development scenario, an initial increase followed by decrease under the status quo scenario, and continuous decline under the economic priority scenario. Total carbon storage values in 2030 are 540.45$\times10^{6}$ t, 539.97$\times10^{6}$ t, and 539.25$\times10^{6}$ t under the sustainable development, status quo, and economic priority scenarios, respectively. Compared with 2020, carbon storage increases by 0.18$\times10^{6}$ t under the sustainable scenario but decreases by 0.30$\times10^{6}$ t and 1.01$\times10^{6}$ t under the status quo and economic priority scenarios, respectively, with the economic priority scenario showing the greatest loss.

3. Discussion

Carbon storage changes in the Turpan-Hami Basin are primarily driven by land cover change. In recent years, continuous population growth and rapid socioeconomic development [43] have led to construction land expansion and large-scale encroachment on grassland and bare land, representing the main cause of ecosystem carbon storage reduction. Therefore, high-carbon-storage land types such as forest, cultivated land, and grassland should be prioritized for protection to prevent conversion to other types and reduce carbon loss.

This study used the InVEST model carbon storage module to estimate carbon storage and spatial distribution in the Turpan-Hami Basin. However, several uncertainties exist. First, carbon density is a critical input parameter and key factor for accurate carbon storage estimation [44]. Our carbon density data were obtained from previous studies in similar regions and corrected using temperature-precipitation relationship models, which provides higher accuracy than using national-scale data directly. Second, the model assumes carbon density remains consistent across temporal scales, neglecting land use internal structure and carbon sequestration differences among vegetation types [45], which introduces errors. Future research should conduct continuous observations of carbon densities for different land cover types to improve estimation accuracy. Third, land use data were derived from the China Annual Land Cover Dataset; limited by its resolution, we only classified data into eight types. Higher-resolution remote sensing data could enable finer classification and more accurate carbon storage calculations. Fourth, while we simulated three scenarios, they cannot cover all development patterns. Future research should incorporate regional development policies more comprehensively to narrow the gap between scenario simulation and actual development.

4. Conclusion

This study analyzed land cover change and its impact on carbon storage in the Turpan-Hami Basin from 2000 to 2020 and predicted changes in land cover and carbon storage under different development scenarios for 2025 and 2030. The main conclusions are:

(1) From 2000 to 2020, land cover change in the Turpan-Hami Basin primarily involved grassland converting to cultivated land, construction land, and bare land. Bare land is the dominant land cover type, accounting for over 65% of the total area. The average carbon storage was 26.01 $t \cdot hm^{-2}$, 25.68 $t \cdot hm^{-2}$, and 25.73 $t \cdot hm^{-2}$ in 2000, 2010, and 2020, respectively, showing an overall declining trend. Carbon storage spatial distribution exhibits significant heterogeneity, characterized by medium-value areas surrounding high-value areas, which in turn surround low-value areas.

(2) Compared with 2020 land cover, all three scenarios project decreasing bare land and increasing construction land by 2030. Cultivated land area continues decreasing under sustainable development and economic priority

scenarios, while grassland area keeps increasing. Under status quo and economic priority scenarios, construction land expands rapidly, increasing by 11.47×10^{3} hm^2 and 12.50×10^{3} hm^2, respectively.

(3) By 2030, total carbon storage shows an initial decrease followed by increase under the sustainable development scenario, initial increase then decrease under the status quo scenario, and continuous decline under the economic priority scenario. Carbon storage values reach 540.45×10^{6} t, 539.97×10^{6} t, and 539.25×10^{6} t under the three scenarios, respectively, with the economic priority scenario incurring the largest loss of approximately 1.01×10^{6} t.

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

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