Climate Impact Mechanisms on Carbon Storage in the Tarim River Basin and Attribution Postprint under Topographic Differentiation

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Abstract

This study estimates long-term carbon storage in the Tarim River Basin based on the InVEST model, characterizes and analyzes its spatiotemporal variation characteristics, employs methods such as trend analysis, correlation coefficient analysis, and band set statistics to investigate the overall spatiotemporal correlation between climate change and carbon storage in the Tarim River Basin, and utilizes partial least squares regression to quantitatively analyze the attribution of carbon storage changes under different terrains in the Tarim River Basin. The results indicate: (1) From 2002 to 2020, the overall carbon storage level in the Tarim River Basin was relatively low, exhibiting a horseshoe-shaped distribution pattern characterized by "low in the center and high in the periphery", with the overall situation showing an improving trend. (2) Carbon storage and annual mean temperature, potential evapotranspiration, and annual mean precipitation all exhibited a pattern where opposite spatial distributions outnumbered same-direction spatial distributions, showing pronounced spatial heterogeneity. (3) At the global scale, the influence of climatic factors on carbon storage, in descending order, was potential evapotranspiration > annual mean temperature > annual mean precipitation. (4) Potential evapotranspiration was the variable with the greatest explanatory power for terrain positions of classes I, III, and IV in the Tarim River Basin, while mean temperature and mean precipitation were the variables with the greatest explanatory power for terrain positions of classes II and V.

Full Text

Abstract

Using the InVEST model, this study estimated long-term carbon storage in the Tarim River Basin and characterized its spatiotemporal variation patterns.

Trend analysis, correlation coefficients, and band set statistics were employed to explore the overall spatiotemporal correlation between climate change and carbon storage in the basin. Partial least squares regression was then used to quantitatively analyze the attribution of carbon storage changes across different topographic positions. The results showed that: (1) From 2002 to 2020, the overall carbon storage level in the Tarim River Basin was relatively low, exhibiting a horseshoe-shaped distribution pattern of "low in the middle and high around the periphery," with an overall improving trend. (2) Carbon storage showed opposite spatial distributions more frequently than consistent ones with mean annual temperature, potential evapotranspiration, and mean annual precipitation, indicating significant spatial differentiation. (3) At the global scale, the influence of climate factors on carbon storage, from strongest to weakest, was: potential evapotranspiration > mean annual temperature > mean annual precipitation. (4) Potential evapotranspiration was the most explanatory variable for terrain levels I, III, and IV, while mean temperature and mean precipitation were the most explanatory variables for terrain levels II and V in the Tarim River Basin.

Keywords: carbon storage; influence mechanism; topographic differentiation; Tarim River Basin

Introduction

Under the "dual carbon" vision, "carbon peak" represents a trajectory of carbon emissions under natural or anthropogenic interventions, while "carbon neutrality" is the ultimate goal to be achieved. Reducing "carbon sources" and increasing "carbon sinks" are two important pathways to realize the carbon neutrality target, and they are mutually complementary. Terrestrial ecosystems continuously absorb CO_2 through vegetation photosynthesis, and their carbon sequestration function plays an irreplaceable role in offsetting carbon emissions from human activities, representing a key component for achieving carbon neutrality. Therefore, in-depth analysis of the attribution of carbon storage changes in terrestrial ecosystems is crucial for fully unlocking their carbon sequestration potential and promoting regional low-carbon development.

Against the backdrop of carbon peaking and carbon neutrality becoming key global concerns, carbon storage issues have attracted extensive scholarly attention. Existing research primarily examines carbon storage from perspectives of spatiotemporal evolution trends, multi-scenario assessment and simulation, and influencing factor exploration. Attribution analysis of carbon storage changes often remains at the level of land cover change as the dominant factor. However, land cover change is only one cause—not the sole driver—of carbon storage variation. Land cover changes may result from combined climate change and human activities, and directly linking them with carbon storage may lead to inaccurate conclusions due to confounding interactions among factors. Directly incorporating climate variables to explore carbon storage change attribution helps establish causal relationships, clarifies associations between different climate factors and carbon storage, and provides more comprehensive, accurate, and predictive information that better reflects the diversity and complexity of carbon storage dynamics, offering guidance for addressing future carbon storage changes and variability. Carbon storage changes represent the integrated outcome of multiple climate factors, making accurate discrimination of their relative contributions a key challenge in attribution research. Furthermore, existing studies often overlook how local water-heat distributions under different topographic habitat conditions affect surface vegetation, thereby influencing terrestrial ecosystem carbon storage, which limits the accuracy and applicability of research on differential contributions of influencing factors.

The Tarim River Basin, located in a typical ecologically fragile and sensitive area in China, is a strategic region for national ecological security and plays a pivotal role in the Silk Road Economic Belt. Recent years have witnessed significant changes in landscape patterns and vegetation dynamics in the basin, making it urgent and practically meaningful to investigate related carbon storage changes. Accordingly, this study estimated long-term carbon storage in the Tarim River Basin using the InVEST model, characterized and analyzed its spatiotemporal variation features, explored the spatiotemporal correlation between temperature, potential evapotranspiration, precipitation, and carbon storage using trend analysis, correlation coefficients, and band set statistics, and quantitatively assessed the relative importance of each climate factor under different topographic habitat conditions using partial least squares regression to analyze carbon storage change attribution across different terrain positions. The findings aim to provide support for actively responding to climate change, promoting regional ecological protection, and facilitating low-carbon development.

1. Materials and Methods

1.1 Study Area Overview

The Tarim River Basin is situated between the Tianshan Mountains, East Pamir Plateau, Karakoram Mountains, and Kunlun Mountains, comprising the main stream of the Tarim River and its surrounding nine major water systems including the Aksu River, Hotan River, and Weigan River in the Tarim Basin. The basin covers an area of 9.96$×10^{5}$ km^2 and consists of three major geomorphic units: mountains, plains, and deserts. Most of the region features an extremely arid climate with single vegetation types and low coverage, forming a closed inland water cycle and relatively independent water balance catchment area.

1.2 Methods

1.2.1 Carbon Storage Estimation Method The InVEST (Integrated Valuation of Ecosystem Services and Trade-offs) Carbon Storage and Sequestration module divides ecosystem carbon storage into four basic carbon pools: aboveground biomass carbon (carbon in all living plant materials above soil), belowground biomass carbon (carbon in living root systems), soil carbon (organic carbon in organic and mineral soils), and dead organic carbon (carbon in litter and standing or fallen dead wood). Carbon storage for each land cover type in the study area is calculated as the product of land cover area and its corresponding carbon density in different pools; total carbon storage is the sum of carbon storage across all land cover types. The specific calculation formula is as follows:

$$C_i = C_{i-above} + C_{i-below} + C_{i-soil} + C_{i-dead}$$

$$C_{i-total} = C_i \times A_i$$

$$C_{total} = \sum_i C_{i-total}$$

where: C_i is the carbon density of land cover type i; $C_{i-above}$ is the aboveground biomass carbon density; $C_{i-below}$ is the belowground biomass carbon density; C_{i-soil} is the soil carbon density; C_{i-dead} is the dead organic carbon density; $C_{i-total}$ is the carbon storage of land cover type i; A_i is the area of land cover type i; and C_{total} is the total carbon storage of the study area.

1.2.2 Trend Analysis The least squares method was used to fit the slope of carbon storage, mean annual temperature, potential evapotranspiration, and mean annual precipitation for each pixel across the study period, simulating the change trend for each grid cell to more intuitively reflect regional spatiotemporal patterns of each research indicator:

$$\text{slope} = \frac{n \times \sum_{i=1}^{n} i \times \text{IND}_{ij} - \sum_{i=1}^{n} i \sum_{i=1}^{n} \text{IND}_{ij}}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where: slope represents the change trend of each research indicator; n is the time series length; j represents different research indicators; and IND_{ij} is the standardized value of indicator j in year i. When slope > 0, the indicator shows an upward trend; when slope < 0, it shows a downward trend. Simultaneously, t-tests were employed to determine the significance of change trends: $P \leq 0.01$ indicates extremely significant; $0.01 < P \leq 0.05$ indicates significant; and $0.05 < P$ indicates non-significant.

1.2.3 Correlation Coefficient Method Panel grid data of carbon storage, mean annual temperature, potential evapotranspiration, and mean annual precipitation in the Tarim River Basin from 2002 to 2020 were integrated. Correlation coefficients between carbon storage and each influencing factor were calculated pixel by pixel to estimate the degree of correlation between variables:

$$R = \frac{\sum_{i=1}^{n}(x_{ij} - \frac{1}{n}\sum_{i=1}^{n} x_{ij})(y_{ic} - \frac{1}{n}\sum_{i=1}^{n} y_{ic})}{\sqrt{\sum_{i=1}^{n}(x_{ij} - \frac{1}{n}\sum_{i=1}^{n} x_{ij})^2 \sum_{i=1}^{n}(y_{ic} - \frac{1}{n}\sum_{i=1}^{n} y_{ic})^2}}$$

where: R is the correlation coefficient with a value range of $[-1, 1]$; n is the time series length; x_{ij} is the standardized value of indicator j in year i; and y_{ic} is the standardized carbon storage value in year i. When $R > 0$, variables are positively correlated; when $R < 0$, they are negatively correlated. The larger the absolute value of R, the stronger the correlation.

1.2.4 Band Set Statistics Cross-sectional grid data of carbon storage, mean annual temperature, potential evapotranspiration, and mean annual precipitation in the Tarim River Basin were grouped by year. Pixel values of each layer in each group were correlated, and the dependence between layers was measured by the ratio of covariance to the product of standard deviations, expressed as a correlation matrix:

$$\mathrm{Cov}_{ij} = \frac{\sum_{k=1}^{N}(Z_{ik} - \mu_i)(Z_{jk} - \mu_j)}{N}$$

$$\mathrm{Corr}_{ij} = \frac{\mathrm{Cov}_{ij}}{\sigma_i \sigma_j}$$

where: Cov_{ij} is the covariance between layer i and layer j; Z is the pixel value; i and j represent stacked layers; μ is the layer mean; N is the number of pixels; k is a specific pixel; Corr_{ij} is the correlation between layer i and layer j; and σ is the layer standard deviation. Corr_{ij} ranges from $[-1, 1]$. When $\mathrm{Corr}_{ij} > 0$, pixel values of one layer tend to increase with those of another; when $\mathrm{Corr}_{ij} < 0$, they change inversely; when $\mathrm{Corr}_{ij} = 0$, no dependence exists. The correlation matrix is symmetric.

1.2.5 Terrain Niche Index The terrain niche index integrates elevation and slope classifications into a comprehensive indicator that more fully reflects topographic conditions:

$$T = \log\left[\left(\frac{E}{\bar{E}} + 1\right) \times \left(\frac{S}{\bar{S}} + 1\right)\right]$$

where: T is the terrain niche index; E and $\bar{E}$ represent the elevation and mean elevation of any grid cell; S and $\bar{S}$ represent the slope and mean slope. Larger T values indicate higher elevation and steeper slopes, and vice versa. The natural breaks method was used to divide the Tarim River Basin terrain into five levels (I-V), with mean elevation and slope gradually increasing from level I to V [Figure 2: see original paper].

1.2.6 Partial Least Squares (PLS) Partial least squares regression overcomes multicollinearity problems caused by interactions among numerous independent variables, combining advantages of principal component analysis and multiple regression. A key discriminant indicator—Variable Importance in Projection (VIP)—is calculated as:

$$\mathrm{VIP}_j = \sqrt{\frac{p \times \sum_{h=1}^{m} \left[R^2(y_k, t_h) \times w_{hj}^2\right]}{\sum_{h=1}^{m} R^2(y_k, t_h)}}$$

where: p is the number of independent variables; m is the number of components extracted from independent variables; k is the kth dependent variable; t_h is the hth component of independent variables; $R^2(y_k, t_h)$ is the squared correlation coefficient between y_k and t_h; and w_{hj} is the contribution weight of independent variable x_j to component t_h. Generally, independent variables with VIP > 1 have significant explanatory power, VIP > 0.5 indicates moderate explanatory power, and VIP ≤ 0.5 lacks explanatory significance.

1.3 Data Sources and Preprocessing

1.3.1 Boundary Data Tarim River Basin boundary vector data were obtained from the National Tibetan Plateau Data Center. Third-level watershed boundary data came from the National Earth System Science Data Center. Administrative boundary data were sourced from the Chinese Academy of Sciences Resource and Environment Data Center.

1.3.2 Land Cover and Climate Data Land cover data were derived from Wuhan University's 30 m resolution annual land cover dataset for China (1985-2021), produced using Google Earth Engine with Landsat imagery, including nine land use types: farmland, forest, shrubland, grassland, water, ice/snow, bare land, impervious surface, and wetland. DEM data (30 m resolution) were obtained from SRTM measurements by NASA and NIMA. Slope data were derived from DEM processing. Climate data (mean annual temperature, potential evapotranspiration, mean annual precipitation) were sourced from the National Tibetan Plateau Data Center at 1 km resolution.

1.3.3 Carbon Density Data Carbon density values for different land cover types were selected based on existing research, primarily referencing studies from regions with similar geographic and climatic conditions to the Tarim River

Basin. Ice/snow cover accounts for approximately 3.48% of the basin area with minimal annual change rate. Due to the lack of reliable reference data for ice/snow carbon density, it was treated as equivalent to water carbon density. The final carbon density values are shown in .

1.3.4 Data Preprocessing To ensure data accuracy and precision of carbon storage estimates, 30 m resolution land cover data were used. For correlation analysis, all grid data were unified using ArcMap10 projection tools: cell size set to 1000 m, columns to 871, rows to 1087, with WGS_{1984} projection. Correlation tests among variables were conducted using band set statistics in ArcMap10, calculating correlation matrices between carbon storage and climate factors. Results showed varying degrees of correlation among variables, satisfying prerequisites for PLS modeling .

2. Results

2.1 Spatiotemporal Characteristics of Carbon Storage in the Tarim River Basin

From 2002 to 2020, the land carbon sequestration capacity in the Tarim River Basin showed a stepwise increasing trend [Figure 3: see original paper]. Total carbon storage increased from 1.94$×10^{9}$ t to 2.26$×10^{9}$ t, with an average annual carbon storage of 7.26$×10^{8}$ t and an annual change rate of 0.13%. The standardized mean carbon storage value revealed a relatively low overall level with obvious spatial heterogeneity, following a "low in the middle, high around the periphery" horseshoe pattern. Areas with pixel values < 0.3 accounted for 72.29% of the basin, while high carbon storage areas (> 0.5) accounted for only 18.31%. High carbon storage areas were densely distributed in the southern and northern parts, gradually becoming sparse toward the center, showing high dispersion. This distribution aligns with the region's topography and human settlements, where mountainous areas with relatively abundant forest and grass resources have stronger carbon storage capacity.

The overall carbon storage trend was positive, with improvement more evident in the south. Pixels showing increased and decreased carbon storage accounted for 96.52% and 3.48% of the basin, respectively. Areas with decreasing carbon storage were concentrated in the north, with the trend gradually weakening from west to east. Areas with increasing carbon storage were mainly distributed as scattered points interspersed with decreasing areas, predominantly in the south, showing fluctuating characteristics from west to east. The spatial pattern of carbon storage change showed high similarity with the distribution pattern of carbon storage values, indicating that climate conditions have a certain spatial correlation with carbon storage and may influence its changes.

2.2 Impact of Climate Change on Carbon Storage

This study examined not only precipitation and temperature effects but also potential evapotranspiration, considered a key link connecting water-heat cycles in climate systems. Correlation analysis between carbon storage and three individual climate factors (mean annual temperature, potential evapotranspiration, mean annual precipitation) from 2002-2020 showed that opposite spatial distributions were more common than consistent ones, with significant spatial differentiation [Figure 5: see original paper]. Potential evapotranspiration had the most profound impact on basin-wide carbon storage. Specifically, areas where mean annual temperature negatively correlated with carbon storage accounted for 61.68% of the total area, with weak negative correlations reaching 44.33%. Positive correlation areas were interspersed with negative correlation areas, particularly around human settlements. Potential evapotranspiration negatively correlated with carbon storage in 74.75% of the area, with weak negative correlations in 58.27%; positive correlation areas were only sparsely distributed around the main Tarim River channel in the north. Mean annual precipitation negatively correlated with carbon storage in 63.29% of the area, with weak negative correlations in 47.13%; positive correlation areas were mainly distributed in the north and southeast.

To explore potential time-lag effects, correlations were calculated between current carbon storage and both current and previous-year climate factors [Figure 6: see original paper]. Mean annual precipitation showed some time-lag effect on carbon storage, while temperature and potential evapotranspiration did not show obvious lag effects. At the global scale, the influence of climate factors on carbon storage ranked as: potential evapotranspiration > mean annual temperature > mean annual precipitation. The correlation between potential evapotranspiration and carbon storage showed fluctuating increases before 2015, then decreased. The correlation between temperature and carbon storage fluctuated upward, with an increase after 2015. The correlation between precipitation and carbon storage fluctuated significantly, with a noticeable increase after 2015, indicating that only potential evapotranspiration had a relatively sustained effect on carbon storage changes.

2.3 Attribution of Carbon Storage Changes Based on Terrain Differentiation

PLS analysis quantified the relative importance of each climate factor on carbon storage across terrain levels [Figure 7: see original paper]. At terrain level I, the relative influence ranked as: potential evapotranspiration (VIP = 1.21) > mean temperature (VIP = 1.18) > mean precipitation (VIP = 1.17). At level II: mean temperature (VIP = 1.21) > mean precipitation (VIP = 1.21) > potential evapotranspiration (VIP = 1.20). At level III: potential evapotranspiration (VIP = 1.21) > mean temperature (VIP = 1.20) > mean precipitation (VIP = 1.19). At level IV: potential evapotranspiration (VIP = 1.21) > mean temperature (VIP = 1.20) > mean precipitation (VIP = 1.19). At level V: mean temperature

(VIP = 1.21) = mean precipitation (VIP = 1.21) > potential evapotranspiration (VIP = 1.20).

The relative influence of each factor varied across years. At terrain level I, temperature and precipitation were dominant before 2010, while potential evapotranspiration became dominant after 2010. At level II, temperature and precipitation were consistently strong, with climate factors showing stable influence. At level III, temperature and precipitation were strong before 2010, after which potential evapotranspiration dominated with stable influence. At level IV, temperature and precipitation were initially dominant with strengthening influence, while potential evapotranspiration's influence weakened. At level V, potential evapotranspiration was dominant before 2010, after which temperature and precipitation became dominant, showing a gradual shift in relative importance.

3. Discussion

Analyzing carbon storage attribution in this ecologically fragile region is crucial for understanding the role of different climate factors and identifying their differential contributions under varying topographic habitats. This study revealed a stepwise increasing trend in carbon storage from 2002-2020, with high values distributed in high-altitude peripheral areas and low values in the Taklamakan Desert and surrounding low-altitude areas, consistent with regional-scale studies in northwest arid regions.

Many studies attribute carbon storage changes to land cover type changes, but deeper reflection reveals that climate and human activity combinations are more fundamental causes. Land use/vegetation cover changes respond to climate and human activity factors, and directly linking them with carbon storage may confuse factor relationships, leading to inaccurate conclusions. This study avoided such confusion by directly incorporating climate factors, providing clearer explanations of factor relationships. Additionally, different research scales often yield different estimates of factor importance. Most previous studies detect factor contributions at provincial or larger scales, ignoring local water-heat condition differences under various topographic habitats, which may cause significant bias due to missing micro-scale differences. This study improved variable selection and scale division, demonstrating that different factors have varying relative importance across terrain levels, supplementing and enriching existing research.

4. Conclusions

Based on the InVEST model, this study estimated long-term carbon storage in the Tarim River Basin, analyzed its spatiotemporal variation characteristics, explored spatiotemporal correlations with climate factors using trend analysis, correlation coefficients, and band set statistics, and quantitatively assessed the relative importance of climate factors across different topographic positions using partial least squares regression. The main conclusions are:

1) From 2002-2020, the Tarim River Basin had relatively low overall carbon storage, following a "low in the middle, high around the periphery" horseshoe distribution. Land carbon sequestration capacity showed a continuous stepwise improvement, with an overall positive trend more evident in the southern region.
2) Carbon storage and mean annual temperature, potential evapotranspiration, and mean annual precipitation showed opposite spatial distributions more frequently than consistent ones, with significant spatial differentiation. Mean annual precipitation had a time-lag effect on carbon storage, while temperature and potential evapotranspiration did not show obvious lag effects.
3) At the global scale, climate factors' influence on carbon storage ranked as: potential evapotranspiration > mean annual temperature > mean annual precipitation.
4) Across different terrain levels, climate factors showed varying influences on carbon storage. Potential evapotranspiration was the most explanatory variable for terrain levels I, III, and IV, while mean temperature and mean precipitation were most explanatory for levels II and V.

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