Postprint: Carbon Sequestration Potential of Xinjiang Oasis Ecosystems

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Abstract

Net Primary Productivity (NPP) is an important indicator characterizing terrestrial carbon cycling, reflecting the carbon sequestration capacity of terrestrial ecosystems. In response to China's "dual carbon" goals of achieving "carbon peak" and "carbon neutrality", enhancing the carbon sequestration capacity of terrestrial ecosystems represents one of the important pathways. Xinjiang covers a vast area with tremendous potential for vegetation restoration. Assessing the current status of carbon sequestration in Xinjiang's ecosystems and exploring its carbon sequestration potential holds important practical significance for actively responding to and achieving the national "dual carbon" goals. This study simulated NPP in Xinjiang from 2001 to 2020 using the Carnegie Ames Stanford Approach (CASA) model, combined with land use data, remote sensing data, and meteorological data (temperature, precipitation, and solar radiation). The Sen-MK method was employed to analyze the trend of NPP change characteristics, and Pearson correlation analysis was used to examine the relationship between NPP variation and climate factors. Furthermore, by adopting different land use and vegetation scenarios for 2001 and 2020, along with NPP change patterns under pure climate scenarios simulated by the Miami model, the maximum NPP potential and maximum NPP increment in Xinjiang were ultimately obtained. The results indicate that: (1) NPP in Xinjiang exhibited an overall fluctuating upward trend during 2001–2020; (2) among climate factors, precipitation exerted the greatest influence on NPP in Xinjiang; (3) among the main land use types in Xinjiang, cropland had relatively high NPP and its area showed an increasing trend; and (4) the incremental potential of overall NPP in Xinjiang reached 79.43 g $C \cdot m^{-2}$. This study can provide a reference basis for implementing ecological restoration and cropland protection measures in Xinjiang.

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Full Text

Carbon Sequestration Potential of Oasis Ecosystem in Xinjiang, China

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Abstract

Net Primary Productivity (NPP) is an essential indicator of the terrestrial carbon cycle that reflects the carbon sink capacity of terrestrial ecosystems. In response to China's strategic goals of achieving "carbon peak" and "carbon neutrality," enhancing the carbon sequestration capacity of terrestrial ecosystems represents a critical pathway. Xinjiang's vast geographical area and substantial potential for vegetation restoration make the assessment of its current carbon sequestration status and the exploration of its carbon sequestration potential highly significant for realizing national "dual carbon" objectives. This study employed the Carnegie Ames Stanford Approach (CASA) model, integrating land use data, remote sensing data, and meteorological data (temperature, precipitation, and solar radiation) to simulate NPP variation characteristics in Xinjiang from 2001 to 2020. The Sen-MK method was utilized to analyze NPP change trends, while Pearson correlation analysis examined relationships between NPP variations and climatic factors. Furthermore, different land use and vegetation scenarios, along with the Miami model's simulation of NPP patterns under pure climate scenarios, were used to determine the maximum NPP potential and increment potential in Xinjiang. Results indicate: (1) NPP in Xinjiang exhibited a fluctuating upward trend from 2001 to 2020; (2) Among climatic factors, precipitation exerted the strongest influence on NPP; (3) Among major land use types, cultivated land demonstrated both high NPP values and an increasing trend; (4) The overall NPP increment potential in Xinjiang reached 79.43 g C $\cdot$ m^{-2}. These findings provide scientific references for ecological restoration and cultivated land protection measures in Xinjiang, supporting the national "dual carbon" goals.

Keywords: oasis; net primary productivity; carbon sequestration potential; CASA model; Xinjiang

Introduction

Net Primary Productivity (NPP) represents the organic matter produced by plants after photosynthesis minus the portion consumed by respiration, most intuitively reflecting vegetation carbon sequestration levels. NPP variations indirectly indicate vegetation responses to climate change. With intensifying global warming and frequent extreme climate events, China has proposed the "carbon peak" and "carbon neutrality" targets to mitigate climate change. Vegetation restoration is considered one of the most effective strategies for climate change mitigation, making studies on vegetation carbon sequestration potential and its influencing factors crucial for regional sustainable development and national dual-carbon goal achievement.

Climate factors significantly influence NPP, with precipitation, temperature, and solar radiation being primary abiotic drivers. These factors affect NPP differently across spatiotemporal scales and vegetation types. Research indicates that NPP spatial patterns correlate with mean annual temperature and precipitation, though NPP sensitivity varies by vegetation type. In arid regions, precipitation serves as the most critical factor, while temperature effects are largely constrained by water availability. Solar radiation positively influences productivity up to a point, but excessive radiation may limit photosynthesis. Under extreme conditions like drought and high temperature, stomatal closure inhibits photosynthesis and reduces productivity.

In recent decades, Xinjiang has experienced warming and wetting trends, significantly enhancing vegetation activity and attracting widespread scholarly attention. Previous studies demonstrate that Xinjiang's NPP has generally increased, with higher values in northern Xinjiang than southern Xinjiang. However, most research has focused on NPP responses to climate factors, while studies on Xinjiang's vegetation carbon sequestration potential remain limited. Remote sensing observations and climate model simulations provide new approaches for assessing vegetation carbon sequestration potential. As China's largest provincial region, Xinjiang's vast grassland and desert ecosystems offer substantial space for increasing national vegetation carbon stocks. Therefore, investigating Xinjiang's NPP spatiotemporal patterns, analyzing influencing factors, and estimating carbon sequestration potential hold significant importance.

This study simulates Xinjiang's NPP from 2001 to 2020 using the CASA model at 0.25°$×$0.25° spatial resolution, analyzing trend characteristics and driving factors through integration with climate factors and land use data. Finally, NPP potential is estimated through scenario simulations, providing scientific basis and data support for Xinjiang's ecological management and China's dual-carbon target implementation.

1.1 Study Area Overview

Xinjiang is located in northwestern China, characterized by complex terrain and diverse landforms. The region features three major mountain ranges from north to south—the Altai Mountains, Tianshan Mountains, and Kunlun Mountains—alternating with the Junggar and Tarim Basins, creating a "three mountains sandwiching two basins" pattern. Remote from oceans and surrounded by high mountains, Xinjiang has a typical temperate continental climate with large diurnal temperature ranges, dry conditions, and unevenly distributed scarce precipitation. Vegetation is dominated by desert and grassland, with cultivated land and forest primarily distributed in oasis areas.

1.2 Data Sources

1.2.1 Meteorological Data

Solar radiation data were obtained from the National Earth System Science Data Center, based on European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data. Temperature and precipitation data were derived from the National Science and Technology Infrastructure Platform's 0.05°$×$0.05° monthly mean temperature and precipitation datasets, generated through spatial downscaling of global climate datasets. These datasets were interpolated to the required resolution using ArcGIS 10.8 software.

1.2.2 Land Use and NDVI Data

Land use data were sourced from NASA's MOD12Q1 product at 500 m resolution, using the International Geosphere-Biosphere Programme (IGBP) classification method. The data categorize land cover into 17 types: evergreen needleleaf forest, evergreen broadleaf forest, deciduous needleleaf forest, deciduous broadleaf forest, mixed forest, closed shrublands, open shrublands, woody savannas, savannas, grasslands, permanent wetlands, croplands, urban and built-up lands, cropland/natural vegetation mosaic, snow and ice, barren or sparsely vegetated, and water bodies. The high spatial resolution and detailed classification make this dataset widely applicable in ecological and geographical analyses.

NDVI data were obtained from MOD13Q1 products (http://lpdaac.usgs.gov) at 500 m spatial resolution. Monthly data were composited into annual datasets using ArcGIS 10.8.

1.3 Research Methods

1.3.1 CASA Model

The CASA model is a typical light use efficiency model. Its main parameters include Photosynthetically Active Radiation (APAR) and light use efficiency ( ). The model estimates NPP through the following formula:

NPP(x,t) = APAR(x,t) × (x,t)

where APAR(x,t) represents the photosynthetically active radiation absorbed by vegetation pixel x in month t, and (x,t) denotes light use efficiency.

APAR is calculated as:

APAR(x,t) = SOL(x,t) × FPAR(x,t) × 0.5

where SOL(x,t) is the total solar radiation accumulated at pixel x in month t ($\mathrm{MJ \cdot month^{-1}}$), FPAR(x,t) represents the fraction of photosynthetically active radiation absorbed by vegetation, and the constant 0.5 indicates the proportion of solar effective radiation utilized by vegetation.

FPAR is estimated through NDVI and SR (Simple Ratio) indices:

$$FPAR(x,t) = FPAR_{min} + (FPAR_{max} - FPAR_{min}) \times (NDVI(x,t) - NDVI_{i,min}) / (NDVI_{i,max} - NDVI_{i,min})$$

$$FPAR(x,t) = FPAR_{min} + (FPAR_{max} - FPAR_{min}) \times (SR(x,t) - SR_{i,min}) / (SR_{i,max} - SR_{i,min})$$

where $NDVI(x,t)$ is the normalized difference vegetation index for pixel x in month t; $NDVI_{i,max}$ and $NDVI_{i,min}$ represent the 95th and 5th percentiles of NDVI for vegetation type i, respectively; $SR(x,t)$ is the simple ratio index; $FPAR_{max}$ and $FPAR_{min}$ are constants (0.95 and 0.001, respectively), independent of vegetation type.

Light use efficiency ( ) is calculated as:

$$(x,t) = T_{1}(x,t) \times T_{2}(x,t) \times W_{}(x,t) \times {}_{max}$$

where T_{1} and T_{2} represent temperature stress factors (too high or too low), $W_{}$ is the water stress coefficient, and ${}_{max}$ is the maximum light use efficiency.

$$T_{1}(x,t) = 0.8 + 0.02 \times T_{opt}(x,t) - 0.0005 \times [T_{opt}(x,t)]^2$$

$$T_{2}(x,t) = 1.0 / (1 + \exp[0.2 \times (T_{opt}(x,t) - 10 - T(x,t))]) \times 1.0 / (1 + \exp[0.3 \times (-T_{opt}(x,t) - 10 + T(x,t))])$$

$$W_{}(x,t) = 0.5 + 0.5 \times E(x,t) / E_p(x,t)$$

where $T(x,t)$ is the monthly mean temperature, T_{opt} is the optimal temperature for plant growth, $E(x,t)$ is actual evapotranspiration, and $E_p(x,t)$ is potential evapotranspiration.

1.3.2 Miami Model

The Miami model estimates potential NPP based purely on climate factors, with simple parameters and strong applicability. The calculation method is:

$$NPP = \min(NPP_T, NPP_R)$$

$$NPP_T = 3000 / (1 + \exp(1.315 - 0.119 \times t))$$

$$NPP_R = 3000 \times (1 - \exp(-0.000664 \times r))$$

where NPP_T and NPP_R represent potential NPP based on temperature and precipitation, respectively; t is mean annual temperature (°C); and r is annual total precipitation (mm).

1.3.3 Trend Analysis

The Theil-Sen Median method and Mann-Kendall test were combined to calculate NPP change trends in Xinjiang. These methods effectively identify trends in long time-series data without requiring specific distribution types and are widely used in meteorological analysis.

The Theil-Sen Median slope is calculated as:

SNPP = Median((NPP_j - NPP_i) / (j - i)), for 2001 $\leq$ i $<$ j $\leq$ 2020

where NPP_i and NPP_j represent pixel values in years i and j, respectively. A positive SNPP indicates an upward trend, while a negative value indicates a downward trend.

The Mann-Kendall test assesses trend significance:

Z = (S - 1) / √Var(S) when S > 0 Z = 0 when S = 0 Z = (S + 1) / √Var(S) when S < 0

where S = Σ_{i=1}^{n-1} Σ_{j=i+1}^{n} sgn(NPP_j - NPP_i), n is the number of years, and sgn is the sign function. At $\alpha = 0.05$ significance level, |Z| > 1.96 indicates a significant trend.

1.3.4 Pearson Correlation Analysis

Pearson correlation coefficient measures linear correlation between two variables, ranging from -1 to 1. A value of 0 indicates no linear relationship. The formula is:

r = Σ_{i=1}^{n} (X_i - X̄)(Y_i - Ȳ) / √[Σ_{i=1}^{n} (X_i - X̄)^2 Σ_{i=1}^{n} (Y_i - Ȳ)^2]

where X̄ and Ȳ are sample means, and the denominator represents the product of standard deviations.

2.1 Spatiotemporal Trends of NPP

From 2001 to 2020, Xinjiang's annual mean NPP showed a fluctuating upward trend. The minimum annual mean was 225 g $C \cdot m^{-2}$ in 2001, 43.3% lower than the multi-year average. The maximum annual mean reached 397 g $C \cdot m^{-2}$ in 2017, 32.24% higher than the multi-year average, with notable fluctuation amplitude. The overall change rate approached zero, indicating a stable yet fluctuating increasing trend.

The spatial distribution of multi-year mean NPP showed significant heterogeneity, generally higher in the north and west than in the south and east. Most western regions exhibited values between 300-660 g $C \cdot m^{-2}$, surpassing eastern areas. The Ili River Valley, influenced by Atlantic westerlies with abundant precipitation, represented a high NPP zone with superior vegetation growth conditions. Mountain ranges and oasis areas also showed high values due to richer water resources compared to desert regions. Southern Xinjiang constituted a low NPP zone, with most areas ranging 0-141 g $C \cdot m^{-2}$, except for slightly higher values at the Tarim Basin's oasis margins.

Since 2001, spatial changes in NPP have been evident. Overall, increasing areas exceeded decreasing areas, with expansion regions concentrated in the Ili River

Valley, northern Tianshan slope, Turpan-Hami Basin, and the northern and western margins of the Tarim Basin. Significantly decreasing areas were sporadically distributed. Increasing regions accounted for 92.53% of all significant change areas, covering 7.47% of Xinjiang's total area, while decreasing regions comprised the remaining 7.47%.

2.2 Impacts of Land Use Change on NPP

Xinjiang's land cover is dominated by desert, grassland, and cultivated land, in descending order of area coverage. Desert is the most extensive land use type, with grassland and cultivated land primarily distributed in northern Xinjiang. During 2001-2020, land type changes mainly occurred in northern and western Xinjiang, with minimal changes in eastern and southern regions.

Grassland experienced the most significant changes, primarily converted from desert, cultivated land, and wetland, with conversion areas of 62,308.16 km^2, 18,168.79 km^2, and 14,053.98 km^2, respectively. Increased grassland areas were distributed at desert margins. In western Xinjiang, some grassland was converted to cultivated land (6,399.52 km^2). Most wetlands transformed into grassland, with some converting to cultivated land. Increased areas were mainly distributed near mountains and basins, particularly at the junctions of the Tianshan and Kunlun Mountains with the Tarim Basin. Desert areas around the Junggar and Tarim Basins converted to grassland, benefiting regional NPP increases. Conversely, NPP decreased in approximately 7.47% of the region, mainly due to grassland conversion to desert in the Ili River Valley and Hotan areas, and desert conversion to ice/snow near the Altun Mountains.

Cultivated land showed the highest mean annual NPP among all land types, followed by grassland. During 2001-2020, cultivated land and grassland exhibited increasing trends, with grassland area showing slight fluctuations before 2005 but significant continuous growth thereafter. Urban/built-up land and wetland areas decreased, with wetland area declining slowly before 2010. Other land types remained relatively stable.

2.3 Impacts of Climate Change on NPP

Precipitation emerged as the most important climate factor affecting NPP in this arid region. During 2001-2020, 72.77% of Xinjiang showed positive correlations between precipitation and NPP, with average positive correlation approximately 0.45 and significant correlation areas exceeding 66.97%. Positive correlation zones were mainly distributed in the western Ili region and southern Kashgar and Aksu areas. Negative correlation areas were primarily located north of the northern Tianshan slope but lacked significance.

Temperature showed weaker correlations than precipitation, with predominantly positive correlations but lower correlation coefficients. Significant positive temperature effects were concentrated in central and eastern Xinjiang, including

Urumqi, Turpan, and Hami. Solar radiation exhibited positive correlations in southern Xinjiang (56.12%) and negative correlations in northern Xinjiang (43.88%), particularly in the Altay and Tianshan regions.

Combined climate factor analysis revealed that precipitation's positive impact covered 44.80% of affected areas, mainly in western Ili and southern Aksu/Kashgar. Temperature's positive impact covered 23.23%, concentrated on the northern Tianshan slope. Solar radiation's positive impact accounted for only 7.85%, mainly in northern Altay. The combined positive impact of precipitation and solar radiation was most significant (6.22%), particularly evident in the Ili region. Precipitation and temperature combined positively affected 3.03% of areas, while the combined effect of precipitation's negative impact and temperature's positive impact was minimal (0.02%). Overall, positive impacts from all three climate factors covered 0.72% of total affected area, distributed in southern Xinjiang.

2.4 Maximum NPP Potential Analysis

The Miami model was used to simulate NPP under pure climate scenarios. Two scenarios were established: CASA2001 (keeping 2001 vegetation constant) and CASA2020 (keeping 2020 vegetation constant), along with Miami climate scenarios. Comparison revealed consistent spatial NPP distribution patterns across scenarios: higher in northern than southern Xinjiang, and significantly higher in Ili and Tacheng regions than other areas.

Quantitatively, under CASA2001, CASA2020, and Miami scenarios, multi-year mean NPP values were 355.78 g $C \cdot m^{-2}$, 397.92 g $C \cdot m^{-2}$, and 411.11 g $C \cdot m^{-2}$, respectively, with CASA2020 showing the highest values. The maximum NPP potential distribution was derived by taking the maximum values across scenarios, revealing a maximum potential threshold of 1,035.36 g $C \cdot m^{-2}$. High values were concentrated in the Ili River Valley and southern slopes of the northern Tianshan Mountains.

The NPP increment potential, calculated as the difference between maximum potential and actual NPP, reached 79.43 g $C \cdot m^{-2}$ across Xinjiang. Areas with increment potential exceeding 200 g $C \cdot m^{-2}$ were concentrated in Ili, Altay, and Tianshan regions. Most areas showed increment potential around 100 g $C \cdot m^{-2}$, except for Hami and Turpan in eastern Xinjiang, indicating substantial room for NPP growth.

Discussion

This study's finding of increasing NPP trends in Xinjiang aligns with previous research, though the trend was not statistically significant, possibly due to the relatively short study period. Large interannual NPP fluctuations likely relate to climate and land use changes. Xinjiang's arid/semi-arid continental climate and human-environment interactions create fragile ecosystems vulnerable to climate change.

Climate factor impacts show clear spatial heterogeneity. In arid regions, soil water deficit makes precipitation a critical water source that effectively replenishes soil moisture, reduces water stress, and facilitates vegetation growth and photosynthesis. Thus, water deficit is the primary limiting factor for vegetation growth in arid zones, with precipitation playing a decisive role. Temperature effects are largely constrained by water availability; in water-rich areas, vegetation growth is temperature-limited, and warming enhances photosynthesis and carbon sequestration. This positive temperature-vegetation relationship is evident in Xinjiang's mountainous areas where water resources are more abundant than in deserts.

Global warming-induced glacier retreat in Xinjiang's three major mountain systems has improved mountain climate conditions, exposing previously ice/snow-covered areas that gradually convert to grassland. Cultivated land expansion also contributes significantly to NPP increases, as crops generally have higher productivity than natural grassland. Therefore, areas converting from grassland to cultivated land show enhanced carbon sequestration.

China's dual-carbon targets represent crucial development goals for reducing greenhouse gas emissions. Afforestation and ecological restoration can offset industrial CO_2 emissions, aiding dual-carbon goal achievement. Various methods including model simulation, logistic equations, and climate scenario assumptions have been used to estimate regional ecosystem carbon sequestration potential. This study's land use scenario assumptions and Miami model simulations indicate high carbon sequestration potential in Xinjiang's Altay and Tianshan regions, with higher potential in northern than southern Xinjiang, consistent with previous research.

However, the Miami model is an idealized pure climate model determined solely by climate factors without considering human activities, whose influence on NPP is increasingly significant and should be incorporated in future studies. Additionally, natural factors such as topography and soil were not considered, and further research should explore multi-factor interactions. Moreover, model validation against measured data is essential for broader remote sensing applications and should be pursued to improve model accuracy.

Conclusions

This study analyzed NPP spatiotemporal evolution characteristics in Xinjiang from 2001 to 2020 and estimated maximum NPP increment potential using the CASA model. Key conclusions are:

1) Xinjiang's NPP showed a fluctuating upward trend temporally and a spatial distribution pattern of higher values in the north and west than in the south and east.

2) Among climate factors, precipitation had a stronger impact on NPP than

temperature and solar radiation. During 2001-2020, 72.77% of Xinjiang showed positive correlations between precipitation and NPP, with average positive correlation of approximately 0.45. Temperature correlations were weaker than precipitation, while solar radiation showed positive correlations in southern Xinjiang and negative correlations in northern Xinjiang, particularly in the northern Tianshan slope and Altay regions.

3) Among land use changes during the study period, grassland changed most extensively, followed by wetland. Grassland primarily converted from desert, cultivated land, and wetland. Cultivated land and grassland had the highest mean annual NPP among all land types.

4) Scenario simulations revealed that under the CASA2020 climate scenario, the multi-year mean NPP reached 397.92 g $C \cdot m^{-2}$, with increment potential of 79.43 g $C \cdot m^{-2}$. The maximum NPP potential threshold reached 1,035.36 g $C \cdot m^{-2}$, with highest values concentrated in the Ili River Valley and southern slopes of the northern Tianshan Mountains.

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