Postprint: Spatiotemporal Patterns of NEP in the Aksu River Basin Based on PLUS Land Use Simulation

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Abstract

Net Ecosystem Productivity (NEP) is an important indicator for assessing carbon absorption in terrestrial ecosystems, while Land Use/Cover Change (LUCC) is one of the main factors influencing regional carbon absorption variations. Analyzing the trends of LUCC and NEP holds significant importance for regional achievement of the "dual carbon" goals. Based on LUCC and MODIS remote sensing data from the Aksu River Basin for the period 2000–2020, the annual average carbon sequestration rate of each land use/cover type within the region was estimated. The PLUS model was employed to simulate LUCC over the next 40 years and predict the spatiotemporal variation trends of NEP in the basin during the future 40-year period. The results indicate that: (1) Over the past 20 years, the total NEP in the basin has exhibited an upward trend, with an increase rate of 0.136 Mt C $\cdot$ $(10a)^{-1}$, and forest land demonstrates the highest average carbon sequestration rate; (2) The total carbon absorption in the Aksu River Basin will continue to increase over the next 40 years. The increase in forest area represents the primary pathway for enhanced carbon absorption in the Aksu River Basin, and the effectiveness of ecological protection projects plays a crucial role in carbon sequestration within the basin.

Full Text

Spatiotemporal Pattern of NEP in Aksu River Basin Based on PLUS Land Use Simulation

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Abstract

Net Ecosystem Productivity (NEP) is a crucial indicator for assessing carbon uptake in terrestrial ecosystems, and Land Use/Cover Change (LUCC) represents one of the primary factors influencing regional variations in carbon sequestration. Analyzing the trends of LUCC and NEP holds significant importance for achieving regional carbon peaking and carbon neutrality objectives. Based on LUCC and MODIS remote sensing data from 2000 to 2020 in the Aksu River Basin, this study quantified the annual average carbon sequestration rate for each land use/cover type in the region. The PLUS model was employed to simulate future LUCC and predict the spatiotemporal trends of NEP over the next 40 years. The results demonstrate that: (1) The total NEP in the basin exhibited a consistent upward trend during the past two decades, with an uptake rate of 0.136 Mt C $(10a)^{-1}$, and forest land demonstrated the highest average carbon sequestration rate; (2) The total carbon uptake in the Aksu River Basin will continue to increase throughout the future 40-year period. The expansion of forest area constitutes the primary pathway for enhanced carbon uptake in the basin, with ecological protection projects playing a critical positive role in this process.

Keywords: NEP; LUCC simulation; PLUS model; Aksu River Basin

1. Introduction

Carbon uptake represents a vital component of the terrestrial carbon cycle and significantly influences global climate change. Enhancing terrestrial ecosystem carbon sequestration is considered an effective approach to mitigating atmospheric carbon dioxide concentration increases and achieving China's carbon neutrality goals. Land use type constitutes one of the main factors affecting terrestrial ecosystem carbon uptake, particularly as future Land Use/Cover Change (LUCC) will impact the attainment of carbon neutrality objectives through ecosystem carbon sequestration. Arid regions, which account for approximately 30% of China's total land area, exhibit high sensitivity and vulnerability in their ecological environments, with their terrestrial carbon cycles substantially affected by anthropogenic disturbances. In recent years, influenced by policies such as the Western Development Strategy, significant changes in land use patterns have occurred in these regions, with the Aksu River Basin serving as a typical case of such transformations.

Currently, simulations of future LUCC have become a focal research direction. The Cellular Automata model demonstrates capability in simulating spatiotemporal changes in complex systems, and the Patch-generating Land Use Simulation (PLUS) model exhibits superior algorithmic performance that yields higher simulation accuracy compared to other models while maintaining satisfactory precision at large scales. For instance, studies by Wu et al., Jin et al., and Zhang et al. have applied the PLUS model in conjunction with other models for analysis. However, LUCC processes are often jointly influenced by natural conditions, socio-economic factors, and human activities. The impacts of recently implemented territorial spatial planning policies and long-standing ecological protection projects on LUCC are undoubtedly substantial, yet most scholars have inadequately considered or even neglected this aspect. In estimating regional carbon uptake trends, researchers primarily employ field measurements, remote sensing models, and carbon sink coefficient methods, each with distinct advantages and limitations. Field measurement methods, while highly accurate, are constrained by ecosystem diversity and the significant variation in carbon sequestration rates among different land use/cover types, making them difficult to apply for large-scale, long-term regional carbon uptake estimation. Remote sensing model estimation methods, which offer good accuracy and accessibility for long time series, have been widely used to assess carbon uptake at large scales through Net Primary Productivity (NPP) and Net Ecosystem Productivity (NEP) derived from MODIS data. The carbon coefficient method, though simple and widely applied, often overlooks regional differences in carbon sequestration coefficients by directly adopting values from other studies, raising questions about its rationality and applicability in the unique context of arid regions.

In summary, although recent research on carbon uptake in arid regions has been extensive, studies examining carbon uptake trends using land use prediction models that incorporate multiple policies remain rare. This research focuses on the Aksu River Basin, utilizing MODIS data to quantify the carbon sequestration rates of various land use/cover types. By combining the PLUS model with multiple policy scenarios to simulate future LUCC, this study predicts future spatiotemporal NEP trends, thereby providing a relatively simple yet efficient reference method for estimating carbon uptake in small to medium-sized regions while enriching explorations of sustainable development pathways in arid zones.

1.1 Study Area Overview

The Aksu River Basin is located in the southwestern part of the Tianshan Mountains in Xinjiang, China (76°21 –81°15 E, 39°59 –42°04 N). The terrain exhibits higher elevation in the north and lower in the south. The region features a pronounced continental monsoon climate characterized by aridity and low precipitation, with annual sunshine hours ranging from 2,571 to 2,967 h, mean annual temperature around 10°C, maximum frost-free period of 295 days, and annual precipitation between 40–90 mm with significant seasonal variation (summer precipitation accounts for approximately 70% of the annual total). Dominant vegetation includes Populus euphratica, Tamarix chinensis, Haloxylon ammodendron, and Phragmites australis, while major soil types comprise inland saline soil, brown desert soil, brown calcic soil, gray-brown desert soil, and gray meadow soil.

1.2 Research Methods

1.2.1 Data Sources Land use/cover data were obtained from the China Land Cover Dataset (CLCD). Driving factors for spatiotemporal LUCC changes were selected based on data availability and representativeness, encompassing three categories: natural environment, socio-economic conditions, and transportation accessibility, totaling 12 factors. For correction factors, the three control lines from territorial spatial planning were considered: ecological protection red line, permanent basic farmland, and urban development boundary. Based on guidelines for the Grain for Green Program and the Three-North Shelter Forest Program, slope ranges, desertification areas, and severe salinization areas were incorporated as correction zones for ecological project implementation. All data were resampled to 1,000 m resolution. Data sources are detailed in .

1.2.2 Data Preprocessing Land use/cover data for 2000, 2010, and 2020 were preprocessed using ArcGIS. MODIS MOD17A3 NPP data were processed using the MODIS Reprojection Tool v4.1 for projection conversion, format conversion, image clipping, and mosaicking.

1.2.3 Carbon Sequestration Rate Estimation NEP, representing the carbon fixed by vegetation through photosynthesis, constitutes a crucial component of terrestrial ecosystem carbon cycles. NEP is calculated as Net Primary Productivity (NPP) minus soil heterotrophic respiration (Rh). When NEP is positive, the ecosystem functions as a carbon sink. The Rh calculation employs a geostatistical model of soil respiration (GSMSR) constructed based on measured soil respiration data in China, which establishes relationships between monthly mean temperature, monthly precipitation, and soil organic carbon density. The relationship between Rh and Rs (soil respiration) adopts the empirical statistical model derived by Xie et al. The carbon uptake estimation model is expressed as:

$$NEP = NPP - Rh$$

$$Rh = 0.592 \times Rs_{,annual}$$

$$Rs_{,annual} = \sum_{i=1}^{12} Rs_{,month} \times 30$$

$$Rs_{,month} = 0.588 + 0.118 \times SOC \times e^{0.118 \times T} \times \ln(1.83 \times e^{P/10} + 5.657) + 2.972$$

where NEP is net ecosystem productivity (g $C \cdot m^{-2}$), NPP is net primary productivity (g $C \cdot m^{-2}$), Rh is soil heterotrophic respiration (g $C \cdot m^{-2}$), Rs is soil respiration (g C·m^{-2}), T is monthly mean temperature (°C), P is monthly precipitation (mm), and SOC is soil organic carbon content density (g C·m^{-2}).

1.2.4 Future Land Use Simulation The PLUS model utilizes random forest algorithms to extract expansion rules for each land use/cover type and incorporates a multi-class random seed growth mechanism, enhancing simulation capability for complex scenarios and yielding higher accuracy. The simulation process involves extracting changed pixels between two periods, mining relationships between these changes and driving factors, evolving spatial expansion probabilities, and simulating future land use patterns based on these probabilities.

To improve simulation reliability, expansion probability data were corrected using spatial expansion probability raster data. The three control lines from territorial spatial planning and key ecological protection project plans served as references for correcting spatial expansion probabilities and setting scenarios in the Aksu River Basin: ecological protection red line, permanent basic farmland, urban development boundary, Grain for Green Program, and Three-North Shelter Forest Program. Correction rules for each land use/cover type's expansion probability raster data are presented in .

TABLE:1 Land use/cover type expansion probability correction rules

Policy Factor	Correction Rule
Ecological Protection Red Line	Artificial surface and cropland expansion probability set to 0 within the red line
Permanent Basic Farmland	Cropland expansion probability set to 1 within the boundary
Urban Development Boundary	Artificial surface expansion probability set to 1 within the boundary
Grain for Green Program	Cropland expansion probability set to 0 in strong salinization, saline, and desertification areas
Three-North Shelter Forest Program	Forest, shrubland expansion probability increased in strong salinization, saline, and desertification areas

Note: Expansion probability of 0 indicates virtually no expansion; 1 indicates priority expansion.

Given the explicit emphasis in the "14th Five-Year Plan for Xinjiang Ecological Environmental Protection" on vigorously promoting key ecological protection projects, this policy orientation is expected to significantly influence future LUCC. To ensure model accuracy and policy adaptability, correction of land use/cover type transfer probability data is essential. Correction rules are detailed in .

TABLE:2 Land use/cover type transfer probability correction rules

Ecological Project Type	Correction Rule
Grain for Green Program	Transfer probability from cropland to forest, grassland, shrubland increased by αij
Three-North Shelter Forest Program	Transfer probability from bare land to forest, grassland, shrubland increased by αij

The Markov chain model was employed to calculate target quantities for each land use/cover type under different scenarios:

$$ST_{t+1} = ST_t \times P_{ij} + ST_t \times \alpha_{ij}$$

where ST_t is the area of each land type at time t (km^2), ST_{t+1} is the area at time $t+1$ (km^2), P_{ij} is the transfer probability from land type i to j, and α_{ij} is the corrected transfer probability.

Three distinct ecological protection scenarios were constructed based on current and planned ecological protection policies:

1. **Natural Development Scenario (Scenario I)**: This baseline scenario continues historical trends without future policy intervention, with $\alpha_{ij} = 0$ for all transfers, providing a reference for analyzing policy effectiveness.
2. **Enhanced Protection Scenario (Scenario II)**: This scenario intensifies ecological intervention and protection measures based on existing policies, including strengthening protection of forest, grassland, and shrubland while curbing disorderly expansion of cropland and bare land. Here, α_{ij} is set to the average P_{ij} value in the basin over recent years.
3. **Maximum Ecological Protection Scenario (Scenario III)**: This scenario extends beyond Scenario II with the most stringent ecological protection systems and more efficient compensation mechanisms, providing comprehensive protection for ecologically fragile areas. All non-construction land is prioritized for conversion to forest, grassland, or shrubland, with α_{ij} set to the maximum P_{ij} value in the basin.

2. Results and Analysis

2.1 Carbon Sequestration Estimates for Different Land Uses in the Aksu River Basin (2000–2020)

The total carbon uptake in the Aksu River Basin showed a consistent upward trend from 2000 to 2020 [Figure 2: see original paper], with an increase rate of 0.136 Mt C $(10a)^{-1}$. Specifically, total carbon uptake grew from 1.806 Mt C in 2000 to 1.922 Mt C in 2020, representing a 9.47% increase, though the growth rate exhibited a declining trend with only 6.44% growth in the last decade.

Spatially, carbon uptake demonstrated pronounced regional heterogeneity [Figure 3: see original paper]. Western and southern regions showed lower uptake than central areas in 2020, coinciding with areas exhibiting continuous decline or initial increase followed by decline. Central regions displayed concentrated high carbon uptake areas with continuous increases, indicating they have been the focus of watershed management efforts.

Among land use types, the average annual carbon sequestration rates from 2000–2020 followed the order: forest land (119.41 g $C \cdot m^{-2} \cdot a^{-1}$) > grassland (101.74 g $C \cdot m^{-2} \cdot a^{-1}$) > cropland (72.85 g $C \cdot m^{-2} \cdot a^{-1}$) > shrubland (33.26 g $C \cdot m^{-2} \cdot a^{-1}$). The average annual total carbon uptake across land types ranked as: grassland (0.628 Mt C) > cropland (0.570 Mt C) > forest land (0.018 Mt C) > shrubland (0.002 Mt C) [Figure 4: see original paper].

2.2 Future Land Use Change Analysis (2020–2060)

Model reliability was validated using 2020 as the base year for simulating 2020 land use, yielding a Kappa coefficient of 84.63%, indicating high model credibility. Based on 2020 data, the PLUS model simulated land use patterns for 2030–2060 under three scenarios, with projected land type areas presented in .

2.3 Future Carbon Uptake Predictions Under Different Scenarios

Using the calculated annual carbon sequestration rates for each land use/cover type, total carbon uptake was computed for 2030–2060 under all three scenarios [Figure 5: see original paper]. Total carbon uptake shows yearly increasing trends in all scenarios, with values reaching 2.257 Mt C, 2.291 Mt C, and 2.402 Mt C by 2060 for Scenarios I, II, and III, respectively.

Ranking the scenarios by total carbon uptake: Scenario III > Scenario II > Scenario I. During 2030–2060, growth rates compared to the previous period were 4.98%, 3.44%, and 3.72% for Scenario I; 4.27%, 5.92%, and 6.15% for Scenario II; and 5.78%, 4.49%, and 6.99% for Scenario III. The average annual growth rate was lowest in Scenario I (3.44–4.98%), stable in Scenario II (around 5.58%), and highest in Scenario III (4.89–6.02%). The total carbon uptake in the Aksu River Basin during 2030–2060 is projected to be approximately 90 Mt C.

3. Discussion

The results reveal that vegetation carbon sequestration rates in arid regions follow the pattern: forest land > grassland > cropland > shrubland, consistent with findings by Wang et al. This study employed MOD17A3 data combined with two empirical models for NEP estimation. While less precise than mechanistic models or field measurements, this approach avoids uncertainties in ecosystem carbon cycle mechanisms and limitations of field data availability. Jiao et al. demonstrated that MODIS data provide high accuracy for estimating vegetation NPP in arid and semi-arid regions. Due to limited flux observation stations in arid zones, this study did not conduct accuracy validation of NEP estimates, representing a direction for future improvement through integration of field measurements.

Given substantial uncertainty in future climate change, this study adopted average carbon sequestration rates from 2000–2020 to eliminate fluctuations. Subsequent research could incorporate CMIP6 climate scenario data for more accurate simulations. Additionally, vegetation carbon sequestration rates correlate not only with climate change but also with growth stages. Previous research has shown that the Three-North Shelter Forest Program has generated substantial ecological benefits. Most artificial forests from this program and the Grain for Green Program in the study area remain in young or middle-aged stages with high carbon sequestration potential. However, due to model limitations, this study primarily examined the impacts of LUCC and policies on carbon uptake without fully considering vegetation growth status effects, which may introduce some uncertainty in future NEP projections.

Arid regions, with their unique geographical locations, exhibit high ecological sensitivity and vulnerability, requiring balanced attention to both vegetation area expansion and quality improvement for enhancing carbon uptake capacity. The results indicate that forests remain a crucial "pillar" for carbon uptake in arid regions, with forest area expansion demonstrating particularly significant effects. This aligns with other scholars' findings that ecological restoration and afforestation projects have important positive impacts on local environments. Therefore, for future development of the Aksu River Basin, recommendations include increasing intensive artificial forest cultivation and strengthening management of existing stands to maintain and enhance carbon uptake capacity, providing economic drivers for achieving carbon peaking and carbon neutrality goals.

4. Conclusion

This study utilized remote sensing models to estimate annual carbon sequestration rates of different land use/cover types in the Aksu River Basin, integrated the PLUS model with multiple policy scenarios to simulate future LUCC, and predicted spatiotemporal NEP trends. The main conclusions are:

1. Forest land exhibits the highest average carbon sequestration rate in the

basin. Total carbon uptake showed a continuous upward trend from 2000–2020 with a rate of 0.136 Mt C $(10a)^{-1}$.

2. Total carbon uptake in the Aksu River Basin will continue to increase with strengthened ecological protection measures. The natural development scenario shows the lowest average carbon sink growth rate (3.44%), the enhanced protection scenario shows moderate growth (4.49%), and the maximum ecological protection scenario demonstrates the highest growth rate (5.75%). The total projected carbon uptake for 2030–2060 is approximately 90 Mt C.

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