STUDY ON CALCULATING NET CARBON SINKS IN AGRICULTURE IN SOUTHWEST CHINA: SPATIOTEMPORAL PATTERNS, DRIVING FACTORS, AND MULTI-SCENARIO PROJECTIONS

HU, F. – GAN, Z. L. – ZHONG, X. Q.* – HU, C. R.

China-ASEAN School of Economics, Guangxi University, 100 East Daxue Road, Nanning, Guangxi 530004, China

**Corresponding author
e-mail: xiongqiangzhong@126.com*

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Abstract. Agricultural net carbon sinks are a key driver for low-carbon agricultural transformation in underdeveloped regions. Based on data from five provinces and municipalities in southwest China, this study employs Intergovernmental Panel on Climate Change (IPCC) coefficients to calculate net carbon sink values, utilizes the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to analyze driving factors, and applies the Long Short-Term Memory (LSTM) model for multi-scenario projections. The core findings are as follows: (1) From 2003 to 2023, agricultural net carbon sinks in southwest China exhibited fluctuating carbon emissions decline while carbon absorption steadily increased. Spatial differentiation was as follows: "Sichuan > Yunnan > Guizhou > Chongqing > Tibet," with Tibet maintaining a net carbon deficit and Chongqing showing the highest growth rate. (2) drivers, farmland area, rural per capita income, and urbanization level exerted significant positive effects on net carbon sink, while rural labor force population had a negative impact. (3) LSTM projections indicate that under the "Comprehensive Optimization" scenario, net carbon sequestration could reach 66.3011 million tons by 2035. Optimizing crop structures and expanding agricultural scale represent the key pathway to enhancing carbon sequestration, while rapid urbanization exerts a suppressing effect. Therefore, we recommend leveraging policy combinations to prioritize crop structure optimization and moderate-scale operations, balancing urbanization with ecological equilibrium.
Keywords: *Southwest China, agricultural net carbon sink, spatial-temporal dynamics, STIRPAT model, scenario analysis*

Introduction

On July 17, 2023, at the National Conference on Ecological and Environmental Protection, General Secretary Xi Jinping delivered an important speech emphasizing the need to "support high-quality development with a high-quality ecological environment and accelerate the advancement of modernization featuring harmonious coexistence between humanity and nature." China is currently undergoing a critical transition from high-speed economic growth to high-quality development. The synergistic advancement of high-quality economic development and high-level ecological conservation, achieve the dual carbon strategic goals, and fulfill the public's dual aspirations for both "clear waters and lush mountains" and "gold mountains and silver mountains" has become a highly debated and deeply explored issue among governments and all sectors of society. The IPCC Sixth Assessment Report indicates that from 2010 to 2019, global anthropogenic greenhouse gas (GHG) net emissions exceeded any period in human history. Specifically, in 2019, carbon dioxide (CO_2) emissions reached 45 ± 5.5 $GtCO_2$, with the Asia-Pacific region emerging as the largest consumer-based CO_2 emitter (IPCC, 2022). China's total CO_2 emissions reached 12.6 $GtCO_2$ in 2024 (IEA, 2025). Global

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atmospheric CO_2 concentrations have surpassed 425 ppm (Lan et al., 2025). Carbon emissions have become an urgent issue facing China and nations worldwide.

Greenhouse gas emissions from agriculture, forestry, and land use sectors account for 22% of global emissions. As a core component of this sector, agriculture has become the world's second-largest source of greenhouse gas emissions (FAO, 2015). The greenhouse effect caused by these emissions directly impacts crop production, food security, and livelihoods (Thi Lan Huong et al., 2017). Extreme weather events damage the environment (Cruz and Krausmann, 2013), and as these events intensify, crop damage becomes more pronounced closer to harvest time (Elahi et al., 2022). Agricultural systems not only fulfill fundamental functions in supplying food, timber, and other renewable resources, but also play a crucial role in biodiversity conservation. They can sequester carbon dioxide from the atmosphere through carbon sequestration and indirectly support emission reduction targets in other sectors by substituting fossil fuels with biomass energy (IPCC, 2022). Agricultural management can increase soil organic carbon sequestration, thereby reducing atmospheric CO_2 concentrations and lowering global temperatures (Mayer et al., 2018). However, in practice, strategies aimed at conserving land and reducing carbon emissions often face implementation challenges due to economic factors and operational difficulties (Lamb et al., 2016). Against this backdrop, precisely understanding the dynamics of carbon emissions and sequestration in agricultural production is crucial.

Southwest China, encompassing Yunnan, Sichuan, Guizhou, Chongqing, and parts of Tibet, features complex terrain dominated by mountains, plateaus, and hills. The region lags in transportation infrastructure, industrial structure, and green finance development, with insufficient marketization posing challenges for green and low-carbon transformation (Hu et al., 2025). The region possesses a unique agricultural system, with approximately 2.38 million km^2 of land resources, accounting for 24% of China's total land area. It serves as China's largest carbon sink and a vital ecological barrier (Piao et al., 2009), holding a special position within China's agricultural landscape. Reviewing existing research, scholars primarily employ diverse calculation methods and modeling approaches to account for agricultural carbon emissions from multiple perspectives, thereby arriving at varying conclusions. Regarding agricultural net carbon sink measurement methods, scholars have identified primary sources of agricultural CO_2 emissions (West et al., 2002; Johnson et al., 2007; Nurse et al., 2010; Tian et al., 2023), with research primarily focusing on the entire agricultural production process and two major sectors: crop cultivation and animal husbandry (Su and Xia, 2024). Measurement methods encompass field measurement, model estimation, coefficient measurement, and life cycle analysis (Hu et al., 2023). Among these, the IPCC carbon emission factor method is widely adopted in academia due to its high precision and operational convenience (Luo, 2016; Zhao et al., 2019). In agricultural carbon sink measurement, research centers on soil carbon sequestration and its quantification, crop carbon uptake, and forest carbon absorption (Mukherjee, 2008; Zhang and Fang, 2013; Zhu et al., 2024). For instance, Huang et al. (2020) quantified emissions from fertilizer, plastic mulch, and machinery inputs in agricultural production. Su et al. (2022) assessed the carbon emissions associated with agricultural energy consumption and examined the spatial correlation effects of these emissions. Regarding modeling for agricultural net carbon sink research, existing studies primarily explore three dimensions: spatiotemporal characteristics (Zhao et al., 2022; Wu and Li, 2022; Liu and Xin, 2023; Wei et al., 2024; Wang et al., 2024), driving factors (Wang et al., 2024), and trend forecasting studies

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(Rosenberg et al., 2016; Tian et al., 2018; Zhang et al., 2022; Ke et al., 2023). They employ common methodologies such as the STIRPAT model (He and Zhang, 2012; Zhang and Zhou, 2016; Liu et al., 2024), LMDI decomposition model (Ye et al., 2017; Moutinho et al., 2018), and Kaya identity (Yang et al., 2020; Zhang and Liu, 2024) for in-depth analysis (Ge et al., 2024).

In summary, while current domestic and international research has established a relatively comprehensive framework for carbon emissions and sequestration, studies on measuring and analyzing net agricultural carbon sinks remain incomplete, exhibiting the following shortcomings: First, from a research perspective, most studies cover national scales or focus on agriculturally developed regions such as East China, South China, and Northeast China (He and Zhang, 2012), with limited research on Southwest China—a region characterized by both ecological fragility and significant agricultural potential. Second, regarding data and methodology, existing studies often employ data with limited temporal coverage, resulting in insufficient representativeness of findings. Additionally, the models used tend to be relatively simple, lacking integrated approaches for driving factor analysis and trend forecasting. Third, in terms of research dimensions, most current analyses focus on either agricultural carbon emissions or carbon sequestration, and the models employed typically address driving factors alone, without incorporating trend prediction models for agricultural net carbon sinks.

Based on the above background, this study aims to systematically address the following objectives: (1) To accurately quantify agricultural net carbon sinks in Southwest China from 2003 to 2023 by calculating carbon emissions and carbon absorption using IPCC emission factors and crop carbon sequestration coefficients; (2) To reveal the spatiotemporal evolution patterns of agricultural net carbon sinks across the five provincial-level regions (Sichuan, Yunnan, Guizhou, Chongqing, and Tibet), identifying regional disparities and dynamic trends; (3) To examine the driving mechanisms underlying net carbon sink changes by employing the STIRPAT model to analyze the impacts of farmland area, rural labor force, urbanization level, economic development, and technological innovation; (4) To project future trajectories of agricultural net carbon sinks through 2035 using the LSTM model under multiple scenarios, thereby assessing the potential of different policy pathways; and (5) To propose differentiated regional strategies and policy recommendations for optimizing agricultural carbon sink capacity and achieving low-carbon transformation in Southwest China. By integrating spatiotemporal analysis, driver decomposition, and multi-scenario forecasting, this study seeks to provide robust scientific evidence and decision-making support for coordinating agricultural development with ecological conservation in underdeveloped mountainous regions.

Data sources and methodology

Study area and data sources

The study area is located in the ethnic regions of southwest China, encompassing five provinces, autonomous regions, and municipalities: Chongqing, Sichuan, Guizhou, Yunnan, and Tibet (78°23'-110°11'E, 21°08'-36°29'N), with a total area of approximately 2.3406 million km² (*Figure 1*). The foundational data used in net agricultural carbon sink calculations are sourced from the China Statistical Yearbook (2003–2023) and the statistical yearbooks of six provinces and municipalities in the Southwest region, China. Missing data for specific years in certain regions were supplemented using linear interpolation. Emission factors were sourced from the Oak Ridge National Laboratory (ORNL), the Institute of Agricultural Resources and Environmental Sciences (IREEA) at Nanjing Agricultural University, the IPCC Sixth Assessment Report, and Min and Hu (2012). Carbon emission coefficients for rice and various livestock and poultry were referenced from the IPCC Sixth Assessment Report and the recommended values in the Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial). Economic coefficients, carbon absorption rates, and moisture content coefficients for various crops were sourced from the relevant research by Tian and Yin (2022).

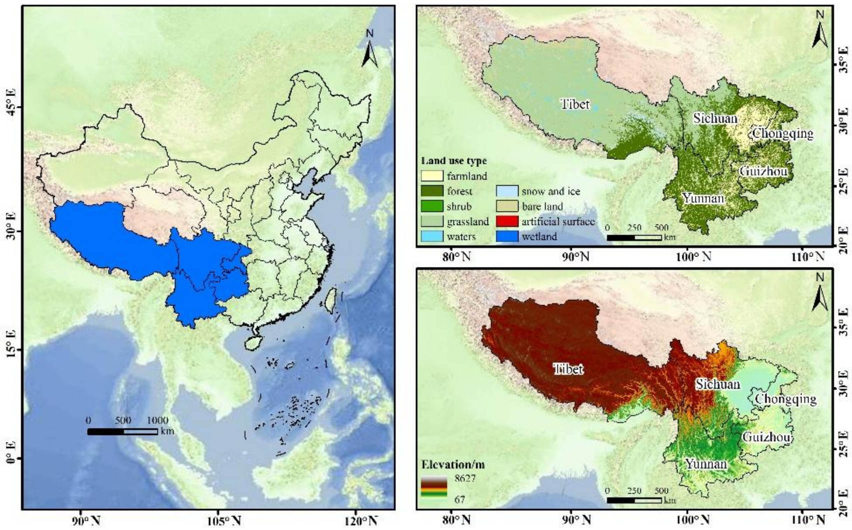

***Figure 1.** Schematic map of the study area*

Calculation of net agricultural carbon sink

Calculation of agricultural carbon emissions

This study calculates carbon emissions across three major sectors: agricultural production processes, crop cultivation, and animal husbandry. Specifically, Cropping system emissions primarily stem from methane (CH_4) emissions during rice cultivation and nitrous oxide (N_2O) emissions from major crop cultivation (Chen et al., 2024); Livestock emissions focus on the quantification of enteric fermentation and manure management (Tian et al., 2024) (*Figure 2*).

Regarding calculation methods, this paper employs the emission factor approach (Tian et al., 2024). Specifically, it multiplies the latest IPCC-published emission factors for each carbon source by the actual quantity of that source to calculate emissions for each sector, then aggregates these to obtain total carbon emissions. The formula is:

$$C = \sum C_c = \sum M_c \times \delta_c \quad \text{(Eq.1)}$$

In *Equation (1)*, *C* represents total agricultural carbon emissions, C_c denotes carbon emissions from various sources, M_c indicates the actual quantity of each carbon source, and δ_c represents the corresponding emission coefficient for each carbon source. This study employs the global warming potential (GWP) values for methane and nitrous oxide from the IPCC's Sixth Assessment Report (2021) to enhance the accuracy and timeliness of the calculations.

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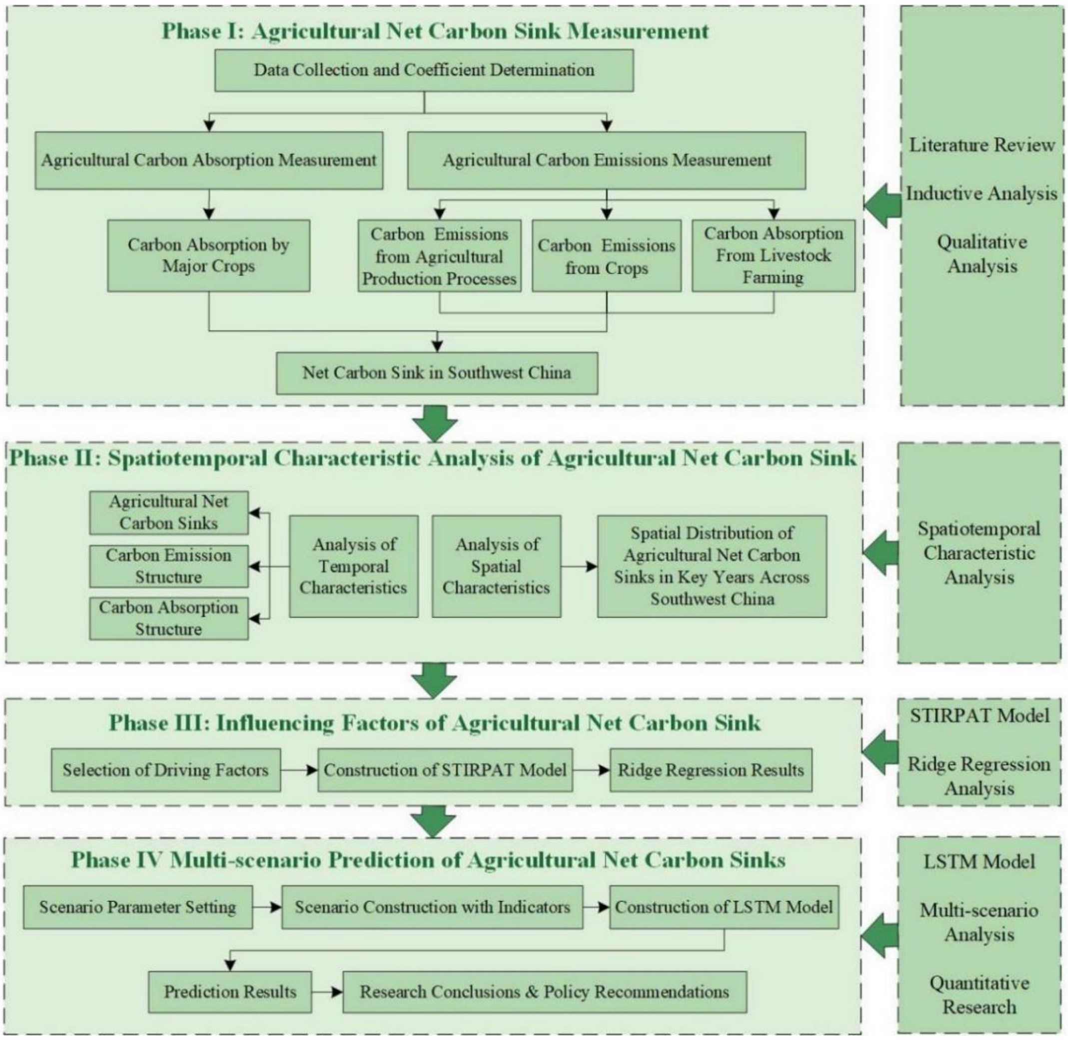

***Figure 2.** Technical roadmap*

(1) Calculation of carbon emissions from agricultural production processes

Carbon emissions from agricultural production primarily originate from six major activities: agricultural fertilizer application, agricultural diesel use, pesticide application, agricultural plastic film use, land tillage, and irrigation operations. This paper calculates carbon emissions by multiplying the quantity of carbon sources in agricultural production processes by their corresponding emission factors, using the following formula:

$$C_{production\ processes} = \sum Q_i \times \gamma_i \quad \text{(Eq.2)}$$

$C_{production\ processes}$ represents carbon emissions generated during the production process, where Q_i denotes the consumption level or activity level of carbon source category i in agricultural production, and γ_i indicates the carbon emission coefficient for carbon source category i. This study employs CLCDv0.7, Ecoinvent v2.2, and carbon emission coefficients provided by **Hiba! A hivatkozási forrás nem található.**Min and Hu (2012) for calculations. Specific carbon emissions and corresponding reference source coefficients are listed in *Table 1*.

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Table 1. *Carbon emission coefficients for agricultural production processes*

Carbon Source	Carbon Emission Coefficient	Reference Source
Fertilizer	0.89 kg·kg^{-1}	Oak Ridge National Laboratory (ORNL)
Pesticides	4.93 kg·kg^{-1}	Oak Ridge National Laboratory (ORNL)
Agricultural film	5.18 kg·kg^{-1}	Institute of Resources and Environmental Sciences, Nanjing Agricultural University (IREEA)
Diesel	0.59 kg·kg^{-1}	IPCC
Agricultural tillage	312.6 kg·hm^{-2}	(Min & Hu, 2012)
Agricultural irrigation	25 kg·hm^{-2}	(Min & Hu, 2012)

(2) Calculation of carbon emissions from crop cultivation

As the primary crop in Southwest China, rice cultivation represents the dominant source of carbon emissions from agriculture. These emissions primarily stem from methane (CH_4) released during the cultivation of rice and other crops. The calculation formula is:

$$C_{crops} = AP \times \varepsilon \tag{Eq.3}$$

where AP represents the rice cultivation area, and ε denotes the carbon emission coefficient for rice cultivation, referencing recommended values from the Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial) and the IPCC.

(3) Calculation of carbon emissions from livestock farming

Carbon emissions from livestock farming primarily originate from enteric fermentation and manure discharge in livestock and poultry (Dong et al., 2024). The calculation formula for enteric fermentation carbon emissions is:

$$C_{enteric\, fermentation} = \sum U_i \times \delta_i \times f_{CH_4} \tag{Eq.4}$$

where U_i represents the year-end livestock inventory (heads) for each animal type in the Southwest region; δ_i denotes the CH_4 emission factor for each animal type; and f_{CH_4} indicates the carbon content per unit of CH_4. The CH_4 emission factors for each animal type were selected from the recommended values in the "Guidelines for Compiling Provincial Greenhouse Gas Inventories (Trial)" and IPCC, focusing on the primary livestock in the Southwest region: cattle, pigs, sheep, and poultry, as shown in *Table 2*.

The calculation method for CH_4 and N_2O emissions from manure is analogous to that for enteric fermentation, using the formula:

$$C_{manure\, discharge} = \sum U_i \times \theta_i \times f_{CH_4} + \sum U_i \times \mu_i \times f_{N_2O} \tag{Eq.5}$$

where θ_i represents the CH_4 emission factor for each livestock manure management process; μ_i represents the N_2O emission factor for each livestock manure management process; f_{N_2O} represents the carbon content per unit of N_2O. The CH_4 emission factors for each livestock manure management process reference the recommended values from the "Guidelines for Provincial Greenhouse Gas Inventory Compilation (Trial)" and Min and Hu (2012), as shown in *Table 2*.

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***Table 2.** Carbon emission factors for livestock farming / kg·a^{-1}*

Species	Enteric Fermentation(CH_4)	Manure Emissions(CH_4)	Manure Emissions(N_2O)
Cattle	80.13	4.86	1.26
Pigs	1.00	4.18	0.16
Sheep	8.33	0.53	0.06
Poultry	—	0.02	0.02

Note: "—" indicates no relevant data is currently available

Agricultural carbon absorption calculation

Agricultural carbon sequestration calculations primarily focus on the biomass carbon absorbed by crops through photosynthesis and stored within plant bodies during their growth cycle. Absorption. Carbon stocks are estimated using four indicators: crop yield, carbon rate, economic coefficient, and moisture content.

The calculation method referenced the approach developed by Tian and Yin (2022). The formula is:

$$S = \sum \frac{K_i \times L_i \times (1-W_i)}{E_i} \quad \text{(Eq.6)}$$

where S represents the total agricultural carbon sink; K_i denotes the yield of the crop i ; L_i indicates the carbon absorption rate corresponding to each carbon sink; W_i represents the average moisture content; and E_i signifies the economic coefficient. Carbon absorption-related data and coefficients for common crops in Southwest China reference Tian and Yin (2022) , as shown in *Table 3*.

***Table 3.** Carbon absorption coefficients for major crops*

Crop Variety	Economic Coefficient	Moisture Content (%)	Carbon Absorption Rate	Coefficient Value
Rice	0.45	12	0.414	0.8096
Wheat	0.40	12	0.485	1.0670
Corn	0.40	13	0.471	1.0244
Legumes	0.34	13	0.450	1.1515
Potatoes	0.70	70	0.423	0.1813
Peanuts	0.43	10	0.450	0.9419
Rapeseed	0.25	10	0.450	1.6200
Cotton	0.10	8	0.450	4.1400
Sugarcane	0.50	50	0.450	0.4500
Sugar Beet	0.70	75	0.407	0.1454
Tobacco	0.55	85	0.450	0.1227
Vegetables	0.60	90	0.450	0.0750
Other Crops	0.40	12	0.450	0.9900

Calculation of net agricultural carbon sink

The calculation of net agricultural carbon sink follows the formula: "Net Agricultural Carbon Sink = Agricultural Carbon Absorption - Agricultural Carbon Emissions." The formula is expressed as:

$$NCS = S - C \quad \text{(Eq.7)}$$

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In *Equation (7)*, *NCS* represents the total net agricultural carbon sink, *S* denotes the total agricultural carbon sink, and *C* indicates the total agricultural carbon emissions. The project aims to calculate agricultural carbon emissions and carbon absorption in four provinces and one municipality in Southwest China, compute their respective net carbon sinks, and aggregate these values to determine the total net agricultural carbon sink for the region.

Decomposition of agricultural net carbon sink drivers

This study employs the STIRPAT model to analyze the drivers of the net agricultural carbon sink in the Southwest region. Its standard form is:

$$I = \alpha \times P^b \times T^c \times A^d \times e \qquad \text{(Eq.8)}$$

where *I* represents environmental change factors; α is the constant term; *P, T, A* denote population factors, technological factors, and economic factors, respectively; *b, c, d* are the influence indices of population factors, technological factors, and economic factors on environmental impact, respectively; *e* is the random error disturbance term.

Based on existing scholarly research (Tian and Yin, 2022) and considering the regional characteristics of Southwest China, the project selected seven primary factors: rural labor force population (Z, 10^4 persons), rural per capita disposable income (I, yuan·person^{-1}), number of agricultural scientific achievements (H, items), R&D investment level (N, 10^8 yuan), farmland area (O, thousand hectares), urbanization level (R, %), and agricultural economic development (K, 10^4 yuan·person^{-1}). Using these seven primary factors as determinants of net agricultural carbon sink in Southwest China, the STIRPAT model was constructed:

$$S = \alpha \times Z^{\beta_1} \times I^{\beta_2} \times H^{\beta_3} \times N^{\beta_4} \times O^{\beta_5} \times R^{\beta_6} \times K^{\beta_7} \times e \qquad \text{(Eq.9)}$$

$$lnS = \ln\alpha + \beta_1 lnZ + \beta_2 lnI + \beta_3 lnH + \beta_4 lnN + \beta_5 lnO + \beta_6 \ln R + \beta_7 lnK + \ln e \qquad \text{(Eq.10)}$$

where: *S* denotes total net agricultural carbon sink (10^4t), *Z* represents rural labor force population, *I* indicates per capita rural income, *H* signifies cultivated land area, *N* reflects urbanization level, *O* represents quantity of agricultural scientific achievements, and *R* denotes R&D investment level.$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ and β_7 are corresponding elasticity coefficients, indicating the degree to which changes in *Z, I, H, N, O, R*, and *K* affect variations in *S*.

Multi-scenario prediction of agricultural net carbon sinks

Based on the ridge regression results from the STIRPAT model, this study constructs multi-scenario projections for the future trajectory of net agricultural carbon sinks in Southwest China. Integrating regional policies such as the 14th Five-Year Plan and actual socioeconomic development conditions, the project selected seven quantitative indicators—Z,O,R,I,K,N and H—and assigned them low, medium, and high growth rates, as shown in *Tables 4 and 5*.

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***Table 4.** Selection of LSTM model parameter indicators*

Driving Factors	Quantitative Metric
Labor Force Size	Number of agricultural labor force (Z, 10^4 persons)
Cultivation Scale	Farmland area (O, thousand hectares)
Urbanization Rate	Urbanization rate (R, %)
Level of Prosperity	Rural Per Capita Disposable Income (I, yuan·person^{-1})
Agricultural Scale	Agricultural Economic Development (K, 10^4 yuan·person^{-1})
Science and Technology Investment	R&D Expenditure (N, 10^8 yuan)
Innovation Capacity	Agricultural Scientific and Technological Achievements (H, items)

***Table 5.** Scenario parameter settings*

Scenario	Time	Annual Change Rate (%)						
		Z	O	R	I	K	N	H
Low (L)	2023-2025	-1.7	0.4	0.6	4.8	8	10	-10
	2026–2030	-1.4	0.3	0.5	3.6	7.5	8	-7
	2031–2035	-0.5	0.2	0.4	2.8	4	4.5	-5
Medium (M)	2023-2025	-2	0.6	0.8	5.3	10	12	12
	2026–2030	-1.5	0.5	0.7	4.2	9.5	10	8
	2031–2035	-0.6	0.4	0.6	3	7	6.5	5
High (H)	2023-2025	-2.3	0.8	1.2	6	12	15	15
	2026–2030	-1.8	0.6	1	4.5	10.5	12	9
	2031–2035	0.2	0.7	-0.1	3.6	7	8	6

The selection of model speed parameters for each driver is based on the following rationale: Z (Labor Force Size) follows the strategic direction of "promoting the urbanization of agricultural migrants" outlined in the national 14th Five-Year Plan, indicating a sustained structural decline in agricultural labor due to its continuous migration to urban areas; O (Cultivation Scale) follows the core policy directives of "strictly upholding the red line for arable land" and "stabilizing arable land area" outlined in the Southwest region's provincial (autonomous region, municipality) 14th Five-Year Plans for agricultural and rural modernization, reflecting a pattern of steady growth with moderate increases; R (Urbanization Level) directly aligns with the explicit national target in the 14th Five-Year Plan to "increase the permanent resident urbanization rate from 60.6% in 2020 to 65% by 2025"; I (Prosperity Level) references the specific requirement in Sichuan Province's 14th Five-Year Plan for Advancing Agricultural and Rural Modernization: "Achieve an annual average growth rate of approximately 8.5% in rural residents' per capita disposable income, reaching 26,000 yuan." K (Agricultural Scale) uses the benchmark of "an annual average growth rate of approximately 5% in agricultural value-added" across Southwest provinces, while also considering comprehensive development goals such as Yunnan Province's target of "achieving an annual average growth rate of over 10% in the total industrial chain output value of key industries." N (Technology Investment) aligns with the national 14th Five-Year Plan's directive for "annual growth of over 7% in total R&D expenditure" and "investment intensity exceeding the actual level during the 13th Five-Year Plan period"; H (Innovation Capacity) responds to the plan's call for agricultural technological innovation to "break through a number of breakthroughs," "overcome a number of challenges," and "create a

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number of innovations," reflecting significant improvements in both the quantity and quality of scientific achievements.

By applying multi-scenario combinations to the seven indicators and integrating them with the policy objectives of the Southwest Region's agricultural development plan, the project constructed eight distinct agricultural net carbon sink development scenario combinations, as shown in *Table 6*.

Table 6. *Scenario indicator settings*

Scenario Combination	Development Rates of Each Indicator						
	Z	O	R	I	K	N	H
Baseline Scenario	Medium	Medium	Medium	Medium	Medium	Chinese	China
Scenario of Labor Force Contraction	High	Medium	Medium	Medium	Medium	Middle	Medium
Rapid Urbanization Scenario	Medium	Low	High	Medium	Medium	Medium	Medium
Crop Structure Optimization Scenario	Medium	High	Medium	Medium	Medium	Middle	Medium
Agricultural Scale Expansion Scenario	Medium	High	Low	Medium	High	Medium	Medium
Scenario of Rapid Technological Advancement	Medium	Medium	Medium	Medium	High	High	High
Economic Optimization Scenario	Medium	Medium	Medium	High	High	Medium	Medium
Comprehensive Optimization Scenario	Medium	Medium	Medium	High	High	High	High

Following the multi-scenario simulation framework proposed by Peng et al. (2025) and Song et al. (2022), the eight scenarios were structured along two dimensions: single-factor sensitivity analysis and multi-factor synergy optimization. Specifically, scenarios 1 to 7 represent isolated policy interventions targeting individual driving forces, while scenario 8 tests for synergistic effects when multiple favorable policies are combined. The structural logic of each scenario is defined as follows: (1) Baseline Scenario maintains medium growth rates for all indicators as a business-as-usual reference; (2) Labor Force Contraction Scenario accelerates rural labor decline (Z-High) to test the negative elasticity identified in *Eq. (11)*; (3) Rapid Urbanization Scenario combines high urbanization growth (R-High) with constrained farmland expansion (O-Low) to capture the trade-off between urban development and carbon sinks; (4) Crop Structure Optimization Scenario expands farmland area (O-High) to enhance carbon sequestration capacity; (5) Agricultural Scale Expansion Scenario couples farmland expansion (O-High) with agricultural economic growth (K-High) and suppressed urbanization (R-Low); (6) Rapid Technological Advancement Scenario intensifies R&D investment (N-High) and innovation output (H-High) to test technology-driven carbon reduction; (7) Economic Optimization Scenario prioritizes rural income growth (I-High) and agricultural development (K-High); (8) Comprehensive Optimization Scenario integrates technological (N-High, H-High), economic (I-High, K-High), and structural (O-Medium) policies to maximize synergistic effects, consistent with the finding of Song et al. (2023) that combined technological progress outperforms single-technology pathways under energy intensity constraints.

Results

Spatiotemporal evolution of agricultural net carbon sinks in southwest China

Analysis of temporal characteristics of agricultural net carbon sinks

Based on the calculation results of *Eq (1) to (7)*, the changes in carbon emissions, carbon absorption, and net carbon sink in the Southwest region from 2003 to 2023 are shown in *Figure 3*. From 2003 to 2023, the total carbon emissions in the Southwest region exhibited an overall fluctuating downward trend. Based on the overall characteristics of this change, it can be divided into three phases: The first phase was from 2003 to 2005, during which carbon emissions in the Southwest region showed a slow upward trend, increasing from 51.3009 million tons in 2003 to 53.6946 million tons in 2005, representing a 4.67% increase. The second phase spans 2005–2019, characterized by an overall fluctuating decline in carbon emissions. Emissions decreased from 53.6946 million tons in 2005 to 41.4368 million tons in 2019, representing a reduction of 12.2578 million tons or 22.83%. The third phase spans 2019–2023, characterized by fluctuating emissions with a slight rebound. Emissions rose from 41.4368 million tons in 2019 to 44.1293 million tons in 2023, an increase of 6.50%.

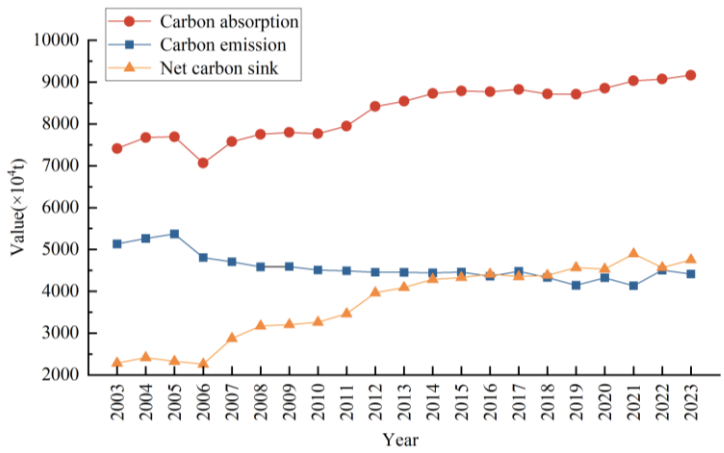

Figure 3. *Agricultural carbon emissions, carbon absorption, and net carbon sink in southwest China*

Carbon absorption demonstrated a steady upward trend overall, rising continuously from 74.1441 million tons in 2003 to 91.6674 million tons in 2023. This represents a cumulative increase of 17.5233 million tons, equivalent to a 23.63% growth rate. Net carbon sink capacity also demonstrated significant growth, rising from 22.8433 million tons in 2003 to 47.5381 million tons in 2023. This represents an increase of 24.6948 million tons, or 108.11%, indicating the region's continuously enhanced carbon sink capacity and markedly improved ecological benefits.

The structure of agricultural carbon emissions in the Southwest Region from 2003 to 2023 is shown in *Figure 4*. Livestock farming has consistently been the primary emission source, with emissions decreasing from 38.2401 million tons in 2003 to 29.9970 million tons in 2023. However, it still accounts for over two-thirds of the total emissions, experiencing a significant decline before stabilizing with slight fluctuations. Agricultural activity emissions exhibited an initial rise followed by a decline, peaking at 11.5337 million tons in 2016 before gradually falling to 9.6179 million tons in 2023. This reflects

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the shift in energy and fertilizer inputs during agricultural intensification—initial increases followed by controlled growth. Crop cultivation emissions remained the smallest and most stable, gradually decreasing from 5.0905 million tons to 4.5144 million tons, indicating continuous optimization of crop structures and fertilization practices. Overall, livestock farming continues to dominate the agricultural carbon emissions structure in Southwest China. Initial emission reduction achievements have emerged, and future efforts should focus on advancing the low-carbon transformation of livestock farming and promoting the application of green agricultural production technologies.

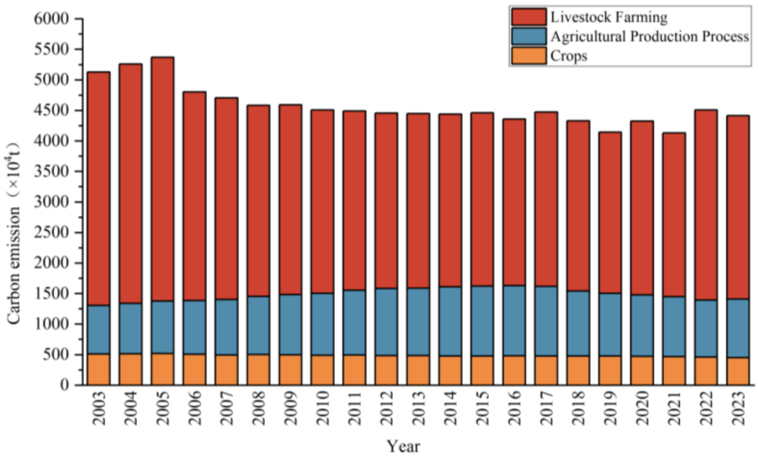

Figure 4. *Structure of agricultural carbon emissions in southwest China, 2003–2023*

The agricultural carbon absorption structure in Southwest China from 2003 to 2023 is shown in *Figure 5*. From the perspective of carbon absorption structure, rice, corn, rapeseed, and sugarcane are the primary contributing crops. Among these, rice maintains a dominant position with an average annual absorption exceeding 30 million tons. Corn absorption has shown significant growth, rising from 12.0764 million tons to 23.3974 million tons, with its proportion continuously increasing. Among cash crops, rapeseed also exhibits sustained carbon uptake growth, rising from 4.2816 million tons to 8.3396 million tons. The carbon uptake capacity of vegetables and legumes continues to strengthen, while crops like wheat and cotton show declining uptake. Tubers, peanuts, and tobacco exhibit relatively low carbon uptake, with tobacco's contribution being nearly negligible.

Spatial characteristics of agricultural net carbon sinks

Based on spatial distribution data of net agricultural carbon sinks in Southwest China from 2003 to 2023, this study selected key years to generate geographical distribution maps (see *Figure 6*). The selection of these years was based on two considerations: first, they correspond to the end years of China’s key national Five-Year Plan periods, which reflect phased policy impacts on agricultural and environmental management; second, these intervals capture representative stages of socioeconomic transformation and agricultural structural adjustment in the region, allowing for a clearer visualization of long-term trends and spatial shifts. Over two decades, the region's total net agricultural carbon sink capacity surged from 22.8433 million tons to 47.5381 million tons—a 108% increase. Contributions varied greatly across provinces and municipalities. Sichuan

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Province emerged as the absolute core contributor, with its net carbon sink growing from 13.4146 million tons to 24.5729 million tons. Its contribution consistently accounted for approximately half of the regional total, serving as the primary driver of regional net carbon sink growth. Yunnan Province served as a crucial supporting force, with its net carbon sink fluctuating from 8.9047 million tons to 14.2802 million tons. Although starting from a low base, Guizhou Province and Chongqing Municipality demonstrated significant growth. Notably, Chongqing's net carbon sink surged from 718,200 tons to 6.8384 million tons, representing an increase exceeding 850% and indicating substantial growth potential. The Tibet Autonomous Region remains the only area in Southwest China with a persistent net carbon deficit, with net carbon emissions declining further from -3.5249 million tons to -4.3174 million tons. This reflects a structural contradiction where carbon emissions from its agricultural system have long exceeded carbon absorption.

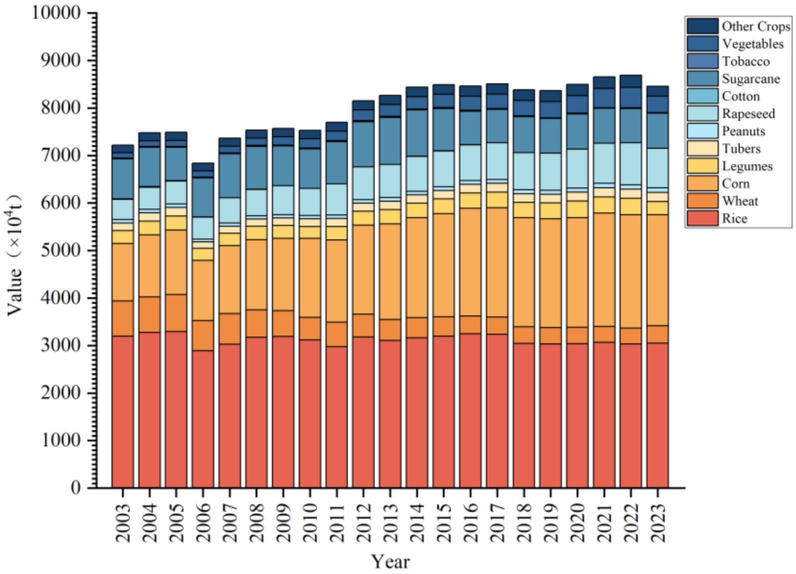

Figure 5. *Structure of agricultural carbon absorption in southwest China, 2003–2023*

Analysis of drivers for agricultural net carbon sinks

Performing linear regression analysis on Equation (8) revealed that most variables had Variance Inflation Factor (VIF) values > 10, indicating strong multicollinearity among variables. Regression analysis was subsequently conducted. Based on the ridge plot, K=0.3 was selected for ridge regression analysis, with results presented in *Table 7*. The results indicate that all influencing factors are significantly correlated with net agricultural carbon sequestration at the $P < 0.01$ level. Among these, I, H, N, O, R, and K exert significant positive effects on net agricultural carbon sequestration. A 1% increase in each of these factors leads to increases in net sequestration of 0.048%, 0.029%, 0.032%, 0.952%, 0.134%, and 0.041%, respectively. Z has a significant negative impact on net agricultural carbon sequestration, with each 1% increase reducing net sequestration by 0.525%. In terms of absolute magnitude of influence: Farmland area (O) > Rural labor force (Z) > Urbanization level (R) > Rural per capita disposable income (I) > Agricultural economic development (K) > R&D investment level (N) > Number of agricultural

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scientific achievements (H). The regression coefficients were organized to derive the formula for factors influencing the net agricultural carbon sink:

$$\ln NCS = -0.525\ln Z + 0.048\ln I + 0.029\ln H + 0.032\ln N + 0.952\ln O + 0.134\ln R + 0.041\ln K + 1.523 \quad \text{(Eq.11)}$$

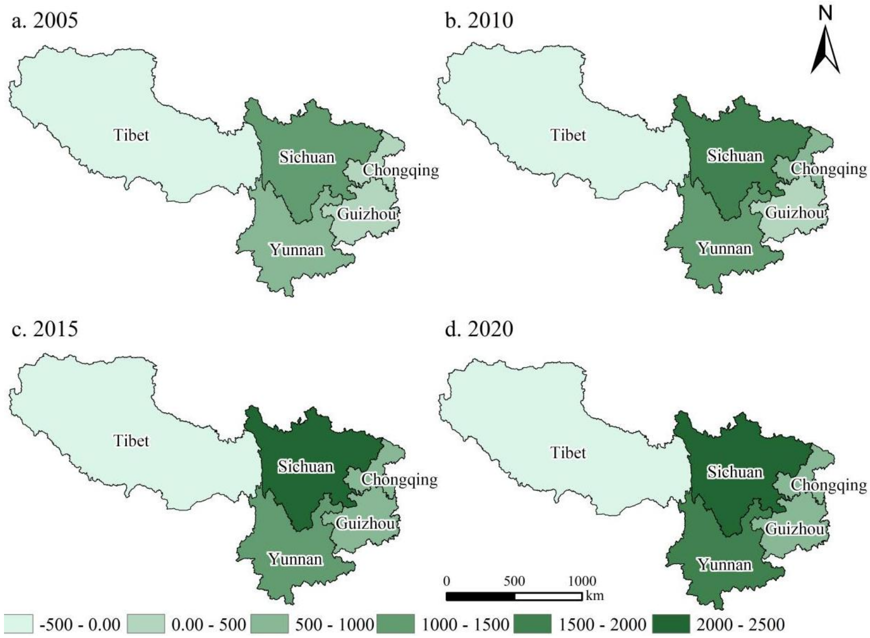

***Figure 6.** Spatial distribution of agricultural net carbon sinks in key years across southwest China. Note: This figure was produced using the standard map with review number GS(2024)0650 downloaded from the Ministry of Natural Resources' Standard Map Service website (http://bzdt.ch.mnr.gov.cn). The base map remains unmodified. Data sourced from the Geospatial Data Cloud Platform*

***Table 7.** Regression results*

K=0.3	Coef.	S.E.	Std. Coef.	t-statistic	p-value
Z	-0.525	0.141	-0.145	-3.725	0.003
I	0.048	0.005	0.131	10.231	0.000
H	0.029	0.008	0.142	3.538	0.004
N	0.032	0.005	0.123	6.964	0.000
O	0.952	0.297	0.178	3.201	0.007
R	0.134	0.019	0.112	7.03	0.000
K	0.041	0.006	0.117	7.247	0.000
Constant	1.523	3.526	—	0.432	0.673

Multi-scenario prediction of agricultural net carbon sink

Based on the LSTM model and *Eq (9) to (11)*, data from the 2003-2023 were selected for training. The prediction results were fitted against actual values, with the fitting results shown in *Figure 7*. Concurrently, the project set different growth rates for variables Z,O,R,I,K,N and H according to the actual national economic and social development

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plans of various regions during the 14th Five-Year Plan period. By simulating specific combinations, eight different agricultural development scenarios for the Southwest region were modeled. The net carbon sink prediction results are presented in *Table 8*.

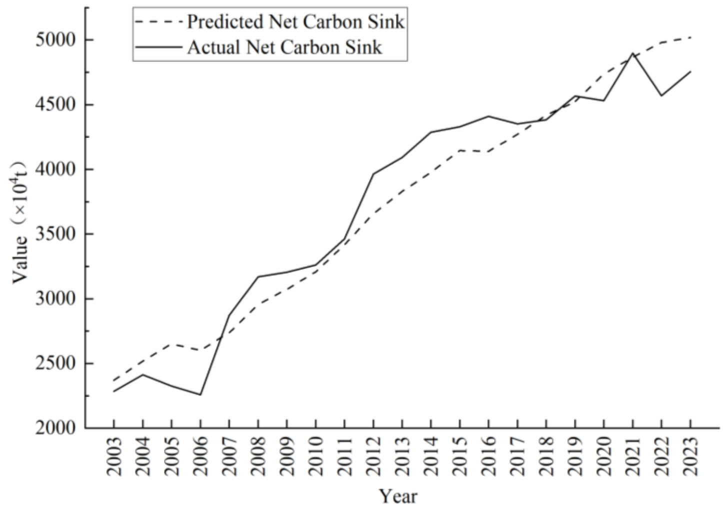

Figure 7. *Fitting effect of predicted vs. actual net carbon sink values*

Table 8. *Predicted agricultural net carbon sink results for each scenario (× 104t)*

Year	Baseline	Labor force contraction	Rapid Urbanization	Crop Structure Optimization	Agricultur Scale Expansion	Rapid Technological Advancement	Economic Optimization	Comprehensive Optimization
2024	5176.18	5184.50	5169.18	5185.98	5188.31	5188.31	5181.55	5189.98
2025	5337.04	5354.23	5322.44	5357.23	5362.46	5362.48	5348.46	5365.88
2026	5469.66	5496.08	5446.80	5496.02	5502.53	5502.88	5484.59	5506.86
2027	5606.14	5642.24	5,574.50	5638.96	5645.43	5646.48	5623.73	5651.54
2028	5745.57	5791.80	5704.99	5785.16	5792.42	5793.93	5766.48	5800.08
2029	5888.55	5945.47	5838.50	5935.23	5943.57	5945.69	5913.29	5952.45
2030	6034.88	6103.15	5,974.92	6088.98	6098.30	6101.03	6063.44	6108.83
2031	6128.46	6171.81	6048.34	6198.89	6206.59	6199.91	6158.94	6209.70
2032	6223.53	6241.27	6122.73	6310.84	6316.68	6300.37	6255.94	6312.25
2033	6319.81	6311.22	6197.69	6424.55	6429.00	6402.84	6354.83	6416.52
2034	6417.78	6382.14	6273.77	6540.52	6543.21	6506.70	6455.00	6522.44
2035	6517.41	6453.99	6350.98	6658.76	6659.71	6612.61	6557.10	6630.11

As shown in *Figure 8*, under the baseline scenario, the net carbon sink will increase from 51.7618 million tons in 2024 to 65.1741 million tons in 2035, with an average annual growth rate of approximately 2.1%. However, scenarios driven by individual policies exhibit divergent characteristics. The scenarios involving crop structure optimization and agricultural scale expansion show the most favorable net carbon sink prospects, reaching 66.5971 million tons and 66.5876 million tons, respectively, by 2035. Both exceed the baseline scenario by approximately 1.41 million tons, representing an increase of about 2.2%. The Rapid Technological Development scenario demonstrates significant effectiveness in the early projection period (2024–2030), but its gap with other optimized scenarios widens progressively in the mid-to-late period (2031–2035), reaching 66.1261 million tons by 2035. While higher than the baseline, its momentum remains insufficient; The Economic Optimization Scenario projected 65.571 million tons,

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exceeding the baseline by 396,900 tons. The Labor Force Reduction Scenario projected 64.5399 million tons for 2035, 634,200 tons below the baseline. The high-speed urbanization scenario yields the lowest projected values across all years, reaching only 63.5198 million tons in 2035—approximately 1.66 million tons below the baseline. The comprehensive optimization scenario presents the most optimistic outlook, with net carbon sinks maintaining relatively high levels from 2024 to 2035 compared to other scenarios. This strongly demonstrates that a "policy combination" outperforms "single-pronged approaches."

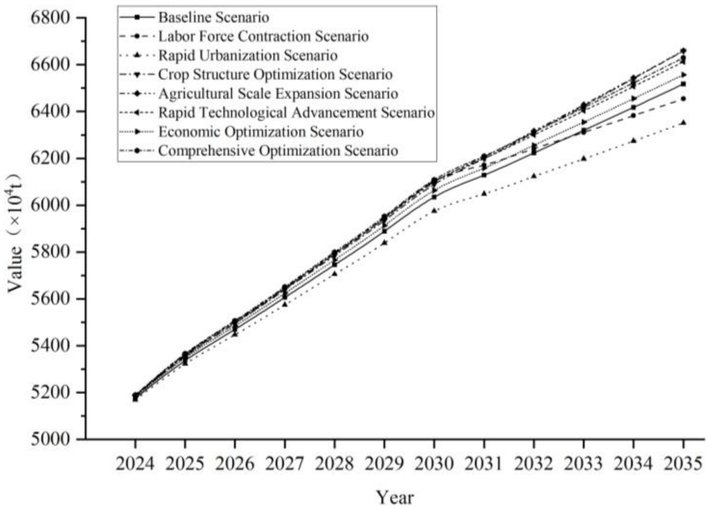

Figure 8. *Projected net carbon sinks in southwest China, 2025–2035*

Discussion

Regional specificity in the spatiotemporal evolution of agricultural net carbon sinks

This study found that from 2003 to 2023, the net agricultural carbon sink in Southwest China increased by 108.11%, exhibiting a positive trend of “fluctuating carbon emissions declining while carbon absorption steadily rising.” This aligns with the overall growth pattern of China's agricultural carbon sinks (Wang et al., 2024). However, the carbon source and sink structure in Southwest China exhibits distinct regional characteristics. Regarding carbon source composition, livestock farming has consistently contributed over two-thirds of total emissions. This is closely tied to the region's mountainous plateau terrain, which is well-suited for animal husbandry, and the disproportionately high share of livestock in the agricultural structure. In contrast, carbon sources in agriculturally developed regions, such as North China, are primarily driven by agricultural inputs, including fertilizers and pesticides, with livestock emissions accounting for a relatively smaller proportion (She et al., 2017). This highlights the distinct differences in agricultural carbon emission structures across different regions.

From a spatial distribution perspective, the net agricultural carbon sink in Southwest China exhibits a gradient differentiation pattern of “Sichuan > Yunnan > Guizhou > Chongqing > Tibet,” with Tibet remaining a persistent net carbon sink deficit area. This spatial pattern arises from the combined influence of natural conditions and agricultural development levels. The Sichuan Basin, with its extensive cultivated land and large-scale cultivation of carbon-sequestering crops such as rice and corn, serves as the primary

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carbon sink in the region. In contrast, Tibet's high altitude and insufficient heat limit crop carbon absorption capacity. Additionally, its livestock industry relies primarily on extensive farming practices with high carbon emission intensity, resulting in a persistent carbon deficit. These findings align with the conclusions of Yu et al. (2022) and Wang et al. (2023), confirming the fundamental role of natural endowments in agricultural net carbon sequestration. Furthermore, Chongqing's net carbon sequestration increased by over 850%, demonstrating the potential for late-developing regions to rapidly enhance carbon sequestration through agricultural restructuring. This provides a reference development path for similar regions.

Analysis of the mechanism of agricultural net carbon sink drivers

The ridge regression results from the STIRPAT model indicate that farmland area is the primary positive driver influencing net agricultural carbon sequestration in the Southwest region. This finding underscores the pivotal role of arable land resources in enhancing carbon sinks within underdeveloped areas. The complex topography of the Southwest region, coupled with scarce and fragmented arable land resources, makes expanding effective cultivated area and improving soil quality crucial. These measures can directly increase the planting scale of carbon-sequestering crops like rice and corn, thereby enhancing carbon absorption capacity. This aligns with Li et al. (2022) research conclusion that protecting arable land is a key lever for boosting agricultural carbon sinks.

The rural labor force exhibits a significant negative effect on net agricultural carbon sinks, a finding that diverges from conventional wisdom. The underlying mechanism lies in the “extensive” nature of labor migration in southwestern China. Following the outflow of large numbers of young and able-bodied workers, the remaining labor force predominantly adopts traditional farming practices, hindering the adoption of low-carbon agricultural technologies. In contrast, labor migration in agriculturally advanced regions is often accompanied by increased agricultural mechanization and intensification, effectively reducing carbon emission intensity (Zhu et al., 2022). This suggests that underdeveloped regions advancing urbanization should prioritize agricultural labor skill training, shifting labor migration from a “quantity-driven” to a “quality-driven” approach.

Factors such as urbanization levels and rural per capita disposable income exert a positive influence on net carbon sinks. As rural residents' incomes increase, their capacity for agricultural production investments grows, leading to higher adoption rates of low-carbon technologies like organic fertilizer substitution for chemical fertilizers and precision irrigation. Meanwhile, infrastructure improvements driven by rising urbanization levels also create conditions for large-scale agricultural operations (Li et al., 2023). This finding aligns with the conclusions of studies by Forte et al. (2017), Sun et al. (2024), and Bhattacharyya et al. (2012). However, caution is warranted regarding the potential displacement of farmland caused by rapid urbanization. The lowest projected net carbon sink values under the high urbanization scenario in this study directly reflect this latent risk.

Policy implications of multi-scenario forecast results

The multi-scenario projections of the LSTM model indicate that under the comprehensive optimization scenario, the net agricultural carbon sink in the southwest region could reach 66.3011 million tons by 2035, significantly higher than both the baseline scenario and the single optimization scenario. This fully demonstrates the effectiveness of the “policy package.” In the single-scenario analysis, optimizing crop

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structure and expanding agricultural scale emerge as the most effective pathways for enhancing carbon sinks. This aligns closely with the policy direction outlined in the Implementation Plan for Consolidating and Enhancing Ecosystem Carbon Sink Capacity, which emphasizes “systematic management of mountains, waters, forests, farmlands, lakes, grasslands, and deserts to increase ecosystem carbon sink increments.”

Comparing the prediction results across different scenarios reveals that the rapid technological advancement scenario demonstrates significant effectiveness in the early stages of forecasting but lacks sustained momentum in the mid-to-late phases. This phenomenon stems from the low efficiency of agricultural technology transfer in the Southwest region, where numerous agricultural technologies remain confined to the laboratory stage and fail to achieve practical implementation (John et al., 2025). Therefore, future efforts should strengthen the “industry-academia-research” collaboration mechanism to accelerate the field deployment of low-carbon technologies. Under the labor force reduction scenario, the net carbon sink is slightly lower than the baseline scenario, further illustrating that optimizing the labor force structure is more crucial than merely reducing its size.

Limitations and future research directions

This study still has several limitations. First, regarding data, missing data for certain years were supplemented using linear interpolation, which may introduce some discrepancies from actual conditions. Furthermore, carbon sink calculations only considered biomass carbon sequestration from crops and did not incorporate the carbon sequestration effect of soil organic carbon, potentially leading to some underestimation in the results. Second, regarding the models, the variable selection in the STIRPAT model did not encompass factors such as climate change and policy frameworks, potentially failing to fully capture the complexity of driving factors. The scenario settings for the LSTM model were based on existing policy orientations and did not sufficiently account for the impacts of uncertainties, such as extreme weather events and sudden public incidents. Third, regarding spatial scale, the study was conducted at the provincial level, without delving into micro-level scales such as counties or individual farms, which makes it difficult to reveal the detailed spatial variations in agricultural net carbon sinks. To address these limitations, future research could be deepened in three areas. First, expand the measurement dimensions by incorporating soil organic carbon and farmland shelterbelts into the carbon sink calculation system to establish a more comprehensive agricultural net carbon sink accounting framework (Pang et al., 2025). Second, refine the research scale by integrating county-level statistical data with household survey data to analyze how different cropping patterns and management entities influence agricultural net carbon sinks, thereby generating more targeted policy recommendations. Third, incorporate uncertainty factors by introducing variables such as climate change and market fluctuations into predictive models to enhance the accuracy of future trend forecasts.

Conclusions and recommendations

Conclusions

Based on panel data from five provinces and municipalities in Southwest China covering 2003–2023, this study systematically calculated agricultural net carbon sink

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capacity. By integrating spatiotemporal analysis, the STIRPAT model, and LSTM multi-scenario forecasting, it thoroughly examined its evolution, drivers, and future trends. Key findings include:

(1) Time-series analysis reveals a significant enhancement in Southwest China's agricultural net carbon sink capacity. From 2003 to 2023, total net carbon sequestration increased by 108.11%, exhibiting a positive trend characterized by fluctuating carbon emissions and steadily rising carbon absorption. Structurally, animal husbandry is the primary carbon emission source, while major crops such as rice and corn constitute the main carbon absorption components.

(2) Spatial distribution reveals distinct gradients and imbalances in agricultural net carbon sequestration. The ranking of net carbon sink totals across provinces (autonomous regions and municipalities) is: Sichuan > Yunnan > Guizhou > Chongqing > Tibet. Sichuan possesses the strongest carbon absorption capacity, Chongqing has the greatest growth potential, while Tibet remains the only region in Southwest China with a persistent net carbon sink deficit, highlighting structural disparities within the region.

(3) Rural labor force size, rural per capita disposable income, agricultural scientific achievements, R&D investment levels, farmland area, urbanization rates, and agricultural economic development intensity vary significantly. STIRPAT model regression results indicate that farmland area is the strongest positive driver, while the rural labor force exhibits the most significant negative effect. Additionally, urbanization levels, rural per capita income, agricultural economic development, technological investment, and innovation capacity all exert significant positive impacts on net carbon sinks.

(4) Multi-scenario simulations predict that by 2035, the "Comprehensive Optimization" scenario will yield the highest net carbon sink annually with the most effective outcomes. Among single-policy scenarios, "crop structure optimization" and "agricultural scale expansion" are the most effective pathways for enhancing net carbon sinks, while "rapid urbanization" exerts a suppressing effect.

Recommendations

Based on the above findings, this paper proposes the following recommendations:

(1) Agricultural and ecological management departments in the Southwest region should implement differentiated regional coordination and control strategies. Given the varying characteristics of net agricultural carbon sinks within Southwest China, a one-size-fits-all management approach should be abandoned. For carbon sink advantage zones like Sichuan and Yunnan, the focus should be on consolidation and enhancement, further promoting ecological agriculture and precision fertilization techniques. For high-growth-potential areas such as Chongqing, encourage exploration of new low-carbon agricultural models to serve as demonstration and leadership. For ecologically fragile regions with agricultural net carbon sink deficits like Tibet, prioritize adjusting livestock structures and controlling livestock density.

(2) Relevant policymakers should implement differentiated policies based on the intensity of factor impacts. Strengthen farmland protection to fully leverage its positive driving role; simultaneously optimize the agricultural labor structure by promoting skill training to transition workers into green production sectors, mitigating negative effects; coordinate urbanization with low-carbon agricultural development to guard against farmland resource displacement; and increase investment in science and technology while accelerating the commercialization of research outcomes to enhance the contribution of technological innovation.

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(3) Relevant policymakers should implement a coordinated multi-policy development approach. Research indicates that single-policy interventions yield limited results. Efforts should focus on deeply integrating "optimal crop structure" with "agricultural scale," encouraging low-carbon crop cultivation and intensive agricultural production. Simultaneously, strengthen agricultural R&D investment and technology commercialization to improve resource efficiency through innovation. During urbanization, strictly protect high-quality farmland to ensure coordinated development between urbanization and green agricultural transformation. Ultimately, this policy synergy will achieve the optimal net carbon sink target under the "Comprehensive Optimization" scenario by 2035.

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Conflict of interest. The authors declare no competing interests. They have not used AI in writing this original empirical research article.

Data availability. The research data set is available from the first author upon request.

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