Dynamic Simulation of County-Level Farmland Soil Organic Carbon in the Eastern Sichuan Parallel Ridge-Valley Region over the Next 30 Years: Postprint

Authors: Zhang Lin, Shao Jing' an

Date: 2017-11-08T00:00:00+00:00

Abstract

Taking Dianjiang County, a typical county in the parallel ridge-valley region of eastern Sichuan, as the study area, this study investigates the dynamics of farmland soil organic carbon (SOC) over the next 30 years under specific climate scenarios, providing data support and scientific basis for sustainable utilization and management of cultivated land in the study area. Using the biogeochemical model DNDC, the B1 scenario of BCCR_{BCM} 2.0 from the IPCC AR4 report was selected to simulate SOC dynamics from 2011 to 2041, supported by a GIS regional database established based on soil properties and agricultural management systems in the study area. The results indicate: The DNDC model can satisfactorily simulate soil organic carbon and its dynamics under specific climate conditions, with a correlation coefficient r of 0.981 between simulated and observed values, reaching an extremely significant correlation at the 0.01 level; the RMSE value between simulated and observed values is 16%, indicating good simulation performance. In the next 30 years, both SOC density and storage in the 0-20 cm soil layer of farmland in the study area will show a significant increasing trend, with a carbon increment of 2,637.07-8,091.55 kg(C) hm^{-2} per unit area, representing an increase of 10%-34%, new carbon sequestration of 2.7$\times10^{\{5\}-8.3\times10}$\{5\}$ t, and an annual growth rate of 87.9-269.7 kg(C) $hm^{-2}\cdot a^{-1}$; In the next 30 years, farmland soils in the counties of the eastern Sichuan parallel ridge-valley region will generally exhibit a continuous carbon sink status, and the differences among carbon sequestration, carbon loss, and relative equilibrium in the study area will gradually become prominent.

Full Text

Dynamic Simulation of Farmland Soil Organic Carbon in the Parallel Ridge-Valley Region of Eastern Sichuan over the Next 30 Years

ZHANG Lin, SHAO Jingan

(Department of Geography and Tourism, Chongqing Normal University / Key Laboratory of Surface Processes and Environmental Remote Sensing in the Three Gorges Reservoir Area, Chongqing 400047, China)

Abstract: This study examines Dianjiang County, a typical county in the parallel ridge-valley region of eastern Sichuan, to explore future trajectories of farmland soil organic carbon (SOC) and its dynamic changes under specific climate scenarios over the next 30 years, providing data support and a scientific basis for sustainable farmland utilization and management. Using the biogeochemical DNDC model and the B1 climate scenario from the BCCR_{BCM} 2.0 model in the IPCC AR4 report, supported by a GIS regional database constructed from soil properties and agricultural management systems, we simulated SOC dynamics in the study area from 2011 to 2041. The results demonstrated that: (1) The DNDC model effectively simulated SOC and its dynamic changes under specific climate conditions, with a correlation coefficient of 0.981 between simulated and observed values, reaching an extremely significant correlation at the 0.01 level; the RMSE value was 16%, indicating good simulation performance. (2) Over the next 30 years, both SOC density and storage in the 0–20 cm soil layer of farmland in the study area showed significant increasing trends, with a carbon increment of 2,637.07–8,091.55 $kg(C) \cdot hm^{-2}$ per unit area, representing an increase of 10%-34%, new carbon sequestration of $2.7\$\times10^{\{5\}-8.3\times10}\{5\}\$$ t, and an average annual increase rate of 87.9-269.7 $kg(C) \cdot hm^{-2}$. (3) Farmland soils in the parallel ridge-valley region of eastern Sichuan generally maintained a continuous carbon sink state, with differences among carbon sequestration, carbon loss, and relative balance becoming increasingly prominent.

Keywords: Farmland soil; Soil organic carbon; DNDC model; Dynamic simulation; Carbon sequestration; Parallel ridge-valley region; Eastern Sichuan

Introduction

As global climate change intensifies, the relationship between greenhouse gas emission reduction and soil carbon sequestration has become a focal point of climate change research [1]. Soil carbon sequestration represents an important mitigation measure, and investigating the response and feedback of soil organic carbon (SOC) dynamic balance to global climate change is crucial for understanding the global carbon cycle and agricultural ecosystems. Literature reviews reveal that early studies primarily estimated soil carbon storage based on profile data [2–3]. For instance, Post [4] estimated global soil organic carbon at approximately 1.4×10^{12} t using 2,696 soil profiles worldwide, with soil carbon storage accounting for about two-thirds of terrestrial ecosystem carbon storage. Wang et al. [5] estimated China' s total SOC storage at approximately 9.24×10^{16} g based on data from the second national soil survey. As research progressed, increasing numbers of scholars utilized soil databases and 3S technologies to optimize carbon pool estimation and spatiotemporal identification, focusing on exploring SOC spatiotemporal distribution characteristics and influencing factors. For example, Chuai et al. [7] used GIS to calculate topsoil carbon density in Jiangsu Province from 1985-2005 and examined the impact of land use change on soil carbon storage. Zhao et al. [8] employed three methods—multiple linear regression, universal kriging, and regression kriging—to predict the spatial distribution patterns of SOC density in Hebei Province. SOC exhibits complex dynamic responses to environmental conditions and undergoes slow transformation processes. Due to temporal and spatial limitations, existing field experiments cannot reveal SOC dynamic changes under different environmental conditions. In recent years, model applications have partially resolved the challenges of simulating and predicting SOC evolution. Han et al. [9] used the DNDC model to predict SOC dynamics in gray desert soil farmland in Xinjiang, while Li et al. [10] employed the DAYCENT model to simulate future SOC changes under different agricultural management practices in Northeast China. The complexity and heterogeneity of climate across spatiotemporal scales, combined with frequent human disturbances, create multiple factors that generate considerable controversy regarding SOC interactions with global climate change in current research. Predicting SOC dynamic changes under future climate scenarios is therefore essential for deepening understanding of interactions between terrestrial ecosystems and global climate change. Currently, model simulation represents an important approach for studying future soil carbon storage changes. The DNDC (DeNitrification-DeComposition) model is a dynamic model that uses mathematical approaches to study biogeochemical cycling processes and simulate carbon, nitrogen, and water cycles in terrestrial ecosystems [11]. It has been widely applied in predicting agricultural soil fertility and greenhouse gas emissions and is increasingly recognized as a typical model capable of detailed simulation of soil carbon sequestration intensity and multiple gas emission processes.

Dianjiang County is a typical representative of the parallel ridge-valley region in eastern Sichuan and one of Chongqing' s important grain and oil production areas. During the transition from traditional to modern agriculture, this region faces dual pressures of ensuring food security and increasing farmland SOC. Therefore, this study selects Dianjiang County as the research area. Building upon our research group' s previous work on SOC dynamic changes in the study area from 1980-2011 [12], we calibrated DNDC model parameters based on the second soil survey and 2011 SOC measured values, selected the B1 scenario from the $BCCR_{BCM}$ 2.0 model in the IPCC AR4 report, and conducted dynamic simulation of SOC in the study area from 2011-2041. The results will help elevate farmland utilization in similar regions to the level of regional strategies for addressing global climate change and ensuring food security, providing data support and a scientific basis for future sustainable farmland utilization practices.

1.1 Regional Overview

The study area, Dianjiang County, is located in the core zone of the parallel ridge-valley region in northeastern Chongqing (29°38 -30°31 N, 107°13 - 107°38 E), covering an area of 1,518 km^2 [Figure 1: see original paper]. Situated on the eastern side of the Huaying Mountains, the region features tectonic landforms with prominent mountain ridges in the east and west, interspersed with valley troughs. The Gaotan River runs longitudinally through the central area, with numerous streams, gullies, and plains embedded within, forming undulating hills at elevations of 320–1,183 m. The terrain slopes from high in the north to low in the south, dominated by plains and shallow hills. The climate belongs to the subtropical humid zone, with an average annual temperature of 17 °C, average annual precipitation of 1,183 mm, and a frost-free period of 289 days, creating suitable conditions for diverse crop cultivation. Dominant soil types include purple soil, paddy soil, yellow soil, and alluvial soil, with paddy soil covering 43,600 ha, accounting for 42.7% of cultivated land resources. The flat terrain and convenient transportation have made this region a key county for Chongqing's transformation from traditional to modern agriculture. To facilitate this transition, the area has been designated as a priority county for high-standard basic farmland construction in Chongqing, making it notably representative of the parallel ridge-valley region. Consequently, the area must shoulder the important function of Chongqing' s granary. Through increased investment in agricultural infrastructure (such as land leveling, roads, ditches, and ponds) and agricultural inputs (fertilizers, organic manure, machinery, etc.), the region has achieved excellent results in improving labor productivity and increasing farmland output. However, these interventions also cause considerable disturbance to farmland soil, such as land leveling and mechanical plowing. From the perspective of SOC conservation, this region experiences both improvement and disturbance, making it representative for studying SOC changes during the transition from traditional to modern agriculture in parallel ridge-valley regions.

1.2 Data Acquisition and Settings

1) Soil data: The 1980 data from the second national soil survey were obtained from Dianjiang County Agriculture Bureau, from which attribute data needed for the soil spatial database were extracted and established, with missing portions supplemented by the *Dianjiang County Soil Species Gazetteer*. For the 2011 measured sample analysis data, we used the original sampling point records from the second soil survey (including soil type, place name, river, elevation, etc.) to relocate sampling points in ArcGIS 10.2. We then established soil sampling points of the same soil type at or near the original locations. Based on the second soil survey data for Dianjiang County, we calculated soil physicochemical properties (such as organic carbon content, clay content, pH, bulk density, etc.) for each sampling point and used the arithmetic mean of the calculated values as the final value for each sampling point' s physicochemical properties.

2) Meteorological data: Daily meteorological data from 1980–2011 (precipitation, temperature, etc.) were provided by the Chongqing Meteorological Bureau and six meteorological stations in and around Dianjiang County. Daily meteorological data for 2011–2041 were configured using the B1 climate scenario from the BCCR_{BCM} 2.0 model in the IPCC AR4 report [13]. According to model requirements, meteorological data were formatted as daily maximum temperature, daily minimum temperature, and daily average precipitation.

3) Crop data: Obtained from the Dianjiang County Statistical Yearbook, we selected six major cropping systems (winter wheat-summer corn, rice-rapeseed, corn-sweet potato, corn-soybean, pepper-potato, rice-green bean) for parameter setting in the crop sub-module. Planting dates, irrigation, harvest, and fertilization practices were comprehensively configured based on phenological records and field survey data from Dianjiang County.

4) Spatial data: The 1980 and 2011 farmland resource distribution maps and administrative division maps were provided by Dianjiang County Land and Resources Bureau. ArcGIS was used for data processing.

1.3 DNDC Model Parameter Settings

The DNDC model version 9.5 was employed. The DNDC model organizes physical, chemical, and biological processes of carbon and nitrogen cycles using computer technology, establishing an idealized ecosystem based on theoretical analysis and experimental observations that requires validation against real ecosystem characteristics using measured data. Although each process in the model is based on theory or observational data and has been validated in numerous farmland ecosystems, soil carbon and nitrogen cycling processes are extremely complex with strong spatiotemporal variability. Moreover, the model involves numerous parameters (e.g., meteorological, soil, fertilization) and the default parameters originally adopted by the model primarily derive from observations in Europe and America. Therefore, when applied to any specific spatiotemporal scale, important parameters affecting carbon and nitrogen cycling processes must be localized and simulation results validated using measured data. Consequently, this study modified and localized several important parameters, particularly soil parameters in the soil input library (Table 1), and adjusted default crop parameters in the model, such as C/N ratios and proportions of different crop components. The process involved first setting soil and crop physiological parameters in the model, then inputting required meteorological, soil, and field management parameters, running the model, and comparing simulated crop biomass and SOC dynamic changes with field measurements. Some DNDC model parameters were adjusted multiple times to achieve optimal agreement between simulated and measured values.

Using townships as the basic simulation units, we overlaid the soil map patch database with the Dianjiang County administrative division map to create a new village boundary patch database. Following the DNDC regional mode default database construction method, we used map patches as basic simulation units and control areas. Geostatistical Analyst was employed for kriging interpolation of soil properties (initial SOC, clay content, pH, bulk density, etc.) across township-village boundary patches to extract mean, maximum, and minimum values for each property. The spatial distribution of nitrogen fertilizer, farm manure input, and straw return for each crop within simulation units was obtained using ArcGIS 10.2 spatial interpolation functions, forming a county-scale soil database.

The DNDC model and GIS database were connected through a unique ID code. DNDC model parameters were calibrated using multi-year observational data from Dianjiang County to conduct farmland SOC simulation from point to regional scales. The model was validated at both point and regional scales, and environmental relationship models were established between regional simulation results and measured data to fit residuals, thereby achieving scaling up of SOC simulations.

1.4 Data Analysis

Factors affecting SOC density include topography, soil physicochemical properties, fertilization, management, biology, and climate [14–17]:

1) The initial SOC density value directly influences SOC changes, with higher values corresponding to slower change rates [15]. Therefore, the 2011 SOC density was the primary consideration for analyzing dynamic changes in Dianjiang County’ s SOC density over the next 30 years.

2) Terrain relief significantly influences the spatial differentiation of soil physicochemical properties, particularly elevation and slope [14–16]. Slope gradient and altitude determine the degree of human disturbance stress, affect soil formation processes, and consequently influence SOC spatial differentiation.

3) Soil physicochemical properties are relatively stable and slow-changing factors in the soil environment and constitute essential considerations in identifying factors affecting SOC dynamic changes. Among physical properties, bulk density and gravel content significantly affect SOC; among chemical properties, besides pH, available phosphorus, total nitrogen, phosphorus, and potassium, and C/N ratio all positively influence SOC [17]. Selected factors included bulk density, gravel content, texture, available phosphorus, total nitrogen, phosphorus, and potassium, and C/N ratio.

4) Chemical fertilizers (phosphorus, nitrogen, and potassium) increase soil

nutrient elements, while organic manure application increases organic matter content.

5) High crop yield indicates good crop growth, producing more litter that increases soil organic matter content. Stubble and straw return also directly increase soil organic matter and SOC content [14].

6) Meteorological data significantly affect model outputs, with rainfall and atmospheric temperature directly influencing soil profile temperature, moisture, oxidation-reduction potential, carbon, and oxygen. This study set soil management for the next 30 years as conventional management mode, with meteorological factors and crop growth conditions influenced by meteorological factors being the main factors affecting SOC storage changes.

Point-based simulation served as the foundation for calibrating model parameters using measured values to conduct regional simulations. Implementing point and regional simulations with the DNDC model required obtaining all necessary input data for regional grid points and storing them in specific GIS and general databases [18]. GIS data covered all polygons and grid point information for the simulation area, such as geographic location, meteorological data, soil properties, cropping systems, and farmland management. General data included plant physiological/phenological and soil hydrothermal performance parameters. To support DNDC model operation, we first generated grids with villages as minimum units to establish a spatial database, assuming these grid properties were homogeneous to enable uniform simulation of each grid. Second, we assumed features within each grid were consistent, with each basic unit containing only one set of model input parameters, and then summed simulations across basic units [19-20]. At the county scale, we first conducted DNDC point simulations to calibrate model parameters, then used the second soil survey and natural environment data as initial simulation data. Using the soil map patch method combined with field-measured farmland management data, we established a 1:50,000 county-scale database and used the DNDC model to simulate future SOC scenarios for 30 years. Subsequently, 40% of measured sample points from Dianjiang County were used as validation data to verify the accuracy of DNDC model simulation results.

1.5 SOC Simulation Results and Accuracy Verification

Point-based simulation selected crop biomass and SOC as validation indicators. Winter wheat-summer corn and rice-rapeseed are typical crop rotation systems in Dianjiang County that have undergone long-term stable observation and soil physicochemical analysis. Using measured soil physicochemical properties, meteorological data, and farmland management information as DNDC model inputs, we compared simulated yield and SOC values with actual observations to verify model accuracy. Actual observations from 2003, 2008, and 2011 under conventional fertilization, reduced fertilization, and no fertilization treatments for winter wheat, and from 2005, 2009, and 2011 under conventional fertilization for rice were used for model validation. The former used 2003 as the initial state with measured SOC data from winter wheat-summer corn dryland; the latter used 2005 as the initial state with measured SOC data from rice-rapeseed paddy fields, coupled with meteorological data and farmland management information to run the model.

As shown in Table 2, the maximum relative error between simulated and measured wheat yield in 2008 was −30.7% to −12.2%, with an average relative error of −16.2%, indicating relatively poor simulation results, with the no-fertilization treatment showing the largest relative error. In 2011, simulated and measured values were relatively close, ranging from −17.8% to −1.7%, with an average relative error of −2.7%, indicating relatively feasible simulation results, with all three scenarios producing simulated values lower than measured values. Table 3 shows that the relative error between simulated and measured SOC in wheat fields in 2008 was 1.75%-16.75%, with an average relative error of 9.1%. In 2011, the relative error for dryland SOC was −2.18%-9.66%, with an average relative error of 3.1%. In the initial simulation stage, simulated values were lower than measured values because Dianjiang County had not yet implemented experimental observations before 2003, with all plots receiving conventional fertilization treatments, after which differential fertilization treatments were implemented. Consequently, simulated values in 2011 became increasingly close to measured values, and as simulation time extended, the model became more stable. Tables 2 and 4 show that relative errors between simulated and measured rice values in 2009 and 2011 were relatively small, at 7.5% and −5.9% respectively, indicating ideal simulation results. SOC simulation results for paddy fields in 2009 and 2011 were also good, with relative errors of 7.5% and −7.1% respectively.

Using calibrated soil properties and crop coefficients, we simulated farmland SOC in Dianjiang County from 1980-2011 and compared simulated means with sampling point observations to test the model. This study used correlation coefficient (r) and relative RMSE (root mean square error) to verify the suitability of the DNDC model at the regional scale. The RMSE calculation formula is:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{OBS}_i - \mathrm{SM}_i)^2}{\sum_{i=1}^{n}\mathrm{OBS}_i^2}} \times 100\%$$

where OBS is the observed value, SM is the simulated value, and n is the sample size. Smaller RMSE values indicate better consistency between simulated and actual values. General reference standards are: RMSE $<$ 10% indicates very good consistency; 10%-20% indicates good consistency; 20%-30% indicates fair simulation performance; $>$ 30% indicates large deviation and poor simulation performance [19].

DNDC-simulated SOC content in the farmland topsoil of the study area showed consistent variation trends with field measurements, with a correlation coefficient r of 0.981, reaching an extremely significant correlation at the 0.01 level, and an RMSE value of 16% between simulated and observed values. Therefore, the DNDC model demonstrated good simulation performance, and using it to simulate SOC trend changes in Dianjiang County from 2011-2041 is feasible.

2.1 Dynamic Changes in SOC Density and Storage

SOC transformation is a long-term and complex process. This study used the DNDC model with the B1 scenario from the BCCR_{BCM} 2.0 model in the IPCC AR4 report to simulate and predict soil organic carbon in Dianjiang County from 2011-2041, assuming identical cultivation management practices throughout the simulation period. Simulation results (Fig. 2) indicated that SOC density and storage in the 0–20 cm soil layer of farmland in Dianjiang County showed significant increasing trends from 2011-2041. The simulated SOC density in 2041 was 110%-134% of the original 2011 density, with SOC density changes of 2,637.07-8,091.55 kg(C) $\cdot$ hm^{-2}. Different soil types showed varying SOC change magnitudes. Alluvial soil, the fourth largest soil type in Dianjiang County, showed the maximum increase at 130%-151%. Purple soil, widely distributed in Chongqing, showed the minimum increase at -9% to -7%. Paddy soil (the second largest area) and yellow soil (the third largest area) showed increases of 30%-42% and 20%-30%, respectively.

Overall SOC storage changes in Dianjiang County from 2011–2041 were consistent with SOC density change trends, with simulated 2041 SOC storage at approximately 110%-168% of the 2011 original value, and new carbon sequestration of 2.7$\times 10^{\{5\}-8.3\times 10}$\{5\} t. Due to area effects, SOC storage changes for different soil types differed from SOC density changes. Although alluvial soil had the largest per-unit-area carbon increment, its small area resulted in relatively small new carbon sequestration. Purple soil, with the largest cultivated area, and paddy soil, with the second largest area, collectively determined SOC gains and losses in Dianjiang County farmland.

The spatial distribution pattern of SOC density changes in Dianjiang County farmland over the next 30 years generally showed high values in the northwest and southeast and low values in the central region. High-change areas appeared in the northwest and southeast, while low-change areas appeared in the central region, consistent with Dianjiang County’ s topographic framework. The largest increases occurred in the three major mountain systems (Mingyue Mountain, Jinhua Mountain, and Huangcao Mountain) and their surrounding areas, followed by the upper left watershed of the Gaotan River in the central region, the lower right watershed of the Dasha River, the southern region, and the Hedatai area. The smallest increases occurred in the interlaced zone of the trough valley area between Mingyue and Jinhua mountains. The spatial pattern of SOC storage changes showed slight differences from density change patterns, with the most obvious storage increase areas located in the valley plain area along the upper Huilong River in the north and the southwestern section of Jinhua Mountain, followed by the three major mountain systems and their surrounding areas. The smallest increases occurred in the trough valley area between Mingyue Mountain and Huilong River and between Jinhua Mountain and Gaotan River.

2.2 Annual Change Rates and Spatial Characteristics of Carbon Sequestration and Loss

Both SOC density and storage change rates in Dianjiang County showed overall increasing trends over the next 30 years (Fig. 3). The simulated average annual increase rate of SOC density in the 0–20 cm soil layer from 2011–2041 was 87.90–269.72 kg(C)$\cdot$hm^{-2}, higher than the corresponding annual growth rate of 72.11 kg(C)$\cdot$hm^{-2} from 1989–2011, with a minimum increase of 21.90%, showing a relatively obvious carbon sink effect. SOC storage change rates in Dianjiang County farmland were consistent with SOC density change rates, with an average annual growth rate of 8.9\$$\times10^{\{3\}-2.8\times10}$\{4\}\$ t$\cdot$a^{-1}, far exceeding the corresponding annual growth rate of 7,373.31 t$\cdot$a^{-1} from 1989–2011. Annual growth rates of SOC density and storage over the next 30 years varied significantly among different soil types. Alluvial soil showed the maximum annual growth rate at 377.9–494.2 kg(C)$\cdot$hm^{-2}, followed by paddy soil at 288.0–401.2 kg(C)$\cdot$hm^{-2}, and yellow soil at 260.0–491.2 kg(C)$\cdot$hm^{-2}. Purple soil showed the minimum growth rate at -186.1 to -51.9 kg(C)$\cdot$hm^{-2}. Compared with annual growth rates of farmland SOC density among different soil types from 1989–2011 [alluvial soil 535.00 kg(C)$\cdot$hm^{-2}, yellow soil 133.46 kg(C)$\cdot$hm^{-2}, paddy soil 218.48 kg(C)$\cdot$hm^{-2}, and purple soil -50.64 kg(C)$\cdot$hm^{-2}], alluvial soil growth rates decreased somewhat, yellow soil growth rates increased substantially, paddy soil growth rates increased slightly, and purple soil growth rates decreased. The reason is that soil SOC capacity is limited. Over the past 30 years, alluvial soil SOC density growth rates were originally large, but after reaching a certain peak, they gradually decreased. Yellow soil growth rates were smaller and in an ascending phase, meaning its SOC capacity potential is larger. Paddy soil SOC capacity remains relatively stable due to long-term human cultivation disturbance, with small fluctuations. Purple soil' s SOC capacity, determined by its physicochemical properties, is difficult to break through. SOC storage change rates also showed obvious increasing trends, with differences among soil types influenced by both SOC density changes and corresponding soil type areas. Although alluvial soil had the maximum annual change rate of SOC density, its small area (only 0.23% of paddy soil) resulted in SOC storage change rates only 4% of paddy soil' s rate—a substantial difference. In SOC management, both the improvement potential of SOC density and the proportion of soil type area must be considered, as only their combination can enhance overall SOC content.

Defining carbon sequestration (>5%), carbon loss (<−5%), and relative balance (between these values) based on the proportion of SOC storage change from 2011–2041 relative to 2011 storage, the area ratios of farmland soil carbon sequestration, carbon loss, and relative balance in Dianjiang County were 58.14%, 31.62%, and 10.24%, respectively. Overall (Fig. 3), the combined area of carbon sequestration and relative balance accounted for two-thirds of the total area over the next 30 years, while carbon loss area accounted for only one-third, consistent with the significant increasing trend of farmland SOC storage. Further analysis revealed that paddy soil, with 30.19% carbon sequestration magnitude, had a large sequestration area proportion of 84.60%, making it key to carbon sink enhancement in Dianjiang County farmland due to its area advantage. Yellow soil' s sequestration area slightly exceeded its loss area, at 57.00% and 43.00%, respectively. Purple soil had a sequestration area of 26.08%, loss area of 58.72%, and relative balance area of only 15.20%. Its loss area significantly exceeding its sequestration area substantially affects farmland carbon sink enhancement at the county scale. The carbon source/sink of Dianjiang County farmland over the next 30 years will be determined primarily by the carbon effects between paddy soil and purple soil. For all soil types, farmland SOC storage changes over the next 30 years did not show a single pattern of carbon loss, sequestration, or relative balance, but rather simultaneous coexistence of loss and sequestration or all three states. This is because numerous factors influence farmland SOC storage changes, and the coexistence of sequestration, loss, and relative balance states during the same evolution period results from the combined effects of multiple factors.

Farmland soil carbon sequestration in Dianjiang County over the next 30 years will mainly occur in the southeastern and northwestern regions, while carbon loss and relative balance will primarily occur in the central region, showing a distribution pattern of sequestration in the southeast and northwest and loss in the center (Fig. 3). Carbon sequestration zones concentrate in the central-southern Hedatai area, the three major mountain systems (Mingyue Mountain, Jinhua Mountain, and Huangcao Mountain), and scattered areas in the trough valley plain where the Huilong River is located. Relative balance zones concentrate in the lower right margin trough valley area of western Mingyue Mountain, the plain area between Gaotan River and Huilong River, the area west and north of the lower Gaotan River, and the area west and north immediately adjacent to Huangcao Mountain. Carbon loss mainly occurs in the interlaced zone between Mingyue Mountain and its lower margin trough valley, the southern section of Jinhua Mountain, and the northern section of Hedatai. Carbon loss areas generally belong to interlaced zones between mountain systems and trough valley plains with large slope variations, which are unfavorable for inorganic and organic fertilizer application and cultivation management, resulting in relatively low crop growth and yield, less aboveground litter, and smaller underground portions, causing overall carbon loss in farmland SOC storage. Conversely, carbon sequestration zones are located in plains and lower margins of major mountain systems, where the former facilitates inorganic and organic fertilizer input and cultivation management, and the latter has abundant aboveground litter and underground portions, both conducive to SOC storage enhancement. The spatial pattern of annual SOC density change rates showed higher values in the west and northwest than in the east and southeast, which were higher than in the northeast and southwest (Fig. 3). The pattern can be broadly divided into three levels: Mingyue Mountain in the west and Huangcao Mountain in the southeast are high-value change areas; the northwest of Gaotan River, southeast of Dasha River, and middle-lower reaches of Dasha River are moderately significant change areas; and the area east of the county seat, north of Dasha River, and the trough valley area between Gaotan River and Hedatai are low-value change areas.

3.1 Discussion

Factors influencing SOC changes are complex, including soil temperature, moisture, oxidation-reduction conditions, soil erosion, and plant biomass, which are themselves controlled by climate, soil quality, vegetation, human activities, and other driving forces. Any changes in factor combinations alter the quality and quantity of farmland SOC. Among these, initial SOC density, soil total nitrogen density, C/N ratio, and soil particle composition significantly affect SOC. Cheng et al. [21] found that initial SOC density had the greatest negative correlation with farmland topsoil SOC density. This study also demonstrated that higher initial SOC density values corresponded to smaller average annual change rates of SOC density in Dianjiang County over the next 30 years. Farmland SOC has an upper capacity limit; higher SOC content makes short-term significant enhancement more difficult, whereas reasonable cultivation, fertilization, and management practices can significantly enhance SOC content in the short term when initial values are lower [22–23]. Under identical cultivation, input, and management conditions in the study area, regions with high initial SOC density in the north and northeast showed lower enhancement rates than regions with relatively lower initial values in the central, southern, and southeastern areas. Soil total nitrogen density and C/N ratio were second only to initial SOC density in their influence on farmland topsoil SOC density, showing positive correlations with SOC. Larger soil total nitrogen density and C/N values corresponded to greater SOC density change rates in Dianjiang County over the next 30 years. Our research group' s dynamic study of Dianjiang County SOC over the previous 30 years also found certain dependencies between total nitrogen density and C/N ratio, with nitrogen accumulation in soil often accompanied by carbon increases.

As national development progresses, cultivated land area in the study area will change according to regional development needs. Increases or decreases in cultivated land area and associated human disturbances will lead to changes in soil SOC density and storage [24–25], which differs from conclusions drawn under the assumption of constant cultivated land area in this study. Using model methods to simulate farmland soil carbon pools and sequestration potential has become an important approach for SOC research. This study used the biogeochemical DNDC model with only the B1 scenario from the BCCR_{BCM} 2.0 model in the IPCC AR4 report to simulate future temperature and precipitation predictions for Dianjiang County in the parallel ridge-valley region of eastern Sichuan, providing a somewhat limited basis for simulating farmland SOC trends over the next 30 years. To accurately and effectively predict farmland SOC change trends in this region, more sampling points and soil data for different crops are needed for model parameter calibration and validation, along with simulations under additional climate scenarios. Furthermore, this study was conducted based on a database founded on statistical data and measured data, so results are closely related to the accuracy of statistical data and precision of measured data, which may cause some deviation between simulation results and reality.

This study used correlation coefficient r and relative RMSE (root mean square error) to verify DNDC model simulation performance for soil organic carbon, with a correlation coefficient r of 0.981, reaching an extremely significant correlation at the 0.01 level, and an RMSE value of 16%, indicating good simulation performance. The DNDC model is suitable for large-scale, long-term spatiotemporal pattern simulation of farmland SOC. As time progresses, model simulation results become more stable and closer to measured values, yielding more ideal results.

Using the DNDC model to simulate farmland SOC density in a typical county of the parallel ridge-valley region of eastern Sichuan over the next 30 years, results showed that SOC density and storage in the 0-20 cm soil layer of Dianjiang County farmland will show significant increasing trends. SOC density will increase from 23,798.68 kg(C) $\cdot$ hm^{-2} in 2011 to 26,435.70-31,890.23 kg(C) $\cdot$ hm^{-2} in 2041, with a per-unit-area carbon increment of 2,637.07-8,091.55 kg(C) $\cdot$ hm^{-2} and new carbon sequestration of 2.7\$$\times 10^{\{5\}-8.3\times 10}$\{5\}\$ t. SOC (density and storage) change rates in the study area over the next 30 years will show overall increasing trends. The DNDC model simulated an average annual growth rate of SOC density in the 0-20 cm soil layer of 87.90-269.72 kg(C) $\cdot$ hm^{-2} from 2011-2041, far exceeding the corresponding annual growth value of 72.11 kg(C) $\cdot$ hm^{-2} from 1989-2011, with a growth magnitude of 21.90%, indicating a relatively obvious carbon sink effect.

DNDC model simulation results showed that over the next 30 years, carbon loss area will account for 31.62%, carbon sequestration area for 58.14%, and relative balance area for 10.24% of the study area. The sequestration area exceeds the sum of loss and relative balance areas, breaking the previous equilibrium state where sequestration area equaled the sum of loss and balance areas in Dianjiang County from 1980-2011, with significance among the three states becoming increasingly prominent.

References

[1] Lal R. Soil carbon sequestration impacts on global climate change and food security[J]. Science, 2004, 304(5677): 1623-1627
[2] Yu D S, Shi X Z, Sun W X, et al. Estimation of China soil organic carbon storage and density based on 1:1,000,000 soil database[J]. Chinese Journal of Applied Ecology, 2005, 16(12): 2279-2283
[3] Wu L Z, Cai Z C. Estimation of the change of topsoil organic carbon of

croplands in China based on long-term experimental data[J]. Ecology and Environment, 2007, 16(6): 1768-1774
[4] Post W M, Emanuel W R, Zinke P J, et al. Soil carbon pools and world life zones[J]. Nature, 1982, 298(5870): 156-159
[5] Wang S Q, Zhou C H, Li K R, et al. Analysis on spatial distribution characteristics of soil organic carbon reservoir in China[J]. Acta Geographica Sinica, 2000, 55(5): 533-544
[6] Zhou T, Shi P J, Luo J Y, et al. Estimation of soil organic carbon based on Remote Sensing and Process Model[J]. Journal of Remote Sensing, 2007, 11(1): 127-136
[7] Chuai X W, Huang X J, Lai L, et al. Accounting of surface soil carbon storage and response to land use change based on GIS[J]. Transaction of the CSAE, 2011, 27(9): 1-6
[8] Zhao Y C, Shi X Z, Yu D S, et al. Different methods for prediction of spatial patterns of soil organic carbon density in Hebei province, China[J]. Acta Pedologica Sinica, 2005, 42(3): 379-385
[9] Han D L, Jia H T, Zhu X P, et al. Using DNDC model to predict soil organic carbon dynamics in a gray desert soil farmland[J]. Resources Science, 2014, 36(3): 577-583
[10] Li Y, Guo L P, Xie L Y, et al. Modeling the future changes of soil organic carbon under different management practices in upland Soils of Northeast China[J]. Scientia Agricultura Sinica, 2015, 48(3): 501-513
[11] Jin L, Li Y E, Gao Q Z, et al. Analysis of the change of soil carbon under cropland management in China between 1981 and 2000 by DNDC[J]. Chinese Journal of Soil Science, 2010, 41(5): 1081-1085
[12] Shao J A, Hui L L, Ci E, et al. Dynamics of farmland SOC in parallel ridge valley of east Sichuan during 1980-2011[J]. Acta Ecologica Sinica, 2014, 34(15): 4347-4360
[13] IPCC. Climate change 2007: Synthesis report. Contribution of working groups I, II and III to the fourth assessment report of the intergovernmental panel on climate change[R]. Geneva, Switzerland: IPCC, 2007
[14] Ding X L, Han X Z, Qiao Y F, et al. Sequestration of organic carbon in cultivated soils: Main factors and their stabilization mechanisms[J]. Chinese Journal of Soil Science, 2012, 43(3): 737-744
[15] Shi K, Chen Z. The effect of the concentration of clay organic carbon on particle-size composition in the hill region of the suitable inhabitancy[J]. Chinese Agriculture Science Bulletin, 2008, 24(8): 274-278
[16] He T T, Hua L, Zhang Z X, et al. Factors influence agricultural soil releases SOC and measures fix C[J]. Journal of Capital Normal University: Natural Science Edition, 2007, 28(1): 66-72
[17] Jiang Y, Zhuang Q L, Liang W J. Soil organic carbon pool and its affecting factors in farm land ecosystem[J]. Chinese Journal of Ecology, 2007, 26(2): 278-285
[18] Wang F, Weng B Q, Wang Y X. Advance in research on effects of land use and management on soil carbon stock and fractions[J]. Fujian Journal of Agricultural Sciences, 2009, 24(3): 270-278

[19] Wang D Y, Yao Y M, Si H Q, et al. Using DNDC model to simulate and predict changes in black soil organic carbon[J]. Chinese Journal of Eco-Agriculture, 2014, 22(3): 277-283
[20] Batur B, Peng Z H, Zhang X D, et al. Biogeochemical model DNDC and its application[J]. Chinese Journal of Soil Science, 2007, 38(6): 1208-1212
[21] Cheng X F, Shi X Z, Yu D S, et al. Spatial variance and distribution of total nitrogen and organic matter of soil in Xingguo county of Jiangxi, China[J]. Chinese Journal of Applied and Environmental Biology, 2004, 10(1): 64-67
[22] Yang Y H, Wu J C, Zhang J M, et al. Effect of tillage method on soil water infiltration, organic carbon content and structure[J]. Chinese Journal of Eco-Agriculture, 2017, 25(2): 258-266
[23] Xu Y M, Liu H, Wang X H. Evolution of soil organic carbon and crop yield under long-term fertilization in grey desert soils[J]. Chinese Journal of Eco-Agriculture, 2016, 24(2): 154-162
[24] Zhou L, Li B G, Zhou G S. Advances in controlling factors of soil organic carbon[J]. Advance in Earth Science, 2005, 20(1): 99-105
[25] Balesdent J. The significance of organic separates to carbon dynamics and its modelling in some cultivated soils[J]. European Journal of Soil Science, 1996, 47(4): 485-493

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