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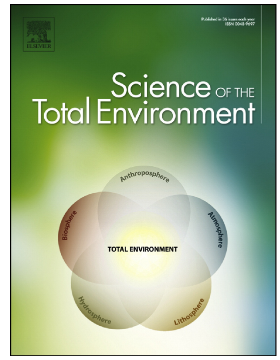

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Increased straw return promoted soil organic carbon accumulation in China's croplands over the past 40 years

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Abstract

Quantifying changes in soil organic carbon (SOC) within croplands across a broad spatiotemporal scale, in response to anthropogenic and environmental factors, offers valuable insights for sustainable agriculture aimed at improving soil health. Here, using a validated and widely used soil carbon model (i.e., RothC), we simulated the SOC dynamics across intensive croplands in China that support ~22% of the global population using only 7% of the global cropland area. Our findings demonstrate that the optimized RothC effectively captures SOC dynamics measured across 29 field trials during 40 years. Between 1980 and 2020, the average SOC at the top 30 cm soil depth in croplands increased from 40 Mg C ha^{-1} to 49 Mg C ha^{-1}, resulting in a national carbon sequestration of 1100 Tg C, with an average carbon sequestration rate of 27 Tg C yr^{-1}. The annual increase rate of SOC (relative to the SOC stock of the previous year), starting at less than 0.2% yr^{-1}in the 1980s, reached around 0.4% yr^{-1} in the 1990s and further rose to about 0.8% yr^{-1} in both the 2000s and 2010s. Notably, the eastern and southern regions, comprising about 40% of the croplands, contributed about two-thirds of the national SOC gain. In northeast China, SOC slightly decreased from 58 Mg C ha^{-1} in 1980 to 57 Mg C ha^{-1} in 2020, resulting in a total decline of 28 Tg C. Increased organic C inputs, particularly from the straw return, was a crucial factor in SOC increase. Future strategies should focus on region-specific optimization of straw management. Specifically, in northeast China,

increasing the proportion of straw returned to fields can prevent further SOC decline. In regions with SOC increase, such as the eastern and southern regions, diversified straw utilization (e.g., bioenergy production), could further mitigate greenhouse gas emissions.

Keywords: RothC, straw return, soil carbon sequestration, soil health, greenhouse gas emission

1 Introduction

Globally, soil is the largest carbon (C) reservoir in terrestrial ecosystems, approximately 2−3 times greater than that of atmosphere and vegetation combined (Friedlingstein et al., 2023). Consequently, even minor changes in soil C pool can strongly affect atmospheric CO_2 concentration (Ciais et al., 2014; Lal, 2004b). Previous findings indicated that soil organic carbon (SOC) sequestration has great potential of natural climate solutions (Bossio et al., 2020; Fuss et al., 2018; IPCC, 2021), while there are also opposing views that SOC sequestration has a limited role in climate change mitigation (Minasny et al., 2023; Moinet et al., 2023). There is a general consensus that, among biomes, croplands have more potential for sequestering SOC (Amelung et al., 2020), offering co-benefits for soil health and food security (Lal et al., 2007; Paustian et al., 2016; Zhang et al., 2014). Currently, global agricultural soils suffered a 50−70% loss of C resulting mainly from long-term tillage (Lal, 2004a;

Post & Kwon, 2000; Sanderman et al., 2017) and erosion. In contrast to other ecosystems, croplands have the ability to recover from these C losses through agricultural management practices, such as, conservation tillage, crop rotation complexity, manure and straw application (Alvarez, 2005; Han et al., 2016; West & Post, 2002). The SOC in the 0−30 cm depth of global agricultural soils can sequester between 0.90 and 1.85 Pg C yr^{-1}, which is sustainable for at least 20 years (Zomer et al., 2017).

SOC sequestration occurs when C inputs surpass losses, and thus augmenting soil C inputs or reducing C losses are the primary approaches to increase SOC sequestration (Paustian et al., 1997; van Wesemael et al., 2010). Organic C inputs, including straw return from previous crops, root residues, rhizodeposition, and manure application, constitute primary sources of SOC, and straw return has emerged as the most effective means for C sequestration and sink enhancement in cropland soils currently (Li et al., 2021; Lu et al., 2010). Throughout the 2010s, the continuously growing grain yield led to increase of crop root biomass and straw production, which further resulted in an increased C input belowground (Li et al., 2018). The widespread use of straw return to fields also contributed to the increase in SOC (Liu & Li, 2017; Shi et al., 2023).

However, there is large uncertainty of soil C inputs to croplands due to the lack of C input data. For example, there is less survey data for straw resources, and the current amount of straw is estimated through crop yields based on empirical formulas

(Huang et al., 2007). The straw return rate and the application rate of farmyard fertilizers are directly related to the way farmers manage their cropland, which are highly decentralized, leading to survey difficulty and lack of relevant data. Numerous experimental studies have demonstrated that SOC can accumulate with increasing carbon inputs when initial SOC levels are relatively low (Grant et al., 2001; Kamoni et al., 2007; Yang et al., 2007). However, once SOC reaches a certain threshold, known as the 'SOC saturation' state, further carbon inputs result in minimal increases (Six et al., 2002; Stewart et al., 2007). Therefore, the impact of straw return on SOC increments varies across regions due to differences in initial soil C content and saturation state.

Decomposition of SOC is difficult to observe under field conditions, so it is often simulated using process-based soil C turnover models (Gautam et al., 2020; Poeplau & Dechow, 2023; Sakrabani & Hollis, 2018; Wang et al., 2015). Such models usually divide soil C into multiple pools, and each pool is mineralized according to a first-order kinetic equation, with decomposition rates of each pool are affected by factors such as soil temperature, water content, clay content, and pH (Luo et al., 2016; Sierra et al., 2012).

China is a major food-producing country supporting ~22% of global population using only 7% of the global cropland area, and its cropland SOC density accounts for two-thirds of the global cropland (Yang et al., 2022; Ying et al., 2019). There are many experimental field management data from Chinese agricultural sites, and statistics from straw utilization surveys, which are suitable for modelling SOC stock dynamics in croplands (Shi et al., 2023; Xie et al., 2020). Since 1999, China has implemented a straw return strategy, leading to a substantial increase in soil C inputs from straw to cropland (MEE, 1999). The nationwide adoption of the straw return strategy in China, especially after 2010, has sparked considerable interest in understanding the changes in China's cropland SOC over the past decade. However, existing studies mainly focused on the period of 1980-2010, with SOC changes in 2010-2020 largely unexplored (Ding et al., 2023; He et al., 2021; Zuo et al., 2023).

We used the Rothamsted C model (RothC, version 26.3) to assess the SOC dynamics. The RothC model is one of the most representative pool-based SOC models, featuring a simple structure that facilitates modification and prediction on large spatial and temporal scales (Teixeira et al., 2021; Wang & Luo, 2021). Recognizing the model' s original design and parametrization for dryland soils, we have modified and validated RothC using data from experimental sites across paddy and dryland soils in China, and derived a parameter optimization scheme for simulation. Subsequently, based on the re-constructed annual gridded cropland soil C input dataset at a high spatial resolution, the modified RothC model was applied to simulate the spatiotemporal dynamics of SOC across China's croplands from 1980 to 2020. Estimations of SOC changes under five scenarios were performed to identify the factors influencing SOC sequestration in croplands.

This study aims to quantify spatiotemporal distribution of SOC in the top 30 cm of croplands over the past four decades. This involves understanding of the mechanisms of SOC increase or decrease in each region and determining how adjusting the quantity of C input can contribute SOC accumulation or mitigate SOC decline. This information can then guide policymakers on effective management of straw/manure resources for SOC sequestration.

2 Materials and Methods

2.1 Site experimental data

A total of 17 experimental sites were included in this study, covering most croplands in China (Fig. 1). These sites were derived from the Long-Term Soil Fertility Experiment Network for China's Cropland (Yu et al., 2012; Zhao et al., 2010), covering variable soil types and cropping systems from five typical agricultural regions and different climatic zones in China. The experimental durations of these sites range from 12 to 26 years, with an average of 18 years. The site-specific information includes the site location (longitude and latitude), soil properties at a depth of 0−30 cm (initial SOC stock and clay fraction content), climate data (mean annual temperature and precipitation), and details of experiment (experimental time span, cropping system, annual C input, and analyzed SOC content). The climate data for the experimental sites were obtained from the nearest climate stations, with the mean annual temperature (MAT) and mean annual precipitation (MAP) range from

4.4 to 18 °C and from 202 to 1650 mm, respectively (Fig. 1). The initial SOC stock ranges from 18 to 46 Mg C ha^{-1} at 0−30 cm depth, much lower than the global average level of 61−82 Mg C ha^{-1} (Qin et al., 2013; Zomer et al., 2017). In cases where soil properties were available only for the top 20 cm depth, we estimated 0−30 cm SOC stock using the SOC vertical distribution assumption (Jobbágy & Jackson, 2000; Qin et al., 2013). The cropping systems at these sites include single, double and triple harvests within a single year. The fertilizer managements of these sites include: control with only C input from crop roots (Contr), manure (Man), high manure (highMan), manure and mineral fertilizer (NPK-Man), and mineral fertilizer inputs (NPK). Limited by data availability, each site only obtains one or two long-term trials with different managements. The site-specific information was collected from the relevant literature (Table S1).

For model calibration, data from 11 treatments at 6 sites (including Beibei, Chuxiong, Gongzhuling, Urumqi, Xuzhou, and Zhengzhou) were selected from diverse agricultural regions in China, and data from 18 treatments at the remaining 11 sites were utilized for validation purpose (Fig. 1).

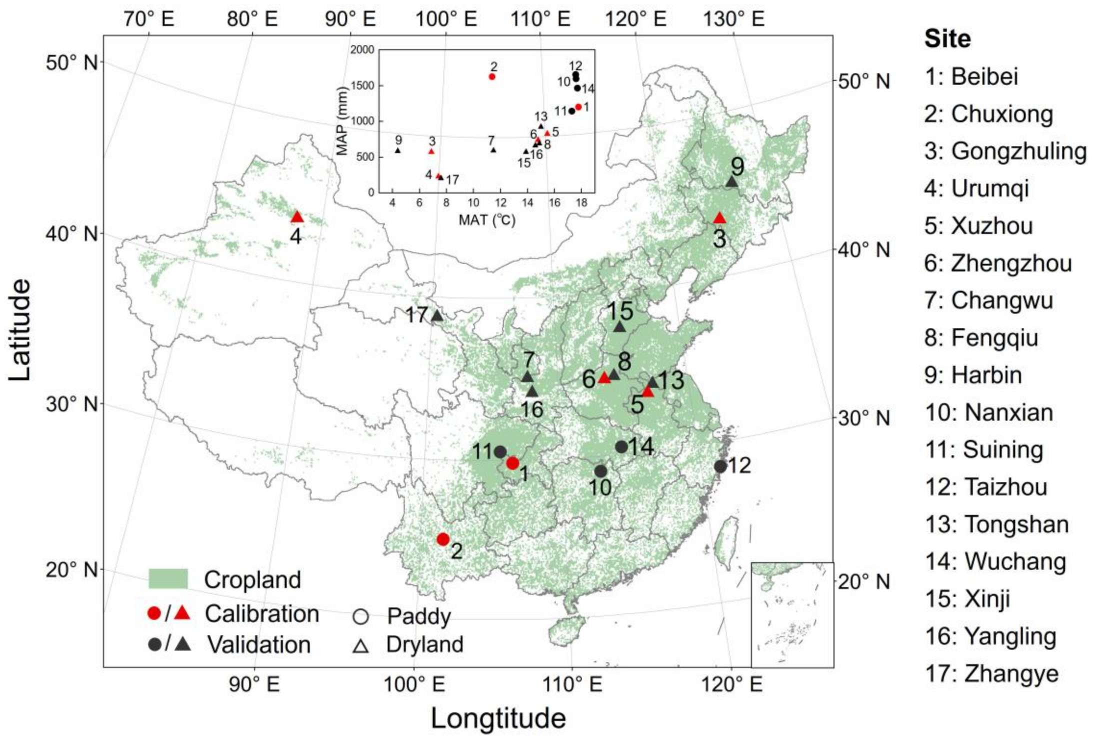

Figure 1. Locations of 17 experimental sites in China. MAT and MAP represent the mean annual temperature and mean annual precipitation, respectively. Sites are marked by color (i.e., calibration and validation) and shape (i.e., paddy and dryland/non-paddy).

2.2 Parameterization and validation of the RothC model

2.2.1 Model initialization and parameterization

RothC is a widely used soil organic matter turnover model to simulate temporal changes in SOC (Falloon & Smith, 2002; Guo et al., 2007). Within the RothC framework, SOC is divided into five compartments: decomposable plant material (DPM), resistant plant material (RPM), microbial biomass carbon (BIO), humified organic carbon (HUM), and inert organic carbon (IOM). DPM and RPM represent the organic carbon inputs, subsequently undergoing decomposition, leading to the production of CO_2, BIO, and HUM. Subsequently, BIO and HUM undergo decomposition, regenerating CO_2, BIO, and HUM in a consistent proportion. IOM represents a C pool presumed to be impervious to biological degradation, and its size can be estimated using Eq. 1 developed by Falloon et al. (1998):

$$IOM = 0.049 \times SOC^{1.139} \#(1)$$

where SOC is the total soil organic carbon density (Mg C ha^{-1}) at 0−30 cm soil depth. In contrast, the decomposition of all remaining soil pools follows a first-order decay, with the pre-defined rates (i.e. 10.0 a^{-1} for DPM, 0.3 a^{-1} for RPM, 0.66 a^{-1} for BIO and 0.02 a^{-1} for HUM) further modified by soil properties including temperature, moisture and clay content (Coleman & Jenkinson, 1996; Jenkinson, 1990). The default yearly rate constants were transformed into monthly rate constants (dividing by 12) to enable monthly time step simulations in the model. These monthly rate constants were then multiplied by a soil cover correction factor of 0.6, as the model was applied to ploughed land where the soil surface was covered by vegetation (Coleman & Jenkinson, 2014).

The main model inputs include monthly temperature, precipitation, evaporation, soil clay content, annual C input, DPM/RPM ratio, total initial SOC stock, initial SOC stock in the pools, soil cover information, and irrigation (Coleman & Jenkinson, 1996). The clay content of the soil was used to calculate how much plant available water the topsoil can hold and plays a pivotal role in SOM partitioning among the evolved CO_2, the BIO and the HUM pools (Coleman & Jenkinson, 2014). Annual C inputs for each experiment were either extracted from the relevant literature (see Table S1) or estimated using the method outlined by Huang et al. (2007) based on crop yields. It was assumed that organic C entered the soil at harvest time, as RothC demonstrates insensitivity to the timing of C input in long-term experiments (Smith et al., 2005). In configuring the model, the DPM/RPM ratio of the C input was set to 1.44, which is a typical value for most agricultural crops and grasses (Jenkinson and Rayner, 1977; Jenkinson, 1990).

When initializing various soil C pools within the model, a conventional method involves running the model incrementally until each pool reaches an equilibrium state. However, this process demands abundant computational resources, particularly when dealing with extended simulation durations or larger spatial scales (Wang et al., 2016). Alternatively, we applied a matrix approach and employed a steady-state assumption, where each C pool influx equaled its outflux when it reached a steady state (Luo et al., 2022). We then determined the proportions of the initial C pools using the RothC differential equations as formulated by Sierra et al. (2012). In general, the SOC simulation results across the 17 long-term experimental sites showed that the model initialized using this method yielded comparable results to the model initialized through the traditional spin-up method (Fig. S1).

The monthly temperature, precipitation, evaporation and irrigation served as key parameters in determining the environmental coefficient that influences SOC decomposition rates. In the model simulations, the environmental coefficient affecting decomposition rates was determined by Eq. 2:

$$xi = fT \times fW \#(2)$$

where xi is the environmental coefficient. fT represents the effects of temperature on decomposition rates calculated by the function in RothC model (Coleman & Jenkinson, 2014). fW represents the soil moisture coefficient, adjusting the default soil C decay rates, which was set to 0.6 for paddy soils with the reference of Huang et al. (2009). This value is based on laboratory incubation studies demonstrating decrease in decomposition rates of soil organic matter under flooded condition (Huang et al., 2001). In dryland soils, fW is determined by various environmental and management factors, including precipitation, evaporation and irrigation (Coleman & Jenkinson, 2014). Irrigation is one of the most common management practices in China's croplands, especially in arid and semi-arid regions, where rainfed conditions alone may not support crop growth throughout the growing season (Deng et al., 2006; Fu et al., 2003; Wang et al., 2002). While detailed information on the extent and frequency of irrigation at a large spatial and temporal scale is lacking, we simplified large-scale model simulations by assuming a value of 1 for fW in dryland soils. This assumption is based on the widespread adoption of irrigation in most dryland regions in China (Wang et al., 2008; Zhang et al., 2022), and we posit that irrigation can effectively mitigate the impacts of water scarcity on organic matter decomposition. The modifications on RothC were implemented using the codes provided in the SoilR package within the R software (Sierra et al., 2012).

2.2.2 Model optimization and validation

Although RothC model has been frequently used worldwide, its performance in projecting SOC dynamics across China's croplands has seldom been evaluated. Consequently, before performing the national scale model simulations, the key model parameters such as first-order decomposition rates of the four C pools (k_{DPM}, k_{RPM}, k_{BIO}, and k_{HUM}) in RothC model need to be calculated and validated. Here, SOC observations from 11 trials at 6 sites (Beibei, Chuxiong, Gongzhuling, Urumqi, Xuzhou, and Zhengzhou) were used to constrain the model parameters. Briefly, we employed a Bayesian method to optimize the four parameters using all measured data from the calibrating sites, regardless of treatment. Firstly, each parameter posited a uniform distribution within a certain range, and the range is set with reference to the study of (Wang & Luo, 2021): from 5 to 15 for k_{DPM}, 0.1 to 1 for k_{RPM}, 0.1 to 1 for k_{BIO}, and 0.001 to 0.1 for k_{HUM}. Within the prior distribution, 20,000 parameter sets were generated randomly adhering to the original relation sequence of RothC, namely $k_{DPM} > k_{BIO} > k_{RPM} > k_{HUM}$. Using these ensembles of parameters, we conducted 20,000 iterations of the adjusted RothC model. Subsequently, we calculated the root mean square error (RMSE) between the predictions and observations of SOC, and the parameter set with the lowest RMSE was regarded as the optimized parameters. The optimized parameters and the results for calibration were shown in the supplementary

(Fig. S2 and S3). The optimized RothC model was validated using independent datasets from 18 treatments at 11 sites (Fig. 1), and the performance of model was evaluated by RMSE and the determination coefficient (R^2) between SOC the predictions and observations.

2.3 Estimating SOC changes across croplands in China

Based on model inputs from RothC, a raster database was created to simulate SOC changes of China's croplands from 1980 to 2020 with a month time step. The database for the national scale model simulations includes monthly data of climate, soil properties, croplands spatial distribution and annual C inputs. The resolution of each raster data is 5' × 5' (~ 10 km × 10 km). Each grid has a set of model inputs, and the model is run grid by grid within the region.

2.3.1 Environment data for national scale simulation

In regional simulations, *fT* is calculated individually based on the monthly temperature data in each grid. Monthly mean temperature data from 1980 to 2020 were derived from the 1 km monthly temperature and precipitation dataset for China, which well captures the detailed climate characteristics over a long time series (Peng et al., 2019). The original data, with a resolution of 0.5'×0.5' (~1 km×1 km), was descaled to a resolution of 5'×5' (~10 km×10 km) by spatial aggregation in ArcGIS 10.4.

Soil properties encompassing clay content (%) and SOC stock (Mg C ha^{-1}) at 0−30 cm soil depth were from the Global Soil Dataset for use in Earth System Models (GSDE) (Shangguan et al., 2014). The GSDE is a dataset with the most abundant soil properties currently and has great performance on the estimation of SOC stock (Lin et al., 2023). Clay content at 0−30 cm soil depth was calculated by depth weighting (Xu et al., 2005). SOC stock for each soil depth was computed using SOC content (%), bulk density and coarse fragments by Eq. 3:

$$SOC_S = SOC_C \times BD \times D \times (1 - CF) \#(3)$$

where SOC_S is SOC stock (Mg C ha^{-1}), SOC_C is SOC content (%), BD is soil bulk density (g cm^{-3}), D is the depth of soil layers (cm), and CF is the fraction of >2 mm coarse fragments (%) in soils. Then SOC stock for each soil depth was aggregated for the depth of 0−30 cm, with detailed calculations provided in our previous work (Lin et al., 2023). All data were descaled to a resolution of 5’×5’ (~10 km×10 km), following the same method applied to the climate data.

Focusing on croplands, we employed the spatial distribution of croplands multi-period land use land cover dataset (CNLUCC) (Xu et al., 2018), including paddy and dryland fields. Since there were no yearly spatial data of cropland available throughout this time, data from 2000 were selected to represent the land use characteristics during the previous 4 decades. This delineation served as a mask to extract climate and soil data corresponding to cropland distribution. The soil moisture coefficient (fW) for each grid was set to 0.6 for paddy fields and 1 for dryland fields based on the distribution data from CNLUCC.

2.3.2 C inputs data for national scale simulation

Soil C inputs include crop residues, roots, rhizodeposition, and farmyard manure in the current agroecosystem. We estimated the C input of crop residues and roots by province based on six major crops: rice, wheat, maize, soybean, rapeseed and cotton. The cropping system in each province was determined according to the Cropping Rotation System Resources in China (CropSysChina) (Xu & Liu, 2014) and Multiple Cropping Systems of the World (Waha et al., 2020). For spatial calculations, the multi-year average net primary productivity (NPP) data from MODIS (MOD17A3) (Zhao et al., 2005; Zhao & Running, 2010) were used as weights to interpolate the crop C input statistics into raster data with a resolution of 5'×5' (~10 km×10 km). Due to a lack of gridded data on manure-derived C inputs to cropland in China from 1980 to 2020, we assumed that C inputs of manure to each grid within a province were the same as the province-wide average value. Thus, the annual C input for each grid was calculated by Eq.4-7:

$$CI_i = CIS_i + CIR_i + CIM_j \#(4)$$

$$CIS_i = CS_j \times SR_j \times NPP_i / MNPP_j \#(5)$$

$$CIR_i = (CR_j + 0.1 \times CS_j) \times NPP_i / MNPP_j \#(6)$$

$$CIM_j = CM_j \times MR_j \#(7)$$

where CI_i, CIS_i and CIR_i represent total C input, straw C input, and root and stubble C input for grid i. Generally, stubbles left on the ground from harvested crops reached about 10% of crop straws (Zhang et al., 2004). CIM_j represents the average manure C input for province j (j = 1, 2, …, 31) corresponding to grid i. Hong Kong, Macao, Taiwan regions were not considered due to data unavailability. CS_j, CR_j and CM_j represent average C content of straw, root and manure for province j, with details of calculation in Supplementary. SR_j and MR_j are the historical rate of straw and manure return to the field for province j. NPP_i represents the NPP for grid i and $MNPP_j$ represents the mean NPP for province j.

The C content of straw and roots were derived from the economic yield of each crop using the approach reported by Huang et al. (2007). Annual crop economic yield data by province from 1980 to 2020 were collected from the National Bureau of Statistics of China (https://data.stats.gov.cn/, last access: 10 March 2024). The relevant constants used in the calculations, including the ratio of residue to economic product, the ratio of roots to shoots, the fraction of C and dry matter for each crop were collected from published literature by Huang et al. (2007). Manure-derived C inputs were determined by factors such as the number of animals, annual excretion, the ratio of manure to urine, water content of manure, C fraction of manure, and collection coefficient. The number of animals was obtained from the National Bureau of Statistics of China and the other relevant constants were derived from NATESC (1999).

Historical rate of straw return to the field was collected from the studies of (Cai et al., 2011; Gao et al., 2002; Shi et al., 2023; Wang, 2011; Xie et al., 2020; Zhang et al., 2017), and the rate of manure return to the field was derived from the studies of Liu and Li (2017). Supplementary shows the detailed calculations of C content of straw, root and manure, and Figures 2 and S4 illustrate the spatial and temporal distribution of C inputs and C resources on croplands.

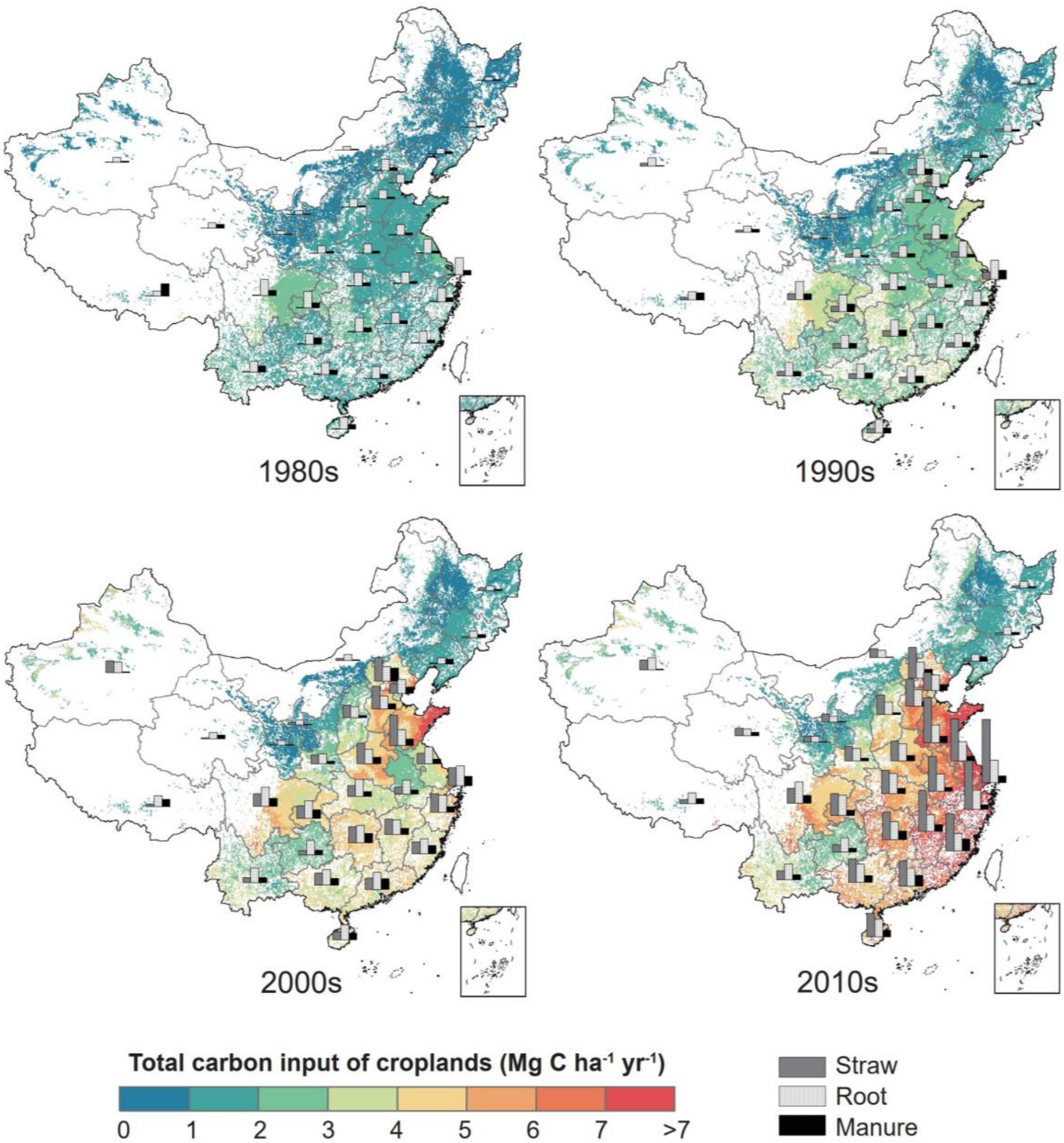

Figure 2. Spatial and temporal distribution of carbon (C) inputs in croplands of China. Hong Kong, Macao, Taiwan regions were not considered due to data

unavailability. The detailed data to each province is presented in Table S2.

2.3.3 Calculating SOC changes depending on management scenarios

To determine the influence factors on SOC sequestration, the simulation of SOC stock changes over the past four decades was carried out under five scenarios: TBL, BL, R, RM, SRM. TBL is considered a baseline scenario assumed without C inputs and climate change effects. In this scenario, croplands are lands without any C inputs from straws, roots and manure, with the assumed monthly temperature equivalent to that in 1980−1984. BL represents bare croplands without any C inputs from straws, roots and manure. R represents croplands with only C input from roots and stubble left on the ground from harvested crops (~10% of crop straws). RM represents croplands with C input from roots (including stubble) and manure. SRM reflects the actual C inputs, representing croplands with C inputs from straw, roots (including stubble), and manure. In the BL, R, RM and SRM scenario, temperature changes align the actual conditions from 1980 to 2020 (Table S3).

3 Results

3.1 Model performance for simulation of SOC stock

The calibrated RothC model underwent validation using SOC stock measurements across 18 treatments at 11 experimental sites. The validation results confirm that the calibrated model effectively captures overall SOC distribution across time and space. (Fig. 3a-k). In sites containing paddy, such as Nanxian, Suining, Taizhou and Wuchang, the simulated and measured values of SOC are closely aligned, indicating that the optimized model is effective for simulating SOC changes under flooded conditions. In control (Contr, with only C input from crop roots) management, SOC gradually declined, while increased under fertilization (i.e., Man, highMan, NPK-Man and NPK). In Harbin site, SOC decreased under both Contr and Man treatment. Overall, there was a strong correlation between simulated SOC and measured values, with R^2 of 0.93 and RMSE of 4.4 Mg C ha^{-1} (Fig. 3l). These findings demonstrate the reliable predictive capability of the optimized RothC model for SOC changes. Although parameter collinearity can potentially lead to biased SOC predictions, especially when model parameters are used for much longer periods than those in model calibrations, this is not the case in this study.

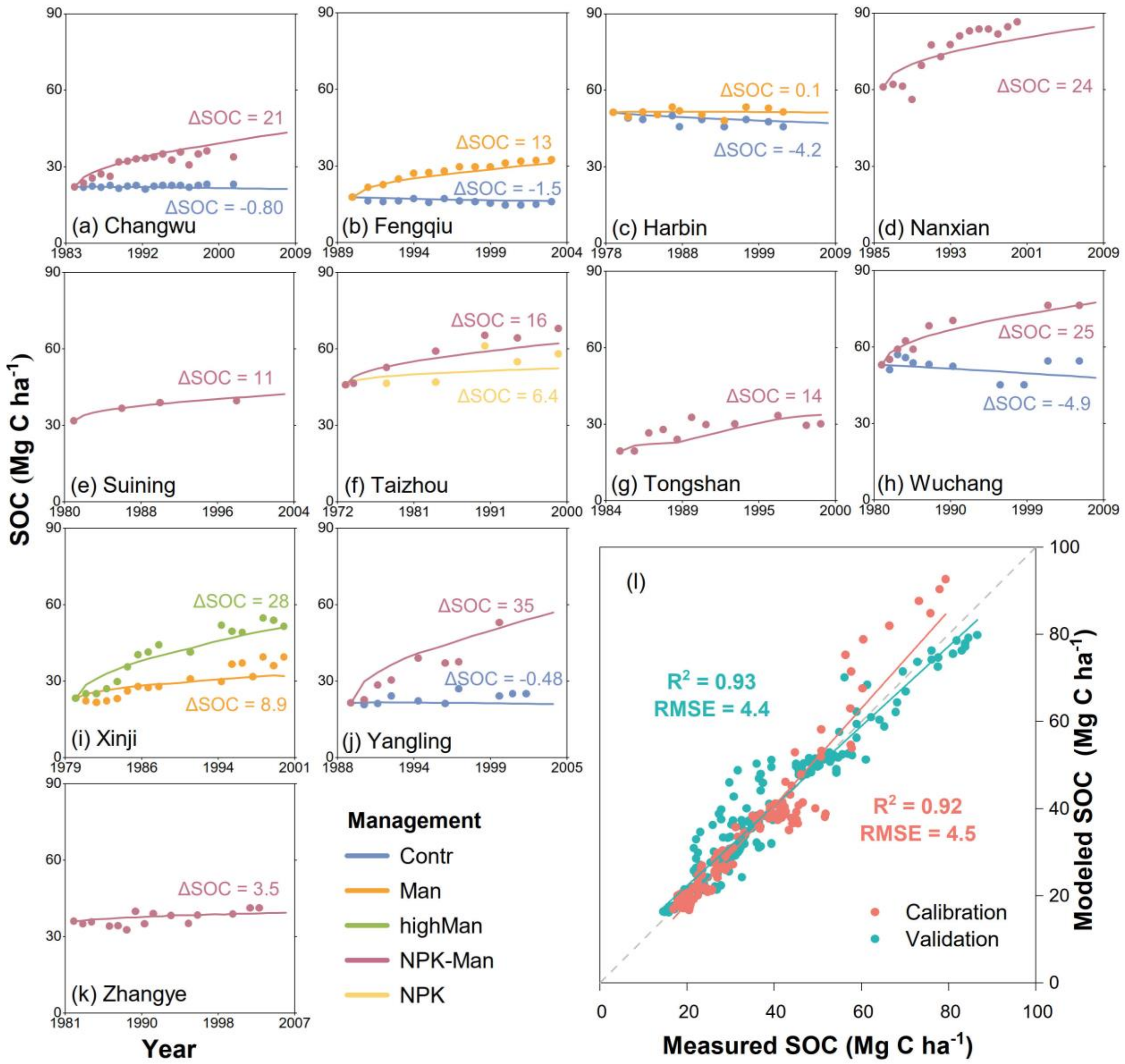

Figure 3. Measured and modeled SOC dynamics at experimental sites. (a-k) Modeled SOC under five fertilization treatments at 11 sites for validation. The points represent SOC analyses from the experiments. ΔSOC represents the difference between the initial and the final C stocks (Mg C ha^{-1}). Fertilizer treatments on these sites include control treatment with only C input from crop roots (Contr), manure (Man), high manure (highMan), manure and synthetic fertilizer (NPK-Man), and synthetic fertilizer inputs (NPK). (l) Modeled vs. measured SOC from calibration and validation. Dashed line is 1:1.

3.2 Spatiotemporal changes in SOC of croplands under historical C inputs

Our modelling results show a strong increasing trend in SOC based on actual C inputs (Fig. 4). The average SOC stock of China's croplands increased from 40 Mg C ha^{-1} in 1980 to 49 Mg C ha^{-1} in 2020, marking a 22% increment over time (Fig. 4e). In the earlier two decades, i.e., 1980s and 1990s, SOC increased slowly at average rates of 0.05 and 0.15 Mg C ha^{-1} yr^{-1}, respectively (Fig. 4e). In the latter two decades (2000−2020), however, the growth rate of SOC accelerated, reaching 0.34 Mg C ha^{-1} yr^{-1} on average (Fig. 4e).

On a regional scale, SOC increased in the in the northwest, north and central, southwest, south and central, and east and central regions, while decreased in northeast region (Fig. 4d). The most substantial increase in SOC was observed in the east and central region, where SOC stock on average increased by 18 Mg C ha^{-1} from 1980 to 2020 (Fig. 4h). Following closely were south and central (Fig. 4g), southwest (Fig. 4f), and north and central regions (Fig. 4b), with SOC increments of 14, 9.3, and 7.6 Mg C ha^{-1}, respectively. Compared with other regions, SOC of the northwest region increased slowly, with a gain of 5 Mg C ha^{-1} over the past four decades (Fig. 4a). Conversely, in the northeast region, SOC lost slightly from 58 Mg C ha^{-1} in 1980 to 57 Mg C ha^{-1} in 2020 (Fig. 4c). The multi-year average rate of SOC change (SOC_{mr}) reached less than -0.3 Mg C ha^{-1} yr^{-1} in the area with most pronounced SOC reduction of northeast region. (Fig. 4d).

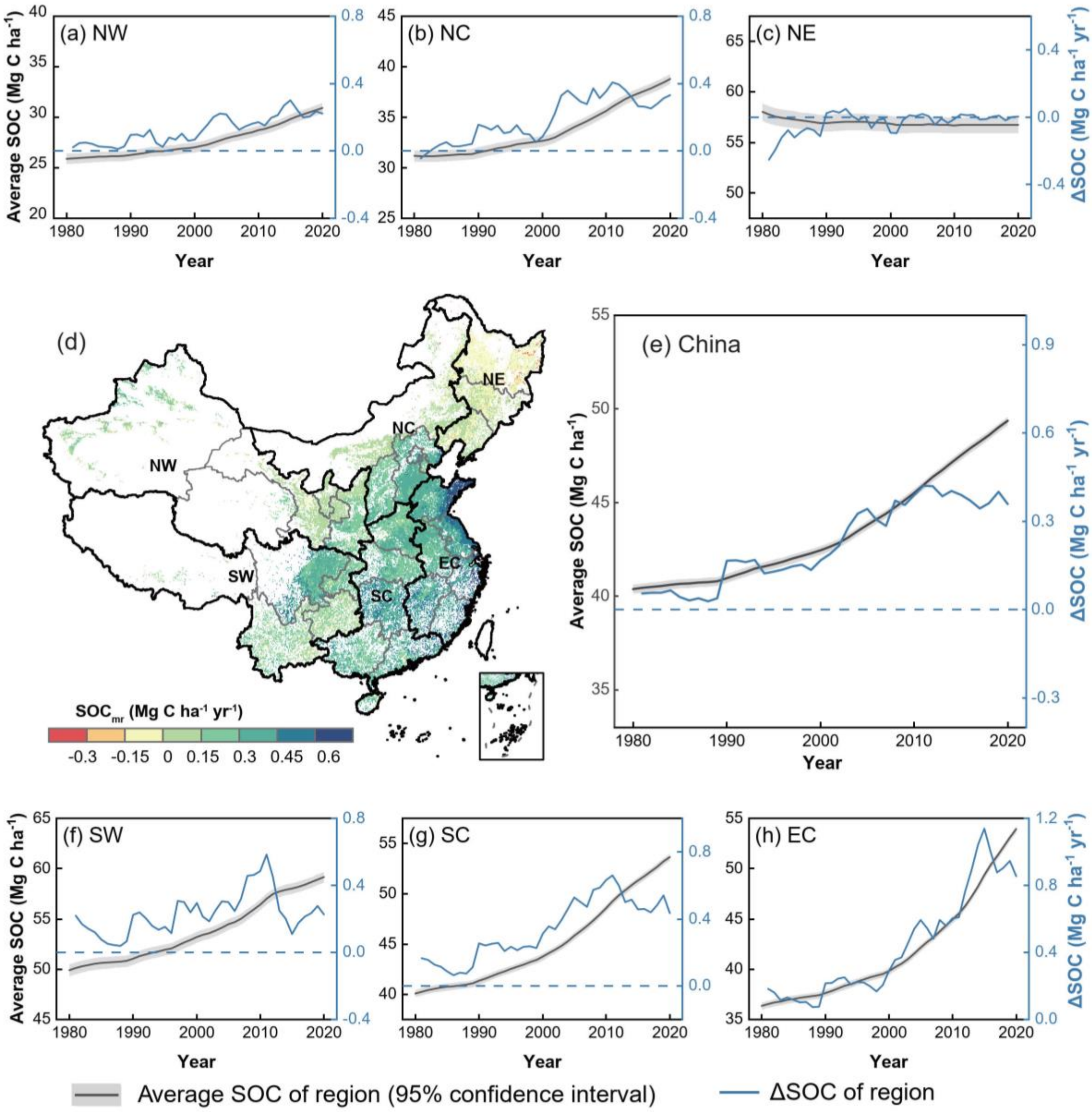

Figure 4. Spatiotemporal changes in SOC stock of croplands in China from 1980 to 2020. (a-c, e-h) Temporal changes in average SOC and ΔSOC of the representative six regions. ΔSOC represents SOC stock in the following year minus that in the previous year. NW, NC, NE, SW, SC and EC represent northwest, north and central, northeast, southwest, south and central, and east and central regions, respectively. (d) Spatial distribution in the multi-year average rate of change in SOC (SOC_{mr}). SOC_{mr}

represents the total change in SOC divided by time.

The results show that China’s croplands sequestrated 1100 Tg C in the soil from 1980 to 2020, with an average C sequestration rate of 27 Tg C yr^{-1} (Table S4). The greatest contributions to the net increase in SOC, approximately 68%, came from the east and central, and south and central regions. The cropland area in these regions accounted for about 40% of the total cropland area in China. SOC decreased in the northeast region despite the substantial area of croplands, comprising 18% of the total croplands. Over the past four decades, the northeast region has incurred a cumulative loss of 28 Tg C, with the greatest decline occurring during the 1980s.

3.3 Factors influencing the change of SOC in China's croplands

The organic C input played a pivotal role in the SOC increase, with straw return to the field proving to be the most influential factor (Fig. 5). Over the last four decades, the organic C input (SRM) resulted in a net SOC increase of 9 Mg C ha^{-1}, with root, manure and straw C inputs contributing 1.1, 2.2 and 5.8 Mg C ha^{-1}, respectively (Fig. 5a). While in BL scenario, where no organic C input was applied, SOC decreased overall, resulting in a net loss of soil C amounting to 5.8 Mg C ha^{-1} between 1980 and 2020, with the most pronounced decline in the southwest region (Fig. 5b). Compared to C inputs, temperature had a smaller effect on SOC changes. The modeled cropland SOC declines under BL and TBL scenarios were in general comparable (Fig. S5). Specifically, SOC decreases under the TBL scenario, where temperature remained constant, were about 0.14 Mg C ha^{-1} lower than that under BL scenario (Fig. 5a).

Notably, under the SRM scenario, the annual rate of SOC change (SOC_r) started at less than 0.2% yr^{-1} in the 1980s, it later reached approximately 0.4% yr^{-1} in the 1990s, and subsequently rose to about 0.8% yr^{-1} in both the 2000s and 2010s (Fig. 5a). Conversely, in scenarios without straw inputs, i.e., RM, R, BL and TBL, SOC_r remained below the 0.4% yr^{-1} over the past four decades, especially in the BL and TBL scenarios without exogenous organic C addition, where SOC_r was only around -0.04% yr^{-1} (Fig. 5a). It indicated that straw C input was the most predominant factor influencing SOC increase.

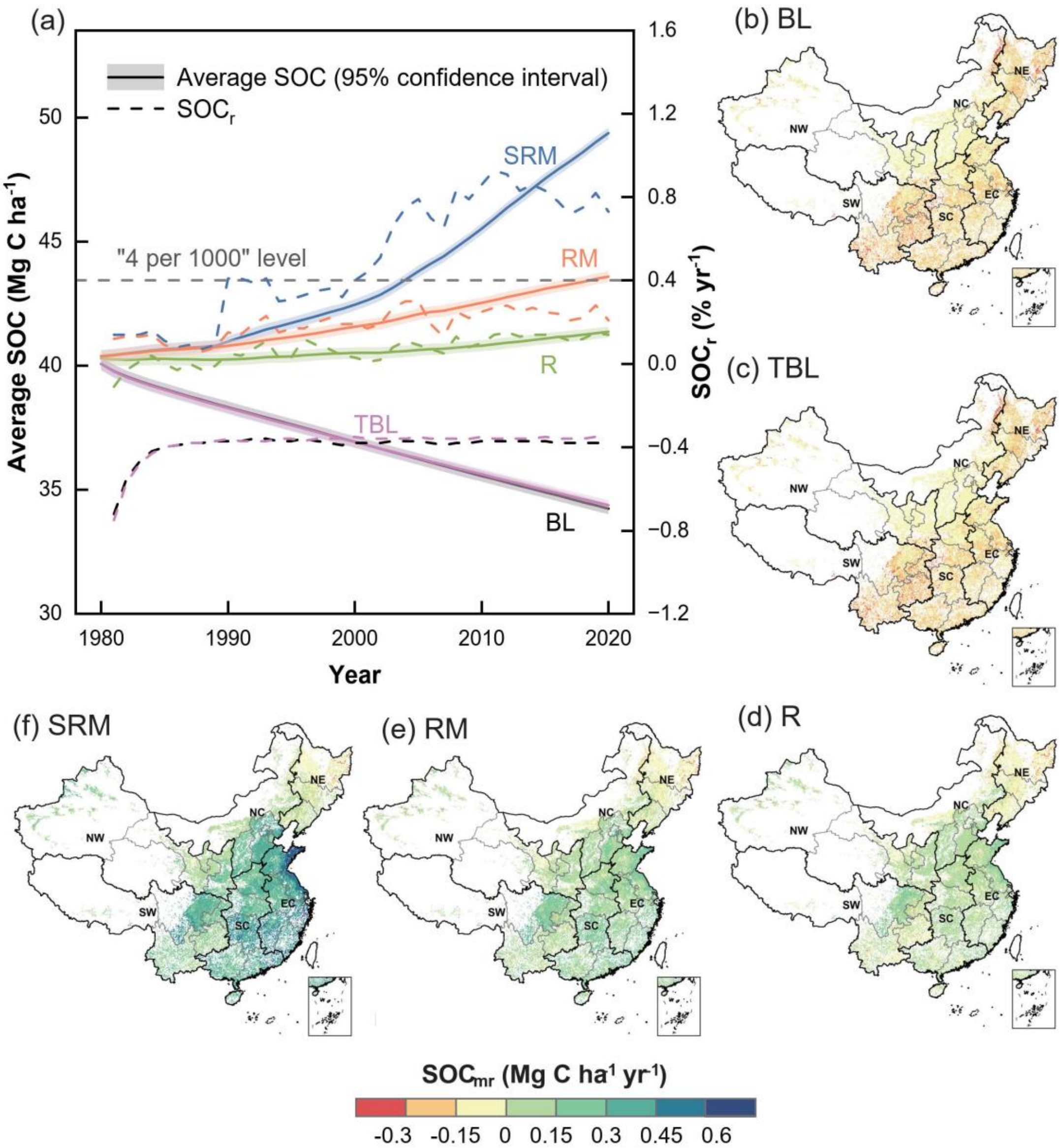

Figure 5. Changes in SOC of croplands from 1980 to 2020 depending on four scenarios. (a) Changes in average SOC of China and annual rate of SOC change (SOC_r) under five scenarios. The calculation of SOC_r is the annual change in SOC divided by SOC in the previous year. (b-f) Spatial distribution of multi-year average rate of change in SOC (SOC_{mr}) under five scenarios. SOC_{mr} represents the total change in SOC divided by time. BL: no C inputs. TBL: no C inputs and temperature

assumed as the same as that in 1980−1984. R: C input from roots and stubble (~10% of crop straws). RM: C input from roots (including stubble) and manure. SRM: historical C inputs with C input from straw, roots (including stubble), and manure.

4 Discussion

4.1 Comparison of changes in cropland SOC

The dynamics of topsoil SOC (0−30 cm) in China's croplands, as estimated by various studies revealed an increasing annual trend over the past four decades, with a range of 0.15−0.31 Mg C ha^{-1} yr^{-1} or 20−38 Tg C yr^{-1} (Table 1). SOC at the 0−30 cm depth increased at an average rate of 27 Tg C yr^{-1}, equivalent to 0.5% yr^{-1} (Fig. 5), consistent with previous studies (ranging from 0.36% to 0.8% yr^{-1}). This implies that China's cropland soils can essentially meet the target of the "4 per 1000" initiative proposed at COP21, with an aspiration to achieve 0.4% annual increase in soil organic matter stocks to offset global anthropogenic greenhouse gas emissions (Minasny et al., 2017). Spatial variation is evident in SOC dynamics across China's croplands, with increases observed in all regions except Northeast China (He et al., 2021; Pan et al., 2010; Yu et al., 2012). SOC stock in the northeast region decreased at a rate of 0.69 Tg C yr^{-1} due to high initial SOC concentrations (around 58 Mg C ha^{-1} on average), limited exogenous organic C inputs (Fig. 2), and the impacts of climate change, including warming and drought (Ou et al., 2017; Zuo et al., 2023).

While there is a consensus in literature about the Chinese cropland soils being sink of C over the past four decades, disparities among studies persist due to variations in monitoring cycles, management practices, and cropland areas. Yu et al. (2012) used the Agro-C model to estimate a SOC change rate of 24 Tg C yr^{-1}, and Ren et al. (2011) applying the DLEM model to estimate a rate of 21 Tg C yr^{-1}, slightly lower than the results of this study. The divergence is attributed to different study periods in different researches. In our study, we included the past decade (2010−2020), when crop yield and proportion of residues returned to the field reached the highest level in the past forty years (Fig. 2 and S2), resulting in increased C inputs and subsequent SOC sequestration. Using the DNDC model, Tang et al. (2010) estimated an overall SOC increase in China's croplands of 37 Tg in 2003. Ding et al. (2023) simulated a SOC increase of 38 Tg in 2020 in the same way and calculated the changes in SOC over the past 17 years by comparing with the results of Tang et al. (2010).These results were higher than our results, attributed to their focus on SOC changes in a certain year after 1999, when the government issued the crop residue return policy leading to more C into soil and SOC increasing rapidly (Li et al., 2018; MEE, 1999).

Differences in estimation methodologies and data sources also contributed to variations among studies. Based on a comprehensive literature analysis, Sun et al. (2010) simulated that SOC at 0−30 cm depth increased by 22 Tg C yr^{-1} between 1980 and 2000, while Pan et al. (2010) estimated that SOC at 0−20 cm depth increased by

26 Tg C yr^{-1} from 1985 to 2006. Utilizing data from the Second National Soil Survey of China in 1980 and 4,060 soil samples collected in 2011, Zhao et al. (2018) estimated a net increase of 18 Tg C yr^{-1} over the past three decades in the 0−20 cm soil of croplands. Similarly, to calculate SOC dynamics in croplands, He et al. (2021) used data from the International Plant Nutrition Institute China Program database, and Zuo et al. (2023) employed data from the Second National Soil Survey of China and the Soil Testing and Formulated Fertilization project. Their analyses reported a 24 Tg C yr^{-1} and 15 Tg C yr^{-1} increase in 0−20 cm SOC in croplands during 1991−2012 and 1980−2010, respectively.

Table 1. Changes in SOC of croplands in China from different studies.

Method	Area (Mha)	Depth (cm)	SOC stock (Mg C ha^{-1} yr^{-1})	SOC stock (Tg C yr^{-1})	Mean SOC_r [a)] (‰ yr^{-1})	Time span	Reference
RothC model	122	30	0.22	27	0.50	1980−2020	This study
DNDC model	121	30	0.31	38	0.63	2020	Ding et al. (2023)
DNDC model	118	30	0.31	37	0.74	2003	Tang et al. (2010)
Agro-C model	130	30	0.19	24	0.58	1980−2009	Yu et al. (2012)
DLEM model	141	20	0.11 (0.15) [c)]	16 (21)		1980−2005	Ren et al. (2011)
Meta analysis	130	20	0.20 (0.26)	26 (34)	0.61	1985−2006	Pan et al. (2010)
Meta analysis	130	30	0.17	22		1980−2000	Sun et al. (2010)
Soil samples (n=4060) [d)]	130	20	0.14 (0.18)	18 (24)	0.49	1980−2011	Zhao et al. (2018)
Soil samples (n=43743)	155	20	0.15 (0.20)	24 (31)	0.80	1991−2012	He et al. (2021)
Soil samples (n=7500000)	135	20	0.11 (0.15)	15 (20)	0.36	1980−2010	Zuo et al. (2023)

a) SOC_r represents the annual rate of 0−30cm SOC change. The calculation is the annual change in SOC divided by SOC in the previous year. When the time span is only one year, SOC_r represents the rate of change of SOC for that year.

b) The values in parenthesis represent adjusted estimates of 0−30 cm soil depth, based on a conversion factor of $SOC_{0–30}$: $SOC_{0–20}$ = 1.32 (Qin & Huang, 2010).

c) N is the number of soil samples used in the study.

4.2 Contribution of straw residues input to the C sequestration

The fertilizer management was effective to mitigate C losses from soils, while raising their role as C sinks, and straw return to the field was the most influential factor on SOC sequestration among fertilization management practices. From 1980 to 2020, the average SOC stock of China's croplands increased by 9 Mg C ha^{-1}, and contributions to this increase were derived from straw, manure, and root inputs, accounting for 5.8, 2.2 and 1.0 Mg C ha^{-1}, respectively (Fig. 5a). Root may contribute largely to soil C inputs, while crop residue may contribute more in certain places of China (Table S2). It is mainly because the majority of croplands are still under conventional tillage, which facilitates the covering straw entering the soils (Cai et al., 2015;Wang et al., 2024). To assess the conversion rate of straw residues C input into SOC, a linear regression analysis of straw inputs and SOC changes over the past four decades was conducted under the SRM scenario (Fig. 6). The slope of the fitted regression model was 0.17, indicating that about 17% of the straw C input has been sequestered in 0−30 cm of cropland topsoil in China over the past four decades.

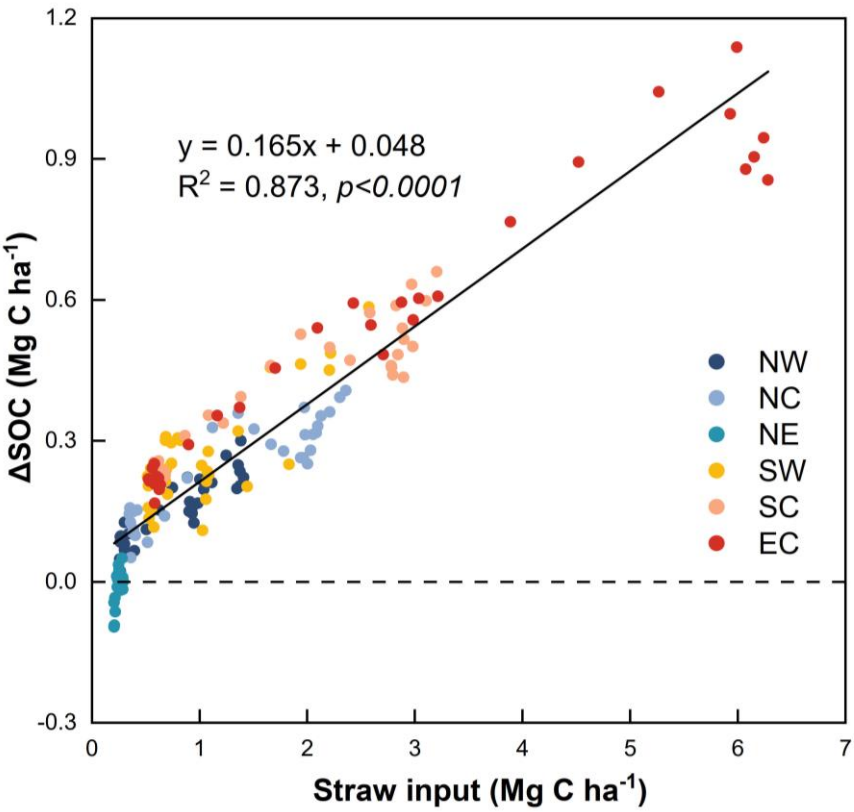

Figure 6. Relationship between ΔSOC and straw input in croplands from 1980 to 2020. ΔSOC represents SOC stock in the following year minus that in the previous year. NW, NC, NE, SW, SC and EC represent northwest, north and central, northeast, southwest, south and central, and east and central regions of China, respectively.

According to the current straw return practice, SOC sequestration in China's agricultural soils appears to essentially meet the goals of "4 per 1000" initiative during the study period. However, in Northeast China, the initial SOC level is high, while the rate of straw return to the field has been low. The straw C input has remained in the range of 0.1-0.3 Mg C ha^{-1} for a long time (Table S2). This prolonged low level of straw C input could not offset the SOC loss caused by respiration (Sun et al., 2010). Many other factors may have contributed to the loss of SOC, such as the change of cropping system (e.g. enlarged rice cultivation area) and crop land use intensity in NE region. For such regions with insufficient straw input, increasing the proportion of straw returned to the fields in the future is a potential strategy to achieve higher soil C sequestration rate and mitigate SOC loss. Conversely, in regions with a high proportion of straw return and a stable increase of SOC (such as east and south regions of China), it is possible to consider the comprehensive utilization of straw, such as bioenergy production. This approach, in addition to traditional straw return to the field, aims to maximize the ecological benefits of crop residue utilization in terms of C sequestration and the mitigation of greenhouse gas emissions (Shi et al., 2023; Xing et al., 2021).

In addition to the increased yield and return rate of crop residues during the study period, the substantial augmentation in SOC stocks may also be related to the low initial SOC levels in China's croplands due to long-term tillage (Zhao et al., 2018). Compared with other countries, policy-oriented agronomic management practices on China's croplands, such as adoption of conservation practices (including reduced tillage and no-tillage) and wide application of organic fertilizer, also promoted SOC sequestration (Deng et al., 2017). At the same time, the majority of croplands in China have adopted double or even triple cropping systems (Waha et al., 2020; Xu & Liu, 2014), and these complex crop rotations can increase SOC sequestration (Lal et al., 2021). It should be noted that the SOC accumulation at such high rate might be challenging in a long run, given that the SOC stock on China's croplands has reached a relatively high level (averaging about 49 Mg C ha^{-1} in 2020) through the last four decades. The impact of straw inputs on SOC sequestration diminishes as SOC stocks approach saturation levels, and many SOC models do not include the C saturation process, inevitably leading to simulation uncertainty (Qin et al., 2013; Stewart et al., 2007; West & Six, 2007). The SOC models (including RothC) could further benefit from more long-term observational data by improving modeling process (e.g., saturation), parameterization, and validation (e.g., with diverse C input types, timing, and initial SOC level).

5 Conclusions

Estimated by the optimized RothC model, SOC stock in the top 30 cm soils of China's croplands increased from 40 Mg C ha^{-1} in 1980 to 49 Mg C ha^{-1} in 2020, resulting in a total national carbon sequestration of 1100 Tg C, with an average annual carbon sequestration rate of 27 Tg C yr^{-1}. The most pronounced SOC increase was observed in eastern and southern China, constituting two-thirds of the total SOC gain, and SOC decreased by 28 Tg C in northeastern China. Organic C input, particularly from straw return to the field, emerged as the primary driver of SOC increase.

However, future strategies should prioritize on increasing the proportion of straw returned to fields in the northeast, where straw alone is insufficient, to prevent ongoing SOC decline. For regions with a consistent SOC increase, such as eastern and southern China, diversified straw utilization (e.g., bioenergy production), could be explored to further mitigate greenhouse gas emissions.

Data availability

All the source data of this study are available online and download links are provided in Table S5 of the Supplementary Information.

CRediT authorship contribution statement

Ziqi Lin: Data curation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Xinqing Lu:** Data curation, Investigation, Writing – review & editing. **Yifan Xu:** Data curation, Writing – review & editing. **Wenjuan Sun:** Writing – review & editing. **Yongqiang Yu:** Data curation, Investigation. **Wen Zhang:** Writing – review & editing. **Umakant Mishra:** Writing – review & editing. **Yakov Kuzyakov:** Writing – review & editing. **Guocheng Wang:** Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. **Zhangcai Qin:** Conceptualization, Methodology, Supervision, Resources, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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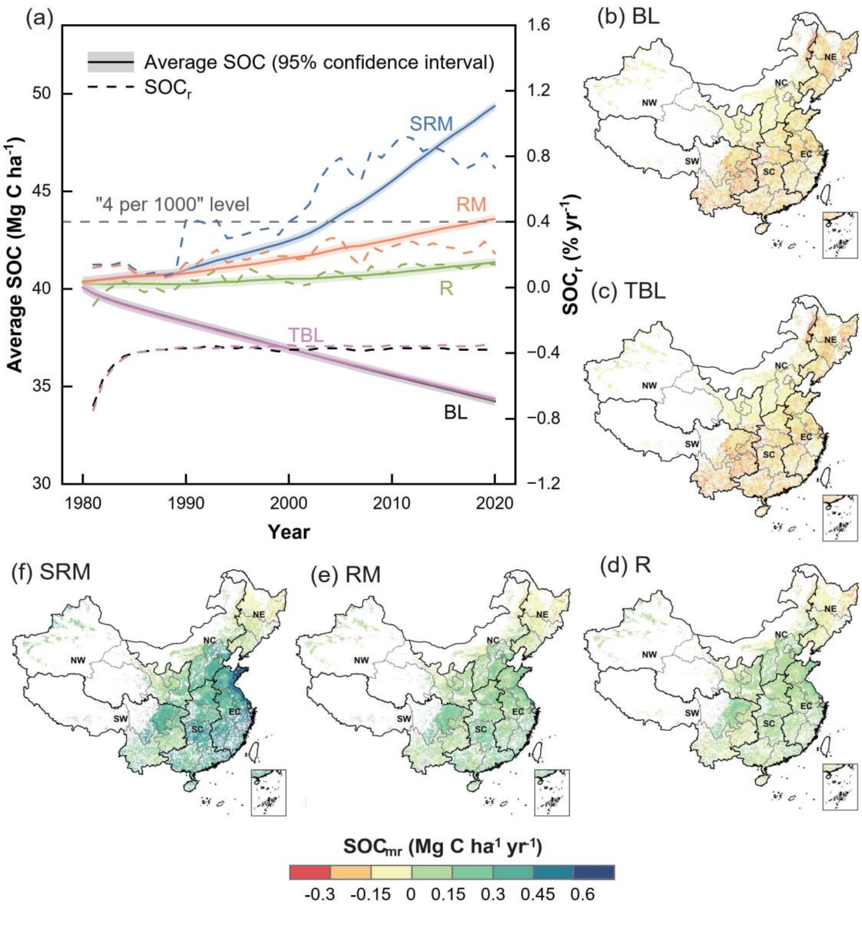
Graphical abstract



Highlights

- RothC is validated to better simulate spatiotemporal changes of SOC in China.
- The average accumulation rate of SOC surpassed 0.4% yr^{-1} since 2000.
- Enhanced organic C inputs, particularly straw return, drove SOC increase.

- Future strategies should optimize region-specific straw management.