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Organic carbon sequestration under straw return: Region-specific modelling framework

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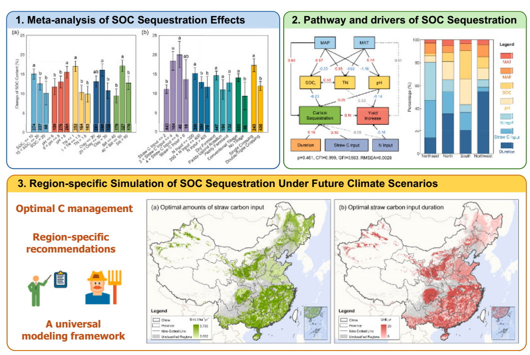
HIGHLIGHTS

- A modelling framework was developed to assess SOC responses to straw return in China.
- SOC gains are higher in alkaline soils with more straw, long duration and moderate N.
- SOC sequestration varies regionally, with an average <4% of straw C stored as SOC.
- Low rainfall limits SOC in Northwest; liming acidic soil in South raises SOC by ~10%.
- Over 20 years, SOC gains highest in Northeast (1.4) and South (0.83 t ha^{-1}) China.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Straw return is widely used to sustain yields, mitigate climate change, and increase soil fertility. However, regional differences in climate, soil, and management lead to divergent magnitudes of soil organic carbon (SOC) responses, while the underlying mechanisms remain unclear.
OBJECTIVE: This study integrates meta-analysis and structural equation modelling to assess topsoil (0–20 cm) SOC responses to straw return across mainland China.
METHODS: K-Means clustering and random forest models were further used to simulate optimal straw carbon input strategies and SOC sequestration potential under future climate scenarios.
RESULTS AND CONCLUSIONS: In arid Northwest China, increasing precipitation raised SOC retention, whereas excessive rainfall in the South and Northeast suppressed C accrual. Alkaline soils (pH > 8) sequestered more SOC than acidic ones due to slower straw decomposition and Ca^{2+} stabilization. Larger straw inputs and longer durations generally increased SOC, though with diminishing marginal benefits. Excessive nitrogen fertilization reduced SOC gains by accelerating acidification and decomposition. Carbon sequestration was region-specific. The highest cumulative increase occurred in the Northeast (1.4 t ha^{-1}) under moderate inputs (3.6 t ha^{-1}

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yr^{-1} for 11 years), followed by the South, where high inputs and long durations (4.7 t ha^{-1} yr^{-1} for 19 years) yielded 0.83 t ha^{-1}. In contrast, gains were lower in the North and Northwest (~0.40 t ha^{-1}) despite extended durations or optimized practices. SOC sequestration in the South would increase by 10% through amelioration of soil acidity.

SIGNIFICANCE: These findings offer insights into regionally tailored SOC responses and a transferable modelling framework for sustainable agricultural C management worldwide under climate change.

1. Introduction

Soil is the largest terrestrial carbon (C) reservoir (Bradford et al., 2016) and stores an estimated 1500–2400 Gt of soil organic carbon (SOC); which is approximately three times the amount in the atmosphere (Patton et al., 2019; Eglinton et al., 2021; Raza et al., 2024). SOC is critical for climate regulation (Lal et al., 2021); soil health; food security; and sustainable agricultural production (Vermeulen et al., 2019; Sun et al., 2020). However, long-term intensive cultivation, residue removal, and excessive fertilizer use have accelerated widespread SOC depletion (Song et al., 2005; Lal, 2007), contributing to the degradation of approximately 75% of global soils (Kopittke et al., 2019; Beillouin et al., 2023; Nogrady, 2024). Climate change further exacerbates soil degradation, threatens productivity, and intensifies greenhouse gas (GHG) emissions from agriculture (Jiang et al., 2024; Yang et al., 2024).

Meeting key United Nations Sustainable Development Goals (SDGs), "No Poverty", "Zero Hunger", and "Climate Action", requires the urgent adoption of nature-based solutions (NbS) to restore soil health and increase C sequestration (Griscom et al., 2017; UN, 2015). The Recarbonization of Global Soils Initiative (RECSOIL) advocates the sequestration of SOC through sustainable agricultural practices to address climate change (Zhao et al., 2024) and restore soil fertility (FAO, 2019). Among these methods; returning crop residues is a cost-effective strategy to increase SOC stocks (Amelung et al., 2020; Zhao et al., 2018a) while stabilizing the soil structure and increasing water retention (Zhao et al., 2020) and crop yields (Ma et al., 2023; Moinet et al., 2023). In parallel, the "4 per 1000" initiative emphasizes the importance of site-specific management to achieve SOC sequestration goals (Chabbi et al., 2017). Accordingly; straw inputs should be tailored to local soil and climate conditions (Mo et al., 2024) and integrated with recommended management practices (RMPs); such as crop rotation; no-tillage; cover cropping; and optimized nitrogen fertilization (Han et al., 2016; Jian et al., 2020; Kan et al., 2022).

As one of the world's major agricultural producers, China feeds 22% of the world's population, with only 7% of the global cropland (Piao et al., 2010; Ye et al., 2020). However, the prolonged reliance on high-input, resource-intensive agricultural practices has placed unsustainable pressure on cropland systems, pushing them beyond planetary boundaries (Campbell et al., 2017). Moreover; China generates an estimated 865 million tons of crop straw annually; making it one of the most straw-abundant countries (Zeng et al., 2007; State Council, PRC, 2020). Returning straw to cropland, when properly managed, not only increases crop yields and soil fertility but also substantially reduces GHG emissions that are associated with open-field burning (Li et al., 2018).

Current research on the impacts of straw return on SOC sequestration in croplands can be broadly categorized into three main approaches. First, meta-analyses and systematic reviews have quantified the effects of straw return on SOC sequestration (Liu et al., 2014; Tian et al., 2015; Gross and Glaser, 2021; Lin et al., 2023b). Second, process-based models (e.g., Agro-C, DNDC, EPIC, and Century), when calibrated and validated with field observations, simulate crop and SOC dynamics at site to regional scales (Wang et al., 2015; Le et al., 2018; Lin et al., 2024c; Zhang et al., 2017). Third, data-driven statistical and machine learning models leverage survey and meta-analysis data to identify the key drivers of SOC sequestration and construct predictive frameworks (Lin et al., 2024a; Wu et al., 2024; Kasim and Ghassan, 2023).

Despite growing attention, key uncertainties persist regarding the effectiveness and scalability of straw return to increase SOC sequestration. Most studies lack spatial stratification or still rely on broad classifications (e.g., climate zones), overlooking heterogeneity that is driven not only by soil–climate interactions (Wang et al., 2021) but also by regional land-use histories and management practices shaped by social and economic contexts. For example; SOC is severely depleted on the Loess Plateau due to long-term erosion (Zheng and Wang, 2014); the North China Plain; which is often reclaimed from saline-alkali soils; has a low SOC content (Liao et al., 2015); and southern paddy fields are increasingly acidified (Liang et al., 2023; Wang and Kuzyakov, 2024). The data-driven models, although predictive, often lack explanatory power for ecological–management linkages. Estimates of SOC sequestration potentials at fine spatial resolutions also remain insufficient, limiting their utility in guiding region-specific straw return strategies.

To develop optimized pathways for cropland SOC sequestration that are regionally adaptable, mechanistically explicit, and policy-relevant, it is imperative to conduct systematic research on regional mechanisms and the spatial optimization of management strategies. This study aims to assess the regional heterogeneity in SOC responses to straw return across diverse environmental conditions and management regimes in China and to develop a meta-model and further simulate the regional sequestration potential of SOC in croplands under four climate scenarios (e.g., SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5). Accordingly, a meta-analysis was first applied to evaluate the impacts of straw return on SOC changes and establish an integrated analytical framework. A structural equation model (SEM) was constructed to clarify the causal relationships linking straw return to SOC sequestration. K-means clustering is subsequently performed using climatic and soil attributes to delineate agroecological zones. Within each zone, random forest (RF) models are used to identify the key drivers of SOC sequestration. On this basis, the amounts and durations of straw input were optimized at the grid scale using RF models, and adaptive strategies were formulated for specific regional contexts and future climate scenarios.

To further explore management interventions, optimized soil pH amelioration strategies were simulated to assess the potential of soil remediation for increasing SOC stocks in southern China croplands. These findings contribute to a deeper understanding of the region-specific SOC sequestration responses to straw return and provide a data-driven basis for designing locally adapted straw management strategies. Moreover, the modelling framework established in this study offers a transferable approach for informing sustainable C management in agricultural systems worldwide under a changing climate.

2. Materials and methods

2.1. Data collection

To systematically assess the impacts of straw return on SOC, a database was compiled on the basis of peer-reviewed meta-analyses that were retrieved from the ISI Web of Science (http://apps.webofknowledge.com/). The initial search was performed on October 31, 2023, and updated on January 9, 2026, using the search string: ("meta-*analysis" OR "systematic review") AND ("soil organic carbon" OR "SOC" OR "soil organic matter" OR "SOM" OR "soil carbon") AND ("straw" OR "residue"). Relevant meta-analyses were identified and manually screened for inclusion. The original studies cited within these meta-analyses were further reviewed. The studies were independently assessed by at least two coauthors and used the following inclusion criteria: (1) the experiment was conducted in China with a paired design comparing straw return to straw removal as the sole treatment; (2) the study was a field-based trial with a minimum duration of three years and did not involve straw decomposition agents (Pal and Broadbent, 1975; Liu et al., 2014; Cai et al., 2018); (3) the publication reported essential experimental information, including geographic coordinates (longitude and latitude), sample size, experiment duration, and soil sampling depth; and (4) the mean and standard deviation (SD) of the topsoil SOC content (g kg^{-1}) were clearly reported.

This study focused specifically on changes in the SOC content within the topsoil (0–20 cm). For studies that did not report the SOC exactly at 20 cm, the value closest to this depth was selected as a proxy (Wang et al., 2013). When only the soil organic matter (SOM) was reported; the SOC content was estimated by multiplying by a conversion factor of 0.58 (Han et al., 2016). If the standard error (SE) was reported instead of the standard deviation (SD); SD was calculated using the formula $SD = SE \times \sqrt{n}$; where n denotes the sample size. For studies lacking both SDs and SEs; the SD was approximated as 10% of the mean value (Luo et al., 2006). Where available, crop yield per hectare (t ha^{-1}; hereinafter yield) data were also recorded alongside the SOC measurements. If the same experimental dataset was published in multiple sources, it was included only once to avoid duplication. In total, the meta-analysis dataset includes 120 publications and 140 experimental sites (see Fig. 1), with 679 paired observations comparing the SOC contents between the straw return (treatment) and control groups. Among these, 408 paired observations (60%) also contain crop yield data. The detailed literature screening procedure is provided in Supplementary Method S1 and illustrated in Fig. S1.

Information on geographic attributes (e.g., latitude and longitude); climate variables (e.g. mean annual temperature (MAT) and mean annual precipitation (MAP)); and soil properties, including the initial soil organic carbon (SOC_i) content, soil pH, total nitrogen (TN), cation exchange capacity (CEC), clay (Clay) and silt contents (Silt), and bulk density (BD), were collected (summarized in Table 1). Categorical variables, including tillage methods, farmland types, crop rotation frequencies, and crop types, were also recorded. Chemical and organic inputs, including nitrogen (N Input), phosphorus (P Input), potassium (K Input), and straw carbon (Straw C Input), were recorded or estimated on the basis of the reported application rates. For studies reporting straw biomass input, the Straw C Input was estimated on the basis of straw type and corresponding C content (Huang et al., 2007). In cases where the straw input was not reported but the crop yield was available; straw yields were estimated using the grain-to-straw ratio (Song et al., 2018).

Fig. 1. Geographic distribution of long-term straw return experiments and agroecological zoning of croplands across China. The circles indicate sites with observations of SOC content only ($n = 271$), whereas the stars represent sites with both SOC and crop yield observations ($n = 408$). The four colours correspond to the agroecological zones identified through K-means clustering. Lighter-coloured grid cells depict the spatial distribution of Chinese croplands classified by climate and soil attributes. The grey grid cells denote cropland areas that were not classified (i.e., below the classification threshold).

Table 1
Indicators and explanations.

Categories	Indicators	Explanations and Classifications
Climate Conditions	MAT	Mean Annual Temperature (°C)
	MAP	Mean Annual Precipitation (mm)
Soil Properties	SOC_i	Initial SOC (g kg^{-1})
	pH	pH Level
	CEC	Cation Exchange Capacity (cmol kg^{-1})
	TN	Total Nitrogen (g kg^{-1})
	Clay	Clay Content (g kg^{-1})
	Silt	Silt Content (g kg^{-1})
	BD	Bulk Density (g cm^{-3})
Chemical Input	N Input	Nitrogen Fertilizer Input (kg ha^{-1} yr^{-1})
	P Input	Phosphorus Fertilizer Input (kg ha^{-1} yr^{-1})
	K Input	Potassium Fertilizer Input (kg ha^{-1} yr^{-1})
Carbon Input	Straw C Input	Straw Carbon Input (t ha^{-1} yr^{-1})
Management Measures	Tillage Methods	Conventional Tillage; No Tillage
	Farmland Types	Dry Farmland; Paddy Farmland; Paddy-Upland Rotation
	Crop Frequency	Single Cropping; Double/Triple Cropping
	Duration	Duration of Experiment (yr)

When straw was applied through mulch; it was assumed that only 10% of the applied straw was distributed in the topsoil; accounting for losses due to wind and microbial decomposition (Xiao et al., 2022). For studies where data were presented graphically; values were extracted using WebPlotDigitizer v5. Missing climate data were supplemented using the WorldClim database (https://worldclim.org) (Fick and Hijmans, 2017). Given the demonstrated reliability of the Global Soil Dataset for Earth System Modelling (GSDE) in China's cropland regions; missing soil variables were imputed using GSDE data (Shangguan et al., 2014; Lin et al., 2024b). Detailed descriptions of the climate and soil variables are provided in Supplementary Method S2. A summary of the modelling approach and all the variable types is provided in Table S2.

2.2. Meta-analysis

A random effects model was used to quantify the effects of various soil properties and management practices on changes in SOC under straw return at the macro scale. The log response ratio (*RR*) was used as the effect size to represent the SOC response (Hedges et al., 1999), which was calculated as:

$$RR = \ln(\overline{X}_t/\overline{X}_c) \tag{1}$$

where $\overline{X_t}$ and $\overline{X_c}$ denote the mean SOC values in the treatment group (straw return) and the control group (no straw return), respectively.

The sampling variance (v) for each *RR* was computed as:

$$v = \frac{S_t^2}{N_t\overline{X}_t^2} + \frac{S_c^2}{N_c\overline{X}_c^2} \tag{2}$$

where S_t and S_c are the standard deviations and where N_t and N_c are the sample sizes of the treatment and control groups, respectively.

Each study was assigned a weight (w):

$$w = \frac{1}{v + \tau^2} \tag{3}$$

where τ is the estimated between-study variance.

The overall effect size ($\overline{RR}$) was then calculated as the weighted average across all observations:

$$\overline{RR} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij} lnRR_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} w_{ij}} \tag{4}$$

where m ($i = 1, 2, \ldots$, m) refers to the number of subgroups (e.g., tillage methods and farmland types) and where n ($j = 1, 2, \ldots$, n) represents the number of observations within each subgroup.

To facilitate interpretability, the average effect size was back-transformed into the percentage change in SOC due to straw return using the following equation:

$$\%\Delta SOC = [exp(RR) - 1] \times 100 \tag{5}$$

Subgroup analyses were conducted using the *rma.mv* function from the metafor R package (Viechtbauer, 2010) to evaluate whether straw return had statistically significant effects on SOC sequestration across conditions. A treatment effect was considered significant if the 95% confidence interval (CI) did not overlap with zero (Hedges and Olkin, 2014). One-way analysis of variance (ANOVA) and least significant difference (LSD) tests were used to examine the heterogeneity among subgroups (Cauvy-Fraunié and Dangles, 2019). Publication bias was assessed using funnel plots and Egger's test (Egger et al., 1997), as detailed in Supplementary Method S3 and Fig. S2. To evaluate whether the findings from the univariate subgroup analysis were influenced by potential study-level confounding, we conducted a multivariable meta-regression using a random-effects model with the DerSimonian–Laird estimator (additional model specifications are provided in Supplementary Method S3).

All the statistical analyses were performed using R version 4.4.2.

2.3. Data analysis

A sequential analytical framework integrating meta-analysis, structural equation modelling (SEM), clustering, and machine learning was employed in this study. Meta-analysis and SEM were used to quantify SOC responses to straw return and guide feature selection. K-means clustering was used to delineate agroecological zones. Within each zone, region-specific random forest models were applied to identify key drivers of SOC sequestration and optimize straw management under current and future climate scenarios.

2.3.1. Causal analysis and feature selection

Structural equation modelling (SEM) was used to investigate the complex effects of climate, soil, and management factors on SOC sequestration and crop yield increases. SEM is a covariance-based statistical approach that quantifies both direct and indirect relationships among multiple variables by constructing a hypothesized causal framework (Fan et al., 2016; Jiang et al., 2026). It has been hypothesized that climatic factors directly influence soil properties; soil properties and management practices jointly affect SOC sequestration and crop growth; and SOC sequestration; in turn; increases crop yields. The conceptual pathway framework was developed based on previously established empirical and mechanistic studies (Lal, 2010; Mo et al., 2024; Niu et al., 2021; Zhang et al., 2023a; Zomer et al., 2017). The hypothesized pathways and model structure are presented in Supplementary Method S5 and Fig. S6. Model fits were evaluated using several goodness-of-fit indices, including the p value of the chi-square (χ^2) test, root mean square error of approximation (RMSEA), comparative fit index (CFI), and goodness-of-fit index (GFI) (Schermelleh-Engel et al., 2003). The direct and indirect pathways that were identified by the SEM provided a theoretical basis for feature selection in subsequent random forest (RF) modelling.

2.3.2. Classification of Agroecological regions

To conduct agroecological zoning and reveal regional heterogeneity in SOC sequestration mechanisms, spatial clustering was first performed on the basis of key climatic and soil attributes. A total of nine variables were selected that represented climatic conditions (MAT, MAP, SR, and WVP) and soil properties (SOC_i, TN, pH, Clay, and Silt) (Ye et al., 2023). These variables were used to conduct K-means clustering on the 679 samples (Hartigan and Wong, 1979). The performance of the K-means model was evaluated using multiple metrics; including the sum of squared errors (SSE); silhouette coefficient; Calinski–Harabasz (CH) index; and Davies–Bouldin (DB) index (Sinaga and Yang, 2020; Ye et al., 2022b) (see Supplementary Method S6 and Fig. S7 for details). Following transparent and reproducible decision-making principles (Hussein and Basel, 2024; Ren et al., 2025), the samples were clustered into four agroecological regions on the basis of these metrics and manual inspection: the northeastern region ($n = 70$), the northern region ($n = 116$), the northwestern region ($n = 177$), and southern region ($n = 316$) (see Fig. 1). These regions differed markedly in key environmental variables and were spatially contiguous, thereby providing a robust basis for the subsequent investigation of region-specific straw return mechanisms (details of clustering evaluation and sensitivity analysis are provided in Supplementary Method S6, Table S6 and Fig. S10).

To extrapolate the regional effects of straw return on SOC sequestration to the national cropland scale at a 1-km resolution, an RF classifier was trained on site-level data (see Supplementary Method S7 for parameter details). The classifier used nine clustering variables as input features and the four agroecological zones as the classification target. During prediction, each cropland grid cell was assigned to one of the four zones on the basis of its feature values, with a classification confidence threshold of 0.8. The raster grids covered the spatial distribution of Chinese croplands in 2020 (Du et al., 2024; Liu et al., 2023a; Ye et al., 2022a, 2024) and the classification results are presented in Fig. 1.

2.3.3. Region-specific modelling of SOC sequestration

A random forest (RF) model (Breiman, 2001; Han et al., 2026) was used to analyse the effects of straw return on changes in SOC content depending on environmental and management conditions. Guided by the causal relationships established through SEM, the model incorporated climatic variables (MAT and MAP); soil properties (SOC_i and pH); and management practices (Straw C Input, N Input, and Duration) as predictor features. Feature importance scores were used to identify the key drivers influencing the rate of SOC change. Model performance was evaluated using the root mean square error (RMSE) and coefficient of determination (R^2) (Xu et al., 2024). The R^2 values were derived from site-level spatial cross-validation; in which all observations from the same location were assigned exclusively to either the training or testing set; thereby reducing information leakage arising from spatial autocorrelation. (see Supplementary Method S7 for details of the partitioning strategy). In addition; partial dependence plots (PDPs) (Greenwell, 2017) were generated to visualize the nonlinear relationships between selected predictors (e.g., MAP) and SOC change rates.

Subsequently, at a 1-km grid resolution, the responses of regional SOC sequestration to straw return practices, including straw input levels and durations, were simulated under future climate scenarios via region-specific RF regression models. Climate projections were derived from the BCC-CSM2-MR model under four shared socioeconomic pathways (SSPs), namely, CMIP6: SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5 (hereinafter SSP1, SSP2, SSP3, and SSP5, respectively). The mean temperature and precipitation data for the period of 2021–2040 were extracted as model inputs (Wu et al., 2021). In addition to climatic variables; the model incorporated SOC_i; soil pH; and N Input (Yu et al., 2021, 2022), along with a matrix of 180 management scenarios consisting of 10 straw input levels and 18 treatment durations ranging from 3 to 20 years (see Supplementary Method S7 and Table S8 for variable settings). For each cropland grid cell, the optimal management strategy—the combination that produced the maximum rate of increase for SOC —was identified. The corresponding straw input level, duration, SOC stock, and C conversion ratio (i.e., the proportion of straw C input converted into SOC over the treatment period) were recorded. Finally, by integrating the spatial distribution of croplands, the total SOC sequestration potential was estimated at both the national and regional scales under each climate scenario, and region-specific strategies for straw C input were proposed.

The calculations of SOC_{stock} and BD were based on the formulas proposed by Guo and Gifford (2002) and Sun et al. (2020b) (Guo and Gifford, 2002; Sun et al., 2020):

$$SOC_{stock} = SOC_{conce} \times BD \times h \times 0.1 \tag{6}$$

$$BD = \frac{100}{\frac{SOM}{0.244} + \frac{100-SOM}{1.64}} \tag{7}$$

$$SOM = SOC_{conce} \times 1.724 \times 0.1 \tag{8}$$

where SOC_{conce} is expressed in g kg^{-1}, SOM is reported as a percentage, and the soil depth h is fixed at 20 cm.

All analyses in this section were performed using Python 3.9 and ArcGIS Pro.

3. Results

3.1. Meta-analysis of the effects of SOC sequestration

A subgroup analysis of %ΔSOC responses to straw return was conducted across Chinese croplands to account for the differences and specific values in soil properties and management practices. Conditions such as unsaturated initial SOC (SOC_i), high *Straw C Input*, slightly alkaline pH, loamy soil texture, and moderate tillage are associated with greater SOC sequestration (Fig. 2; Supplementary Table S3). The SOC sequestration efficiency decreased with increasing SOC_i: when the SOC_i was less than 10 g kg^{-1}, the %ΔSOC reached 15 ± 1.3%, but it decreased when the SOC_i exceeded 20 g kg^{-1}. The response to Straw C Input was nonlinear. Across the lower input range (<6 t ha^{-1} yr^{-1}), %ΔSOC generally increased, with the highest mean value (20 ± 3.4%) observed within the 4–6 t ha^{-1} yr^{-1} interval. However, inputs above this threshold suppressed sequestration, with %ΔSOC decreasing to 14 ± 5.1%.

Alkaline soils (pH > 8) were associated with greater SOC gains (16 ± 1.5%) than were less alkaline soils. Moderate clay (20–30%) and silt (40–50%) contents also contributed to increased sequestration. Nitrogen surplus was a major driver: soils with TN < 1 g kg^{-1} had the highest %ΔSOC (17 ± 1.4%) values, whereas excessive N Input (>400 kg ha^{-1} yr^{-1}) led to reduced gains (12 ± 2.7%). Among farmland types, dryland systems performed best (15 ± 1.2%). Conventional tillage, which facilitates straw incorporation, resulted in greater sequestration (14 ± 1.0%) than did no-tillage (9.3 ± 3.6%). Similarly, single-cropping systems (17 ± 1.7%) outperformed multicropping systems (12 ± 1.2%) in terms of SOC sequestration.

The multivariable meta-regression showed a significant overall moderator effect (QM, $p < 0.001$) and reduced between-study variance (τ^2) by 18%. The directions of the main effects were generally consistent with the univariate subgroup analysis. Full results are provided as a robustness assessment in Supplementary Table S4.

3.2. Causal relationship between SOC sequestration and crop yield increases

We developed an SEM to evaluate the effects of straw return on both SOC sequestration and crop yield increases (Fig. 3). The model fit indices indicated a good overall model fit, with a chi-square p value of 0.461, RMSEA of 0.0028, and CFI and GFI values of 0.999 and 0.983, respectively (see Supplementary Table S5 for additional path coefficients and significance levels). The proposed causal framework is robust and offers theoretical insights into the underlying mechanisms involved. Overall, climatic factors had direct effects on soil properties, and both factors jointly influenced SOC sequestration and crop productivity.

For SOC sequestration, increased MAP contributed to greater plant growth and C input ($\beta = 0.53$, $p < 0.001$). Other influential factors aligned with the patterns observed in Sections 3.1 and 3.2: SOC sequestration increased with lower SOC_i ($\beta = -0.23$, $p < 0.001$), higher pH ($\beta = 0.39$, $p < 0.001$), longer durations ($\beta = 0.16$, $p < 0.001$), and greater Straw C Input ($\beta = 0.10$, $p < 0.05$). In contrast, the drivers of

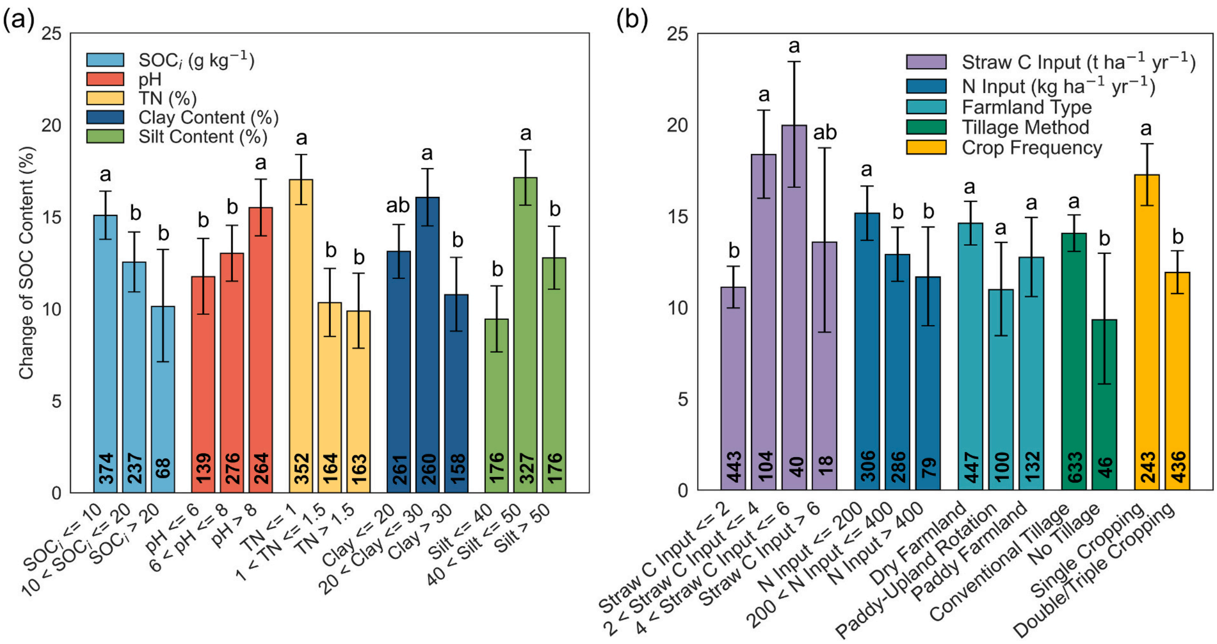

Fig. 2. Subgroup analysis of the effects of straw return on SOC sequestration, stratified by soil properties and management practices. The bars show the mean effect sizes with 95% confidence intervals (CIs). Letters (a, ab, and b) indicate significant differences between subgroups. The numbers on the bars represent the sample size within each subgroup.

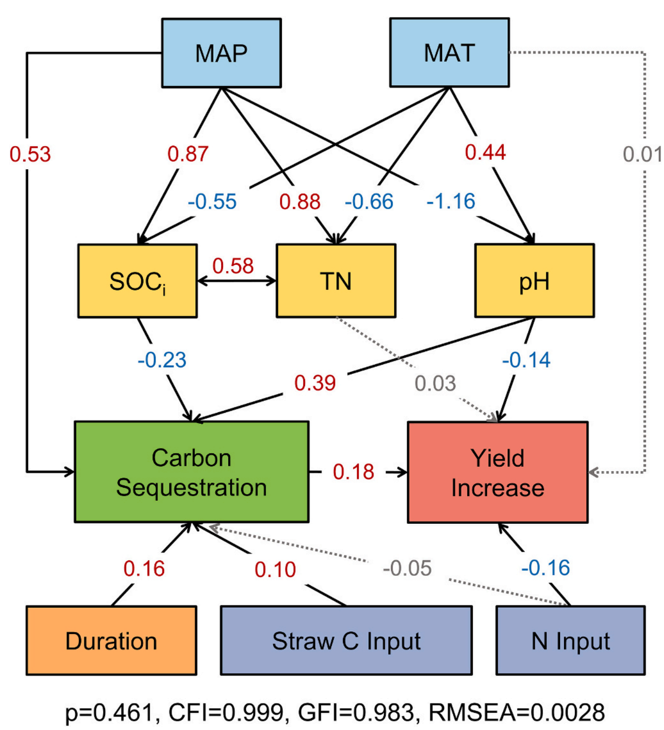

Fig. 3. SEM of SOC sequestration and crop yield increase. Black arrows indicate statistically significant paths ($\alpha < 0.05$), while grey dashed arrows represent $\alpha \geq 0.05$. Numbers on the paths denote standardized coefficients (β) between variables. The colours represent different variable groups: blue for climate variables (MAT and MAP); yellow for soil properties (TN, SOC$_i$, and pH); orange for duration; purple for management practices (N Input, Straw C Input); green for the SOC sequestration effect ($ln\frac{SOC_t}{SOC_c}$); and red for the yield increase effect ($ln\frac{Yield_t}{Yield_c}$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

yield increases followed specific pathways. In acidic soils ($\beta = -0.14$, $p < 0.05$), cations such as potassium, calcium, and magnesium from straw help neutralize soil acidity, increasing soil quality and crop productivity. However, high N Input ($\beta = -0.16$, $p < 0.01$) was associated with reductions in yields, reflecting the widespread overuse of fertilizers in Chinese croplands. A higher SOC$_i$ led to greater TN ($\beta = 0.58$, $p < 0.001$), as microbial activities and nutrient cycling increased accordingly, reflecting tight C-N coupling. As SOC accumulates, the amelioration in soil physicochemical properties creates a more favourable environment for plant growth, ultimately increasing crop yields ($\beta = 0.18$, $p < 0.001$). These findings highlight the dual benefits of straw return in supporting both soil health and food production, contributing to sustainable agroecosystem development.

3.3. *Regional heterogeneity in the SOC sequestration effect of straw return*

On the basis of the causal relationships established through SEM, region-specific RF models were developed for the four agroecological regions (Fig. 1). The feature importance scores and RMSE values are reported in Table S7, and the R^2 values for the training and testing sets derived from site-level spatial cross-validation are shown in Fig. S11. As indicated by the feature rankings, and PDPs (Figs. 4–5 and Fig. S12), soil and management factors exerted a more substantial influence on SOC sequestration under straw return than did climatic factors. In general, Straw C Input and duration consistently contributed to SOC accumulation across most regions.

These primary drivers were dependent on region, underscoring the necessity of region-specific C management strategies. In Northeast China ($R^2 = 0.75$), Straw C Input was the dominant factor ($\gamma = 0.34$), reflecting long-term SOC depletion in the region's historically fertile black soils (Zhao et al., 2018a). Both higher N Input ($\gamma = 0.33$) and longer duration ($\gamma = 0.14$) contributed to SOC sequestration. In North China ($R^2 = 0.60$), the duration of straw return emerged as the most influential driver ($\gamma =$ 0. 36). In South China ($R^2 = 0.73$), a low SOC$_i$ was strongly linked to a higher sequestration potential ($\gamma = 0.25$). SOC accumulation increased with pH ($\gamma = 0.22$), with a pronounced rise at higher pH values, suggesting stronger model-derived sensitivity in this region. In arid Northwest China ($R^2 = 0.67$), MAP was the key determinant ($\gamma = 0.11$), highlighting the critical role of water availability in limiting agricultural

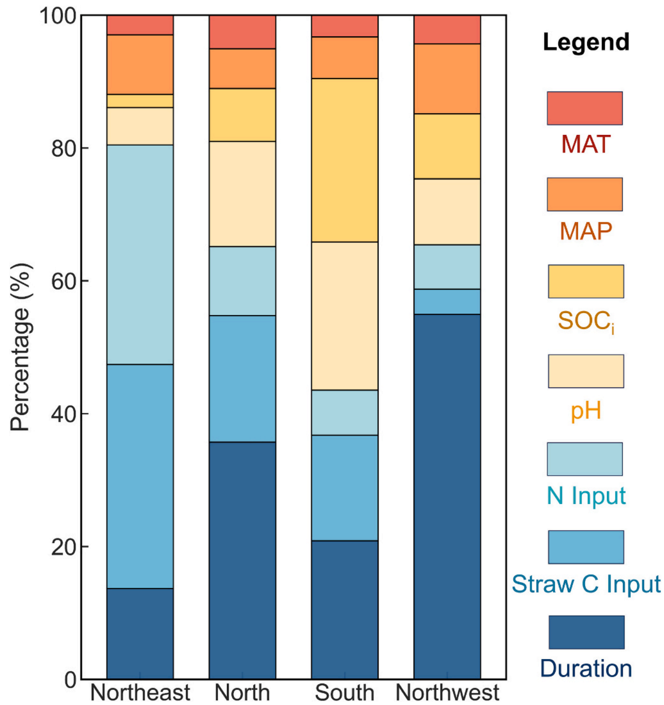

Fig. 4. Variable importance in regional SOC sequestration under straw return.

productivity and SOC sequestration.

3.4. Regional simulations of SOC sequestration under future climate scenarios

Under the SSP1 scenario, the spatial distributions of the optimal straw C input level, duration, SOC sequestration per unit area, and straw C conversion ratio are shown in Fig. 6. Optimizing both the amount and duration of straw C inputs led to an increase in SOC stocks across 67% of China's cropland (0–20 cm topsoil), increasing from 4.8×10^2 Tg to 5.9×10^2 Tg, a net gain of 1.0×10^2 Tg or 21% (see Supplementary Table S9 for details). At the regional scale (Fig. 7), Northeast China achieved substantial SOC gains under moderate Straw C Input (3.6 t ha^{-1} yr^{-1}) and a relatively short duration (approximately 11 years), resulting in a total increase of 38 Tg and an average of 1.4 t ha^{-1}, corresponding to a 21% increase. This region also had the highest C conversion ratio (3.7%), particularly in Liaoning and the border areas between Heilongjiang and Inner Mongolia. In contrast, the North China Plain tended to have a lower sequestration potential. Under a low Straw C Input level (1.8 t ha^{-1} yr^{-1}) and a moderate duration (approximately 14 years), the SOC stocks increased by only 9.4 Tg (0.42 t ha^{-1}), with a growth rate of 17%. Despite the modest increase, the conversion ratio reached 1.6%, with stronger responses observed in major grain-producing areas such as northern Jiangsu and Henan. In southern China, higher Straw C Input (4.7 t ha^{-1} yr^{-1}) and longer durations (approximately 19 years) are needed to achieve moderate sequestration, resulting in a total SOC increase of 42 Tg (0.83 t ha^{-1}), or 22%. Although the overall conversion ratio was lower (0.93%), relatively high SOC sequestration was observed in Sichuan, Chongqing, and Hubei. The Northwest region has management characteristics similar to those in South China. With 4.4 t ha^{-1} yr^{-1} of Straw C Input sustained over 19 years, the SOC increased by 13 Tg (0.40 t ha^{-1}), corresponding to a 26% increase and a conversion ratio of 0.48%.

In the broader context of global climate change, future trends in temperature (MAT) and precipitation (MAP) under specific socioeconomic pathways are expected to create region-specific heterogeneity in SOC accumulation rates and optimal management strategies (see Fig. 7). Under the SSP5 scenario, the northeast, southern, and northwestern regions presented the highest SOC sequestration potentials, with increases of 39 Tg, 42 Tg, and 14 Tg, respectively. In contrast, the largest SOC gain in North China occurred under the SSP3 scenario, reaching 9.4 Tg. The spatial heterogeneity of SOC sequestration across all SSP scenarios is illustrated in Supplementary Figs. S13–S16, providing a scientific basis for the formulation of precise, region-specific straw management strategies.

4. Discussion

4.1. Regional specifics of SOC sequestration and straw management strategies

Compared with straw removal, straw return leads to higher SOC stocks in cropland soils. However, the effectiveness of SOC sequestration is dependent on climate conditions, soil properties, and management practices. From a climatic perspective, in arid and water-limited regions, relatively high precipitation increases crop biomass production and straw yields, thereby facilitating SOC accumulation (Mo et al., 2024); with particularly strong effects observed in Northwest China (see Fig. 3 and Fig. 5). In terms of soil properties; the initial SOC content; pH; and clay content have been identified as key factors influencing SOC sequestration (Yin et al., 2024). Soils with lower SOC$_i$ generally have greater C sequestration potentials; as a high SOC$_i$ often indicates that the soil is approaching its C saturation threshold (Zhao et al., 2018b); thereby reducing the marginal gains from additional straw inputs (Ibrahim, 2024); which is a pattern that was observed in both Northeast China and South China (Qin and Huang, 2010). Alkaline soils are more conducive to the formation of stable organomineral complexes; e.g.; those with Ca^{2+}; that protect SOC from microbial decomposition (Kasim and Ghassan, 2023). Furthermore, moderate levels of clay and silt were beneficial for SOC stabilization, as these textures typically provide greater specific surface areas, greater surface charges and water retention, good pH buffer capacities, and soil structures favourable for microbial processes, all of which contribute to the long-term preservation of SOC.

In terms of management practices, straw C input, treatment duration, nitrogen application, cropping system, and tillage regime all influenced SOC accumulation. SOC sequestration generally increases with increasing straw input and duration, but threshold effects are common (Wang et al., 2021). Excessive straw input may increase the soil C/N ratio; thereby limiting decomposition (Dong et al., 2019). Similarly; prolonged straw return can lead to residue buildup; reduced soil aeration; and suppressed microbial activity; ultimately constraining SOC storage; a pattern that was observed in both North China and South China (Tong et al., 2009). The effects of nitrogen input followed an inverted U-shaped curve (Zhao et al., 2018a). Moderate nitrogen application increases crop biomass and straw C input; thus contributing to SOC accumulation. In contrast; excessive nitrogen input can stimulate microbial degradation of residues (Fog, 1988) and SOC (Wang and Kuzyakov, 2024) and lead to soil acidification (Zamanian et al., 2024); which limits root growth and accelerates SOC loss (Guo et al., 2010; Chen et al., 2023). SEM results show that mean annual precipitation negatively affects soil pH, indicating soil acidification under higher rainfall, especially in warm and humid regions. This coupling suggests that SOC sequestration by straw return depends on both climate and soil buffering capacity. Compared with dry farmlands, paddy fields presented lower SOC sequestration potentials, possibly due to acidification caused by the exudation of H^+ from rice roots, reductive conditions under flooding, and associated mineral dissolution. SOC sequestration was further reduced under paddy–upland rotation systems, where repeated redox oscillations increased SOC turnover and offset the stabilizing effects. Similarly, moderate tillage with a reduced disturbance frequency, such as conventional tillage rather than no-till, facilitates straw decomposition and supports long-term SOC retention (Liu et al., 2023b; Zhang et al., 2023b), which is consistent with observations from

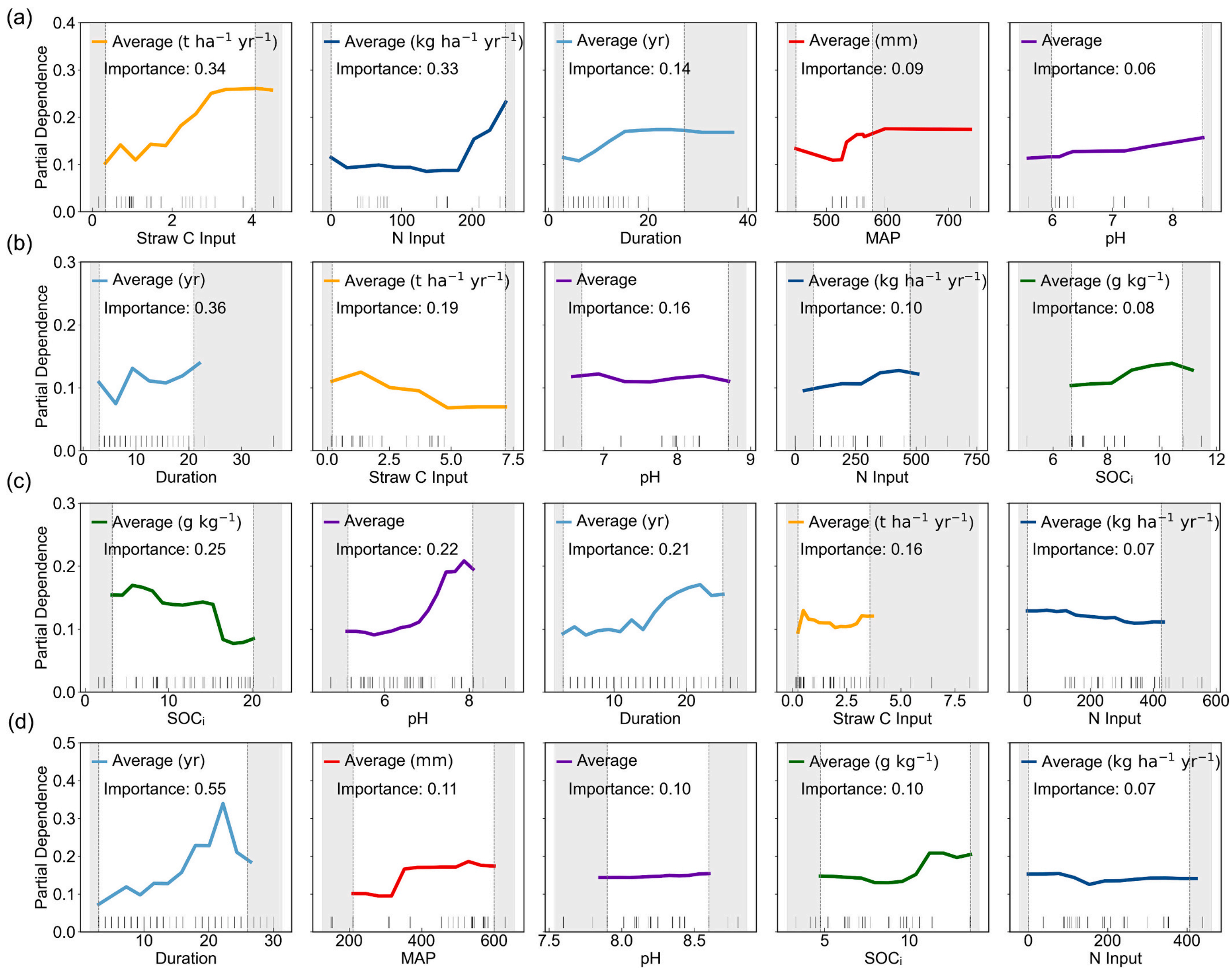

Fig. 5. Partial dependence plots (PDPs) of the top five important variables in region-specific random forest models. Each panel displays the five most influential predictor variables and their relative importances for each region: (a) Northeast China, (b) North China, (c) South China, and (d) Northwest China. Short vertical tick marks along the x-axis indicate the distribution of observed data. The shaded grey regions represent the 5%–95% range of observed predictor values.

Northeast China (Zhang et al., 2023a). In addition, monocropping may be more favourable for SOC accumulation than double or triple cropping systems are, as intensive multiple cropping often shortens crop cycles, increases turnover frequency, and reduces fallow periods, thereby depleting nutrients and limiting SOC buildup when not supported by sufficient carbon inputs.

Region-specific straw management strategies have been proposed on the basis of the natural and agronomic characteristics of each agroecological zone. Such a region-specific modelling framework enables an explicit consideration of context-specific optimization and climate–soil interactions, beyond generalized national-scale assessments (Ibrahim, 2024; Pan et al., 2023). In Northeast China, lower annual temperatures slow straw decomposition, making straw return particularly ecologically beneficial. Increasing straw C inputs and optimizing nitrogen management may help mitigate ongoing SOC loss in this region. In the North China Plain, although the overall sequestration potential is relatively limited, extending the duration of straw return and adopting conservation tillage practices, such as reduced ploughing, subsoiling, and surface mulching, can increase crop yields and help sustain soil aggregate stability (Ning et al., 2022). In South China; high temperatures and rainfall increase microbial activities and exacerbate soil acidification. Thus; pH regulation (e.g.; liming) and adjustments to rotation systems (e.g.; alternating wet and dry cultivation) are recommended for SOC retention. In Northwest China; limited precipitation constrains both straw decomposition and its conversion into SOC. To address this; integrating straw mulching with drip irrigation (Enrique et al., 1999) is recommended to reduce evaporative water loss and increase both the straw conversion efficiency and water use effectiveness.

4.2. Increasing soil carbon sinks through soil remediation in Southern China

In much of southern China, severe soil acidification has limited the effective conversion of straw C into stable SOC. This is reflected in Fig. 6d, which illustrates consistently low C conversion ratios across the region. The Chinese government's *High-Standard Farmland Construction Plan* (2021) explicitly called for the remediation of acidic soils in southern provinces (MARA, 2021), suggesting that future adjustments in soil pH could unlock substantial additional SOC sequestration potential in these areas. On the basis of this context, a refined C management strategy that integrates soil pH modification is proposed. Within the simulation framework for pH remediation in South China, soil pH was incorporated as an adjustable input variable. Seventeen discrete pH levels were defined on the basis of the observed regional pH range,

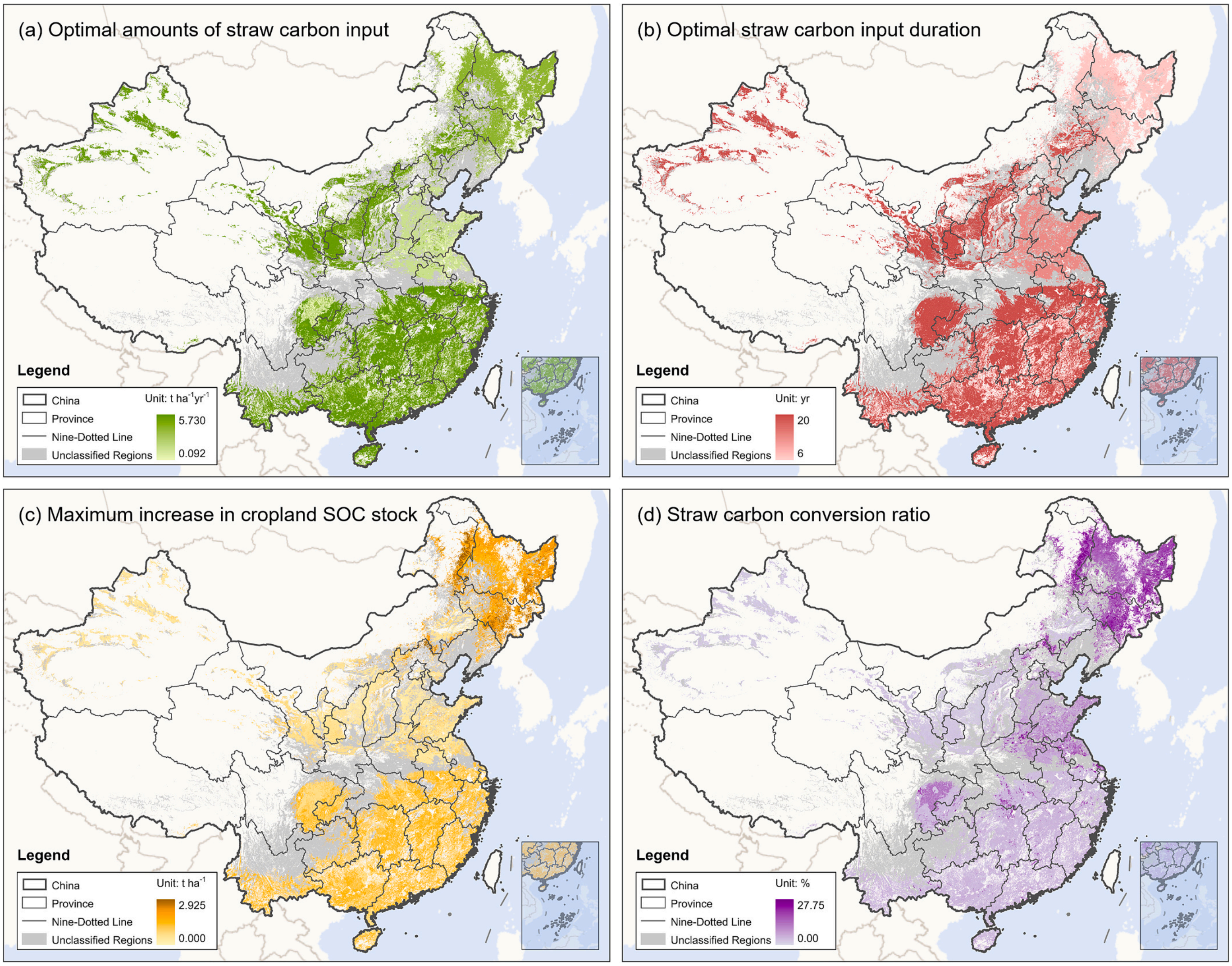

Fig. 6. Optimized straw C input and duration strategies and SOC sequestration potential under the SSP1 scenario at a 1 km resolution. (a) Optimal annual straw C inputs (t C ha^{-1} yr^{-1}); (b) Optimal durations of continuous straw return (yr); (c) SOC stock increases under the optimal management combination (t C ha^{-1}); (d) Straw C conversion ratios (%), defined as the proportion of total straw C input accumulated in the SOC stock over the entire simulation period.

expanding the original 180 management combinations to a total of 3060 scenarios (see Method S7 and Table S10 for detailed parameters).

The spatial distribution and a statistical summary of the SOC sequestration potentials before and after soil pH remediation are presented in Fig. 8 and Fig. S17, respectively. Under the SSP1 scenario, when the grid-level pH, Straw C Input, and duration were jointly optimized, the total SOC sequestration in South China reached 46 Tg, an increase of 4.0 Tg (9.5%) compared with the baseline scenario without pH adjustments (see Section 3.5; detailed values in Table S11). Although both the pH remediation outcomes and straw management strategies varied across provinces, pH modification consistently led to substantial potential gains in SOC sequestration. On average, the regional soil pH increased by 1.2 units relative to the initial simulated conditions (Table S12), with large areas of strongly acidic soils (pH < 6.5) shifting to neutral or slightly alkaline conditions (pH > 6.5). In some provinces, such as Tibet and Guizhou, the pH increase exceeded 1.5 units.

To maximize SOC sequestration, continuous straw return over 20 years was required across all the cropland grids in South China. Notably, the average Straw C Input decreased by 1.6 t ha^{-1} yr^{-1} across the region. Reductions exceeding 4.5 t ha^{-1} yr^{-1} were observed in provinces such as Tibet and Shanghai, whereas areas such as eastern Sichuan and Chongqing required increased inputs. In terms of SOC sequestration per unit area, the regional average reached 0.08 t ha^{-1}, with the highest values observed in Tibet (0.25 t ha^{-1}) and Guizhou (0.18 t ha^{-1}).

4.3. Uncertainties and future perspectives

Despite the application of multiple methods to assess the factors influencing SOC sequestration under straw return, several uncertainties remain in this study. Although an extensive set of relevant literature has been compiled, certain regions, such as Guizhou, Tibet, and Yunnan, remain underrepresented in terms of site-level observations, limiting full national coverage. Similar spatial gaps have been noted in previous studies (Zhao, 2017; Lin et al., 2023a). Moreover, the optimal straw C input estimated for Northeast China was higher than the historical average reported for the region (Wang et al., 2015). This discrepancy may reflect differences in data sources and methodologies, as it is based on site-level experimental data, in contrast with previous estimates that were derived from field-scale trials or model simulations.

Although the cropland samples and grid cells were stratified on the basis of climatic and soil attributes, approximately one-third of the national cropland area remained unclassified due to complex topography or transitional climatic zones. This may have affected the accuracy of the regional-scale SOC sequestration predictions. Spatial variability in land-

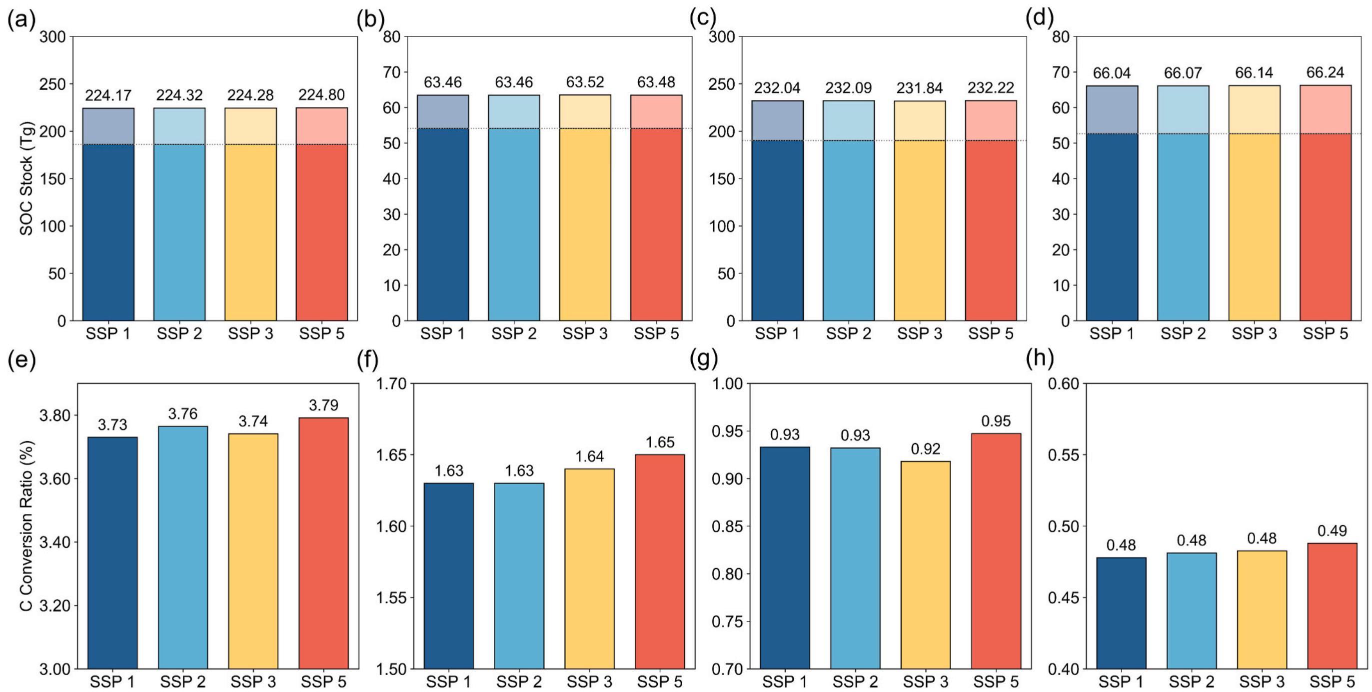

Fig. 7. Simulated regional SOC stocks (0–20 cm) under optimal straw return scenarios across four climate pathways. Panels (a)–(d) illustrate the projected SOC stocks (Tg) under the optimal straw input scenarios for the northeastern, northern, southern, and northwestern regions, respectively. The grey dashed lines denote the baseline SOC stocks in each region (SOC_i): 1.9 × 10^2 Tg, 54 Tg, 1.9 × 10^2 Tg, and 53 Tg. The differences between the projected and baseline values indicate the regional SOC sequestration potential. Panels (e)–(h) display the average straw C conversion ratios (%) in the corresponding regions.

use history and long-term management practices, which could not be fully represented at the grid scale, represents an additional source of uncertainty (Ren et al., 2025). Additionally; while meta-analysis contributes to the generalizability of results by synthesizing findings across studies; it may introduce publication bias; which was accounted for and corrected in this study (Supplementary Fig. S2). The absence of in situ climate and soil property measurements in some studies may also lead to biased estimates of SOC response rates; despite supplementation with gridded data where needed. In addition; BD used to derive SOC stock was estimated using pedotransfer functions rather than direct measurements; which may introduce uncertainty in the absolute values of SOC stock. Finally; the machine learning models with explicit site-level spatial cross-validation achieved solid predictive performance (Meyer and Pebesma, 2022; Xiao et al., 2023). However, they cannot explicitly capture the biogeochemical processes of SOC dynamics, and uncertainty associated with spatial extrapolation (including its mapping) warrants further discussion. Model outcomes are also limited by the representativeness of the input data, and the exclusion of potentially important environmental variables, such as soil microbial communities and soil moisture, may further contribute to uncertainties in the results.

Future research should integrate crop growth process-based models with a broader range of environmental variables, including soil microbial activities and moisture dynamics, to better understand the mechanisms governing SOC sequestration. In addition, explicit diagnostics of higher-order interactions could be further investigated to better understand potential mechanistic linkages among climate, soil, and management factors. At the management level, greater efforts are needed to adapt farmers to straw return through economic and policy incentives, along with targeted training programs to strengthen their agronomic skills (Zhao et al., 2018a). Moreover; integrating SOC monitoring with crop yield assessments will facilitate the identification of synergies between C retention and productivity gains; enabling win–win strategies for sustainable agriculture. In parallel; future work should also focus on simulating the long-term stability of SOC sequestration under climate change by incorporating C-N coupling processes (Lin et al., 2024a; Zang et al., 2024) and evaluating the combined effects of conservation practices such as biochar application and cover cropping on regional SOC accumulation and crop productivity (Lin et al., 2024c; Teng et al., 2024).

5. Conclusions

This study identified the key regional drivers of SOC sequestration under straw return across China's croplands and quantitatively assessed the C sequestration potentials under multiple climate change scenarios. These findings provide a scientific foundation for designing a region-specific modelling framework to guide agricultural management and soil remediation strategies aimed at increasing C storage and supporting sustainable land use.

High straw inputs and long return durations increase SOC accumulation by increasing the organic matter supply and improving the soil structure. Moderate tillage intensities and optimized nitrogen inputs increase the efficiency of C incorporation and stabilization. Soils with low SOC saturation (SOC_i), alkaline pH, loamy texture, and good structure (e.g., moderate clay or silt content) are more conducive to long-term SOC retention.

Climatic factors influence SOC sequestration primarily through indirect pathways by modifying soil conditions and regulating the coupling between SOC accumulation and crop productivity. The pronounced regional heterogeneity observed in the SOC responses highlights the importance of spatially optimized management strategies. For example, in Northeast China, increasing straw input and adjusting nitrogen application resulted in 38 Tg of SOC being sequestered in the topsoil (0–20 cm), helping mitigate the ongoing nutrient loss in degraded black soils. In North China, a low-input long-duration strategy resulted in a 9.4 Tg increase in SOC, counteracting the degradation associated with intensive farming. In South China, high C inputs maintained over two decades yielded 42 Tg of SOC, despite challenges from elevated temperatures and precipitation. Even arid regions in Northwest China can achieve substantial C gains (13 Tg) through persistent, high-intensity straw return. Collectively, these findings provide actionable

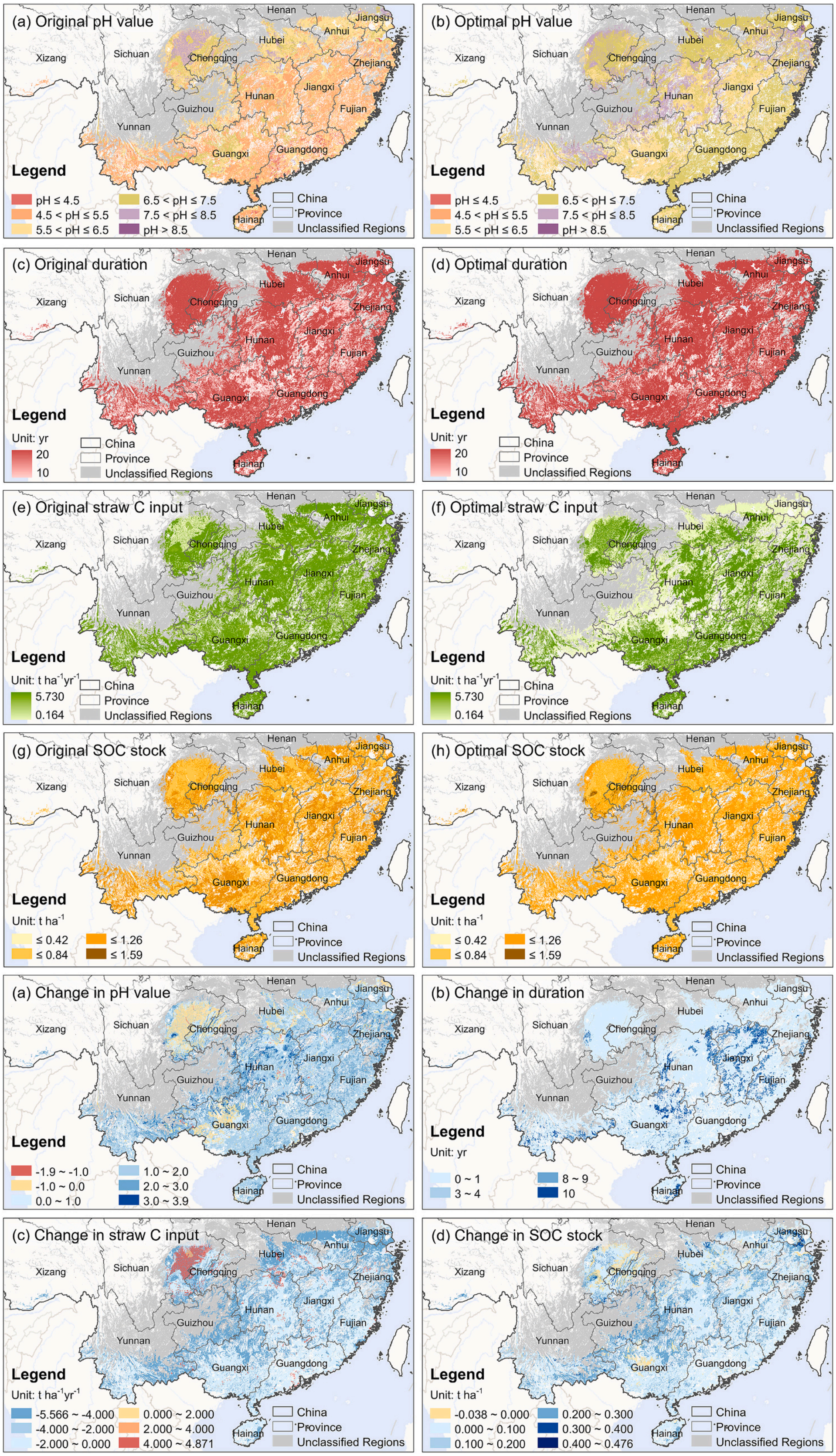

Fig. 8. Comparison of SOC sequestration potentials in South China before and after soil pH adjustments under the SSP1 scenario. Panels (a), (b) and (i) illustrate the initial pH, optimized pH, and changes in pH values; (c), (d) and (j) display the durations of straw return; (e), (f) and (k) show the amounts of Straw C Input; and (g), (h) and (l) show the changes in SOC stocks. In panels (e) and (f), the upper values of Straw C Input (up to 5.7 t C ha^{-1} yr^{-1}) fall within the range of observed experimental data.

insights for regionally differentiated C management, contribute scalable solutions to increase soil health and agricultural sustainability, and contribute to food security under a changing climate.

CRediT authorship contribution statement

Bin Du: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Changqing Song:** Supervision, Funding acquisition, Conceptualization. **Guocheng Wang:** Writing – review & editing, Methodology. **Shuyi Ren:** Writing – review & editing, Investigation. **Jiayi Jiang:** Investigation. **Peichao Gao:** Resources, Funding acquisition. **Sijing Ye:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Yakov Kuzyakov:** Writing – review & editing, Methodology.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2026.104757.

Data availability

Data and code for the meta-analysis generated in this study are available at Zenodo (DOI: 10.5281/zenodo.18863272).

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