Agriculture, Ecosystems and Environment 359 (2024) 108749

Contents lists available at ScienceDirect

Agriculture, Ecosystems and Environment

journal homepage: www.elsevier.com/locate/agee

Major contributions of agricultural management practices to topsoil organic carbon distribution and accumulation in croplands of East China over three decades

Yue Pu[a], Lin Yang[a,*], Lei Zhang[a], Haili Huang[a], Ganlin Zhang[b], Chenghu Zhou[a,c]

[a] School of Geography and Ocean Science, Nanjing University, Nanjing 210023, China
[b] State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Science, Nanjing 210008, China
[c] State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

ARTICLE INFO

Keywords:
Agricultural management
Soil organic carbon distribution
Temporal change
Path analysis

ABSTRACT

Multiple natural and anthropogenic factors jointly drive the spatial distribution of soil organic carbon (SOC) and its dynamics in croplands. Among these factors, agricultural management practices have caused considerable impacts. Previous studies on the driving factors of SOC in croplands have provided significant understanding on this matter. However, whether and how the effects and interplay of these drivers change over time is often unknown, especially agricultural activities. To measure the effects of agricultural management practices on the spatial distribution and temporal change of SOC incorporating the network relationships with other natural drivers at the regional scale, we conducted partial least squares path analysis on the topsoil organic carbon content using two historical soil datasets from cropland samples in East China obtained during the 1980s and the 2010s. Eight indicators and their temporal changes reflecting climate, agricultural management, and edaphic conditions were used to quantify the driving mechanisms of the spatial distribution and temporal change of SOC. The drivers of SOC distribution showed that high SOC was mostly distributed in soils with a relatively low pH and high clay content in warm humid climates. High SOC was associated with the application of N fertilizer, crop residue input, and agricultural machinery in the 1980s and 2010s. The effect of N fertilization on SOC distribution increased from the 1980s to the 2010s, whereas the total edaphic effects significantly decreased from 0.62 to 0.25 ($P < 0.01$). Regarding the drivers of SOC change over the three decades, the edaphic effects presented the strongest effect (path coefficient of 0.74, $P < 0.01$), including the negative effects of topsoil acidity and baseline SOC level, as well as the positive effects of total nitrogen (TN) and clay content change. Croplands with lower intensity of management practices in the 1980s generally attained more development in agricultural modernization, which led to a considerable SOC increase. Our research revealed the importance of agricultural management practices on the spatial distribution and temporal change of cropland SOC at the regional scale. The results emphasize the need to measure the changing driving mechanisms of SOC dynamics. The findings indicate that indicators reflecting the effects of agricultural management practices should be included in digital mapping and process-based modeling of soil carbon at different spatiotemporal scales to improve prediction accuracy.

1. Introduction

Soil organic carbon (SOC), along with its quality and dynamics are crucial for soil multifunctionality, global C cycle, and ecosystem services (Kopittke et al., 2022; Lal, 2016; Wiesmeier et al., 2019). Soil C decomposition and sequestration processes are vulnerable to climate, topography, biotic activity, and human-induced disturbances. An increasing number of studies have discussed the driving mechanisms of the spatial distribution and/or the temporal change of SOC from site- to global-scale (O'Rourke et al., 2015; Wiesmeier et al., 2019). Previous studies on the climatic sensitivity of SOC (e.g., Carvalhais et al., 2014; Davidson and Janssens, 2006; Hartley et al., 2021) and soil physiochemical interactions (e.g., Bosatta and Ågren, 1997; Doetterl et al., 2015) have provided mechanistic insights into SOC mapping and Earth

* Corresponding author.
E-mail address: yanglin@nju.edu.cn (L. Yang).

https://doi.org/10.1016/j.agee.2023.108749
Received 9 July 2023; Received in revised form 25 August 2023; Accepted 15 September 2023
Available online 23 September 2023
0167-8809/

system modeling (Luo et al., 2016). Human activities have been heterogeneously intensifying across terrestrial ecosystems. However, their role in the regulation of SOC dynamics coupled with environmental interference have not been fully examined. In the context of global warming and food security problem, it is important to clarify the manner through which the natural environment and human activities interact to drive SOC dynamics. This information can be used to provide guidance for a rational land management, considering C sequestration and planetary survival.

Croplands occupy a large part of the global land area and present substantial C sequestration potential (Zomer et al., 2017). They have become the ecosystem most intensively affected by human interference worldwide. The SOC in croplands usually changes faster than that in natural ecosystems because of the implementation of agricultural management practices. Several studies have elucidated the effects of various agricultural management practices on SOC, including the effects of chemical and manure fertilization (Mayer et al., 2022; Ren et al., 2021; Yang et al., 2022), tillage strategies (Cui et al., 2022; Kan et al., 2021; Zhang et al., 2023), irrigation (Amorim et al., 2021), crop residue incorporation (Berhane et al., 2020; Haas et al., 2022; Lu, 2015), and cover cropping (Hu et al., 2023; Jian et al., 2020; Vendig et al., 2023). However, most assessments focus on a single type of agricultural management practice or crop species. Moreover, these studies are restricted to site-level field experiments (Das et al., 2022; Sanaullah et al., 2020; Xu et al., 2020) or are based on meta-analyses through the collection of various datasets (Wooliver and Jagadamma, 2023; Zheng et al., 2023). This has led to an ongoing interest regarding the impacts of agricultural activities on SOC and the associated changes. Further regional to global scale spatial analyses and modeling are necessary to assess the role of agriculture in SOC dynamics. In addition, agricultural management practices not only directly influence SOC, but also jointly control SOC through interconnections with environmental conditions (such as climate and topography), microbial processes, and soil geochemistry. The direct and indirect effects of agricultural management on SOC should be quantified to clarify the mechanisms driving SOC dynamics in agricultural ecosystems.

Agricultural activities are diverse and constantly changing along with advances in technology and changes in policies (Jiao et al., 2018). For example, the application of chemical fertilizers has boosted substantially because of their efficiency in grain production (Li et al., 2013). Moreover, plows have been gradually replaced by tractors to improve tillage efficiency, along with the application of other agricultural machinery, such as combines, sprayers, and planters (Liao et al., 2022; Shi et al., 2021). However, the changes in the relationships between SOC and the changing agricultural activities over time remain unclear. Under the severe circumstances of global warming, food security, and land degradation (IPBES, 2018; IPCC, 2019; Prăvălie, 2021), the temporal changes in the driving mechanisms of SOC dynamics should be quantified to help in mapping and modeling of soil C processes in croplands and in formulating solutions to enhance agriculture production and soil climate mitigation (Amelung et al., 2020).

The Yangtze River Delta is one of the most developed regions of China. Because of its suitable climatic conditions and intense implementation of agricultural management practices, this region is an important grain-producing area in China. Rapid urbanization and agricultural modernization have occurred after the 1980s in this region (Yang et al., 2021; Zhang et al., 2022). Agricultural activities were constantly strengthened because of the considerable economic development, but they were restrained in some regions owing to the transformation from cropland to industrial and urban lands. The content of organic carbon in soils with different physical and chemical characteristics is affected by various agricultural management practices and their changes over the years (Deng et al., 2018; Zhao et al., 2018), which interacted with the effects of climate. Therefore, anthropogenic and natural influences on SOC over time can be identified in this region at a large regional scale. The topsoil is the layer of cropland soil most affected by agricultural management. In this study, we collected two historical soil datasets sampled in the 1980s and 2010s and a series of environmental indicators reflecting the climate, agricultural management, and soil physiochemical conditions in the Yangtze River Delta region. We conducted partial least squares path analyses of SOC content (at the standardized depth of 0–20 cm) in the 1980s and 2010s, as well as the SOC change during these 30 y, by using the abovementioned observational data to answer the following questions: (1) How do climatic, edaphic conditions, and agricultural management practices control the spatial distribution of SOC in croplands at the regional scale? (2) Have the driving mechanisms of SOC distribution changed between the 1980s and the 2010s? (3) How do these drivers jointly control the temporal change in SOC content under long-term agricultural intensification?

2. Materials and methods

2.1. Study area

The Yangtze River Delta region administratively covers three province-level divisions of East China including Jiangsu, Zhejiang, and Shanghai (27°02′–35°08′N, 116°21′–123°10′E) (Fig. 1). The study area covers ∼219,000 km^2 and it has warm and humid subtropical monsoon climate. The annual average temperature is 13–18 ℃, and the annual precipitation is 700–2000 mm. The elevation ranges from 0 to 1926 m in this region. Over 80% of Jiangsu consists of flat plains, whereas most mountains and valleys are distributed in Southern Zhejiang. This region is suitable for agriculture and has become one of the most important grain-producing regions in China. Croplands are the major land use type in this region, and the elevation ranges from 0 to 1625 m. With a long cultivation history and rapid socio-economic development, agricultural management practices and techniques have been widely applied in the Yangtze River Delta region. From the 1980s to the 2010 s, the grain yield per unit of arable land nearly doubled under the influence of agricultural intensification. Agricultural machinery, chemical fertilization, and crop straw/stover return have been advocated since the 1980s.

2.2. Soil sample data

We used two soil datasets from the 1980s and the 2010 s in our analysis. Sample data from the 1980s were digitalized from records of *Soil Species of China*, which was based on the Second National Soil Survey of China (Office for the Second National Soil Survey of China, 1993). These data were used to investigate typical soil species based on the Chinese soil genetic classification. Sample data from the 2010 s were obtained from *Soil Series of China*, which was compiled after the National Soil Series Survey from 2009 to 2019 (Huang and Pan, 2017; Ma and Zhang, 2017; Yang, 2017). These data were used to investigate typical soil series based on the Chinese soil taxonomic classification. Each soil sampling point included the soil physiochemical properties measured for different soil layers of a typical soil profile. A typical soil profile was sampled based on the characteristics of its corresponding soil type and its natural environmental conditions. Detailed descriptions of the location, topography, sampling date, land use type, and crop types of each profile were also recorded. We assembled 128 soil observations from the 1980s and 141 from the 2010s for the entire study area. The spatial distribution of the sampling points is shown in Fig. 1.

Soil properties at each sampling point were standardized for the topsoil depth of 0–20 cm because of the unequal depths of soil layers of different sampling profiles. These properties included soil organic matter content (SOM, g kg^{-1}), clay content (%), total nitrogen content (TN, g kg^{-1}), and soil pH. The soil properties of many points were measured at the depth of 0–20 cm or were measured in too few soil layers to fit a spline curve along the profile to standardize. Therefore, we adopted a linear transformation approach to process as per the following equations:

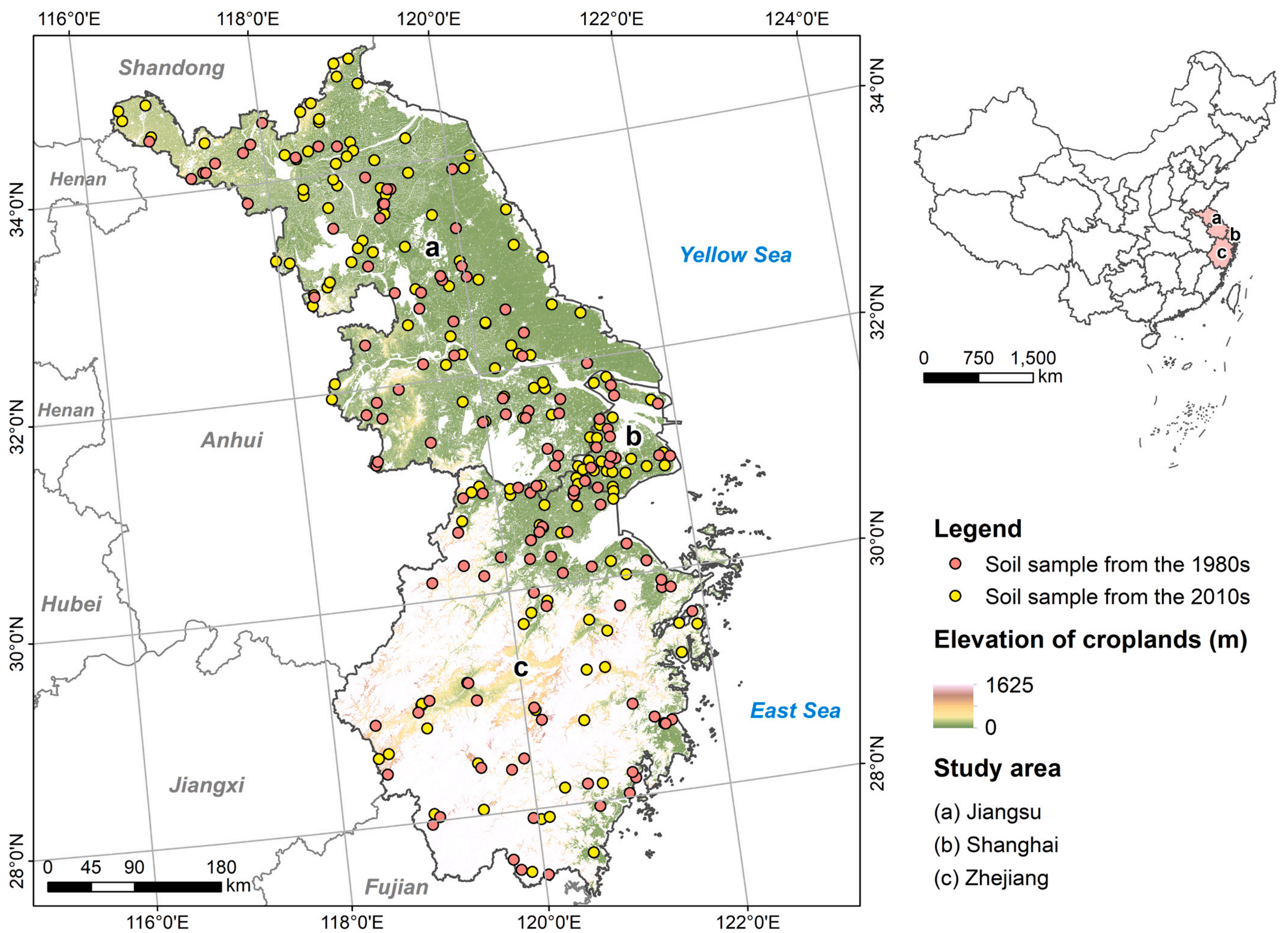

Fig. 1. The spatial distribution of the soil sampling points in the Yangtze River Delta region of East China. The red dots are from the 1980 s (128 soil observations) and yellow dots are from the 2010 s (141 soil observations). The elevation of croplands was extracted from the ASTER GDEM V3.

$$SP_{20} = \frac{\sum_{i=1}^{n} SP_{d_i} \times d_i + SP_{d_j} \times (20 - d_j)}{20} \tag{1}$$

$$pH_{20} = -\lg \frac{\sum_{i=1}^{n} 10^{-pH_{d_i}} \times d_i + 10^{-pH_{d_j}} \times (20 - d_j)}{20} \tag{2}$$

where SP_{20} represents the value of topsoil properties such as SOM, clay, and TN at the depth of 0–20 cm; and d_i is the depth of a soil layer less than 20 cm. When the next soil layer is deeper than 20 cm, d_j represents the depth of the final soil layer. Soil pH was standardized using Eq. (2) because of the logarithmic relationship between pH and H^+ ions. SOM was converted to soil organic carbon content (SOC, g kg^{-1}) by a divisor of 1.724 for follow-up processes.

2.3. Climatic indicators

Table 1 lists the drivers and indicators used in this study. Mean annual precipitation (MAP) and mean annual average ground surface temperature (MGST) for the decade prior to the sampling time were obtained from the National Meteorological Dataset of China from the Resource and Environment Science and Data Center (RESDC) of the Chinese Academy of Sciences (https://www.resdc.cn) as climatic indicators.

Table 1
Main drivers of SOC content and their indicators used in this study.

Driver	Indicator	Unit	Dataset	Data source
Climate	Mean annual precipitation (MAP)	mm	National meteorological dataset of China	Resource and Environment Science and Data Center (RESDC), Chinese Academy of Sciences (https://www.resdc.cn)
	Mean annual average ground surface temperature (MGST)	℃		
Agricultural management	N fertilizer use rate	g N m^{-2} yr^{-1}	Historical nitrogen fertilizer use in China	(Yu et al., 2022)
	Total power of agricultural machinery	kW ha^{-1}	China County-level Rural Economic Statistical Summary and Provincial statistical yearbooks	China Socio-Economic Big Data Research Platform (https://data.cnki.net/)
	Crop residue input	t ha^{-1}		
Soil physiochemistry	Total nitrogen (TN)	g kg^{-1}		The second National Soil Survey and the National Soil Series Survey
	Clay content	%		
	Soil pH			

2.4. Agricultural management indicators

We selected three indicators to represent agricultural management practices: N fertilizer use rate, total power of agricultural machinery, and crop residue input. N fertilizer use rate was obtained from *Historical nitrogen fertilizer use in China from 1952 to 2018* dataset (Yu et al., 2022). County-level grain yield, total power of agricultural machinery, and grain-sown area data from the *China County-level Rural Economic Statistical Summary* and provincial statistical yearbooks were used to calculate the mean grain yield and total power of agricultural machinery per unit grain sown area for each county.

The crop residue input was calculated based on the grain yield data. For each crop type, the crop residue input was from crop straw/stover and crop root, which were estimated using Eqs. (3) and (4), as proposed by Zhao et al. (2018).

$$RR_s = GY \times \frac{1 - WC}{GSratio} \times \alpha \times 0.45 \quad (3)$$

$$RR_r = GY \times \frac{1 - WC}{GSratio} \times RSratio \times 0.45 \quad (4)$$

where RR_s and RR_r represent the residue input from straw/stover and root of a crop type, respectively. GY represents the grain yield of a county. WC is the water content of the crop type. $GSratio$ and $RSratio$ are the grain:straw and root:straw ratios of the crop type, respectively. α is the straw/stover return ratio at the different time. Finally, 0.45 is the conversion factor for converting crop biomass to SOC content (Fang et al., 2007).

Agricultural management practices vary between cropping systems. Based on the descriptions in *Soil Species of China* and *Soil Series of China*, we determined the main crop types and rotations in the study area for each sampling point. For the 1980 s' data, we classified the main crop rotations as: "Single-season rice," "Rice-Rape (Wheat)," "Rice-Wheat," "Wheat." For the 2010 s' data, we defined four groups, namely "Single-season rice," "Rice-Rape (Wheat)," "Rice-Wheat," "Wheat-Maize." When there was more than one crop type, the crop residue input was calculated as the mean value. The water content, grain:straw ratio and root:straw ratio of the crop types used in this study are listed in Table S1. The α for each crop type was set based on a previous study (Liu and Li, 2017).

2.5. Linking soil datasets in the 1980s and 2010s to model SOC change

To overcome the absence of repeated soil sampling, we adopted a sampling point-pairing approach to simulate the temporal changes in SOC content over the 30 y. In the *Soil Series of China*, every typical soil profile was sampled based on a reference soil species, so the soil series corresponded to the reference soil species in terms of physiochemical properties and environmental conditions. Based on this correlation, we established the links between soil series and soil species, and linked the soil sample data from the 2010 s to those from the 1980s to model SOC change. Every pair of sampling points should fall within the same province to avoid differences in statistical caliber. If more than one soil series matched the same soil species, the point within the same county as and/or closest to the soil species point was selected. After removing the

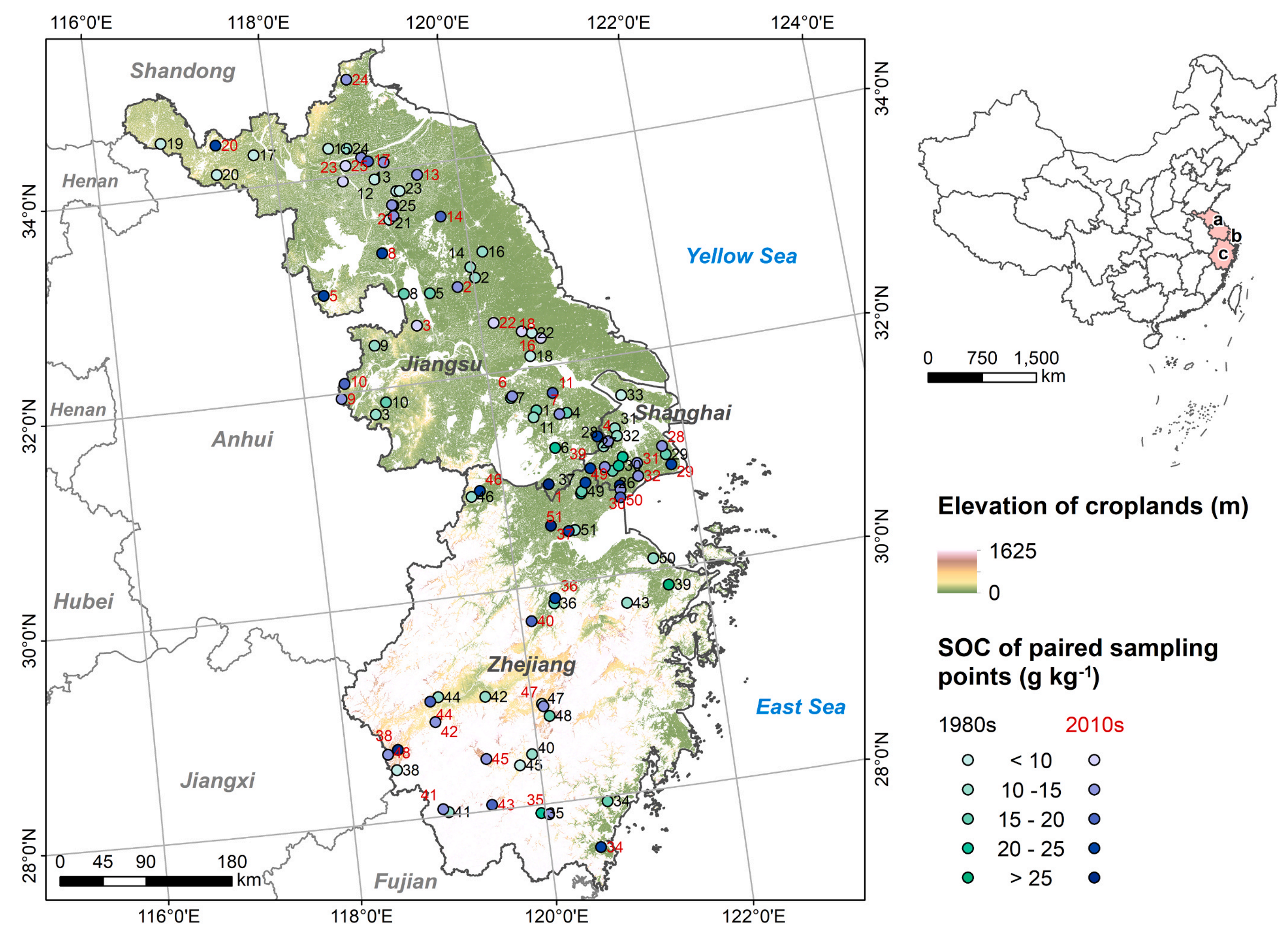

Fig. 2. The spatial distribution of the paired sampling points. Dots with same serial numbers are points paired together. Numbers in black are from the 1980s, and red from the 2010 s.

points that did not meet the requirements, we obtained 51 paired sampling points, which precisely matched unique reference soil species. The paired sampling points are shown in Fig. 2.

2.6. Statistical analyses

The SOC datasets were tested for normal distribution using the Shapiro-Wilk normality test and for homogeneity of variances using Levene's test. It showed that the SOC datasets were not normally distributed. Therefore, a non-parametric Kruskal-Wallis test was used to conduct the one-way analysis of variance (ANOVA) to test whether SOC samples differed between the main crop rotations by ranks. A significant Kruskal-Wallis test indicates that there are at least one group of SOC stochastically dominates one other group. If so, another non-parametric Dunn's test with Bonferroni correction was used to identify the differences between specific pairs of groups using rank sums. All statistical analyses were performed using the *rstatix* package (Kassambara, 2023) in R 4.2.3 (R Core Team, 2023).

2.7. Path analysis

We used a hypothesis-oriented partial least squares path model (PLS-PM) to measure the direct and indirect effects of climate, agricultural management practices and soil properties on SOC. PLS-PM is a type of structural equation models (SEM) based on the partial least squares approach (PLS) (Mateos-Aparicio, 2011; Sanchez, 2013). Conventional covariance-based SEMs aim to fit a model and reproduce the observed covariances, so that statistical inferences are highly related to the distributional assumptions of the observed data. PLS-PMs are considered an approximation of the ground truth to predict without imposing distributional assumptions on the data. PLS-PM provides a practical summary of the manner through which the dependent variables are systematically explained by their indicators.

A PLS-PM is composed of a set of latent variables and their corresponding manifest variables, which is linked by the potential paths between latent variables indicating their correlation relationships. The correlations between latent variables are measured by path coefficients. In our study, a latent variable is considered the cause of the manifest variables, which is called a reflective mode. The correlations between latent and manifest variables are measured by loadings, which build the outer model. The network of latent variables is referred to as the inner model.

According to the "Clorpt" equation of soil formation (Jenny, 1994), the hypothesis is as follows. The spatial distribution of SOC is influenced by climate, agricultural management, and soil physiochemistry. We considered six latent variables in our PLS-PMs to build a path framework, namely "Climate," "Fertilizer," "Machinery," "Soil," "Residue," and "SOC." "Climate" was measured by MAP and MGST. "Soil" was measured by clay content and soil pH. TN was excluded from "Soil" to reduce the multicollinearity attributed to its high correlation with SOC. Other latent variables were measured by their single corresponding manifest variable. All five latent variables jointly influenced "SOC." "Climate" also influenced "Residue" and "Soil." "Machinery" and "Fertilizer" simultaneously influenced "Residue" and "Soil." Whereas "Residue" received an effect from "Soil." Negative loadings were converted to positive by using the opposite number of indicators. A non-parametric bootstrap validation method was used to evaluate the robustness of the path coefficients and identify the precision of the model fit. M samples ($M = 100$ in this study) were randomly created by replacing observations from the original datasets. Each sample was the same size as the original sample. Then, M estimates were obtained for the path coefficients. The bootstrap mean values, standard errors, and 95% confidence intervals were used as auxiliary indices to the t-test to determine whether a path coefficient was robust.

For the paired data, we fitted a PLS-PM to model relationships between SOC change and climate, agricultural management, soil physiochemistry, and possible changes in these main drivers of SOC. We considered six latent variables: "Climate," "Initial Agriculture," "Agricultural Intensification," "Baseline SOC," "Soil," and "SOC Change." "Initial Agriculture" consisted of N fertilizer use rate, total power of agricultural machinery, and crop residue input in the 1980s, and it represented the initial agricultural level before SOC change. "Agricultural Intensification" was measured by the differences in the three agricultural indicators from the 1980s to the 2010 s so as to represent the level of agricultural intensification. "Baseline SOC" was the SOC content in the 1980s "Soil" consisted of clay content change and TN change, as well as pH in the 1980s. All five latent variables jointly influenced "SOC Change." "Climate" also influenced "Baseline SOC" and "Soil." "Initial Agriculture" influenced "Agricultural Intensification," "Baseline SOC," and "Soil." Bootstrap validation was performed to test the robustness of model fitting. The PLS path modeling was performed using the *plspm* package (Sanchez, 2013) in R 4.2.3 (R Core Team, 2023).

3. Results

3.1. Statistical characteristics of SOC content in the 1980s and 2010 s in the Yangtze River Delta

The SOC content of the 1980s dataset ranged from 2.73 to 33.37 g kg^{-1}, whereas that of the 2010 s dataset ranged from 3.04 to 40.08 g kg^{-1}. The frequency distribution of SOC for the two datasets is illustrated in Fig. 3a. Table 2 lists the descriptive statistics of SOC. The results show that the average SOC content in the 2010 s was higher than that in the 1980s in the Yangtze River Delta region and in each of the three provinces. This indicated that SOC stocks in this region likely increased, which is consistent with previous estimations (Huang and Sun, 2006; Zhao et al., 2018). Although the standard deviation (SD) of SOC in the 2010 s was higher than that in the 1980s, the coefficient of variation (CV) of SOC in the 2010 s was lower than that in the 1980s.

As for the selected paired sampling points, the average SOC content in the 1980s and 2010 s was 13.14 and 16.07 g kg^{-1}, respectively. The frequency distribution was similar to that of the entire datasets (Fig. 3b), which implied that this subset could be a representative sample of the entire datasets. The SOC change ranged from -12.50 to 30.46 g kg^{-1}, with an average of 2.92 g kg^{-1}, which indicated that SOC tended to increase throughout the three decades.

3.2. Statistical characteristics of the indicators of main drivers of SOC content

Table 2 shows the descriptive statistics of the indicators of main drivers used in this study. Generally, the indicators changed directionally from the 1980s to the 2010 s. In the context of global warming, the average value of MGST increased from 17.74 to 18.25 ℃. Agricultural management indicators increased substantially under the agricultural modernization process. The average rate of N fertilizer use increased from 11.41 to 19.39 g N m^{-2} yr^{-1}. Total power of agricultural machinery boosted from 1.89 to 8.79 kW ha^{-1}. The average crop residue input increased from 0.60 to 2.36 t ha^{-1}. The variability of agricultural management indicators represented by coefficient of variation (CV) decreased respectively as their standard deviation increased. For soil properties, clay content and soil pH decreased especially for pH. The statistical characteristics of TN were very consistent with SOC.

3.3. SOC content under different crop rotations and management practices

The sampling points in this study were distributed across croplands with four types of main crop rotations, in areas characterized by particular agricultural management practices. Boxplots of the SOC content of the sampling points under different main crop rotations are

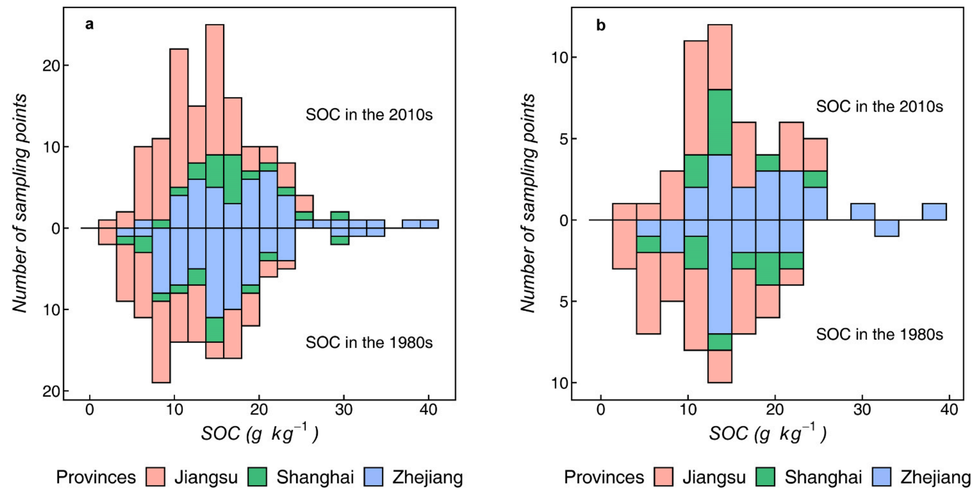

Fig. 3. (a) The frequency histograms of the SOC content (g kg^{-1}) in the 1980s and 2010 s, respectively. Red bars stand for the sampling points in Jiangsu Province. Green bars stand for Shanghai and blue stand for Zhejiang. (b) The frequency histograms of the SOC content (g kg^{-1}) in the 1980s and 2010 s of the paired sampling points.

Table 2
Descriptive statistics of SOC and the indicators of main drivers used in this study.

		MGST (℃)	MAP (mm)	Fertilizer (g N m^{-2} yr^{-1})	Machinery (kW ha^{-1})	Residue (t ha^{-1})	Clay (%)	pH	TN (g kg^{-1})	SOC (g kg^{-1})
Min	1980s	15.71	816	0.92	0.61	0.38	3.14	5.30	0.30	2.73
	2010s	16.18	799	3.23	3.34	1.16	4.69	4.22	0.26	3.04
Max	1980s	20.41	1976	26.17	5.14	0.88	62.75	8.70	3.42	33.37
	2010s	21.61	2021	36.35	26.06	3.64	53.63	8.66	4.43	40.08
Mean	1980s	17.74	1196	11.41	1.89	0.60	26.66	6.91	1.38	13.29
	2010s	18.25	1143	19.39	8.79	2.36	21.00	6.60	1.41	15.11
SD	1980s	1.13	268	5.23	0.91	0.10	11.99	0.99	0.60	6.12
	2010s	1.29	219	7.65	4.21	0.36	10.04	1.11	0.62	6.52
CV (%)	1980s	6.40	22.39	45.86	48.01	16.07	44.97	14.26	43.75	46.04
	2010s	7.07	19.21	39.43	47.90	15.34	47.82	16.83	43.66	43.19

*SD: standard deviation; CV: coefficient of variation; Fertilizer: N fertilizer use rate; Machinery: total power of agricultural machinery; Residue: crop residue input.

presented in Fig. 4. The vertical gray lines under the boxes indicate the overall average SOC of the dataset. The results showed that sampling points planted with wheat in the 1980s presented a SOC value lower than the average value. In the 2010 s, this gap decreased, and the SOC was distributed more randomly among the rotation types.

We conducted a non-parametric one-way ANOVA using the Kruskal-Wallis test for the non-normally distributed datasets. Significant differences were observed in each dataset. The results of the Dunn's test further explained where the stochastic dominance occurred. In the 1980s, the SOC of upland soils planted with wheat was significantly lower than that of all other types of paddy soils. There were no significant differences between the paddy soils dominantly planted with rice (other three main crop rotations). In the 2010 s, croplands under wheat-maize rotations were significantly different from those under rice-rape rotations or planted with single-season rice. Croplands under rice-wheat rotations also showed significant difference from croplands planted with single-season rice, because of the higher SOC in the latter compared to the values in the 1980s. These results indicated that crop

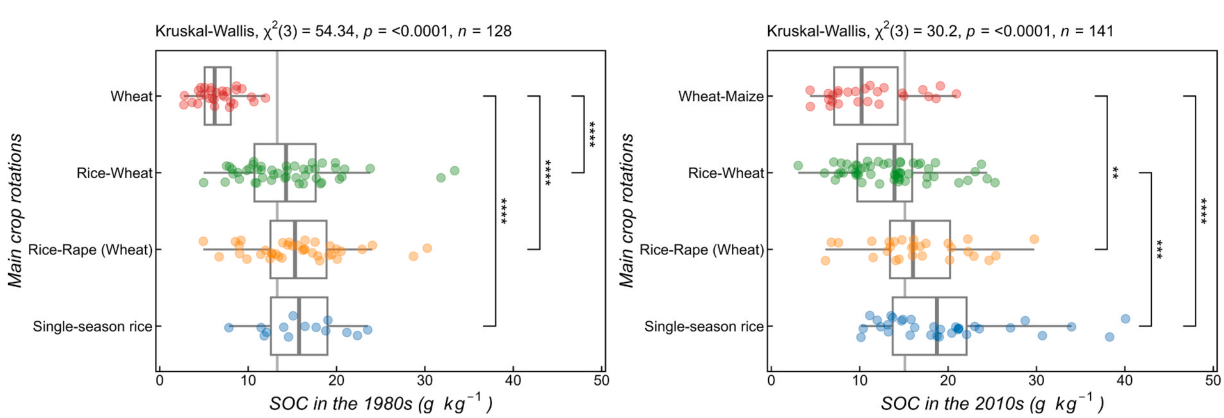

Fig. 4. The SOC content of sampling points under different main crop rotations in the 1980s (left) and the 2010 s (right). The vertical gray lines show the overall average SOC content of the dataset. Significance marks for Dunn's multiple comparisons test: * ** *, $P \le 0.0001$; * ** , $P \le 0.001$; * *, $P \le 0.01$; * , $P \le 0.05$.

rotations influenced SOC distribution, which could be attributed to the amount of crop residue return or the corresponding agricultural management practices for each crop type required.

3.4. Direct and indirect effects of indicators on SOC distribution in the 1980s and 2010s

We conducted a PLS path analysis of the sample data from the 1980s and the 2010s using the same inner model structure. The fitted PLS-PMs for SOC distribution in the 1980s and 2010 s are shown in Fig. 5a and c. The PLS-PM explained 44% of the variance in SOC of the 1980s dataset ($R^2 = 0.44$). Soil properties had the strongest positive effect on SOC, with a total effect of 0.62, followed by climate (0.38). The climatic effect on SOC was mainly realized through the influence on soil properties. Among the agricultural management indicators, agricultural machinery power and crop residue input positively contributed to SOC distribution with direct effects of 0.24 and 0.18, respectively. Whereas the effect of N fertilization remained mixed in the 1980s (−0.06), which means it was difficult to determine whether the effect was positive or negative.

The PLS-PM explained 29% of the variance in SOC of the 2010s dataset ($R^2 = 0.29$). In contrast to the 1980s, soil properties (mainly soil pH) caused significantly lower effect on SOC in the 2010s, with a total effect of 0.25, compared to 0.62 in the 1980s. An increased direct effect of climate on SOC (0.34) offset the reduced indirect climatic effect from weaker soil physiochemical effects. Consequently, the strongest driver of SOC in the 2010 s was climate. The total effects of agricultural machinery and crop residue input were similar in the 2010s. However, the indirect effect of machinery through influencing other soil properties increased and the direct effect decreased from 0.24 to 0.15. N fertilization exerted a significantly positive effect on SOC (0.19) in the 2010s compared to the insignificant effect in the 1980s.

Both PLS-PMs revealed that agricultural management practices had positive effects on SOC. In other words, croplands with more intense management tended to have higher SOC. Moreover, the soil physiochemical effects on SOC decreased as the part of variance in SOC that all indicators explained decreased, which suggested more independent SOC change after long-term cultivation.

3.5. Direct and indirect effects of indicators on SOC change from the 1980s to the 2010s

The fitted PLS-PM on SOC change (calculated as the difference in SOC content between the 2010s and the 1980s) based on the paired soil sample data measured the effects of different indicators on the temporal

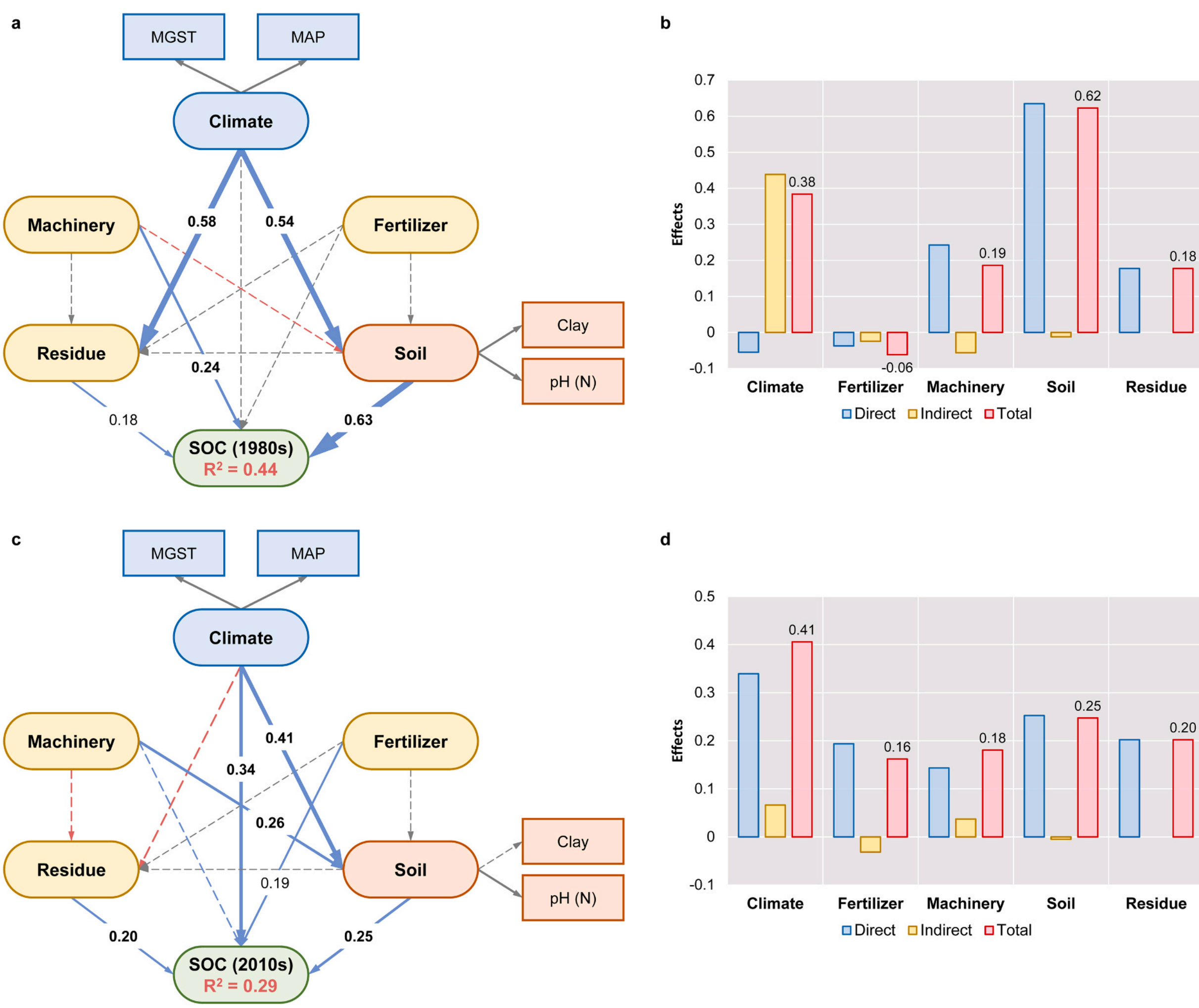

Fig. 5. PLS-PMs of the (a) 1980s and (c) 2010 s. Rounded blocks represent latent variables and rectangular blocks are their corresponding manifest variables. Blue/red arrows between latent variables indicate positive/negative path coefficients, among which solid lines are significant with $P(>|t|) \leq 0.05$ and bolded path coefficients are significant with $P(>|t|) \leq 0.01$. Dashed gray lines are insignificant with mixed effects (path coefficients < 0.10 in absolute value). Gray arrows between latent variables and manifest variables indicate loadings. Loadings with dashed lines are insignificant. "N" means the loading is converted to positive by using the opposite number of the indicator. (b) and (d) show direct/indirect and total effects of latent variables on SOC. MGST: mean annual average ground surface temperature; MAP: mean annual precipitation.

change of SOC (Fig. 6). The initial agricultural level in the 1980s directly influenced SOC change through an insignificantly positive path (0.20). The most important manner through which it influenced SOC change was through the level of agricultural intensification. These two pathways led to an insignificant total effect. SOC change benefited more from agricultural intensification than the initial agricultural level, with a direct effect of 0.38. In general, most sampling points underwent intense enhancement in terms of agricultural management. The strong negative effect of initial agricultural level on the changes in agricultural management indicators (−0.63) suggest that croplands deficient in agricultural management in the 1980s attained more development, and this effect led to higher SOC accumulation up to the 2010s. For each type of agricultural activity, PLS-PM revealed that changes in agricultural machinery power and crop residue input were the main factors driving SOC change, as N fertilizer use rate did not significantly contribute to this pathway. Furthermore, sampling points with more increase in residue return rate tended to generate less SOC change as crop residue input was taken as the opposite number in the PLS-PM.

Edaphic conditions were the strongest driver of SOC change, with a path coefficient of 0.74. The "Soil" latent variable included clay content change, TN change, and pH in the 1980s as the initial acidity level. The results showed that croplands with high SOC change normally presented more clay and TN change, and this tended to occur in soils with relatively high pH. Although TN change did not contribute the most to "Soil", the correlation between TN change and SOC change was important (Spearman's correlation coefficient of 0.79). The baseline SOC was negatively correlated with SOC change, which indicated that croplands with a low SOC content in the 1980s accumulated more SOC over time. The climatic effects on SOC change were divergent. Although climate positively influenced both the baseline SOC and SOC change, it exerted a negative effect on soil physiochemistry, which indirectly neutralized its direct effect on SOC change.

4. Discussion

4.1. Drivers of SOC distribution and changes in their effects from the 1980s to the 2010s

Although the relationships between soil C and the environment is crucial for C cycling research, few studies have measured the temporal changes in these relationships. Our study quantifies the driving mechanisms of SOC spatial distribution over two time periods in a well-developed region with a long cultivation history and examined the changes in the relationships between SOC distribution and its main drivers. The results showed that agricultural activities exerted important positive effects on SOC distribution, and these effects increased over 30 y, especially that of N fertilizer input. Soil physiochemistry was crucial in controlling the SOC distribution in the study area, and climate exerted constant positive effects on SOC through different pathways.

Few studies have incorporated agricultural management practices into quantitative analysis of SOC distribution. Our results suggest that agricultural management practices were indispensable driving factors of SOC distribution in a positive manner (Fig. 5). Machinery was the strongest driving factor in the 1980s, and N fertilization became significant in the 2010s. The addition of these agricultural management indicators to PLS-PMs improved the R^2 of SOC by 20.4% and 20.7% in the 1980s and 2010s, respectively (compared to that shown in Fig. S2). The effects of agricultural management on SOC are related to crop types. Fig. 4 shows the significant differences in the SOC content under different crop rotations. Every type of main crop rotation is characterized by a specific spatial distribution and agricultural management. Single-season rice was mostly planted in paddy fields on the terraces of Zhejiang Province (Fig. S3), which are located at high altitudes and benefited from warm humid climates, while lacking in the necessary management in the 1980s. Rice-rape rotation was common in this region, often with green manure or wheat after rice harvest. Croplands under rice-wheat rotation were usually a transition from drylands to paddy fields to improve productivity. Wheat-dominated drylands were mostly distributed in the northern part of the study area, with sandy soils of low fertility, which were less intensively managed in the 1980s. The three agricultural management practices used in this study differed among crop rotations (Fig. S1). The advocacy of straw/stover return started after the 1980s (Huang and Sun, 2006). In the early 1980s, the crop residue input in rice-dominated croplands was higher than those in wheat-dominated croplands and generated more C input from crop roots owing to their higher grain yield, which was associated with higher SOC. The application of agricultural machinery contributed to SOC distribution as well as soil texture and acidity, as evidenced by higher indirect effect and consistent positive direct effect on SOC. The N fertilizer use rate was low in the 1980s, especially in the terraces of single-season rice, which resulted in an insignificant effect on SOC in the PLS-PM.

In PLS-PMs of the 1980s and the 2010s, soil pH and clay content were used to reflect soil acidity and texture, respectively. The results indicated that SOC tended to be high in croplands with low pH and high clay

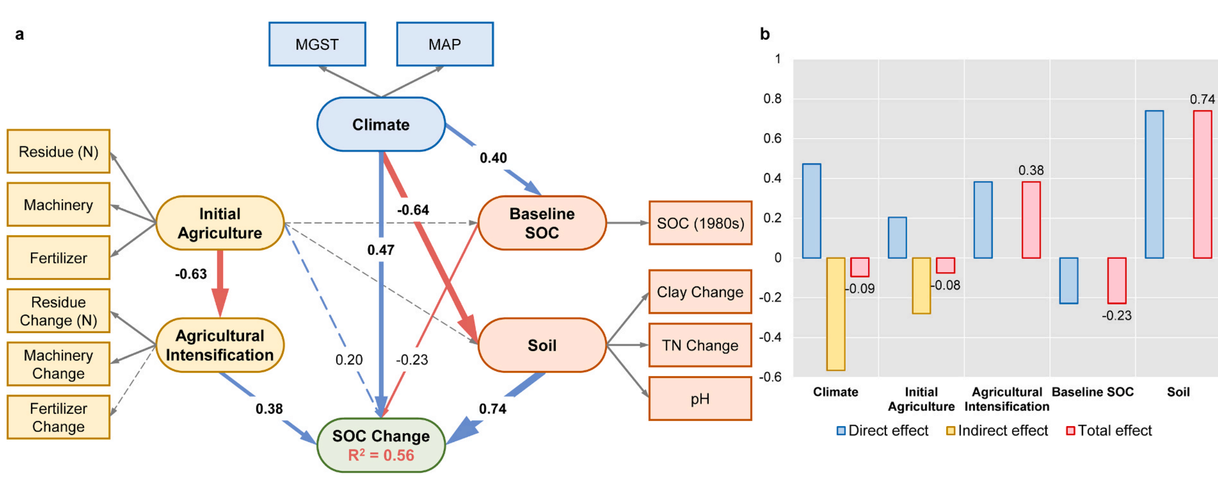

Fig. 6. (a) PLS-PMs of paired soil sample data to model SOC dynamics from the 1980–2010s. Rounded blocks represent latent variables and rectangular blocks are their corresponding manifest variables. Blue/red arrows between latent variables indicate positive/negative path coefficients, among which solid lines are significant with $P(>|t|) \leq 0.05$ and bolded path coefficients are significant with $P(>|t|) \leq 0.01$. Dashed gray lines are insignificant with mixed effects (path coefficients < 0.10 in absolute value). Gray arrows between latent variables and manifest variables indicate loadings. Loadings with dashed lines are insignificant. "N" means the loading is converted to positive by using the opposite number of the indicator. (b) Direct/indirect and total effects of latent variables on SOC change. MGST: mean annual average ground surface temperature; MAP: mean annual precipitation.

content, which is consistent with previous studies (Zhang et al., 2021). This effect might be attributed to the slower decomposition process of SOM after soil acidification by N input (Guo et al., 2010). The effect of edaphic conditions on SOC distribution decreased significantly compared to that of other drivers, indicating a more complex and interfered SOC regulation mechanism in the topsoil of croplands. A possible cause was the various human interference in croplands, such as C or N input from fertilizers and crop residue, tillage strategies, or targeted farmland transformations, which disrupted the natural balance of soil physiochemical processes.

Climate is often considered a primary factor controlling SOC (Beillouin et al., 2021; Bradford et al., 2016; Tang et al., 2018). However, many studies have demonstrated only the direct effects of temperature and precipitation on SOC. Our results highlighted the importance of indirect climatic effects on SOC through other soil properties. In this study, temperature and precipitation presented a positive total effect on SOC in the PLS-PMs of the 1980s and the 2010 s, which is consistent with the results of other previous studies (Luo et al., 2017; Osland et al., 2018). In the 2010 s, the direct climatic effect on SOC increased as the indirect effect through soil properties decreased. This maintained a constant influence of climate on SOC, which indicated the indispensable effect of climate on SOC distribution. The decrease in the indirect climatic effects on SOC was attributed to the pathways through soil properties and crop residue input. The lower edaphic effects on SOC from the 1980s to the 2010s was a cause of the decrease in indirect climatic effects. Moreover, climate presented a significantly positive effect on crop residue input in the 1980s, which further enhanced SOC (Fig. 5a). However, this positive effect decreased in the 2010 s. This might result from the general improvement in grain yield in the study area from the 1980s to the 2010s (Fig. 7) and the widely applied straw/stover return policies, which led to the more similar crop residue input among all sampling points (Table S2).

4.2. Drivers of SOC change based on the paired soil sample data

From a spatial perspective, it is unclear how natural and anthropogenic factors jointly influence SOC changes in croplands. As previously reported, the cropland SOC stocks in East China increased from 22.10 to 30.42 Mg C ha^{-1} from 1980 to 2011 (Zhao et al., 2018), which indicates a general SOC accumulation in our study area. The present study quantified the climatic, agricultural management, and soil physiochemical effects on SOC change in this region and separated direct and indirect effects.

Long-term agricultural management implementations and intensification have potential effects on soil C dynamics, as reported in many studies (Amelung et al., 2020; Beillouin et al., 2021). Agricultural management practices and agronomic policies in Yangtze River Delta region underwent major changes from the 1980s to the 2010 s. For instance, burning used was a prevailing approach for the disposal of crop residue until the government enhanced monitoring and economic penalties to prevent air pollution. Related crop straw/stover return policies and subsidies were implemented after the late 1980s, which led to the increase in C input from crop biomass (Huang and Sun, 2006; Qu et al., 2012). Crop residue input increased substantially with the rapid increase in grain yield (Fig. 7). However, our results indicated that SOC tended to change in croplands with smaller increase in crop residue input (Fig. 6). This suggests that SOC change could be induced by the initial grain yield of each rotation type to a higher extent than by the increase in straw/stover input rate, as the yield of every type of crops increased sufficiently.

Agricultural machinery use and its expansion were the strongest agricultural factors driving SOC change. Accompanied by advances in agricultural technologies and socio-economics, labor-intensive manuring and plowing practices have decreased owing to the increasing labor costs and shortages (Gao et al., 2006). Since the 1990s, the conventional tillage strategies have shifted to rely on farm machinery (Han et al., 2018). In wheat-maize rotated drylands, rapid agricultural mechanization improved efficiency of seeding, harvesting, and the application of fertilizers and pesticides, which boosted grain yield. In paddy fields, the application of agricultural machinery helped in plowing, irrigation, and planting to modify the soil structure and texture, which helped SOC accumulation (Dikgwatlhe et al., 2014).

Since the 1980s, chemical fertilizer use has rapidly increased in China to improve soil fertility and grain yield. Inorganic N fertilizer prevailed first. Compound and organic fertilizers have been successively advocated to balance soil nutrient cycling (Fig. 7). The overall massive improvement in N fertilization was an important factor driving SOC change (Fig. 6), especially in wheat-maize rotated drylands which were rapidly mechanized.

Except for the intensification of agriculture from the 1980s to the 2010 s, the initial agricultural level also presented positive direct effects on SOC change, which indicated that croplands with earlier implementation of agricultural management practices attained a higher SOC increase in the 1980s. However, croplands that were deficient in agricultural management in the 1980s attained more development in agricultural modernization. The correlations between the initial levels of all three agricultural management indicators and their changes were negative (Figs. 6 and 8), and this effect led to a higher SOC accumulation up to the 2010 s

Soil physiochemistry was the strongest driver of SOC change in this study (Fig. 6). This importance of soil physiochemistry in SOC dynamics has been emphasized in previous studies (Doetterl et al., 2015; Luo et al.,

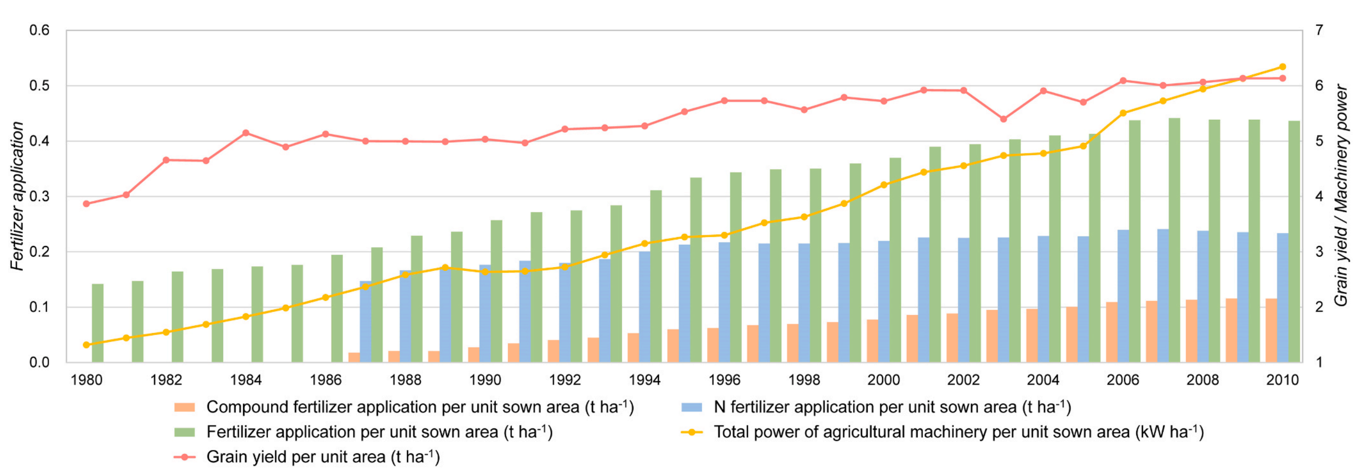

Fig. 7. The changes in different types of fertilizer application, total power of agricultural machinery, and grain yield in the Yangtze River Delta region from 1980 to 2010. The data were obtained from the National Bureau of Statistics of China (http://www.stats.gov.cn/sj/).

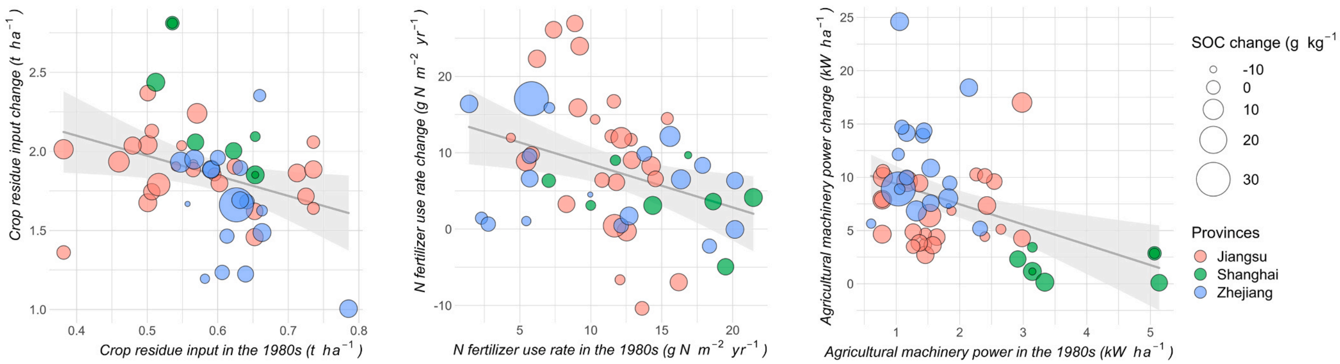

Fig. 8. The relationships between the initial levels of agricultural management indicators and their changes from the 1980s to the 2010 s. The size of the bubbles represents the SOC change of the paired sampling points. Gray lines are the linear regression line for all sampling points.

2019). Among the indicators of edaphic conditions shown in Fig. 6a, TN change was the most closely related to SOC change. This mainly occurred because of the close connection between soil N and C (Cleveland and Liptzin, 2007; Tian et al., 2010; Deng et al., 2020). In intensively cultivated agroecosystems with sufficient N supply, the C:N ratio remains stable (Tian et al., 2010). Constant application of N fertilizer since the 1980s has enhanced the TN and crop growth in the study area, and consequently, SOC. In addition, N fertilization can lead to a considerable decrease in soil pH (Lu et al., 2022; Tian and Niu, 2015), which induced soil acidification in the study area (Sun et al., 2023; Zhang et al., 2020). We observed that croplands with higher topsoil pH in the study area experienced a greater decrease in pH, and this trend was consistent with the TN change, as they influenced SOC change together. Furthermore, the negative path coefficient from baseline SOC to SOC change (Fig. 6) indicated that croplands with lower SOC in the 1980s generally attained a greater increase in SOC after 30 y of cultivation, which has been demonstrated in previous studies as the baseline effect (Bellamy et al., 2005; Goidts et al., 2009; Luo et al., 2020).

Climate has divergent effects on SOC change. It directly influenced SOC change, which indicated that SOC accumulation tended to occur in croplands under warm and humid climates. However, the baseline SOC also benefited from more suitable climatic conditions. indicators of edaphic conditions in the PLS-PM were negatively affected by climate. Both pathways offset the direct climatic effect on SOC change, so that the total effect of climate was insignificant. This implied that despite the low overall climatic effect on SOC change, climate could still exert a noticeable influence on SOC change.

4.3. Implications

Agricultural management indicators proved significant in driving SOC dynamics in croplands. The results indicate that the driving mechanisms of SOC distribution can change over time, which suggests that the relationship between soil C and environmental covariates can be a function of time. This implies that human activities have drastically changed cropland C cycling processes at an interdecadal scale. Therefore, process-based modeling and digital mapping of soil C should incorporate indicators that reflect agricultural management, cropping systems, and more information. Future studies should avoid using fixed model parameterizations to model SOC distribution at different time by only replacing different datasets of environmental covariates.

Among the agricultural management practices, the application of crop residue input and agricultural machinery can lead to significant SOC accumulation. The effects of N fertilization in this study were relatively weak, which could be attributed to the surplus of N input in croplands of China (Schulte-Uebbing et al., 2022). Therefore, more rational fertilization strategies should be applied in the future. The use of organic fertilizers and implementation of conservation practices should be encouraged to prevent cropland degradation and improve sustainable production (Bohoussou et al., 2022; Cai et al., 2023). Cropland restoration and transformation were other anthropogenic factors beneficial to SOC accumulation in the study area. In Jiangsu Province, the extensive conversion from drylands to rice-wheat rotated paddy fields with improved irrigation efficiency has led to a major increase in grain yield since the 1980s, accompanied by improved soil structure (Huang and Pan, 2017). In this study, 18% of paired soil sampling points were converted to paddy fields from drylands over the 30 y, and their average SOC increased 6.07 g kg^{-1}, which was significantly higher than the average of 2.92 g kg^{-1} in all points. Moreover, salt-tolerant cash crops were planted in reclaimed saline lands in coastal areas, which also enhanced SOC accumulation in these barren soils (Wang et al., 2016).

4.4. Limitations

The present study analyzed the driving mechanisms of the spatio-temporal dynamics of topsoil organic carbon content in croplands of the Yangtze River Delta region from a statistical perspective. PLS-PM is a method casual in data distribution to model multivariate relationships (Esposito Vinzi et al., 2010), which is suitable for building semi-empirical models using our datasets. When interpreting the results, the magnitude of the effects is relatively less precise than whether the effects are positive or negative because of the existing statistical bias.

This study presented some limitations that could have influenced the results. For instance, the agricultural management indicators were extracted from raster or county-level data. Although these are the most detailed available data, they may reduce the reliability in depicting the characteristics of the sampling points. Remote sensing-based datasets can be options to provide more information on the features of agricultural activities to improve model performance in the future (Weiss et al., 2020). More detailed repeated sampling and other high-quality datasets should be combined to better quantify the effects of driving factors on SOC dynamics. Moreover, the indicators may have lagged or cumulative effects on SOC at the current temporal scale. Therefore, time series data of SOC and environmental indicators are required for further research.

5. Conclusions

Our study quantified the direct and indirect effects of climate, agricultural management, and soil physiochemical properties on topsoil organic carbon content in croplands of the Yangtze River Delta region in the 1980s and 2010s, and analyzed the joint effects of these factors on SOC change over 30 y. The results of the drivers of SOC distribution showed that SOC tended to be higher in soils with a relatively low pH and high clay content in warm humid climates. Furthermore, higher SOC was associated with the application of N fertilizer, crop residue input, and agricultural machinery in the 1980s and 2010s. From the 1980s to the 2010s, the effect of N fertilization on SOC distribution increased, whereas the edaphic effects decreased. Regarding the drivers of SOC change over the three decades, initial agricultural level and agricultural intensification were indispensable drivers of SOC accumulation. Croplands with lower intensity of management practices in the 1980s generally attained more development, which led to a considerable SOC increase. Edaphic effects were the strongest driver of SOC change, including the positive effects of TN and clay content change, and the negative effects of topsoil acidity and baseline SOC. Our results indicate that agricultural activities in croplands can induce drastic changes in topsoil organic carbon. Future studies should incorporate the temporally changing agriculture-related driving mechanisms of SOC dynamics into process-based models and digital mappings at different spatiotemporal scales.

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.

Data Availability

Data will be made available on request.

Acknowledgements

This study was supported by the National Natural Science Foundation of China [Project No. 41971054] and the Fundamental Research Funds for the Central Universities [0209-14380115].

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2023.108749.

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