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Influences of Environmental Variables and Their Interactions on Chinese Farmland Soil Organic Carbon Density and Its Dynamics

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Abstract: Farmland is one of the most important and active components of the soil carbon pool. Exploring the controlling factors of farmland soil organic carbon density (SOCD) and its sequestration rate (SOCDSR) is vital for improving carbon sequestration and addressing climate change. Present studies provide considerable attention to the impacts of natural factors and agricultural management on SOCD and SOCDSR. However, few of them focus on the interaction effects of environmental variables on SOCD and SOCDSR. Therefore, using 64 samples collected from 19 agricultural stations in China, this study explored the effects of natural factors, human activities, and their interactions on farmland SOCD and SOCDSR by using geographical detector methods. Results of geographical detectors showed that SOCD was associated with natural factors, including groundwater depth, soil type, clay content, mean annual temperature (MAT), and mean annual precipitation. SOCDSR was related to natural factors and agricultural management, including MAT, groundwater depth, fertilization, and their interactions. Interaction effects existed in all environmental variable pairs, and the explanatory power of interaction effects was often greater than that of the sum of two single variables. Specifically, the interaction effect of soil type and MAT explained 74.8% of the variation in SOCD, and further investigation revealed that SOCD was highest in Luvisols and was under a low MAT (<6 °C). The interaction effect of groundwater depth and fertilization explained 40.4% of the variation in SOCDSR, and fertilization was conducive to SOCD increase at a high groundwater depth (<3 m). These findings suggest that low soil temperature, high soil moisture, and fertilization are conducive to soil carbon accumulation. These findings also highlight the importance of agricultural management and interaction effects in explaining SOCD and SOCDSR, which promote our knowledge to better understand the variation of SOCD and its dynamics.

Keywords: soil organic carbon density and its dynamics; interaction effects; geographical detector methods; agricultural management; natural factors

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1. Introduction

Farmland is the most important and active component of the soil carbon pool, which is strongly affected by human activities and has great potential for carbon sequestration [1–3]. Canadell [4] determined that the adoption of the best agricultural management could yield 0.4–0.8 Pg of carbon per year in farmland soil. Minasny et al. [5] surveyed farmland soil organic carbon (SOC) stock and sequestration potential in 20 regions across the world (e.g., Russia, Canada, China, America, and Australia) and reported that 4 per mille or even higher sequestration rates can be achieved under best management practices. Carbon sequestration in farmland soil improves soil fertility, thus increasing crop yield and ensuring food security [6–9]. It also affects regional and global carbon cycles by reducing greenhouse gas concentration, thus achieving the target of the Paris Climate Agreement to limit global warming to less than 2 °C [10–12]. The SOC density (SOCD) is used to measure SOC stock, and the sequestration rate in SOCD (SOCDSR) reflects the carbon sequestration in soil or loss from soil. Therefore, exploring the controlling factors of farmland SOCD and SOCDSR is vital for improving carbon sequestration rate, ensuring food security, and addressing climate change.

The farmland SOCD is directly affected by human activities, such as cropping systems and agricultural management [1,13–15]. Many studies have proven that appropriate agricultural management, such as planting rice, conservation tillage, fertilization, irrigation, and straw return, is conducive to SOC accumulation [1,8,13,16,17]. The SOCD is also affected by natural factors, including soil properties (e.g., soil type and texture), climate (e.g., temperature and precipitation), organisms (e.g., vegetation and soil microbes), topographical factors (e.g., elevation, slope, and aspect), and parent materials [18–21]. The integration of natural factors and human activities could explain the spatial variation of farmland SOCD at the regional scale [16,22–25]. Present studies pay more attention to the impacts of natural factors on SOCD and SOCDSR. However, studies on the impacts of human activities are limited to land use types and vegetation index and ignore the agricultural management [26–29]. Moreover, few of the studies concentrate on the interaction effects of environmental variables on SOCD.

Several studies have found that the relationship between SOCD and a controlling factor is affected by the value of another factor. For instance, Zhong et al. [30] found that the relationship among SOCD, mean annual precipitation (MAP), and mean annual temperature (MAT) changes at different MAP or MAT levels. Liu, et al. [31] determined that the relationship between SOC and multiple land use percentages has a land-use dependency. Zhu, et al. [32] identified that the effects of topographical factors on SOC depend on land use because the intensities of soil erosion and deposition on slopes are mediated by vegetation cover. These studies highlighted the importance of interaction effects on SOCD. Hence, the consideration of natural factors, human activities, and their interactions may well explain the variations in SOCD and SOCDSR.

Univariate/multivariate analysis methods, such as correlation analysis, one-way/multifactor analysis of variance, and multiple linear regression, are widely used for quantitatively determining influencing factors [33–36]. Nevertheless, these methods usually assume normality, homoscedasticity, and independence of the error term [37], which are difficult to satisfy. Geographical detector methods have relaxed assumptions and are able to explore the interaction effects of explanatory variables on target variables [33,38]. They assume that if geographical phenomenon A is controlled by factor B, then B will exhibit a spatial pattern similar to that of A. The interaction effect of two factors can be assessed by comparing the explanatory power by overlaying and using them alone. The Q-statistic is developed to quantify the explanatory power of predictors and their interactions with geographical phenomena. Compared with classical variance analysis methods (e.g., one-way/multifactor analysis of variance), geographical detectors are more sensitive to variance fluctuation and can quantitatively determine the explanatory power of predictors and their interactions [38]. Geographical detector methods have been successfully applied to reveal the interaction effects of covariates on various soil properties, such as soil organic matter/carbon [39,40], soil erosion [41–43], and heavy metals [44–46]. Therefore, geographical detectors may have great potential for identifying the effects of environmental variables and their interactions on SOCD and SOCDSR.

With its wide extent and diverse climate and agricultural systems, China is an excellent study area that allows us to explore the differences of SOCD and its dynamics under different natural environments and agricultural systems. Revealing the drives of SOCD and SOCDSR of Chinese farmlands contributes to national agricultural management. Therefore, using 64 samples collected from 19 agricultural stations in China, this study aims to explore the effects of natural factors, human activities, and their interactions on farmland SOCD and SOCDSR by using geographical detector methods.

2. Materials and Methods

2.1. Study Area and SOCD Data Acquisition

This study used a dataset of topsoil organic carbon density of 19 agricultural field stations of the Chinese Ecosystem Research Network (CERN) from 2005 to 2015 [47]. These stations cover the typical cropping systems of China, including paddy fields in plains and irrigated lands in plains, hills, mountains, Loess Plateau, and desert oases. Their spatial locations are shown in Figure 1. Each station uses the control group to explore the change in SOCD with time under the influence of irrigation, fertilization, or straw return. Each station has 2–5 sampling points, and 64 sampling points exist in total. Each point adopts the same specification for soil property measurement, which makes the SOCD among different stations comparable. Specifically, bulk density was determined by the cutting ring method [48], SOM was measured through the potassium dichromate method [49], and SOCD (kg/m^2) was calculated as follows [50,51]:

$$SOCD = SOM \times 0.58 \times BD \times H/100$$

where 0.58 is the Bemmelen transform coefficient, BD is the bulk density (g/cm^3), and H is the soil thickness (cm). The soil thickness is 20 cm in this study.

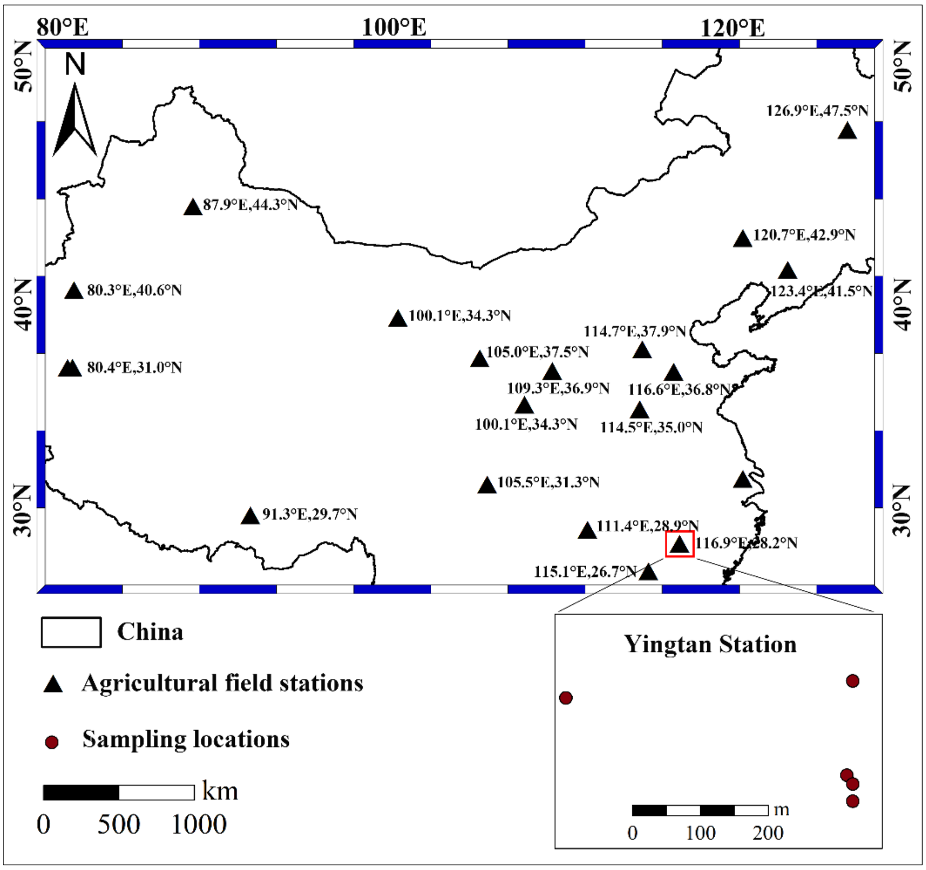

Figure 1. Study area and spatial locations of agricultural field stations.

The SOCD in 2005 was used as the initial SOCD, which in 2015 was regarded as the current SOCD. SOCDSR [$kg/(m^2 \cdot a)$] was equal to the current SOCD minus the initial SOCD and divided by time. The SOCD in 2015 and SOCDSR were used as target variables.

2.2. Environmental Variables

A number of environmental variables were chosen as potential influencing factors. The natural factors included elevation, soil type, groundwater depth, clay content, MAT, and MAP. The human activities included cropping duration, initial SOCD, cropping systems, irrigation, fertilization, and residue management.

Many covariates, including elevation, soil types, groundwater depth, cropping systems, irrigation, fertilization, and residue management, were recorded in the CERN dataset [47]. The soil types are classified into Luvisols, Anthrosols, Gleysols, Cambisols, and other soils (Acrisols, Calcisols, and Phaeozems soils). The cropping systems included rice, rice–dry crops, and dry crops. Agricultural management methods included fertilization (fertilizer and blank control), irrigation (irrigation and rainfall), and residue management (straw return and blank control). The initial SOCD (i.e., the SOCD in 2005) was used only for SOCDSR. The cropping duration was the time from the establishment of the station (probably before 2005) to 2015, and it was used only for SOCD. The clay content, MAP, and MAT were derived from 1 km-resolution raster images shared by the Resource and Environment Data Cloud Platform (http://www.resdc.cn, access on 1 January 2022). The clay content, MAP, and MAT of each sampling point were extracted via ArcGIS software (version 10.2.1, Esri, Redlands, CA, USA).

2.3. Geographical Detector Methods

The geographical detector methods are developed to detect the spatial heterogeneity of geographical phenomena among strata or subregions [33,38,52]. They include four detectors: factor, risk, interaction, and ecological detectors. The first three detectors were used in this study.

2.3.1. Factor and Risk Detectors

The factor detector can quantitatively determine the explanatory power of each environmental variable and thus its relative importance. The q-statistic was employed to quantify the explanatory power, as shown as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}$$

where categorical factor X contains L classes, N is the total sample number, N_h is the sample number of class h (h = 1, 2, ... , L), σ^2 is the variance of the population, σ_h^2 is the variance of class h (h = 1, 2, ... , L), SSW is the within the sum of squares, and SST is the total sum of squares. The significance of the q-statistic was determined through F-test [53]. The q value ranges from 0 to 1, and it indicates that factor X can explain q $\times$ 100% of the variation in dependent variable Y. The q values of the environmental variables indicate their relative importance, i.e., the greater the q value is, the greater the impact on Y will be.

The risk detector was developed to test whether a significant difference in the mean value of Y exists between any two classes of X through *t*-test as follows:

$$t_{\overline{Y}_{h=1}-\overline{Y}_{h=2}} = \frac{\overline{Y}_{h=1} - \overline{Y}_{h=2}}{\sqrt{\frac{\sigma_{h=1}^2}{N_{h=1}} + \frac{\sigma_{h=2}^2}{N_{h=2}}}}$$

where $\overline{Y}_h$ is the mean value of Y in class h. If the t-test result is significant, the mean values of Y between the two classes are significantly different. After pairwise comparison, we can determine whether there are significant differences in the mean values of Y among different classes.

2.3.2. Interaction Detector

The interaction detector was developed to assess the interaction effect of two factors (e.g., X1 and X2) on Y. The q (X1∩X2) was compared with q (X1) and q (X2), and the type of interaction effect was determined as follows:

$$q\ (X1 \cap X2) > q\ (X1) + q\ (X2), \text{ Nonlinear enhancement;}$$

$$q\ (X1 \cap X2) = q\ (X1) + q\ (X2), \text{ Independent;}$$

$$q\ (X1 \cap X2) > \text{Max}\ [q\ (X1), q\ (X2)], \text{ Bi-enhancement;}$$

$$q\ (X1 \cap X2) > \text{Min}\ [q\ (X1), q\ (X2)]\ \&\ q\ (X1 \cap X2) < \text{Max}\ [q\ (X1), q\ (X2)], \text{ Bi-weakening;}$$

$$q\ (X1 \cap X2) < \text{Min}\ [q\ (X1), q\ (X2)], \text{ Non-linear-weakening;}$$

where X1∩X2 is a new stratum created using overlaying factors X1 and X2 and indicates the interaction effect of X1 and X2.

2.3.3. Data Preprocessing for Geographical Detectors

The geographical detector methods require that the independent variables are categorical variables, and continuous variables should be stratified [33]. In this study, quantile and manual methods were used for the stratification of continuous variables (Table 1). The quantile method makes the sample number in each stratum equal, and the manual method relies on expert knowledge. Specifically, elevations of 200 and 500 m are the boundaries of plains, hills, and mountains; MAPs of 400 mm and 800 m distinguish semiarid, semi-humid, and humid zones. The stratification of MAT was based on the study by Li, et al. [54]. Table 1 shows the basic information and stratification methods for continuous variables. The GeogDetector software was used to implement the geographical detector methods (downloaded from http://geodetector.cn/ (accessed on 1 January 2022)) [55].

Table 1. Basic information and stratification methods of environmental factors.

Factors	Range	Cutting Value	Method
Groundwater depth	0.57–84.48 m	3, 8, 16	Quantile
Clay content	4–37%	14, 30	Quantile
Cropping duration	9–29 a	12, 19	Quantile
Initial SOCD	0.34–5.19 kg/m^2	1.58, 2.59	Quantile
Elevation	3–3688 m	200, 500	Manual
MAT	2 °C–18.2 °C	6, 10, 15	Manual
MAP	39.3–1696 mm	400, 800	Manual

Note: MAT: mean annual temperature; MAP: mean annual precipitation.

3. Results

3.1. Descriptive Statistics of SOCD and SOCDSR

Figure 2a exhibits the boxplots of SOCD and SOCDSR. The SOCD ranged from 0.59 kg/m^2 to 5.70 kg/m^2, and the SOCDSR ranged from -0.07 $kg/(m^2{\cdot}a)$ to 0.22 $kg/(m^2{\cdot}a)$. The mean and median values of SOCD were 2.54 and 2.035 kg/m^2, respectively. The mean and median values of SOCDSR were 0.037 $kg/(m^2{\cdot}a)$ and 0.025 $kg/(m^2{\cdot}a)$, respectively. The SOCDSR values of 77% of the sampling points were larger than 0, indicating that SOCD increased at most sampling locations in the previous 11 years. The scatter plot (Figure 2b) shows a positive correlation between SOCD and SOCDSR. This positive correlation was significant in accordance with Pearson correlation analysis ($R^2 = 0.421$, $p < 0.001$).

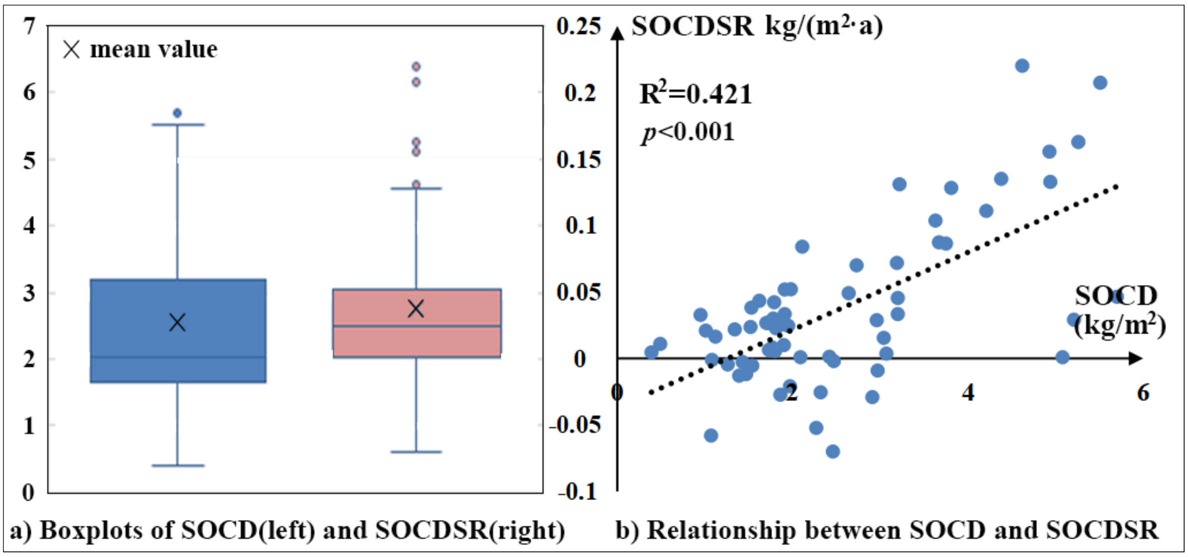

Figure 2. Boxplots of SOCD and SOCDSR (**a**) and their relationship (**b**). Note: SOCD and SOCDSR: soil organic carbon density and its sequestration rate.

3.2. Factor and Risk Detectors

The factor detector results of SOCD and SOCDSR are shown in Table 2. Groundwater depth, soil type, clay content, MAT, MAP, and cropping duration had significant effects on SOCD. MAT, soil type, and groundwater depth were the three most influential factors and explained 40.3%, 35.7%, and 31.2% of the variation in SOCD, respectively. Groundwater depth, MAT, and fertilization had significant effects on SOCDSR, and they explained 18.2%, 16.4%, and 14.2% of the variation in SOCDSR, respectively. Therefore, SOCD and SOCDSR were affected by natural factors and human activities. The explanation power of existing factors on SOCD was stronger than that on SOCDSR.

Table 2. q values of natural factors and human activities for SOCD and SOCDSR.

Influencing Factors		q Value of SOCD	q Value of SOCDSR
natural factors	elevation	0.117	0.007
	groundwater depth	0.312 ***	0.182 **
	soil type	0.357 ***	0.084
	clay content	0.286 ***	0.060
	MAT	0.403 ***	0.164 *
	MAP	0.264 ***	0.078
human activities	cropping duration	0.290 **	-
	initial SOCD	-	0.077
	cropping system	0.102	0.080
	irrigation	0.049	0.019
	fertilization	0.047	0.142 **
	residual management	0.014	0.001

Note: MAT—mean annual temperature; MAP—mean annual precipitation; and SOCD and SOCDSR—soil organic carbon density and its sequestration rate. *—Correlation is significant at the 0.1 level; **—Correlation is significant at the 0.05 level; ***—Correlation is significant at the 0.01 level.

On the basis of the risk detector results (Figures 3 and 4), SOCD was related positively to MAP, clay content, and cropping duration and negatively to elevation. In particular, SOCD first decreased and then increased with the increase in groundwater depth and MAT. In general, a high SOCD value was found in the farmland with low relief (<200 m), high groundwater depth (<3 m), high MAP (>400 mm), high clay content (>30%), low and high MAT (<6 °C and >15 °C), Luvisols and Anthrosols, long cropping duration (>21 a), rice planting, and manual irrigation. The SOCDSR was related positively to MAP and negatively to groundwater depth. The high initial SOCD contributed to the high SOC accumulation, but the effect was insignificant. SOCDSR generally peaked under the conditions of high groundwater depth (<3 m), high MAP (>800 mm), low and high MAT (<6 °C and >15 °C, respectively), and fertilization.

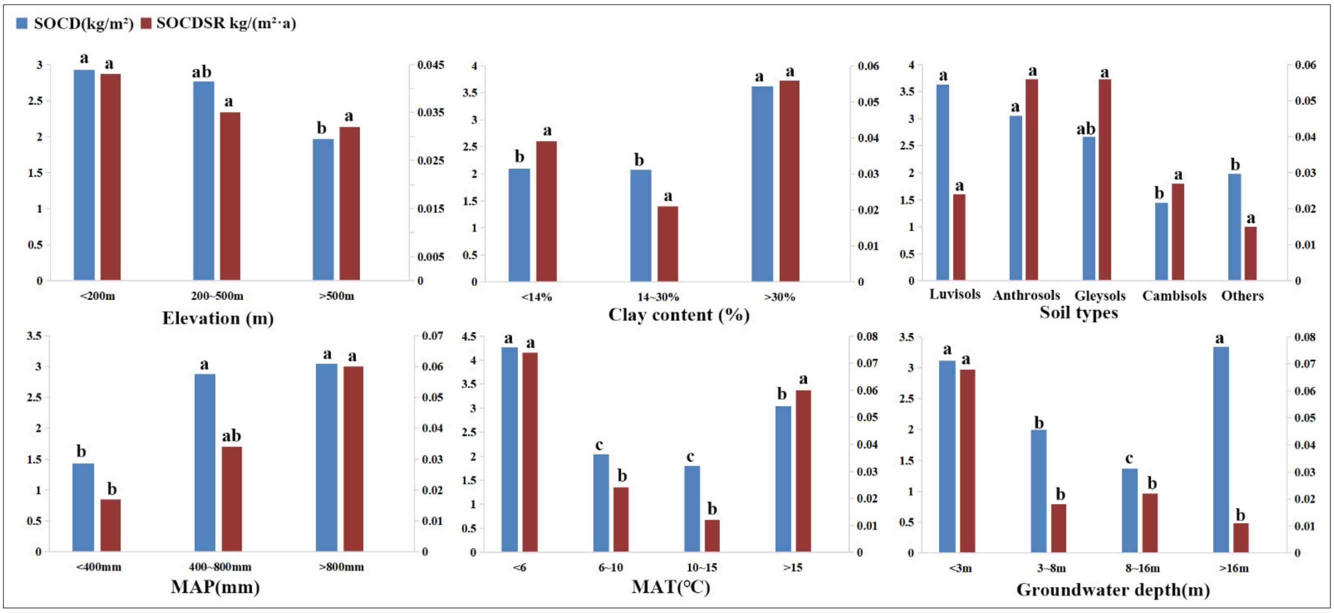

Figure 3. Effects of natural factors on SOCD and SOCDSR via the risk detector. Note: MAT: mean annual temperature; MAP: mean annual precipitation; SOCD and SOCDSR: soil organic carbon density and its sequestration rate. The same letters in the histogram represent insignificant differences.

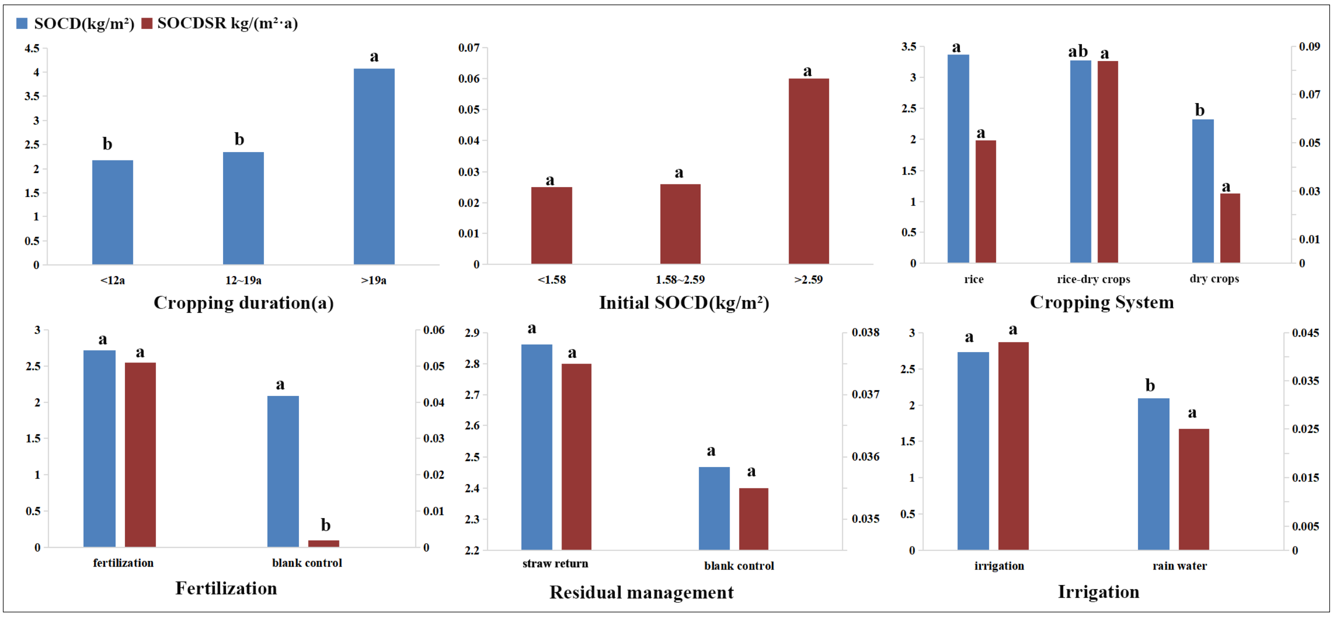

Figure 4. Effects of human activities on SOCD and SOCDSR via the risk detector. Note: SOCD and SOCDSR: soil organic carbon density and its sequestration rate. The same letters in the histogram represent insignificant differences.

3.3. Interaction Detector

A total of 121 pairs of interactions of SOCD and SOCDSR were calculated, and q values of these interactions are shown in Tables S1 and S2. These interactions were divided into three types: pairs of natural factors, pairs of human activities, and pairs of natural and human factors. Table 3 exhibits the dominant interaction effects on SOCD and SOCDSR with corresponding q values. The interaction effect of soil type and MAT was the most influential factor of SOCD, which explained 74.8% of the variation in SOCD. q values of the interactions between pairs of natural factors were higher than those of the two other types of interactions. The SOCDSR was mostly affected by the interaction effect of groundwater depth and fertilization. The joint impact of groundwater depth and fertilization explained 42.4% of the variation in SOCDSR. The interaction effects between pairs of natural and human factors had the greatest influence on SOCDSR, followed by those between pairs of human activities and pairs of natural factors. SOCD was mainly determined by the interactions between pairs of natural factors, whereas SOCDSR was mainly controlled by the interactions between natural and human factors.

Table 3. Interaction effects of environmental variables on SOCD and SOCDSR.

Influencing Factors	SOCD			SOCDSR		
	Interactions	q Value	Types	Interactions	q Value	Types
natural factors	ST∩MAT	0.748	Bi-E	ST∩GD	0.305	Nonlinear-E
	ST∩Elev	0.725	Nonlinear-E	ST∩MAT	0.287	Nonlinear-E
	ST∩Clay	0.702	Nonlinear-E	GD∩MAT	0.274	Nonlinear-E
natural and human factors	MAT∩CD	0.630	Bi-E	GD∩Fert	0.424	Nonlinear-E
	MAT∩CS	0.614	Nonlinear-E	MAT∩Fert	0.389	Nonlinear-E
	ST∩CD	0.602	Nonlinear-E	MAT∩CS	0.311	Nonlinear-E
human activities	CD∩CS	0.451	Nonlinear-E	Fert∩CS	0.374	Nonlinear-E
	CD∩Fert	0.366	Nonlinear-E	IS∩CS	0.312	Nonlinear-E
	CD∩Irri	0.358	Nonlinear-E	Fert∩IS	0.293	Nonlinear-E

Note: ST—soil types; MAT—mean annual temperature; Elev—elevation; Clay—clay content; CD—cropping duration; CS—cropping system; Fert—fertilization; Irri—irrigation; IS—initial SOCD; GD—groundwater depth; Bi-E and Nonlinear-E—bi-enhancement and nonlinear-enhancement, respectively; and SOCD and SOCDSR—soil organic carbon density and its sequestration rate.

Each type of interaction effect was determined by comparing q (X1∩X2) and the sum of q (X1) and q (X2). The joint impacts of soil type and MAT (q = 0.748), cropping duration, and MAT (q = 0.629) on SOCD were greater than the effects of individual factors (q (soil type) = 0.357, q (MAT) = 0.403, and q (cropping duration) = 0.290) but lower than their sum effect, which indicated that they were bi-enhanced. Other joint impacts on SOCD or SOCDSR were greater than the sum effect of two factors, indicating that the two factors enhanced each other (i.e., non-linear enhancement). In particular, the Q-statistic results showed that the cropping system exerted an insignificant effect on SOCD or SOCDSR ($p > 0.05$), but it played an important role in the interaction effects—with five other factors—on SOCD and SOCDSR. In general, interaction effects had greater explanatory power on SOCD and SOCDSR than single factors had.

The interaction effects with the greatest impacts on SOCD and SOCDSR are separately shown in Figure 5. Figure 5a exhibits the interaction effect of soil type and MAT on SOCD. The effect of MAT on SOCD was different in diverse soil types. The SOCD under low and high MAT (<6 °C and >15 °C, respectively) was much higher than that under medium MAT (6 °C–10 °C and 10 °C–15 °C) in Luvisols, Anthrosols, and Gleysols, but the difference in SOCD under low and high MAT and medium MAT was small in Cambisols and other soils. Figure 5b shows the interaction effect of groundwater depth and fertilization on SOCDSR. The effect of fertilization on SOCDSR varied in different groundwater depths. The difference in SOCDSR between fertilization and blank control was large when the groundwater depth was smaller than 3 m and larger than 16 m but was relatively small when the groundwater depth ranged from 3 m to 8 m and from 8 m to 16 m.

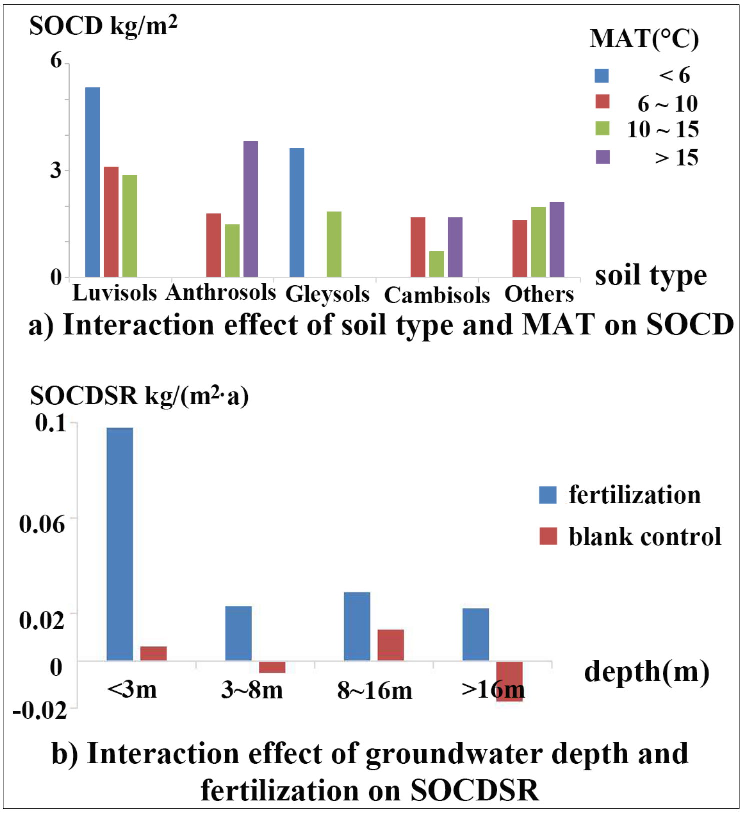

Figure 5. Interaction effect of soil type and MAT on SOCD (**a**) and interaction effect of groundwater depth and fertilization on SOCDSR (**b**). Note: SOCD and SOCDSR: soil organic carbon density and its sequestration rate.

4. Discussion

4.1. Influencing Factors of SOCD and SOCDSR

The SOCD was affected by natural factors—mainly groundwater depth, soil type, clay content, MAT, and MAP—while SOCDSR was affected by natural factors and agricultural management—mainly MAT, groundwater depth, and fertilization (Table 2).

Natural factors play vital effects on SOCD and SOCDSR. Soil types are the comprehensive expression of parent materials and soil-forming processes and are associated with various soil properties, such as texture, pH, soil moisture, and temperature [56–60]. Diverse soil types have different initial fertility and ability to maintain soil nutrients; consequently, the difference in soil types affects the spatial distribution of SOCD. In this study, we found that the SOCD of Luvisols and Anthrosols was significantly higher than that of Cambisols and other soils, such as Calcisols. Luvisols have a thick humus layer with a good aggregate structure and high moisture [61,62]. Anthrosols are mainly paddy soil and usually have a low decomposition rate of SOC and thereby a high SOCD value [13,63,64]. Cambisols have high sand content, low clay content, and high soil porosity, which are unconducive to nutrient storage [65,66]. As a result, the SOCD in Luvisols and Anthrosols was high, whereas the SOCD in Cambisols and Calcisols was low. Clay content is also an important indicator of SOCD. Clayey soil can stabilize SOC because it physically protects SOC against microbial mineralization within soil aggregates and chemically stabilizes SOC through adsorption to clay particles [67,68]. The SOCD is hence often positively related to clay content [69–71]. This study confirmed the positive effect of clay content on SOCD. The results also showed that SOCD with a clay content of more than 30% was significantly higher than that with a clay content of less than 30%. The SOCDSR in diverse soil types and clay content levels differed. However, the difference was insignificant. This condition may be due to the fact that soil type and clay content determine the spatial distribution of SOCD in a natural state, but they have minimal effects on the dynamics of SOCD in a short time.

Temperature and precipitation affect SOCD by determining plant species, plant productivity, and carbon decomposition [27,72–75]. With an increase in temperature, plant productivity increases, and the decomposition of plant residues accelerates; soil carbon input then increases [76–78]. Nevertheless, the increase in temperature leads to increases in microbial activity and soil respiration and thus the decomposition rate of SOC [27,79]. Therefore, the relationship between temperature and SOCD is complex and often depends on the balance of vegetation productivity and soil respiration [80,81]. In this study, SOCD and SOCDSR first decreased and then increased with an increase in MAT. The SOCD and SOCDSR under MAT lower than 6 °C or higher than 15 °C were significantly higher than those under MAT between 6 °C and 15 °C. This condition may be due to that low temperature (e.g., lower than 6 °C) inhibits soil respiration [82]. As the temperature increases, the increase in soil respiration is more influential than the increase in crop productivity, which leads to low SOCD [83,84]. The regions with high temperatures (e.g., higher than 15 °C) in South China, where farmlands are dominated by paddy fields, often adopt a multicropping system, which inhibits soil respiration and enhances carbon inputs [13,27,63,85]. As a result, the SOCD under high/low MAT is higher than that under moderate MAT. This finding is similar to that of the research of Li, et al. [54] and Xu et al. [62], who explored the national scale influencing factors of SOC in China's farmlands and found that when MAT is lower than 10 °C, SOC is negatively correlated with MAT, whereas when MAT is higher than 10 °C, SOC is positively correlated with MAT. Nonetheless, many studies have found that MAT is negatively correlated with SOCD and SOCDSR [84,86–90], which seems inconsistent with our findings. This difference may be due to the fact that these studies were conducted in relatively small-scale areas with moderate/low MAT and mainly natural coverage.

Precipitation affects soil moisture and thus controls SOCD. Low precipitation leads to low soil moisture and high soil salinity, which limit plant productivity and constrain SOM accumulation [72,78]. Moreover, low soil moisture results in high soil aeration and thereby enhances aerobic microbial activity and carbon decomposition [73,91]. As a result, precipitation often exhibits a positive correlation with SOCD and SOCDSR [27,84,88–90]. In this study, precipitation had a significant positive effect on SOCD. By contrast, the effect of precipitation on SOCDSR was insignificant (p = 0.066). This condition may be due to the fact that most farmlands are irrigated; consequently, the dependence of soil moisture on precipitation is reduced.

Fertilization (e.g., N, P, and K), straw return, and irrigation can enhance crop yield and biomass productivity, which in turn increases the carbon input into the soil from crop residues and roots [92–96]. Several field experiments have proven that different fertilization treatments sequestrate large amounts of carbon compared to no fertilizer application, and the integration of chemical fertilizers, organic manures, and straw return fixes most carbon [97–100]. Irrigation water is a good supplement to rainfall, which can improve the soil quality of farmland and has have a high potential for increasing SOCD, especially in arid and semiarid areas [17,94,101–103]. In this study, fertilization (e.g., urea, N, P, and K fertilizers), straw return and irrigation (e.g., flood irrigation) exhibited positive effects on SOCD and SOCDSR. However, the difference of SOCD among fertilization, straw return, irrigation, and blank control was not significant, which may be due to insufficient cropping duration.

The aforementioned findings indicated that the spatial distribution of SOCD is mainly controlled by natural factors, such as climate and soil environment. Human activities, especially fertilization, play more important roles in SOCDSR. It can be predicted that with the increase of cropping duration, agricultural management will play a more important role in carbon sequestration.

4.2. Interaction Effects of Environmental Variables on SOCD and SOCDSR

This study explored the interaction effects of environmental variables on SOCD and SOCDSR. The results showed that interaction effects existed in all environmental variable pairs, and the q value of interaction effects was often greater than the sum of q values of two single variables. This condition indicated that the influences of environmental variables on SOCD were often dependent on one another, and the consideration of interactions could well explain SOCD and SOCDSR.

We explored the specific interaction effect of environmental variable pairs and identified that the relationship between SOCD and MAT depended on soil types. For example, the SOCD under high MAT (>15 °C) was higher than that under medium MAT (6 °C–15 °C) in Anthrosols, which may be because high MAT promotes vegetation growth, whereas submerged environment inhibits microbial respiration [13,78]. However, the SOCD under high MAT (>15 °C) was not higher than that under medium MAT (especially 6 °C–10 °C), which may be due to the fact that high MAT promotes microbial respiration that exceeds the effect of vegetation growth [83,84]. Similarly, the effect of fertilization on SOCDSR depends on groundwater depth. Fertilization was conducive to SOCD increase at a high groundwater depth (<3 m), which may be because a high groundwater depth (<3 m) implies high soil moisture and thus promotes fertilizer absorption and vegetation growth [94,102]. The abovementioned findings highlight the importance of interaction effects in explaining SOCD and SOCDSR.

4.3. Limitations

This study used 64 sampling points that were collected from the typical cropping systems in China. However, the number of sampling points is far from sufficient to capture the spatial variation of farmland SOCD in China. In our future work, we will collect more samples to explore the dominant factors of spatial variation of SOCD and SOCDSR. Moreover, the consideration of soil environment indicators, such as soil moisture, temperature, and electric conductivity, may better explain SOCD and SOCDSR variation. Several abiotic and biotic factors, such as tillage practice [96,104], seasonal temperature and precipitation [73], and microbial activities [105,106], were not considered because of the lack of data.

We found that interaction effects played an important role in explaining SOCD and SOCDSR. Nevertheless, how to apply interaction effects to improve the mapping of soil properties remains unclear. Song et al. [107] divided the study area on the basis of soil type and climate and then used machine-learning models to estimate the SOC of each pedoclimate zone in combination with other environmental variables. This method considered the interaction effects of soil type, climate, and other continuous environmental variables and thus improved the SOC mapping accuracy. However, it did not consider the interaction effects among those continuous variables. The application of interaction effects in improving soil mapping accuracy requires further exploration.

5. Conclusions

This study explored the effects of natural factors, agricultural management, and their interactions on farmland SOCD and SOCDSR using geographical detector methods. It was revealed that SOCD was associated with natural factors, while the SOCDSR was related to natural factors and agricultural management. It was also revealed that interaction effects existed in all environmental variable pairs, and the explanatory power of the interaction effect was often greater than that of the sum of two single variables. Specifically, the interaction effect of soil type and MAT explained 74.8% of the variation in SOCD, and further investigation revealed that SOCD was highest in Luvisols and was under a low MAT (<6 °C). The interaction effect of groundwater depth and fertilization explained 40.4% of the variation in SOCDSR, and fertilization was particularly conducive to SOCD increase at a high groundwater depth (<3 m). These findings suggest that low soil temperature, high soil moisture, and fertilization are conducive to soil carbon accumulation. These findings also highlight the importance of agricultural management and interaction effects in explaining SOCD and SOCDSR, which promote our knowledge to better understand the variation of SOCD and its dynamics.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land11020208/s1, Table S1: Interaction detector results of SOCD; Table S2: Interaction detector results of SOCDSR.

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