# Modeling soil organic carbon dynamics and their driving factors in the main global cereal cropping systems

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**Abstract**

Changes in the soil organic carbon (SOC) stock are determined by the balance between the carbon input from organic materials and the output from the decomposition of soil C. The fate of SOC in cropland soils plays a significant role in both sustainable agricultural production and climate change mitigation. The spatiotemporal changes of soil organic carbon in croplands in response to different carbon (C) input management and environmental conditions across the main global cereal systems were studied using a modeling approach. We also identified the key variables that drive SOC changes at a high spatial resolution (0.1°× 0.1°) and over a long time scale (54 years from 1961 to 2014). A widely used soil C turnover model (RothC) and state-of-the-art databases of soil and climate variables were used in the present study. The model simulations suggested that, on a global average, the cropland SOC density increased at an annual rate of 0.22, 0.45 and 0.69 MgC $ha^{-1}$ $yr^{-1}$ under crop residue retention rates of 30%, 60% and 90%, respectively. Increasing the quantity of C input could enhance soil C sequestration or reduce the rate of soil C loss, depending

largely on the local soil and climate conditions. Spatially, under a specific crop residue retention rate, relatively higher soil C sinks were found across the central parts of the United States, western Europe, and the northern regions of China. Relatively smaller soil C sinks occurred in the high latitude regions of both the northern and southern hemispheres, and SOC decreased across the equatorial zones of Asia, Africa and America. We found that SOC change was significantly influenced by the crop residue retention rate (linearly positive) and the edaphic variable of initial SOC content (linearly negative). Temperature had weak negative effects, and precipitation had significantly negative impacts on SOC changes. The results can help guide carbon input management practices to effectively mitigate climate change through soil C sequestration in croplands on a global scale.

## 1 Introduction

On a global scale, the soil is the largest terrestrial carbon (C) pool, and it stores approximately three times the quantity of C that is in the atmosphere. Consequently, a small variation in soil carbon stock can lead to substantial changes in atmospheric carbon dioxide ($CO_2$) concentrations (Schlesinger and Andrews, 2000; Scharlemann et al., 2014). Soil organic carbon (SOC) stored in croplands constitutes approximately 10% of the global soil carbon stock (Jobbagy and Jackson, 2000), and cultivation generally leads to marked changes in SOC by influencing the processes regarding soil C production and decomposition (Luo et al., 2013; Wang et al., 2016). Changes in cropland SOC are regulated by complex interactions between the local soil environmental and climatic conditions as well as the management regimes (Brady and Weil, 2008). Moreover, continuity in the soil C monitoring data over meaningfully large scales of both time and space is lacking. Consequently, the ability to characterize the SOC dynamics on a fine spatiotemporal resolution over a large scale is substantially hindered.

Basically, cropland SOC is a balance of carbon inputs (mainly dependent on biomass productivity that is controlled by the climate and management conditions) and outputs (strongly regulated by climatic conditions). Since the start of the 1960s, the “green revolution,” which aims to provide more food to feed the increasing population, has been widely launched across the global agricultural systems (Evenson and Gollin, 2003). During this period, numerous efforts regarding crop variety improvement, and the applications of irrigation and nitrogen fertilization have been taken to enhance the global crop production (Fischer and Edmeades, 2010; Evenson and Gollin, 2003). As a result, the global crop production tripled from 1961 to 2010, which is mostly due to greater yields per unit area (Zeng et al., 2014). Increases in crop production provide more carbon inputs (e.g., organic matter from crop roots and residues) into soils, thereby substantially affecting the SOC sequestration (Wang et al., 2016). However, the degrees of these impacts at fine spatiotemporal resolutions on a global scale are still unclear and have seldom been comprehensively studied.

Over the past several decades, a number of agricultural system models have been developed and used to reproduce the dynamic processes, including carbon flows, that occur between the agroecosystems and the atmosphere (Li et al., 1994; Parton et al., 1994; Keating et al., 2003; Huang et al., 2009). These models have been reported to be able to capture the soil C changes under different environmental and management conditions, thereby providing an opportunity for quantifying the soil C dynamics at larger spatial and temporal scales. Based on the process-based models, efforts have already been taken to quantify the soil C dynamics in croplands at the national and continental scales. For example, using the CENTURY model, Ogle et al. (2010) and Lugato et al. (2014) estimated that the average soil C density increased under improved management at rates of 1.3 Mg C $ha^{-1}$ $yr^{-1}$ from 1990 to 2000 in the US, and 0.12 Mg C $ha^{-1}$ $yr^{-1}$ from 2013 to 2050 in Europe, respectively. Using another biogeophysical model (i.e., Agro-C), Yu et al. (2012) quantified that China's cropland soils sequestered approximately 0.20 Mg C $ha^{-1}$ annually from 1980 to 2009. Using the same model, however, Wang et al. (2013) found that the average soil C annually decreased by 0.20 Mg C $ha^{-1}$ from 1960 to 2010 in the Australian wheat-belt. The large disparities in the signs and the magnitudes of estimated soil C changes could be attributed to the different local soil and climate conditions and various agricultural management practices. Moreover, the differences in the regional model input data obtained from different sources and simulating procedures, such as model configurations and parameterizations in different studies with different models, can also bias the regional simulation results, thereby hampering the ability for a comprehensive and robust evaluation of the soil C dynamics in croplands on a global scale.

Currently, most existing process-based models require many detailed parameters as the model inputs, which are not readily obtainable at a large scale. As one of the most classic and widely used soil C turnover models, the RothC model (Jenkinson et al., 1990), however, requires only a few easily obtainable parameters and input data. The model has been widely and frequently adopted to simulate the soil C changes under different management treatments and soil and climate conditions across the world's cropping systems (Falloon and Smith, 2002; Guo et al., 2007; Yang et al., 2003; Bhattacharyya et al., 2011; Skjemstad et al., 2004; Smith et al., 2005). More recently, by adopting the model's original default parameters, the RothC model has been tested against the measurements obtained from 16 long-term experimental sites across the global croplands and showed a generally good performance in representing the SOC dynamics under different treatments at different sites (Wang et al., 2016).

In this study, we simulated the spatiotemporal soil C dynamics across the main global cereal (i.e., wheat, maize and rice) cropping systems, using the RothC model and state-of-the-art databases of soil and climate. The soil C revolutions were simulated under different scenarios of C inputs (calculated from crop residues, roots and manure) on a monthly time step from 1961 to 2014 at a high spatial resolution of $0.1° \times 0.1°$. Based on the model simulations, we presented the spatiotemporal changes in SOC across the main global cereal growing areas under different residue retention rates. The impacts of C input management, edaphic and climatic variables on SOC changes were also statistically analyzed to identify the key factors driving the soil C dynamics.

## 2 Materials and methods

*Study area*

The study area covered the main cereal (i.e., wheat, maize and rice) cropping regions of the world (Fig. S1). We selected the wheat, maize and rice cropping areas because they are the most widely planted (covering approximately 72% of the global cereal cropping areas) and productive (constituting approximately 80% of the global cereal yield) cereals in the world (FAOSTAT, 2017). The geographic distribution of the global croplands ($0.1° \times 0.1°$ spatial resolution, with a cropland percentage value within each pixel) (Ramankutty et al., 2008), and the areas growing wheat, maize and rice (Monfreda et al., 2008) were sourced from the Center for Sustainability and the Global Environment (SAGE). The main cereal cropping regions were then obtained by masking the global croplands with the wheat, maize and rice cropping areas using a geographic information system (GIS) analysis approach. According to Vancutsem et al. (2013), we selected the pixels that were made up of more than 30% cropland areas as the study area in the present study (Fig. S1). These areas were selected because such pixels more efficiently represent the croplands in the real world.

*RothC model and its initialization*

The Rothamsted carbon model (RothC, version 26.3) was used to simulate the soil C dynamics in croplands in the present study. The RothC model is a widely used soil organic matter (SOM) decomposition model used to simulate the C dynamics in agricultural soils under various environments and management practices (Smith et al., 2005; Guo et al., 2007; Skjemstad et al., 2004). Recently, Wang et al. (2016) evaluated the model's performance in simulating soil C variations using observations from 16 long-term experimental sites across the world's wheat-growing regions. The validated results suggested that the model could reasonably reproduce the SOC dynamics under a wide range of soil and climatic conditions and agricultural management practices. Detailed information on the RothC model description can be found in Jenkinson et al. (1990).

The soil carbon pool in the RothC model is divided into five conceptual components, i.e., decomposable plant material (*DPM*), resistant plant material (*RPM*), microbial biomass (*BIO*), humified organic matter (*HUM*), and inert organic matter (*IOM*). These conceptual pools are difficult to measure directly in most cases and can only be empirically initialized because only the quantity of total soil organic carbon is obtainable without finer level partitioning among the sub-pools. In the present study, following Wang et al. (2016), we adopted the approach of Weihermüller et al. (2013), who developed a validated set of pedotransfer functions to initialize C pools in the RothC model:

$$IOM = 0.049 \times SOC^{1.139} \tag{1}$$

$$RPM = (0.1847 \times SOC + 0.1555) \times (Clay + 1.2750)^{-0.1158} \quad (2)$$

$$HUM = (0.7148 \times SOC + 0.5069) \times (Clay + 10.3421)^{0.0184} \quad (3)$$

$$BIO = (0.0140 \times SOC + 0.0075) \times (Clay + 8.8473)^{0.0567} \quad (4)$$

where *SOC* is the total soil organic C content in the top 30 cm soil layer (Mg C $ha^{-1}$), and *Clay* is the soil clay fraction (%).

The default yearly decomposition rates for the five abovementioned soil C sub-pools were divided by 12 to run the model on a monthly time step (Jenkinson et al., 1990). The annual carbon inputs to soils from crop residue, root and manure were assumed to occur after harvest, which is acceptable because the model is insensitive to the time of C input, particularly in long-term simulations (Smith et al., 2005). The default value of the DPM/RPM ratio (i.e., 1.44) of the C input is adopted in this study because it is suggested as a typical value for most crops (Jenkinson et al., 1990).

*Spatial data*

The soil parameters used in the present study, such as soil carbon density and the clay fraction in the top 30 cm of the soil profiles, were sourced from the Harmonized World Soil Database (HWSD) (Fao and Isric, 2012). This soil dataset combines information from various sources such as the World Inventory of Soil Emission Potentials (WISE), the Soil Terrain Database (SOTER) and the FAO Soil Map of the world. The HWSD is recommended as the most recent and most detailed globally consistent and continuous map of SOC with the highest spatial resolution of 0.1°× 0.1° (Fig. S2) that is available (Hiederer and Köchy, 2011; Scharlemann et al., 2014). The soil cover data were derived from the crop calendar dataset (Sacks et al., 2010), which is documented in the Center for Sustainability and the Global Environment (SAGE) and provides gridded maps of the global planting and harvesting dates for 19 major crops including wheat, maize and rice.

The global climate data layers with a 0.5°× 0.5° spatial resolution (Harris et al., 2014) were sourced from the Climatic Research Unit (https://crudata.uea.ac.uk/cru/data/hrg/). The most recent version of the climate data product (i.e., CRU TS v.4.00) was used in this study. The time-series of the monthly climate data layers include mean air temperature, precipitation and potential evapotranspiration, spanning from 1901 to 2014. According to Jenkinson et al. (1990), the potential evapotranspiration was converted to open pan evaporation (one of the required model inputs of RothC) by dividing 0.75, i.e., open pan evaporation = potential evapotranspiration / 0.75. The climate data have a coarser spatial resolution than that of the soil dataset (i.e., 0.1°× 0.1°) that we used in the RothC model simulations. Here, the climate data in each coarser pixel were assumed to be the same as in the finer pixels (0.1°× 0.1°) located within that coarser pixel (0.5°× 0.5°).

Carbon inputs are mainly sourced from crop residues, roots and manure (Yu et al., 2012). We derived this information at a high spatial resolution from the various sources of existing datasets. First, the global crop yields for wheat, maize and rice in 2005 at a 0.1°× 0.1° spatial resolution were obtained from the 2005 Spatial Production Allocation Model (SPAM) (You et al., 2014). The SPAM provides crop-specific information on yield at a high spatial resolution, and it has undergone a significant validation and has shown promising performance globally (Liu et al., 2010). However, the SPAM dataset does not include continuous time-series data. As such, we adopted the global annual rates of change of the major cereal crop yields at a 0.1°× 0.1° resolution (Ray et al., 2012) to generate the crop yield data time-series. Here, we calculated the annual crop yields from 1961 to 2014 based on the percentages of the annual rates of change of the crop yields and the crop yield data in 2005 (i.e., SPAM dataset) by assuming a linear rate of change in the crop yields. This is acceptable because the rates of increase of the global yield have been found to be linear for most of the major cereal crops since the start of the 1960s (Fischer and Edmeades, 2010; Hafner, 2003). In each grid, the annual amounts of crop residue and roots were then calculated based on the yield data by adopting the residue/economic product ratio and the root/shoot ratio as described by Huang et al. (2007). All residues and roots were assumed to have a carbon content of 45% when the quantity of the carbon input from the crops was determined (Skjemstad et al., 2004).

The annual carbon input from manure application at a global scale was derived from Zhang et al. (2017), who used the Global Livestock Impact Mapping System (GLIMS) dataset in conjunction with the country-specific annual livestock population to reconstruct the manure nitrogen production and application of global croplands during 1860-2014 at a high spatial resolution of 0.1°× 0.1°. Following Lugato et al. (2014), the C input to soils from manure was calculated according to the average C:N ratios of the different types of manures. The average C:N ratio of manures was set to 20 because various studies have found that manure, in general, maintains a relatively stable C:N ratio of approximately 20 (Sharpley and Moyer, 2000; Ko et al., 2008; Eghball et al., 2002). All of the calculated C inputs from crop roots and manure were assumed to be incorporated into the soils. The amount of C inputs from the above-ground residues of the crops, however, were further determined by setting different residue retention scenarios as described below.

*Simulation scenarios and identification of the controls of SOC dynamics*

The crop residue that is retained in the system after harvest can benefit the sequestration of soil carbon in the croplands. The amount of above-ground residue that is retained in the system, however, shows vast spatial disparity and uncertainty across the global croplands. In developing regions such as Asia and Africa, it has been suggested that only approximately 30% of the crop residues are retained in the soils after harvest (Jiang et al., 2012; Baudron et al., 2014). In developed regions such as Europe and North America, however, the crop residue retention rate can reach over 60% (Scarlat et al., 2010; Lokupitiya et al., 2012). Furthermore, in Australia, it has been reported that 100% of the crop residue was retained across 72–100% of the cropping area of the country from 2010 to 2014 (National Inventory Report 2013, 2015). However, this information is based on rough estimations and statistical data. To the best of our knowledge, detailed information on the residue retention rates over a meaningfully large scale of both time and space across different countries and continents is still lacking. Consequently, a scenario modeling approach was adopted to assess the dynamics of SOC as determined by various potential management practices on crop residues. We specified three crop residue retention rates in the present study, i.e., 30%, 60% and 90% (hereafter simply denoted as R30, R60 and R90, respectively).

In total, we ran 461,586 (3 crop residue retention scenarios × 153,862 grids) RothC simulations. Each simulation quantified the SOC content in the top 30 cm of the soil from 1961 to 2014 on a monthly basis. Based on the model simulations, we showed the spatiotemporal changes of SOC under different crop residue retention rates. We also assessed the impacts to SOC changes of crop residue retention, climatic and soil variables using Spearman's rank correlation coefficient (*rho*). The selected climatic variables included mean annual temperature (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *precipitation*). These two variables have been suggested to be uncorrelated and could reasonably represent the spatial variation over a wide range of climate patterns (Bryan, 2003). For the correlation analysis, the long-term monthly climate variables were summarized to the mean annual values for each grid. The selected soil parameters included the model's edaphic inputs, i.e., initial SOC content and soil clay fraction. The change in the soil C is calculated as the difference in SOC between 2014 and 1961. Spearman's rank correlation coefficient was then calculated between the SOC change and crop residue retention rates and the soil and climate variables across the full set of RothC simulations. The sign of *rho*, positive or negative, indicates the direction of the association between the independent and dependent variables. The absolute magnitude of *rho*, between 0 and 1, suggests the strength of the correlation between the two variables. All analyses were performed using statistical and graphical software R 3.3.2 (R Development Core Team, 2017).

## 3 Results

On a global average, soil organic carbon (SOC) generally increased over time under the different specified crop residue retention rates in the present study (Fig. 1). The median SOC increased from 46.2 MgC $ha^{-1}$ in 1961 to 58.3 MgC $ha^{-1}$ under R30 (Fig. 1a), 70.9 MgC $ha^{-1}$ under R60 (Fig. 1b), and 84.1 MgC $ha^{-1}$ under R90 (Fig. 1c) in 2014. In general, the annual rates of change in SOC were 0.22 MgC $ha^{-1}$ $yr^{-1}$ under R30, 0.45 MgC $ha^{-1}$ $yr^{-1}$ under R60, and 0.69 MgC $ha^{-1}$ $yr^{-1}$ under R90 (Fig. 1).

Figure 2 shows the spatial patterns of the estimated SOC changes under R30 (Fig. 2a), R60 (Fig. 2b) and R90 (Fig. 2c). Among the three scenarios, a relatively higher increase in SOC generally occurred in the middle latitudes of the northern hemisphere, such as the central parts of the United States, western Europe, the northern regions of China (Fig. 2). A relatively small increase in SOC generally occurred in the high latitude regions of both the northern and southern hemisphere, while the SOC decreased across the equatorial zones of Asia, Africa and America (Fig. 2). On a global average, 69%, 82% and 89% of the study area acted as a net carbon sink during the study period under R30 (Fig. 2a), R60 (Fig. 2b) and R90 (Fig. 2c), respectively.

The quantified SOC changes also showed large spatiotemporal disparities across different continents (Fig. 3). In general, among the three scenarios, the SOC of the cropland across Europe, Asia, and North America showed a linearly increasing trend over time (Fig. 3). In Oceania, the SOC increased faster in the first two decades and showed a relatively lower increasing rate during the latter three decades (Fig. 3). In South America and Africa, the SOC decreased in the first few decades and increased or remained relatively stable during the latter periods under R30 (Fig. 3a) and R60 (Fig. 3b). Under R90, however, the average SOC on all continents increased over time (Fig. 3c). In general, the regions with higher annual C input rates (e.g., Europe and North America) experienced higher SOC increases than the areas with relatively lower C input rates (e.g., Oceania and Africa) across all three crop residue retention scenarios (Fig. 3 and S4).

The quantified SOC changes were regulated by soil, climate and management practices. The initial SOC was significantly but negatively correlated (*rho* = -0.20) with SOC change, while the soil clay fraction showed a negligible correlation (*rho* = -0.17, Fig. 4). The selected climatic variables displayed a negligible correlation (temperature, *rho* = -0.18), and a significant but negative correlation (precipitation, *rho* = -0.22) with SOC change (Fig. 4). The crop residue retention rate showed a strong and positive correlation (*rho* = 0.34) with the SOC change (Fig. 4). Figure 5 presents the impacts of crop residue retention, initial SOC content and precipitation on SOC change. In general, crop residue retention seemed to be linearly and positively correlated with SOC change (Fig. 5a), whereas the initial SOC content (Fig. 5b) and precipitation (Fig. 5c) had negative linear effects on SOC change.

## 4 Discussion

### *4.1 Interpretation and implication of the results*

Soil organic carbon change is a balance between C input from crops and manures and C output through decomposition. The linear increase in the global average SOC that was quantified in this study (Fig. 1) can be mainly attributed to the increasing rate of C input throughout the study period (Fig. S3). This is associated with the increased crop production that began at the start of the "green revolution," which was launched during the 1960s (Fischer and Edmeades, 2010; Evenson and Gollin, 2003). In the present study, we found that the crop residue retention rate is strongly and positively correlated with the change in SOC (Fig. 4). This is similar to the findings of our previous studies (Wang et al., 2016; Wang et al., 2015), which found that higher amounts of C input can lead to higher soil C sink capacities. On a global average, the total amount of C input to soils is 1.7, 2.7 and 3.7 Mg C ha$^{-1}$ under the crop residue retention rates of 30%, 60% and 90%, respectively (Fig. S3). The corresponding annual rates of SOC changes under R30, R60 and R90 were 0.22, 0.45 and 0.69 Mg C ha$^{-1}$ yr$^{-1}$, respectively (Fig. 1), indicating approximately doubled and tripled SOC sequestration rates after enhancing the residue retention rate from 30% to 60% and 90%. This is consistent with the estimations of Lal (2004), who reported that the rates of SOC sequestration in croplands range from 0.02 to 0.76 Mg C ha$^{-1}$ yr$^{-1}$ when improved systems of crop management are adopted. However, it should be noted that the increased SOC sequestration rate that is contributed to by the increased C input can be limited at longer periods, as the SOC would eventually reach a relatively stable threshold (Stewart et al., 2007).

Apart from the residue retention rate, the initial SOC is one of the major controlling factors of SOC change. The results in Figures 4 and 5 indicate that under otherwise similar environmental and managed conditions, soils with lower initial SOC contents would experience greater SOC increases or smaller soil C losses. This negative correlation between SOC change and initial SOC content has also been documented in other studies (Zhao et al., 2013; Wang et al., 2014). The relationship is further supported by the distribution of global SOC changes (Fig. 2) and the global initial SOC densities that are quantified in this study (Fig. S2). For example, soils with lower initial SOC contents in western Europe generally showed higher SOC increases than the soils in eastern Europe with relatively higher initial SOC contents (Fig. 2 and Fig. S2). Spatial patterns of lower initial SOC associated with higher SOC changes in neighboring areas can also be found in other regions such as the United States and China (Fig. 2 and Fig. S2). The soil clay fraction has been suggested to benefit C stabilization through the mineralogical protection of soil C (Oades, 1988; Amato and Ladd, 1992). However, we identified a negligible but negative correlation between soil C accumulation and soil clay fraction in this study (Fig. 4). The adverse effects of soil clay could be a result of the strong correlation between initial soil C content and the soil clay fraction (*rho* = 0.31, data not shown). Here, the soils with higher initial SOC contents generally had higher clay fractions, and this would overshadow the beneficial contributions of soil clay to soil C accumulation.

The negative effects of higher temperature and precipitation on SOC change identified in the present study (Figs. 4 and 5) can be attributed to the higher SOC decomposition rates in warmer and wetter soils, which is consistent with the description of the RothC model (Jenkinson et al., 1990) and the other findings by Bond-Lamberty and Thomson (2010). Here, it should be noted that such correlations between the climate and SOC changes might only be valid in a soil carbon turnover model that only consists of the dynamic C processes in the soil (e.g., RothC model). In other agricultural model simulations, climatic variables may play a different role in affecting the SOC change through jointly regulating both crop productions and soil C dynamics. For example, Wang et al. (2014) used a process-based agricultural system model (i.e., Agro-C model) to simulate the SOC dynamics in the semi-arid regions of the North China Plain and found positive effects of temperature and precipitation on SOC accumulation. This is because, in temperature and water deficient areas (e.g., the North China Plain), increased temperature and precipitation promote crop production and hence increases the C input to soils, which favors SOC sequestration.

Can we estimate the actual historical soil C dynamics across the world? A large challenge exists due to a lack of data availability, particularly for the two main RothC model inputs, initial SOC content and annual C input. First, the soil properties presented by the HWSD were derived from different sources with unevenly sampled soil profiles over time and space. As such, the value of initial SOC content can hardly, if at all, represent the actual SOC content at the beginning of the study period. However, the modeled dynamics of the SOC in the present study may be appropriate, to a certain extent, to represent the spatiotemporal patterns of the soil C source and sink processes. Second, a lack of detailed information on crop residue management across both time and space remains, which hinders our ability to accurately characterize the SOC changes on a large scale at fine spatiotemporal resolutions. However, we can roughly assume that the above-ground residue retention rates were approximately 30% in developing regions such as Asia and Africa (Jiang et al., 2012; Baudron et al., 2014; Erenstein, 2011) and 60% in other regions (Lokupitiya et al., 2012; Scarlat et al., 2010; Baudron et al., 2015). Based on these assumptions, we further quantified that the global average SOC increased at a rate of 0.34 MgC $ha^{-1}$ $yr^{-1}$ under an average annual C input rate of 2.4 MgC $ha^{-1}$ $yr^{-1}$ from 1961 to 2014. On a global scale, the estimated efficiency of the conversion of C input to SOC (i.e., the ratio of SOC change to C input) is 14%, which falls within the 10-18% range estimated by Campbell et al. (2000). It should be noted that the conversion efficiency varies across space and is highly dependent on the local climatic and edaphic conditions (Yu et al., 2012).

By extrapolating these results to the global total cropland area of 1,400 Mha (Jobbagy and Jackson, 2000), it was found that the global cropland soils could have sequestered 0.48 Pg C annually from 1961 to 2014, which equals approximately 8% of the contemporaneous global average annual C emissions from fossil fuel combustions (http://cdiac.ornl.gov/ftp/ndp030/global.1751_2014.ems). By enhancing the crop residue retention rates to 60% and 90% in all global croplands, the soil C accumulation would offset approximately 11% and 16%, respectively, of the fossil fuel-induced C emissions. Although soil C can be increased by enhancing the quantity of C input, it would eventually reach a threshold at a higher level (Stewart et al., 2007). Until then, more carbon input would be needed to maintain the soil C at higher levels (Wang et al., 2016). Otherwise, the soil C in croplands would decrease, and soils would again act as a net C source.

### *4.2 Uncertainties and limitations*

Several uncertainties and limitations should be considered when interpreting the simulation results in this study. First, the SOC change modeled in the present study could be biased due to the spatial inconsistency in the time of soil sampling, which varied widely over the second half of the twentieth century (Fao and Isric, 2012). In some places, the initial soil C information derived from the HWSD only represented the actual soil C levels during the periods after the early 1960s. For example, the soil profile measurements used to produce the soil map of China, which is included in the HWSD datasets, were generally collected in the late 1970s and early 1980s (Yu et al., 2007). Considering that the spatial patterns of cropland SOC could have substantially changed over the study period under the changing environments and management practices (Figs. 1 and 2), the initial SOC used in the present study (derived from HWSD) might significantly differ from the actual soil C levels in the early 1960s. In addition, it has been reported that soils with higher initial C contents would experience smaller increases or greater C losses under otherwise similar conditions, and *vice versa* (Zhao et al., 2013; Wang et al., 2015). Consequently, for those regions with soil sampling times much later than the early 1960s, our quantified SOC changes may be underestimations in the areas where substantial soil C increases had occurred before measurements were collected. In contrast, the SOC changes could be overestimated in the areas that are accompanied by a previous significant decrease in soil C.

Second, the RothC model was developed to simulate the soil organic matter turnover in upland soils (Jenkinson et al., 1990), and it generally performs well in the global wheat systems with non-waterlogged soils (Wang et al., 2016). In the paddy soils, particularly during the rice-growing seasons, the soil C decomposition rate might be reduced when subjected to anaerobic conditions. For example, Shirato and Yokozawa (2005) used the RothC model to simulate the C changes in Japanese paddy soils and suggested that the model's performance can be improved by modifying the SOC decomposition rates during the rice growing season. As such, the default parameters adopted in the present study may bias the simulations of the SOC changes across the rice systems that are mainly distributed in Southeast Asia. In the present study, we adopted the model's default parameters rather than the modified factors from Shirato and Yokozawa (2005) mainly because the rice-growing areas in Japan constitute approximately 1% of the world's total (FAOSTAT, 2017), and the associated climatic and edaphic conditions differ significantly from the other rice systems. We highlight the need to robustly calibrate the model's soil C decomposition rates against the long-term experimental data across the rice paddy soils to represent the different patterns in climate, soil and management conditions of Southeast Asia in the future.

Finally, the limitations of the current first-order decay model (e.g., RothC) may cause significant bias in the model simulations. For example, our results suggested a general linear relation between C input and SOC variation (Figs. 1 and S3), which contradicts previous findings that increasing the incorporated amount of crop residue may affect the SOC change in a variety of ways other than linearly (Powlson et al., 2011). Moreover, it has been reported that although soil can accumulate a significant amount of C when the preexisting soil C content is low, the SOC reaches a threshold level (i.e., carbon saturation state) where little or no significant further changes occur even when more C is added (Stewart et al., 2007; Qin et al., 2013). Without considering the C saturation state, the first-order decay model might overestimate the SOC in longer time scale simulations particularly in regions where the C input is higher and the SOC decomposition rate is lower.

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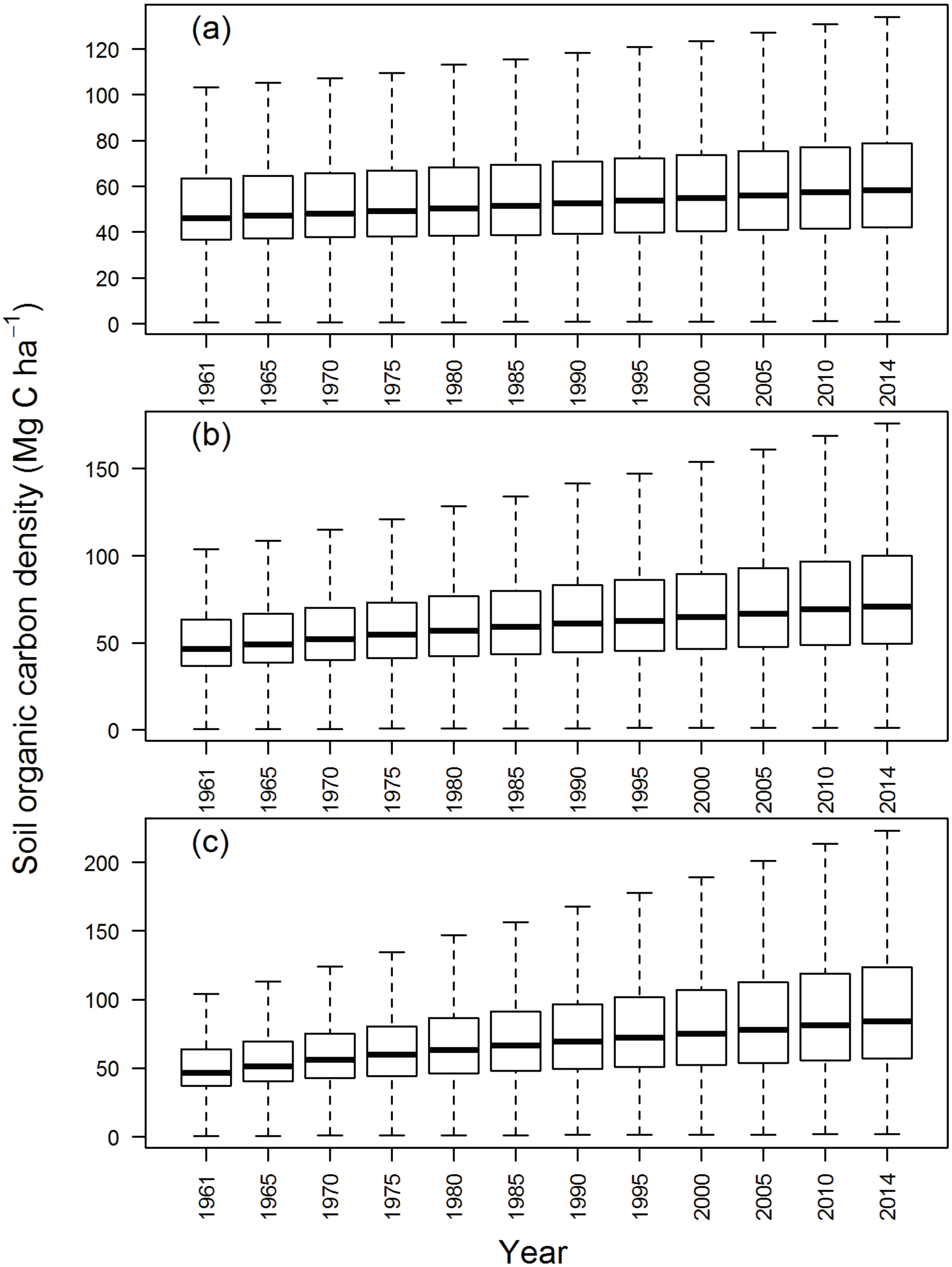


**Figure 1.** Temporal changes in the soil organic carbon (MgC ha$^{-1}$) of the main global cereal cropping regions under different above-ground crop residue retention rates of 30% (a), 60% (b) and 90% (c). Boxplots show the median and interquartile range with the whiskers extending to the most extreme data points within the 1.5×(75-25%) data range.

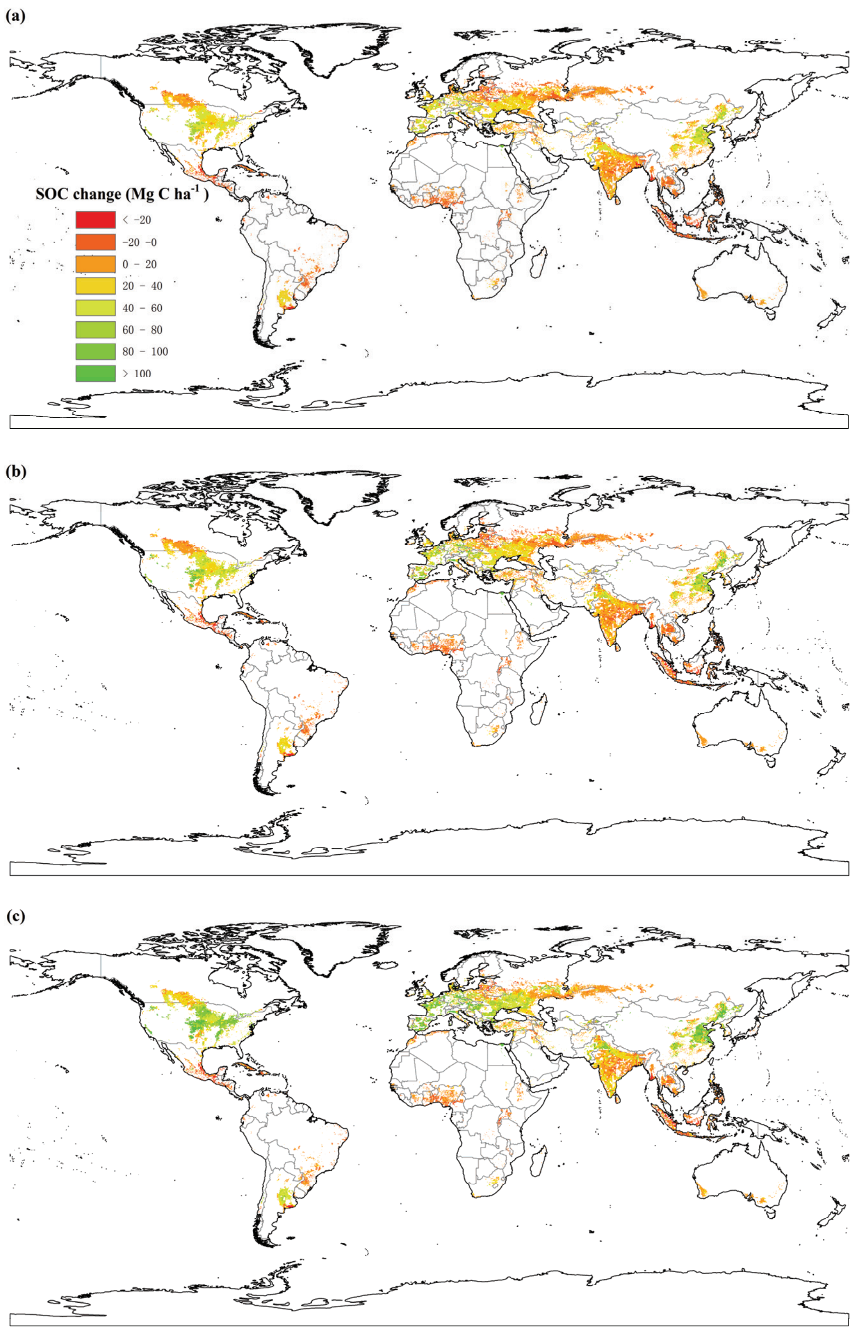


**Figure 2.** Spatial distribution of the SOC change (1961-2014, MgC $ha^{-1}$) across the main global cereal cropping regions under different above-ground crop residue retention rates of 30% (a), 60% (b) and 90% (c).

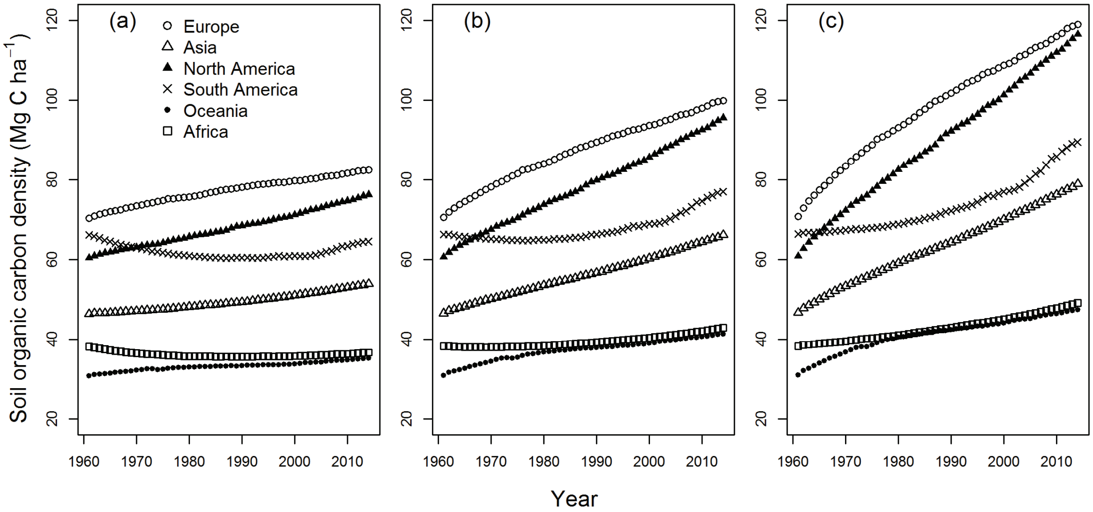


**Figure 3.** SOC evolution of five continents in the main global cereal cropping regions under different above-ground crop residue retention rates of 30% (a), 60% (b) and 90% (c).

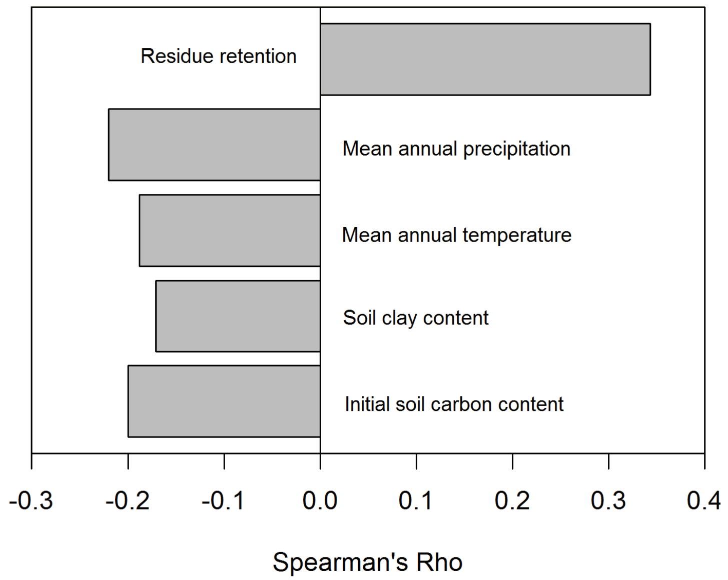


**Figure 4.** Spearman's rank correlation coefficients between SOC change (1961-2014, MgC $ha^{-1}$) and residue retention and soil and climate variables. All tests were significant ($P$<0.001).

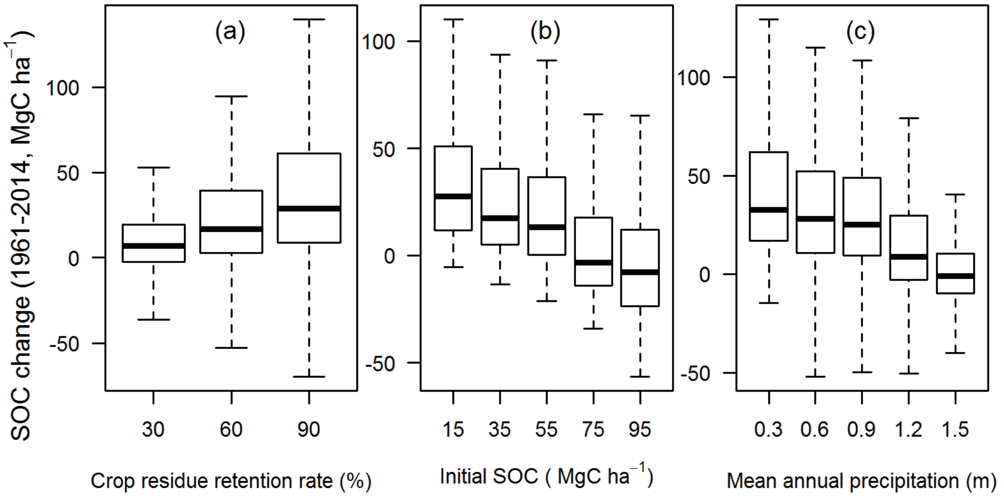


**Figure 5.** Response of SOC change (1961-2014, MgC ha$^{-1}$) to the three most influential variables of crop residue retention rate (a), initial SOC (b), and mean annual precipitation (c). Boxplots show the median and interquartile ranges with the whiskers extending to the most extreme data point within the 1.5×(75-25%) data range.