Interactive comment on "Modeling soil organic carbon dynamics and its driving factors in global main cereal cropping systems" – by G. Wang *et al.*

G. Wang, on behalf of all authors (<u>wanggc@mail.iap.ac.cn</u>)

Reviewer #1:

The spatiotemporal variation of cropland soil organic carbon (SOC) across the global main cereal cropping system were analyzed based on the result of soil C turnover model (RothC), and the relationship between SOC changes and C input management, edaphic and climatic variables were also investigated in this article. Though, the modeled SOC may have bias due to the defect of the RothC model and the lack of model inputs datasets, it was still a better way to understand the spatiotemporal distribution of the SOC and its variation in a certain extent. It is very interesting and useful for the carbon input management and investigating the soil C sequestration on a global scale under the background of climate change. This paper is well presented, but the English of this paper need to be improved.

Authors' Response: We greatly appreciate the reviewer's comments and their understanding of our work. We have submitted our MS to American Journal Experts (<u>http://www.aje.com/</u>) for editing and improvement of the English language.

The following is the concerns: 1.It was confused by direct relationship between the net fluxes of carbon dioxide (CO2) and soil organic carbon (SOC). "The net fluxes of carbon dioxide (CO2) between the atmosphere and agricultural systems are mainly characterized by the changes in soil carbon stock, which. . ." in Page1 Line 10-12. CO2 flux mainly depends on the CO2 exchange between land surface and atmosphere by photosynthesis and respiration of the plant and decomposition of the microbe, but the variation of soil organic carbon was dominated by the carbon input. Detailed physical mechanism was suggested to be involved to link these two terms. And , the same question is also found in Page 2 Line 8-9, "a small variation in soil carbon stock can lead to substantial changes in atmospheric carbon dioxide (CO2) concentrations".

Authors' Response: Yes, we have modified the sentences to the following form to avoid any possible misunderstandings:

"Changes in the soil organic carbon (SOC) stock are determined by the balance between the carbon input from organic materials and the output from soil C decomposition. The fate of SOC in cropland soils plays a significant role in both sustainable agricultural production and climate change mitigation."

For the second point, we further clarified this in the revised MS: "On a global scale, the soil is the largest terrestrial carbon 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 (CO₂) concentrations". This is a widely accepted view in the existing literature, please refer to Cleveland and Townsend (2006), Davidson and Janssens (2006), Luo *et al.* (2010), and West and Post (2002).

2. What does the abbreviation stand for? e.g., GIS, WISE, SOTER, HWSD, ...

Authors' Response: We have clarified these abbreviations in the revised MS. GIS: geographic information system; WISE: World Inventory of Soil Emission Potentials; SOTER: Soil Terrain Database; HWSD: Harmonized World Soil Database.

3. Why did the authors choose the 30%, 60% and 90% of the crop residue retention rates in this study?

Authors' Response: We have explained and clarified the use of these rates in the revised MS (XXX): "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%."

These three scenarios represent the residue retention rates typically adopted in developing regions with relatively poorly managed systems (30%), developed regions with better managed systems (60%), and the areas with well-managed agricultural conservation systems (90%).

4."enhancing the crop residue retention rate from 30% to 60% and 90% approximately induced a double and triple SOC sequestration rate, respectively (Fig. 1 and Fig. S3)" in Page 10 Line 20-21. It was difficulty to get the information of a double and triple SOC sequestration rate from these two Figures.

Authors' Response: We have clarified this in the revised MS:

"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%."

5. Because the air temperature and precipitation datasets are the input parameters, there should have some parameterization schemes to calculate the SOC based on the effect of temperature and precipitation in the RothC model. The derived SOC from the model has already included the information of climate change. How did you strip out this effect when attributing the variation of SOC under the background of climate change?

Authors' Response: The quantified dynamics of soil carbon are regulated by complex interactions between C input, climate conditions such as temperature and precipitation, and soil conditions such as initial soil C density and clay fraction. To assess the contribution of each controlling factor to soil C changes, we adopted the Spearman's rank correlation approach, using the *cor.test* function in the *stats* package in R. The sign of Spearman's rank correlation coefficient (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. We have specified this approach in the Methods section and presented the statistical analysis results in the Results section (and Fig. 4).

Reviewer #2:

This study simulated the spatiotemporal soil C dynamics across the global main cereal cropping systems using the RothC model and databases of soil and climate. The impacts of C input management, and soil and climatic variables on SOC changes were also analyzed. With the right reframing of the questions and additional detail, the study may become more novel and useful for the community. I think the study warrants publication in ACP after minor revision.

Authors' Response: We greatly thank the reviewer for their thoughtful comments and understanding of our work.

Detailed comments: 1. There is a focus on three crop residue retention rates (i.e., 30%, 60% and 90%) throughout the manuscript, yet the reason or context for this is not provided.

Authors' Response: As mentioned above, we have provided more information and clarified this in the revised MS: "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/or 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%."

These three scenarios represent the residue retention rates typically adopted in developing regions with relatively poorly managed systems (30%), developed regions with better managed systems (60%), and the areas with well-managed agricultural conservation systems (90%).

2. I suggest authors compare the present results with other modeling studies for SOC changes at the global scale.

Authors' Response: We have further compared the global cropland soil C sequestration rates quantified in this study to the estimations of Lal (2004). The efficiency of the conversion of C input to SOC (i.e., ratio of SOC change to C input) estimated in the present study was compared to that of Campbell *et al.* (2000) in the revised MS. We found that our modeled results are comparable and fall within the ranges of their estimations.

3. The modeled SOC density would be more valuable if the present results are compared with the observed SOC density in the five continents.

Authors' Response: In this study, we adopted the HWSD soil dataset (can be referred to as the observed SOC density) as one of the model's driving inputs, and our goal was to simulate the soil carbon changes under changing environmental and management conditions during the last half century. As such, the modeled SOC density in the final year is highly dependent on the initial SOC density (HWSD soil dataset, also as the model's soil input data) and the modeled SOC changes. Comparing the soil C changes to the initial SOC density (observed SOC density) is meaningful and useful to extrapolate the regulating effects of soil conditions on SOC dynamics. We assessed the impacts of initial SOC density on the modeled SOC changes in the present study (Fig. 4 and Fig. 5), and found that under otherwise similar conditions, the soil would lose more C with a higher initial SOC density, and *vice versa*.

4. If a correction coefficient for RothC model be used to model SOC density in rice paddy, the results would be more reliable. I suggest authors discuss this issue by integrating corrected SOC density in rice paddy.

Authors' Response: We have discussed this issue in the revised MS:

"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 are that mainly distributed in the 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 the Southeast Asia in the future."

5. Change "cropland soil organic carbon" to "soil organic carbon in cropland".

Authors' Response: Modified accordingly.

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Modeling soil organic carbon dynamics and <u>itstheir</u> driving factors in <u>the</u> <u>main global main</u> cereal cropping systems

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10 *Correspondence to:* Guocheng Wang (wanggc@mail.iap.ac.cn) Abstract

The net fluxes of carbon dioxide (CO₂) between <u>Changes in</u> the atmosphere and agricultural systems are mainly characterized by the changes in soil organic carbon (SOC) stock, which is are determined by the balance between the carbon input from organic materials and the output through soil C 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 cropland soil organic carbon (SOC) in croplands in response to different carbon (C) input management and environmental conditions across the main global-main cereal systems were studied using a modeling approach. We also identified the key variables drivingthat drive SOC changes at a high spatial resolution ($0.1^{\circ} \times 0.1^{\circ}$) and over a long time scale (54 years from 1961 to 2014). The<u>A</u> widely used soil C turnover model (RothC) and the 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 a-crop residue retention raterates of 30%, 60% and 90%, respectively. IncreasedIncreasing the quantity of C input could enhance the soil C sequestration or reduce the rate of soil C loss-rate, depending largely on the local soil and climate conditions. Spatially, under a certainspecific crop residue retention rate, a-relatively higher soil C sinksinks were-generally found across the central parts of the United States, western Europe, and the northern regions of China, while a relatively. Relatively smaller soil C sink generallysinks occurred in the high latitude regions at high latitudes of both the northern and southern hemispherehemispheres, 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 weaklyweak negative effects, and precipitation had significantly negative impacts on SOC changes. The results can help targetguide carbon input management for practices to effectively mitigatingmitigate climate change through eropland-soil C sequestration in croplands on a global scale.

1 Introduction

SoilOn 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 (CO₂) concentrations (Schlesinger and Andrews, 2000; Scharlemann et al., 2014). Soil organic carbon (SOC) stored in croplands constitute aroundconstitutes approximately 10% of the global soil carbon stock (Jobbagy and Jackson, 2000), and cultivation generally leads to marked changes in SOC throughby influencing the processes regarding soil C production and decomposition (Luo et al., 2013; Wang et al., 2016). CroplandChanges in cropland SOC—changes are regulated by complex interactions between the local soil environmental and climatic conditions, as well as the management regimes (Brady and Weil, 2008). Moreover, there lacks a 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 <u>dependentdependent</u> on biomass productivity that <u>is</u> controlled by the climate and management conditions) and outputs (strongly regulated by climatic conditions). Since the start of <u>the</u> 1960s, the "green revolution" <u>aiming at providing</u>," which <u>aims to provide</u> 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 <u>the</u>-crop variety improvement, and <u>application the applications</u> of water 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 <u>due</u> mostly <u>due</u> to greater <u>yieldyields</u> per unit area (Zeng et al., 2014). Increases in crop production <u>would certainly</u> provide more carbon inputs (e.g., organic <u>mattersmatter</u> from crop roots and residues) into soils, thereby substantially affecting the SOC sequestration (Wang et al., 2016). However, <u>such the degrees of these</u> impacts at fine spatiotemporal resolutions on a global scale <u>isare</u> still unclear and <u>hashave</u> seldom been comprehensively studied.

DuringOver 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 agro-ecosystemsagroecosystems 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-over time and space. Based on the process-based models, efforts have already been taken to quantify the soil C dynamics in croplands at the national and continental scale eropland soil C dynamicsscales. For example, using the CenturyCENTURY model, Ogle et al. (2010) and Lugato et al. (2014), respectively;) estimated that the average eropland-soil C density increased at a rateunder 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-under improved management, respectively. Using another biogeophysical model (i.e., Agro-C), Yu et al. (2012) quantified that China's cropland soils have been annually sequestering around sequestered approximately 0.20 Mg C ha⁻¹ grom 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 <u>either</u> the <u>sign orsigns and</u> the <u>magnitude inmagnitudes of estimated</u> soil C changes could be attributed to the different local soil and climate conditions and/<u>or_various</u> agricultural management practices. Moreover, <u>the</u> differences in <u>the</u> regional model input data obtained from different sources and/<u>or</u> simulating procedures, such as model configurations and parameterizations in different studies with different models, can also bias the regional simulation results, thereby hampering <u>the ability for</u> a comprehensive and robust evaluation of <u>eroplandthe</u> soil C dynamics<u>in croplands</u> on a global scale.

Currently, most existing process-based models require many detailed parameters as the model inputs, which wereare not readily obtainable onat 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 and easily obtainable parameters and input data. The model has already 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 generalgenerally good performance in representing the SOC dynamics under different treatments at different sites (Wang et al., 2016).

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In this study, we simulated the spatiotemporal soil C dynamics across the <u>main global-main</u> 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_7 at a high spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$. Based on the model simulations, we presented the spatiotemporal changes in SOC across the <u>main global-main</u> 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

The study area covered the main cereal (i.e., wheat, maize and rice) cropping regions inof the world (Fig. S1). We selected the wheat, maize and rice cropping areas because they are the most widely planted (covering aroundapproximately 72% of the global cereal cropping areas) and productive (constituting aroundapproximately 80% of the global cereal yield) cereals in the world (FAOSTAT, 2017). The geographic distribution of the global croplands $(0.1^{\circ} \times 0.1^{\circ})$ spatial resolution, with a cropland percentage value within each pixel) (Ramankutty et al., 2008), and the areas growing-areas of 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 through by masking the global croplands by cropping areas of 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 with that were made up of more than 30% cropland areas as the study area in the present study (Fig. S1), this is). These areas were selected because such pixels can in general 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 eropland-soil C dynamics in croplands 15 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 offrom 16 long-term experimental sites across the world's wheat-growing regions. The validating validated results suggested that the model could reasonably reproduce the SOC 20 dynamics under a wide range of soil and climatic conditions and agricultural management practices. Detailed information of on the RothC model description can be found in Jenkinson et al. (1990).

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Soil 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 can hardly beare difficult to measure directly measured 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

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

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

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

$$BIO = (0.0140 \times SOC + 0.0075) \times (Clav + 8.8473)^{0.0567}$$
(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 <u>raterates</u> for the <u>above mentioned</u> five <u>abovementioned</u> soil C sub-pools were divided by 12 in order to run the model on a monthly time step (Jenkinson et al., 1990). The annual carbon <u>input-inputs</u> <u>to soils</u> from crop residue, root and manure to <u>soils</u> were assumed to occur at the time after <u>harvestsharvest</u>, 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 <u>the_DPM/RPM</u> ratio (i.e., 1.44) of the C input is adopted in this study because it is suggested as a typical value for most <u>agricultural</u> crops (Jenkinson et al., 1990).

Spatial data

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model:

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

The global climate data layers at with a $0.5^{\circ} \times 0.5^{\circ}$ 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 monthly-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 hashave a coarser spatial resolution than that of the soil dataset (i.e., $0.1^{\circ} \times 0.1^{\circ}$), at which) that we performed used in the RothC model simulations. Here, the climate data in each coarser pixel were assumed to be the same as that-in the finer pixels $(0.1^{\circ} \times 0.1^{\circ})$ locatelocated within that coarser pixel $(0.5^{\circ} \times 0.5^{\circ})$.

The carbon<u>Carbon</u> inputs are mainly sourced from crop residues, roots and manure (Yu et al., 2012). We derived these<u>this</u> information <u>onat</u> a high spatial resolution from <u>the</u> various sources of existing datasets. FirstlyFirst, the <u>global</u> crop <u>yieldyields</u> for wheat, maize and rice in 2005 <u>on a global scale</u> at a $0.1^{\circ} \times 0.1^{\circ}$ spatial resolution were obtained from the <u>2005</u> Spatial Production Allocation Model (SPAM) <u>2005</u> (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 a continuous time-series data. As such, we adopted the global annual rates of change-rates of the major cereal crop yields at a $0.1^{\circ} \times 0.1^{\circ}$ resolution

(Ray et al., 2012) to generate a time-seriesthe crop yield data time-series. Here, we calculated the annual crop yields from 1961 to 2014 based on the percentages of the annual percent change-rates of change of the crop yieldyields and the crop yield data in 2005 (i.e., SPAM dataset);) by assuming a linear rate of change rate in the crop yields. This is acceptable because the rates of increase of the global yield increase rates 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 rootroots 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% in determiningwhen the quantity of the carbon input from the crops was determined (Skjemstad et al., 2004).

- Annual<u>The annual</u> carbon input contributed by from manure application at a global scale werewas derived from Zhang et al. (2017), who used the dataset from Global Livestock Impact Mapping System (GLIMS) dataset in conjunction with the country-specific annual livestock population to reconstruct the manure nitrogen production and application inof 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 ratiorations of the different typetypes 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 aroundapproximately 20 (Sharpley and Moyer, 2000; Ko et al., 2008; Eghball et al., 2002). TheAll of the calculated C inputs from crop roots and manure were assumed to be all-incorporated into the soils. The amount of C inputs from eropthe above-ground residues of the crops, however, were further determined by setting different residue retention scenarios as described below.
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Scenario simulations Simulation scenarios and identifying identification of the controls on 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 retention rates show athat is retained in the system, however, shows vast spatial disparity and uncertainty across the global croplands, and generally increase from 30% in the ... 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) to more than 60% in the-). 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, there lacks a-detailed information on the residue retention raterates 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. In general, we 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 stepbasis. 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 on SOC change-using Spearman's rank correlation coefficient (*rho*). SelectedThe selected climatic variables included mean annual temperature (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and mean annual precipitation (hereafter simply denoted as *temperature*) and temperate patterns (Bryan, 2003). For the correlation analysis, the long-term monthly climate variables were summarized to the mean annual values for each grid. SelectedThe selected soil parameters included the model's edaphic inputs, i.e., initial SOC content and soil clay fraction. ChangeThe 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

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

5 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), and to 70.9 MgC ha⁻¹ under R60 (Fig. 1b), and to 84.1 MgC ha⁻¹ under R90 (Fig. 1c). respectively.) in 2014. In general, the annual changing rates of change in SOC were 0.22 MgC ha⁻¹ yr⁻¹ under R30, 0.45 MgC ha⁻¹ vr⁻¹ under R60, and 0.69 MgC ha⁻¹ vr⁻¹ under R90, respectively, (Fig. 1),

10 Figure 2 shows the spatial patterns of the estimated SOC changes under R30 (Fig. 2a), R60 (Fig. 2b) and R90 (Fig. 2c)respectively.). Among the three scenarios, a relatively higher increase in SOC generally occurred atin 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 at high latitudes 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 15 during the study period under R30 (Fig. 2a), R60 (Fig. 2b) and R90 (Fig. 2c), respectively.

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The quantified SOC changes also showed large spatiotemporal disparities across different continents (Fig. 3). In generallygeneral, among the three scenarios, the SOC of the cropland SOC across Europe, Asia, and North America generally 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 laterlatter 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 laterlatter periods under R30 (Fig. 3a) and R60 (Fig. 3b). Under R90, however, the average SOC inon 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 those the areas with relatively lower C input rates (e.g., Oceania and Africa);) across all the three crop residue retention scenarios (Fig. 3 and S4).

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The quantified SOC changes were regulated by soil, climate and management practices. Initial 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, respectively (Fig. 4). CropThe crop residue retention rate showed a strong and positive correlation (rho = 0.34) with the SOC change (Fig. 4). Figure 5 presented presents the impacts of crop residue retention, initial SOC content and precipitation, respectively, 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 a linearly negative effect 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 quantified-linear increase in the global average SOC that was quantified in this study (Fig. 1) can be mainly be attributed to the increased-increasing rate of C input rate throughthroughout the study period (Fig. S3). This is associated with the increased crop production since-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 SOCthe 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 amountamounts of C input can lead to higher eropland soil C sink capacities. On a global average, enhancing the 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 rate from rates of 30% to%, 60% and 90% approximately induced a double and triple SOC sequestration rate,%, respectively (Fig. 4<u>S3</u>). 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. S3)-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-amount can be limited at longer periods as the SOC would eventually reach a threshold of a relatively stable levelthreshold (Stewart et al., 2007).

Apart from the residue retention rate, the initial SOC is one of the major controlling factors onof SOC change. The results in Figure Figures 4 and 5 indicates indicate that under otherwise similar environmental and managed conditions, soils with lower initial SOC contentcontents 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 quantified distribution of global SOC ehangechanges (Fig. 2) and the global initial SOC density densities that are quantified in this study (Fig. S2). For example, soils with lower initial SOC contentcontents in western Europe generally showed a-higher SOC increase increases than that the soils in the eastern Europe with relatively higher initial SOC content (Fig. 2 and Fig. S2). Such spatial Spatial patterns that 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). Soil The soil clay fraction has been suggested to benefit C stabilization through the mineralogical protection of soil C (Oades, 1988; Amato and Ladd, 1992), whereas). However, we identified a negligible but negative correction correlation between soil C accumulation and soil clay fraction in this study (Fig. 4). This 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 contentcontents generally had a-higher clay fraction fractions, and this would overshade overshadow the beneficial contributions of soil clay in benefiting to soil C accumulation.

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The negative effects of higher temperature and precipitation on SOC change identified in the present study (Fig.Figs. 4 and 5) can be attributed to the higher SOC decomposition raterates in warmer and wetter soils, which is consistent with the RothC model's description of the RothC model (Jenkinson et al., 1990) and the other findings of by Bond-Lamberty and Thomson (2010). Here, it should be noted that such correlations between the climate and SOC ehangechanges might only be valid in a soil carbon turnover model consisting that only consists of the-C dynamic C processes in the soil (e.g., RothC model). In other agricultural system-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 a-positive effects of temperature and precipitation on SOC accumulation. This is because, in the-temperature and water deficient areas (e.g., the_North China Plain), increased temperature and precipitation promoted promote crop production and hence increasing increases the C input to soils-and favoring, which favors SOC sequestration.

Can we estimate the actual historical soil C dynamics across the world? There exists a bigA large challenge exists due mainly to a lack of data availability, particularly for the two main RothC model inputs such as initial SOC content and annual C input. FirstlyFirst, the soil properties presented withby the HWSD were derived from different sources with unevenunevenly sampled soil profiles over time and space. As such, the value of initial SOC content can hardly, if not impossibleat all, represent the actual SOC content inat the beginning of the study period. However, the modeled dynamics of the_SOC in the present study eanmay be validappropriate, to a certain extent, to represent the spatiotemporal patterns of the soil C source/_and_sink processes. Second, there remains a lack of detailed information on crop residue management across both time and space_remains, which_also hinders our ability to accurately characterize the SOC changes on a large scale at fine spatiotemporal resolutions. Such as it isHowever, we can still roughly assume that the above-ground residue retention rates were generallyapproximately 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 furtheredfurther

quantified that the global average SOC increased at a rate of 0.34 MgC ha⁻¹ yr⁻¹ atunder 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 <u>the</u> conversion of <u>C</u> input C-to SOC (i.e., <u>the</u> ratio of SOC change to C input) equals to <u>is</u> 14%, which falls into<u>within</u> the <u>10-18%</u> range of <u>estimated</u> by Campbell et al. (2000)'s result of 10-18%.). It should be noted that the conversion efficiency varies across space and is highly dependent on <u>the</u> local climatic and edaphic conditions (Yu et al., 2012)._

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By extrapolating these results to the world's whole croplands with a global total cropland area of 1,400 Mha (Jobbagy and Jackson, 2000), it was found that the global cropland soils could have annually sequestered 0.48 Pg C annually from 1961 to 2014, which equals to around approximately 8% of the contemporaneous global average annual C emissions from fossil fuel combustions (http://cdiac.ornl.gov/ftp/ndp030/global.1751_2014.ems). ThroughBy enhancing the crop residue retention raterates to 60% and 90% in all the global croplands, the soil C accumulation would offset around approximately 11% and 16%, respectively, of the fossil fuel-induced C emissions. Again, it is noteworthy that although 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 amount of carbon input would be needed to maintain the soil C at higher levels (Wang et al., 2016). Otherwise, the cropland-soil C in croplands would decrease, and soils would again act as a net C source again.

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4.2 Uncertainties and limitations

Several uncertainties and limitations should be noticed inconsidered when interpreting the simulation results in this study. First, the modeled SOC change modeled in the present study could be biased due to the spatial inconsistency in the time of soil sampling, which generally rangesvaried widely duringover the second half of the twentieth century (Fao and Isric, 2012). In some places, the initial soil C information derived from the HWSD could only represent the actual soil C levels during the later periods other than after the early 1960s-. For example, the soil profile measurements used for producing produce the soil map of China, –which is further-included in the HWSD datasets, were generally madecollected in the late 1970s and early 1980s (Yu et al., 2007). Considering that the

spatial patterns of cropland SOC-across space could have substantially changed over the study period under the changing environments and management practices (FigFigs. 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. BesidesIn addition, it has been reported that soils with higher initial C contents would experience smaller increase or greater C losslosses under otherwise similar conditions, and vice versa (Zhao et al., 2013; Wang et al., 2015). Consequently, for those regions with soil sampling timetimes much later than the early 1960s, our quantified SOC changes could may be underestimated underestimations in the areas with where substantial soil C increase increases had occurred before then. On the contrary measurements were collected. In contrast, the SOC changes could be overestimated acrossin the areas accompanying with that are accompanied by a previous significantly decreased significant decrease in soil C.

10 Second, the RothC model was developed for simulating to simulate the soil organic matter turnover in upland soils (Jenkinson et al., 1990), and it generally showed performs well performance acrossin 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). Consequently.) used the RothC model, used to simulate the C changes in Japanese paddy soils and suggested 15 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, could have underestimated may bias the simulations of the SOC changes across the rice systems that are mainly distributed in the 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). 20 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.

Last but not leastFinally, 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 (FigFigs. 1 and S3), which contradicts theprevious findings ofthat increasing the incorporated amount of crop residue incorporation may affect the SOC change in variablea 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 pre-existingpreexisting soil C content is low, the SOC reaches a certain higherthreshold level (i.e., carbon saturation state) withwhere little or no significant further changechanges occur even withwhen more C inputsis added (Stewart et al., 2007; Qin et al., 2013). Without considering the C saturation state, the first-order decay model might overestimate the SOC atin longer time scale simulations particularly in regions withwhere the C input is higher C-input and lowerthe SOC decomposition rate is lower.

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Figure 1. Temporal changes in <u>the</u> soil organic carbon (MgC ha⁻¹) of the <u>main_global maincereal cropping regions</u> 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 $1.5 \times (75-25\%)$ 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). Boxplots show the median

and interquartile range, with whiskers extending to the most extreme data point within 1.5×(75-25%) data range.



Figure 2. Spatial distribution of SOC change (1961-2014, MgC ha⁻¹) across the global main 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 <u>main global main</u> 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 range-ranges with the whiskers extending to the most extreme data point within the $1.5 \times (75-25\%)$ data range.