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Soil organic carbon sequestration potential of cropland in China

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[1] Soil organic carbon (SOC) in cropland is of great importance to the global carbon (C) balance and to agricultural productivity, but it is highly sensitive to human activities such as irrigation and crop rotation. It has been observed that under certain improved management practices, cropland soils can sequestrate additional C beyond their existing SOC level before reaching the C saturation state. Here we use data from worldwide, long-term agricultural experiments to develop two statistical models to determine the saturated SOC level (SOC_S) in upland and paddy agroecosystems, respectively. We then use the models to estimate SOC sequestration potential (SOC_P) in Chinese croplands. SOC_P is the difference between SOC_S and existing SOC level (SOC_E). We find that the models for both the upland and paddy agroecosystems can reproduce the observed SOC_S data from long-term experiments. The SOC_E and SOC_S stock in Chinese upland and paddy croplands (0–30 cm soil) are estimated to be 5.2 and 7.9 Pg C with national average densities of 37.4 and 56.8 Mg C ha^{-1}, respectively. As a result, the total SOC sequestration potential is estimated to be 2.7 Pg C or 19.4 Mg C ha^{-1} in Chinese cropland. Paddy has a relatively higher SOC_E (45.4 Mg C ha^{-1}) than upland (34.7 Mg C ha^{-1}) and also a greater SOC_P at 26.1 Mg C ha^{-1} compared with 17.2 Mg C ha^{-1} in the upland. The SOC varies dramatically among different regions. Northeast China has the highest SOC_E and SOC_S density, while the Loess Plateau has the greatest SOC_P density. The time required to reach SOC saturation in Chinese cropland is highly dependent on management practices applied. Chinese cropland has relatively low SOC density in comparison to the global average but could have great potentials for C sequestration under improved agricultural management strategies.

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1. Introduction

[2] Soil organic carbon (SOC) is a great component of the global carbon budget and is important to agricultural productivity [*Lal*, 2004a; *Piao et al.*, 2009]. It is estimated that around 2500 Pg carbon (C) is stored in soils globally, which means that the soil C pool is about 3 times the size of the atmospheric C pool and 4 times the biotic C pool [*Batjes*, 1996; *Eswaran et al.*, 1993; *Lal*, 2004a]. Of the soil C pool, over 60% is SOC that is sensitive to both macroscale environmental conditions and microscale soil conditions, and 40% is soil inorganic carbon, which can be relatively resistant to environmental changes. SOC, in this sense, is a key component in determining the carbon budget. Also, SOC is an important indicator for soil fertility and soil quality, acting as an active sink and source reservoir for plant nutrients, improving soil microenvironments through physical, chemical, and biological processes, and thus determining ecosystem productivity [*Bronick and Lal*, 2005; *Kimetu et al.*, 2009; *Six et al.*, 2002]. Cropland soils in particular are highly disturbed by intensive human activities including various agricultural management practices [*Lal and Bruce*, 1999; *Lu et al.*, 2009; *Sun et al.*, 2009]. The cropland SOC pool, especially the top layer (0–30 cm), is critical to the soil C storage and crop yield [*Smith et al.*, 2000; *Sun et al.*, 2010].

[3] Cropland SOC is correlated with both environmental factors and management practices. For a given cropland, short-term SOC dynamics are strongly affected by management activities such as fertilization, tillage, and rotation. For example, organic carbon input like manure could significantly increase SOC content when preexisting SOC is at a low level [*Kimetu et al.*, 2009; *Shen et al.*, 2007; *Stewart et al.*, 2007], and conservation tillage can prevent soil carbon loss, compared to conventional tillage [*Follett*, 2001; *Lal*, 2004a, 2004c; *Smith*, 2004; *West and Post*, 2002]. *Lal* [2004a] estimated that by applying conservation tillage, cover crops, manure, and other recommended management practices (RMP; e.g., mulch farming, reduced tillage, integrated nutrient management, integrated pest management, and precision farming), global soils could have a C sequestration potential

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of 0.4–0.8 Pg C yr^{-1} [*Lal*, 2004a]. For croplands under given management practices, the environmental factors, such as climate and soil conditions, determine long-term SOC variations across space. Experiment-based studies indicate that temperature has a negative impact on SOC content while precipitation has a positive impact [*Dai and Huang*, 2006; *Müller and Höper*, 2004], and this relationship tends to be nonlinearity [*Alvarez and Lavado*, 1998; *Chapin et al.*, 2002]. Soil texture, especially fine particle fractions such as clay or silt content, is believed to be positively related to SOC content, especially in soils with high percentage of fine particles [*Angers et al.*, 2011; *Liang et al.*, 2009; *Müller and Höper*, 2004; *Zhao et al.*, 2006]. Soil acidity affects soil physical and biological properties, e.g., soil microbe activity, and therefore soil carbon decomposition [*Chapin et al.*, 2002; *Krug and Frink*, 1983; *Schmidt et al.*, 2011]. However, the soil acidity effects may only be applied in a very narrow range of soil pH, since cropland soils are always adjusted to certain acidity for crop growth.

[4] It has long been assumed that SOC level is positively related with C input level in a linear relationship, and most SOC models employ first-order kinetics to model decomposition processes; however, recent studies found little or no SOC change observed in response to varying C input in a number of long-term agroecosystem experiments, and, to the contrary, a ceiling on the capacity of SOC content was observed, which limits increases in SOC, even with additional C inputs [*Gulde et al.*, 2008; *Six et al.*, 2002; *Stewart et al.*, 2007]. After tens or even hundreds of years of field experiments, studies in Africa [*Kamoni et al.*, 2007], Asia [*Manna et al.*, 2005; *Manna et al.*, 2007; *Shen et al.*, 2007; *Yang et al.*, 2007], Australia [*Coleman et al.*, 1997; *Smith et al.*, 1997], Europe [*Powlson et al.*, 1998; *Schmidt et al.*, 2000; *Smith et al.*, 1997], North America [*Grant et al.*, 2001; *Huggins et al.*, 1998; *Izaurralde et al.*, 2001; *Paul et al.*, 1997], and South America [*Bayer et al.*, 2006, 2000] show that soil can accumulate a significant amount of C when the preexisting SOC is still at a low level, and therefore, SOC at steady state increases with C inputs; however, after SOC content reaches a certain level, it shows little or no significant change, even with more C inputs. It is believed that soil at the final SOC stable state reaches its "carbon saturation" state, and the SOC achieves the SOC saturation level [*Six et al.*, 2002; *Stewart et al.*, 2007]. Based on long-term field experiment observations, *Stewart et al.* [2007] proposed nonlinear carbon saturation models against the linear model to test the SOC-C input relationship. Results suggest that the saturation of soil C does occur, and the highest efficiency of C fixation is in soils further from C saturation [*Stewart et al.*, 2007].

[5] In the case that SOC level will reach its ceiling or saturation level, whether in the short or long term, soil carbon sequestration potential could be used to assess the carbon holding capacity in soil. Soil carbon sequestration potential measures the difference between the theoretical SOC saturation level and the existing SOC level and corresponds to the soil saturation deficit [*Hassink*, 1996; *Stewart et al.*, 2007]. Soil carbon sequestration potential may represent the potential for an additional transfer of C from the atmosphere [*Powlson et al.*, 2011]. *Lal* [2002] estimated that by applying RMPs to cropland might enhance SOC sequestration at the rate of 200–300 kg ha^{-1} yr^{-1}, and therefore, a total of 25–37 Tg C yr^{-1} can be accumulated in Chinese cropland. By extrapolating site-level SOC sequestration rates, *Lu et al.* [2009] suggested that the carbon sequestration potentials of Chinese cropland can reach 34.4 and 4.60 Tg C yr^{-1} using straw return and no-tillage techniques, respectively. Based on several agricultural management scenarios of crop residue return and tillage, *Yan et al.* [2007] simulated the SOC dynamics using a process-based ecosystem model and predicted an annual soil C sequestration of 32.5 Tg C in China as a result of practicing no-tillage on 50% of the arable lands and returning 50% of the crop residue to soils. The soil carbon sequestration rate varies much among different studies, due to variations from data sources, methods, and management scenarios.

[6] Even with reliable estimations of soil carbon sequestration rates at the site level, large uncertainties still may be introduced into regional or national extrapolation. Simply applying local management practices into broader areas ignores the spatial variations in climate, soil, and vegetation conditions, and results in upscaling uncertainty [*Lal*, 2002; *Sun et al.*, 2010]. Processes-based modeling, by comparison, provides a more reliable theoretical foundation by integrating SOC dynamics with spatial environmental factors and quantifying the importance of management practices [*Smith et al.*, 1997; *Yan et al.*, 2007]. However, most SOC models do not include the carbon saturation process and predict linearity between SOC level at steady state and C input level, which inevitably leads to simulation uncertainty [*Stewart et al.*, 2007]. Moreover, biogeochemical and biogeophysical processes are involved in most process-based models, which requires a huge number of vegetation-specific or soil-specific parameters and generally lots of input data which may not necessarily be available. These extra efforts might make process-based models less accessible and more challenging for people to use [*Huang et al.*, 2009; *Smith et al.*, 1997].

[7] In order to incorporate a carbon saturation concept and spatial environmental variations in estimating SOC sequestration potential, we developed a statistical nonlinear model to simulate SOC at the saturation level (0–20 cm soil) in response to climate and soil conditions [*Qin and Huang*, 2010]. This model is based on global, long-term agroecosystem experiments and is well validated using field data from nationwide upland experiments in China [*Qin and Huang*, 2010]. In this study, we further extend this model to 0–30 cm in upland soils and develop a similar model for simulating SOC at the saturation level in paddy agroecosystems using long-term observational data. Additionally, by applying these models to Chinese agroecosystems, we estimate SOC at the saturation level and SOC sequestration potential at both regional and national scales. The SOC sequestration rate and duration are also discussed in this study in the context of understanding the importance of management practices in preserving soil C. SOC is estimated and presented for the top 30 cm of the soils where the great majority of SOC changes occur in cropland [*Smith et al.*, 2000; *Sun et al.*, 2010].

2. Materials and Methods

2.1. C Saturation and SOC Sequestration Potential

[8] SOC changes with time. SOC steady state describes a dynamic soil condition where carbon input rate equals loss rate. At a given C input level, SOC changes with environment and finally reaches a relatively stable state, the "steady

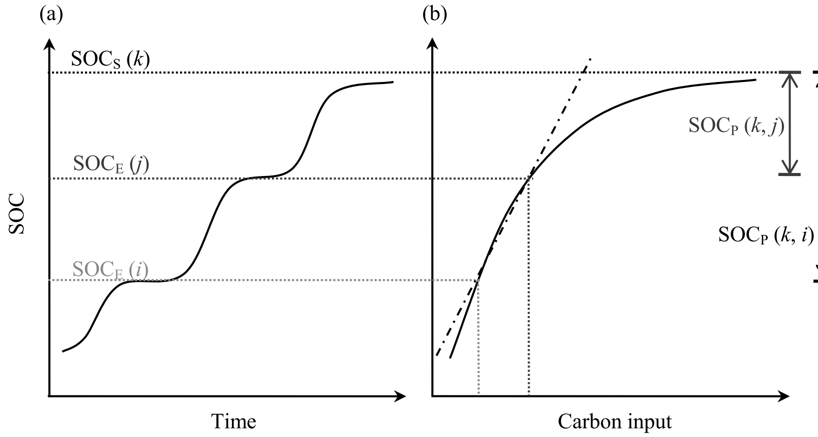

Figure 1. SOC dynamics following (a) time and (b) carbon input. SOC density at the steady state varies with carbon input level. SOC sequestration potential (SOC_P) is the difference between existing SOC at the steady state (e.g., SOC_E (*i*) or SOC_E (*j*)) and saturated SOC (e.g., SOC_S (*k*)). Adapted from *Qin and Huang* [2010].

state" (e.g., $SOC_E(i)$ of Figure 1a). However, with additional C input, SOC will increase asymptotically with time and achieve a new steady state (e.g., $SOC_E(i)$ of Figure 1a) in response to C input level [*Chapin et al.*, 2002; *Johnson et al.*, 1995]. However, the SOC-C input relationship is not positively linear as the dash-dotted line in Figure 1b that SOC increases with continuous C input indefinitely. Instead, with greater C input, the SOC sequestration efficiency declines, and the SOC at steady state (solid curve in Figure 1b) increases much more slowly than the linear change; with enough C input, the SOC sequestration rate finally approaches zero, and SOC at steady state reaches the ceiling (e.g., $SOC_S(k)$ in Figure 1b) [*Stewart et al.*, 2007; *West and Six*, 2007].

[9] Theoretically, the maximum steady state SOC is defined as saturated SOC (SOC_S). SOC sequestration potential (SOC_P) is defined as the difference between SOC_S and the preexisting SOC level (SOC_E) (Figure 1b). For example, SOC_P (*k*, *j*) is SOC sequestration potential between the saturate SOC level at state k ($SOC_S(k)$) and the existing SOC level at state j ($SOC_E(j)$) (Figure 1b). For any given soil type, theoretical SOC_S is believed to be unique and mainly determined by inherent soil physicochemical properties [*Six et al.*, 2002; *Angers et al.*, 2011]. However, at any given location, changing nvironmental factors such as temperature regime, precipitation or soil moisture, and management practice can all lead to variable steady state SOC level and therefore should be considered when simulating the SOC_S achieved under given environment. The apparent SOC_S (referred to as SOC_S hereafter, unless otherwise stated) can be modeled as a function of local climate and soil conditions, no matter what the existing SOC level is. The corresponding apparent SOC_P (referred to as SOC_p hereafter, unless otherwise stated) will be determined by the difference between apparent SOC_S and current SOC level.

2.2. Long-Term Experimental Data and Spatial Data

[10] Over 100 field experiments that last no less than 10 years were selected for model development. For upland agroecosystems, a total of 95 long-term agricultural experiments with high C input level were introduced to develop the model SOC_S (U) for estimating saturated SOC (Tables S1 and S2); these experiments are distributed across a vast cropland area spanning wide ranges of temperate, subtropical, and tropical climates (Figure S1). For paddy agroecosystems, datasets from 36 long-term experiments are included for developing the model of SOC_S (P) (Tables S3 and S4). These experiments are mostly from Asian countries, such as China, India, and Japan, and cover a majority proportion of the world's rice planting areas (Statistics Division of the Food and Agriculture Organization of the United Nations, http://faostat.fao.org/) and representing a variety of climate conditions (Figure S1). For each site, the treatment with highest C input was selected to detect SOC-time relationship (as in Figure 1a). Apparent SOC_S was determined as SOC approximates to steady state SOC level through time. Local apparent SOC_S in practice may not necessarily be theoretical SOC_S and is probably lower than $SOC_S(k)$ (Figures 1a and 1b), which however indicates the SOC_S could achieve at the site.

[11] The long-term experiment database includes site-specific climate information (temperature, precipitation), soil properties (clay fraction, pH, total nitrogen, bulk density), and SOC concentrations. Site information (e.g., location and experiment duration), cropping description (e.g., crop rotation, irrigation, and annual organic matter input), and sampling methods (e.g., soil sampling depth) are also included for reference. SOC concentration is converted to SOC density using [*Pan et al.*, 2003; *Sun et al.*, 2010]

$$SOC_D = SOC_C \times D \times BD \times (1 - F) \times 10^{-1}, \qquad (1)$$

where SOC_D is SOC density (Mg C ha^{-1}) and SOC_C is SOC concentration (g C kg^{-1}). D and BD refer to corresponding soil sampling depth (cm) and soil bulk density (g kg^{-1}), respectively. F is the fraction of >2 mm fragments (i.e., stones) (%) in soils. For sites where observational data are not available, BDs are determined using soil organic matter (SOM) concentration (%) according to the equation developed by *Adams* [1973] and further parameterized and used by *Rawls* [1983] and *Post and Kwon* [2000]:

Table 1. Cropland Distribution at Regional and National Scales in China

Region[a]	Area (Mha) Upland	Paddy	All Cropland
NE	30.4	3.7	34.1
NC	24.6	1.3	25.9
YZ	17.9	21.6	39.5
TP	5.6	0.1	5.7
LP	16.1	0.9	17.0
SC	10.4	7.4	17.8
China	105.0	35.0	140.0

[a]Regions: NE, Greater Northeast; NC, North China Plain; YZ, Yangtze River; TP, Greater Tibetan Plateau; LP, Loess Plateau; SC, South China. National upland and paddy area data were reported for year 2000 [*Liu et al.*, 2005].

$$BD = 100 \times \left(\frac{SOM}{0.244} + \frac{100 - SOM}{1.64}\right)^{-1}. \quad (2)$$

[12] SOC conversion between different soil depths is calculated according to the SOC vertical distribution in agricultural soils [*Jobbagy and Jackson*, 2000; *Wang et al.*, 2004]:

$$SOC_{0-10} : SOC_{10-20} : SOC_{20-30} : SOC_{30-40} = 23 : 18 : 13 : 10, \quad (3)$$

where the subscripts are intervals of soil depth and SOC is regarded to be evenly distributed among each interval. Detailed information on quality control of the long-term experiment data can also be found in a previous study [*Qin and Huang*, 2010].

[13] Spatially referenced driving data, including climate, irrigation, soil, and land use data, are organized at a 10 km × 10 km spatial resolution to estimate regional and national SOC_P in China. Mean annual temperature and mean annual precipitation for the 1990s are collected and computed from 751 nationwide meteorological observing stations and extrapolated to the national grid scale using the nearest neighbor method and the inverse distance method according to the interpolation method of *Thornton et al.* [1997]. Mean annual irrigation data are collected at a provincial scale according to local management practices and regional irrigation requirements [*Liu et al.*, 2009]. Mean annual water input is calculated by adding up mean annual precipitation and mean annual irrigation. Spatial soil data, including soil clay, soil pH, soil buck density, and SOM, are extracted from the Soil Spatial Database of China, developed by the Institute of Soil Science, Chinese Academy of Sciences [*Liu et al.*, 2006b; *Shi et al.*, 2002; *Yu et al.*, 2007]. This database is based on the 1:1,000,000 scale Soil Map of China and incorporates databases from the 2nd National Soil Survey conducted from the late 1970s to the early 1990s [*Liu et al.*, 2006b; *Shi et al.*, 2002; *Yu et al.*, 2007]. Cropland is classified as either upland or paddy; paddy is cropland where irrigated rice is grown, and upland is that where other crops are planted. Upland and paddy distribution data are based on remote-sensing land use data from the Data Center for Resources and Environmental Sciences (www.resdc.cn). In the mainland China, there are total of 140 Mha of croplands, with 105 Mha of upland and 35 Mha of paddy croplands [*Liu et al.*, 2005]. SOC concentration (%) used in spatial soil data is converted from SOM concentration (%) data using the Van Bemmelen value $\delta(\delta = 0.58)$ [*Howard and Howard*, 1990].

2.3. Developing SOC_S Model Using Long-Term Experiments

[14] To simulate SOC change in response to climate and soil factors, SOC_S can be modeled integrating temperature, precipitation, soil clay content, and soil pH according to previous studies [*Alvarez and Lavado*, 1998; *Chapin et al.*, 2002; *Dai and Huang*, 2006; *Krug and Frink*, 1983; *Liang et al.*, 2009; *Müller and Höper*, 2004; *Zhao et al.*, 2006]. An earlier test study [*Qin and Huang*, 2010] and preliminary analysis in this study suggested that temperature, precipitation, and soil clay content are major factors affecting SOC_S while soil pH has a less significant impact on SOC_S. In this study, SOC_S is modeled according to the following function for top soils of either upland or paddy:

$$\begin{aligned} SOC_s(X) &= f(MT, MW, CL, PH) \\ &= \tau_1 \cdot e^{\tau_2 \cdot MT} + \omega_1 \cdot e^{\omega_2 \cdot MW} + \varsigma_1 \cdot e^{\varsigma_2 \cdot CL} + \rho \cdot PH + \theta + \varepsilon \ , \end{aligned} \quad (4)$$

where SOC_S(X) is saturated SOC level in the top 30 cm soil in upland or paddy (Mg C ha^{-1}) agroecosystems and X is U for upland and P for paddy. MT, MW, CL, and PH indicate mean annual temperature (°C), mean annual water input (100 mm), soil clay content (%), and soil pH, respectively. Mean annual water input accounts for both mean annual precipitation and mean annual irrigation. In equation (4), τ_1, τ_2, ω_1, ω_2, ς_1, ς_2, ρ, and θ are parameters, and ε is error. The model is similar to *Qin and Huang* [2010] with same components and structures. But the parameters are recalibrated separately for upland and paddy soils, by fitting model with corresponding long-term experiment data (Table S1 for upland and Table S3 for paddy).

[15] To test the performance of the SOC_S simulation in upland and paddy agroecosystems, the models are validated against the rest of the experimental data from the global, long-term experiment database. Specifically, 19 long-term upland experiments in China (Table S2) and 12 global long-term paddy experiments (Table S4) are applied to SOC_S(U) and SOC_S(P), respectively, by fitting modeled SOC_S against observed SOC_S correspondingly. Modeled SOC_S for upland and paddy systems are computed with respective sets of parameters using site-specific data of mean annual temperature, mean annual water input, soil clay content, and soil pH. Root-mean-square error (RMSE), model efficiency (EF) [*Huang et al.*, 2009; *Loague and Green*, 1991], and the index of agreement (IA) [*Willmott*, 1982] are also reported to evaluate modeling performance.

2.4. Regional SOC Estimation

[16] In this study, China is divided into six food-producing regions according to the cropland distribution and climate conditions; Taiwan is not included due to the lack of data (Table 1 and Figure S3a). Among the six regions, the greater Northeast (NE), including Inner Mongolia and three provinces in Northeast China, the North China Plain (NC), and the Yangtze River region (YZ) share 70% of the national total upland area (Table 1 and Figure S3b). YZ together with South China (SC) account for over 80% of the national total paddy area (Table 1 and Figure S3c). The Tibetan Plateau

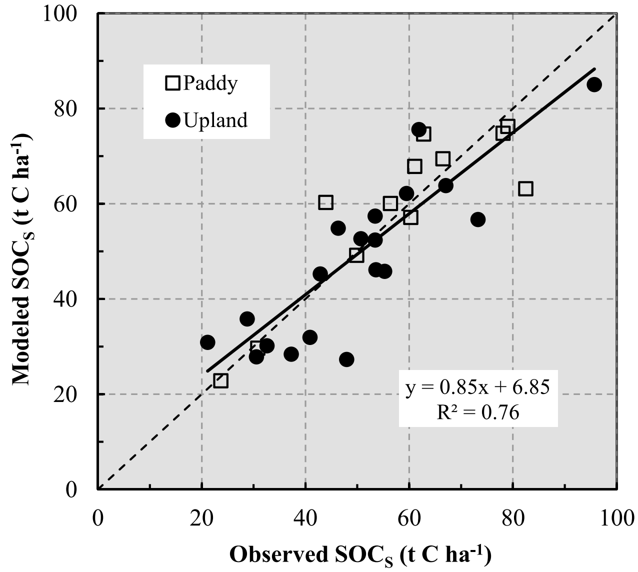

Figure 2. Modeled versus observed SOC_S in croplands. SOC_S in upland soils is modeled according to equation (8a) ($n = 19$), and SOC_S in paddy soils is modeled according to equation (8b) ($n = 12$). Dashed line is 1:1.

(TP) and Loess Plateau (LP) possess very limited cropland area. The climate in China is extremely diverse and ranges from tropical in the south to subarctic in the northeast, with a higher mean annual temperature in the south and lower in the north. Precipitation, however, varies regionally even more than temperature. The regions south of the Qinling Mountains, such as the YZ and SC regions, experience abundant annual precipitation, usually above 1000 mm. The north and west parts of this boundary, especially the TP regions, however, have scantier and very uncertain rainfall.

[17] For a regional assessment, both existing SOC (SOC_E) and saturated SOC (SOC_S) are estimated at regional and national scales. Using soil spatial data, we compute the grid level SOC density according to equation (1). Cropland and noncropland SOC were separated according to grid-level vegetation coverage. Grid level SOC_S of upland and paddy systems are modeled according to separate models, using the spatial driving data. Then grid level SOC_E and SOC_S are aggregated for regional estimations and at a national scale. The potential for future SOC sequestration (SOC_P) is estimated from SOC_E and SOC_S at grid, regional, and national levels accordingly (equation (5)). Cropland area weighted SOC density, and total SOC storage are presented for SOC_E, SOC_S, and SOC_P.

$$SOC_P = SOC_S - SOC_E. \tag{5}$$

[18] Propagation of uncertainty measures the effect of input variables' uncertainties (or errors) on the uncertainty of related output variables and is evaluated for linear and nonlinear combinations. For linear combinations (e.g., equation (6a)) where the variables x are uncorrelated, the simplified general expression for the propagation of uncertainty from one set of variables onto another is given by equation (6b) [*Taylor*, 1997]. In this study, for spatial SOC_E estimation, the uncertainties are calculated accordingly.

$$f(x_1,\ x_2, \ldots, x_n) = \sum_i^n a_i x_i, \tag{6a}$$

$$\delta_f^2 = \sum_i^n a_i^2 \delta_i^2, \tag{6b}$$

[19] In equations (6a) and (6b), x is the input variable and a is the corresponding coefficient in the combination; δ_i and δ_f are uncertainties for input and output variables, respectively.

[20] For nonlinear combinations of the variables x, the combination is first linearized by approximation to a first-order Taylor series expansion (equation (7a)) and then applied to the linear case above to estimate the propagation of uncertainty (equation (7b)) [*Taylor*, 1997].

$$f(x_1,\ x_2, \ldots, x_i) = f^0(x_1,\ x_2, \ldots, x_i) + \sum_i^n \frac{\partial f}{\partial x_i} x_i + \varepsilon, \tag{7a}$$

$$\delta_f^2 = \sum_i^n \left[\left(\frac{\partial f}{\partial x_i} \right)^2 \delta_{xi}^2 \right], \tag{7b}$$

where x is input variable in both equations. $\partial f / \partial x$ denotes the partial derivative of output variable f to variable x, and ε indicates the error due to the approximation. δ_x and δ_f are uncertainties for input and output variables, respectively. In this study, uncertainties of the spatial SOC_S are calculated according to this nonlinear case. We assume an error of ±5% for input driving data in equation (4) due to data measurement and interpolation [*Zhang*, 2004].

3. Results

3.1. Modeling and Validation of SOC_S Estimates

[21] Seventy-six upland soil datasets from global field experiments outside China (Table S1) and two thirds of paddy soil datasets (Table S3), selected randomly, were used to parameterize the SOC_S model (equation (4)) under different cropland types (i.e., upland and paddy). Equations (8a) and (8b) show the parameterized SOC_S model for upland and paddy soils, respectively, suggesting that 59% (upland soils) and 56% (paddy soils) of the observed variations in SOC_S could be explained by a nonlinear combination of mean annual temperature, mean annual water input, soil clay fraction, and soil pH (Figure S2).

$$SOC(U) = 167.6e^{-0.026MT} - 118.1e^{-0.373MW} - 50.4e^{-0.110CL} \\ -3.9PH - 24.9 \quad \left(R^2 = 0.59, n = 76\right), \tag{8a}$$

$$SOC(P) = 126.7e^{-0.015MT} - 152.7e^{-0.349MW} - 44.2e^{-0.054CL} \\ -10.4PH + 42.7 \quad \left(R^2 = 0.56, n = 24\right). \tag{8b}$$

[22] Nineteen datasets of upland soils from long-term agricultural experiment in China (Table S2) and the remaining one third of the datasets of paddy soils (Table S4) were used to validate the $SOC_S(U)$ and $SOC_S(P)$ models, respectively. Observed SOC_S ranges from 21.1 to 95.7 Mg C ha^{-1} with an average of 50.1 ± 17.5 (mean ± SD) Mg C ha^{-1} for upland soils and from 23.7 to 82.5 Mg C ha^{-1} with an average of 57.9 ±18.4 Mg C ha^{-1} for paddy soils. Modeled SOC_S ranges from

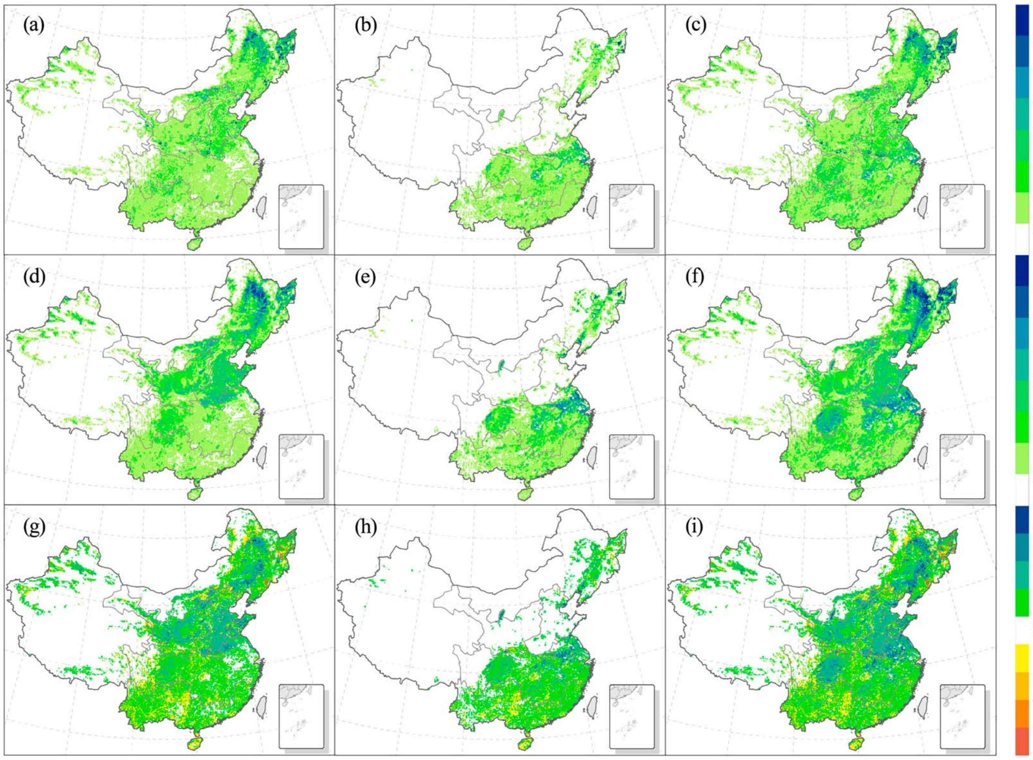

Figure 3. Existing and potential SOC density in Chinese cropland. Existing SOC densities of (a) upland, (b) paddy, and (c) upland and paddy together are based on National Soil Survey date from the late 1970s to the early 1990s. Saturated SOC densities of (d) upland, (e) paddy, and (f) upland and paddy are estimated using average climate data from the 1990s and soil data. The SOC potential of (g) upland, (h) paddy, and (i) upland and paddy are the differences between corresponding saturated SOC density and existing SOC density. Values are cropland area weighted SOC density (Mg C ha^{-1}).

27.3 to 85.0 Mg C ha^{-1} with an average of 47.9 ± 16.8 Mg C ha^{-1} for upland soils (equation (8a)) and from 22.8 to 76.2 Mg C ha^{-1} with an average of 58.7 ± 17.2 Mg C ha^{-1} for paddy soils (equation (8b)), in agreement with observations.

[23] The regression of the modeled versus observed SOCs (Figure 2) yields an R^2 of 0.76, with a slope of 0.85 and an intercept of 6.85 Mg C ha^{-1} ($n = 31$, $P < 0.001$). Values of RMSE, EF, and IA are 17.6%, 0.73, and 0.92 for upland soils, and 14.8%, 0.76, and 0.93 for paddy soils.

3.2. SOC_E, SOC_S, and SOC_P

[24] SOC_E, estimated from the soil database based on the 2nd National Soil Survey, shows the existing SOC levels of upland (Figure 3a) and paddy (Figure 3b) agroecosystems from the late 1970s to the early 1990s. Simulated SOC_S of upland (Figure 3d) and paddy (Figure 3e) agroecosystems, as estimated according to equations (8a) and (8b), respectively, indicate the saturated SOC level under current climate and soil conditions. The difference between the corresponding SOC_S and SOC_E, as estimated according to equation (5), indicates the SOC sequestration potential level of upland (Figure 3g) and paddy (Figure 3h) systems. For cropland, its SOC_E (Figure 3c), SOC_S (Figure 3f), and SOC_P (Figure 3i) are estimated as cropland area weighted combination of both upland and paddy SOC levels, accordingly. Results show that SOC level is strongly spatially correlated, with high variances (Figures 3a–3i). In particular, SOC_E varies greatly from one grid to another, with a number of abrupt changes at certain locations (Figures 3a–3c); this may be due to uncertainty in soil sampling, soil analysis [*Wang et al.*, 2004, 2001; *Yu et al.*, 2007], and spatial interpolation [*Huang et al.*, 2006].

[25] For upland soils, there is an average density of 34.7 Mg C ha^{-1} for "up to date" national SOC_E, whereas an average of 51.9 Mg C ha^{-1} for "potential" national SOC_S (Table 2).

Table 2. National SOC Density and Stock in Chinese Croplands[a]

Soil Usage	Area (Mha)	SOC_E C Density (Mg C ha^{-1})	SOC_E C Stock (Pg C)	SOC_S C Density (Mg C ha^{-1})	SOC_S C Stock (Pg C)	SOC_P C Density (Mg C ha^{-1})	SOC_P C Stock (Pg C)
Upland	105.0	34.7 (±5.0)	3.64 (±0.52)	51.9 (±4.5)	5.45 (±0.47)	17.2 (±6.8)	1.81 (±0.70)
Paddy	35.0	45.4 (±7.6)	1.59 (±0.27)	71.5 (±7.4)	2.50 (±0.26)	26.1 (±10.6)	0.91 (±0.37)
All cropland	140.0	37.4 (±5.7)	5.23 (±0.47)	56.8 (±5.4)	7.95 (±0.43)	19.4 (±7.9)	2.72 (±1.10)

[a]Existing SOC (SOC_E), saturated SOC (SOC_S), and SOC sequestration potential (SOC_P) are estimated for upland, paddy, and cropland (upland + paddy) at the national scale. SOC_E density is based on the Soil Spatial Database of China. SOC_S density is estimated according to models. SOC_P is the difference between average SOC_S and average SOC_E (equation (5)). Values in parentheses are corresponding errors. Values may not total due to numerical rounding.

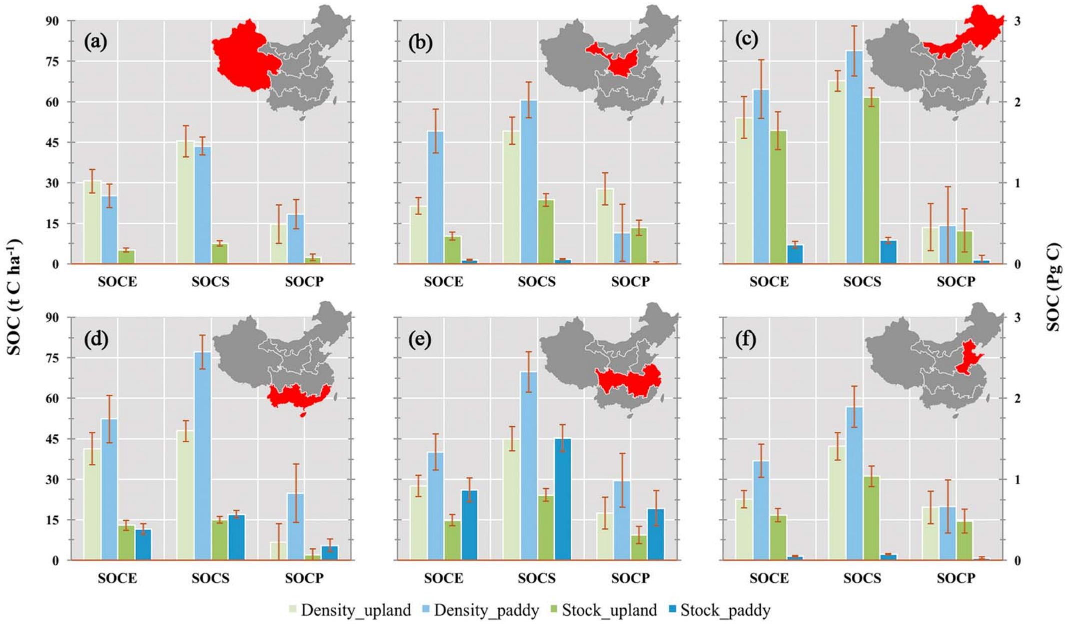

Figure 4. Regional SOC in Chinese croplands. SOCE, SOCS, and SOCP are existing SOC, saturated SOC, and potential SOC, respectively. Both SOC density (Mg C ha^{-1}, primary axis) and SOC stock (Pg C, secondary axis), in upland and paddy agroecosystems, are estimated for regions (a) TP, (b) LP, (c) NE, (d) SC, (e) YZ, and (f) NC. See region descriptions in Table 1 and Figure S3.

Regionally, the northern parts of China have relatively higher SOC content than the southern parts, in the form of SOC_E (Figure 3a), SOC_S (Figure 3d), and even SOC_P (Figure 3 g). It is estimated that the NE region, covering a vast proportion of upland areas in China, has the highest SOC_E and SOC_S densities, with an average of 54.1 and 67.8 Mg C ha^{-1}, respectively, 56% and 31% higher than the national average SOC_E and SOC_S correspondingly (Table 2 and Figure 4c). The SC region has the second highest SOC_E (Figure 4d), and the LP region has the second highest SOC_S (Figure 4b). For projected SOC_P density, however, the NC (Figure 4f), LP (Figure 4b), and YZ (Figure 4e) are the top three regions with the highest potential for sequestrating additional SOC in future, above the national average potential (Table 2). Taking the upland area into consideration, the NE region has a total SOC_E and SOC_S stock of 1.6 and 2.1 Pg C, respectively (Figure 4c), accounting for over one third of the national total SOC_E and SOC_S stocks (Table 2). The NC (Figure 4f), NE (Figure 4c), and LP (Figure 4b) regions own similar SOC_P stocks of 0.4–0.5 Pg C and account in total for three fourths of the national potential (Table 2). Nationally, to reach the saturated SOC level of 51.9 Mg C ha^{-1}, China can sequestrate an additional 17.2 (±6.8) Mg C ha^{-1} of SOC in upland soils, with a total additional SOC stock of 1.8 Pg C (Table 2).

[26] Paddy soils generally have much higher SOC density in the form of either SOC_E or SOC_S, at both regional and national scales, compared with those of upland soils (Figure 4). The NE region, in particular, possesses the highest existing and saturated SOC density, with SOC above 60 Mg C ha^{-1} (Figure 4c); the regional average SOC_E density (64.6 ± 10.8 Mg C ha^{-1}) is close to the SOC_S density (78.9 ± 9.2 Mg C ha^{-1}), indicating relatively limited potential (14.3 Mg C ha^{-1}) for further SOC sequestration (Figures 3g and 4c). Besides possible errors in measuring [*Wang et al.*, 2004, 2001; *Yu et al.*, 2007] and calculating SOC_E [*Qin and Huang*, 2010], the abnormally high SOC contents in the NE are mainly due to the extremely fertile soil type, the Black Earth [*Liu et al.*, 2006a; *Meng et al.*, 2002; *Sun et al.*, 2010], and the long-term favorable climate conditions [*Liu et al.*, 2006a; *Liu et al.*, 2006b]. Other regions normally own a SOC_P between 18 and 30 Mg C ha^{-1} (Figures 4a and 4d–4f), except for the LP region which has a SOC_P of only 11.6 Mg C ha^{-1} (Figure 4b). The YZ region in particular (Figure 4e), covering 60% of the total paddy area in China, has a potential of adding 29.6 ± 10.1 Mg C ha^{-1} more SOC in future, with a total potential stock of 0.64 Pg C, which accounts for 70% of the national total SOC_P stock in paddy soils (Table 2). Regions, such as TP (Figure 4a), LP (Figure 4b), and NC (Figure 4f) have very small quantities of SOC_P due to their limited paddy areas. For the whole nation, it is predicted that paddy soils can achieve a saturated SOC density of 71.5 Mg C ha^{-1}, approaching the SOC density of grassland [*Jobbagy and Jackson*, 2000; *Ni*, 2002; *Wang et al.*, 2004]. An average SOC_P of 26.1 Mg C ha^{-1} is expectable for paddy soils nationally, with a total potential stock of 0.91 Pg C (Table 2).

[27] Cropland SOC, estimated as the corresponding area-weighted total of both upland and paddy SOC, provides a full picture of the distribution of SOC_E (Figure 3c), SOC_S (Figure 3f), and SOC_P (Figure 3i). Generally, when a SOC_E (Figure 3c) comes up with a relatively higher SOC_S (Figure 3f), the result is a positive SOC_P at given regions and locations (Figure 3i). This is especially the case in the central part of the NE region, most parts of the NC region, the eastern part of YZ region, and almost the whole of the Sichuan Basin (Figures 3c, 3f, and 3i). It is estimated that the highest densities of SOC_E and SOC_S appear in the NE region with an average of 55.3 (±8.1) and 69.0 (±4.8) Mg C ha^{-1}, respectively; the lowest SOC_E density is 23.0 (±3.6) Mg C ha^{-1} in the LP region, and the lowest SOC_S density is 42.9 (±5.3) Mg C ha^{-1} in the NC region (Figure 5). The SOC_P density

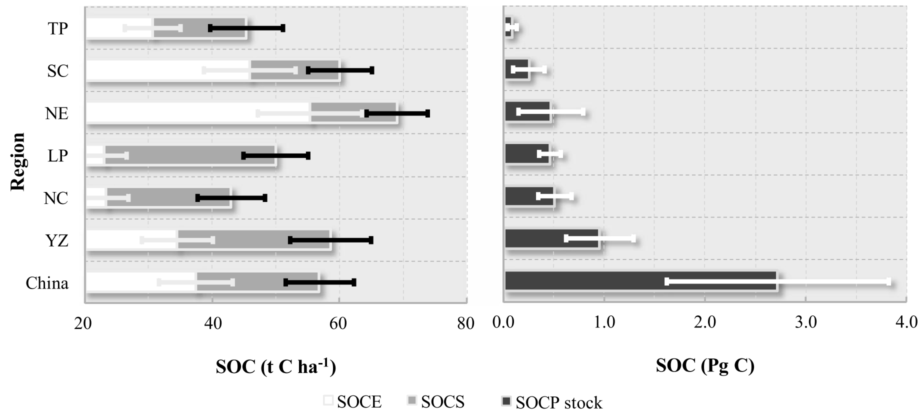

Figure 5. Regional and national SOC in Chinese cropland. SOCE, SOCS, and SOCP stock are existing SOC density (Mg C ha^{-1}), saturated SOC density (Mg C ha^{-1}) (left), and potential SOC stock (Pg C) (right) for all croplands. See region descriptions in Table 1 and Figure S3.

ranges from 13.7 (±9.4) Mg C ha^{-1} in the NE region to 26.9 (±6.2) Mg C ha^{-1} in the LP region (Figure 5). However, the highest regional SOC$_P$ stock is 0.95 (±0.3) Pg C in the YZ region (Figure 5). Nationally, the SOC density of Chinese croplands was 37.4 (±5.7) Mg C ha^{-1} and the SOC stock was 5.2 (0.5) Pg C during the late 1970s to the early 1990s, with a theoretical saturated level of SOC density of 56.8 (±5.4) Mg C ha^{-1} and SOC stock of 8.0 (±0.4) Pg C. This suggests that there is a SOC sequestration potential of 19.4 (±7.9) Mg C ha^{-1}, with a national total potential SOC sock of 2.7 (±1.1) Pg C in the croplands of China (Table 2).

4. Discussion

4.1. China's SOC Role in the Global Carbon Budget

[28] It is estimated that the total SOC of the global croplands is 69–89 Pg C, with an average SOC density of 43–60 Mg C ha^{-1} in the top 30 cm of soils [*Jobbagy and Jackson*, 2000; *Lal*, 2004c]. However, SOC density changes enormously from region to region. For example, the European regions have a SOC density of about 53 Mg C ha^{-1}, and the US has an average of 33 to 87 Mg C ha^{-1}; countries in Asia, such as India and China, have much lower SOC density and account for only one third to two thirds of the global average (Table 3).

[29] In China, the SOC density among all vegetation types, including agroecosystems and natural ecosystems, on average is 43–58 Mg C ha^{-1} or 38–48 Pg C at the 0–30 cm range of soils (Table 3). Based on the 2nd National Soil Survey, *Song et al.* [2005] estimated that topsoil SOC density in cultivated soils with the average being 35 ± 32 Mg C ha^{-1} and a stock of 5.1 Pg C, which is very close to our results of 37.4 ± 5.7 Mg C ha^{-1} or 5.2 Pg C for cropland (Table 3). The SOC density in cropland is about 60–90% of the national average SOC level, and the total SOC pool accounts for 11–14% of the national total (Table 3). *Zhao et al.* [1997] estimated that the SOC density of upland and paddy soils in Southeast China is 24 and 46 Mg C ha^{-1}, respectively (Table 3), similar to the results in the related YZ and SC regions in this study (Table 3 and Figures 4d and 4e). For paddy soils, our estimates also fall into the range of other estimates (Table 3).

[30] For comparison, the regional or global SOC$_P$ density and stock are estimated such a way that they can be used to describe the additional SOC holding capacity beyond current or existing capability [*Powlson et al.*, 2011; *Sun et al.*, 2010]. By using data from other studies [*Jin et al.*, 2008; *Lal*, 2002,

Table 3. Global and Regional Cropland SOC$_E$ From Different Estimates

Region	Land Type	Area (Mha)	SOC$_E$ (Mg C ha^{-1})	SOC$_E$ Stock (Pg C)	Data Source
Global	Cropland	1400	60.5 (±41.6)^a	84.8^a	*Jobbagy and Jackson* [2000]
	Cropland	1600	43–56	69–89	*Lal* [2004a]
Europe	Cropland	135.4	53.2	7.2	*Smith et al.* [1997, 2000]
EU15	Cropland	72.8	53.6	3.9	*Smith et al.* [1997, 2000]
USA	Cropland	132.6	32.5–87.1^a	4.3–11.6^a	*Guo et al.* [2006a, 2006b]
India	Cropland	162	19.1–38.3	3.1–6.2	*Lal* [2004b]
China	All^b	880–930	43–58	38–48	*Yu et al.* [2007], *Wang et al.* [2001], *Wu et al.* [2003], and
	Cropland	137.7	35.1 (±31.6)	5.1	*Song et al.* [2005]
		140.0	37.4 (±5.7)	5.2 (±0.5)	This study
	Upland	7.2	23.8(±11.2)^{a,c}	0.2^a	*Zhao et al.* [1997]
		105.0	34.7 (±5.0)	3.6 (±0.5)	This study
	Paddy	29.8	52.8^a	1.6^a	*Pan et al.* [2003]
		45.7	49.5^a	2.3^a	*Liu et al.* [2006b]
		13.6	46.4(±26.0)^{a,c}	0.6^a	*Zhao et al.* [1997]
		35.0	45.4 (±7.6)	1.6 (±0.3)	This study

[a]SOC is converted to the 0–30 cm soil depth according to the SOC vertical distribution as in equation (3).
[b]SOC is estimated for soils under all land uses.
[c]SOC is estimated for Southeast China. SOC$_E$ is existing SOC, presented as mean with error reported in parenthesis.

Table 4. Global and Regional Cropland SOC_P From Different Studies

Region	Land Use	Area (Mha)	SOC_P (Mg C ha^{-1})[a]	SOC_P Stock (Pg C)[a]	Data Source
Global	Cropland	1600	13.1–18.1	21–29	*Lal* [2004a] and *Lal and Bruce* [1999]
Europe	Cropland	135.4	0.4–27.7	0.1–3.8	*Smith et al*. [2000]
EU15	Cropland	72.8	5.8–34.1	0.4–2.5	*Smith et al*. [1997]
USA	Cropland	134	2.2–37.6	0.3–5.4	*Metting et al*. [2001]
India	Cropland	162	12–15	2.0–2.5	*Lal* [2004c]
China	Cropland	140.4[c]	8.5–82.2	1.2–8.2	*Jin et al*. [2008]
		124	10.1–14.9	1.3–1.9	*Lal* [2002]
		60.7	5.0–37.3	0.3–2.3	*Lu et al*. [2009]
		130	15.4–19.2	2–2.5	*Sun et al*. [2010]
		179	1.3–33.6	0.2–6.0	*Yan et al*. [2007]
		140.0	19.4 (±7.9)	2.7 (±1.1)	This study
	Upland	105.4[c]	7.2–51.4	0.7–5.4	*Jin et al*. [2008]
		105.0	17.2 (±6.7)	1.8 (±0.7)	This study
	Paddy	35.0[c]	5.3–50.0	0.2–1.8	*Jin et al*. [2008]
		29.8	17.6–75.5[b]	0.7–3.0[b]	*Pan et al*. [2003]
		45.0	0.6–18.8	0.03–0.8	*Xu et al*. [2011]
		35.0	26.1 (±10.6)	0.9 (±0.4)	This study

[a]SOC_P is calculated either as difference of SOC_S and SOC_E or as the product of the reported SOC sequestration rate and the SOC sequestration duration; SOC is converted to the 0–30 cm soil depth according to the SOC vertical distribution as in equation (3); default SOC sequestration duration is set to be 50 year [*DOE*, 1999; *Lal*, 2004a; *Metting et al*., 2001]. Values are presented as mean with error reported in parenthesis.

[b]SOC is for soil depth of 23–31 cm as reported.

[c]As estimated by *Liu et al*. [2005].

2004b, 2004c; *Lal and Bruce*, 1999; *Lu et al*., 2009; *Metting et al*., 2001; *Pan et al*., 2003; *Smith et al*., 1997, 2000; *Sun et al*., 2010; *Xu et al*., 2011; *Yan et al*., 2007], SOC_P is calculated either as the difference of SOC_S and SOC_E, as done in this study, or as the product of the reported SOC sequestration rate and the SOC sequestration duration for areas where data are provided (Table 4). For cases where SOC sequestration duration is not available, 50 years are believed to be an acceptable and reliable default value [*Department of Energy* (*DOE*), 1999; *Lal*, 2004c; *Metting et al*., 2001]. Globally, cropland soils have a potential to sequestrate an additional 13–18 Mg C ha^{-1} of SOC, with a total additional SOC stock of 21–29 Pg C. However, huge uncertainties exist among studies based on different SOC sequestration assumptions and estimation methods; the actual SOC_P is highly dependent on the management practices and degraded soil restorations [*Lal*, 2002; *Metting et al*., 2001; *Sun et al*., 2010].

[31] For Chinese cropland, the SOC_P varies from 1.3 to 82.2 Mg C ha^{-1} among different studies. By extrapolating observational SOC sequestration rates from sites to six regions in China, *Jin et al*. [2008] estimated that crop residue return and manure application can significantly increase SOC content; a national average SOC_P of 8.5–82.2 Mg C ha^{-1} can be achieved for the top 30 cm soils depending on management practices applied, by assuming a default sequestration duration of 50 year (Table 4). *Lu et al*. [2009] used a similar method of extrapolation, but at a more accurate provincial scale rather than a regional scale. Their results show that 5.0–37.3 Mg C ha^{-1} is achievable with the application of management practices such as fertilization and crop residue return (Table 4). *Sun et al*.'s [2010] results are based on a simplified SOC decomposition model accounting management practices of crop residue return and no-tillage (Table 4). Using a remote sensing-based production efficiency model and a process-based ecosystem model, *Yan et al*. [2007] estimated that 1.3–33.6 Mg C ha^{-1} SOC_P is expectable, depending on scenarios of management practice regarding residue return and no-tillage. Our result of 19 ± 7.9 Mg C ha^{-1} agrees well with these management scenario-based estimates [*Lu et al*., 2009; *Sun et al*., 2010; *Yan et al*., 2007] but is slightly higher than 10–15 Mg C ha^{-1} of *Lal* [2002], which used similar methods as *Jin et al*. [2008] and *Lu et al*. [2009] but at a relatively roughly national scale. For separate SOC estimates on upland and paddy soils, our results are also comparable with others (Table 4).

[32] Chinese cropland soils have a high efficiency of SOC sequestration in terms of SOC_P density relative to SOC_E density. Specifically, the existing SOC density is only 60–90% of the global average level and may be even lower than some countries (e.g., USA); with 9–10% of world cropland area, the SOC pool accounts for only 6–8% of the total global SOC stock (Table 3). But, the SOC_P in Chinese cropland is close to the global average and even higher compared with some countries (e.g., India); the national SOC_P stock of 2.7 Pg C makes up 9–13% of the global total (Table 4). Our analyses support the conclusion that China may be considered as a country with low SOC density, but a country with great potential for C sequestration under well-defined management situations [*Song et al*., 2005].

4.2. Sequestration Duration Under Improved Agricultural Management

[33] Many previous studies have observed that given improved agricultural management practices, the cropland would be capable of sequestrating additional C into soil beyond the current SOC level [*Lal*, 2002; *Lu et al*., 2009; *Sun et al*., 2010; *Yan et al*., 2007]. A SOC sequestration rate of 100–746 kg C ha^{-1} yr^{-1} is anticipated for Chinese agroecosystems under different management practices (Table S5). Therefore, the SOC sequestration duration, reaching 19.4 Mg C ha^{-1} of SOC_P, can be calculated for different scenarios (Table S5). We find that Chinese cropland soils will achieve the saturated SOC level in 26–194 years, depending on management practices if applicable (Table S5). Crop residue return, no-tillage, and even nitrogen fertilization could be beneficial for SOC sequestration, if practiced under good management [*Lal*, 2002; *Lu et al*., 2009; *Sun et al*., 2010; *Yan et al*., 2007]. Crop residue return and no-tillage alone may not contribute much to SOC_P but together could make a great difference; it

is technically applicable for China to practice residue return and no-tillage in the near future [*Sun et al*., 2010; *Yan et al*., 2007]. However, the actual SOC sequestration duration may be longer than predicted, since that SOC sequestration efficiency gets smaller when soils are approaching the SOC saturation level [*Stewart et al*., 2007]. Estimates could be improved if further information were available regarding time-dependent carbon sequestration rates under given management. Also, actual steady state SOC level depends on given C input relative to management practice, while model-predicted SOC_P is based on global-scale approximation of maximum C input assumption, not every improved management practice would eventually achieve the SOC_S or fill the SOC_P. Therefore, even though the improved management practices are applicable nationwide, gaps may still exist between actual steady state SOC and SOC_S.

4.3. Uncertainties

[34] Major uncertainty in this study comes from the input data. SOC_E results are obtained largely from soil survey-based data, and the processes of soil sampling, soil analysis, and data interpolation could all contribute to uncertainties in the final SOC density and stock estimations [*Liu et al*., 2006b; *Zhao et al*., 2005]. Besides these uncertainties from soil data collection, extrapolating site-level data of temperature, precipitation, and irrigation onto nationwide spatial data brought additional interpolation errors to the SOC_S estimation [*Huang et al*., 2006]. Although an average input data interpolation error of 5% has been applied in uncertainty estimation, the spatial heterogeneity of soil and climate data cannot be accounted for, and this may contribute to the uncertainties of SOC spatial distribution estimations.

[35] Another source of uncertainty for SOC_S estimation may come from model itself. The upland SOC_S model is developed from worldwide, long-term agricultural experiments; even with good quality control, the uncertainties from observational data due to investigator biases, experimental condition, and methodology variations may contribute to model parameterization errors [*Easter et al*., 2007; *Müller and Höper*, 2004]. The paddy SOC_S model is developed from a relatively small number of long-term experiments due to limited data availability; it may not be appropriate to apply this model to regions outside Asia without further validation. Additionally, uncertainty due to covariance among the fitted variables and the lack of other environmental factors, such as soil nitrogen, may also limit our ability to estimate the SOC density in cropland soils [*Khan et al*., 2007; *Pan et al*., 2003]. For future work, more information (e.g., soil nitrogen) should be collected for a larger number of long-term experiments, to better understand SOC_S dynamics and constrain model uncertainties. It is expected that the descriptive power for the present models could be improved when a considerable number of field measurements were made under various conditions of climate, soils, cropping systems, and agricultural practices. More accurate input data, including soil and climate data, with a higher spatial resolution and smaller extrapolation errors could significantly improve regional estimates. Also, parameter uncertainty could be assessed in regional estimation, if further information were available regarding variations of model parameters (e.g., probability density function).

[36] For the sake of depicting spatial distribution of existing SOC level in this study, we adopted the latest available data based on the 2nd National Soil Survey; by doing this, we may inevitably miss the information of SOC change during the past several decades when estimating SOC_P. According to more recent studies, additional 0.7–0.8 Pg C of SOC was accumulated in the top 30 cm of Chinese cropland soils since the 1980s, mainly due to crop yield increase and improved crop residue management [*Pan et al*., 2010; *Yu et al*., 2012]. It suggested that even based on current SOC level, national SOC_P of 1.9–2.0 Pg C can be still achievable in future, if optimized agricultural management practices can be widely applied.

[37] Some further improvements could also improve the estimates, if data are available. For example, the estimated cropland area of 141 Mha was used for regional estimates through time, which however was still subject to change due to land use / land cover change [*Liu et al*., 2005]. SOC vertical distribution was acquired from a large-scale data assimilation [*Jobbagy and Jackson*, 2000; *Wang et al*., 2004], which may introduce errors for site-scale SOC assessments due to temporal and spatial heterogeneity of SOC content in different cropland types.

[38] Land use change alters the soil carbon content and may also affect "apparent" soil carbon potential. To assess the "true" or theoritical saturation level and therefore the soil carbon sequestration potential for ecosystem soils, it may be intersting to look beyond the cropland and evaluate soil carbon dynamics under other land use types, e.g., grassland or forest. It should be noted that soil carbon saturation in theory can hardly be achieved in reality as actual C input could not be infinite. The apparent SOC_S acquired at high C input level may not necessarily represent the highest possible saturation level in the field. The theory of soil carbon saturation and approach to calculate it could be improved if further information are available regarding SOC-time-C input relationships.

5. Conclusions

[39] By using data from global, long-term agricultural experiments, two statistical models were developed to estimate the saturated SOC level and SOC sequestration potential in upland and paddy agroecosystems. A total SOC_P stock of 2.7 Pg C was estimated for cropland (upland and paddy systems) in China, with an average density of 19.4 Mg C ha^{-1}. Paddy soils have a relatively higher SOC_E, SOC_S, and even SOC_P level, compared with upland soils; however, the total SOC_P stock of paddy soils is only 0.9 Pg C, lower than the 1.8 Pg C in upland soils, due to relatively limited land area. SOC density varies dramatically among different regions, with the highest SOC_E and SOC_S in the northeast region of China and the greatest SOC_P in the Loess Plateau region. Compared with other regions, such as the U.S. and Europe, China has relatively low SOC_E and SOC_S density but a comparable SOC_P level for potential carbon sequestration in cropland soils. To approximate soil carbon saturation in Chinese croplands, the SOC sequestration time depends highly on management practices applied. Improved practices, such as crop residue return and no-tillage, could benefit soil carbon sequestration.

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