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Uncertainty of organic carbon dynamics in Tai-Lake paddy soils of China depends on the scale of soil maps

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ABSTRACT

Agro-ecosystem models have been widely used to quantify soil organic carbon (SOC) dynamics based on digital soil maps. However, most of the studies use soil data of single or limited choices of map scales, thus the influence of map scales on SOC dynamics has rarely been quantified. In this study, six digital paddy soils databases of the Tai-Lake region in China at scales of 1:50,000 (P005), 1:200,000 (P02), 1:500,000 (P05), 1:1,000,000 (P1), 1:4,000,000 (P4), and 1:14,000,000 (P14) were used to drive the DNDC (DeNitrification & DeComposition) model to quantify SOC dynamics for the period of 2001–2019. Model simulations show that the total SOC changes from 2001 to 2019 in the top layer (0–30 cm) of paddy soils using P005, P02, P05, P1, P4, and P14 soil maps would be 3.44, 3.71, 1.41, 2.01, 3.57 and 0.10 Tg C, respectively. The simulated SOC dynamics are significantly influenced by map scales. Taking the total SOC changes based on the most detailed soil map, P005, as a reference, the relative deviation of P02, P05, P1, P4, and P14 were 7.9%, 58.9%, 41.6%, 3.9%, and 97.0%, respectively. Such differences are primarily attributed to missing soil types and spatial variations in soil types in coarse-scale maps. Although the relative deviation of P4 soil map for the entire Tai-Lake region is the lowest, substantial differences (i.e., 22–1010%) exist at soil subgroups level. Overall, soil map scale of P02 provides best accuracy for quantifying SOC dynamics of paddy soils in the study region. Considering the soil data availability of entire China, P1 soil map is also recommended. This study suggested how to select an appropriate scale of input soil data for modeling the carbon cycle of agro-ecosystems.

1. Introduction

Soil plays an important role in the global carbon cycle and contains more carbon than the atmosphere and vegetation combined (Eswaran et al., 1993). It is thus of importance to quantifying the soil organic carbon (SOC) dynamics and their feedback on global climate change (Marques-Lopez et al., 2009). As an important component of the global soil system, SOC dynamics in agricultural soils is crucial for estimating soil fertility and managing crop production (Shi et al., 2010). Loss of SOC from agricultural soils not only diminishes soil sustainability but also elevates CO_2 emissions from terrestrial ecosystems (Lal, 2004). In particular, paddy rice area in China ranks the second largest agricultural area in the world, spanning temperate, subtropical and tropical zones (Liu et al., 2006). The total area of paddy soils in China is 45.7 Mha, accounting for 34% of the total cultivated land (Liu et al., 2006; Xu et al., 2012). Accurate quantification of the SOC change in paddy soils shall thus significantly help to improve current understanding of global carbon cycle.

Process-based agro-ecosystem models are useful tools for quantifying SOC dynamics in soils at regional scales (Paustian et al., 1992; Bricklemyer et al., 2007; Wang et al., 2011). Soil databases at different spatial resolutions have been used in existing studies. For example, Ardö and Olsson (2003) assessed SOC dynamics during the period 1900–2100 in the province of Northern Kordofan in semi-arid Sudan using 1:5,000,000 FAO/UNESCO data and CENTURY model. Tang et al. (2006) simulated SOC changes in croplands of China in 1998 using the 1:14,000,000 soil database

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and DNDC (DeNitrification & DeComposition) model. Cerri et al. (2007) used CENTURY, RothC, the Intergovernmental Panel on Climate Change (IPCC) model, and 1:5,000,000 SOTER data to estimate SOC changes for the years 2000–2030 in the Brazilian Amazon. Xu et al. (2013) used DNDC model and three digital soil maps with scales of 1:1,000,000, 1:4,000,000, and 1:14,000,000 to estimate SOC stocks of paddy soils from 1980 to 2008 in China. Qin et al. (2013) used two statistical models and a 1:1,000,000 digital soil map to estimate SOC sequestration potentials in croplands of China. Wang et al. (2015) used DNDC model and 1:50,000 digital soil map to estimate the SOC balance between impacts arise from rising temperatures and elevated atmospheric CO_2 in the Tai-Lake region of China. However, these SOC estimates were often made using a single or a narrow range of scales of soil databases for a specific agriculture region.

Spatial variability of soil properties is expressed by map delineations and map unit composition, which varies with map scales (Heuvelink, 1998). Spatial soil processing methods affect the accuracy for the simulation of the spatial distribution of soil properties (Shi et al., 2009, 2011, 2012; Emadi and Baghernejad, 2014; Arslan and Turan, 2015). The ability to represent the soil properties differs significantly at different mapping scales (Zhao et al., 2006). Many datasets were mapped at scales appropriate to maintain details in soil properties for SOC estimation in a designated agricultural region. Studies demonstrated that the spatial heterogeneity of soil properties (e.g., texture, SOC content, bulk density, and pH) is the major source of uncertainty in simulating SOC dynamics under specific agricultural management conditions at regional scales (Li et al., 2004; Pathak et al., 2005). As such, the choice of soil map scales used in the estimation of regional SOC may lead to large uncertainties (Zhao et al., 2006). To date, there is still a lack of research to quantify the effects of map scales on SOC dynamics simulation in agro-ecosystems.

This study uses six soil databases at scales of 1:50,000 (P005), 1:200,000 (P02), 1:500,000 (P05), 1:1,000,000 (P1), 1:4,000,000 (P4), and 1:14,000,000 (P14) to drive the DeNitrification & DeComposition (DNDC) model for quantifying SOC dynamics in the rice-dominated Tai-Lake region. These scales involve all basic national map scales of soil data in China. We aim to: (1) simulate the total SOC changes in the study area for 19 years based on the six soil database, (2) analyze the uncertainties in the simulated SOC dynamics from each soil database in rice field ecosystems, and (3) determine the appropriate scales of soil data for simulating SOC dynamics of higher accuracy in the paddy region of China.

2. Materials and methods

2.1. Study area

Tai-Lake region (118°50′–121°54′E, 29°56′–32°16′N) located in the middle of the Yangtze River paddy soil region of China includes the entire Shanghai City and a part of Jiangsu and Zhejiang provinces, with total area of 36,500 km^2 (Fig. 1) (Li, 1992). It features a warm and moist climate and with annual rainfall of 1100–1400 mm and annual mean temperature of 16 °C. This region is one of the oldest agricultural regions in China, which has a long history of rice cultivation for more than 7000 years. The Tai-Lake region is considered to be the most typical rice production area under intensified agricultural management in China.

Approximately 66% of the total land area is covered with paddy soils (Zhang et al., 2012). Paddy soils in the region are derived mostly from alluvium, loess, and lacustrine deposits. According to the Genetic Soil Classification of China (GSCC) system, soils could be classified into 6 paddy soil subgroups, 137 soil families and 622 soil species in the 1:50,000 map. The six GSCC subgroups according to the U.S. Soil Taxonomy (ST) are Submergenic (Typic Endoaquepts), Gleyed (Typic Endoaquepts), Degleyed (Typic Endoaquepts), Hydromorphic (Typic Epiaquepts), Percogenic (Typic Epiaquepts), and Bleached (Typic Epiaquepts) (Shi et al., 2006; Soil Survey Staff in USDA, 2010). Its main croplands are managed with rice and winter-wheat rotation systems (Xu et al., 1980).

2.2. DNDC model and regional simulations

DNDC is a process-orientated model that simulates crop yield, C sequestration, nitrate leaching loss, and emissions of C and N gases in agro-ecosystems (Li et al., 2004; Li, 2007a). It has six sub-models to estimate soil climate, plant growth, decomposition, nitrification, denitrification and fermentation. The model has been tested and optimized against numerous field observations with regard to SOC dynamics across various agro-ecosystems in Asia (Tang et al., 2006; Xu et al., 2012), Europe (Abdalla et al., 2011), and America (Tonitto et al., 2007). DNDC model has also been applied to simulate biogeochemical processes occurring in rice paddies (Cai et al., 2003; Li et al., 2004; Zhang et al., 2006, 2014; Giltrap et al., 2010; Xu et al., 2012).

DNDC uses counties as basic simulation unit (Li et al., 2004). Thus the model estimates may be biased by ignoring the spatial heterogeneity of soil within a simulation unit (Zhang et al., 2014).

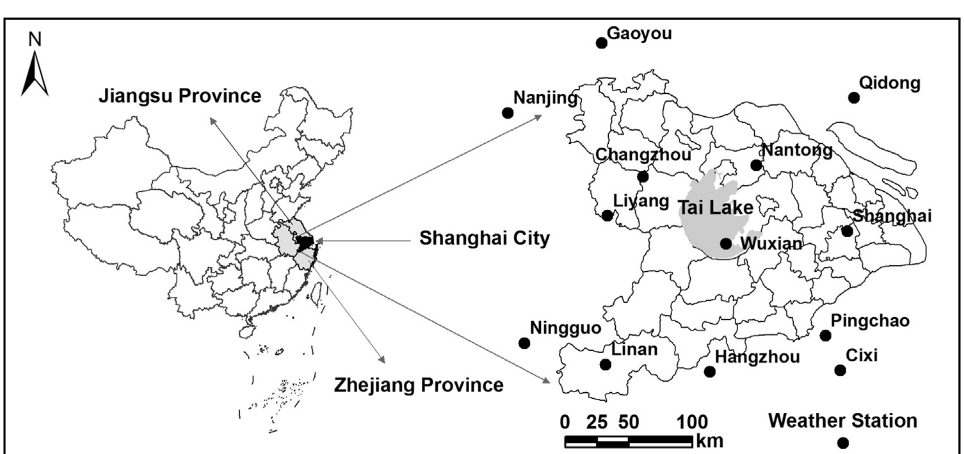

Fig. 1. Geographical location of the study area in China.

In our study, polygons representing specific soil types were used as the basic simulation unit instead (Zhang et al., 2012) and the simulation was done for the top 30 cm of soils (Tang et al., 2006). More discussion of DNDC model validation for this region can be found in Zhang et al. (2012). We used the same forcing data and parameters for crops, agricultural management, and climate, while only vary soil maps (e.g., *list soil data type here, bulk density etc.*) for different simulations.

2.3. Data preparation

To quantify SOC dynamics in the Tai-Lake region, soil properties, daily weather, and information on cropping systems and agricultural management practices was collected for the area covering 37 counties. Below we describe how data were organized for the DNDC simulations.

2.3.1. Soil data

In China, the six soil maps with scales of P005, P02, P05, P1, P4, and P14 are widely used for SOC estimation at national or regional scales (Tang et al., 2006; Zhao et al., 2006; Xu et al., 2013; Zhang et al., 2014). Soil maps were often compiled at different administrative division levels including county level of 1:50,000 (P005), district level of 1:200,000 (P02), province level of 1:500,000 (P05), and nation levels of 1:1,000,000 (P1), 1:4,000,000 (P4), and 1:14,000,000 (P14) (Shi et al., 2006; Zhao et al., 2006; Zhang et al., 2014). In this study, in order to comprehensively assess the uncertainty of using soil databases of different scales, all of the above-mentioned soil map scales were used in DNDC regional simulations for the Tai-Lake region.

Our soil data maps collected from the Second Soil Survey of China from 1980 to 1999 are the most comprehensive and detailed survey of the Chinese soil (Xu et al., 2011). The P005 dataset contain 52,034 simulation units and were generated using 1107 paddy soil profiles (Zhang et al., 2012) (Table 1). The soil profiles were taken from *soils of county* (Zhang et al., 2012). The P02 datasets were developed from 136 soil profiles described in *soils of district* (Zhao et al., 2006). The P05 datasets were developed from 127 soil profiles described in *soils of province* (Zhao et al., 2006). The P1, P4 and P14 datasets were developed from 49 soil profiles described from Office for the Second National Soil Survey of China (1994) (Table 1). The P14 datasets were widely used to simulate SOC at national or regional scales in China (Tang et al., 2006; Zhang et al., 2006). The soil attributes assignment at different mapping scales was compiled using the pedological Knowledge Based (PKB) method (Shi et al., 2006; Yu et al., 2007). These soil data include soil name (in GSCC), horizon thickness, bulk density, organic carbon content, texture, and pH.

2.3.2. Climate data

Daily weather data (precipitation, maximum and minimum air temperature) for 1982–2000 from 13 weather stations in the Tai-Lake region was collected by the China Meteorological Administration (Fig. 1) (China Meteorological Administration, 2011). Climate data of the nearest weather station were assigned to each county in model simulations (Tang et al., 2006). We assume that all polygons in one county have the same climate.

In our previous studies, we have simulated the SOC dynamics in paddy soils of the Tai-Lake region during the period of 1982–2000 (Zhang et al., 2012). In order to quantify the effects of various map scales on the SOC dynamics in the future, the most recent 19-year climate data (1982–2000) was used for the period of 2001–2019 (Xu et al., 2011).

2.3.3. Crop and farming management data

Crop type data including physiological data of summer rice and winter wheat rotation systems were used. The crop parameters for rice–wheat rotation system can be found in Li (2007b) and Gou et al. (1999). Field data collected in 2000 include the information on crop growing period, tillage, fertilizer application, water management, and crop residue management. Specifically, rice is planted in June and harvested in October; wheat is planted in November and harvested in May of the next year (Xu et al., 1980). Conventional tillage was conducted twice at 20 cm for rice and no tillage applied for wheat (Zhang et al., 2014). Organic manure (20% of livestock manure and 10% of human manure) was applied twice per year as base fertilizer for rice and wheat at the rates calculated based on the local livestock numbers (44, 866, 23, and 95 kg C head^{-1} y^{-1} for sheep, cattle, human and swine manure, respectively) (Lu and Shi, 1982; Tang et al., 2006). Nitrogen synthetic fertilizer was applied three times across in the basal, tillering and heading stage for rice, three times in the basal, jointing and heading stage for wheat. One time of midseason and 5 times of shallow flooding were applied for summer rice (Gou et al., 1999). 15% of non-grain post harvest crop biomass was returned to soil (Tang et al., 2006). The same management practices of 2000 are assumed to be continuously applied from 2001 to 2019.

2.4. Data comparison and analysis

Area of paddy soils (APS, ha), total SOC changes (TSC, Tg C or Gg C) and average annual SOC changes (AASC, kg C ha^{-1}) of different

Table 1
Characteristics of different mapping scales of paddy soils in the GSCC system in the Tai-Lake region, China.

Soil database	Map scale	Area (Mha)	Source of soil maps	Source of soil data	Number of soil profiles	Number of simulation units	Basic map units
P005	1:50,000	2.32	Soil Survey Office of County in Jiangsu Province, Zhejiang Province and Shanghai City	Soil Series of County in Jiangsu Province, Zhejiang Province and Shanghai City	1107	52,034	Soil Species
P02	1:200,000	2.60	Soil Survey Office of Prefecture-level city in Jiangsu Province, Zhejiang Province and Shanghai City	Soil Series of District in Jiangsu Province, Zhejiang Province and Shanghai City	136	8064	Soil Genus
P05	1:500,000	2.53	Soil Survey Office of Jiangsu Province, Zhejiang Province and Shanghai City	Soil Series of Jiangsu Province, Zhejiang Province and Shanghai City	127	5451	Soil Genus
P1	1:1,000,000	2.59	The Office for the Second National Soil Survey of China	Soil Series of China	49	1511	Soil Genus
P4	1:4,000,000	2.74	Institute of Soil Science, Chinese Academy of Sciences	Soil Series of China	49	305	Subgroups
P14	1:14,000,000	2.80	Institute of Soil Science, Chinese Academy of Sciences	Soil Series of China	49	205	Subgroups

mapping scales were calculated using Eqs. (1), (3) and (4), respectively:

$$\mathrm{APS} = \sum_{i=1}^{n} \mathrm{APS}_i \tag{1}$$

$$\mathrm{AMSC}_i = \sum_{f=1}^{h} \mathrm{ASC}_f \tag{2}$$

$$\mathrm{TSC} = \sum_{i=1}^{n} (\mathrm{APS}_i \times \mathrm{AMSC}_i) \tag{3}$$

$$\mathrm{AASC} = \mathrm{TSC}/\mathrm{APS}/19 \tag{4}$$

where APS_i is the area of i-th polygon of paddy soil; AMSC_i (kg C ha^{-1}) is the accumulated annual SOC change in a specific polygon from 2001 to 2019; ASC_f (kg C ha^{-1}) is the annual SOC change in a specific polygon, as estimated using DNDC; n is the polygon number; and h is the order of simulation years (h = 1, 2, 3 . . . 19).

The accuracy of DNDC simulations using the six soil databases was analyzed using the most detailed digital soil map (P005) as a reference simulation (Zhang et al., 2009). The relative deviation (y) of P02, P05, P1, P4, and P14 was calculated using the following equation (Cai et al., 2003; Zhang et al., 2014):

$$y = \mathrm{ABS}\left(100 \times \frac{x_s - x_0}{x_0}\right) \tag{5}$$

where ABS is absolute function, x_0 is the total SOC change with P005, and x_s is the total SOC change produced by P02, P05, P1, P4, or P14.

To test the most sensitive factors of soil properties at different scales, the correlation of soil properties and average annual SOC changes was analyzed. A multiple stepwise regression analysis was performed using the Statistical Package for Social Sciences (SPSS) statistical software (Leech et al., 2008).

3. Results and discussion

3.1. Variation of input soil properties

Variations in soil texture (0–10 cm), SOC content (0–5 cm), pH (0–10 cm), and bulk density (0–10 cm) for all six soil maps in the Tai-Lake region are shown in Table 1S. In the region, the average initial SOC and clay content based on P14 map were higher than those from other maps. As map scales decreased from P005 to P14, the paddy soil subgroups on the other five maps other than P14 were merged into the hydromorphic and gleyed subgroups. The area of gleyed soil subgroup in P14 map reaches 0.41 Mha, much higher than that in the other maps (Table 1S). The SOC and clay content of gleyed paddy soil subgroups is generally higher than other subgroups (Table 1S). Since the gleyed paddy soil subgroup is developed in submerged area where metabolic activity of aerobic microbes is inhibited, this soil type usually has a low decomposition rate (Wang et al., 2007). The average bulk density of soils in P14 and P4 maps were lower than that in P005, P02, P05, and P1. Compared to other soil properties, the average pH of different maps exhibited minor differences, ranging from 6.5 to 6.7.

Overall, statistical analysis showed that most of the soil properties in six databases exhibited large differences in the Tai-Lake region (Table 1S). The SOC spatial variability expressed by map unit composition and map delineations varies with scales (Heuvelink, 1998; Zhao et al., 2006; Zhong and Xu, 2011). Such differences of soil properties at different scale maps would propagate into SOC simulations. Thus an improper selection of soil maps may bias SOC estimation.

3.2. Baseline SOC pools in soil data of different map scales

Regional SOC stock sin the baseline SOC pools of the top 20 cm depth of soil for the P005, P02, P05, P1, P4, and P14 maps were 83.09, 93.47, 101.75, 95.46, 103.01, and 112.44 Tg C in 1982, respectively (Yu et al., 2014). Corresponding average SOC densities were 3.58, 3.59, 4.02, 3.69, 3.77, and 4.02 kg C m^{-2}, respectively. The higher SOC stocks in the coarser soil maps might be because other soil types with small polygons have been merged into paddy soil types with larger polygons as map scales decreased (Zhao et al., 2006; Zhang et al., 2014). Statistics shown that the total paddy soil areas of Tai-Lake region increased as map scales increased from

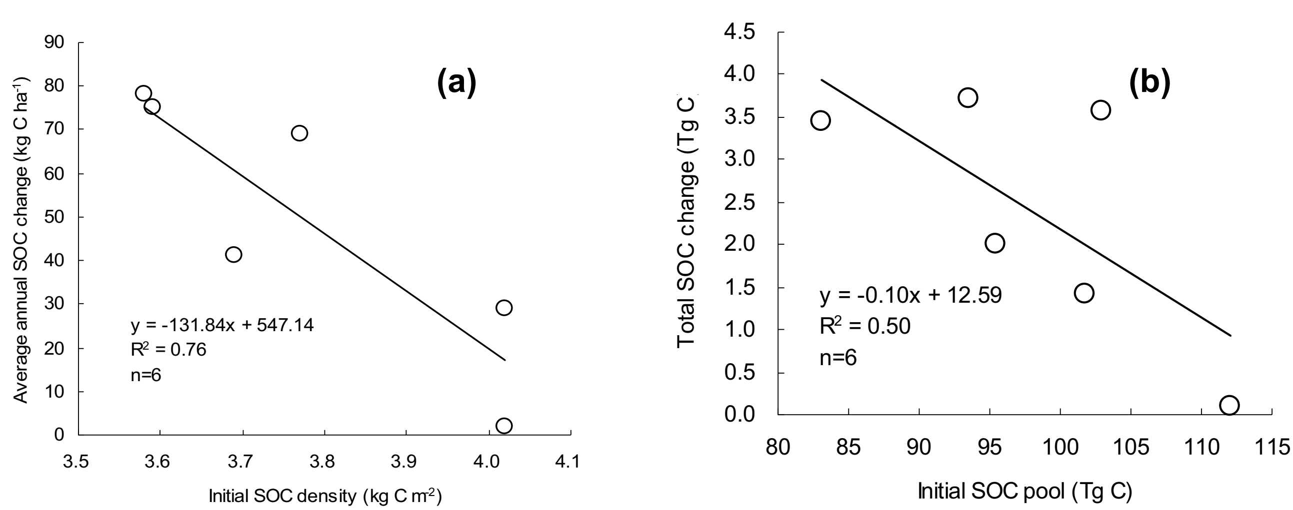

Fig. 2. (a) Relationship between average annual SOC change and initial SOC density (0–20 cm) on different mapping scales of the Tai-Lake region, China. (b) Relationship between total SOC change and initial SOC stock (0–20 cm) on different mapping scales of the Tai-Lake region, China.

1:50,000 to 1:14,000,000 (Table 1S). However, this results are contrary with Xu (2011) and Xu et al. (2013), they found that the total SOC stocks in Chinese paddy soils estimated from the three soil polygon-based databases decreased from 2.51 to 1.51 Pg C in 1980 as map scales decreased from 1:1,000,000 to 1:14,000,000. In addition, our results also showed that there was a significant negative linear relation between rate of change and the initial SOC stocks at different maps (Fig. 2). This is generally consistent with previous studies (Lark et al., 2006; Tan and Liu, 2013). Soil carbon dynamics and change rate caused by land surface disturbances and climate change are generally related to the level of baseline SOC stock (Lark et al., 2006). Specifically, soils with higher baseline SOC

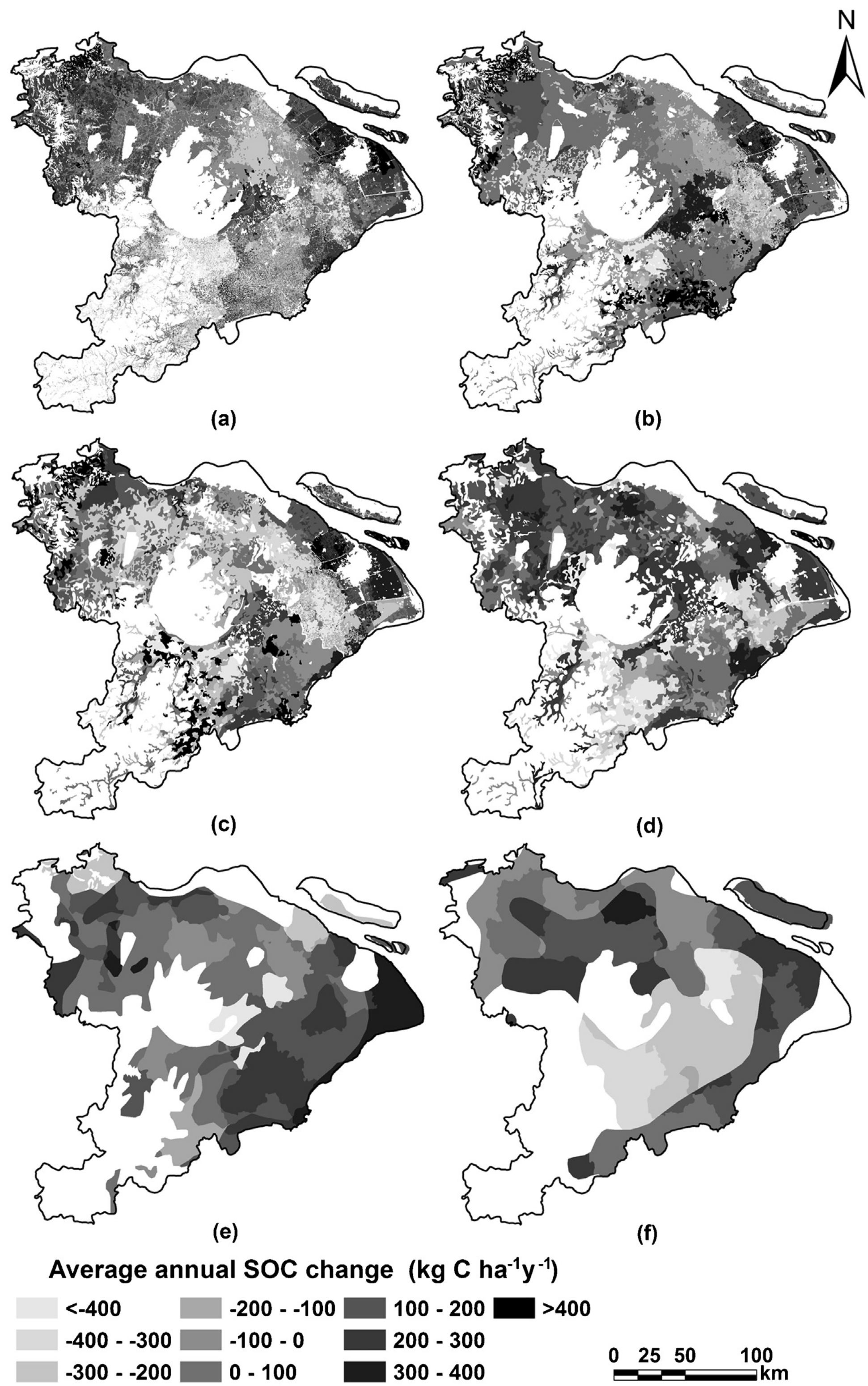

Fig. 3. Spatial distribution of annual SOC change of different mapping scales from 2001 to 2019 in the Tai-Lake region, China: (a) P005 (1:50,000); (b) P02 (1:200,000); (c) P05 (1:500,000); (d) P1(1:1,000,000); (e) P4 (1:4,000,000); (f) P14 (1:14,000,000).

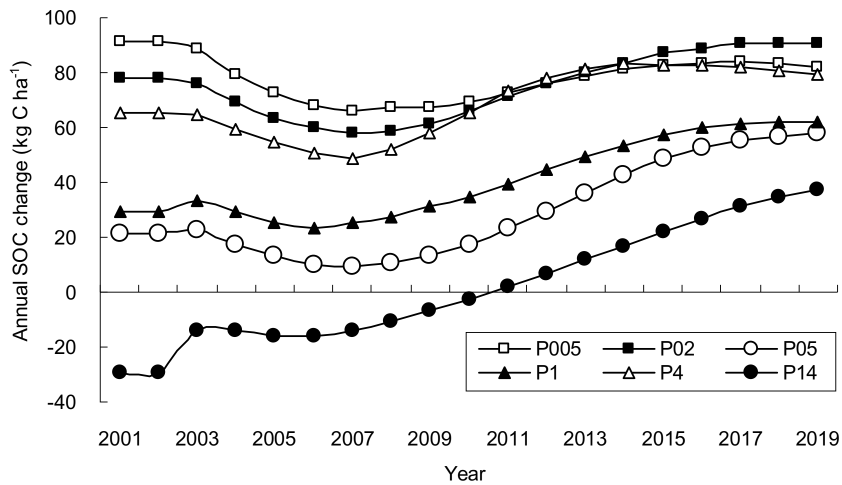

Fig. 4. Temporal distribution of annual SOC change of different mapping scales from 2001 to 2019 in the Tai-Lake region, China.

stock tend to be C sources; otherwise, they are likely to turn into C sinks following conservation management practices (Tan and Liu, 2013). This phenomenon supported the general concept that soils evolve towards a SOC stock at a steady state, which depends on the C input and the decomposition process involved (Janzen et al., 1998).

3.3. Effects of map scales on SOC changes

The simulation based on P005 map showed that the SOC in the top soils (0–30 cm) increases 3.44 Tg C in the 2.32 Mha paddy soils for the study period, with the average annual SOC change of 78 kg C ha^{-1} (Figs. 3 and 4). 70.6% of the paddy soils gained C and 29.4% lost C in the 19 simulated years. This is mainly because of intense fertilizer application and farmyard manure incorporation which were as high as 335 kg N ha^{-1} y^{-1} and 270 kg C ha^{-1} y^{-1}, respectively. Increasing fertilizer and manure application could increase SOC levels linearly by enhancing crop production and residue accumulation (Li et al., 2004). Additionally, most of the region has been utilized no-tillage practices in planting wheat since 1991, which reduces SOC decomposition by providing the lowest soil disturbance (Zhang et al., 2012).

The SOC dynamics is affected by the spatial heterogeneity of soil properties represented in different maps (Figs. 3 and 4). Regional SOC changes using P02, P05, P1, P4, and P14 maps were 3.71, 1.41, 2.01, 3.57, and 0.10 Tg C, respectively. Corresponding annual SOC changes were 75, 29, 41, 69, and 2.0 kg C ha^{-1}, respectively. Since the P005 map is the most detailed soil database, it was used as a reference for comparison. Thus the relative deviation of P02, P05, P1, P4, and P14 databases were 7.9%, 58.9%, 41.6%, 3.9%, and 97.0%, respectively. These relative deviations are different from the results of Xu et al. (2013), who found the total SOC stock simulated using the 1:1,000,000 database is 27% and 40% higher than that using coarser-scale maps of 1:4,000,000 and 1:14,000,000, respectively (Xu et al., 2013).

P14 soil map was widely used in DNDC model applications at national or regional scales in China (Tang et al., 2006; Zhang et al., 2006). However our study demonstrates that using the P14 soil map yields biased SOC estimates. The estimated SOC decreased throughout the study area from 2001 to 2010, ranging from −3.0 to −29 kg C ha^{-1} (Fig. 4). In contrast, the simulated SOC using P005, P02, P05, P1, and P4 soil maps shows an increase trend during the period (Fig. 4). Overall, the DNDC simulations based on different soil maps show divergent SOC estimates in the region.

Many studies have demonstrated that soil properties are dominant factors in SOC simulations at regional scales (Li et al., 2004; Pathak et al., 2005; Zhang et al., 2014). As Table 2 shows, initial SOC content in different scale soil maps is the most sensitive parameter controlling SOC changes among all soil factors according to the stepwise linear regression. Initial SOC content accounts for 69.8–88.5% of the variations in average annual SOC change for paddy soils from 2001 to 2019; while soils with lower initial SOC display a greater SOC increase in the early stages following cultivation (Zhao et al., 2013). Similar results were also reported by Lark et al. (2006) and Tan and Liu (2013). They observed a strong negative relationship between the rate of SOC change and the initial SOC content, compared to other soil properties. P005 map with the lowest initial SOC among the six soil maps has the greatest average annual SOC sequestration rate during 2001–2019 (Fig. 4 and Table 1S). High SOC sequestration rate also occurred in the simulation based on the P02 and P4 maps, higher than 69 kg C ha^{-1} (Fig. 4), due to the low initial SOC content

Table 2
Variability of average annual SOC change contributed from different soil properties in Tai-Lake region paddy soils from 2001 to 2019.

Soil database	Number of simulation units	ΔR^{2a}				Adjusted R^2
		Initial SOC (g kg^{-1})	Clay (%)	pH	Bulk density (g cm^{-3})	
P005	52,034	0.730***	0.086***	0.056***	0.004***	0.876***
P02	8064	0.698***	0.005***	0.038***	–	0.741***
P05	5451	0.779***	0.002***	0.009***	0.000	0.790***
P1	1511	0.826***	0.065***	0.000	0.001**	0.892***
P4	305	0.791***	0.047***	0.019***	0.007***	0.863***
P14	205	0.885***	0.033***	–	0.007***	0.925***

, * Significant at 0.01 and 0.001 probability levels, respectively.
[a] The change in the R^2 statistic is produced by adding a soil property into stepwise multiple regressions.

(Table 1S). Moreover, the average clay content derived from P02 was as high as 29%. Soil with elevated clay content shows a greater degree of SOC protection by soil organo-mineral association and stabilization (Six et al., 2002). In contrast to other maps, the use of P05, P1, and P14 DNDC estimated lower SOC sequestration rates (Fig. 4). The initial SOC in P05 and P14 soil maps is 16.8 and 19.4 g kg^{-1}, respectively (Table 1S). Moreover, the pH derived from P1 soil map is near neutral (~6.7). Soils with high SOC content and neutral pH are favorable for CO_2 production by providing better living environment for microbes (Pacey and DeGier, 1986; Li et al., 2004).

3.4. Effects of map scales on SOC change in paddy soil subgroups

The effects of different map scales on simulated SOC changes are significantly dependent on paddy soil subgroups (Fig. 5). The hydromorphic paddy soils in P005 cover 1.23 Mha and accounts for 53% of the total paddy soil area in the Tai-Lake region. These paddy soils possessed relatively low initial SOC content and high clay content (Table 1S). Additionally, high rate of farmyard manure (287 kg C ha^{-1} y^{-1}) and fertilizer (323 kg N ha^{-1} y^{-1}) use and return of crop residue to soils in this subgroup likely increases SOC. Therefore, the modeled average annual SOC change in hydromorphic paddy soils is 88 kg C ha^{-1} (Fig. 5a). For the entire Tai-Lake region, the total SOC change from hydromorphic paddy soils is 2.05 Tg C, accounting for 60% of the total SOC change from 2001 to 2019.

Although similar trends can be observed in simulations of average annual SOC changes in hydromorphic paddy soils over the 19-year study period using six soil maps, discrepancies existed because of the spatial heterogeneity of soil properties in the six soil map scales (Fig. 5a). The difference in average annual SOC change is over 150 times between the simulation from the largest map scale of P4 and the smallest map scale of P05. The main reason is that the initial SOC value of hydromorphic paddy soils in P05 is much higher than that in P4 (Table 1S).

The degleyed paddy soils, gleyed paddy soils, and submergenic paddy soils in P005 account for 16, 4.4 and 0.32% of the total paddy soil area in the Tai-Lake region, respectively. The total SOC changes of different maps during 2001–2019 range from −2.59 to 0.48 Tg C in gleyed paddy soils, −1.98 to 0.95 Tg C in degleyed paddy soils, and −0.32 to 0.27 Tg C in submergenic paddy soils. The gleyed soil subgroup has the greatest influence on SOC simulation at different map scales (Fig. 5). The choice of P1 or P14 results in a difference of over 7 times in the highest and lowest total SOC changes (Fig. 5a). The main reason is that the area of gleyed soil subgroup in P14 is much higher than that in P1. Moreover, the initial SOC value of gleyed soil subgroup in P14 is as high as 28.0 g kg^{-1} (Table 1S).

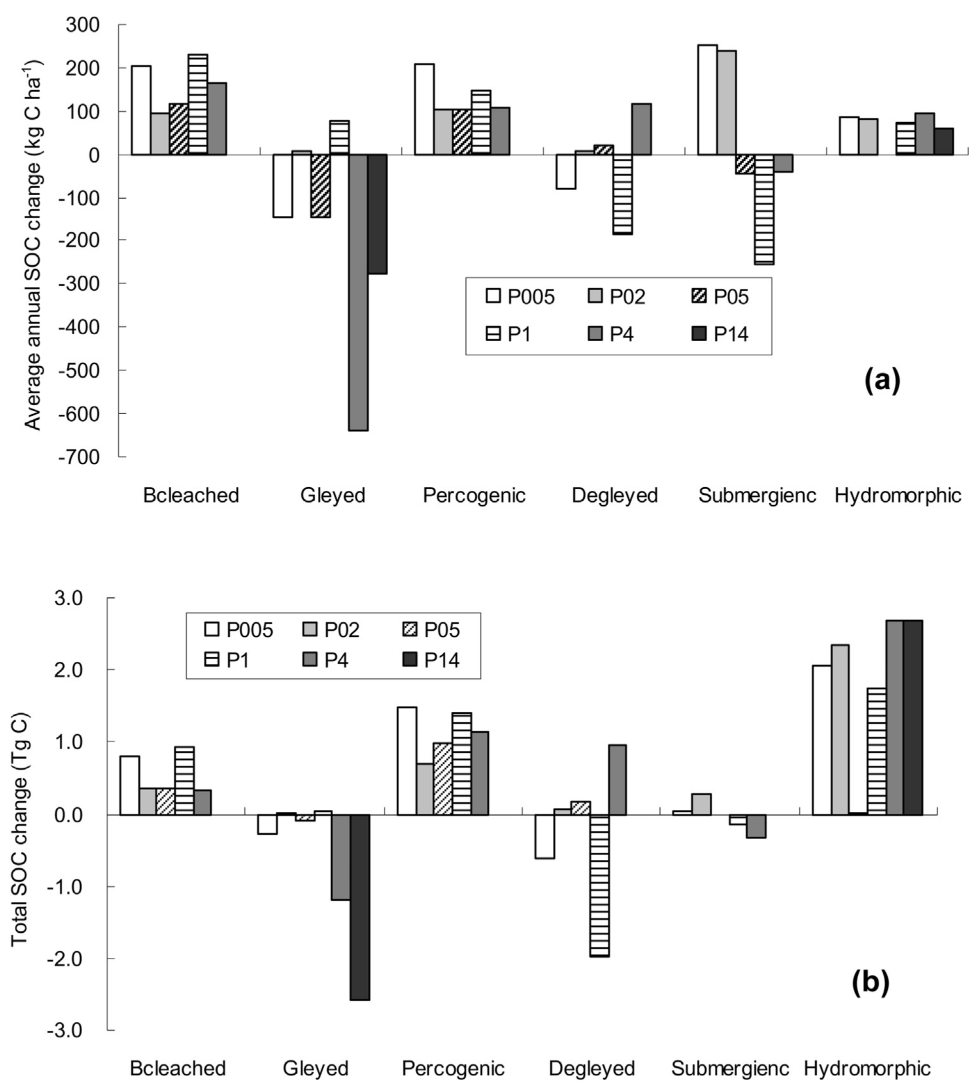

Fig. 5. Comparison of average annual- (a), total-SOC change (b) modeled with the six map scales in different paddy soil subgroups in the Tai-Lake region, China.

Therefore, the simulation in gleyed soil subgroup using P14 results in high SOC losses (Li et al., 2004).

The percogenic paddy soils and bleached paddy soils in P005 account for 18 and 8.8% of the total paddy soil area in the Tai-Lake region, respectively. In contrast to other paddy soil subgroups, these two types of paddy soils have smaller influences on SOC at different scales (Fig. 5). The difference between the highest and lowest SOC changes is less than threefold (Fig. 5b).

Modeled SOC changes at different scales depend on areas and properties of soils. In general, soil types with small areas may merge into their neighboring soil types when the map scale changing from fine to coarse scales (Zhao et al., 2006). Such a 'scaling effect' causes the area and attribute variations of different soil types, especially the coarse soil maps that missed relatively small soil patches containing high or low soil properties which were sensitive to SOC change (Zhang et al., 2014). For example, although the P4 soil map has the lowest relative deviation (3.9%) for the entire Tai-Lake region, the relative deviations in different paddy soil subgroups ranged from 22 to 1010% (Table 2S). This demonstrated that the scale of P4 soil map might have produced a large uncertainty of SOC dynamics in the Tai-lake region. In addition, different soil databases have different influences on SOC simulation based on paddy soil subgroups. The relative deviation of different maps ranged from 62 to 833% in gleyed paddy soils, 110–251% in degleyed paddy soils, 18–59% in bleached paddy soils, 4.9–53% in percogenic paddy soils, 122–1010% in submergenic paddy soils, and 14–99% in hydromophic paddy soils (Table 2S). Therefore, when considering the DNDC accuracy in SOC simulations at regional scales, it is necessary to identify an appropriate soil map scale as well as appropriate paddy soil subgroups.

3.5. Effects of map scales on SOC changes in administrative areas

There are 0.46, 0.54, and 1.33 Mha of paddy soils of the Tai-Lake region distributed in Shanghai City, Zhejiang and Jiangsu Province, respectively (Zhang et al., 2012). The average annual SOC changes of most counties in Jiangsu province noticeably increased from 2001 to 2019 using P005, P02, and P1 datasets as model inputs, whereas the values decreased when using P05 datasets as model inputs (Table 3S). This is likely because the formers possessed relatively low initial SOC (14.0, 14.9, and 13.9 g kg^{-1}, respectively) and high clay content (25.8, 30.7, and 27.4%, respectively). In contrast, P05 has high initial SOC (16.1 g kg^{-1}) for the same type of soils, leading to a decrease in CO_2 emissions (Zhao et al., 2013).

The average annual SOC changes of most counties in Zhejiang province noticeably increased from 2001 to 2019 based on P05 and P4 (Table 3S). However, the SOC changes of most counties using P005, P1, and P14 is estimated to decrease from 2001 to 2019, due to their high initial SOC (17.9, 19.3, and 21.1 g kg^{-1}, respectively) (Li et al., 2004).

The SOC changes of most counties in Shanghai city from 2001 to 2019 are estimated to be relatively high when using P005, P4, and P14. This is because the initial SOC content of P005 and P4 is 16.1 and 14.0 g kg^{-1}, respectively, which are low. Additionally, the clay content (31.6%) derived from the P14 is the highest in the three provinces. Therefore, high rate of SOC sequestration occurred when using P005, P4, and P14 (Table 3S). In contrast, the SOC change of most counties in Shanghai city from 2001 to 2019 is relatively low using P02, P05, and P1, due to their high initial SOC (17.6, 17.3, and 16.5 g kg^{-1}, respectively) and neutral pH (7.5, 7.5, and 7.2, respectively). Soils with higher SOC and neutral pH are often linked to high CO_2 emissions (Pacey and DeGier, 1986; Ngwira et al., 2012).

Overall, the relative deviation of different counties in the Tai-Lake region ranged from 3.0 to 386% in P02, 0.31–730% in P05, 2.3–672% in P1, 7.0–919% in P4, and 13–681% in P14 (Table 2S). The effects of map scales on DNDC simulations at the county level depend on initial SOC values and clay content (Table 2). In China, counties are generally used as the basic management units to implement the government policies for soil C sequestration (Shi et al., 2006; Xu et al., 2011). Although more detailed soil units (e.g., 1:50,000) are more valuable for C sequestration (Zhang et al., 2009), such finer scale soil maps require more efforts to develop. As a result, different counties have established different digital soil map scales under various situations. Thus, the most sensitive factors (e.g., initial SOC values and clay content) of different map scales for modeling SOC dynamics should be identified as they contribute more to reducing uncertainties of SOC simulations.

3.6. SOC simulation uncertainties

Uncertainty is inevitable for modeling studies (Li et al., 2011). In this study, polygons of soil maps are used as the basic DNDC simulation units to take advantage of the spatially explicit soil information (Zhang et al., 2009). However, other uncertainty sources also existed. For instance, soil properties and SOC content in a single simulation unit are assumed to be uniform, which may also induce a large uncertainty (Li et al., 2011).

Climate information is an important driver of SOC (Lal, 2004). However, climate data from only 13 meteorological stations at national scales are used in this study, higher resolution data from meteorological stations at provincial scale should be collected in future studies. In addition, global warming effects were not considered due to the limitation of available meteorological data. The recent 19-year climate data of 1982–2000 have to be taken as representative for the period 2001–2019 for all soil map scales runs, and the 19-year shift in climate data may bias the model simulations.

Another uncertainty source is the agricultural management information, which was uniform in each county. Since the effects of field management information on model results vary with soil properties (Rüth and Lennartz, 2008), the single field management dataset for the DNDC model for all soil types may induce uncertainties in the simulated SOC dynamics. Field management information of high spatial accuracy on regional scales is difficult to organize, although it is critical in regional studies for agro-ecosystems (Bareth, 2009; Mulla, 2013).

Fine spatial scale data of climate and agricultural management, together with soil maps, are essential to accurately quantify region-scale SOC dynamics in the region.

4. Conclusions

Here we applied an agro-ecosystem model (DNDC) by linking six soil maps with different scales as model input in the rice-dominated Tai-Lake region of China. We found that soil map scales significantly affect the accuracy of model predictions for SOC, with a relative difference ranging from 3.9% to 97%. Changes in soil types and their attributes as well as soil type areas are the main sources of SOC variability. The soil datasets with scale of P4 and P14 were too coarse to simulate SOC dynamics in the Tai-lake region. Finer soil maps (e.g., 1:50,000) can reduce the uncertainty in regional SOC simulation effectively. However, the considerable labor costs hinder developing such a map for large agricultural regions. We recommend P02 for SOC simulations in this region. Soil data at P1 scale are also recommended considering the accuracy and data availability at the national level. At present, a soil map of 1:1,000,000 is the most detailed available soil data at the national scale in China (Liu et al., 2006; Shi et al., 2006).

Finally, our study also provides a guideline to the research community to develop soil maps at appropriate scales for carbon modeling studies. The sensitivity of the modeled SOC dynamics to different soil map scales for regional studies in agro-ecosystems needs further investigation.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agee.2016.01.049.

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