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Carbon sequestration in the uplands of Eastern China: An analysis with high-resolution model simulations

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ABSTRACT

Using the DeNitrification-DeComposition (DNDC, version 9.5) model, we investigated the soil organic carbon (SOC) changes from 1980 to 2009 in Eastern China's upland-crop fields in northern Jiangsu Province. A currently most detailed high-resolution soil database, containing 17,024 polygons at a scale of 1:50,000, derived from 983 unique upland soil profiles, was used. A coarser county-level soil database was also used for a pair-wise simulation for comparison. We found that SOC changes modeled with the county-level soil database differ significantly from those with high-resolution soil data, with the deviation ranging from −64% to 8.0% in different counties. This implies that coarse soil data may lead to large biases in SOC simulation. With the high-resolution database, the model estimates a SOC increase of 37.89 Tg C in the top soils (0–50 cm) over the study area of 3.93 Mha for the past three decades, with an average rate of 322 kg C ha^{-1} year^{-1}. The SOC accumulation in the study region accounts for 10.2% of annual national carbon sequestration of upland soils, compared with the fraction of 3.7% in the total upland area of China. This underscores its significance to national climate mitigation. The annual SOC change varied between 61 to 519 kg C ha^{-1} year^{-1}, mainly driven by the variations in N-fertilizer and manure applications. This study highlights the significance of high-resolution soil databases in quantifying SOC changes. Our high-resolution estimates of SOC will support farming and carbon management in this region.

1. Introduction

Soils play a pivotal role in global carbon (C) budget because they store over 1550 Pg of soil organic carbon (SOC) in the terrestrial ecosystem, which is 2–3 times larger than that in the atmospheric pool with 750 Pg and biotic pool with 500–600 Pg (Batjes, 1996). The SOC storage in the global agroecosystem (140–170 Pg) accounts for ~10% of the total terrestrial SOC storage and plays a significant role in adopting appropriate soil conservation measures and greenhouse gas mitigation strategies (Buringh, 1984). Therefore, quantification of regional SOC changes in agroecosystem is crucial for assessing and mitigating global climate change (Li et al., 2011).

Nationwide, China possesses ~140 million ha of agricultural lands, including 110 Mha of upland-crop fields and 30 Mha of paddy rice fields (Li et al., 2010). The SOC pool of upland soil is about 3.5 times larger than that of paddy fields (Wang et al., 2011a). Upland soil thus plays an important role in sequestrating carbon and mitigating climate change, because of its vast area and tremendous amount of SOC. Winter wheat-maize rotation is one of the most popular cropping systems in upland soil of China, which is widely distributed across wide ranges of climatic zones and geographic regions. Among these regions, the Huang-Huai-Hai region is the most important one, providing 99.77 million tons of grain and ~27.5% of the total crop production in China (Lei et al., 2006). The upland soil region of northern Jiangsu Province is located in the lower reaches of the Huang-Huai-Hai region of China. It is considered to be a typical area of winter wheat-maize rotation because of the long history of cultivation and intensified agricultural management (Yang et al., 2009). Accurate estimation of SOC dynamics for upland soils in the northern Jiangsu Province

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is therefore vital in understanding the contribution of the Huang-Huai-Hai region in the national carbon inventory.

Due to the complexity of carbon turnover processes and the dynamic response of carbon to environmental conditions, process-based models are extensively used to simulate the dynamics of SOC in agricultural system (Paustian and Álvaro-Fuentes, 2011; Gottschalk et al., 2012; Goglio et al., 2014). The DeNitrification-DeComposition (DNDC) model is one of the most widely accepted agroecosystem model in the world (Gilhespy et al., 2014). Encouraging performances of the DNDC model have been demonstrated at the plot scale through long-term applications in Asia (Wang et al., 2008), America (Tonitto et al., 2007) and Europe (Abdalla et al., 2011). It has also been used to upscale estimates of SOC changes from local sites to regional scales. However, most of these studies were conducted with county- or town-based soil databases that were characterized with relatively coarse resolution (e.g., 1:14,000,000 soil map was widely used for the simulations in China) or large spatial simulation units with a resolution about $0.5° \times 0.5°$ (Li, 2000; Pathak et al., 2005; Tang et al., 2006; Gao et al., 2014). Large uncertainties may exist in these simulations, as areal averaging of soil properties for each county/town ignores the impacts of soil heterogeneity within a county (Pathak et al., 2005; Giltrap et al., 2010; Xu et al., 2013). Another drawback of the county scale model simulations is that soil type-specific crop management practices cannot be identified because the coarse soil database is unable to differentiate soil types (Zhang et al., 2009). With high spatial heterogeneity, the qualities of soil data (e.g. resolution) critically determine the accuracies of regional model results (Kersebaum et al., 2007). Thus, the model results driven by coarse soil data may fail to efficiently inform the field management strategies that aim at SOC increase. Therefore, improving the accuracy of soil information and resolution of simulation unit are essential for enhancing the accuracy of SOC simulations with process-based models (e.g. DNDC) at regional scale.

Driven by the needs of decreasing model uncertainty derived from input soil database, the primary objective of this study is to improve the accuracy of model estimate and analyze the annual-, and total SOC changes in upland soils of the northern Jiangsu Province from 1980 to 2009. To that end, we conducted a pair-wise experiment with two sets of DNDC model simulations to investigate the soil-induced model uncertainties: one used the county-based soil database and the other one used the high-resolution polygon-based 1:50,000 soil database (hereafter referred to as county- and polygon-based database, respectively). The goal of the pair-wise simulations was to examine how far the results from the coarse soil data deviate from those of the fine one – the uncertainty induced from difference in simulation unit and representation of soil heterogeneity. Next, the set of more desirable simulation with high-resolution soil data was then used to analyze the SOC changes for this region. Strategies for improving the biogeochemical model application at the regional scale were also discussed.

2. Materials and methods

2.1. Study area

The study area, an upland soil region of northern Jiangsu Province (116°21′–120°54′E, 32°43′–35°07′ N), is located in the lower reaches of the Huang-Huai-Hai plain of China. This region includes five cities of Xuzhou, Lianyungang, Suqian, Yancheng and Huaian, and encompasses 29 counties. It covers a total area of 52,300 km^2 (Fig. 1) (Yang et al., 2009). It is located in a climate transitional zone from warm temperate to subtropical, with annual rainfall of 800–1200 mm, mean temperature of 13–16 °C, and average annual sunshine of 2000–2600 h. The frost-free period is about 220 days. The study area is one of the oldest agricultural regions in China, and upland soils cover about 85% of the cropland area – 3.93 Mha (Yang et al., 2009). Most cropland in the region is managed as a summer maize- winter wheat rotation. Maize is planted in June and harvested in September and wheat is planted in October and harvested in June of the next year. The upland soils are derived mostly from Yellow River flood alluvial, river alluvium, lacustrine deposit, fluvio-marine deposit and loess deposits.

2.2. Description of the DNDC model

The DNDC (DeNitrification-DeComposition) model version 9.5 is a biogeochemical model of the plant–soil system that simulates carbon-nitrogen dynamics and greenhouse gas (GHG) emissions in agroecosystems. It integrates crop growth and soil

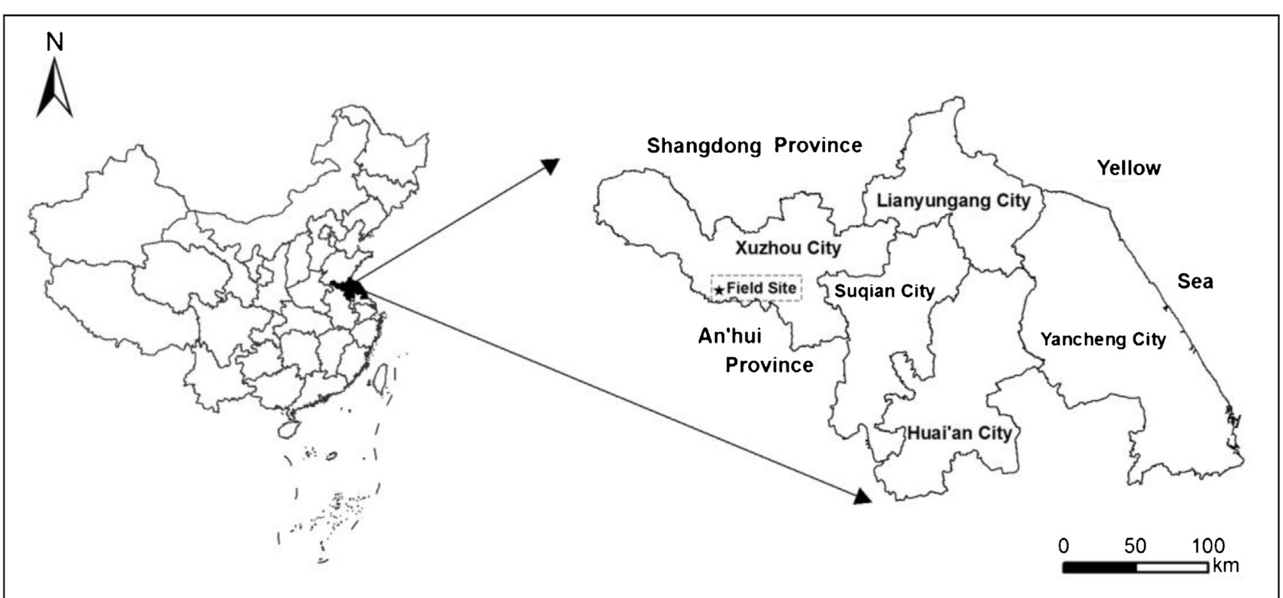

Fig. 1. Geographical location of the study area in China.

biogeochemical processes on a daily or sub-daily time step. The model consists of two components, which describe the generation, decomposition, and transformation of organic matter (Li et al., 1994; Smith et al., 2010). The first component includes soil, climate, crop growth and decomposition sub-models, predicting soil moisture, temperature, redox potential (Eh), pH and substrate concentration profiles driven by ecological factors (e.g., soil, climate, vegetation and anthropogenic activity). The second component includes nitrification, denitrification and fermentation sub-models, predicting emissions of GHG from the plant-soil systems. These sub-models consist of a series of functional equations derived from classical laws of physics, chemistry and biology theories and from empirical equations generated from laboratory studies. More details are described in previous publications (e.g., Li, 2007a; Gilhespy et al., 2014).

The default setting of basic spatial simulation unit in the DNDC model is county (Li et al., 2004). In this study, we also used polygon as a substitute to conduct the pair-wise experiment (see Section 1). The polygon-based database includes information of specific soil types (Zhang et al., 2009), which accounts for the effects of spatial heterogeneity in soil characteristics. The SOC simulation was conducted for the top 50 cm of soils (Tang et al., 2006).

2.3. Database construction

The inputs required for the DNDC model include data of soil properties, daily weather, cropping systems and agricultural management practices.

2.3.1. Soil data

A spatially-explicit and polygon-based soil database (1:50,000) was developed to support the DNDC simulations for the study region. The digital soil database contains 17,024 upland soil polygons, which was derived from 983 unique upland soil profiles. The resolution of this database is far higher than that of the 1:1,000,000 soil map of China, which was the most detailed digital soil database at the national scale to date (Yu et al., 2007; Xu et al., 2012, 2013). According to the Genetic Soil Classification of China (GSCC) system, upland soils in northern Jiangsu Province are classified into 8 soil groups, 22 soil subgroups, 85 soil families and 338 soil species, which were represented in the 1:50,000 digital soil map. The 8 soil groups in GSCC nomenclature based on the World Reference Base Soil Taxonomy (WRB) system include: Fluvo-aquic soil (Fluvisols), Cinnamon soil (Eutric Cambisols), Lime concretion black soil (Eutric Acrisols), Limestone soils (Regosols/leptisols), Lithosols soil (Regosols/leptisols), Saline soil (Chloridic Solonchaks), Purplish soil (Cambisols), and Brown soil (Haplic Luvisols) (Shi et al., 2010).

The soil attributes assignment in the polygon-based soil database was compiled using the Pedological Knowledge Based (PKB) method (Zhao et al., 2006) or the GisLST (Gis linkage based on soil type) method (Yu et al., 2007). The soil properties of 983 upland soil profiles were collected in the Second Soil Survey of China in 1980s–1990s, which is the most comprehensive and detailed study of Chinese soil characteristics to date (Xu et al., 2013). This database contains many soil properties for each polygon, such as soil names, profile locations, bulk density, total N, soil organic carbon, available P, texture and pH, etc.

The county-based soil data was built from the default method developed for DNDC (Li et al., 2000), in which the maximum and minimum values of soil texture, pH, bulk density, and soil organic carbon were recorded for each county. For the pair-wise simulations, soil parameters in the county-based database were the same as those of the polygon-based soil database of 50,000. After regional runs with the county-based soil database, the DNDC model produced two SOC change resulting from two runs with the maximum and minimum soil values for a specific county. In this paper we present the mean results (average of maximum and minimum estimates) (Tang et al., 2006).

2.3.2. Climate data

Daily climate data (i.e., precipitation, maximum and minimum air temperature) for 1980 to 2009 from 7 weather stations in northern Jiangsu Province were obtained from the China Meteorological Administration (China Meteorological Administration, 2011). The climate data of the nearest weather station was assigned to each county.

2.3.3. Crop data

Summer maize-winter wheat rotation system was assigned for each county based on the agricultural census data. Phenological and physiological parameters (e.g., maximum yield, biomass partitions, C/N ratio, water requirement, and cumulative thermal degree days) for each crop were obtained from sample tests that reflected the typical conditions of the northern Jiangsu Province (Li, 2007b).

2.3.4. Farming management data

In the regional simulation, agricultural management data were needed, including growing period, planting and harvest dates, application rates of N fertilizer and manure, and crop residue. These data at the county level from 1980 to 2009 were obtained from the Resources and Environmental Scientific Data Center, Chinese Academy of Sciences (Xu et al., 2013). The main measures of farming management in the study area included: (1) tillage: conventional tillage was conducted twice at 20 cm for maize and 20 cm for wheat on planting days; (2) manure application: annual manure wastes were estimated based on the local livestock numbers and agricultural population (40, 2.3, 5.1, and 5.3 kg N head^{-1} year^{-1} for cattle, sheep, swine and human, respectively), and 20% of the annual livestock wastes and 10% of that of human were used as farmyard manure; (3) crop residue management: 15% of the above ground crop residue was returned to the soil annually (Tang et al., 2006; Zhang et al., 2014).

2.4. Field measurements for DNDC model verification

A set of 9-years ground measurements from a field site, which is located in the west of the study region (see Fig. 1), was used for model validation. The soil type at the validation site is fluvo-aquic soil, which is dominant soil type in the study region. The DNDC input parameters for this site are presented in Table 1, and the current management practices are listed in Table 2.

Three statistical metrics – root mean square error (RMSE), mean absolute error (MAE) and relative error (E) were used to measure the differences between observed and model predicted SOC values

Table 1
Characteristics of the field site in northern Jiangsu Province, China.

Site	Location (province)	Latitude	Time span	Cropping system	Soil group	Bulk density (g cm^{-3})	pH	SOC (g kg^{-1})	Clay (%)
Tongshan	Jiangsu	32.3°N	1999–2007	Maize–wheat	Fluvo-aquic soil	1.26	5.2	13.8	14.0

Table 2
Management practices baseline for the field site in northern Jiangsu Province, China.

Site	Cropping system	Planting date [a]	Harvest date [a]	Tillage date [a]	N application rate ($kg\,N\,ha^{-1}$)	N application times
Tongshan	Maize–wheat	8/6, 4/10	20/9, 6/6	8/6, 4/10	211, 316	2, 3

[a] Dates are expressed as Day/Month system.

at the field site, as recommended by Loague and Green (1991), Zhang et al. (2012) and Whitmore et al. (1997). They are defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(V_{oi} - V_{pi})^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} ABS(V_{oi} - V_{pi}) \tag{2}$$

$$\mathrm{E} = \frac{100}{n} \times \sum_{i=1}^{n}\frac{V_{oi} - V_{pi}}{V_{oi}} \tag{3}$$

where V_{oi} are the observed values, V_{pi} are the predicted values, $\overline{V_{oi}}$ is the mean of the observed data, $\overline{V_{pi}}$ is the mean of the predicted data, n is the number in the sequence of the observed and predicted data pairs. The lower the RMSE or MAE, the better is the agreement between model predicted and measured SOC values. By contrast, higher RMSE or MAE value indicates lower prediction accuracy. If E is less than 5%, the modeling at the experimental site is considered to be satisfactory; and if E is greater than 5% and less than 10%, the modeling is acceptable; otherwise, the modeling is deemed to be unacceptable (Whitmore et al., 1997).

2.5. Statistical analysis

Area of upland soils (APS, ha), average annual SOC change (AASC, $kg\,C\,ha^{-1}\,year^{-1}$) that represents a region aggregated long-term average, and total SOC change (TSC, Tg C) during the study period for the study region were calculated using Eqs. (4), (6) and (7), respectively:

$$\mathrm{APS} = \sum_{i=1}^{n} APS_i \tag{4}$$

$$\mathrm{AMSC} = \sum_{f=1}^{h} ASC_f \tag{5}$$

$$\mathrm{TSC} = \sum_{i=1}^{n}(APS_i \times AMSC_i) \tag{6}$$

$$\mathrm{AASC}\ (kg\,C\,ha^{-1}\,year^{-1}) = \mathrm{TSC}/\mathrm{APS}/30 \tag{7}$$

where APS_i is the area of i-th polygon of upland soil; ASC_f ($kg\,C\,ha^{-1}\,year^{-1}$) is the annual SOC change in a specific polygon, as estimated by the DNDC modeling; $AMSC_i$ ($kg\,C\,ha^{-1}\,year^{-1}$) is the accumulated annual SOC change in a specific polygon from 1980 to 2009; n is the polygon number; and h is the order of simulation year from 1980 to 2009 (h = 1, 2, 3 . . . . . . 30).

Previous studies indicated that the effect of soil properties (e.g. SOC content, texture, bulk density, and pH) on simulating SOC changes at regional scale is a major source of uncertainty for use of DNDC model (Li et al., 2004; Pathak et al., 2005). In order to better evaluate the most sensitive factor of soil properties in affecting SOC, the correlation between AASC and soil properties was determined by using Pearson's test and multiple stepwise regression analysis (Santiago-Martín et al., 2014). All of the statistical analyses were performed using the Statistical Package for Social Sciences (SPSS) statistical software (Leech et al., 2008).

The relative deviation (y) of polygon- and county-based databases of 1:50, 000 was calculated by the Eq. (8) (Zhang et al., 2014):

$$y = (x_s - x_0)/x_0 \times 100 \tag{8}$$

where x_0 is an average annual- (or total-) SOC change of polygon-based database, and x_s is an average annual- (or total-) SOC change of county-based database.

3. Results and discussion

3.1. Evaluation of the DNDC model

The pattern of the simulated SOC changes matches well with the observations (Fig. 2). Specifically, the average simulated SOC content was 13.66 $g\,kg^{-1}$ from 1999 to 2007, close to 13.13 $g\,kg^{-1}$ reported by the observations. Furthermore, a relative error (E) of 4.34% indicated that the DNDC model was satisfactory for modeling SOC of the study region. Likewise, the low values of RMSE and MAE reflected encouraging model performance (Fig. 2).

3.2. Comparison of SOC changes modeled with polygon- and county-based soil databases

A pair-wise model experiment with polygon- and county-based soil data, where the former contains 17,024 polygons with unique soil information as opposed to 29 polygons representing the 29 counties in the latter, were conducted to investigate the uncertainty derived from soil data. Counties are used as the basic

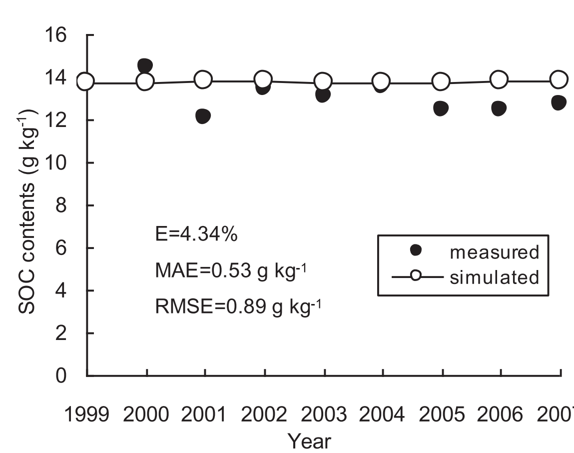

Fig. 2. Comparison between observed and simulated SOC dynamics from upland soil in Tongshan County of the northern Jiangsu Province.

simulation unit for regional simulations in the DNDC model as the default method (Li, 2000), where the county-based database usually requires relatively less soil data with a resolution of about $0.5^{\circ} \times 0.5^{\circ}$ (Li et al., 2004). Detailed Descriptions of the default method in the DNDC model can be found in Zhang et al. (2014). As a result, the default method produces higher uncertainty due to missing spatially differentiated soil information (Pathak et al., 2005; Zhang et al., 2014). In the polygon-based simulation, DNDC ran for each polygon once and produced a single annual SOC change for that polygon; differently, in the county-based simulation, DNDC ran twice for each county and produced a range of annual SOC changes.

The total SOC changes modeled with the county-based database ranged from 22.79 to 43.98 Tg C, and with an average of 33.39 Tg C for the study region, while the SOC change modeled with the polygon-based database was 37.89 Tg C. The relative deviation of total SOC changes in county-based simulation ranged from −40 to 16%, with an average of −12%. This underestimation was likely because the coarse soil data missed relatively small soil patches containing low SOC contents (6.0 vs. 7.0 (2.2–11.8) g kg^{-1}) and low bulk density (1.31 vs. 1.32 (1.13–1.52) g cm^{-3}), which are favorable for SOC accumulation (Li et al., 2004; Blanco-Canqui et al., 2009; Zu et al., 2011).

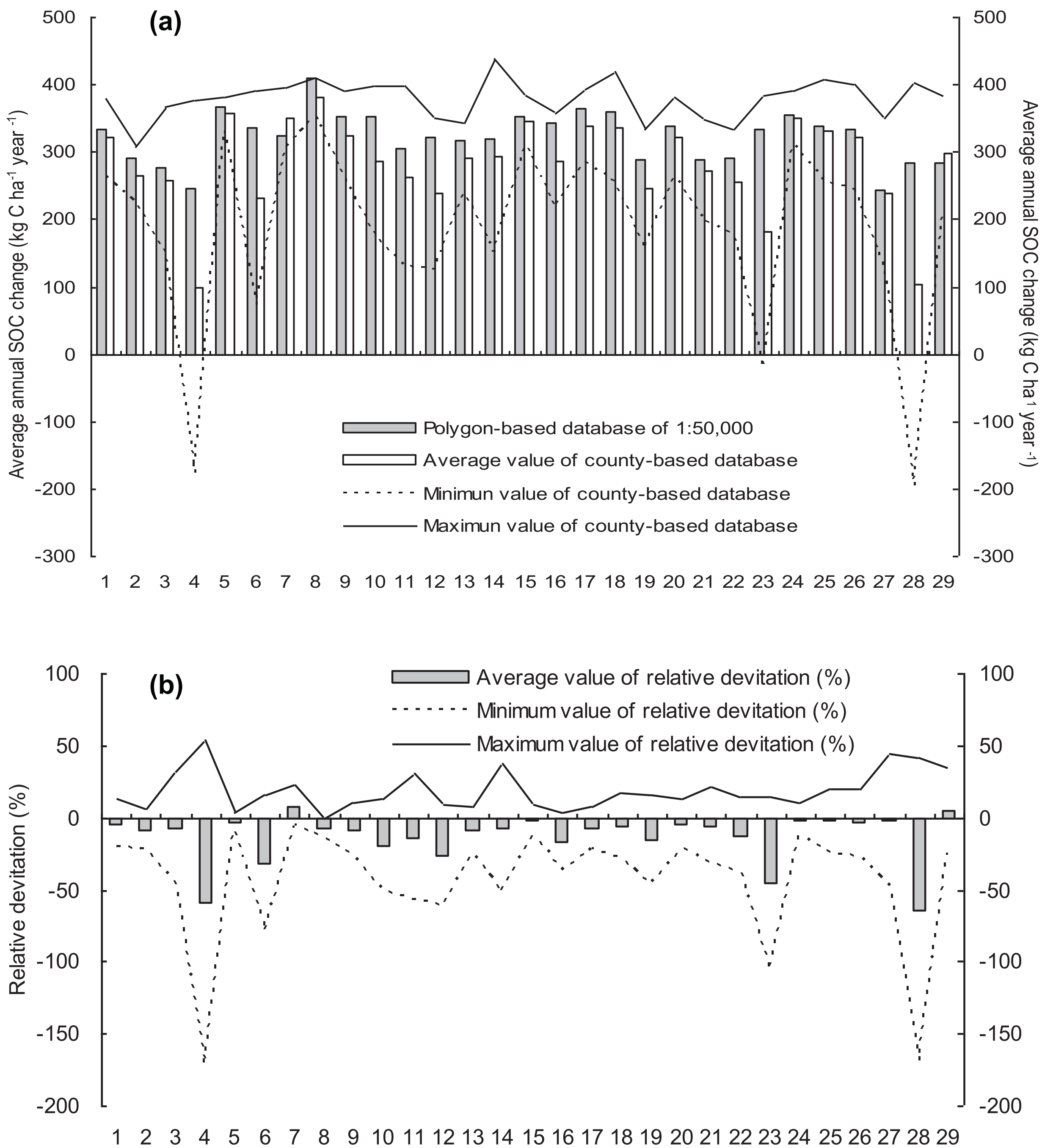

Fig. 3. (a) Comparison of the average annual SOC changes modeled with the county- and polygon-based database for the northern Jiangsu Province China; and (b) relative deviation of the average annual SOC changes modeled with the county-based database from that with the polygon-based one for the northern Jiangsu Province, China. (1. Binhai; 2. Dafeng; 3. Donghai; 4. Dongtai; 5. Fengxian; 6. Funing; 7. Ganyu; 8. Guannan; 9. Guanyun; 10. Hongze; 11. Huaian; 12. Huaiyin; 13. Jianhu; 14. Jinhu; 15. Suining; 16. Lianshui; 17. Peixian; 18. Peizhou; 19. Sheyang; 20. Muyang; 21. Sihong; 22. Siyang; 23. Tongshan; 24. Xiangshui; 25. Xinyi; 26. Suqian; 27. Xuyi; 28. Xuzhou; 29. Yancheng.).

We noticed that average annual SOC changes (AASC) in the pair-wise simulations differed largely from each other, with overall lower estimates in county-based simulation (Fig. 3a). Taking the AASC quantified using the polygon-based database as reference, the relative deviation of AASC derived from the county-based database ranged from −64% to 8.0% across all counties (Fig. 3b). Take Xuzhou County as an example, the AASC in the county-based simulation was 103 kg C ha^{-1} $year^{-1}$, nearly 2.5 times less than that in the polygon-based one. By comparing the two databases, we found that the county-total SOC contents for Xuzhou in the county-based database were higher than that in the polygon-based database (12.2 (2.8–21.5) vs. 9.3 g kg^{-1}). The higher total SOC contents tend to be less favorable for SOC accumulation (Li et al., 2004); consequently, the AASC in Xuzhou simulated with the county-based soil database is lower than that of polygon-based one. This phenomenon seems prevalent across most counties. However, the AASC of two counties (Ganyu and Yangcheng) in the county-based database were higher than that in the polygon-based (Fig. 3a). This is likely because the clay content of Ganyu County in the county-based database were higher (44 (10–78) vs. 28%, Zhao et al., 2013) – soil with higher clay content possesses a greater capacity to protect SOC and better stabilizing conditions (Six et al., 2002; McLauchlan, 2006), and that the initial SOC of Yangcheng County in the county-based database was lower (5.4 (8.2–2.6) vs. 6.7 g kg^{-1}, Li et al., 2004) – soils with lower initial SOC displayed greater SOC increase due to low decomposition rate (Zhao et al., 2013).

The large discrepancies between the simulations with the county-based soil data and the polygon-based soil data imply that coarse soil database causes large bias in model estimates. In the following sections, the set of desirable simulation with polygon-based soil data was used to analyze the SOC changes in our study region.

3.3. Inter-annual changes of SOC in northern Jiangsu province

The model results based on the 1:50,000 soil database showed that 3.93 Mha of upland soils increased 37.89 Tg C in the top layer (0–50 cm) from 1980 to 2009, with the AASC of 322 kg C ha^{-1} $year^{-1}$. The SOC changes in this region accounts for 10.2% of annual national carbon sequestration of upland soils, compared with the fraction of 3.7% in the total upland area of China (Wang, 2011b). In general, most upland soils in this region were a strong sink of atmospheric CO_2 during the period of 1980–2009 (Fig. 4). The AASC in the range of <0, 0–100, 100–300, 300–500, and >500 kg C ha^{-1} $year^{-1}$ correspond to 0.06, 0.54, 28.84, 67.29 and 3.26% of the total upland soil area, respectively. These results are consistent with the current management practices in this region. As increased use of chemical fertilizer and farmyard manure would increase SOC by enhancing plant productivity and returning crop residue to soil (Brar et al., 2013), a high rate of 340 kg N ha^{-1} $year^{-1}$ fertilizer and 15.49 kg N ha^{-1} $year^{-1}$ manure input is likely to increase SOC in this region (Fig. 5). Further, the two most sensitive soil factors to SOC changes (Fig. 6), initial SOC content (r = 0.62**, n = 17024) and clay content (r = 0.18**, n = 17024), presented propitious circumstances for C sequestration as indicated above – the upland soils have low initial SOC content (6.0 g kg^{-1}) and high clay content (28%) (Table 3).

Our model results are comparable to those of Liao et al. (2009). In their study, the average of topsoil SOC content (0–20 cm) in Jiangsu Province increased from 9.45 g kg^{-1} in 1982–10.9 g kg^{-1} in 2004, based on 662, 690 and 24, 167 measured samples, respectively. This means an AASC of 160 ± 90 kg C ha^{-1} $year^{-1}$ during their study period. A lower result was obtained by Pan et al. (2010), who found that the AASC of China's upland soils was 56 ± 200 kg C ha^{-1} $year^{-1}$ from 1985 to 2006. These results imply a high SOC sequestration potential in the upland soils of China under the proper agriculture management practices (e.g., no-tillage, cover crops and manure application).

The inter-annual variations in the modeled annual SOC change are large (Fig. 7). One of the key reasons was related to fertilizer application. During the period of 1980–1997, the SOC increased rapidly across the entire region, with the annual changes ranging from 185 to 519 kg C ha^{-1} $year^{-1}$. Coincidently, the application rates of synthetic fertilizers continuously increased during the time period (Fig. 5). The chemical fertilizer application rate increased from 142 to 468 kg N ha^{-1} $year^{-1}$ and the manure rate increased from 11.5 to 21.5 kg N ha^{-1} $year^{-1}$. However, the SOC increasing rate slowed down or fluctuated for the period of 1998–2009 (Fig. 7), which was associated with decreased agricultural input. According to agricultural historical data, the amounts of synthetic fertilizer and farmyard manure used in the region have fluctuated since

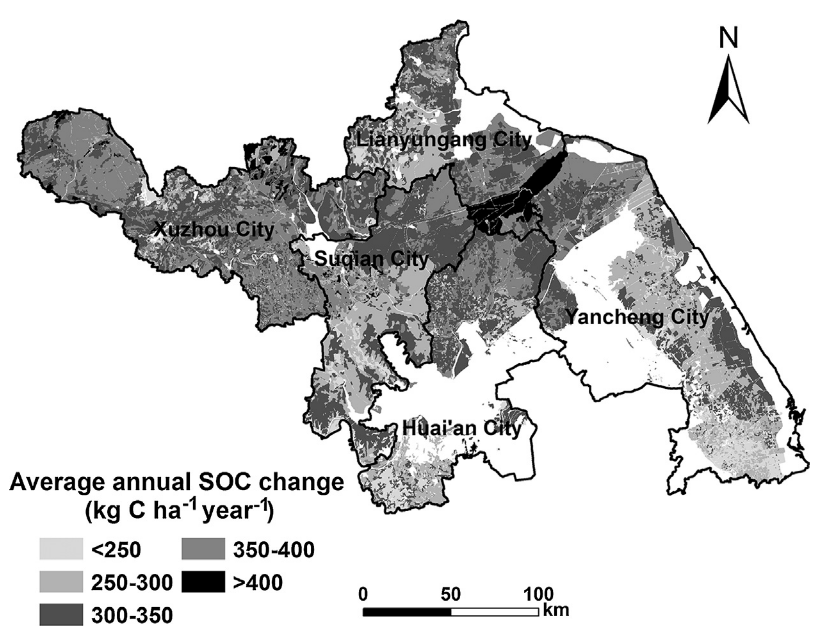

Fig. 4. Spatial distribution of average annual SOC change in northern Jiangsu Province, China.

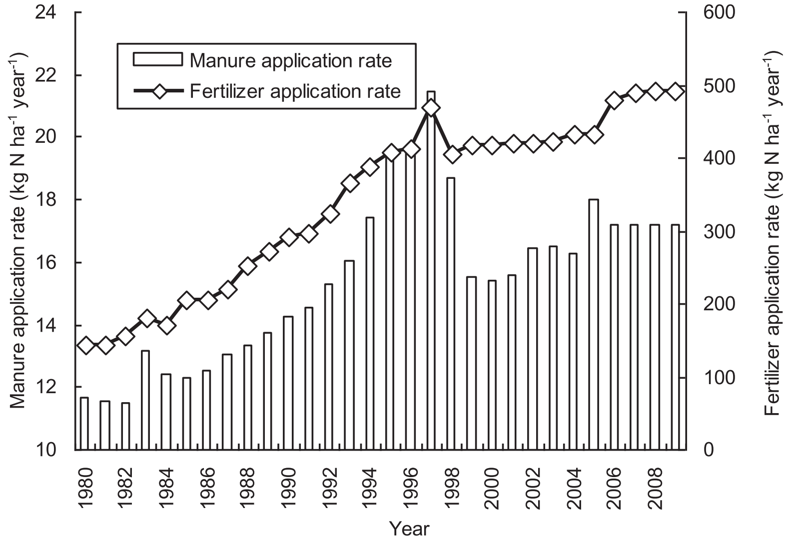

Fig. 5. Variation of chemical fertilizer and manure application rate from 1980 to 2009 in northern Jiangsu Province, China.

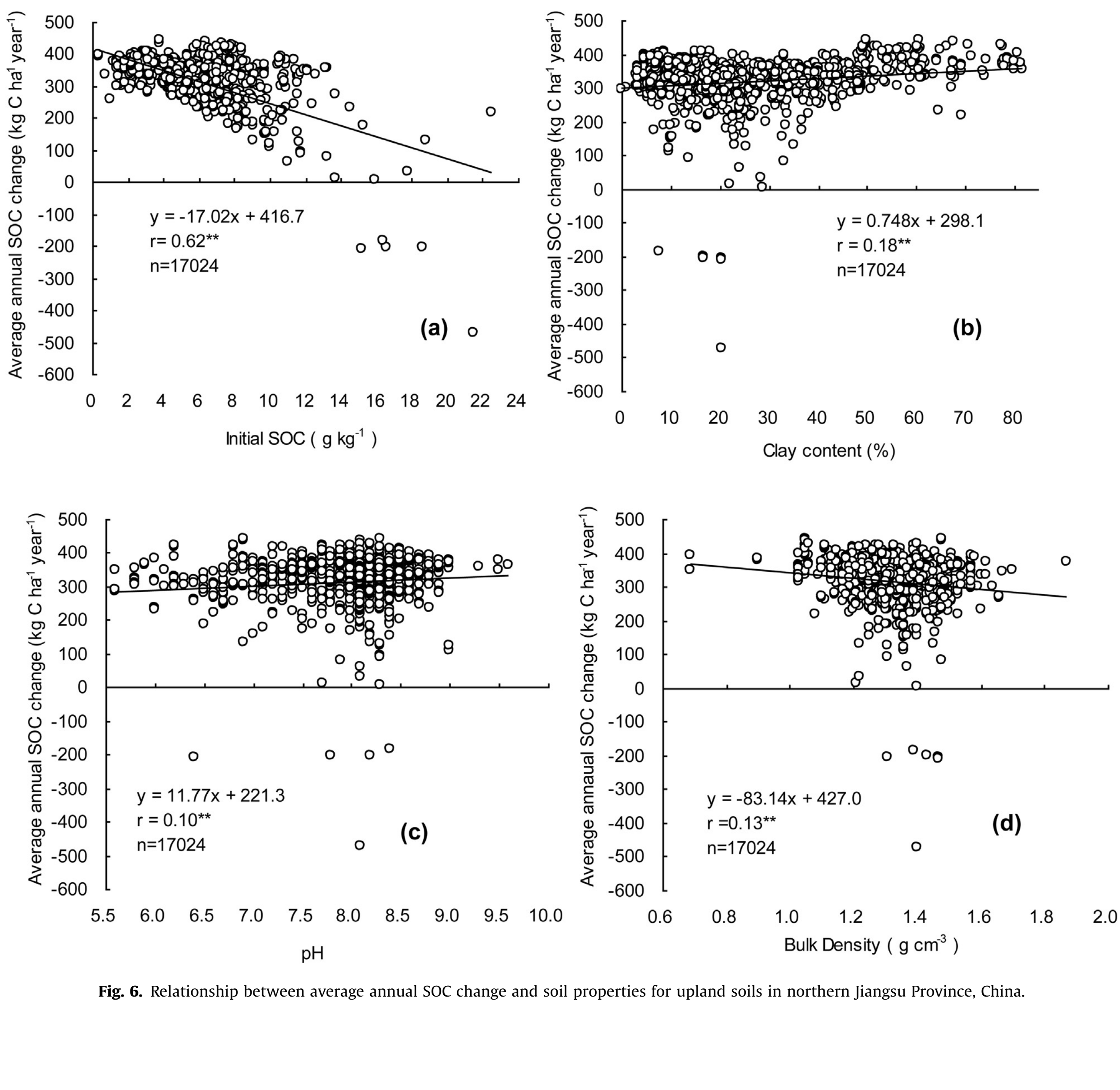

Fig. 6. Relationship between average annual SOC change and soil properties for upland soils in northern Jiangsu Province, China.

Table 3
Model input of soil properties, climatic factors and fertilizer amount at the entire region and soil group levels.

	Soil properties				Climatic factors		Fertilizer amount	
	Initial SOC ($g\,kg^{-1}$)	Clay (%)	pH	Bulk density ($g\,cm^{-3}$)	Annual mean rainfall (mm)	Mean annual temperature (°C)	Fertilizer ($kg\,N\,ha^{-1}\,year^{-1}$)	Manure ($kg\,N\,ha^{-1}\,year^{-1}$)
Whole northern Jiangsu Province								
Northern Jiangsu Province	6.00	28	8.0	1.31	948	14.7	340	15.49
Soil groups								
Fluvo-aquic soil	5.55	26	8.2	1.31	918	14.7	344	16.16
Saline soil	6.51	29	8.3	1.28	1010	14.6	371	13.52
Brown soil	4.53	18	6.7	1.44	938	14.3	284	17.74
Cinnamon soil	5.93	36	8.0	1.33	947	15.1	309	14.05
Lime concretion black soil	8.23	41	7.7	1.29	942	14.6	310	16.03
Lithosols soil	9.16	38	7.3	1.29	1048	15.4	274	15.42
Limestone soil	9.39	40	7.1	1.35	1048	15.4	274	15.42
purplish soil	4.27	14	7.5	1.38	912	14.1	318	16.88

*The value of all factors is weighted average by the area of each polygon.

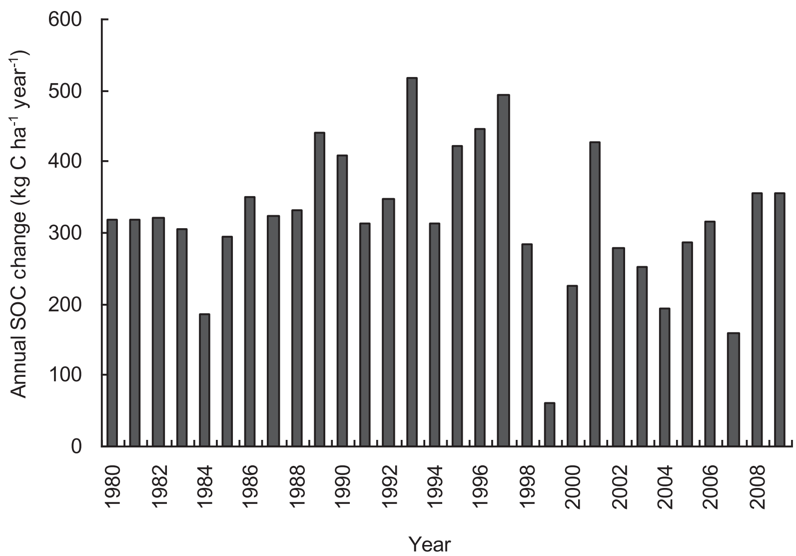

Fig. 7. Temporal variation of annual SOC change from 1980 to 2009 in northern Jiangsu Province, China.

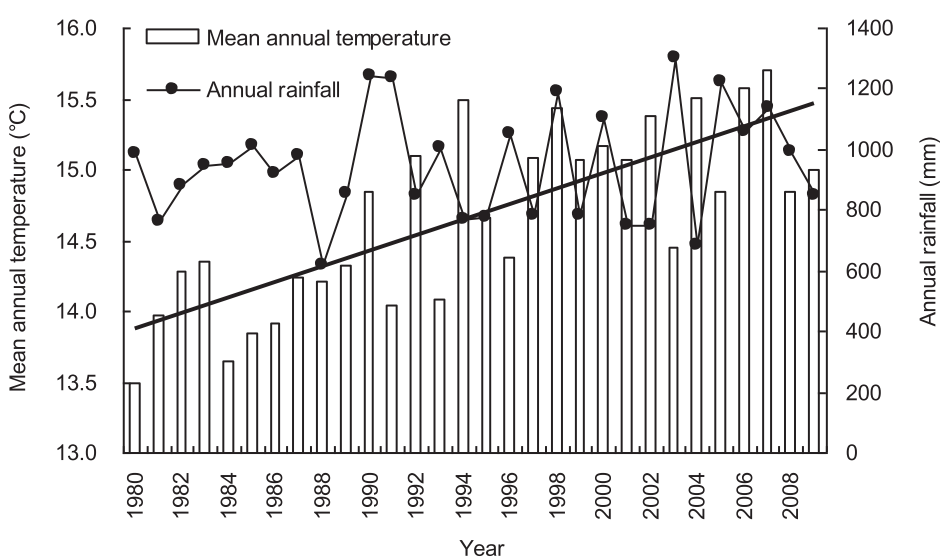

Fig. 8. Variations of annual rainfall and annual mean temperature from 1980 to 2009 in northern Jiangsu Province, China.

1998 (Fig. 5), which was in line with the fluctuation of SOC changes. The model results were in agreement with many reports, which indicated the annual SOC sequestration rate of Chinese rice paddies balanced or declined since the mid-1990s (Zhang et al., 2007; Xu et al., 2012).

Climate change could play a role in the long-term SOC change trend as well, although the mechanisms would be much more complex. It is commonly observed that SOC accumulation increases with increasing annual rainfall (Paul et al., 2002). High average annual rainfalls were observed in the study region, with 892, 844 and 984 mm during the periods of 1980–1989, 1990–1999 and 2000–2009, respectively. The annual mean temperature has also been increased from 1980 to 2009 (Fig. 8) – average annual mean temperature during the periods of 1980–1989, 1990–1999 and 2000–2009 were 14.0, 14.8 and 15.2 °C, respectively. Rising temperature leads to the increase of soil temperature, and thus stimulates SOC decomposition (Gaumont-Guay et al., 2006). However, the modeled results showed that the upland soils of study region were always a strong sink of atmospheric CO_2 during the study period (Fig. 7). The most likely reason was that the C increase by increasing fertilizer and manure input was relatively higher than the C loss caused by rising temperature.

3.4. Comparison of SOC change for different upland soil groups

The potential for carbon sequestration were significantly different across the eight soil groups (Fig. 9 a and b). The difference may attribute to many factors, which may be either soil related ones affecting C decomposition, or climate related ones affecting productivity (Luo et al., 2010).

The fluvo-aquic soil group covers about 2.07 Mha and accounts for 52.7% of the total upland soil area (Fig. 9a). As Tables 4 and 5 illustrate, initial SOC content and clay content account for 60.9% of the variations in average annual SOC change for fluvo-aquic soils from 1980 to 2009, while other soil parameters only account for less than 4.0% of the variations. Fluvo-aquic soil group possesses relatively low initial SOC and high clay according to analysis of our soil database, which enables their high capacity of carbon sequestration (Table 3) (Li et al., 2004). Moreover, the average chemical fertilizer application rate in fluvo-aquic soils was as high

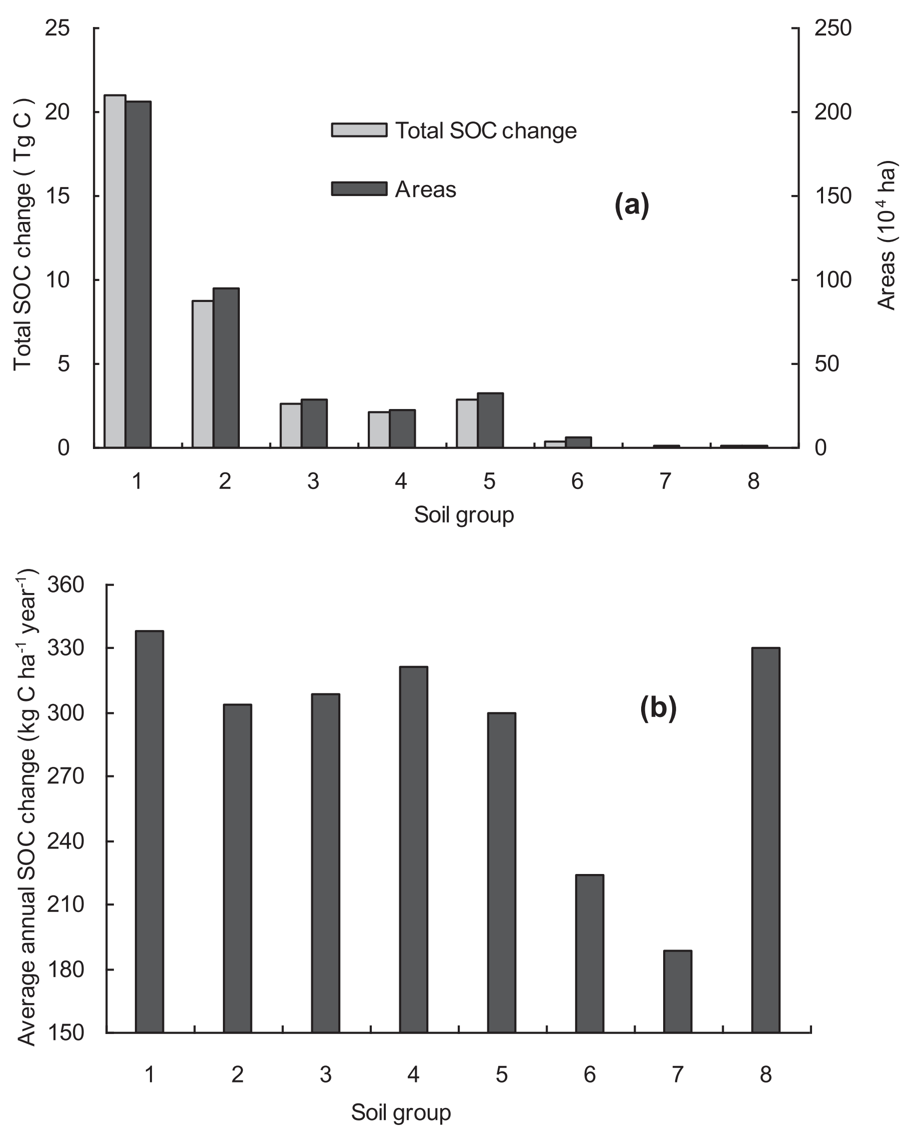

Fig. 9. (a) Comparison between area coverage and total SOC change in various upland soil groups of the northern Jiangsu Province, China; (b) Comparison of average annual SOC change in various upland soil groups of the northern Jiangsu Province, China. (Number 1–8 represents Fluvo-aquic soil, Saline soil, Brown soil, Cinnamon soil, Lime concretion black soil, Lithosols soil, Limestone soil, and Purplish soil, respectively.).

Table 4
Correlation coefficients (Pearson's test) between soil properties and average annual SOC change as well as their significance levels in different soil groups.

Soil group	Number of polygons	Initial SOC (g kg^{-1})	Clay (%)	pH	Bulk density (g cm^{-3})
Fluvo-aquic soil	10,451	−0.578**	0.094**	0.073**	−0.139**
Saline soil	3354	−0.600**	0.476**	−0.056**	−0.255**
Brown soil	1206	−0.819**	0.390**	−0.190**	−0.280**
Cinnamon soil	1166	−0.417**	0.190**	0.043	0.066*
Lime concretion black soil	497	−0.312**	0.550**	0.194**	0.073
Lithosols soil	229	−0.919**	0.606**	0.575**	0.288**
Limestone soil	66	−0.990**	0.947**	0.537**	−0.802**
purplish soil	55	−0.334*	0.643**	0.219	−0.453**

* and ** Significant at the 0.05 and 0.01 levels, respectively.

Table 5
Individual contributions of major soil properties to the variations of average annual SOC change in different soil groups.

Soil group	Number of polygons	ΔR^{2} [a]				Adjusted R^2
		Initial SOC (g kg^{-1})	Clay (%)	pH	Bulk density (g cm^{-3})	
Fluvo-aquic soil	10,453	0.334***	0.275***	0.001***	0.038***	0.646***
Saline soil	3354	0.360***	0.456***	0.005***	0.011***	0.831***
Brown soi	1206	0.174***	0.171***	0.012***	0.012***	0.366***
Cinnamon soil	1166	0.671***	0.086***	0.008***	0.001**	0.766**
Lime concretion black soil	497	0.280***	0.303***	0.022***	0.011***	0.613***
Lithosols soil	229	0.844***	0.117***	0.030***	0.003***	0.993***
Limestone soil	66	0.979***	–	–	–	0.979***
purplish soil	55	0.214***	0.413***	–	–	0.613***

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

as 344 kg N ha^{-1} year^{-1} (Table 3). As a result, the modeled average annual SOC sequestration rate in fluvo-aquic soils was 338 kg C ha^{-1} y $^{-1}$, which was the highest in all the upland soil groups (Fig. 9b). The rapid increase of SOC in fluvo- aquic soils of this region has also been reported in Yu et al. (2006). They found that the SOC of fluvo-aquic soils and brown soils in the Huang-Huai-Hai plain obviously increased during the periods of 1980–2000, and the increase rates reached to 19 and 14%, respectively.

The saline soils, lime concretion black soils, cinnamon soils, lithosols soils, purplish soils and limestone soils account for 24.31, 8.13, 5.64, 1.48, 0.27 and 0.18% of the total area of upland soils, respectively (Fig. 9a). High SOC changes occurred in the groups of saline soils, lime concretion black soils, cinnamon soils and purplish soils (Fig. 9b), due to their low initial SOC and high clay content (in lime concretion black soils) (Table 3). In contrast, low SOC changes were located in the lithosols soils and limestone soils (Fig. 9b), attributing to its high initial SOC content, neutral pH value (in lime concretion black soils) and low fertilizer application rate (in lime concretion black soils) (Table 3). Soils with higher SOC and neutral pH value provide a better living environment for microbes, which are favorable for decomposition, and thus may result in low SOC sequestration (Pacey and DeGier, 1986; Li et al., 2004).

The group of brown soils covers about 7.31% of the total area of upland soils (Fig. 9a). In contrast to other upland soil groups, initial SOC value and clay content of the brown soils account for less than 34.5% of the variations in AASC from 1980 to 2009 (Table 5). Low annual mean temperature (14 °C) in brown soils was identified as the predominant environmental variables on SOC change (Table 3). Some studies indicated that air temperature is significantly and positively correlated with changes in soil respiration (Bond-Lamberty and Thomson, 2010), and a slower SOC turnover associated with lower temperatures could result in the increase of significant amounts of C stored in agricultural soils (Álvaro-Fuentes et al., 2012). The model results revealed an increase about 2.66 Tg C from 1980 to 2009 in the brown soil group (Fig. 9a), with an average annual SOC sequestration rate of 309 kg C ha^{-1} year^{-1} (Fig. 9b).

The model results at soil group classification levels indicated that the carbon sequestration rate is greatly influenced by the most sensitive soil factors (e.g., initial SOC and clay content) in addition to environmental factors, with greater C accumulation in soils having a lower initial SOC content and higher clay content. This is also recognized in models such as CENTURY (Parton et al., 1993) and RothC (Coleman et al., 1997). Therefore, to reduce model uncertainties, the factors such as initial SOC content and clay content, should be given a high priority in acquiring more accurate and finer input data for simulating SOC changes.

3.5. Model uncertainties and limitations

In the study, to improve the spatial accuracy of the DNDC regional simulations, a spatially-explicit and polygon-based soil database (1:50,000) in northern Jiangsu Province was used. However, there are many other sources inducing model uncertainty that need to be considered for a better understanding of the SOC dynamics.

Firstly, the modeling approach usually adopt the county as the basic geographic simulation unit for GIS database construction since most of the statistical cropland data was county-based, especially in China. For example, climate data and fertilizer application were obtained from county-based sources although they are highly differentiated within a county. Therefore, the temporally and spatially varying climate data and fertilizer application rate were not well captured at county scale dataset, resulting in large uncertainty in estimates.

Secondly, the management practice databases were also established at county level because it is currently the most spatially detailed level in China (Xu et al., 2013). Consequently, county level management practices might not be able to capture the field-specific on-farm measures. For example, the assumption of a 15% of aboveground crop residue returning to the soil annually was a national average value derived from the Agricultural Ministry (Tang et al., 2006). But in fact the fraction may vary greatly within a county. Some studies indicated that the quantity and quality of organic C additions is a key factor affecting SOC dynamics in most agro-ecosystems (Li et al., 1994). As a result, this uncertainty may lead to bias in the SOC estimates.

The third possible source of the modeling uncertainty is land-use change in the study area. During the periods of 1980–2009, the land-use of upland soils in northern Jiangsu Province has changed significantly due to urban development and heavy management. However, the effects from the land-use change cannot be quantified by the DNDC model because current dataset does not allow us to build a transformable relationship between other land-uses and upland-crop fields. One feasible approach is to apply remote sensing data at different simulation periods, as remote sensing could potentially provide temporally and spatially explicit delineation of land-use change.

4. Conclusions

Upland is the dominant agricultural land use type in China, covering more than 70% of the national total cropland area. It is crucial to accurately estimate soil organic carbon (SOC) change from the upland soils. Based on spatially differentiated information, process-based models integrated with GIS databases enables simulations of soil carbon cycling and capturing of spatial variations of SOC changes. In the study, the DeNitrification and DeComposition (DNDC) model was applied for quantifying SOC changes in an important upland soil domain, the northern Jiangsu Province, which is located in the downstream of the Huang-Huai-Hai plain of China. Besides a county-based coarse soil database, a set of newly developed high-resolution polygon-based soil databases (1:50,000) were linked to DNDC to improve the accuracies of regional simulations. The pair-wise simulations indicated that the average total SOC change modeled with the coarse database was only 88% of the high-resolution simulation due to missing of the small soil patches, and the relative deviation ranged from −64% to 8.0% across different counties. This corroborates the uncertainty that induced from coarse simulation unit and failure of soil heterogeneity representation in coarse soil database. In addition, the effective use of high-resolution soil databases is beneficial to optimize local fertilizer use and inform agricultural management for efficient carbon sequestration.

The high-resolution simulation indicated a C increase of 37.89 Tg from the 3.93 M ha of upland soils in this region during the period of 1980–2009, which accounts for 10.2% of annual national carbon sequestration of upland soils, compared to its fraction of 3.7% in the national upland area. The annual SOC change varied between 61 to 519 kg C ha^{-1} $year^{-1}$, mainly driven by the historical variations in N-fertilizer and manure application. Moreover, various climate conditions play a significant role in the annual SOC change as well. Thus, accurate estimate of SOC changes and the investigation of the mechanisms behind for the study region are crucial for national climate mitigation due to its significant role in carbon sequestration.

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