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Profile stock of soil organic carbon and distribution in croplands of Northeast China

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A R T I C L E I N F O

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A B S T R A C T

Soil organic carbon (SOC) stock is one of the most important carbon (C) reservoirs on the Earth and plays a vital role in the global climate change. However, SOC stock at a regional scale is still uncertain due to the lack of soil bulk density data, differences in sample depth, geography, and soil properties. Based on data from 78 soil profiles, we estimated SOC density (SOCD) and its distribution at 0–100 cm depth of croplands in three typical Counties (Lindian, Hailun and Baoqing Counties) in Northeast China. Soil organic carbon content and variations significantly decreased with increased soil depth. The SOCD in 100-cm depth ranged from 52.3 to 323.1 Mg ha^{-1}, with an average of 163.6 Mg ha^{-1}. The SOCD in the top 20 cm accounted for 32.8% of that in 100 cm soil profile. A good mathematical equation between SOCD of 0–20 cm and 0–100 cm would be a useful tool to estimate SOCD in soil profiles. In addition, soil depth, bulk density, soil pH, and elevation were significantly correlated with SOC content. Regression of SOC in the data set to individual factors (soil depth, BD, soil pH, clay content, and elevation) is relevant to understand how C changes over time and depth.

1. Introduction

Soil is the largest pool of organic carbon (C) in terrestrial ecosystems (Eswaran et al., 1993; Schlesinger, 1990). About two thirds of global C in soil is held as soil organic carbon (SOC) (Scharlemann et al., 2014). A slight change in soil C pool will greatly impact the concentration of atmospheric C dioxide (CO_2) and affect global climate change. The SOC stock and its different horizontal and vertical distributions play an important role in C-based greenhouse gas abundance (Hobley et al., 2015; Xu et al., 2011). Besides the important roles in mitigating climate change, soil C is critical to maintaining soil productivity and soil health in agricultural systems. Therefore, an accurate estimation of SOC stock and distribution is essential in alleviating C emissions and improving soil health.

In recent years, SOC distribution and stock have become an increasing concern (Hunziker et al., 2017; Mishra et al., 2017). Numerous studies have estimated SOC distribution on global (Bohn, 1982), country (Arrouays et al., 2001; Krogh et al., 2003) and regional (Sun et al., 2004; Wang et al., 2002a) scales. However, many of these results are fraught with regional data uncertainty resulting in unreliable data at larger scales, for the following reasons. First, many previous studies mainly focused on top 20 cm soil (Li et al., 2016; Pan et al., 2009; Zhao et al., 2015), despite a considerable fraction of total SOC stock stored in the subsoil (Jandl et al., 2014; Jobbagy and Jackson, 2000) should not be neglected. Second, SOC content or soil bulk density (BD) data were often deficient when estimating SOC stock in regional scale studies. In many studies, SOC data was not obtained by directly sampling and analyzing, but was estimated by converting from soil organic matter (SOM), obtained from reported references, using the Bemmelen index of 0.58 when the SOC data was unavailable (Pan et al., 2010; Yan et al., 2011). In addition, soil BD, necessary to calculate SOC stock, was often lacking in many large-scale soil inventories (Allen et al., 2010; Kaur et al., 2002; Manrique and Jones, 1991). Moreover, due to high spatial heterogeneity of SOC and BD, there is considerable variation in the calculated SOC stock using the estimated BD and SOC data (Pan et al., 2010; Schrumpf et al., 2011; Wiesmeier et al., 2012; Yan et al., 2011).Third, due to complex SOC composition caused by variable human activities, terrain and climate conditions, and chemical interactions, SOC quantity derived from different estimations was still inconsistent.

Previous studies reported that SOC depends on climate, soil depth, land use, and relevant soil properties (Haynes and Naidu, 1998; Poeplau et al., 2011; Wiesmeier et al., 2012). However, the factors influencing SOC stock were unique in different regions, so it remains unclear which factors play the dominant role in a specific climate zone. Understanding the factors might be helpful for the development of

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strategies to access C sequestration and improve soil quality in a specific region.

Northeast China has a large acreage of cultivated soils, and its SOC distribution and stock have been increasingly gaining interests due to its unique and central role in China's agriculture and high soil C content in the region (Liu et al., 2006a; Liu et al., 2013; Wang et al., 2002b; Zhao et al., 2015). Our research sites are located in the Heilongjiang Province of Northeast China, the largest area of cropland (80% of area) in China. However, the cropland SOC stock in the 100 cm soil profile has not been reported at the regional scale. The present study was designed to provide such information for extensive croplands in Northeast China.

Based on soil types and land uses (dry croplands and rice (*Oryza sativa* L.) paddies), three typical Counties (Lindian, Hailun, Baoqing) were selected in Heilongjiang Province and represents major soil types of Northeast China. Using the measured SOC concentration and BD, we estimated the cropland stock of SOC (100 cm soil profile) in the three typical counties and evaluated the factors influencing the SOC stock and distribution in soil profile.

2. Materials and methods

2.1. Study area

The study was conducted in the Lindian, Hailun, and Baoqing Counties (longitude 124°32′–131°42′, latitude 45°55′–47°59′) in Heilongjiang Province, Northeast China (Fig.1). The study sites have elevations ranging from 46 to 402 m and cover an area of 859.2 M ha cropland. The sites have a temperate continental monsoon climate. The mean annual temperature ranged from 2.4 °C for Hailun County to 4.4 °C for Baoqing County, and the mean annual precipitation ranges from 440 to 550 mm. The main soil types include Haplic Phaeozems, Haplic Chernozems, Luvic Phaeozems, and Albic Luvisols (FAO/UNESCO, 1974) (Table 1). Seventy-five percent of the annual rainfall in this region is concentrated in July to September. The main crops include maize (*Zea mays* L.), soybean (*Glycine* max L.), and rice. Other detailed description can be seen in Li et al. (2016).

2.2. Soil sampling and analyses

Soil samples were collected in 2011 under a “Carbon Project” financed by the Chinese Academy of Sciences. Based on the area of soil types and land uses (dry croplands and rice paddies), a total of 78 sampling sites were selected in the three counties, which included most of the soil types in Northeast China. At each sampling site soil profiles were excavated and soil samples were collected by pedologic horizons. During the sampling within each county, soil types, residue management, and land use types were simultaneously recorded in the field. In addition, a portable Global Positioning System (GPS) receiver was used to locate the position of each sampling site.

Soil samples were air-dried and divided into two portions. One was sieved through 0.25 mm for SOC and total nitrogen (STN) analyses, and the other through 2 mm sieve for particle size (soil texture) and pH value analyses. The SOC concentration was measured following the Walkley and Black method (Nelson and Sommers, 1982), and the STN was determined following the Kjeldahl method (Bremmer and Mulvaney, 1982). Soil BD was determined using the core method with three replicates (Culley, 1993). Soil texture was determined by the pipette method with three replicates (Gee and Bauder, 1986). Soil pH was measured on a 1:2.5 (w/v) mixture of soil and deionized water with a pH meter (Delta 320, Mettler Toledo, Switzerland).

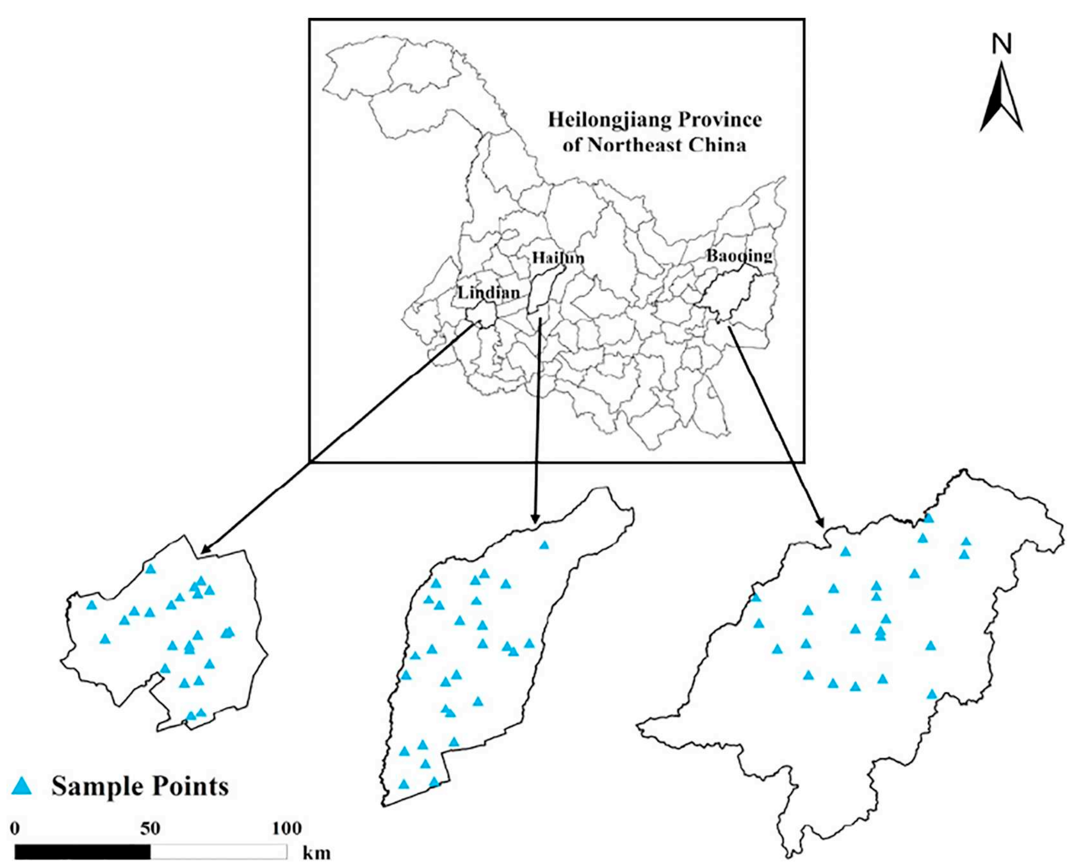

Fig. 1. Study area and soil sampling locations in Lindian, Hailun, and Baoqing Counties, Heilongjiang Province of northeast China.

Table 1
General description of three Counties in northeast China.

Items	Lindian	Hailun	Baoqing
No. of sites	25	28	25
Sampling geographical range	47°02′–47°59′N 124°32′–126°38′E	47°00′–47°43′N 126°09′–127°25′E	45°55′–46°47′N 131°42′–133°05′E
Mean annual temperature (°C)	2.6	2.4	4.4
Mean annual precipitation (mm)	437	547	488
FAO/UNESCO soil classification	Haplic Chernozems Haplic Phaeozems	Luvic Phaeozems Haplic Chernozems	Haplic Chernozems Albic Luvisols

The mean annual temperature and mean annual precipitation data were cited from Li et al. (2016). The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

2.3. Calculations and data processing

The SOC concentration at each fixed depth (20 cm) was calculated from the data obtained from pedologic horizons using a depth-weighted average function for each soil profile. Each profile was divided into five 20-cm layers (0–20, 20–40, 40–60, 60–80, and 80–100 cm). The BD and STN data were also calculated and processed the same as for the SOC transformations.

The SOCD (Mg C ha^{-1}) for a certain soil depth h was calculated using the following equation:

$$SOCD_h = \frac{\sum_{i=1}^{n} SOC \times \rho \times L \times \left(1 - \frac{F}{100}\right)}{10} \quad (1)$$

where SOC is the SOC concentration (g kg^{-1}) for a certain depth, ρ is the bulk density (Mg m^{-3}), L is the thickness (0.2 m), and F represents the proportion of coarse fragments (> 2 mm). The occurrence of coarse particles in soils was rare in our study area, and thus F was negligible. Soil total nitrogen density (STND) was also calculated similar to SOCD calculation.

2.4. Statistical analyses

In our study, 39 samples were randomly selected from the 78 samples as one group (group 1) to build a linear regression equation between the SOCD in 0–20 cm depth and 0–100 cm depth. Using the modeled equation obtained from group 1, the measured SOCD in 0–20 cm depth of the other group (group 2) was used to calculate the predicted SOCD in 0–100 cm depth, which was further compared with the measured SOCD in 0–100 cm depth of group 2. Their differences were tested using paired-sample *t*-test. In addition, all the 78 samples were used to build the linear regression equation between SOCD and STND in 0–100 cm depth.

All statistical analyses were performed using the SPSS 18.0 statistical package (SPSS Inc., Chicago, IL, USA). The figure of SOCD spatial distribution was created using the Geostatistical tool package of ArcGIS (Environmental Systems Research Institute Inc., Redlands, CA, USA). Figures were drawn using Origin 8.5 software (Origin Lab Inc., Washington, USA). The SOC concentration was normally distributed, as indicated by shape parameters (skewness and kurtosis) of the data ($P > 0.05$) which met the requirement of geostatistical analysis.

The relationships between the measured SOCD in 0–20 cm and in 0–100 cm, measured and predicted SOCD in 0–100 cm, measured SOCD and STND in 0–100 cm were examined using linear regressions and paired-sample *t*-test. One-way analysis of variance (ANOVA) and bivariate correlations were performed to examine the relationships between the SOC and the influence factors (soil depth, BD, soil texture, soil pH, elevation). The different differences in SOCD among layers were tested by one-way ANOVA with Tukey; the differences in SOCD between DC and RP at the given layer in each county were tested by independent-sample *t*-test. Statistical significance was determined at the 95% confidence level.

3. Results

3.1. Soil BD, clay content, and SOC content in soil profile

Soil BD increased significantly ($P < 0.05$) with increasing depth, but the vertical profile distribution was significant different among three counties (Fig. 2A). Soil BD in Baoqing County reached the maximum at the depth of 40 cm at a depth of 100 cm for Lindian and Hailun Counties (Fig. 2A). The highest clay contents were observed in Baoqing County (Fig. 2B). In addition, the surface (0–20 cm) clay contents were significant ($P < 0.05$) lower compared with the layers below 60 cm in Baoqing. There were no significant differences among layers in Lindian and Hailun Counties. Soil pH was > 7.0 across the profile in Lindian, and significantly ($P < 0.05$) higher than those in Hailun and Baoqing (Fig. 2C). In addition, no significant differences in pH value were observed among layers in Hailun and Baoqing, whereas it was significantly lower in the surface 20 cm than those below 20 cm in Lindian County.

The SOC concentration decreased with the depth in the three counties, and their variations also decreased with the depth (Fig. 3). The SOC concentration showed negative relationships with soil depth ($r = -0.720$, $P < 0.01$), soil bulk density ($r = -0.762$, $P < 0.01$), clay content ($r = -0.120$, $P < 0.05$), and pH value ($r = -0.352$, $P < 0.01$), and a positive relationship with elevation ($r = 0.205$, $P < 0.01$). While SOC concentration showed negligible correlations with sand and silt contents ($P > 0.05$).

3.2. SOCD in soil profile

The SOCD at a depth of 0–100 cm throughout our study area ranged from 52.3 to 323.1 Mg ha^{-1}, with an average of 163.6 Mg ha^{-1}. Among the three counties, the highest SOCD was observed in Hailun (229.3 ± 46.8 Mg ha^{-1}), followed by Baoqing (156.8 ± 57.7 Mg ha^{-1}) and Lindian (98.2 ± 19.7 Mg ha^{-1}). The average SOCD for each layer (0–20, 20–40, 40–60, 60–80, and 80–100 cm) of the three Counties accounted for 32.8%, 23.8%, 18.2%, 13.7%, and 11.6% of total SOCD in the 0–100 cm soil depth, respectively. The proportion at 0–20 cm was the highest among these layers, and with increasing soil depth, the SOCD significantly decreased. Except the 40–60 cm layer in Baoqing County, no significant differences in SOCD were found between the dry croplands and rice paddies in all layers of the three counties (Table 2).

The SOCD in 0–100 cm depth was significantly related with the SOCD in 0–20 cm depth ($R^2 = 0.618$, $P < 0.01$, Fig. 4A). A good model fitting was also observed between the predicted and measured SOCD in 0–100 cm layer ($R^2 = 0.602$, $P < 0.01$, Fig. 4B). In addition, the relationship between SOCD and the STND in 0–100 cm can be well fitted using a linear equation ($R^2 = 0.666$, $P < 0.01$, Fig. 4C).

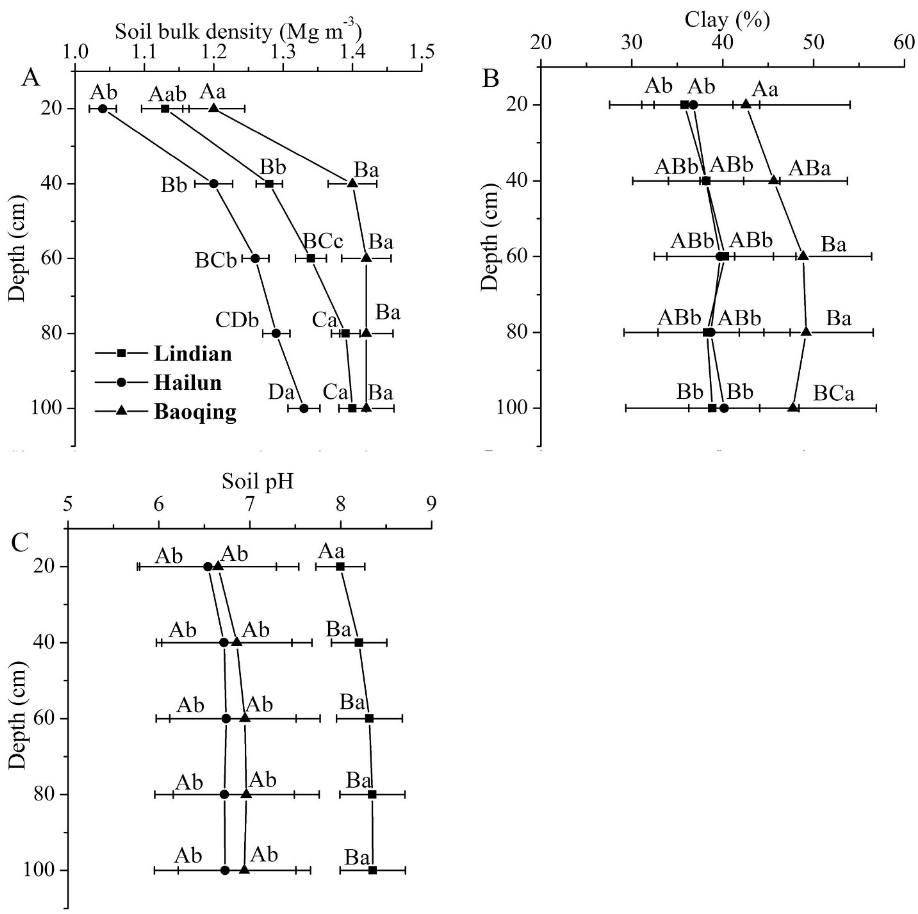

Fig. 2. Vertical distribution of soil bulk density (A), clay content (B), and pH value (C) in soil profiles in Lindian (n = 25), Hailun (n = 28), and Baoqing Counties (n = 25) in northeast China. Different lowercase letters within the same horizon represent significant ($P < 0.05$) differences among counties; different capital letters for each county represent significant ($P < 0.05$) differences among layers. The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

3.3. Spatial distribution of SOCD

The distribution maps of ordinary kriging showed that the high patches of SOCD were gradually transformed to low patches from north to south of Lindian County, suggesting a gradient effect (Fig. 5). In Hailun, the highest SOCD was observed in the central area and the lowest in the south. While for Baoqing, the highest was found in the southwest of the county.

4. Discussion

4.1. SOCD distribution and stock

Using Multi-Purpose Regional Geochemical Survey data, Xi et al. (2011) reported that the SOCD was 149.0 Mg ha^{-1} for croplands in Heilongjiang Province. Our study indicated that the average SOCD was 161.4 Mg ha^{-1} in 0–100 cm for Lindian, Hailun, and Baoqing Counties, which was slightly higher than the average of the province. Our study showed that the SOCD in 0–20 cm depth accounted for about 32.8% of 0–100 cm depth, which was similar to the previous reported percentage of approximately 35% (Ding et al., 2013; Sun et al., 2004). This percentage can be used to estimate the subsoil C in 0–100 cm in the areas where SOC data is lacking. The SOCD decreased significantly with increased soil depth in this study (Table 2), which has been extensively reported globally (Ding et al., 2013; Wang et al., 2017). Many reports showed that soil organic matter is easier to accumulate in rice paddy than upland soils, especially in topsoil, due to lower decomposition rate resulting from surface waterlogging (Liu et al., 2006b). Thus, the average SOCD in paddy field is generally higher than that in dry croplands (Pan et al., 2004; Yu et al., 2004). However, we did not find significant differences in SOCD between paddy field and dry croplands in the present study (Table 2), which indicated that the differences in SOCD between land uses were influenced by many factors, such as soil layers and soil types (Liu et al., 2006b).

Estimating soil C stock of the deeper layers in a large region is time-consuming, laborious, and expensive. If the SOC stock of topsoil can be used to accurately estimate SOC stock of subsoil, it will save time and cost to estimate C stock in soil profiles. In our study, the good model fittings between the SOCD in 0–100 cm depth and that in 0–20 cm depth ($R^2 = 0.618$, $P < 0.01$, Fig. 4A) and between the predicted and measured SOCD in 0–100 cm layer ($R^2 = 0.602$, $P < 0.01$, Fig. 4B) suggests that SOCD in a soil profile (0–100 cm) can be estimated based on the data obtained from the topsoil (0–20 cm). In addition, the significant relationship between SOCD and the STND in 0–100 cm ($R^2 = 0.666$, $P < 0.01$, Fig. 4C) indicates that the STND in a profile can also be estimated with SOCD data. These relationships would be useful tools to estimate SOC and STN in subsoil based on numerous previous studies with only shallow sampling data. But the estimation should be made with due caution and based on the following condition: the relationship of SOC between topsoil and subsoil can be modeled by mathematical equations. In addition, the pattern of SOC distribution in soil profile should be relatively stable in long term. Furthermore, because of the differences in geomorphology, topography, slope, parent material, and land use, the distribution of SOC is different among different soil types. Therefore, low soil classification units, such as subclasses or soil genera, are suggested to be used to establish models to improve the estimation accuracy (Sun et al., 2003). Since the topsoil is under a dynamic state with agricultural management, the latest surface data obtained from fields should be used to estimate the subsoil SOC stock (Ma et al., 2014).

Generally speaking, the spatial variation of soil properties is mainly influenced by human activities (such as land use, soil management) in a

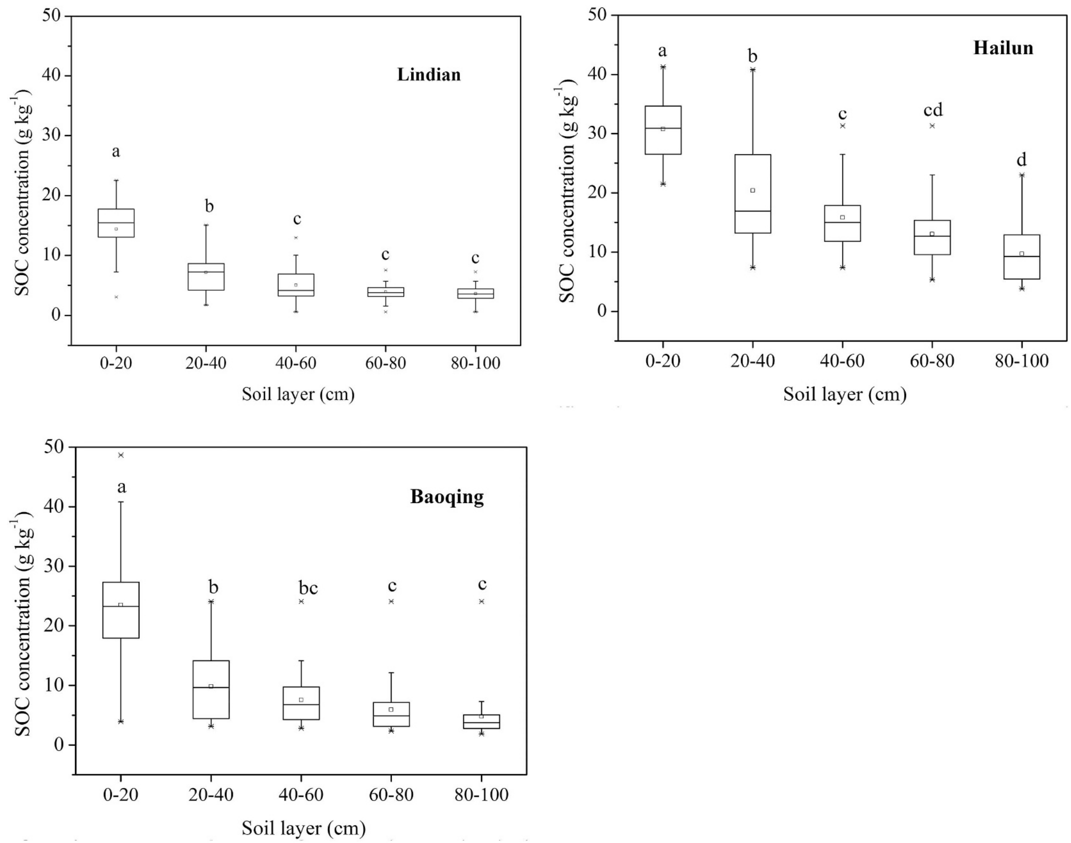

Fig. 3. Box plot of soil organic carbon (SOC) concentration at 0–100 cm depth in Lindian (n = 25), Hailun (n = 28), and Baoqing (n = 25) Counties in northeast China. The boxes indicate the range of the 99% confidence interval and the line inside represents the median. The top and lower bars are the maximum and minimum values, respectively. The different lowercase letters represent the significant differences at $P < 0.05$ among layers. The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

small scale, while in a large scale it is mainly controlled by climate, parent material and other factors (Ponge et al., 2014; Yemefacka et al., 2005). In our study, the maximum county value of SOCD was located at north for Lindian, central in Hailun, and southwest in Baoqing Counties. The distribution pattern is likely owing to the difference in the air temperature, monsoon circulation, intensive cultivation, and land reclamation time (Li et al., 2016; Liu et al., 2006a). However, these related data (e.g., cultivation history) are lacking in our study area, and thus future studies are needed to allow future enhancements to the soil C model.

4.2. The factors influencing SOC distribution

4.2.1. Soil depth

Consistent with many previous studies (Hobley et al., 2015; Li et al., 2013b), SOC concentration decreases with soil depth as shown above. The relationship between SOC and the depth can be modeled using a regression function ($r = -0.720$). Similar findings have been reported

Table 2
The distribution of soil organic carbon density (SOCD, Mg ha^{-1}) at different depth (0–20 cm, 20–40 cm, 40–60 cm, 60–80 cm, and 80–100 cm) in soil profile of dry croplands (DC) and rice paddies (RP) in Lindian, Hailun, and Baoqing Counties in northeast China. The different lowercase letters with the same line represent significant ($P < 0.05$) differences in SOCD among layers. The P values represent significance between DC and RP at the given layer in each county at the 0.05 probability level.

Layers		0–20 cm	20–40 cm	40–60 cm	60–80 cm	80–100 cm	0–100 cm
Lindian	DC (n = 20)	35.3 ± 4.7 a	23.4 ± 7.7 b	16.8 ± 8.3 c	10.5 ± 4.1 d	10.6 ± 4.1 d	96.6 ± 19.4
	RP (n = 5)	43.8 ± 5.8 a	12.0 ± 5.8 b	24.9 ± 12.4 b	12.7 ± 5.4 b	11.2 ± 6.9 b	104.7 ± 21.7 b
	P value	0.33	0.49	0.21	0.43	0.21	0.55
Hailun	DC (n = 23)	63.2 ± 13.3 a	50.5 ± 19.1 ab	46.0 ± 20.8 bc	35.6 ± 12.6 cd	30.3 ± 10.3 d	225.6 ± 47.9
	RP (n = 5)	72.0 ± 12.8 a	61.0 ± 14.5 ab	43.8 ± 15.3 bc	36.8 ± 14.6 bc	28.1 ± 14.4 c	241.8 ± 43.0
	P value	0.90	0.36	0.59	0.68	0.43	0.76
Baoqing	DC (n = 14)	53.2 ± 19.2 a	44.8 ± 21.4 ab	27.1 ± 16.4 bc	22.5 ± 14.8 c	19.0 ± 13.9 c	166.7 ± 68.6
	RP (n = 11)	60.9 ± 16.9 a	37.1 ± 11.9 b	19.3 ± 8.2 c	15.3 ± 7.3 c	10.6 ± 6.0 c	143.2 ± 39.5
	P value	0.88	0.12	0.02	0.06	0.14	0.15

Data represents means ± standard deviation. The different lowercase letters with the same line represent significant ($P < 0.05$) differences in SOCD among soil layers. The P values represent significance between DC and RP at the given layer in each county at the 0.05 probability level. The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

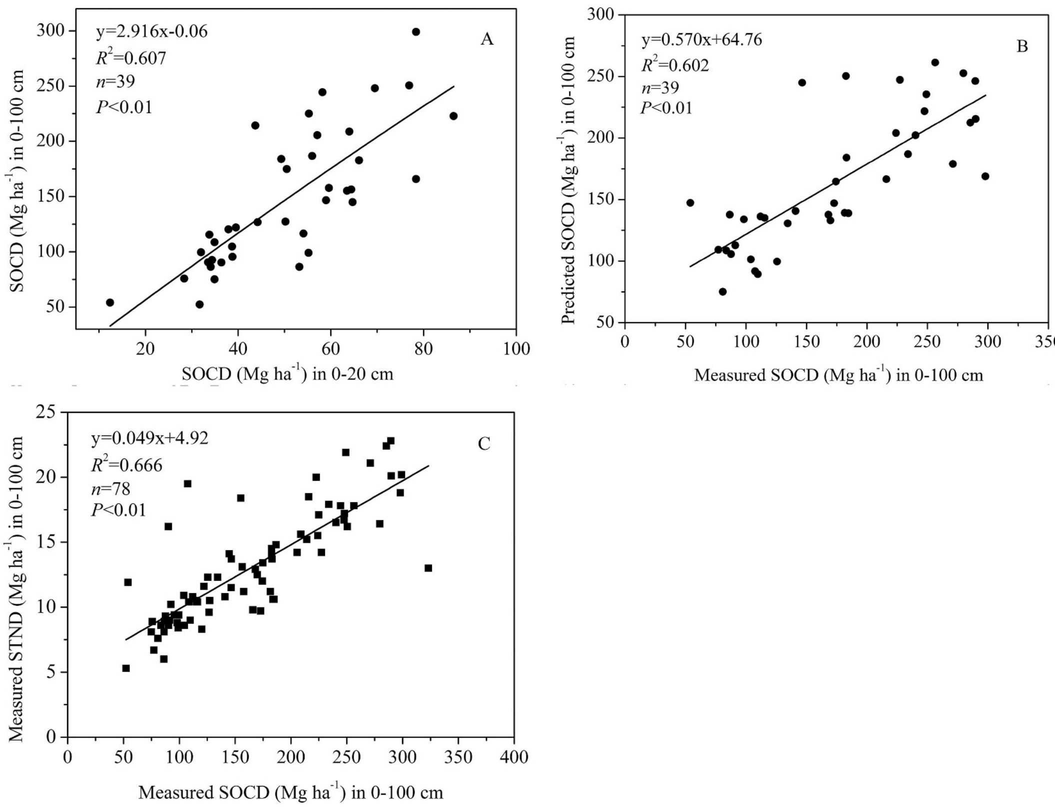

Fig. 4. Relationships between measured soil organic carbon density (SOCD) in 0–20 cm depth and measured SOCD in 0–100 cm depth (A), between measured SOCD in 0–100 cm depth and predicted SOCD in 0–100 cm depth (B), and between measured SOCD in 0–100 cm and measured soil total nitrogen density (STND) in 0–100 cm depth (C). The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

in previous studies (Wang et al., 2017), who reported that the SOC concentration and depth could be well described by the power function ($R^2 > 0.9$). The content of SOC depends on the balance of C inputs and outputs in soils. The distribution of SOC in soil profile is usually influenced by the vertical distribution of crop root system (Li et al., 2013a). The decreased variation of SOC content with soil depth (Table 2) indicated that the influence of crop root and soil management on SOC becomes less with increasing soil depth. In addition, SOC

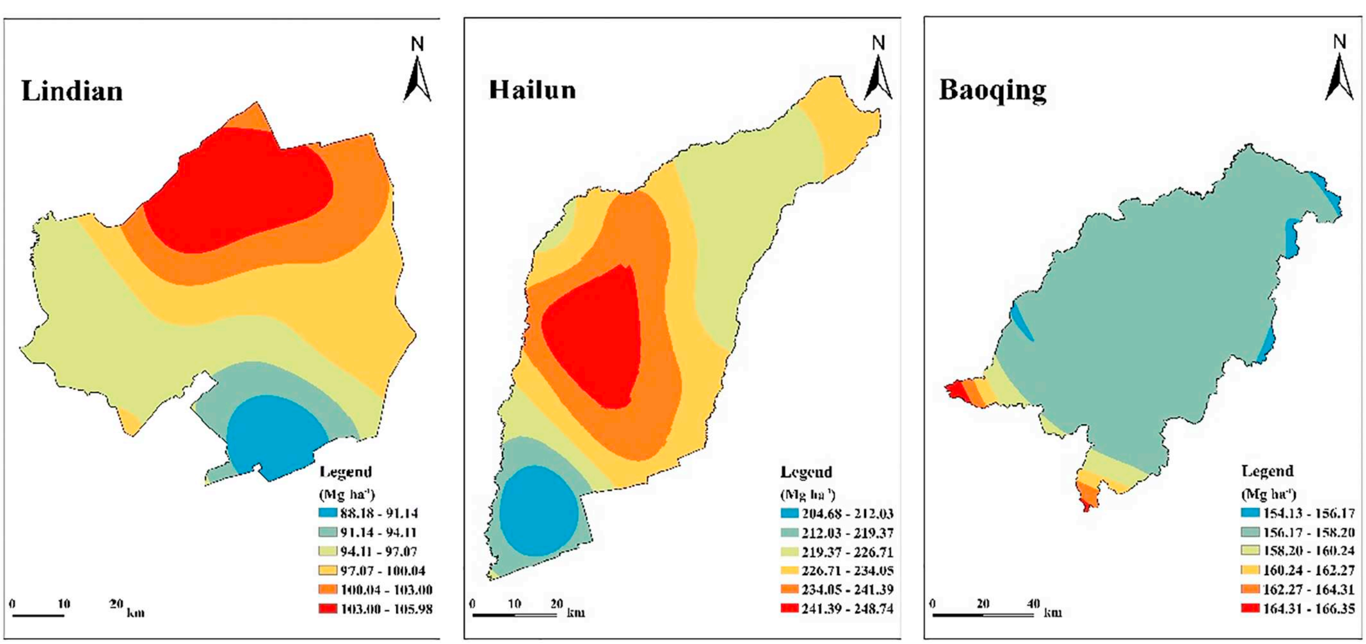

Fig. 5. Spatial distribution map of soil organic carbon density in Lindian (n = 25), Hailun (n = 28), and Baoqing (n = 25) Counties in northeast China. The main soil types are Haplic Chernozems and Haplic Phaeozems in Lindian County, Luvic Phaeozems and Haplic Chernozems in Hailun County, and Haplic Chernozems and Albic Luvisols in Baoqing County, according to the FAO/UNESCO soil classification.

content varied significantly in a given soil layer among the different Counties, suggesting that SOC content and its distribution in the soil profile depended on study locations which determine soil types and parent material.

4.2.2. Soil bulk density

Soil BD characterizes the compaction of soil and its water permeability and is an important index used to assess SOC (Howard et al., 1995). Soil BD information for entire soil profiles is usually lacking for many large-scale soil inventories (Allen et al., 2010; Kaur et al., 2002) due to the time needed to do deep BD sampling. One approach is to use the average BD for the lack of BD data (Wiesmeier et al., 2012; Wu et al., 2003), and another way is to use the regression function built from measured SOC concentration and BD data (Xu et al., 2011). In our study, the relationship between SOC concentration and BD can be expressed as a function ($y = -0.0132x + 1.45$, $R^2 = 0.582$, $P < 0.01$) (Fig. 5). However, the estimation of BD is influenced by soil structure and pedotransfer functions (Xu et al., 2015), and thus should be cautiously used to estimate BD data in specific soil profiles.

4.2.3. Clay content

Clay content is suggested as another critical parameter related to SOC concentration. Soils with higher clay content usually have higher soil moisture content and lower permeability. Thus, in these soils, the aerobic microbial activity is restrained to a certain extent, and soil organic matter accumulates. Many investigations report that clay protection usually favor SOC accumulation (Paul, 1984), but here it was not true for the SOC distribution. Our results showed SOC concentration had a weak negative correlation with clay content. This finding could be attributed to the following hypothesis. In the present study region, due to the concentrated precipitation in the July and August, the soils are likely subject to clay migration and leaching illuviation from topsoil to subsoil in the soil profile, as confirmed by the lower clay content in the topsoil than the subsoil (Fig. 2B). The clay illuviation probably contributed to the negative relationship between SOC content and clay amount in soil profiles. In addition, previous studies have shown that SOC content can be jointly affected by soil texture, climate factors, and soil depth (Wang et al., 2013).

4.2.4. Soil pH and elevation

By directly affecting species, size and activity of soil microorganisms (Aciego Pietri and Brookes, 2009), soil pH can affect SOC decomposition and further soil C density. Previous studies considered that SOC concentration was significantly correlated with soil pH (Ou et al., 2017; Suarez and Gonzalez-Rubio, 2017). In contrast, a negative correlation of soil pH with SOC content was observed in the present study ($r = -0.352$, $P < 0.01$). This finding could result from the contrasting responses of soil pH and SOC content to increasing N fertilizer application. Nitrogen is one of the main nutrients that contributes to biomass production. Its application generally results in an increase in root biomass with increasing yield production, and thus, with increases of organic matter and N inputs, SOC content can increase. Meanwhile, N application has been widely recognized as one of major factors of soil acidification (Guo et al., 2010). Therefore, the increase of SOC and decrease of soil pH with fertilization, usually from excess N application, could be responsible for their negative relations.

By affecting temperature, vegetation, and soil moisture content, elevation indirectly affects soil properties, and further alters plant litter quantity and quality, and thus SOC accumulation. In many studies, SOC content has a significant correlation with elevation (Li et al., 2017; Tesfaye et al., 2016; Tsui et al., 2013). In our study, the positive relation of SOC content with elevation ($r = 0.205$, $P < 0.01$) might be jointly caused by several factors. The lower temperature in areas with higher elevation might favor soil C accumulation owing to lower C decomposition. In addition, the area with lower elevation is usually subject to intensive cultivation, which probably contributes to greater soil C loss compared to these areas with higher elevation (Li et al., 2016).

5. Conclusions

The study revealed the SOC distribution and amounts in Northeast China croplands. The SOC content and its variation significantly decreased with increasing soil depth. The SOCD at a depth of 0–100 cm ranged from 52.3 to 323.1 $Mg\ ha^{-1}$, with an average of 163.6 $Mg\ ha^{-1}$. The relationship of SOCD in 0–20 cm and 0–100 cm depth would be a useful tool to estimate SOCD in subsoil with topsoil SOCD data. The negligible differences in SOCD between dry croplands and rice paddies indicated that the changes in SOCD with land use change was probably influenced by other factors, such as soil layers and soil types. Regression of SOC in the data set to individual factors (soil depth, BD, soil pH, clay content, and elevation) is relevant to understand how C changes over time and depth.

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