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Cropland soil organic matter content change in Northeast China, 1985-2005

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Abstract: Soil organic matter (SOM) content is one of the most important indicators of soil quality and hence the productive capacity of soils. Northeast China (NEC) is the most important region in grain production in China. In this study, we assessed the spatiotemporal change of cropland SOM content in NEC using sampling data of 2005 and survey data of 1985. We also analysed the driving forces behind the SOM content change. Our results showed that SOM content decreased in 39% of all the cropland in NEC, while increase in SOM content was only detected on 16% of the cropland. SOM remained unchanged in nearly half (i.e. 45%) of the cropland. Our results also revealed that cropping intensity and fertilizer application were the two most important factors driving SOM change. Overall, results from this research provided novel details of the spatiotemporal patterns of cropland SOM content change in NEC which was not revealed in earlier assessments. The datasets presented here can be used not only as baselines for the calibration of process-based carbon budget models, but also to identify regional soil quality hotspots and to guide spatial-explicit soil management practices.

Keywords: Agriculture, Geostatistics, Kriging, Soil quality, Organic carbon, Change attribution

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1 Introduction

Soil is a vital non-renewable natural resource which plays many essential roles in terrestrial ecosystems. The productive capacity of soils in particular, underlies the foundation of the well-being of humanity on Earth. Soil organic matter (SOM) content is one of the most important indicators of soil quality and hence the productive capacity of soils [1–3]. Therefore assessment of SOM content change in space and time is of great importance for food security decision-making both globally and in populous countries like China [4–8].

Northeast China (NEC) is one of the most important regions in grain production in China. In 2009, it produced 15% of the country's total grain output on 17% of the country's cropland, resulting in a much higher regional level of per capita grain of 620 kg than the national average level of 370 kg. However, soil fertility in NEC has been observed declining after long-time cultivation of agricultural crops [9, 10]. Assessments suggested that the magnitude of this decline could be as high as 30-40% and 60% after 20 and 100 years of agricultural land use respectively [11], posing risks to the stable supply of food either for the region or for the country as a whole. Moreover, crop production has been increasingly intensified in NEC since the 1980s alongside the general warming trend observed in the region. The cropping intensity, or the ratio between sown area and cropland area, increased from 66% in 1985 to 87% in 2005 [12] at an average rate of 1% yr^{-1}, casting uncertainties on current SOM levels in regional cropland.

During the past decade, research efforts have increasingly focused on improving our knowledge about soil C enhancement and its potential to offset atmospheric CO2 concentrations and safeguard national food security in China. The majority of the research employed processed-based C budget models to characterize historical patterns and predict future trends, such as DNDC [13], RothC [14] and Agro-C [15]. However, empirical studies revealing spatial changes of soil C since the 2nd National Soil Survey (NSS-2), which was conducted in the 1980s, are still lacking, especially at regional scale. The objectives of this paper are therefore to (1) assess the spatiotemporal change of SOM content in NEC using data from NSS-2 in 1985 and from the grid sampling of SOM in 2005 under the Cropland Fertility Monitoring Network (CFMN) program in China [16]; (2) characterize spatial and temporal patterns in SOM content change at the regional scale; and (3) reveal major factors driving SOM change in Northeast China over space and time.

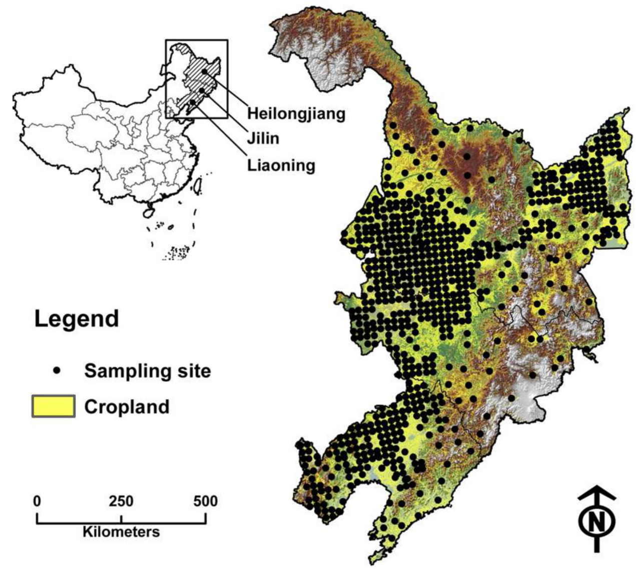

Figure 1: SOM sampling sites in Northeast China in 2005. A sampling site is represented by a black dot on map. The underlying digital terrain is extracted from the USGS 30 arc-second global elevation dataset [52].

2 Methods

2.1 SOM sampling and interpolation

NEC occupies a land mass of 788,000 km^2 and consists of three provinces: Heilongjiang, Jilin and Liaoning. Cropland is accounted for 21% of the land mass or 16.4 million ha. In 2005, a regular grid of 20×20 km was established on cropland in NEC with a total of 750 composite sampling sites (Figure 1). At each site, three to five points were randomly selected within a radius of 100 m where the topsoil (0-20 cm) was sampled. These samples were pooled for laboratory analysis. Organic carbon content was determined using the Walkley-Black wet combustion method [17], the same method as in 1985 for NSS-2. The soil organic carbon (SOC) content was measured directly by chemical oxidation with a mixture of dichromate and sulphuric acid solutions. Heat was applied at 170°C to accelerate the reaction. A correction factor of 1.1 was adopted to compensate the incomplete oxidation. The obtained SOC content was then converted to SOM content by using the inverse of the van Bemmelen index of 0.58 [18, 19]. The SOM measurements were statistically analysed to reject outliers and tested for normal distribution. Values that lie more than 1.5 times of the inter-quartile range from the first or the third quartile were considered as outliers [20] and rejected. Normality was achieved by logarithmic transformation of the outlier-free SOM data, and confirmed by the Shapiro-Wilk test [21]. This statistically processed point dataset of SOM observations in 2005 was finally interpolated into a continuous surface of 1 km spatial resolution using ordinary kriging [19, 22].

The soil map of NEC at the scale of 1:4 million was obtained from the National Soil Survey Office [23] based on soil survey conducted in NEC in 1985 as part of the NSS-2. In total, 314,813 samples were taken from the top soil in NEC at an average sampling density of 1 sample per 67 ha of cropland [23]. Vector-format soil maps were produced from these samples at the scale of 1:10,000 in the county level, and upscaled to 1:1 million at the provincial level and finally to 1:4 million at the national level. The SOM attribute associated with this 1985 soil map was given in value ranges or classes (Table 1) derived from multiple samples within a single soil mapping unit. It was a common practice to report SOM classes in NSS-2, as stipulated by the National SOM Grading System of China [23, 24]. Although the soil map in 1985 was produced based on a dense sampling scheme, these samples were not georeferenced due to technological limitations. Consequently, a revisit to the exact 1985-sampling localities in 2005 was unfeasible. In order to compare the SOM maps in 1985 and in 2005, therefore, the SOM attribute was extracted from the vector soil map in 1985 and converted to a grid map at 1 km spatial resolution using the centre-point value assignment method implemented with the Spatial Analyst extension of the ArcGIS 9 software package.

Table 1: Cropland area change per SOM class in Northeast China, 1985-2005.

SOM class	SOM range (w/w %)	1985		2005		Area change million ha	Percentage change
		million ha	percent	million ha	percent		
I	< 0.6	0.27	0.9	0.51	1.8	0.25	0.9
II	0.6–1.0	1.32	4.7	2.03	7.2	0.71	2.5
III	1.0–2.0	5.11	18.0	7.95	28.1	2.85	10.1
IV	2.0–3.0	4.22	14.9	3.92	13.8	-0.30	-1.1
V	3.0–4.0	6.79	24.0	3.99	14.1	-2.80	-9.9
VI	4.0–8.0	9.66	34.1	9.90	35.0	0.24	0.9
VII	> 8.0	0.93	3.3	0.00	0.0	-0.93	-3.3
I–III	< 2	6.70	23.7	10.50	37.1	3.80	13.4
V–VII	> 3	17.39	61.4	13.89	49.1	-3.50	-12.4

2.2 Geostatistical model estimation and validation

Ordinary kriging (OK) was employed to model the spatial variability of measured SOM samples and to predict SOM values at unsampled locations. The prediction is based on the following model:

$$Z(S) = \mu + \varepsilon(S), \tag{1}$$

where μ is the location-irrelevant trend term and $\varepsilon(S)$ is the spatially correlated stochastic error term. The SOM content, Z, at an unsampled location S_0, $\hat{Z}(S_0)$, is estimated as the weighted average of n neighboring samples of S_0:

$$\hat{Z}(S_0) = \sum_{i=1}^{n} \{\lambda_i \cdot Z(S_i)\}, \tag{2}$$

where λ_i is the kriging weight assigned to sampling site S_i. The weighting factor λ_i is estimated by using the semivariances γ derived from neighboring samples:

$$\gamma(h) = \frac{1}{2}[Z(S_i) - Z(S_i + h)]^2, \tag{3}$$

where h is the distance between two neighboring samples. A set of n point observations yield $0.5n(n-1)$ sample pairs. A mathematical model (e.g., spherical, exponential or Gaussian model) is then fitted to the semivariance-distance plot, which is called a variogram, to minimize the variance of errors and the parameters of this variogram model are used to assign weights in OK interpolation.

The goodness of a fitted variogram model was evaluated using the leave-one-out cross validation (LOOCV) method [19] based on the following three measurements of errors: the root-mean-squared error (RMSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{Z}(S_i) - Z(S_i)\right)^2}, \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=i}^{N}\left|\hat{Z}(S_i) - Z(S_i)\right|, \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=i}^{N}\left\{\frac{\left|\hat{Z}(S_i) - Z(S_i)\right|}{Z(S_i)} \cdot 100\right\}, \tag{6}$$

where $Z(S_i)$ and $\hat{Z}(S_i)$ are measured and predicted SOM levels, respectively, at location S_i, and N is the number of validation sites.

2.3 Detection of SOM content change

To compare with the SOM classes in 1985, the kriging-interpolated SOM content values in 2005 were grouped into SOM classes as given in Table 1. The map of cropland SOM content change between 1985 and 2005 was obtained by deducting the SOM content map in 1985 from the map in 2005. A SOM content change was only detected when the SOM content in 2005 was one class higher or lower than the SOM content in 1985.

2.4 Factor analyses

Single- and multi-factor regression analyses were employed to reveal the cause-effect relationships between SOM content change and crop management practices. Two indicators, namely cropping intensity and fertilizer application, were used to represent crop management practices. Cropping intensity was characterized by the total sown area of all agricultural crops per grid cell. The grid dataset of crop areas in 1985 and 2005 was obtained from the Chinese Academy of Agricultural Sciences [25]. The dataset was produced using a plausible spatial disaggregation method, cross-entropy, on the basis of multiple data sources including crop area and yield census, satellite imagery of crop distribution and irrigation, crop suitability map, etc. [25]. The grid dataset of the application rate of mineral fertilizers and manures in crop production in circa 2000 was obtained from the Center for International Earth Science Information Network [26]. The R statistical software package [27] was used to conduct the regression analysis.

3 Results

3.1 Sampling results

The results of the laboratory analysis showed that the SOM content of the soil samples taken from cropland in NEC in 2005 was averaged at 2.7%, with a standard deviation of 1.9% (Table 2). This corresponds to a SOC content level of 1.46±0.98%.

3.2 Kriging interpolation and validation

Three types of variographic models were fitted to the semivariogram calculated from the SOM sampling dataset in 2005. These included the spherical, exponential and Gaussian models (Table 3). The prediction performance of each fitted semivariogram model (Figure 2) was tested using the LOOCV method [19] and given in Table 3. The results showed that the obtained exponential model had the highest performance in predicting SOM contents at unsampled locations.

3.3 Cropland SOM contents in 1985 and 2005

The spatial distribution of cropland SOM content in terms of SOM classes [23], based on NSS-2 in 1985 and CFMN in 2005, is given in Figures 3a and 3b. These two maps showed that cropland in the northeastern NEC had considerably higher SOM content, indicated by the dominant greenish colours, than in the southwestern NEC where the dominant colours were brownish. This downward gradient of SOM along the northeastern-southwestern axis was largely persisted during the 1985-2005 period, supporting earlier findings either at regional scale in NEC [28] or at national scale [5, 29]. Area statistics (Table 1) showed that Class VI (i.e. SOM content ranging at 4-8%) covered an area of 9.66 million ha or 34.1% of all the cropland in NEC in 1985. In 2005, Class VI still took the largest area share of 35.0%, a small increase of 0.9% since 1985. However, the biggest increase in cropland area was attributed to Class III which expanded from 5.11 million ha in 1985 to 7.95 million ha in 2005 by a margin of 10.1%. To the contrary, area of Class V was observed to decrease substantially by 9.9%, from 6.79 million ha in 1985 down to 3.99 million ha in 2005 (Table 1). Overall, cropland with SOM < 2% including Classes I through III occupied an area of 10.50 million ha in 2005, a 13.4% increase since 1985 (see the expansion of reddish/brownish-colour regions marked by annotations A and B on maps in Figure 3). Area statistics also showed that cropland of SOM classes IV, V and VII occupied an area of 11.94 million ha or 42.2% in 1985; but in 2005 the area collectively taken by these three classes shrank to a mere of 7.91 million ha or 27.9%.

3.4 SOM content change between 1985 and 2005

The SOM content change between 1985 and 2005 in terms of changes in SOM classes from 1985 to 2005 is shown in Figure 3c. Spatial statistics revealed that cropland with decreasing SOM classes was accounted for 11.05 million ha or 39% of total cropland area in NEC (e.g. annotations A and B in Figure 3c). In contrast, the area of cropland whose SOM classes were increased during the same period was much smaller. An increase in SOM content was identified only on 4.43 million ha or 15.7% of all the cropland in NEC (e.g. annotation C in Figure 3c). Spatial statistics also revealed that SOM in nearly half (i.e., 45.31%) of the cropland in NEC remained unchanged during the last 20 years. Cropland with decreasing SOM was mainly located in southwestern Heilongjiang, the bulk of Jilin and eastern Liaoning province. Large areas in Heilongjiang province, especially in the Three-River Plain in the northeast of the province, had stable or improved SOM levels.

3.5 Attribution of SOM content change

Results of the single- and multi-factor regression analyses (Table 4) showed that the SOM class change between 1985 and 2005 (Figure 3c) was closely related to cropping intensity change (Figure 4a) and to the application of mineral fertilizers and manures (Figure 4b) during the same period. Linear relationships were successfully established taking SOM class change as the response variable and cropping intensity change (Figure 4c, R^2 = 0.82) or fertilizer application (Figure 4d, R^2 = 0.89) as the explanatory variable. Results also showed that variations in crop-

Table 2: Descriptive statistics of the SOM sampling dataset in 2005, %.

Data	Variation				Quartiles		
set	Min	Max	Mean	Standard deviation	Q1	Median	Q3
N = 750	0.1	9.62	2.7	1.9	1.0	2.3	3.95

Table 3: Semivariogram models fitted to the SOM sampling data in Northeast China in 2005 and their prediction performances. The prediction performance is measured both by the coefficients of a linear trend in the form of $y = a + bx$ fitted to the predicted versus measured data, and by the prediction error resulting from the cross validation of the models.

Model	Model fitting				Cross validation					
type	Range (m)	Sill	Nugget	Lag (m)	a	b	R^2	RMSE	MAE	MAPE (%)
Spherical	371280	0.2664	0.2492	44618	0.65	0.80	0.64	1.04	0.78	52.31
Exponential	442821	0.3368	0.1992	44618	0.45	0.85	0.73	1.03	0.78	51.27
Gaussian	319339	0.2268	0.2903	44618	0.70	0.78	0.62	1.08	0.81	54.45

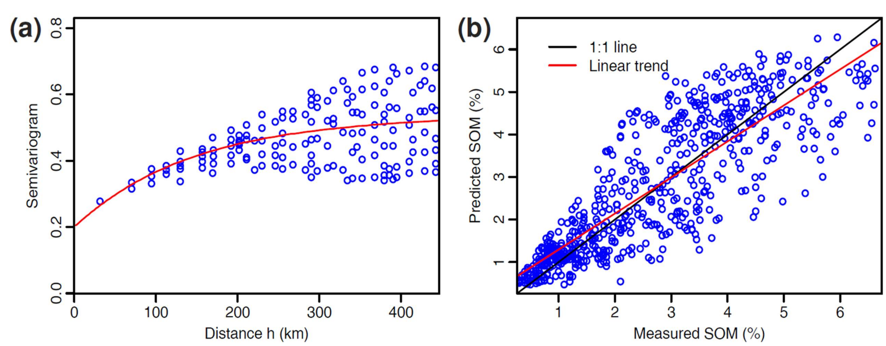

Figure 2: Semivariogram fitted with an exponential model (a) and cross validation of the obtained variogram model (b) for the interpolation of SOM content in 2005. The obtained linear regression equation in (b) is $y = 0.85x + 0.45$ ($R^2 = 0.73$).

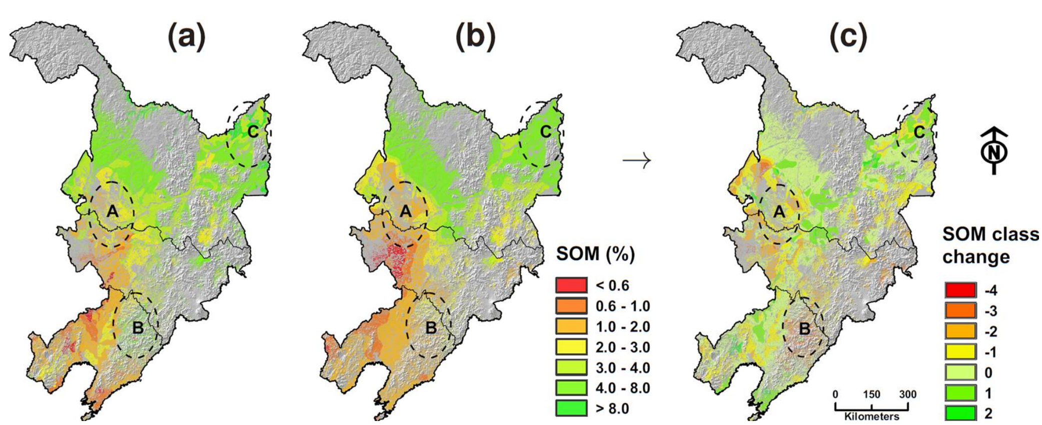

Figure 3: Cropland SOM content in 1985 (a), 2005 (b) and SOM change in terms of content classes between 1985 and 2005 in Northeast China (c). Value 1 in (c) means SOM has increased by one content class from 1985 to 2005, while value -1 means decrease by one class. Dashed ovals annotated by A and B indicate regions where SOM content decreased, while dashed oval C indicates where SOM content increased during the period.

Table 4: Single- and multi-factor regression models in the form of $Y = a + bX_1 + cX_2$ where Y is SOM class change (dimensionless) from 1985 to 2005, X_1 is percent change of cropping intensity (%) from 1985 to 2005 and X_2 is the application rate of fertilizers and manures (kg/ha) in circa 2000.

Predictor	Model obtained	R^2
Cropping intensity change (X_1)	$Y = -0.04X_1$	0.82***
Fertilizer and manure† (X_2)	$Y = -4.51 + 0.11X_2$	0.89***
X_1 and X_2	$Y = -2.63 + -0.02X_1 + 0.07X_2$	0.93***

† Source: Center for International Earth Science Information Network [26]

ping intensity change and in fertilizer application simultaneously could explain 93% of the variations in SOM class change (Table 4). This suggested that both cropping intensity change and fertilizer application were significant predictors of SOM change over time.

The cause-effect relationship characterized in this paper is in accordance with earlier findings that proper application of mineral fertilizers in combination with manures tends to increase the SOM content [30] and that long-term crop cultivation tends to decrease the SOM content [10]. A fundamental difference is that earlier findings were mostly based on controlled experiments, while this finding was established using much larger datasets in space and time. It was not only more robust, but also extended the validity of earlier findings to larger tempospatial scales.

4 Discussion

4.1 Comparison with previous assessments

Comprehensive analyses of spatial change of cropland SOM content in NEC are relatively rare, compared to other regions of the country [18]. Using NSS-2 data from 11 counties in NEC, Yu et al. [29] reported a decrease in topsoil OC stock between 1980 and 2000, contrasting the general upward trend in SOC for China as a whole based on the same data. At national scale, a similar trend was also observed by Yan et al. [18], who compared soil profile data from the periods of 1979-1982 and 2007-2008 and found that SOC slightly increased from 1.20% in 1980s to 1.27% in 2000s for the top layer of Chinese cropland, despite increasing intensity in crop production. However, at the regional scale in NEC, most studies showed a general downward trend in cropland SOM content during the past 20 years. For example, Cheng et al. [31] reported that SOC content declined slightly from 1.70% in 1988 to 1.67% in 2007 according to data from long-term monitoring and experimental stations in NEC. More importantly, this downward trend in cropland SOM content was confirmed by meta-analyses. Using frequency change as an indicator, Pan et al. [32] found that SOC decreased on 49.2% of cropland area in NEC between 1985 and 2006 based on 62 observations published. Similarly, a decrease in SOC content between 1993 and 2006 was found in 74.4% of all the soil samples published in 132 references in NEC [10].

The results obtained in this paper are consistent with these earlier assessments for the detection of a downward trend in cropland SOM in NEC during the past 20 years. But our assessment on the extent of this downward trend in terms of cropland area differs from previous studies [10, 32]. Firstly, we adopted a systematic sampling strategy and collected 750 samples on cropland of NEC, resulting in a considerably fair spatial coverage (Figure 1). The previous assessments, such as those by Huang and Sun [10] or Pan et al. [32], used much more limited data in a somewhat compromised spatial coverage of cropland in NEC. Secondly, we used SOM classes (Table 1) to detect the temporal SOM content change between 1985 and 2005. This approach may be less "sensitive" than using the absolute difference to represent SOM content change as adopted by e.g. Pan et al. [32]. However, it is more robust to use class changes because the results can be more easily verified in field surveys. Moreover, management decisions made based on SOM class changes are more relevant to fertility levels in field and thus more reliable to implement in practice. This is because the adoption of the SOM class change approach is in effect the adoption of a higher threshold in SOM change detection, which consequently lowers the likelihood of false identification of carbon hotspots in soil management.

Overall, the cropland SOM class maps (e.g. Figure 3) resulting from this research provide fairly detailed spatial information, which was absent from earlier assessments, and can be used to assist eco-environmental and agro-economic decision-making at regional scale.

4.2 Spatial change of cropland SOM

Cropland SOM in NEC is observed to decrease along a NE-SW gradient (Figure 3), providing regional evidence to an

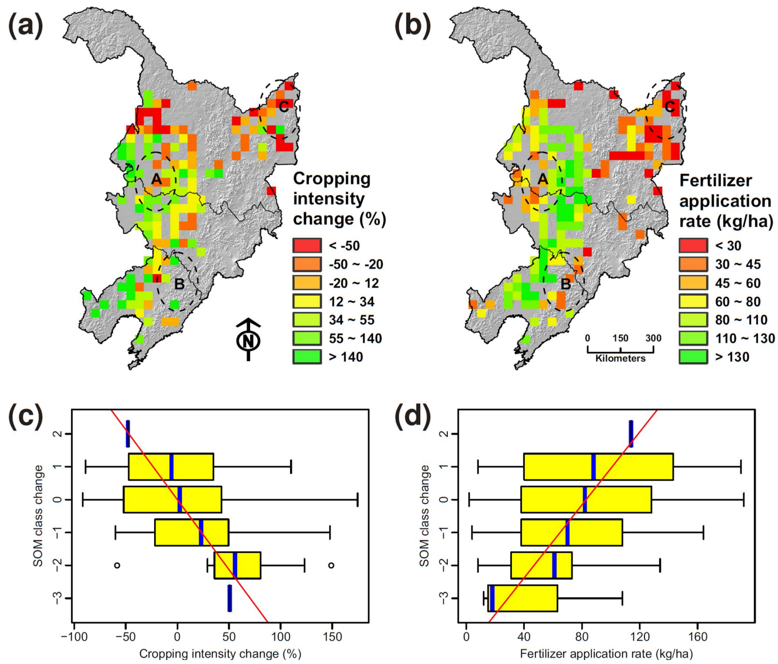

Figure 4: Percent change of cropping intensity between 1985 and 2005 (a) and application rate of mineral fertilizers and manures in circa 2000 (b), and their relationships to SOM class change (c and d), respectively, in Northeast China. The red, solid line in (c) and (d) is the linear trend fitted between the x–axis and y–axis variables; R^2 = 0.82 for (c) and 0.89 for (d). Spatial resolution of maps in (a) and (b) is 40 km. Dashed ovals annotated by A, B and C have the same meaning as in Figure 3.

already observed pattern at the national scale. While the SOM content in NEC is estimated to be the highest among regions in China, surface SOM contents in croplands of the North China Plain [33], the Loess Plateau [34], the Southwest Highlands [35], etc. are found decreasing gradually from the northeast to the southwest of China. The major driving forces for this NE-SW gradient are, among others, climate [36], land use change [37] and soil management [38].

Firstly, temperature is a key factor controlling the rate of decomposition of organic materials in soil [39]. Overall, the SOM mineralization rate on the Southwest Highlands is two times higher than in NEC because of the difference in annual temperatures. The annual temperature varies from 10°C to 21°C in the southwest, but in the northeast the temperature varies at a much lower range, i.e. from -2°C to 10°C. It has been observed in experiments that the mineralization rate doubled for an increase in mean annual temperature by 8-9°C [40]. The observed SOM gradient correlates well with the temperature gradient along the NE-SW axis in China. On the other hand, surface temperature in China has risen 0.8°C in the twentieth century, being consistent with the general global trend [41]. The warming has been observed stronger in NEC and weaker in southwest China. The average annual temperature in NEC has risen 1.0°C in the past 50 years. However, the magnitude of this temperature change is obviously less influential on SOM mineralization rate compared to the temperature difference between northeast and southwest China. Evidence from Belgium, which is in a similar climate zone, also suggested that climate trends have little effect on observed SOC change [42].

Secondly, dynamic changes have occurred to cropland in NEC since the early 1980s. Fertile cropland has been lost to other uses such as infrastructure and urbanization. Large areas of cropland expansion have been observed too. NEC is one of the few regions in China that still have a net gain in cropland area [43]. According to She et al. [44] NEC gained 3 million ha of cropland during 1993-2003, either by converting natural grassland and forestland into cropland (Figure 3, annotation C or northern NEC in general) or by re-cultivating marginal lands which were previously set aside (Figure 3, annotation B or southeastern Jilin). Meanwhile, some 670,000 ha of cropland was lost during the same period. This loss was mainly caused by rapid urbanization during the past few decades. It has been observed that urbanization in NEC followed a reverse NE-SW pattern [45], [Figure 14], meaning that a higher urbanization rate in the southwestern part of NEC took more cropland out of agricultural use than in northeast NEC where the urbanization rate was lower.

Thirdly, management plays an important role in maintaining SOM levels in agro-ecosystems [42]. Although soil-use duration and intensity have a strong impact on SOM content [37, 46], proper management can substantially improve cropland SOM content under intensive farming. Long-term experiments conducted in Gongzhuling [30] in Jilin province and Hailun [28] in Heilongjiang province show that the dual goal of optimal crop yield and higher SOM content can be simultaneously met by fine-tuned application of mineral fertilizers, farmyard manures and crop residues according to nutrient requirements. At the end of the experiments, surface SOM contents were found 20-50% higher under soybean-maize rotation in Jilin and maize mono-cropping in Heilongjiang respectively. This suggests that in addition to climate and land conversion, soil and crop management is another important driver responsible for SOM content variability across NEC.

4.3 Temporal change of cropland SOM content

As observed earlier, cropland SOM tends to increase in northern NEC and decrease in southern NEC during the 1985-2005 period (Figure 3c). In the main part of the Heilongjiang province, for example, SOM content either increased by 1-2 classes or remained unchanged in 2005, compared to 1985. However, different processes are found behind this largely optimistic temporal change of SOM content in the province. In central Heilongjiang province, for example, changes in cropping intensity were hardly observed (Figure 4a); continuous fertilization at near-optimal rates [28] maintained at least a stable SOM level during 1985-2005. Taking the Three-River Plain in northeastern Heilongjiang province (Figure 3c, annotation C) as another example, a 50% decrease in cropping intensity (Figure 4a) and a relatively low fertilizer application rate of 30-40 kg/ha (Figure 4b) were simultaneously observed. The collective effects of these two factors (Table 4) may lead to an increase of SOM by one content class, which is lower than the observed increase of 1-2 classes (Figure 3c). The uncharacterized, residual magnitude of increase in SOM content can be explained by the conversion of grassland or forestland to cropland [43], a phenomenon which is usual in this region but rare in other regions.

A general pattern on cropland SOM content change between 1985 and 2005 is that cropland with lower-than-average SOM levels was gaining area from cropland with higher SOM levels, meaning that cropland SOM content tends to decrease when the initial SOM content is high. As shown in Table 1, the area of cropland with SOM > 3% decreased by a margin of 3.5 million ha or 12.4% from 1985 to 2005, while the area of cropland with SOM < 2% increased by 3.8 million ha. This finding of a negative relationship between the spatial extent of temporal change and the magnitude of initial SOM content supports earlier findings of the dependence of relative annual change in SOM content on the baseline SOM value using monitoring data from China [18, 32] or inventory data from the UK [47]. This characterized temporal pattern of SOM content change in NEC has important implications on carbon management in practice. Firstly, attention is needed on the regions with high SOM values, because these regions are highly vulnerable to carbon losses. Management measures should therefore be tailored to specific natural and socio-economic conditions of these regions. Secondly, investments in soil management in SOM-poor regions will more likely generate higher returns than in other regions [24]. Ideally, soil management in these regions should be guided through extension programs for smallholder farmers as in NEC. Thirdly, although the concept of soil management is not new, the importance of it has not been fully recognized in agricultural practice in the past two decades in NEC [38], as evidenced by the general declining trend in cropland SOM and by the spatial extent of cropland with decreasing SOM classes (Figure 3).

4.4 Uncertainties

Major sources of uncertainty in this paper include the rasterization of polygon-based soil map, kriging interpolation of SOM samples and scaling of the grid datasets. Although the errors associated with the vector-to-raster or raster-to-vector conversion methodologies were well documented [48], much less has been known on how these errors propagate to the assessment results or whether these errors are large enough to impact the assessment results. High-resolution soil datasets are useful to decrease uncertainties, but such datasets are either not always available or too expensive to collect. In trying to search for an optimal resolution, Yu et al. [49] recently evaluated the effect of varying raster grid sizes on the estimated SOC stock in the Taihu Lake region in China, using vector-converted soil maps. Such efforts deserve more attention. Attention should also be given to researches on error quantification, propagation, uncertainty control [2, 50], and so forth.

Cause-effect analyses used coarse grid datasets at a resolution of 40 km to attribute SOM changes to cropping intensity and/or fertilization in NEC between 1985 and 2005.

Although such census-based, spatially disaggregated grid maps are the best available datasets, they may not be sufficiently detailed to isolate the effects of individual factors by statistical analyses [51]. Further research is needed, not only to fine-tune the spatial disaggregation method itself but also to validate its result maps against denser samples.

5 Conclusions

Based on systematic sampling of cropland soils in NEC in 2005 and the Second National Soil Survey in 1985, an overall decrease in cropland SOM was detected in NEC for the last 20 years. Although this downward trend is mostly consistent with earlier findings, the spatial extent (40% in area terms) of it is substantially smaller than in previous assessments (50-70% of cropland). We suggest that previous assessments overestimated the area extent of the declining trend of cropland SOM due to limited spatial coverage of soil data used. We also find that SOM-rich croplands tend to lose carbon when SOM is higher than 2%. Moreover, our results reveal that cropping intensity and fertilizer application are two most important factors driving SOM change in NEC. These findings indicate that better soil management strategies need to be urgently established through research so that the dual goal of optimal crop yield and higher SOM content can be met.

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