ORIGINAL ARTICLE

Number of soil profiles needed to give a reliable overall estimate of soil organic carbon storage using profile carbon density data

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Abstract

Soil profile data are the basis for estimating soil organic carbon (SOC) storage and any changes in SOC storage, which are of great significance in terms of global climate change. Estimates based on various profile data have been made for SOC storage in China. Modeling studies have given contrasting results on changes in SOC storage in Chinese croplands. A certain number of measured soil profile data are needed to validate the modeled results. In the present study, we examined the relationships between sample size, population variance and detection limit using the central limit theorem and the statistical properties of the normal distribution. Based on the profile dataset from the Second National Soil Survey in China, we calculated that to derive a reliable estimate of the overall mean SOC density for all the soils of China, a sample size of 4,000 soil profiles is needed. In this case, a reliable estimate is defined as having a 95% confidence interval and allowing a ±5% detection limit of SOC. The necessary sample size for cropland soils is 1,250. Our results indicate that approximately 100 samples only are needed to validate a modeled SOC loss of 20–30% in cropland soils in China. By aggregating the soil profiles in the dataset into soil orders and calculating the variance of each soil order, we show that the sample sizes in the dataset are insufficient to give reliable estimates on the carbon densities of most soil orders; thus, we conclude that there is considerable uncertainty in the SOC distribution maps resulting from the Second National Soil Survey.

Key words: central limit theorem, minimum detectable change, sample size, soil organic carbon, variance.

INTRODUCTION

Global soils contain approximately 1,500 Pg carbon (1 Pg = 1 × 10¹⁵ g), which is twice the level in the atmosphere and threefold that in vegetation (Intergovernmental Panel on Climate Change 2001; Schimel 1995). Soil carbon sequestration can help reduce the buildup of carbon dioxide (CO₂) in the atmosphere, while improving the agricultural economy. Global agricultural soils have the potential to sequester 20–30 Pg carbon from the atmosphere over the next 50–100 years (Paustian et al. 1997). Soil organic carbon (SOC) storage has been proposed as an indicator of environmental quality because it is directly linked to global change and ecosystem performance (Janzen 2005).

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selection of representative values for each aggregated group (e.g. mean, median). Third, the number of profiles taken can result in different estimates. The first two sources of error are methodology issues and can be clearly compared among different estimations. Discrepancies resulting from the third source of error are rarely discussed and are the focus of the present study.

Changes in SOC are a global concern. There are usually two methods of monitoring changes in SOC: intensive sampling campaigns and computer modeling. An example of the former is given by Bellamy et al. (2005), who collected soil profile samples over England and Wales from every 5 km × 5 km grid, with a total of 5,662 samples, and showed a SOC loss of 0.6% per year from 1978 to 2003. If we adopted this method for China, we would need to take approximately 360,000 soil profile samples, which is unfeasible.

Different modeling studies on SOC changes in croplands of China have yielded contrasting results. Using the Denitrification–Decomposition model with 1990 as the base year, Li et al. (2003) estimated a SOC loss rate of 1.6% per year for the surface 30 cm soils of croplands of China; using the same model with 1998 as the base year, Tang et al. (2006) estimated a loss rate of 2.0% per year. Huang (2006), however, using the Agro-Carbon model, and estimated that SOC in the surface soil of Chinese croplands increased by approximately 5% from 1980 to 2000. In general, this large discrepancy can be attributed to different judgments on the use of crop residues, which are affected by many factors, such as socio-economic development and policy; these factors are difficult to estimate. Recently, Xie et al. (2007) estimated a SOC increase of 3.6% in Chinese agricultural soils between 1980 and 2000 using sporadic monitoring data.

Therefore, it is necessary to validate the change in SOC of agricultural soils in China by direct measurement. The most reliable way to detect changes in SOC is by systematic measurements of carbon density at two specific time periods. China conducted a national soil survey from 1979 to 1982. The main results were published in China Soil Series I–VI (National Soil Survey Office 1993, 1994, 1995, 1996). The six books contain 2,473 typical soil profile descriptions, of which 2,364 profiles have data for organic matter. A map showing the locations of the profiles can be found in Wu et al. (2003). For each soil profile, the SOC density (SOCD [kg m⁻²]) is simply integrated from the organic matter contents of all soil layers:

\[
SOCD = \sum_{i=1}^{k} OM_i \times 0.58 \times \rho_i \times D_i
\]

where \(k\) is the number of soil layers, \(OM_i\) is the organic matter content (kg kg⁻¹) of the \(i\)th soil layer, 0.58 is the van Bemmelen index, which converts organic matter content to organic carbon content, \(\rho_i\) is the bulk density of the \(i\)th soil layer (kg m⁻³) and \(D_i\) is the depth of the \(i\)th layer (m).

Bulk density data of some soil profiles are missing from the dataset. In this case, we used \(1.3 \times 10^3\) kg m⁻³ as the default value, which is the average bulk density of all soils in the dataset (Jin 2000). This simplification would slightly underestimate or overestimate the calculated profile carbon density. However, because the purpose of the present study is not to give an accurate estimate of SOC density, but rather to analyze the statistical characteristics of SOC density, we consider these simplifications acceptable.

A histogram of the 2,364 calculated profile carbon density data is shown in Fig. 1a. The mean and the standard deviation are 11.86 and 18.98 kg C m⁻³, respectively. Obviously, the data are not normally distributed, but rather log-normally distributed because they fit a normal distribution after log-transformation (Fig. 1b; skewness and kurtosis are both close to zero and are 0.097 and 1.70, respectively).

Statistical analysis
The essence of the present study is the application of the central limit theorem to the soil profile dataset of

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China. The central limit theorem is a very basic and well-tested element of statistics that relates the properties of an underlying population of smaller components to larger aggregates constructed from these components. The theorem is described below.

Let \(X_1, X_2, \ldots, X_n\) be independent observations of random variable \(X\) (irrespective of whether or not it is normally distributed), which has a mean value \(\mu\) and a variance \(\sigma^2\), then, as \(n\) increases,

\[
\bar{X} = \frac{1}{n}(X_1 + X_2 + \ldots + X_n) \sim N(\mu, \frac{\sigma^2}{n})
\]

(2)

and then

\[
\sqrt{n}\left(\frac{\bar{X} - \mu}{\sigma}\right) \sim N(0,1)
\]

(3)

According to the properties of a normal distribution, the probability (confidence interval) that \(\mu\) falls within the range \(\bar{X} \pm z_{\alpha} \frac{\sigma}{\sqrt{n}}\) is:

\[
P(\bar{X} - z_{\alpha} \frac{\sigma}{\sqrt{n}} \leq \mu \leq \bar{X} + z_{\alpha} \frac{\sigma}{\sqrt{n}}) = 1 - \alpha
\]

(4)

where \(z_{\alpha}\) stands for a critical value below which the cumulative probability of a standard normal distribution is less than \(\frac{\alpha}{2}\). In other words, at a given confidence interval \(1 - \alpha\) the margin of error of the estimate of \(\mu\) (Bernstein and Bernstein 1999) is:

\[
\nabla \bar{X} = z_{\alpha} \frac{\sigma}{\sqrt{n}}
\]

(5)

Inversely, to achieve a margin of error of \(\nabla \bar{X}\), the necessary sample size \((n)\) is:

\[
n = \left(\frac{z_{\alpha} \sigma}{\nabla \bar{X}}\right)^2
\]

(6)

The population of carbon density profiles is infinite; thus, we do not know its true standard deviation. However, the standard deviation can be approximated using the sample standard deviation, provided we have a large sample size (usually > 30 samples). The larger the sample size \((n)\), the more accurate the estimated standard deviation is to the true value. As there are 2,364 profile samples, the population standard variation can be represented by the sample standard deviation, which is 18.98 kg C m\(^{-2}\).

All statistical analyses were carried out using spss 13.0 for Windows (SPSS, Chicago, IL, USA).

RESULTS

From the 2,364 carbon density profile data, we estimated the mean and standard deviation of the population. According to Eq. 2, the distribution of sample means changes with sample size. The probability (confidence interval) that the estimated mean falls within the 11.86 ± 0.59 kg C m\(^{-2}\) range (± 5% of the mean of the 2,364 samples) increases with sample size. At approximately 4,000 samples, there is a 95% possibility that the mean falls within the range, and by approximately 6,800 samples, the possibility increases to 99% (Fig. 2 drawn according to Eq. 4).

Of the original soil-profile dataset, 1,461 profiles were collected from croplands and include the data needed to calculate profile carbon density. Again the population standard deviation is approximated by the standard
deviation of the 1,461 samples, which is 8.99 kg C m\(^{-2}\). Using this value and Eq. 6, by approximately 1,250 and 2,200 profile samples, there is a 95 and 99% probability, respectively, that the mean falls within ±5% of the mean of the 1,461 cropland soil carbon density profiles (Fig. 2).

Equation 5 indicates that, at a given confidence level, the margin of error (minimum detectable change) is dependent on the standard deviation of the population (\(\sigma\)) and the sample size (\(n\)). As shown in Fig. 3, when the standard deviation of the carbon density profile is 18.98 kg C m\(^{-2}\), which is the case for all soils in China, with 4,000 samples we can detect a change of 0.5 kg C m\(^{-2}\); while with 1,000 samples we can only detect a change of 1.0 kg C m\(^{-2}\). The carbon density profile of cropland soils in China has a standard deviation of 8.98 kg C m\(^{-2}\); to detect a change of 0.5 kg C m\(^{-2}\) we need only 1,000 samples, and with 4,000 samples we can detect a change as low as 0.2 kg C m\(^{-2}\).

It has been more than 20 years since the Second National Soil Survey was done. According to the modeled results of the Denitrification–decomposition model, SOC in cropland soils of China is being lost at a rate of 1.6–2.0% per year (Li et al. 2003; Tang et al. 2006); thus, there has been a loss of at least 20–30% SOC in cropland soils in the past 20 years. According to Eq. 6, we need approximately 100 profile samples only to validate this result at a 95% confidence interval (Fig. 4). However, if there has been a change of only 5%, as modeled by Huang (2006), we need more than 1,000 samples for validation.

**DISCUSSION**

According to Eq. 5 and 6, what essentially determines the minimum detectable change and sample size is the population variance or standard deviation, which in the present study is approximated by the standard deviation of the 2,364-sample carbon density profile data from the Second National Soil Survey. However, the sample profiles in the survey were not uniformly or completely randomly located in China, but rather occurred with a higher frequency in the eastern part and a lower frequency in the western part of the country. Because the western part mostly consists of arid areas and the soils have relatively low carbon density, the estimated population standard deviation from this sample dataset might be slightly understated. If we were to collect profile samples again, we might need to increase the standard deviation by 10–20% to determine the sample size. Nevertheless, the present study demonstrates how to determine the
necessary sample size to estimate the mean profile carbon density and the minimum detectable change in SOC from given samples.

The change in SOC is often expressed as a relative percentage, not an absolute amount of change, and variability in carbon density can be expressed as the coefficient of variation. To make the method of estimating sample size applicable to this more general case, Eq. 6 can be re-written as:

\[ n = \left( \frac{z_{\alpha/2} \cdot cv}{ch} \right)^2 \]  

(7)

where \( cv \) is the coefficient of variation (%) of the population and \( ch \) is the minimum detectable change relative to the population mean (%). The dependence of sample size on these two parameters is illustrated in Fig. 5. This figure applies to other similar cases and is not restricted to SOC research.

A number of previous studies have used the \( t \)-statistic to calculate the necessary sample size for SOC or other soil properties (e.g. Conen et al. 2004; Johnson et al. 1990). However, in the present study, we used the \( Z \)-statistic because, first, when the sample size is large (> 30) the \( t \)-statistic approximates the \( Z \)-statistic and, second, the \( t \)-statistic requires the population to be normally distributed (Bernstein and Bernstein 1999), whereas this is not the case for carbon density profile data in China (see Fig. 1).

The derived sample sizes in the present study are able to give estimates of the overall mean carbon densities for all soils and cropland soils in China. For a spatially explicit distribution of SOC density, however, a sample size for each mapping unit is needed, and the sample

Figure 4 Sample size needed to detect changes in soil organic carbon (SOC) in cropland soils in China.

Figure 5 Dependence of sample size on the coefficient of variation of a population and the relative detectable change estimated at 95% confidence interval.
size will depend on the standard deviation of the SOC density of each unit. We show the necessary sample size for some major soil orders in China (Fig. 6) using soil order as the mapping unit. By comparing the number of profiles in the Second National Soil Survey with the necessary sample size (Fig. 6), we are able to state that from the dataset of the Second National Soil Survey, we can make a reliable estimate (95% confidence level) for organic carbon storage of cropland soils as a whole. For all soils as a whole, the dataset (2,364 profiles) can give an estimate with an approximately 90% confidence level. However, Yu et al. (2007) claimed that they had collected more than 7,000 profile samples. In this case, a more reliable estimate can be made. For most soil orders, the number of profile samples in the Second National Soil Survey is not enough to make reliable estimates; thus, there is considerable uncertainty in the SOC distribution maps resulting from the Second National Soil Survey.

The calculated national mean SOC density in the present study (11.86 kg m\(^{-2}\)) is the arithmetic mean, and this mean is higher than the means reported from most other studies (e.g. Wang et al. 2000; Xie et al. 2004; Yu et al. 2007), which were area-weighted means. The reason for this is that the original soil profiles in the Second National Soil Survey were not randomly distributed over the country, but rather were collected with a higher density in the eastern part and a lower density in the arid western part of China. Thus, if we were to randomly sample soil profiles again in China to make an updated estimate, an arithmetic mean could be used to calculate the national total SOC storage; however, to compare changes in SOC, an area-weighted mean derived from the Second National Soil Survey dataset should be used to calculate the SOC storage 20 years ago.

Equation 6 indicates that, to detect an absolute amount of change, the number of samples needed is determined by the standard deviation; while Eq. 7 indicates that, to detect a change relative to the mean value (%), the number of samples needed is determined by the coefficient of variance. Figure 7 shows the relationship between the standard deviation and the population mean, and between the coefficient of variance and the population mean of those soil orders with more than 30 samples in the Second National Soil Survey. It is clear that the standard deviation increased with the population mean, while the coefficient of variance did not. Therefore, if we were to investigate the overall change in SOC in China in absolute amounts, the number of samples can be weighted by the population mean of the soil orders, and more samples should be taken from northeastern China where soils are rich in organic carbon and fewer samples are needed from the arid western region of China. However, if we were to investigate regional SOC change relative to a previous time, the number of samples should not be simply weighted by the population mean, but rather by the coefficient of variance.
Conclusions

Using soil profile carbon data from the Second National Soil Survey in China and the central limit theorem and the properties of normal distribution, we have shown that approximately 4,000 profile samples are needed to give a reliable estimate of the overall mean profile carbon density of China, with a 95% confidence interval and allowing ±5% detection precision. The corresponding sample size for cropland soils is 1,250. There is considerable uncertainty in the current distribution maps of SOC, which were mostly derived from the Second National Soil Survey, because the sample size was not large enough to give a reliable estimate for each mapping unit (e.g. soil order, soil suborder). Approximately 100 samples only are needed to validate the modeled results that SOC storage in cropland soils of China has decreased by 20–30% in the past two decades.

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REFERENCES


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