Spatial distribution of soil organic carbon stock in Moso bamboo forests in subtropical China

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Moso bamboo (Phyllostachys heterocycla (Carr.) Mitford cv. Pubescens) is an important timber substitute in China. Site specific stand management requires an accurate estimate of soil organic carbon (SOC) stock for maintaining stand productivity and understanding global carbon cycling. This study compared ordinary kriging (OK) and inverse distance weighting (IDW) approaches to study the spatial distribution of SOC stock within 0–60 cm using 111 soil samples in Moso bamboo forests in subtropical China. Similar spatial patterns but different spatial distribution ranges of SOC stock from OK and IDW highlighted the necessity to apply different approaches to obtain accurate and consistent results of SOC stock distribution. Different spatial patterns of SOC stock suggested the use of different fertilization treatments in Moso bamboo forests across the study area. SOC pool within 0–60 cm was 6.46 and 6.22 Tg for OK and IDW; results which were lower than that of conventional approach (CA, 7.41 Tg). CA is not recommended unless coordinates of the sampling locations are missing and the spatial patterns of SOC stock are not required. OK is recommended for the uneven distribution of sampling locations. Our results can improve methodology selection for investigating spatial distribution of SOC stock in Moso bamboo forests.
of spatial maps. Therefore, geostatistical analysis has been widely used to predict regional and landscape scale SOC stocks and other soil variables. Bamboo forests are a typical forest type in Southern China (south of the Qinling Mountain–Huai River line), representing an area of 6.16 million hectares; and more than 70% of the bamboo forests consist of Moso bamboo (Phyllostachys heterocycla (Carr.) Mitford cv. Pubescens). Moso bamboo forests are noted for fast biomass accumulation; after shoot emergence in spring, this bamboo species can attain full growth (height and diameter) within 35–40 days. After attaining full growth, the diameter and height of the bamboo remain unchanged due to the lack of secondary cambium and it begins to slowly accumulate dry mass. Total C stock in bamboo forests amount to 11% of the total C stock of China’s forest ecosystems, thus bamboo forests play a critical role in regional, national and even global C cycling. In recent decades, due to market prices and sustainable forest development policy, Moso bamboo forests have rapidly expanded. In China, natural forests are protected from felling in order to protect the environment. Consequently, as a large timber consuming county, Moso bamboo has become a major wood substitute and can be harvested every year. Therefore, to maximize the economic benefits for the increasing timber market, intensive management of bamboo forests has been widely applied, such as fertilization and regular understory removal, especially in the main bamboo producing provinces such as Zhejiang and Fujian. These management practices have been shown to change soil chemical compositions and increase soil C mineralization. Thus, to maintain stand productivity, scientific management and estimation of regional scale SOC is necessary because SOC facilitates the growth of soil biota by providing energy from C compounds and nutrients in inorganic forms.

Numerous investigations have been conducted to estimate SOC stock in Moso bamboo forests, for example by Tang, et al. and Xiao, et al. To our knowledge, only one investigation has studied the spatial distribution of SOC stock using ordinary kriging (OK) and one study has investigated the soil properties in Moso bamboo forests. However, some unresolved questions still remain: (1) is there a consistent result of SOC stock using different geostatistical approaches, such as OK, IDW and CA? and (2) if there is a consistent result in total SOC stock derived from different approaches, is there any difference in the spatial distribution of SOC stock? In addition, site specific maps of SOC stocks for scientific management of Moso bamboo forests are still lacking in our study area. Therefore, this study aims to: (1) study the spatial distribution of SOC stock at four depths (0–20, 20–40, 40–60 and 0–60 cm) in Moso bamboo forests; (2) calculate the SOC pool for the whole study area; (3) compare SOC stock derived from OK, IDW and CA; and (4) compare the spatial distribution of SOC derived from OK and IDW. These objectives will improve our understanding of methodology selection for predicting SOC stock.

**Results**

Descriptive statistics. The summary of descriptive statistics for measured SOC stock is presented in Table 1. Results show that SOC stock showed a decreasing trend with increasing soil depth; for 0–20 cm, SOC stock fell within 20.7–90.0 Mg ha$^{-1}$, and it was 10.5–72.2 Mg ha$^{-1}$ for 20–40 cm, 6.6–80.1 Mg ha$^{-1}$ for 40–60 cm and 52.8–229.7 Mg ha$^{-1}$ for 0–60 cm. Mean SOC stock was 50.9, 42.6, 33.3 and 126.7 Mg ha$^{-1}$ for soil layers 0–20 cm, 20–40, 40–60 cm and 0–60 cm, respectively. The lowest coefficient of variation (CV, 32%) was identified for SOC stock at the 0–60 cm layer while the highest CV (47%) was at the 40–60 cm. A CV value of 10% indicates low variability and values ranging from 10–90% indicate a moderate variability; CV values >90% indicate high variability. Therefore, SOC stock in our study area suggested a moderate variability. p values for the Shapiro-Wilk test ranged from 0.007 to 0.041, indicating a non-normal distribution of SOC stock for the different soil layers at the 0.05 level of significance. Therefore, before conducting spatial interpolation, a natural log-transformation was undertaken to meet the assumption of normal distribution.

**The relationships between SOC stock and topographic variables.** The relationships between topographic variables (elevation, slope and aspect) and SOC stock at the different soil layers were analysed using linear regression. Positive significant relationships between elevation and SOC stock (Table 2) were identified, indicating SOC stock increased with elevation. However, no significant relationship was found between slope, aspect and their interactions, and SOC stock. The interactions between elevation and slope and elevation and aspect led to significant effects on SOC stock, except for SOC stock at 20–40 cm and 40–60 cm layers for the interactions between elevation and slope.

**Spatial autocorrelation and trend surface analysis.** Moran’s I value was used to determine the spatial autocorrelation of SOC stocks at different soil layers. Moran’s I value ranged from 0.15 to 0.19 (Table 3), indicating that SOC stocks in all soil layers exhibited a significant positive spatial autocorrelation (all $p < 0.001$). This result

| Layers | Mean | Minimum | Maximum | Median | SD | CV (%) | 1st Qu | 3rd Qu | Skewness | Kurtosis | p of S-W test |
|--------|------|---------|---------|--------|----|--------|--------|--------|----------|----------|--------------|
| 0–20 cm | 50.9 | 20.7    | 90.0    | 47.4   | 16.5| 32.42  | 38.7   | 62.8   | 0.45     | −0.58    | 0.009        |
| 20–40 cm | 42.6 | 10.5    | 72.2    | 43.1   | 15.4| 36.15  | 29.6   | 56.0   | −0.05    | −1.05    | 0.028        |
| 40–60 cm | 33.3 | 6.6     | 80.1    | 32.1   | 15.7| 47.15  | 21.1   | 42.9   | 0.44     | −0.23    | 0.007        |
| 0–60 cm  | 126.7| 52.8    | 229.7   | 119.9  | 40.6| 32.04  | 93.7   | 150.6  | 0.36     | −0.58    | 0.041        |

Table 1. Statistical description of soil organic carbon stocks for different soil layers (Mg ha$^{-1}$).

SD = standard deviation; CV = coefficient of variation; 1st Qu = 25% quartile; 3rd Qu = 75% quartile; S-W test = Shapiro – Wilk test.
a larger Nugget effect than at other soil layers, followed by 20–40 cm, 0–60 cm and 0–20 cm layers. The ratio of 0.55 to 0.75 with a residual range of 0.0141–0.109. The semivariogram of SOC stock at the 40–60 cm layer showed spatial correlation ranges decreased from 30,900 m at 0–20 cm to 15,800 m at the 0–60 cm layer.

Nugget/Sill was lowest for the 40–60 cm (27%) layer and highest for the 20–40 cm (42%) layer. Spatially, the variogram of SOC stock for the 20–40 cm layer in the southern part of the study area varied from 45–60 Tg ha\(^{-1}\) for CA.

The values of AME, ME, RMSE and pseudo R\(^2\) are shown in Table 5. The closer the AME, ME and RMSE values were plotted against the measured values (Fig. 2) The linear model intersected 1:1 line for SOC stock. Before the intersection, the linear model (continuous line) overestimated SOC stock, after intersection SOC stock was underestimated. This result was due to the nature of the algorithms used for parameter estimation which aimed to achieve unbiased prediction of the mean values\(^{32,33}\).

The values of AME, ME, RMSE and pseudo R\(^2\) are shown in Table 5. The closer the AME, ME and RMSE values are to zero, the better the model performed. ME of SOC stock at different soil layers varied from −0.94 to −6.98 Mg ha\(^{-1}\) and determination coefficient of OK and IDW ranged from 0.35 to 0.46, indicating that predicted values derived from OK and IDW slightly underestimated SOC stock, but they were suitable for mapping SOC. Results for OK analysis had a higher determination coefficient and lower AME, ME and RMSE values than IDW for all soil layers, therefore having a better performance. This finding may be attributed to the sampling design and the nature of the algorithm of OK (see the discussion section for more details).

Comparison of OK and IDW. To check the interpolation performance of OK and IDW, the predicted values were plotted against the measured values (Fig. 2) The linear model intersected 1:1 line for SOC stock. Before the intersection, the linear model (continuous line) overestimated SOC stock, after intersection SOC stock was underestimated. This result was due to the nature of the algorithms used for parameter estimation which aimed to achieve unbiased prediction of the mean values\(^{32,33}\).

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Spatial prediction of SOC stock. To further compare the differences of OK and IDW for the spatial interpolation of SOC stock at different soil layers, spatial distribution maps were produced using both OK and IDW (Fig. 3); results of which showed a strong spatial variability of SOC stock across the whole study area. Generally, SOC stocks were highest in the northeast of the study area for all soil layers and lowest in the central areas, correlating to city centre locations. For 0–20 cm, 20–40 cm, 40–60 cm and 0–60 cm layers, SOC stock derived from OK fell by 30–77, 19–68, 12–62 and 61–200 Mg ha\(^{-1}\), respectively. These ranges were lower than those derived from IDW. The distribution patterns for OK and IDW were generally similar, however the absolute values of SOC differed. For example, SOC stock for the 20–40 cm layer in the southern part of the study area varied from 45–60 Mg ha\(^{-1}\) for OK (Fig. 3c) and 35–45 Mg ha\(^{-1}\) for IDW (Fig. 3d).

Total SOC stock prediction. The SOC pool from the different soil layers are shown in Table 6. Although different ranges of SOC stock derived from OK and IDW were observed amongst the different soil layers (see above description), SOC pool derived from OK and IDW were comparable (1.67–2.59 Tg for OK and 1.61–2.58 Tg for IDW). However, SOC stock estimated from CA was higher than that of OK and IDW for the different soil layers. Total SOC pool of Moso bamboo forests within the study area was 6.46 Tg for OK, 6.22 for Tg and 7.41 Tg for CA.

### Table 2. Coefficients of the relationships between elevation (ele), slope (slo), aspect (asp) and soil organic carbon stocks in different soil layers. * and ** indicates significant difference at level of 0.05 and 0.01, respectively.

| Soil layers | Ele | Slo | Asp | Ele:Slo | Ele:Asp | Slo:Asp |
|-------------|-----|-----|-----|---------|---------|---------|
| 0–20 cm     | 0.019 | 3.38 × 10^{-4} | −0.006 | 4.6 × 10^{-4} | 4.0 × 10^{-7} | −1.7 × 10^{-4} |
| 20–40 cm    | 0.014* | −0.040 | 0.008 | 3.9 × 10^{-4} | 3.76 × 10^{-7} | 4.4 × 10^{-4} |
| 40–60 cm    | 0.018* | −0.149 | 0.029 | 2.91 × 10^{-4} | 5.8 × 10^{-7} | 4.02 × 10^{-4} |
| 0–60 cm     | 0.050 | −0.170 | 0.029 | 1.23 × 10^{-4} | 1.28 × 10^{-7} | 8.01 × 10^{-4} |

### Table 3. Moran’s I analysis and second-order trend surface analysis of polynomial surface for soil organic carbon stocks in different soil layers.

| Soil layers | Moran’s I | Trend surface |
|-------------|-----------|---------------|
| Estimates   | p         | R^2           | p         |
| 0–20 cm     | 0.1616    | <0.001        | 0.2678    | <0.001    |
| 20–40 cm    | 0.1635    | <0.001        | 0.3931    | <0.001    |
| 40–60 cm    | 0.1528    | <0.001        | 0.2654    | <0.001    |
| 0–60 cm     | 0.1928    | <0.001        | 0.3486    | <0.001    |
Soil is the largest C pool and accurate estimation of SOC is therefore necessary to assess C sequestration or emission potential caused by global environmental changes \(^1\). SOC stock in the top 60 cm of the Moso bamboo forests was 126.7 Mg ha\(^{-1}\), falling within the SOC stock range of other major forests (16–572 Mg ha\(^{-1}\))\(^3\)\(^4\), and being greater than the average SOC stock of main forest types (78 Mg ha\(^{-1}\)) in China\(^3\)\(^4\). This result indicates that the Moso bamboo forest soil is a larger carbon pool compared to the average soil results of other forest types. In south China, driven by fast and high economic benefits due to annual harvests, the area of Moso bamboo is increasing by the rate of 3% per year\(^3\)\(^5\). The increase of Moso bamboo forest area indicates an increase of SOC stock in Moso bamboo forests under the intensive management. In addition, the carbon stock of (including above- and below-ground) Moso bamboo is dynamically balanced between annual harvest and growth of new bamboos, and one sixth of aboveground biomass is harvested for timber every year\(^3\)\(^6\), thus leading to a higher ecosystem production than the fast-growing Chinese fir plantations\(^2\)\(^8\). Our results suggest that Moso bamboo forest soils play an important role in alleviating future climate change. In contrast, deforestation of Moso bamboo forests could lead to significant losses of carbon to the atmosphere, thus causing a negative feedback to climate change.

SOC stock results were also higher than those from Moso bamboo forests in Hubei Province (65–99 Mg ha\(^{-1}\))\(^2\)\(^7\), Zhejiang Province (94 Mg ha\(^{-1}\))\(^2\)\(^9\) and Jiangxi Province (111 Mg ha\(^{-1}\))\(^2\)\(^9\). The higher SOC results of our
investigation are mainly attributed to fertilization treatment in the majority of Moso bamboo forests in our study area to improve stand production and bamboo shoots; the other three comparison bamboo forests did not receive fertilization treatments. The SOC stock in this study was also higher than the average SOC stock of plantations (104 Mg ha⁻¹), and it was comparable to natural forests across China (129 Mg ha⁻¹). This indicates that Moso bamboo forests act as an important role in global C cycling with storing more C in soil.

Figure 2. Cross-validation of OK and IDW interpolation for SOC stock at 0–20 cm, 20–40 cm 40–60 cm and 0–60 cm layers (dashed line denotes a 1:1 line).
SOC stock results decreased as soil depth increased, a finding which is in general accordance with the majority of previous investigations: SOC in Moso bamboo forests showed a diminishing trend. However, some investigations also reported a positive trend of SOC stock with increasing soil depth, a finding which we attribute to an unusual trend due to mixing effects of tillage.

Many approaches have been developed in the framework of geostatistical analysis techniques for spatial interpolation, such as OK, co-kriging and universal kriging. As the OK technique normally performs better and is easy to apply, it has been widely used in spatial interpolation of SOC stock and soil physical properties. To describe the spatial variability of soil properties, semivariograms are fitted and used for spatial interpolation. This suggests that A0 can therefore be an effective criterion for evaluating sampling design.

Table 5. Cross-validation indices for ordinary kriging (OK) and inverse distance weighting (IDW) methods. AME = absolute mean error; ME = mean error; RMSE = root mean square error; Pseudo R² = pseudo determination coefficient.

| Layers     | Methods | AME  | ME   | RMSE  | Pseudo R² |
|------------|---------|------|------|-------|-----------|
| 0–20 cm    | OK      | 10.6770 | -0.9439 | 12.4573 | 0.429     |
|            | IDW     | 10.9094 | -1.2024 | 12.9752 | 0.381     |
| 20–40 cm   | OK      | 9.5465  | -1.1636 | 11.9914 | 0.401     |
|            | IDW     | 10.3646 | -3.4654 | 12.6668 | 0.349     |
| 40–60 cm   | OK      | 9.5449  | -0.9499 | 11.8575 | 0.427     |
|            | IDW     | 10.0389 | -2.4074 | 12.9184 | 0.341     |
| 0–60 cm    | OK      | 24.5449 | -2.3665 | 29.8196 | 0.462     |
|            | IDW     | 26.3927 | -6.9758 | 32.1667 | 0.398     |

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Figure 3. Spatial distribution of SOC stock derived from OK and IDW at 0–20 cm, 20–40 cm 40–60 cm and 0–60 cm layers (non-bamboo areas are excluded). This figure was generated using ArcMap 10.2 (http://www.esri.com/).
or Random Forest may improve the accuracy of spatial interpolation of SOC stock, including both intrinsic and extrinsic factors.

Generally, OK and IDW produced similar results for the spatial pattern of SOC stock, together with comparable total SOC stock derived from OK and IDW for different soil layers, demonstrating the suitability of OK and IDW for spatial interpolation of SOC stock. However, a larger range was produced by IDW compared to OK, indicating the necessity of using different approaches to study the spatial SOC stock, particularly areas with a complex topography. This issue is related to the different algorithms and computational efficiencies for the spatial interpolation of OK and IDW, thus selection of the appropriate approach is important to improve the interpolation accuracy and efficiency. Theoretically, OK can provide the best linear unbiased estimations and information on the spatial patterns of estimation errors. However, it is important to note that the assumption of stationarity may be not appropriate in practice. The IDW method involves a simple and quick calculation and does not require assumptions about the data. However, IDW does not have the statistical advantages compared to OK (Table 4). The IDW formula has the effect of giving data points close to the interpolation point relatively large weights, while points further away from the interpolation point exert little effect. The higher the weighting

| Soil layers | Approaches | SOC stocks (Tg) |
|------------|------------|----------------|
| 0–20 cm    | OK         | 2.59           |
|            | IDW        | 2.58           |
|            | CA         | 2.98           |
| 20–40 cm   | OK         | 2.28           |
|            | IDW        | 2.15           |
|            | CA         | 2.49           |
| 40–60 cm   | OK         | 1.67           |
|            | IDW        | 1.61           |
|            | CA         | 1.95           |
| 0–60 cm    | OK         | 6.46           |
|            | IDW        | 6.22           |
|            | CA         | 7.41           |

Table 6. SOC pool for different soil layers (1 Tg = 1 × 10¹² g).

Figure 4. Study area, the distribution of bamboo forests (grey polygons) and sampling locations (solid black circle). This figure was generated using ArcMap 10.2 (http://www.esri.com/).
used, the more influence the point close to the estimation value is given. Therefore, as a result of the irregular
distribution of the sampling locations, combined with better statistical performances, OK is recommended as a
more suitable approach for similar studies in the future. Although OK and IDW generated a similar result of SOC pool of Moso bamboo forests for the study area, SOC pool derived from CA was higher than that of OK and IDW, demonstrating the importance of selecting the
appropriate approach to estimate SOC stock. Although CA is a simple approach once the mean SOC stock per
unit and area of the study site are known, CA is unable to provide information about the continuous mapping of
SOC stock and therefore cannot test the accuracy of spatial distribution of SOC stocks. CA can only provide
limited information for optimizing stand management to improve stand productivity, thus making CA of lim-
ited use in studying the spatial pattern of SOC stock. Therefore, CA is only recommended to be used when the
coordinates of the sampling locations are missing and the spatial patterns of SOC stock are not required; different
goostatistical approaches are recommended to be used to obtain accurate and consistent spatial patterns of SOC
stock and regional SOC pools.

Compared to other studies on SOC stock in Moso bamboo forests, such as Zhang, et al.45 and Fu, et al.29, this
study is the first to attempt to (1) compare different spatial interpolation approaches; and (2) compare geostatistical
categories and CA for regional SOC stock estimates. These results can improve the methodology selection of
studying spatial distribution of SOC stocks. In addition, scientific management of Moso bamboo forests requires
site specific maps of SOC stock to improve stand productivity. Regarding stand management, this study further
proposed that rather than using a consistent treatment of fertilizers across the whole study area, different distrib-
ution patterns of SOC stocks indicated different fertilizer treatments should be conducted in different sites since
SOC is an important indicator for soil fertility. For example, organic fertilizer treatment could be applied in the
centre areas of the southern study regions (Fig. 3). Together with organic fertilizers, the addition of other nutri-
ents, such as nitrogen, phosphorus and potassium, should be added since, nitrogen and phosphorus are the most
important limited nutrients in Moso bamboo forests in south China51.

Regarding to uncertainties, analysis of random soil cores for the presence of stones and rocks suggested low
contents (<5%), thus we did not correct for gravel content. This could be a source of uncertainty for regional SOC
stock estimates, especially in nutrient poor soils. However, data from poor soils is sporadic as the stands were fer-
tilized and managed every year. The estimates of SOC stock from OK and IDW differed by 13% and 16%, respec-
tively, compared to CA. This difference is due to the lack of the relative area weighted mean of CA. Although
model efficiency of different models fitted for semivariograms ranged from 55% to 75% (Table 5), R2 of the model
values and predicted values varied from 0.35 to 0.46. This could be an important uncertainty of regional estimates
of SOC stock. However, despite the uncertainty in model efficiency, both geostatistical interpolation (OK) and
deterministic (IDW) approaches compared and produced similar estimates of regional SOC stock (3.8% differ-
ence, Table 6). This result highlighted that the estimates of total SOC stock were accurate.

Conclusions
In this study, OK and IDW were applied to study the spatial interpolation of SOC stock at 0–20 cm, 20–40 cm and
40–60 cm using the measured data from 111 plots in Moso bamboo forests in Yong’an City, subtropical China. OK,
IDW and CA were applied to estimate the regional SOC pool. These results can facilitate the accurate estima-
tion of spatial distribution of SOC stock and regional SOC pool.

Spherical and exponential models were selected to describe the spatial pattern of SOC stock. A moderate
spatial dependence of SOC stock was observed, indicating that SOC stock was controlled by both intrinsic fac-
tors (e.g. soil parent materials and soil texture) and extrinsic factors (e.g. application of fertilizers and tillage
treatment).

OK and IDW produced similar spatial patterns of SOC stock, together with comparable SOC pool, indicating
the suitability of both approaches in studying the spatial interpolation of SOC stock. However, OK produced a
smaller distribution range of SOC stock compared to IDW, highlighting that it is essential to apply different
approaches to obtain accurate and consistent results of SOC stock distribution. SOC pool derived from CA was
higher than that from OK and IDW, thus CA is not recommended unless coordinates of the sampling locations
are missing and the spatial patterns of SOC stock are not required.

Materials and Methods
Study area. The study area was located in the Yong’an City, Fujian Province, China (117°56’–117°47’E, 25°33’–
26°12’N, Fig. 4). The area is characterized by a subtropical southeast monsoon climate with an average annual
temperature of 19.3 °C (ranging from −11 °C to 40 °C) and precipitation of 1600 mm44,52. Elevation in the study
area spans 580 m to 1605 m above sea level44,52. The accumulated temperature of ≥10 °C is 4,520–5,800 °C, last-
ing for 225–250 days and relative humidity is about 80%44. The forest cover is 82% with 5.85 × 106 ha of Moso
bamboo forests52. Moso bamboo forests are mainly distributed below 800 m, most of which are pure stands and
are seldom mixed with Schima Superba, Cunninghamia lanceolata, Myrica rubra, Cheirophandanis axillaris,
Liriodendron chinense, Schima Superba, etc. To improve the stand output and increase income, fertilizers have
been widely applied to most of the Moso bamboo forests.

Soil sampling. Soil samples were collected from the sub-compartment of the forest resource management of
Fujian province, China, an area which was established by the local Forest Bureau for soil mapping (Fig. 4). In the
targeted sub-compartment, a cluster of three circular plots with a size of 33.3 m2 were established, and 138 clusters
were created in total. However, due to soil sample damage during transportation, soil samples from 111 plots were
used for spatial interpolation of SOC stock. In each plot centre, soil samples from three layers (0–20 cm, 20–40 cm
and 40–60 cm) were collected. Soil samples were air-dried at room temperature in the laboratory and prepared
for sieving through 2-mm and 0.15-mm meshes for SOC content analysis. Identifiable plant residues and root
materials were removed during sieving. As the majority of bamboo roots were distributed within the top 40 cm\(^2\), soil samples to a depth of 60 cm was deemed suitable to meet the research aims of this investigation. To determine bulk density, a cutting ring approach was used in the soil cores\(^53\). During fertilizer treatment in the plots, identical stones and rocks were removed from the Moso bamboo forests. This resulted in few stones and rocks being found in the cores, therefore correction for gravel content was not undertaken. Information about sample elevation, coordinates, soil depth, soil type, nitrogen content, phosphorus content and bamboo diameters were recorded and determined according to State Forestry Administration\(^53\).

SOC content was analysed using the K\(_2\)Cr\(_2\)O\(_7\)-H\(_2\)SO\(_4\) wet oxidation method\(^53\). Specifically, 0.1–0.5 gram of air-dried soil was passed through a 0.15-mm sieve and digested with 5 mL 0.8 mol L\(^{-1}\) K\(_2\)Cr\(_2\)O\(_7\) and 5 mL concentrated H\(_2\)SO\(_4\) (1.84 g mL\(^{-1}\)) for 5 min at 170–180 °C. The digested solutions were then titrated using standardized 0.2 mol L\(^{-1}\) FeSO\(_4\) solution mixed with 15 ml concentrated H\(_2\)SO\(_4\) per liter to prevent oxidization\(^53\). SOC stock was calculated as\(^39,54\):

$$\text{SOC stock} = \text{SOC} \times \text{BD} \times \frac{D}{10}$$

where, SOC is the soil organic C concentration (g kg\(^{-1}\)); BD is bulk density (g cm\(^{-1}\)); and D is the depth of the soil layer (cm).

**Extraction of topographic variables from a Digital Elevation Model (DEM).** A DEM with a resolution of 90 m was obtained from Geospatial Data Cloud (http://www.gscloud.cn/). Mean values of aspect, elevation and slope were extracted for each sample plot in ArcGIS 10.2 (http://www.esri.com/). Further details of the calculation of aspect, elevation and slope are described by Pierce, et al.\(^55\).

**Statistical and geostatistical analyses.** Traditional statistical analysis, such as mean, standard deviation and coefficient of variation, were calculated to describe the original data. The relationships between topographic variables (elevation, slope and aspect) were analysed using linear regression. Before starting geostatistical analysis, raw data was initially tested for normality using the Shapiro-Wilk test in R\(^56\). Instances where the data did not meet the assumption of normal distribution, the raw data was log-transformed and then transformed back using weighting mean in GS + 10.0 (www.gammadesign.com). In this study, OK and IDW were applied to estimate the spatial distribution of SOC stock.

**Spatial autocorrelation and trend surface analyses.** Moran’s index (I), a common indicator of spatial autocorrelation\(^44\), provides negative or positive values. A Moran’s I value greater than 0 means a positive spatial autocorrelation (high values or low values cluster together), while values less than 0 indicate a negative spatial autocorrelation (a checkerboard pattern); 0 values indicate perfect spatial randomness\(^45\). Trend surface analysis is the most widely used surface-fitting procedure. The target soil variables are expressed by a polynomial model of geographic coordinates, and the coefficients of the polynomial model are modelled by the method of least squares\(^58\). In this study, second degree of polynomial surface was used because the increase of degree did not result in a significant increase of determination coefficient and F ratio.

**Ordinary Kriging (OK).** Kriging is based on the theory of regionalized variables which are spatially distributed and autocorrelated\(^49\). The spatial autocorrelation can be indicated by Moran’s I (see above). Spherical, exponential and Gaussian models are commonly used to calculate experimental semivariograms using the observed data\(^69\). The semivariograms are expressed as a function of distance between sampled points and calculate the integrity of spatial continuity in one or multiple directions using the following expression\(^13\):

$$\gamma(h) = \frac{1}{2Nh} \sum_{i=1}^{N(h)} [z(x_i) - z(x_{i+h})]^2$$

where, \(i\), \(z(x_i)\) and \(z(x_{i+h})\) are values of \(z\) at locations \(x_i\) and \(x_{i+h}\), respectively; \(h\) is the lag and \(N(h)\) is the number of pairs of sample points separated by \(h\). In this study, spherical, exponential, linear and Gaussian models were used to describe the semivariograms of SOC stock at 0–20 cm, 20–40 cm and 40–60 cm layers. The models with highest coefficient of determination and the smallest of residuals were chosen. These models where then applied to analyse spatial structure and to provide the input parameters for interpolation.

There are three major parameters derived from the fitted models to identify the spatial structure of SOC stock for a given scale. The parameters are nugget (\(C_0\)), the sill (\(C + C_0\)) and the range (\(A_0\)).

The sill (\(C + C_0\)) represents total variation, and the ratio of nugget and sill is considered as a criterion to classify spatial dependence\(^45\); \(A_0\) represents the separation distance, beyond which the measured data are not spatially dependent\(^46\). More details about the semivariograms and kriging can be found in Goovaerts\(^49\). The most likely value \(R(x)\), which was expected to be encountered in a particular grid cell when using \(m\) neighbouring observations, was defined as:

$$R(x) = \sum_{j=1}^{m} b_j z(x_j)$$

**Inverse distance weighting (IDW).** Similarly, IDW is another important approach for spatial interpolation which assumes that each point influences the resulting surface to a finite distance\(^60\). IDW calculated an unsampled point as a weighting average of a known data point within local surroundings. The formula can be
expressed by Eq. (4)\textsuperscript{50}. In this study, data points of 16 without a fixed radius and the weight power of one were used; the weight power of one was found to perform better than the weight powers of two, three and four if the skewness is below one\textsuperscript{32,33,62};

\[
R(x) = \frac{\sum_{j=1}^{m} z_{i} d_{ij}^{-r}}{\sum_{j=1}^{m} d_{ij}^{-r}}
\]

where, \( r \) is the weight and \( d_{ij} \) is the distance, which is the distance between the estimation point and the measured point.

**Data validation.** The prediction accuracy of SOC stock was evaluated using the leave-one-out cross-validation techniques\textsuperscript{3,33,47}. In the determination of errors, one point was omitted and this value was estimated by the remaining values. Afterwards, the estimated value was compared with the real value in the situation of omitted point\textsuperscript{3}. This process was repeated for all the observations. Four commonly used indices, i.e., absolute mean error (AME), mean error (ME), root mean square error (RMSE) and model efficiency (\( R^2 \)), were used to compare the interpolation accuracy for OK and IDW. These indices were calculated as follows:

\[
AME = \frac{1}{n} \sum_{i=1}^{n} \left| \hat{M}_i - M_i \right|
\]

\[
ME = \frac{1}{n} \sum_{i=1}^{n} (\hat{M}_i - M_i)
\]

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{M}_i - M_i)^2}
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{M}_i - M_i)^2}{\sum_{i=1}^{n} (M_i - \bar{M})^2}
\]

where, \( \hat{M}_i, M_i \) and \( \bar{M} \) are predicted values, observed values and the mean value of the observations, respectively.

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Author Contributions
X.T., M.X., F.G. wrote the manuscript, F.G. and S.F. conceived and designed the experiments; X.T. and M.X. analyzed the data and produced figures; C.P.C. improved data analysis, reviewed and improved language. All authors contributed to manuscript revision.

Additional Information
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