CrossMark

How environmental and vegetation factors affect spatial patterns of soil carbon and nitrogen in a subtropical mixed forest in Central China

Qianxi Li[1,2] · Xinggang Wang[1,2] · Mingxi Jiang[1] · Yu Wu[1,2] · Xiaolu Yang[1] ·
Chang Liao[1,2] · Feng Liu[1]

Abstract

Purpose Soil properties are highly heterogeneous in forest ecosystems, which poses difficulties in estimating soil carbon (C) and nitrogen (N) pools. However, little is known about the relative contributions of environmental factors and vegetation to spatial variations in soil C and N, especially in highly diverse mixed forests. Here, we examined the spatial variations of soil organic carbon (SOC) and total nitrogen (TN) in a subtropical mixed forest in central China, and then quantified the main drivers.

Materials and methods Soil samples ($n = 972$) were collected from a 25-ha forest dynamic plot in Badagonshan Nature Reserve, central China. All trees with diameter at breast height (DBH) ≥ 1 cm and topography data in the plot were surveyed in detail. Geostatistical analyses were used to characterize the spatial variability of SOC and TN, while variation partitioning combined with Mantel's test were used to quantify the relative contribution of each type of factors.

Results and discussion Both surface soil (0–10 cm) and subsurface soil (10–30 cm) exhibited moderate spatial autocorrelation with explainable fractions ranged from 31 to 47 %. The highest contribution to SOC and TN variation came from soil variables (including soil pH and available phosphorus), followed by vegetation and topographic variables. Although the effect of topography was weak, Mantel's test still showed a significant relationship between topography and SOC. Strong interactions among these variables were discovered. Compared with surface soil, the explanatory power of environmental variables was much lower for subsurface soil.

Conclusions The differences in relative contributions between surface and subsurface soils suggest that the dominating ecological process are likely different in the two soil depths. The large unexplained variation emphasized the importance of fine-scale variations and ecological processes. The large variations in soil C and N and their controlling mechanisms should be taken into account when evaluating how forest managements may affect C and N cycles.

Keywords Forest ecosystems · Soil organic carbon · Spatial variation · Total nitrogen · Variation partitioning

✉ Feng Liu
liufeng@wbgcas.cn

[1] Key Laboratory of Aquatic Botany and Watershed Ecology, Wuhan Botanical Garden, Chinese Academy of Sciences, Wuhan, China

[2] University of Chinese Academy of Sciences, Beijing, China

1 Introduction

Soil carbon (C) and nitrogen (N) are often characterized by high spatial variation in forest ecosystems due to their high environmental heterogeneity (Kleb and Wilson 1997; Gallardo 2003; Townsend et al. 2008). Local soil organic carbon (SOC) and total nitrogen (TN) patterns can be influenced by many biotic and abiotic factors such as disturbance history (Chen and Shrestha 2012), vegetation composition (De Deyn et al. 2008; Díaz-Pinés et al. 2011), geomorphic features (Tsui et al. 2004; Seibert et al. 2007), and soil physical and chemical properties (Silver et al. 2000; Hook and Burke 2000) through various ecological processes. However, little is known about the relative contributions of these factors to SOC and TN patterns since there are complex interrelations between different factors (Peri et al. 2012; Yuan et al. 2013). This knowledge gap limits our understanding of the sensitivity of biogeochemical cycles to environmental changes in terrestrial ecosystems and poses huge difficulties in estimating soil C and N pools. In

addition, the spatial structure of ecological data, which represents a synthetic variable for the underlying processes that generated it, has often been overlooked to some extent (Borcard et al. 1992; Legendre et al. 2002).

SOC and TN content can be affected by many vegetation attributes at individual or community level such as species life form (Mueller et al. 2012), species richness (Fornara and Tilman 2008; Cong et al. 2014), and age structure (Pregitzer and Euskirchen 2004; Bradford et al. 2008). Most studies were interested in only one of these attributes while other attributes were not considered. Better understanding of the relative roles of each groups of variables in shaping soil C and N variations should shed new light on the plant-soil interaction mechanism in the context of global change.

Although the development of geostatistics facilitates evaluation of the spatial variation of soil properties (Goovaerts 1998), evidence showed that sampling design and sampling density (the number and distribution of sampling points) could affect the ultimate results (Liski 1995). Due to the large amount of samples required to analyze spatial pattern of soil properties, few studies have sufficient sampling density in forest ecosystems to study SOC and TN patterns (Muukkonen et al. 2009; Yuan et al. 2013). Here, we address this knowledge gap by presenting a detailed sampling investigation of both soil and vegetation in a highly heterogeneous subtropical mixed forest, providing a comprehensive analysis of SOC and TN patterns, and their controlling factors.

Surface soil is in close contact with the outside environment and has been shown to be sensitive to environmental change and human disturbances (Mills et al. 2014). However, environment factors do not act on subsurface soil directly. Subsurface soil has a weaker connection with outside environmental changes than surface soil. So, the spatial variation of surface soil would have a larger uncertainty, especially at heterogeneous regions with strong influences from fine-scale variations in environmental factors. In addition, the proportion of recalcitrant carbon in soil carbon pool usually increases with soil depth, and the recalcitrant carbon is less sensitive to soil properties (Rumpel and Kögel-Knabner 2011).

The evergreen and deciduous broad-leaved mixed forests in the Badagongshan (BDGS) National Nature Reserve are located in mid-subtropical region in central China. There are a wide variety of combinations of environmental variables, according to the high biodiversity and the complex topography in this region (Qiao et al. 2015). Considering the complexity of the combined environment in this region and the differences between surface soil and subsurface soils, we hypothesized that (1) the spatial autocorrelation of SOC and TN in surface soil is weaker than subsurface soil, and (2) the explanatory power of environmental factors is lower for subsurface soil, compared with surface soil. To test these hypotheses, we were interested in the natural variability of SOC and TN and the relative contribution of their major determinants.

So, the two main objectives are (1) to estimate the spatial variations of SOC and TN for both surface and subsurface soils and (2) to quantify the relative contributions of environmental factors including vegetation, soil properties, topography, and spatial structure to the spatial variations of SOC and TN.

2 Materials and methods

2.1 Study site

Our study site is the BDGS 25-ha (500 m × 500 m) forest dynamic plot, one of the nodes in CForBio (China Forest Biodiversity Monitoring Network), located in the Badagongshan National Nature Reserve (Fig. 1) in central China (29° 46.041′ N, 110° 5.248′ E). The climate is subtropical mountain humid monsoon with annual precipitation averages of 2100 mm. Topography is characterized by deep valleys, steep slopes, and flat tops. The soil, developed mainly on shale with a thin mineral A horizon (about 10 cm), is classified as mountain yellow-brown earths (Hapludalfs according to US Soil Taxonomy Series 1999). Pedogenic processes are characterized by leaching, clay accumulation, and litter deposition. The plot has a total of 238 tree species (94 evergreen and 144 deciduous) with dominant canopy trees include *Fagus lucida*, *Carpinus fargesii*, *Schima parviflora*, *Sassafras tzumu*, *Castanea seguinii*, *Cyclobalanopsis multinervis*, and *Cyclobalanopsis gracilis* (Guo et al. 2013).

2.2 Field sampling and laboratory analyses

Soils were sampled from June to September, 2013. We used the same sampling design as the 24-ha Gutianshan forest dynamic plot survey (Zhang et al. 2011). The main part (480 m × 480 m) of the plot was divided into 30 m × 30 m quadrat. The remaining part was divided into 32 20 m × 30 m grids and 1 20 m × 20 m grid (Fig. 2). Soils were sampled at the intersections of grid lines. In order to capture variations in soil properties at finer scales, two additional sampling points were selected in a random compass direction from each intersection. The distances from the intersection to the two additional points were chosen randomly without replacement from 2, 5, and 15 m (Zhang et al. 2011). Thus, a total number of 972 sampling points were selected. We collected soil at two depths (0–10 and 10–30 cm) using a 3.4-cm diameter soil auger. Three soil samples 0.2 m apart from the sampling point were obtained after litter layer was removed, if present, then bulked for laboratory analysis.

Each soil sample was air-dried, then divided into subsamples to analyze different soil properties. Soil pH was measured as a soil to solution ratio of 1:2.5 of air-dried soil and deionized water. SOC and TN concentrations were determined

Fig. 1 The location and contour map of the 25-ha BDGS forest plot, China. The number in the contour map is elevation (m)
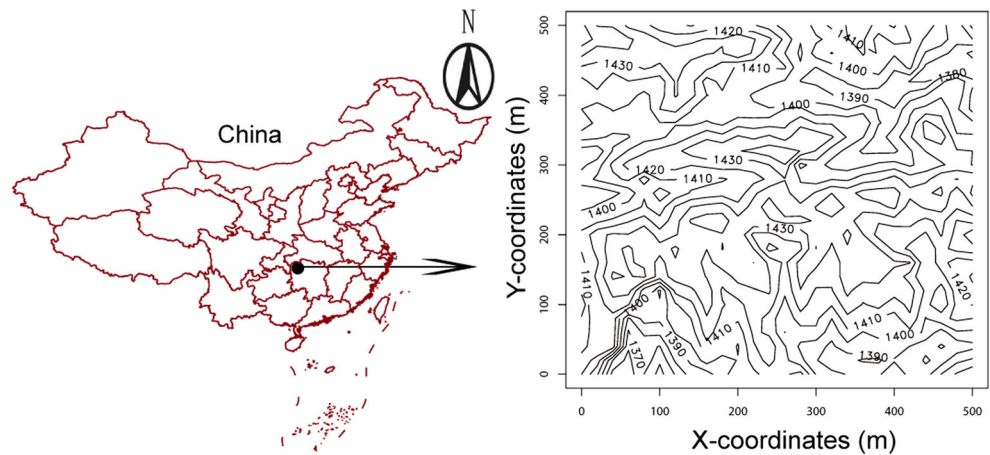
using dry combustion method on elementary analyzer (Thermo Scientific Flash 2000 HT, German). Soil available phosphorus (AP) was extracted with 0.03 mol/L NH$_4$F - 0.1 mol/L HCl solution, and then was determined using colorimetry (TECAN Infinite M200pro). Soil texture was determined only for soil samples in 0–10 cm, using the laser diffraction method on a Mastersizer 3000 (Ryżak and Bieganowski 2011).

Topography data including slope, aspect, and slope position at each sampling point were recorded using compass. To measure elevation accurately, we first used electronic distance measuring device (EDMD) to survey every intersection of the

grid lines (Condit 1998), and then used GPS to obtain the elevation data at several randomly selected intersections. After that, we calculated the elevation of the remaining points using kriging interpolation.

All trees with diameter at breast height (DBH) ≥1 cm were identified to species level and measured. Geographic coordinates of each tree were recorded during July 2010–November 2011.

2.3 Data analyses

Geostatistics in combination with descriptive statistics were used to characterize the spatial variability of SOC and TN.

Fig. 2 Soil sampling points in the 25-ha (500 m × 500 m) BDGS plot, China
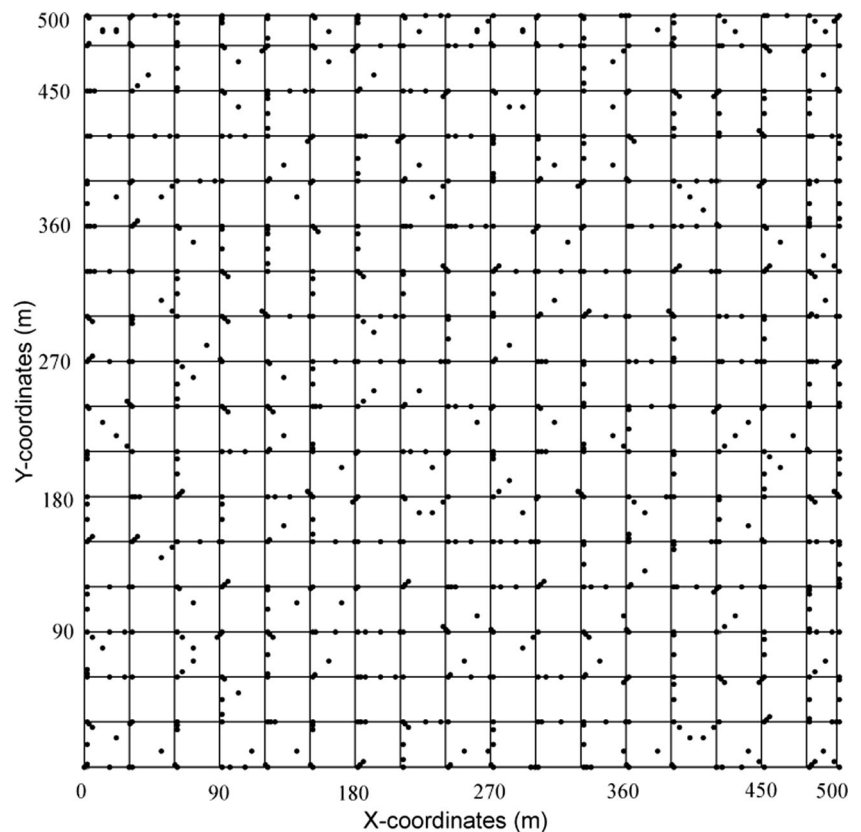
Soil data were transformed by using the Box-Cox transformation to reduce skewness prior to geostatistical analyses (Gallardo and Paramá 2007). Semivariograms were calculated to identify the degree of spatial variations for SOC and TN, and then were fitted by spherical models to facilitate comparisons. Interpolations of SOC and TN were conducted using kriging; however, cross-validation results indicated that the accuracy of kriging was not suitable to predict soil C and N maps ($R^2 < 0.3$).

To assess the relative contributions of environmental and spatial variables and their interactions to the variations of SOC and TN, a variation partitioning method based on constrained and partial canonical ordination techniques was adopted (Borcard et al. 1992). However, if all four types of variables were involved in the variation partitioning process, complex interactions among them will make the results difficult to understand and interpret. To enhance comprehensibility of the results, we chose three types of explanatory variables for variation partitioning, including soil, vegetation, and spatial variables (according to the preliminary results of variation partitioning, explanatory power of topography was about 4 %, and was smaller than other types of variables). A separate multiple regression analysis for topographic variables was conducted due to its low explanatory power.

Soil variables include soil pH, soil AP, and soil texture. Due to the lack of soil texture data for soils in 10–30-cm depth range, we introduced only soil pH and soil AP as soil variables in variation partitioning to facilitate comparison between 0–10- and 10–30-cm depth range. The effect of soil texture on SOC and TN variations was analyzed only for soils in 0–10-cm depth range.

When constructing vegetation-related variables, we chose three different sizes of circles (radius of 5, 10, or 20 m) with sampling points as the center, then we calculated eight vegetation parameters for each circle size (Table 1). Considering the distance of different trees from the sampling point and the

strong positive relationship between leaf litter production and tree basal area (Adu-Bredu et al. 1997; Yuan et al. 2013), we calculated the weighted sum of basal area of trees in each circle (SBA_w). The computation formula is as follows:

$$SBA_w = \sum_{i=1}^{n} \frac{BA_i}{Dist_i},$$

where BA_i is the basal area of tree i, $Dist_i$ is the distance of tree i from the sampling point, and n is the number of trees in a circle. All the calculated vegetation variables are listed in Table 1. Finally, the vegetation variables calculated in a 20-m radius were used in variation partitioning, since the explanatory power of vegetation variables at 20-m radius were was much greater than that in 5- or 10-m radius.

As for spatial variables, we used principal coordinates of neighbor matrices (PCNMs) to produce a series of dummy variables, to represent the spatial structure of the study site at multiple spatial scales. This method is based on principal coordinate analysis of a truncated Euclidean distance matrix among sampling points using the geographic coordinates (Borcard and Legendre 2002). Topographic variables include aspect, slope, slope position, and elevation at each sampling point.

Forward selections of variables were conducted before the variation partitioning analyses to keep only the variables that significantly affect SOC and TN variations (Blanchet et al. 2008). Because a large spatial trend in the data across the site violates the stationarity assumption, detrending of data was conducted (Gallardo 2003). PCNM variable selection was accomplished after data was detrended.

As a complement, we used Mantel test to identify correlations among matrices transformed by different variables, and we also used partial Mantel test to examine relationships after exclude the effect of spatial structure.

Statistical and geostatistical analyses were performed in R 3.3.0, using "geoR" package (R Development Core Team 2016). Forward selections were accomplished by using the "packfor" package (Dray 2011). We used the "PCNM" package to generate the PCNM variables (Blanchet et al. 2008). Both variation partitioning analyses and Mantel test were performed by using the "vegan" package (Oksanen et al. 2016).

Table 1 Abbreviations and explanations of different vegetation variables

Abbreviation	Explanation
Num	The number of trees DBH ≥1 cm
Prop	The proportion of the number of trees DBH ≥5 cm in all trees
SBA_W	The weighted sum of basal area of all trees DBH ≥1 cm
BA_W	The weighted basal area of the nearest trees DBH ≥5 cm
DSBA_W	The weighted sum of basal area of deciduous trees DBH ≥1 cm
ESBA_W	The weighted sum of basal area of evergreen trees DBH ≥1 cm
SR	Species richness
BI	Biodiversity index (Shannon-Wiener index)

3 Results

3.1 Semivariogram analysis of SOC and TN

Descriptive statistics of soil data at different depth ranges are shown in Table 2. The difference of SOC in 0–10- and in 10–30-cm depth range was statistically significant ($p < 0.05$), while no difference were discovered for TN between different

Table 2 Descriptive statistics and parameters for the spherical semivariogram models of SOC and TN in the BDGS 25-ha plots

	Unit	Mean	SD	CV	Range[a]	C	C_0	$C/C_0 + C$
$SOC_{0-10\ cm}$	%	8.42	2.61	0.31	29.21	0.01	0.03	0.31
$SOC_{10-30\ cm}$	%	4.71	1.46	0.31	23.66	0.04	0.06	0.42
$TN_{0-10\ cm}$	%	0.63	0.17	0.27	38.92	0.02	0.05	0.31
$TN_{10-30\ cm}$	%	0.34	0.10	0.30	54.29	0.02	0.02	0.47

C and C_0 are Box-Cox transformed variances

[a] Units in meters

depth ranges (Table 2). SOC concentration ranged from 3.15 to 22.33 % in 0–10-cm depth range and from 0.25 to 1.42 % in 10–30-cm depth range, respectively.

Both SOC and TN in both depth ranges showed a moderate CV (27–31 %). Furthermore, the fitted spherical models showed that there were moderate spatial autocorrelations at the observed scale with explainable fractions ($C/C + C_0$) ranged from 31 % for 0–10-cm depth range to 47 % for 10–30-cm depth range. Semivariogram ranges (the distance of spatial autocorrelation) of SOC were 29.21 m in 0–10-cm depth range and 23.66 m in 10–30 cm, while semivariogram ranges of TN were 38.92 m in 0–10-cm depth range and 54.29 m in 10–30 cm. However, the results of cross-validation indicated a poor prediction when using kriging interpolation based on the fitted model. Semivariograms of SOC and TN also showed relatively large nuggets (Fig. 3).

3.2 Mantel's test between variables

For soils of 0–10 cm, results of simple Mantel tests indicated significant effects of environmental variables on both SOC and TN (Table 3). Partial Mantel test (removing the effects of spatial structure) found similar significant effects of environmental variables on both SOC and TN.

For soils of 10–30 cm, simple Mantel tests showed significant correlation between soil variables and SOC; this significant correlation maintains when using partial Mantel to remove the effects of spatial structure. Topographic variables were found to be significantly correlated with TN for both simple and partial Mantel tests. Meanwhile, the correlations between soil variables and TN were found to be marginally significant with a *p* value close to 0.05 for both simple and partial Mantel tests (Table 3).

3.3 Variation partitioning of SOC and TN

According to the results of variation partitioning, the explained SOC variation by these groups of variables in 0–10-cm depth range and 10–30-cm depth range were 47.8 and 24.4 %, respectively (Fig. 4). Likewise, the explained TN variation in 0–10 and 10–30 cm were 39.0 and 29.9 %,

respectively. The pure effects of each group of factors on SOC and TN were significant in both depth ranges. The pure effect of vegetation was lower than the interactions between vegetation and other variables, but pure effects of soil mostly had greater explanatory power for both SOC and TN. The pure effect of space always has greater power than the interactions. However, in terms of absolute values, they were all very low.

For SOC in 0–10-cm depth range, the highest contribution came from soil variables (35.8 %, including soil pH and AP), followed by spatial structure (21.6 %, including 20 PCNMs) and vegetation composition (11.1 %, including SBA_w and SR). For SOC in 10–30-cm depth range and TN in both depth ranges, the contributions consistently followed the order of spatial variables > soil variables > vegetation variables.

When soil texture was taken into account, explanatory power of soil variables for SOC in 0–10-cm depth range increased from 35.8 to 42.7 %, and explanatory power of soil variables for TN in 0–10-cm depth ranged from 18.8 to 22.6 %. According to multiple regressions, topographic variables were also significantly related with SOC and TN, even if only about 4 % of SOC variation was explained by topography. In addition, the results also indicated that soil pH and clay content were negatively related with SOC, while soil AP, SBA_w, and SR exhibited positive correlations with SOC.

4 Discussion

4.1 SOC and TN concentration and their spatial variability

The estimation of the SOC and TN concentration in our study, which was consistent with the technologic report for BDGS in 1982 (Liu 1983), was higher than that in other subtropical forests under the same latitude (Ding et al. 2011; Xu et al. 2008). These results indicated that precise local estimates of soil carbon stock with large sample size were indispensable for regional and global estimates. Although semivariogram analyses demonstrated that there were similarities in the patterns of spatial variation for SOC at two different depth ranges in our study site, the relatively lower $C/C + C_0$ value (0.31) of SOC and TN in 0–10-cm depth range, compared with that value (0.42–0.47) in 10–30-cm depth range, confirm the first hypothesis that subsurface soil has a stronger spatial autocorrelation of SOC and TN than surface soil.

Because the nugget (C_0) represents the variance due to sampling error and/or spatial dependence at scales not explicitly sampled (Ettema and Wardle 2002), the relatively high value of C_0 suggested that there still existed a large variation at finer scales. It has been reported that microbial biomass, structure, and activity have a strong correlation with the mineralization of SOC (Von Lützow and Kögel-Knabner 2009).
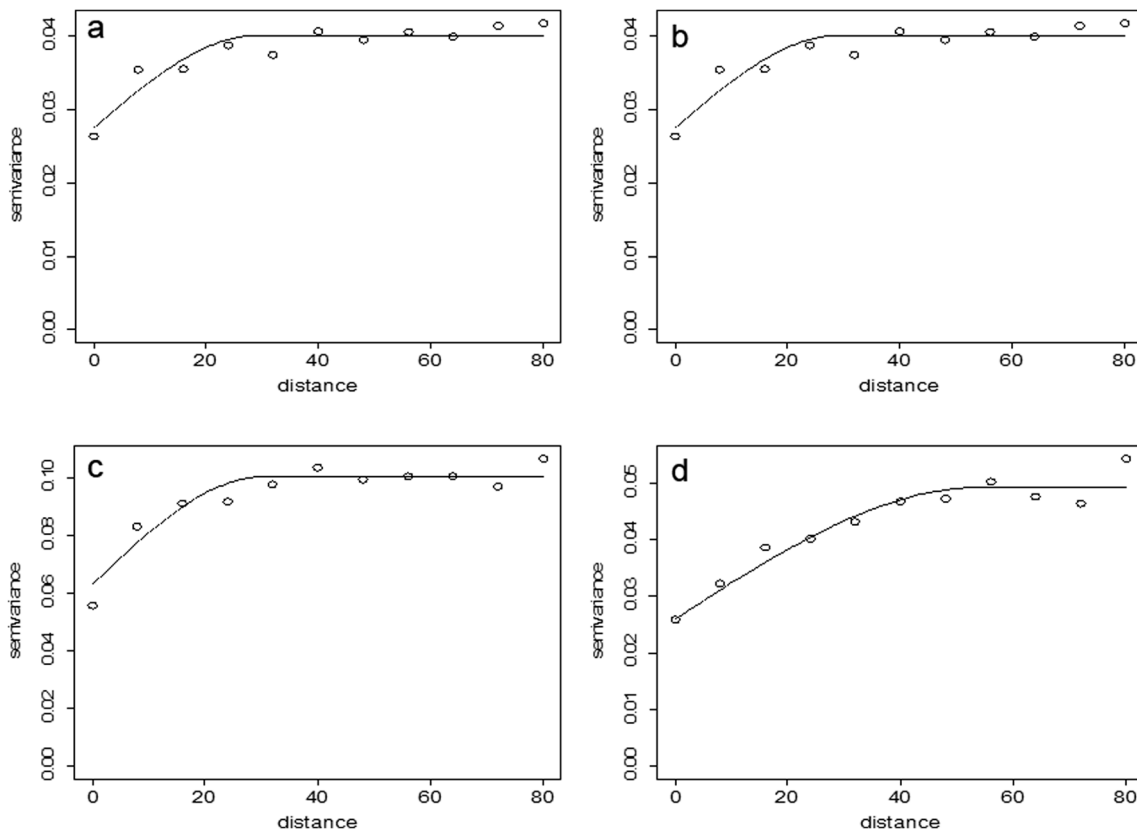
Fig. 3 Semivriograms of Box-Cox transformed SOC (**a**) and TN (**b**) concentration in 0–10cm depth range and SOC (**c**) and TN (**d**) concentration in 10–30 cm using the 972 soil samples. Distance is in meters

High spatial variations of soil respiration and microbial community composition at small scale in our plot have been found (unpublished data). Thus, fine-scale microbial characteristic, regulated by fine-scale environmental factors, may play a key role in fine-scale (<2 m) spatial variation of SOC. Furthermore, the higher heterogeneity of soil properties may be one of the reasons for the higher plant diversity in this forest than other subtropical forests.

### 4.2 The relative contributions of variables to SOC and TN

The determinants of SOC dynamics change with the spatial scales (O'rourke et al. 2015). At local scale, many different local environmental factors may influence the spatial dynamics of SOC and TN, few studies used variation partitioning with spatial variables to address the relative influence of these factors (Yuan et al. 2013).

Table 3 Results of simple and partial Mantel tests between SOC and TN matrices, environmental variables matrices (soil, vegetation, and topography) and spatial structure matrices (space) in the BDGS plot

Variable	Variable~space		SOC~variable		SOC~variable | space		TN~variable		TN~variable | space	
	r	p	r	p	r	p	r	p	r	p
0–10-cm depth range										
Space	–	–	0.03	0.043	–	–	0.01	0.254	–	–
Soil	0.02	0.112	0.34	0.001	0.34	0.001	0.22	0.001	0.22	0.001
Vegetation	0.04	0.002	0.09	0.001	0.08	0.001	0.05	0.008	0.05	0.009
Topography	0.09	0.001	0.05	0.027	0.04	0.026	0.07	0.002	0.07	0.002
10–30-cm depth range										
Space	–	–	0.03	0.016	–	–	0.03	0.032	–	–
Soil	0.02	0.145	0.1	0.002	0.1	0.001	0.04	0.057	0.04	0.047
Vegetation	0.01	0.176	0.01	0.227	0.01	0.258	0	0.499	0	0.482
Topography	0.08	0.001	0.02	0.127	0.02	0.145	0.1	0.001	0.1	0.001

The Mantel correlation coefficient (r) and significance level (p) is shown for each test

Fig. 4 Variation partitioning results of SOC (**a**) and TN (**b**) in 0–10-cm depth range and SOC (**c**) and TN (**d**) in 10–30-cm depth range against the soil (without soil texture data), vegetation, and spatial variables. Values <0 were not shown. Significant values (*p* < 0.05) after 999 permutations are indicated with *asterisk*
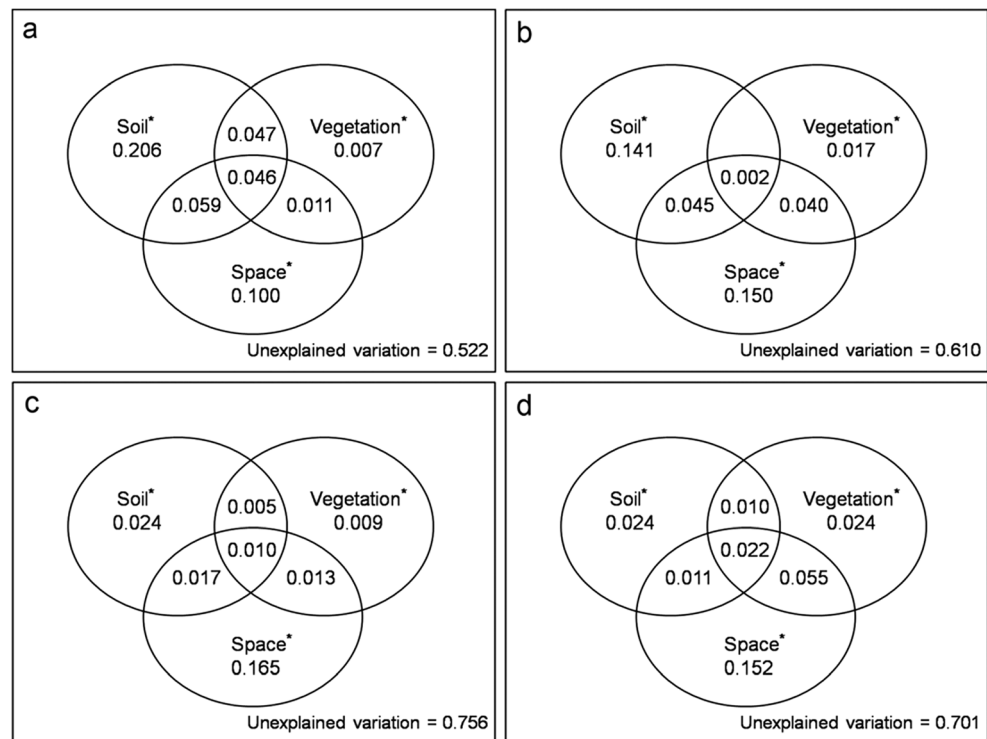
In our study site, soil variables are the main determinants of SOC patterns in surface soil. Soil conditions can directly influence the functional composition, activity, and biomass of microbes that control the rate of litter decomposition (Davidson and Janssens 2006) and SOC mineralization (Von Lützow and Kögel-Knabner 2009). Despite the well-demonstrated positive relationship between soil clay content and SOC at regional or global scale (Jobbágy and Jackson 2000), soil sampling points with higher clay content may experience stronger soil leaching in this area due to the high annual precipitation; thus, the strong soil leaching and the deposition of clays may result in an opposite phenomenon that the SOC concentration were negatively related with clay content at local scale.

It has been argued that the mineralization of soil organic matter was influenced by soil acidity through regulating soil microbial and enzyme activity, and this may lead to a significant correlation between soil pH and SOC (Curtin et al. 1998; Rousk et al. 2009). It is widely considered that phosphorus is the limiting factors of primary production and litter decomposition in tropical and subtropical forests (Kaspari et al. 2008). High soil P availability can promote the growth of tree species and increase the rate of litter decomposition, thus facilitate the accumulation of SOC (Hobbie and Vitousek 2000; Cleveland et al. 2006). Soil ecological processes at fine scale like the physical protection of soil organic matter by soil particles may also play an important role in the spatial variability of SOC and TN (Stockmann et al. 2013; Vogel et al. 2014).

Vegetation composition can alter soil properties which are important for SOC decomposition (Huang et al. 2013, 2014).

As for vegetation, compared with its pure effect, the interaction between vegetation and soil was greater in the 0–10-cm depth range which indicated that trees might regulate SOC and TN indirectly through changing soil conditions. In addition, several studies have reported that the main source of SOC were litter input and root exudates which have a strong relationship with tree basal area (Yuan et al. 2010). Therefore, the larger the basal area and the smaller the distances of trees from sampling point, the more soil carbon input and accumulation.

A strong positive relationship between plant species richness and soil C storage has been reported in previous studies (Cong et al. 2014). Plant species richness or functional diversity has a positive influence on aboveground primary production, litter degradation, and microbial biomass (Díaz and Cabido 2001; Chung et al. 2007). These processes may be key contributors to the positive relationship between plant diversity and soil C. Studies on how species richness may affect ecosystem functions were mostly limited to grassland ecosystems. More studies on forest ecosystem are imperative to understand the mechanisms of tree diversity effects on soil C.

The effects of spatial structure on SOC and TN variations are shared by soil, and vegetation variables may partly be a consequence of abiotic and biotic processes such as soil leaching and litter input which can be affected by soil autocorrelation and the spatial distribution of tree individuals, respectively. However, a large majority of variation was unexplained by these selected variables, a follow-up study refer to other important variables such as root biomass and activities

are helpful to understand the mechanism of SOC and TN patterns further (Wiesmeier et al. 2013).

It has been reported that the proportion of recalcitrant carbon in soil carbon pool increased with soil depth, and soil properties have little effect on the decomposition of recalcitrant carbon (Rumpel and Kögel-Knabner 2011). In our study, compared with surface soil, the explanatory power of environmental variables was much lower for subsurface soil. This result was consistent with the second hypothesis. This also indicated that surface soil carbon and nitrogen were more sensitive to soil properties than subsurface soil in this region. These results suggest that the mechanisms of SOC and TN patterns in 0–10-cm depth range are different from that in 10–30 cm, although variation explained by vegetation and spatial variables and their interactions in 0–10-cm depth range were similar to 10–30-cm depth range. Few climate change models distinguished the difference between surface soil and subsurface soil (Ortiz et al. 2013). A better understanding of the SOC and TN patterns of subsurface soil and their impact factors are helpful to improve these climate change models.

Yuan et al. (2013) found that topographic variables explained 17 % of SOC variation in an old-growth temperate forest. By contrast, only 4 % of variation was explained by topography in our studies. Topography can affect the formation and decomposition of SOM by changing soil hydrothermal conditions (Hicks and Frank 1984). However, because of the very high canopy closure and the very high annual precipitation, soil temperature, and moisture may be not limiting factors in subtropical forests at BDGS.

5 Conclusions

Our results demonstrated that subsurface soil had a slightly stronger spatial autocorrelation in SOC and TN than surface soil. There was a relatively high portion of spatial variations, and SOC and TN were mainly determined by soil properties like soil pH and AP and soil texture. Vegetation distribution and topography also contributed significantly by changing soil conditions, since a strong interaction of these variables were discovered. The overall low explanatory power of these variables in this study also suggested that fine-scale environmental factors such as microtopography, soil microbes and the composition of litterfall are likely important factors in affecting SOC and TN distribution, which should be given more attention in further studies.

The results of this study illustrated the large variation in soil C and N and the differences in their determining mechanisms should be taken into account when evaluating how forest management may affect C and N cycles regionally and globally. When evaluating the effects of global climate change on forest ecosystem, its effects on individual controlling ecological processes should be carefully examined before drawing any conclusion on its synthetic effects on the spatial distribution of soil C and N.

References

Adu-Bredu S, Yokota T, Ogawa K, Hagihara A (1997) Tree size dependence of litter production, and above-ground net production in a young hinoki (*Chamaecyparis obtusa*) stand. J Forest Res 2:31–37

Blanchet FG, Legendre P, Borcard D (2008) Forward selection of explanatory variables. Ecology 89:2623–2632

Borcard D, Legendre P (2002) All-scale spatial analysis of ecological data by means of principal coordinates of neighbour matrices. Ecol Model 153:51–68

Borcard D, Legendre P, Drapeau P (1992) Partialling out the spatial component of ecological variation. Ecology 73:1045–1055

Bradford JB, Birdsey RA, Joyce LA, Ryan MG (2008) Tree age, disturbance history, and carbon stocks and fluxes in subalpine Rocky Mountain forests. Glob Chang Biol 14:2882–2897

Chen HYH, Shrestha BM (2012) Stand age, fire and clearcutting affect soil organic carbon and aggregation of mineral soils in boreal forests. Soil Biol Biochem 50:149–157

Chung H, Zak DR, Reich PB, Ellsworth DS (2007) Plant species richness, elevated CO2, and atmospheric nitrogen deposition alter soil microbial community composition and function. Glob Chang Biol 13:980–989

Cleveland CC, Reed SC, Townsend AR (2006) Nutrient regulation of organic matter decomposition in a tropical rain forest. Ecology 87:492–503

Condit R (1998) Tropical forest census plots: methods and results from Barro Colorado Island, Panama and a comparison with other plots. Springer, Heidelberg

Cong WF, van Ruijven J, Mommer L, De Deyn GB, Berendse F, Hoffland E (2014) Plant species richness promotes soil carbon and nitrogen stocks in grasslands without legumes. J Ecol 102:1163–1170

Curtin D, Campbell CA, Jalil A (1998) Effects of acidity on mineralization: pH-dependence of organic matter mineralization in weakly acidic soils. Soil Biol Biochem 30:57–64

Davidson EA, Janssens IA (2006) Temperature sensitivity of soil carbon decomposition and feedbacks to climate change. Nature 440:165–173

De Deyn GB, Cornelissen JHC, Bardgett RD (2008) Plant functional traits and soil carbon sequestration in contrasting biomes. Ecol Lett 11:516–531

Díaz S, Cabido M (2001) Vive la difference: plant functional diversity matters to ecosystem processes. Trends Ecol Evol 16:646–655

Díaz-Pinés E, Rubio A, van Miegroet H, Benito M, Montes F (2011) Does tree species composition control soil organic carbon pools in Mediterranean mountain forests? For Ecol Manag 262:1895–1904

Ding J, Wu Q, Yan H, Zhang SR (2011) Effects of topographic variations and soil characteristics on plant functional traits in a subtropical evergreen broad-leaved forest. Biodivers Sci 19:158–167 (in Chinese)

Dray S (2011) Pack for: Forward Selected with Multivariate Y by Permutation Under Reduced Model. Laboratoire Biométrie et Biologie Évolutive, Lyon

Ettema CH, Wardle DA (2002) Spatial soil ecology. Trends Ecol Evol 17:177–183

Fornara DA, Tilman D (2008) Plant functional composition influences rates of soil carbon and nitrogen accumulation. J Ecol 96:314–322

Gallardo A (2003) Spatial variability of soil properties in a floodplain forest in northwest Spain. Ecosys 6:564–576

Gallardo A, Paramá R (2007) Spatial variability of soil elements in two plant communities of NW Spain. Geoderma 139:199–208

Goovaerts P (1998) Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. Biol Fert Soils 27:315–334

Guo YL, Lu JM, Franklin SB, Wang QG, Xu YZ, Zhang KH, Bao DC, Qiao XJ, Huang HD, Lu ZJ, Jiang MX (2013) Spatial distribution of tree species in a species-rich subtropical mountain forest in central China. Can J For Res 43:826–835

Hicks RR, Frank PS (1984) Relationship of aspect to soil nutrients, species importance and biomass in a forested watershed in West Virginia. For Ecol Manag 8:281–291

Hobbie SE, Vitousek PM (2000) Nutrient limitation of decomposition in Hawaiian forests. Ecology 81:1867–1877

Hook PB, Burke IC (2000) Biogeochemistry in a shortgrass landscape: control by topography, soil texture, and microclimate. Ecology 81: 2686–2703

Huang ZQ, Wan XH, He ZM, Yu ZP, Wang MH, Hu ZH, Yang YS (2013) Soil microbial biomass, community composition and soil nitrogen cycling in relation to tree species in humid subtropical China. Soil Biol Biochem 62:68–75

Huang ZQ, Yu ZP, Wang MH (2014) Environmental controls and the influence of tree species on temporal variation in soil respiration in subtropical China. Plant Soil 382:75–87

Jobbágy EG, Jackson RB (2000) The vertical distribution of soil organic carbon and its relation to climate and vegetation. Ecol Appl 10:423–436

Kaspari M, Garcia MN, Harms KE, Santana M, Wright SJ, Yavitt JB (2008) Multiple nutrients limit litterfall and decomposition in a tropical forest. Ecol Lett 11:35–43

Kleb HR, Wilson SD (1997) Vegetation effects on soil resource heterogeneity in prairie and forest. Am Natural 150:283–298

Legendre P, Dale MRT, Fortin M-J, Gurevitch J, Hohn M, Myers D (2002) The consequences of spatial structure for the design and analysis of ecological field surveys. Ecography 25:601–615

Liski J (1995) Variation in soil organic carbon and thickness of soil horizons within a boreal forest stand-effect of trees and implications for sampling. Silva Fenn 29:255–266

Liu BX (1983) The soil in the Badagongshan National Nature Reserve. J Central South For Inst 3:141–158 (in Chinese)

Mills RTE, Tipping E, Bryant CL, Emmett BA (2014) Long-term organic carbon turnover rates in natural and semi-natural topsoils. Biogeochemistry 118:257–272

Mueller KE, Hobbie SE, Oleksyn J, Reich PB, Eissenstat DM (2012) Do evergreen and deciduous trees have different effects on net N mineralization in soil? Ecology 93:1463–1472

Muukkonen P, Häkkinen M, Mäkipää R (2009) Spatial variation in soil carbon in the organic layer of managed boreal forest soil—implications for sampling design. Environ Monit Assess 158:67–76

O'Rourke SM, Angers DA, Holden NM, McBratney AB (2015) Soil organic carbon across scales. Glob Chang Biol 21:3561–3574

Oksanen J, Blanchet FG, Kindt R, Legendre P, O'Hara RB, Simpson GL, Solymos P, Stevens MHH, Wagner H (2016) Vegan: community ecology package, version 2.3–5. URL http://CRAN.R-project.org

Ortiz CA, Liski J, Gärdenäs AI, Lehtonen A, Lundblad M, Stendahl J, Ågren GI, Karltun E (2013) Soil organic carbon stock changes in Swedish forest soils—a comparison of uncertainties and their sources through a national inventory and two simulation models. Ecol Model 251:221–231

Peri PL, Ladd B, Pepper DA, Bonser SP, Laffan SW, Amelung W (2012) Carbon (δ^{13}C) and nitrogen (δ^{15}N) stable isotope composition in plant and soil in southern Patagonia's native forests. Glob Chang Biol 18:311–332

Pregitzer KS, Euskirchen ES (2004) Carbon cycling and storage in world forests: biome patterns related to forest age. Glob Chang Biol 10: 2052–2077

Qiao XJ, Li QX, Jiang QH, Lu JM, Franklin S, Tang ZY, Wang QG, Zhang JX, Lu ZJ, Bao DC, Guo YL, Liu HB, Xu YZ, Jiang MX (2015) Beta diversity determinants in Badagongshan, a subtropical forest in central China. Sci Rep 5:17043

R Development Core Team (2016) R: A language and environment for statistical computing. Vienna, Austria. URL http://www.R-project.org

Rousk J, Brookes PC, Bååth E (2009) Contrasting soil pH effects on fungal and bacterial growth suggest functional redundancy in carbon mineralization. Appl Environ Microbiol 75:1589–1596

Rumpel C, Kögel-Knabner I (2011) Deep soil organic matter—a key but poorly understood component of terrestrial C cycle. Plant Soil 338: 143–158

Ryżak M, Bieganowski A (2011) Methodological aspects of determining soil particle-size distribution using the laser diffraction method. J Plant Nutr Soil Sci 174:624–633

Seibert J, Stendahl J, Sørensen R (2007) Topographical influences on soil properties in boreal forests. Geoderma 141:139–148

Silver WL, Neff J, McGroddy M, Veldkamp E, Keller M, Cosme R (2000) Effects of soil texture on belowground carbon and nutrient storage in a lowland Amazonian forest ecosystem. Ecosys 3:193–209

Soil Survey Staff (1999) Soil taxonomy: A basic system of soil classification for making and interpreting soil surveys. 2nd edition. Natural Resources Conservation Service. U.S. Department of Agriculture Handbook 436. Washington DC, USA

Stockmann U, Adams MA, Crawford JW, Field DJ, Henakaarchchi N, Jenkins M, Minasny B, McBratney AB, de Courcelles V, Singh K, Wheeler I, Abbott L, Angers DA, Baldock J, Bird M, Brookes PC, Chenu C, Jastrow JD, Lal R, Lehmann J, O'Donnell AG, Parton WJ, Whitehead D, Zimmermann M (2013) The knowns, known unknowns and unknowns of sequestration of soil organic carbon. Agric Ecosyst Environ 164:80–99

Townsend AR, Asner GP, Cleveland CC (2008) The biogeochemical heterogeneity of tropical forests. Trends Ecol Evol 23:424–431

Tsui CC, Chen ZS, Hsieh CF (2004) Relationships between soil properties and slope position in a lowland rain forest of southern Taiwan. Geoderma 123:131–142

Vogel C, Mueller CW, Höschen C, Buegger F, Heister K, Schulz S, Schloter M, Kögel-Knabner I (2014) Submicron structures provide preferential spots for carbon and nitrogen sequestration in soils. Nat Commun 5:149–168

Von Lützow M, Kögel-Knabner I (2009) Temperature sensitivity of soil organic matter decomposition—what do we know? Biol Fertil Soils 46:1–15

Wiesmeier M, Hübner R, Barthold F, Spörlein P, Geußd U, Hangend E, Reischld A, Schillingd B, Von Lützowa M, Kögel-Knabner I (2013) Amount, distribution and driving factors of soil organic carbon and nitrogen in cropland and grassland soils of southeast Germany (Bavaria). Agric Ecosyst Environ 176:39–52

Xu ZH, Ward S, Chen CR, Blumfield T, Prasolova NV, Liu JX (2008) Soil carbon and nutrient pools, microbial properties and gross nitrogen transformations in adjacent natural forest and hoop pine plantations of subtropical Australia. J Soils Sediments 8:99–105

Yuan ZQ, Li BH, Bai XJ, Lin F, Shi S, Ye J, Wang XG, Hao ZQ (2010) Composition and seasonal dynamics of litter falls in a broad-leaved Korean pine mixed forest in Changbai Mountains, Northeast China. Chin J Appl Ecol 21:2171–2178 (in Chinese)

Yuan ZQ, Gazol A, Lin F, Ye J, Shi S, Wang XG, Wang M, Hao ZQ (2013) Soil organic carbon in an old-growth temperate forest: spatial pattern, determinants and bias in its quantification. Geoderma 195: 48–55

Zhang LW, Mi XC, Shao HB, Ma KP (2011) Strong plant-soil associations in a heterogeneous subtropical broad-leaved forest. Plant Soil 347:211–220