Journal of Integrative Agriculture 2020, 19(9): 2313–2325

Available online at www.sciencedirect.com

ScienceDirect

RESEARCH ARTICLE

Spatial variability of soil properties in red soil and its implications for site-specific fertilizer management

SONG Fang-fang[1, 2], XU Ming-gang[1, 3], DUAN Ying-hua[1], CAI Ze-jiang[1], WEN Shi-lin[1], CHEN Xian-ni[4], SHI Wei-qi[3], Gilles COLINET[2]

[1] *National Engineering Laboratory for Improving Quality of Arable Land, Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences, Beijing 100081, P.R.China*

[2] *Gembloux Agro-Bio Tech, University of Liege, Gembloux 5030, Belgium*

[3] *South Subtropical Crop Research Institute, Chinese Academy of Tropical Agricultural Sciences, Zhanjiang 524091, P.R.China*

[4] *College of Agriculture, Henan University of Science & Technology, Luoyang 471003, P.R.China*

Abstract

Assessing spatial variability and mapping of soil properties constitute important prerequisites for soil and crop management in agricultural areas. To explore the relationship between soil spatial variability and land management, 256 samples were randomly collected at two depths (surface layer 0–20 cm and subsurface layer 20–40 cm) under different land use types and soil parent materials in Yujiang County, Jiangxi Province, a red soil region of China. The pH, soil organic matter (SOM), total nitrogen (TN), cation exchange capacity (CEC), and base saturation (BS) of the soil samples were examined and mapped. The results indicated that soils in Yujiang were acidified, with an average pH of 4.87 (4.03–6.46) in the surface layer and 4.99 (4.03–6.24) in the subsurface layer. SOM and TN were significantly higher in the surface layer (27.6 and 1.50 g kg^{-1}, respectively) than in the subsurface layer (12.1 and 0.70 g kg^{-1}, respectively), while both CEC and BS were low (9.0 and 8.0 cmol kg^{-1}, 29 and 38% for surface and subsurface layers, respectively). Paddy soil had higher pH (mean 4.99) than upland and forest soils, while soil derived from river alluvial deposits (RAD) had higher pH (mean 5.05) than the other three parent materials in both layers. Geostatistical analysis revealed that the best fit models were exponential for pH and TN, and spherical for BS in both layers, while spherical and Gaussian were the best fitted for SOM and CEC in the surface and subsurface layers. Spatial dependency varied from weak to strong for the different soil properties in both soil layers. The maps produced by selecting the best predictive variables showed that SOM, TN, and CEC had moderate levels in most parts of the study area. This study highlights the importance of site-specific agricultural management and suggests guidelines for appropriate land management decisions.

Keywords: spatial variability, soil pH, CEC, BS, site-specific fertilizer management

Received 18 September, 2019 Accepted 23 March, 2020

SONG Fang-fang, E-mail: songfang422@163.com; Correspondence XU Ming-gang, Tel: +86-759-2858168, E-mail: xuminggang@caas.cn; DUAN Ying-hua, Tel: +86-10-82106239, E-mail: duanyinghua@caas.cn

doi: 10.1016/S2095-3119(20)63221-X

1. Introduction

Soil acidification (i.e., soil pH decline) is one of the most serious land degradation processes that is often triggered by unsustainable land management practices worldwide (Ulrich 1986). Soil acidification has received considerable attention for its profound influences on crop productivity, landscape management, and terrestrial ecosystem nutrient cycling (Guo *et al.* 2010; Zhu *et al.* 2018). Soil acidification leads to nutrient loss, toxic metal enrichment, and potential environmental risk to the bulk soil and surrounding environment (Duan *et al.* 2004; Horswill *et al.* 2008; Hao *et al.* 2018). Soil pH, carbon (C), nitrogen (N), cation exchange capacity (CEC), and base saturation (BS) are key indexes for maintaining soil fertility, especially in acidic soils. Declining soil pH limits the availability of soil nutrients, increases the toxicity of heavy metal elements and decreases underground microorganism activity, which disturbs the cycles of soil C and N (De Vries and Breeuwsma 1987). Soil nutrients (C and N) in turn, can help to enhance soil buffering capacity and the exchangeable base cations that have positive effects on relieving soil acidity (Fujii *et al.* 2017). Soil chemical elements, however, tend to have high spatial variability, especially in intensively managed agricultural soil (Bogunovic *et al.* 2014). Thus, a better understanding of the spatial variability of these vital soil chemical properties in acidic soils is necessary for evaluating the current and potential soil productivity and identifying site-specific fertilizer management practices (Behera and Shukla 2015).

The spatial variability of soil properties is usually influenced by land use types, topography, soil forming characters, soil depths, human activities, and time (Fu *et al.* 2010; Liu *et al.* 2013; Zhang *et al.* 2014; Behera and Shukla 2015; Zhang *et al.* 2015; Rosemary *et al.* 2017; Vasu *et al.* 2017). Most of these studies have mainly focused on soil macro-elements (e.g., C, N, P, and K) (Bogunovic *et al.* 2014; Blanchet *et al.* 2017) and soil pH (Tang *et al.* 2017), while microelements and other soil parameters (e.g., Ca, Mg, K, Na, CEC, BS, and soil buffering capacity) have been largely neglected (Fu *et al.* 2010; Behera and Shukla 2015). Usually, soil pH shows strong spatial dependence due to structural factors, such as soil types and soil parent materials. Soil nutrient spatial variations are usually determined by both intrinsic (e.g., soil forming factors) and extrinsic factors (e.g., fertilizer, irrigation, tillage, etc.), and they are also mediated by study scale and soil depth. Land use and field management were identified as two important factors for the spatial distribution of soil properties (Mayes *et al.* 2014; Ferreiro *et al.* 2016). A more thorough understanding of the distribution of soil properties, under their independent influencing factors within soil layers, will contribute to better field management in agricultural areas (Bogunovic *et al.* 2017).

Geostatistical analysis technology is widely used for evaluating the spatial variability of soil properties in agroecosystems (Bogunovic *et al.* 2014). The interpretation of the spatial variability of soil properties is mainly conducted using semi-variogram analysis and kriging interpolation. Ordinary kriging (OK) is one of the most popular interpolation methods for predicting the spatial distribution of soil properties (Cambardella *et al.* 1994; Zhang *et al.* 2015; Yang *et al.* 2016; Tang *et al.* 2017), while it ignores the spatial structures and patterns of soil variables that are related to other environmental factors (Qu *et al.* 2012; Ferreiro *et al.* 2016). Studies have proven that land use types have a profound effect on the spatial distribution of soil nutrients at different scales (Liu *et al.* 2013; Ferreiro *et al.* 2016). Soil parent materials can also affect and control the spatial variation of soil acidity and soil fertility (Qu *et al.* 2012). Regression kriging (RK) can better explore the spatial patterns and distribution of soil properties and improved prediction performance accuracy has been shown in some studies (Hengl *et al.* 2004). The proposed reasons for this include little or no relations between the predictors and the soil variables. Therefore, a more accurate spatial distribution of soil variables, which considers the significant influencing factors, is very important for site-specific fertilizer management in agricultural regions (Liu *et al.* 2010).

Addressing the spatial variability of key soil properties by combining their significant influencing factors in red soil regions in southern China is important for designing site-specific sustainable soil strategies and making appropriate crop management decisions (Sun *et al*. 2003; Liu *et al*. 2010). The objectives of this study were: (1) to investigate the differences in properties of soils under various land uses and soil parent materials at two soil depths; and (2) to explore the spatial variability of soil properties and produce spatial distribution maps.

2. Materials and methods

2.1. Study area

This study was conducted in Yujiang County (28°04´–28°37´N, 116°41´–117°09´E), Jiangxi Province, China, with a total area of 932 km^2, and spanning 59.6 km from south to north and 28.6 km from east to west (SSOYC 1986; Fig. 1). The study area has a subtropical monsoon climate with a mean annual temperature (MAT) of 17.8°C and mean annual precipitation (MAP) of 1 788 mm. The topography is dominated by hills, which cover 78% in the northern and southern parts, and by plains which cover the remaining 22% of the county. Soil texture varies from silt to clay, and is dominated by clay earth. The dominant soil types in this county are red soil (covering 64.67% of land area) (Acrisols; IUSS Working Group 2015) and paddy soil (covering 85.5% of cultivated land with an area of 2.48×10^4 ha) (SSOYC 1986; Anthrosol; IUSS Working Group 2015). The soil parent materials are dominated by Quaternary Red Clay

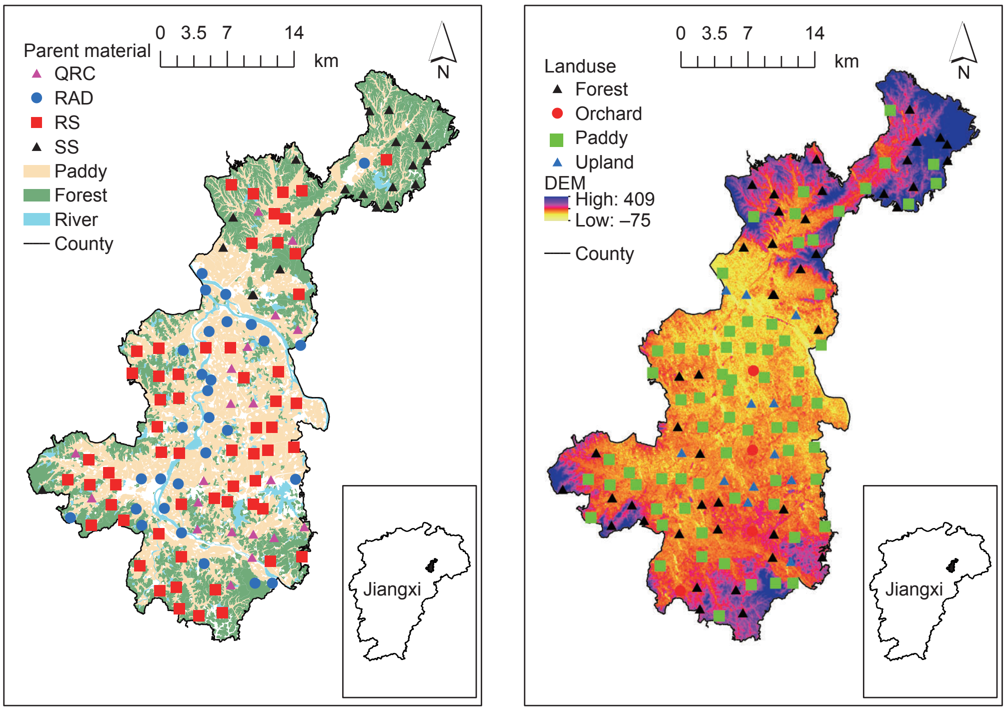

Fig. 1 The study site and sample locations in Yujiang, Jiangxi Province, China. QRC, quaternary red clay; RAD, river alluvial deposits; RS, red sandstone; SS, slate shale; DEM, digital elevation model.

clay, Red Sandstone, River Alluvial Deposits, and Slate Shale (SSOYC 1986; Xu *et al.* 2016), which are abbreviated as QRC, RS, RAD, and SS, respectively, in this study.

2.2. Soil sampling

Soil samples were collected at the beginning of January 2016 after crop harvesting. A total of 256 geo-referenced samples were chosen at two depths (0–20 and 20–40 cm, respectively) with a grid of 2.5 km×2.5 km designed in ArcGIS 10.0. These depths were chosen because these layers are most influenced by plants and soil management practices, especially in acid soils. The distribution of sample sites under different categories of land use and parent materials are shown in Fig. 1. Specifically, there are 69, 16, and 44 samples from paddy, upland, and forest under the two layers (paddy had 67 samples in the surface layer due to missing), respectively. For QRC, RS, RAD, and SS, the numbers are 20, 59, 29, and 21 for two depths, respectively (RS had 57 samples in the surface layer due to missing). Due to the randomness of soil sampling, numbers (proportions) of samples were as close as possible to the distribution areas of the different categories of land use and soil parent materials. Soil samples were collected using a stainless soil auger, and three composite samples were mixed into a compound sample for homogeneity. After air-drying at room temperature, a 1 kg of sub-sample was divided and sieved to 2 mm before removing the debris and plant material. Then, samples were stored in a glass bottle for further analysis.

2.3. Laboratory analysis and soil nutrient indexes

All soil properties were tested using the national standard analysis methods. Specifically, soil pH was determined using a soil:water ratio of 1:2.5 and a glass pH meter. The SOM was estimated using the oil heating oxidation with potassium dichromate ($K_2Cr_2O_7$-H_2SO_4) method (Page 1965). Soil total nitrogen (TN) was determined using the Kjeldahl method (Page 1965). Cation exchange capacity (CEC) and base cations (here referring to exchangeable Ca^{2+}, Mg^{2+} and K^+) were extracted using the ammonium acetate method (NH_4OAc at pH 7.0) and determined using an atomic absorption meter (for Ca^{2+} and Mg^{2+}) (Jones 1998) and spectrophotometer (for K^+) (Hanway and Heidel 1952). Base saturation (BS) was the percentage of the ratio of the sum of base cations to CEC in this study, according to the principles reported by IUSS Working Group (2015).

Soil nutrient indexes used for soil pH, SOM, TN, and CEC were based on the Second National Standard Classification and regional guidelines (SSOYC 1986). These indices could be regarded as the optimum values for fertilizer, manure, and lime applications. These critical values were also used for the prediction map. In this study, fertilization was recommended for soils with a pH above 5.0. This is because the soil buffering stage would change from a cation exchange system (at pH range 4.2–5.0) dominated by exchangeable cations to an iron-aluminum oxide buffer system (at pH lower than 4.2), including potentially toxic metal elements (e.g., Al^{3+}, Mn^{2+}, and Fe^{3+}) (Bowman *et al.* 2008), which is typical for highly weathered soil like the red soil in southern China. In addition, moderate levels (classes 3 and 4) of SOM and TN suggest suitability for sustainable soil fertility and crop production, so that low levels (classes 1 and 2) of these two variables are used as recommendations for fertilizer application, whereas high-level (classes 5 and 6) areas suggest a need for maintenance and balance. High levels (classes 5 and 6) of TN are concerning, suggesting a risk of nitrogen pollution of the deeper soil and surrounding water bodies.

2.4. Geostatistical analysis

Geostatistical analysis was used to describe the spatial variation of each soil variable in this study, including semi-variogram estimator, fitting-model, interpolation and validation (Cambardella *et al.* 1994). From the semi-variogram and fitted model, three key parameters (nugget, nugget to sill ratio, and range) can be estimated as the inputs for kriging. Detailed information on the geostatistical steps can be found in Fu *et al.* (2010). Before this, predictive factors affecting soil variables were selected based on the results from single and multi-linear regression fitting models. The criterion for selection was the minimum Akaike information criterion (AIC) value obtained from individual and combined influencing factors for each soil variable. Then, RK was employed to produce predictive maps for soil variables based on the results from the selected predictive factors. Similar results from previous studies have proven that RK could improve the accuracy of spatial prediction compared with OK (Bogunovic *et al.* 2017).

2.5. Classical statistics

Descriptive analyses for each soil variable, including mean, median, minimum, maximum, standard deviation (SD), and coefficient of variation (CV) were calculated for the entire dataset (Table 1). Normality was tested using the Shapiro–West (S–W) method with skewness and kurtosis values. This is used because: 1) nonnormality of distribution with outliers has a profound influence on spatial variogram analysis (Armstrong and Boufassa 1988; Kerry and Oliver 2007; Fu *et al.* 2010); and 2) conservational normality tests evaluated by *P*-value (P>0.05) typically do not produce satisfying results, and environmental data are commonly asymmetric (Fu *et al.* 2010; Bogunovic *et al.* 2014; Tang *et al.* 2017). Thus, data transformation has been employed in many soil survey studies to obtain a near-normal distribution in the dataset (Fu *et al.* 2010; Tesfahnegn *et al.* 2011; Bogunovic *et al.* 2017; Tang *et al.* 2017). In this study, logarithmic (log) and Box-Cox transformation methods were employed due to their popularity and effectiveness (Fu *et al.* 2010; Bogunovic *et al.* 2014, 2017). A non-parametric test (e.g., Kruskal–Wallis test) was employed to investigate significant differences among land use types (considering the limited samples of upland and orchard, we combined them into one group named "upland") and parent materials for the two depths due to the unequal number of samples between categories. A correlation coefficient matrix was carried out among soil variables and topography parameters (elevation, slope, and aspect) that were extracted from the digital elevation model (DEM) with a resolution of 90 m for Yujiang. This digital picture was obtained from the Geospatial Data Cloud (http://www.gscloud.cn/).

All statistical analyses and plots were conducted in R Version 3.4.1 (R Core Team 2017). Basic descriptions of soil variables were based on the *describe* function from the *psych* package (Revelle 2018). The *gstat* (Pebesma 2004) and *raster* (Robert 2017) packages were used for spatial

Table 1 Description of soil variables in layers of 0–20 and 20–40 cm in Yujiang, Jiangxi Province, China[1)]

Variables	*n*	Mean	SD	Median	Minimum	Maximum	CV (%)	Skewness	Kurtosis	S–W test
0–20 cm										
pH	127	4.82	0.38	4.86	4.03	6.46	7.88	0.81	2.55	0.00
SOM	127	27.60	13.07	26.77	3.17	62.49	47.36	0.21	–0.68	0.56
TN	127	1.50	0.74	1.38	0.15	3.79	49.33	0.44	–0.30	0.01
CEC	127	9.01	2.52	8.72	3.08	17.01	27.97	0.58	0.75	0.02
BS	127	29.09	17.01	27.90	2.12	86.94	58.47	0.65	0.45	0.00
20–40 cm										
pH	129	4.99	0.51	5.00	4.03	6.24	10.22	0.31	–0.63	0.04
SOM	129	12.11	6.01	10.96	1.52	36.02	49.63	1.50	3.25	<0.00001
TN	129	0.70	0.35	0.64	0.13	2.10	50.00	1.05	1.71	<0.00001
CEC	129	8.00	2.58	7.68	2.88	16.42	32.25	0.88	0.67	<0.00001
BS	129	37.82	26.51	34.40	2.28	100	70.10	0.53	–0.73	<0.00001

[1)] SD, standard deviation; CV, coefficient of variation; S–W test, Shapiro–Wilk test.

analysis, including variogram estimator and validation. Distribution maps of soil variables were carried out in ArcGIS 10.0 Software (Environmental Systems Research Institute, Redlands, CA).

3. Results and discussion

3.1. Descriptive statistics

The mean, median, minimum, maximum, SD, CV, and normality distribution test of soil properties in this study are presented in Table 1. The Shapiro-Wilk test indicated that none of the soil variables in the topsoil layer and subsurface layer fit a normal distribution, except for SOM in the surface layer. A highly skewed dataset has been proved to negatively affect spatial structure (Kerry and Oliver 2007), whereas data transformation methods of logarithmic (log) and Box-Cox were typically employed to improve the normality of the data (Fu *et al.* 2010; Bogunovic *et al.* 2014, 2017). In this study, data in the surface layer followed a Gaussian distribution after Box-Cox transformation, except for soil pH, while data in the subsurface layer fitted a normal distribution after log transformation, except for BS (Appendix A). Finally, soil pH, SOM, TN (Box-Cox), CEC (Box-Cox), and BS (Box-Cox) in the surface layer, and soil pH (log), SOM (log), TN (log), CEC (log) and BS with transformed data set in the subsurface layer were used for further analysis.

According to the criterion reported by Wilding *et al.* (1985), soil heterogeneity is weak with a CV value lower than 15%, moderate when between 15 and 35%, and strong when above 35%. In this study, soil pH showed weak variation (7.8% in the 0–20 cm layer and 10.2% in the 20–40 cm layer), while CEC was moderate and SOM, TN, and BS were strong in both soil layers (Table 1). Similar results have been reported for soil pH ranging from 3.4 to 14.5% around the world (Fu *et al.* 2010; Tesfahunegn *et al.* 2011; Behera and Shukla 2015; Li *et al.* 2019). The high variation of SOM in this study was consistent with that in other agricultural areas in Croatia (Bogunovic *et al.* 2017) and Sri Lanka (Rosemary *et al.* 2017), with values of 51.9 and 37%, respectively. Denton *et al.* (2017) reported a CV value of 21.19% for CEC in the 0–20 cm layer and 21.17% in the 20–40 cm layer in Nigeria, whereas a high variation (44%) for CEC was noted in Sri Lanka. These results might be explained by long-term interactions between soil forming factors and soil management practices.

Soil pH had an average value of 4.82 in the 0–20 cm layer and 4.99 in the 20–40 cm layer, indicating the severe acidity in this study. The minimum soil pH was 4.03, which was considered unsuitable for most croplands, especially for rice in southern China (Cai *et al.* 2015). The average concentrations of SOM and TN were significantly higher in the surface soil layer (27.6 and 1.50 g kg^{-1} for SOM and TN, respectively) than those in the subsurface layer (12.1 and 0.70 g kg^{-1} for SOM and TN, respectively), implying fertilizer management and traditional filed practices may have had greater impacts on the plow layer in this study. This could be accounted for in several ways. First, traditional soil management practices (e.g., fertilizer, irrigation, tillage, and plantation) usually occurred in the layer of 0–20 cm, and this was benefit for the accumulation of soil nutrients, such as carbon and nitrogen (Gelaw *et al.* 2014). In addition, soil microbial activity and biomass are usually more intense in upper layer than in deep layer in agricultural and natural ecosystems (Liu *et al.* 2010; Zhang *et al.* 2014).

CEC and BS are indexes related to soil buffering capacity and concentrations of soil exchangeable base cations when soil is suffering from inputs of acidic and/or alkaline substances. In this study, the concentrations of CEC in the two soil layers were 9.0 and 8.0 cmol kg^{-1}, respectively, while BS values were 29 and 38%, respectively. The low concentrations of CEC in study area were probably related to the low soil acidity, and this probably results from the natural highly weathered soil type and acidic soil parent material, where basic cations could leach from bulk soil (Nsor and Ibanga 2009; Gruba and Socha 2016). Besides, the imbalance of elements involved in crop management could also contribute to this result (Duan *et al.* 2004). Evidence suggests that crop harvesting (base cation removal) could make a considerable contribution to soil acidification in agricultural systems (Guo *et al.* 2010; Song *et al.* 2017; Hao *et al.* 2018).

3.2. Correlation between soil variables and topography parameters

The correlation coefficient matrix plots are shown in Fig. 2. Elevation was negatively correlated with soil pH and BS in both soil layers, while no correlations were observed between the studied variables and slope or aspect (Fig. 2-A and B). SOM and TN had a good positive relationship for both soil layers. Additionally, significantly negative relationships were observed between soil pH and CEC, BS and CEC, respectively (Fig. 2), which might be associated with the components of CEC and their corresponding proportions. For the severely acidic soil in this study, exchangeable Al^{3+} was a major part of CEC regardless of land use and parent materials, whereas exchangeable Ca^{2+} has a lower percentage with 26% (Appendix B). No significant relationship was observed between topographic parameters and SOM, TN in this study, which was inconsistent with results reported from a bamboo plantation

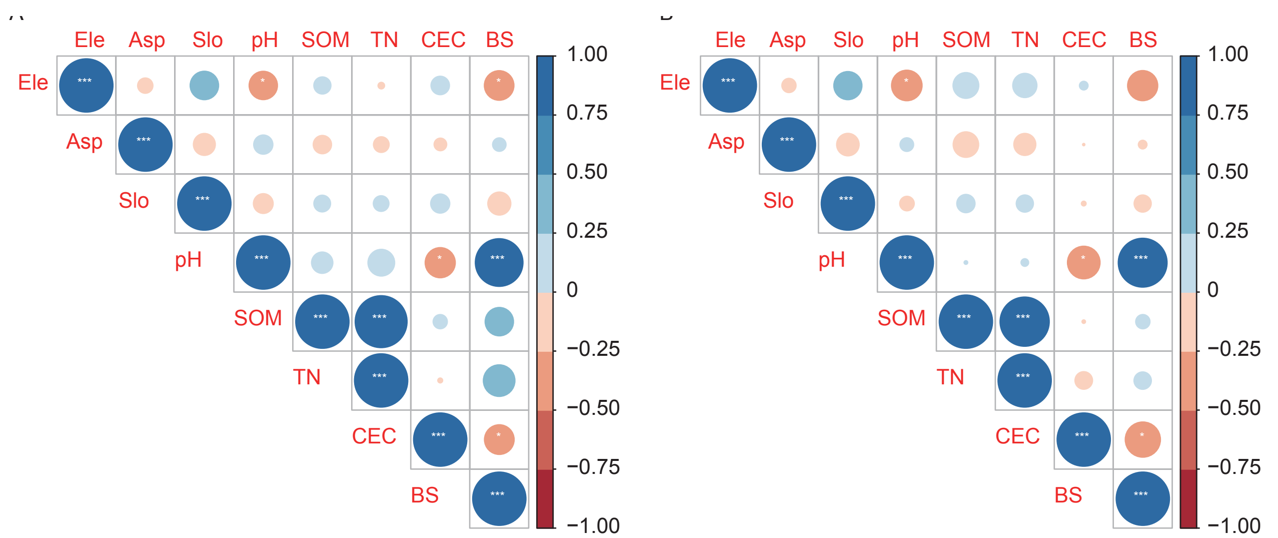

Fig. 2 Heatmap of the Pearson correlation coefficients among soil variables (pH, SOM, TN, CEC, and BS) and topography parameters (elevation, slope, and aspect) at 0–20 cm (A) and 20–40 cm (B) in Yujiang, Jiangxi Province, China. Ele, elevation; Asp, aspect; Slo, slope; SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation. * and *** mean significant difference between participating variables at P<0.05 and P<0.001, respectively.

system by Guan *et al.* (2017) and Tang *et al.* (2017), who reported a remarkably positive relation between elevation and C and N. These differences may result from different fertilization practices between agricultural and natural ecosystems.

3.3. Land use, parent materials, and their interactions

Overall, soil properties in this study showed different trends under various land use types and soil parent materials, as well as their interactions and soil layers (Figs. 3–5). First, soil pH and BS in the surface layer were significantly lower than those in the subsurface layer (P=0.004 and 0.03, respectively), while SOM, TN, and CEC showed significantly higher values in surface layer (P<0.001 for all) (Fig. 3). For different land use types, soil pH in paddy was markedly higher than that in forest and upland in both soil layers, as were SOM, TN, BS (P<0.001 for all in both layers), while CEC was the lowest in paddy regardless of soil layer (P<0.001 for both layers).

The effect of soil parent materials on soil properties under the two studied layers is shown in Fig. 4. For the topsoil layer, soil pH, SOM, TN, and BS in RAD were significantly higher than those in QRC, RS, and SS, while CEC in RAD was the lowest. For the subsurface layer, soil pH and BS in RAD were the highest while SOM and TN were the highest in SS. There was no significant difference in CEC among parent materials under both soil layers in this study. Lastly, non-parametric statistical analysis indicated significant differences for all soil variables among groups under both soil layers (P<0.05) in this study (Fig. 5).

3.4. Geostatistical analysis

An appropriate spatial variogram model and kriging technique are not only important for spatial prediction of soil variables, but also for identifying hot-spots appropriate for site-specific fertilizer management (Fu *et al.* 2010; Bogunovic *et al.* 2014, 2017). For the 0–20 cm layer, land use was the best selected for predicting soil pH, CEC, and BS, while the combination of land use and elevation was the best for SOM and TN in this study (Appendix C). For the 20–40 cm layer, the best predictor for soil pH and CEC was land use, while the combination of land use and parent material was the best predictor for TN and BS. The combination of land use, parent material, and elevation was the best for SOM in the subsurface layer in this study (Appendix C). The impacts of land use on spatial distribution for soil variables were also verified by previous studies (Liu *et al.* 2013; Ferreiro *et al.* 2016), as well as topographical parameters (Liu *et al.* 2010; Tang *et al.* 2017), and soil forming factors (Qu *et al.* 2012; Ferreiro *et al.* 2016).

An exponential model (variogram) performed the best for soil pH and TN in both soil layers, while spherical was selected for BS in the two soil layers (Table 2). SOM and CEC were the best fitted with spherical in the 0–20 cm layer and Gaussian in the 20–40 cm layer. Mousavifard *et al.* (2013) reported Gaussian was the best for soil pH while spherical was reported by Denton *et al.* (2017), Fu *et al.* (2010), Li *et al.* (2019) and Rosemary *et al.* (2017). Guan *et al.* (2017) reported a similar result for nitrogen with an exponential model, whereas Denton *et al.* (2017)

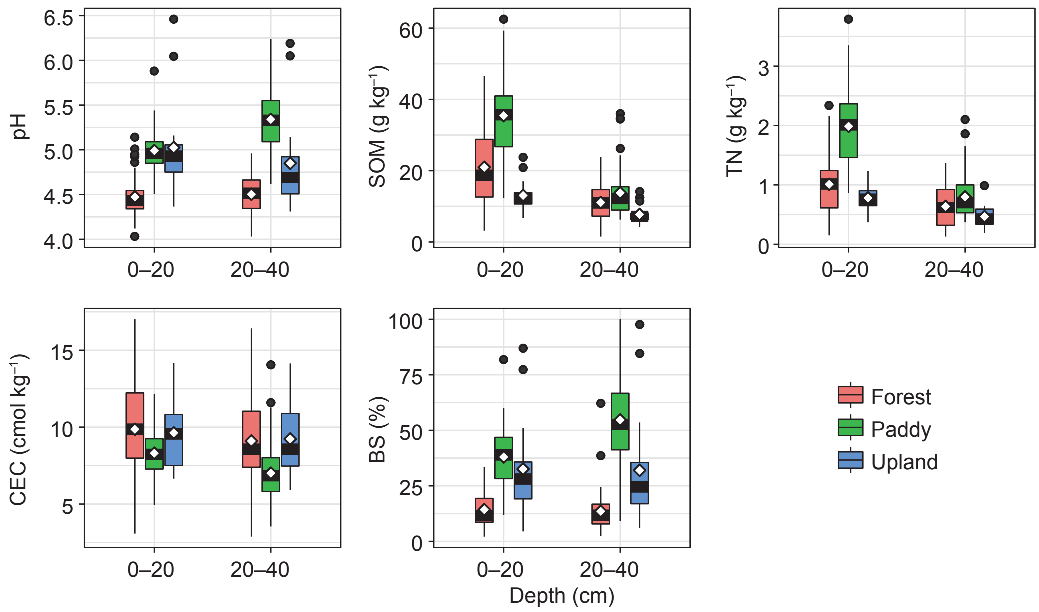

Fig. 3 The effect of land use types on soil variables in the 0–20 and 20–40 cm layers in Yujiang, Jiangxi Province, China. SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation. The points and lines in the box indicate the average and median values of the content of soil variables, respectively. Outliers (over 95% and below 5%) of each group dataset are shown outside of the box with solid points.

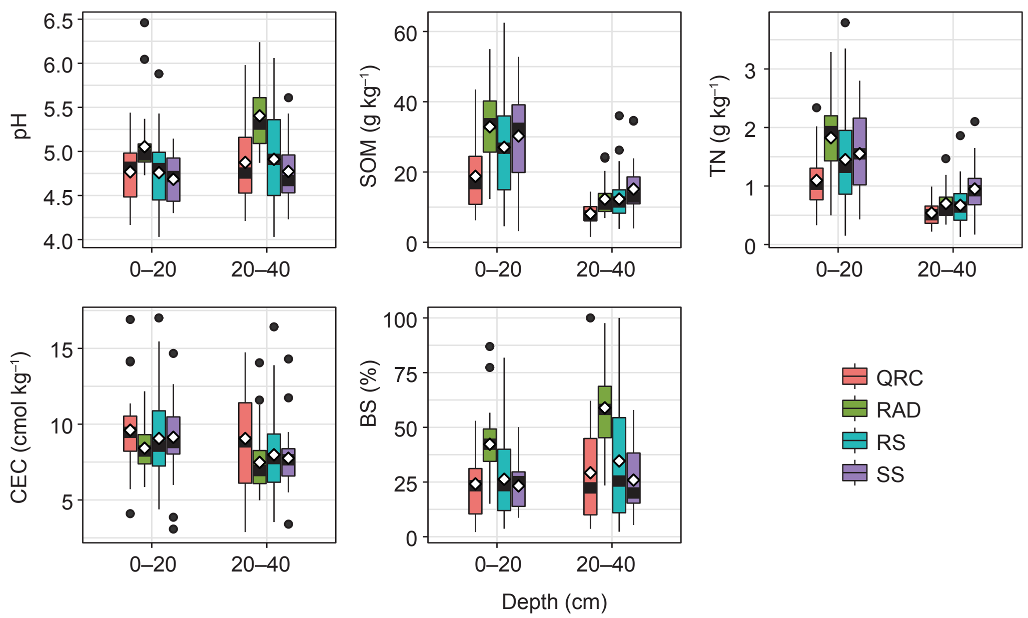

Fig. 4 The effect of parent materials on soil variables in the 0–20 and 20–40 cm layers in Yujiang, Jiangxi Province, China. SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation; QRC, quaternary red clay; RAD, river alluvial deposits; RS, red sandstone; SS, slate shale. The points and lines in the box indicate the average and median values of the contents of soil variables, respectively. Outliers (over 95% and below 5%) of each group dataset are indicated with solid points.

found Gaussian to be the best. Different best-fitted models proposed in previous studies reflect the complexity and variability of spatial structures of soil variables over different regions (Bogunovic *et al.* 2014; Ferreiro *et al.* 2016; Tang *et al.* 2017).

According to the ratio of nugget to sill, the spatial dependence was strong for CEC in the 0–20 cm layer and SOM and BS in the 20–40 cm layer; moderate for soil pH, SOM, and BS in the 0–20 cm, and TN in both layers; and weak for soil pH and CEC in the 20–40 cm layer (Table 2).

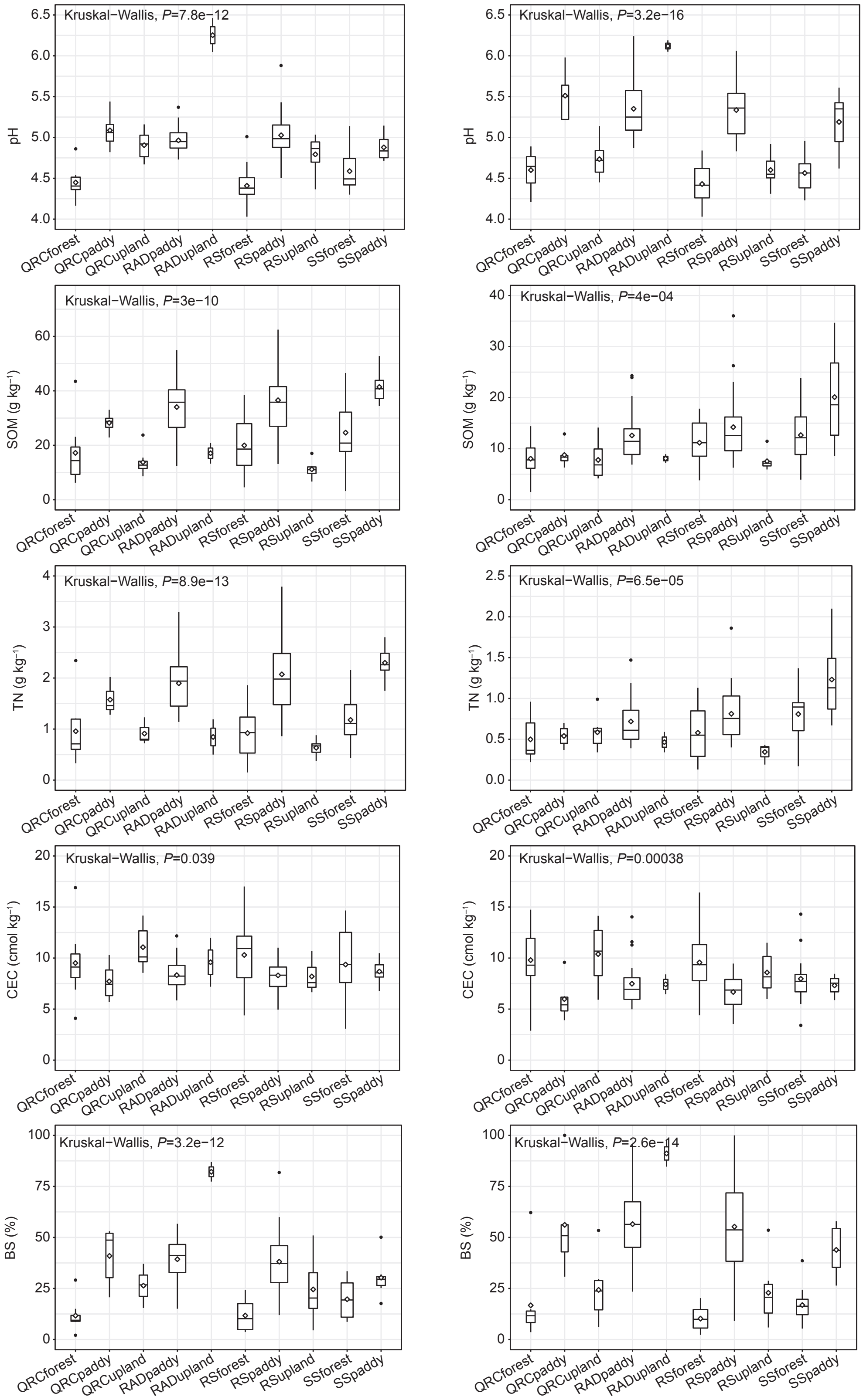

Fig. 5 The effect of group (combined land use types and soil parent materials, e.g., QRCforest means the forest land use type derived from QRC) on soil variables in the 0–20 cm (left) and 20–40 cm (right) layers in Yujiang, Jiangxi Province, China. QRC, quaternary red clay; RAD, river alluvial deposits; SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation. The points and lines in the box indicate the average and median values of the contents of soil variables, respectively. Outliers (over 95% and below 5%) of each group dataset are indicated with solid points. The size of each box-plots is proportional to the number of samples in each group.

Besides, the small nugget values (from 0.00 to 5.89) for pH, SOM, TN, and CEC indicated sampling errors are likely to be negligible. BS had a large nugget value of 56 in the 20–40 cm layer possibly because of the calculation function of BS. These results may suggest the representative nature of sample numbers in the study area and small variance among samples.

Ranges of soil pH, SOM, TN, CEC, and BS were 48, 2.2, 10, 4.9 and 2.4 km in the surface layer, respectively, and 3.9, 1.2, 2.3, 7.7 and 3.0 km in the subsurface layer, respectively (Table 2). Following the principle that sampling should be less than half of the ranges resulting from the semi-variogram (Kerry and Oliver 2007), sampling intervals for soil pH, TN, CEC, and BS in this study were suitable. For SOM, however, the proposed sampling distance should be at least 1.1 km and 625 m in the two layers, which was also suggested by Bogunovic *et al.* (2014) (with 864 m in a sandy-loam soil) and Behera and Shukla (2015) (with 323 m in an acidic soil). Though the current soil sampling strategy in Yujiang is suggested to satisfy the criterion from geostatistical theory, various sampling intervals should be considered based on independent soil variables and research aims. For example, small values of RMSE (0–4.52) and SE (0–0.008) indicated good performance of interpolation for all soil variables in this study (Table 2). A large value of RMSE for BS (26.5%) in the 20–40 cm layer, suggested that comparisons of different kriging technologies (e.g., Cokriging, RK, and Inverse Distance Weighting (IDW) method) (Liu *et al.* 2010; Bogunovic *et al.* 2014; Tang *et al.* 2017) might help to arrive at a better conclusion.

3.5. Spatial distribution maps for site-specific fertilizer management

To facilitate the interpretation of the spatial distributions of soil variables, back-transformed datasets were used to generate interpolation and prediction maps (Fig. 6). In general, soil acidity was severe in both layers throughout the whole county (Fig. 6-A and F). This could be explained by the interactions of natural factors (e.g., high MAP and MAT) and human-induced impacts (e.g., fertilization, acid deposition, and crop removal) in this region. For example, soil acidification in similar regions in southern China was widely proven to be attributed to excessive fertilizer application and the growing intensity of acid-rain (Guo *et al.* 2018) while Wang *et al.* (2018) also found a dominant role of fertilization for acidification in cropland by means of an artificial intelligence approach. The contribution of crop removal was also suggested as a profound cause of soil acidification in cropland systems in China (Hao *et al.* 2018). Soil pH, to some extent, was a foundation of soil properties, especially for agriculture cropland, so a balanced field management practice and varied fertilization regime could stabilize soil physical and chemical properties, a strategy which was advanced to decentralized decision making and farm management (Guo *et al.* 2010).

The concentrations of SOM and TN were moderate to high in most regions (Fig. 6-B, C, G and H), indicating favorable accumulation of carbon and nitrogen. CEC and BS both had low values in the plow layer (Fig. 6-D and E). The low concentration of CEC in this study was mostly attributed to the leaching processes associated with this highly weathered soil type. Thus, the dominant base cations (Ca^{2+}, Mg^{2+}, and K^+) were likely to be leached from the top layer into the deeper layers, where consequences of base cation leaching might lead to reduction of CEC and replacement of Ca^{2+} by Al^{3+} simultaneously. A higher concentration of exchangeable Al^{3+} has potential risk for soil and plant function. Increasing pH and CEC was beneficial to strengthen soil buffering capacity which has advantage

Table 2 Semi-variogram and fitted models for transformed soil variables in the 0–20 and 20–40 cm layers in Yujiang, Jiangxi Province, China[1)]

Variable[2)]	Model	C_0	$C+C_0$	$C_0/(C+C_0)$	Range	Residue	Spatial class	RMSE	ME
0–20 cm									
pH	Exponential	0.0000	0.0000	66.30	48 759	7.29e–17	Moderate	0.009	0.000
SOM	Spherical	5.8900	9.0100	65.37	2 197	5.47e–05	Moderate	4.520	0.007
TN	Exponential	0.1108	0.2006	55.23	10 823	1.29e–08	Moderate	0.635	0.000
CEC	Spherical	0.0303	0.6046	5.01	4 951	1.12e–07	Strong	0.710	0.008
BS	Spherical	3.4927	4.8881	71.45	2 401	1.36e–05	Moderate	3.556	–0.001
20–40 cm									
pH	Exponential	0.0024	0.0030	79.95	3 878	3.36e–12	Weak	0.016	0.000
SOM	Gaussian	0.0000	0.1746	0.00	1 255	1.31e–08	Strong	0.479	0.002
TN	Exponential	0.0904	0.1807	50.04	2 351	5.42e–09	Moderate	0.481	0.001
CEC	Gaussian	0.0800	0.0873	91.65	7 692	1.09e–08	Weak	0.316	0.000
BS	Spherical	56.0350	289.9850	19.32	3 013	4.19e–02	Strong	26.500	0.005

[1)] C_0, nugget; $C+C_0$, sill; $C_0/(C+C_0)$, the ratio of the nugget to the sill; RMSE, root mean square error; ME, mean error.
[2)] SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation.

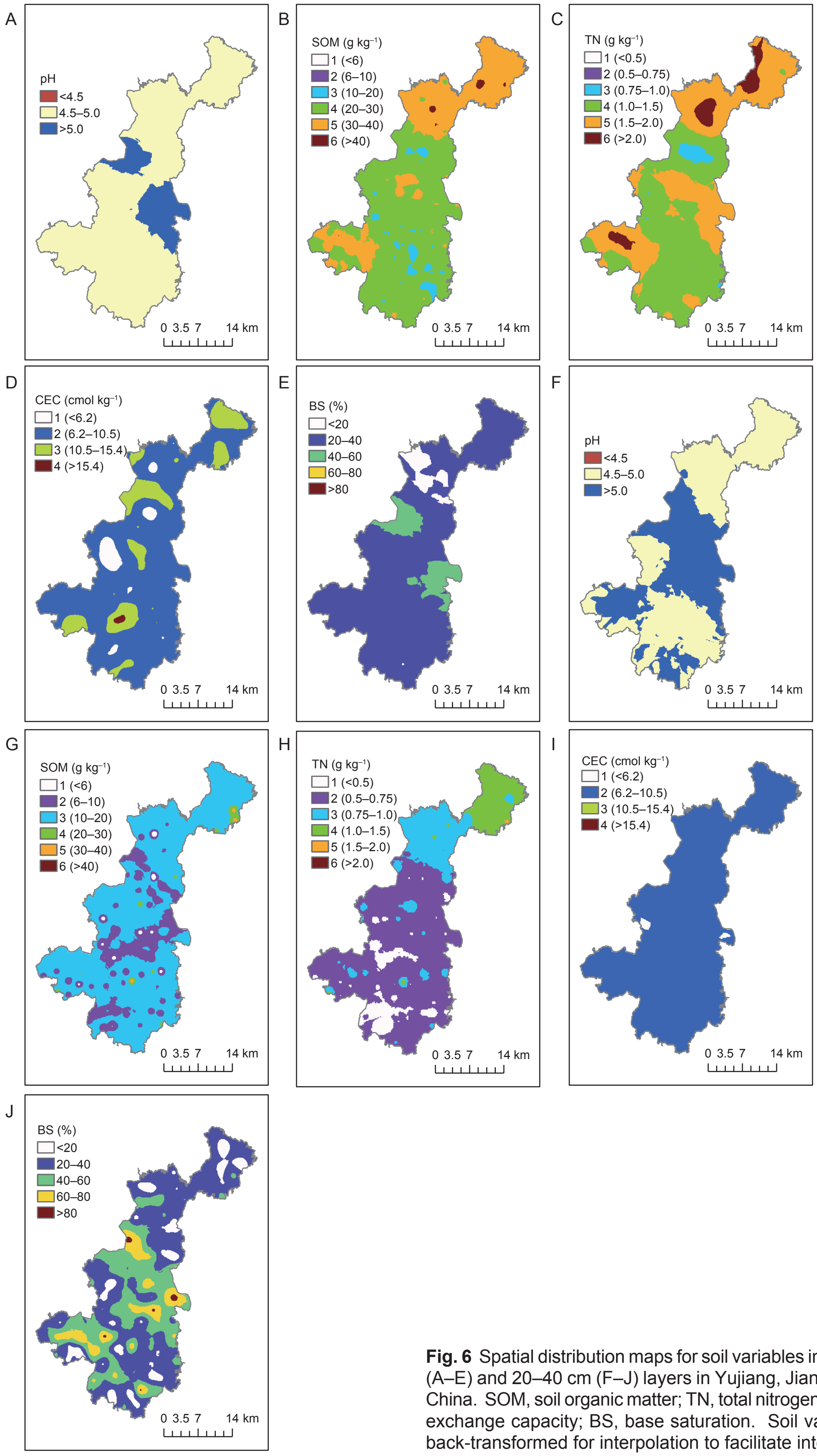

Fig. 6 Spatial distribution maps for soil variables in the 0–20 cm (A–E) and 20–40 cm (F–J) layers in Yujiang, Jiangxi Province, China. SOM, soil organic matter; TN, total nitrogen; CEC, cation exchange capacity; BS, base saturation. Soil variables were back-transformed for interpolation to facilitate interpretation.

for mitigating the toxicity risk caused by exchangeable Al^{3+} (Duan *et al.* 2004). In line with the higher acidity (low soil pH), CEC was low (class 2) across most areas of the county (Fig. 6-D and I). Several hotspots of low and moderate concentration of CEC were identified in the surface layer, which might be due to individual field management practices. BS was also low overall, and 92.4% samples had a BS lower than 40% (Fig. 6-E). These results were closely related to agricultural management, where human agricultural activity of applying a single chemical fertilizer might cause irreversible soil acidification by changing the composition and distribution of soil mineral materials (Mcgahan *et al.* 2003; Matocha *et al.* 2016), worsening soil bulk structure, and damaging the belowground biological organisms (Ramirez *et al.* 2010; Chen *et al.* 2013), which could increase the high risks of food production and food security around the world.

These results clearly revealed the status of soil fertility and the capacity of exchangeable substances, which put forward a big challenge for sustaining agricultural management in the highly weathered soils in southern China.

4. Conclusion

In this study, soil acidity in Yujiang was severely acidic at two depths (0–20 and 20–40 cm). The concentrations of SOM and TN were higher in the surface than in the subsurface layer, respectively. CEC and BS were both low in the two depths. Soil pH, SOM, TN, and BS were higher in paddy soil than in upland and forest soils in both layers, in contrast to CEC, which was lower in paddy soil. Soil derived from RAD had higher soil pH, SOM, TN, and BS than the other three soil parent materials, except for CEC. All the measured soil properties showed weak to strong variability in their spatial distribution patterns. For the purpose of site-specific fertilizer management, it was imperative to focus on the improvement of soil acidity by appropriate soil management practices, for instance, by liming or adding manure.

Acknowledgements

This study was supported by the National Natural Science Foundation of China (41620104006 and 41977104), the Central Public-interest Scientific Institution Basal Research Fund for Chinese Academy of Tropical Agricultural Sciences (1630062018005). We thank the staff from Yujiang Soil and Fertilizer Extension Station, Jiangxi, China for help with soil sampling.

Appendices associated with this paper can be available on http://www.ChinaAgriSci.com/V2/En/appendix.htm

References

Armstrong M, Boufassa A. 1988. Comparing the robustness of ordinary kriging and lognormal kriging: Outlier resistance. *Mathematical Geology*, **20**, 447–457.

Behera S K, Shukla A K. 2015. Spatial distribution of surface soil acidity, electrical conductivity, soil organic carbon content and exchangeable potassium, calcium and magnesium in some cropped acid soils of India. *Land Degradation Development*, **26**, 71–79.

Blanchet G, Libohova Z, Joost S, Rossier N, Schneider A, Jeangros B, Sinaj S. 2017. Spatial variability of potassium in agricultural soils of the canton of Fribourg, Switzerland. *Geoderma*, **290**, 107–121.

Bogunovic I, Mesic M, Zgorelec Z, Jurisic A, Bilandzija D. 2014. Spatial variation of soil nutrients on sandy-loam soil. *Soil & Tillage Research*, **144**, 174–183.

Bogunovic I, Pereira P, Brevik E C. 2017. Spatial distribution of soil chemical properties in an organic farm in Croatia. *Science of the Total Environment*, **584–585**, 535–545.

Bowman W D, Cleveland C C, Halada Ĺ, Hreško J, Baron J S. 2008. Negative impact of nitrogen deposition on soil buffering capacity. *Nature Geoscience*, **1**, 767–770.

Cai Z J, Wang B R, Xu M G, Zhang H M, He X H, Zhang L, Gao S D. 2015. Intensified soil acidification from chemical N fertilization and prevention by manure in an 18-year field experiment in the red soil of southern China. *Journal of Soils and Sediments*, **15**, 260–270.

Cambardella C A, Moorman T B, Parkin T B, Karlen D L, Novak J M, Turco R F, Konopka A E. 1994. Field-scale variability of soil properties in central Iowa soils. *Soil Science Society of America Journal*, **58**, 1501–1511.

Chen D M, Lan Z C, Bai X, Grace J B, Bai Y F. 2013. Evidence that acidification-induced declines in plant diversity and productivity are mediated by changes in below-ground communities and soil properties in a semi-arid steppe. *Journal of Ecology*, **101**, 1322–1334.

Denton O A, Aduramigba-Modupe V O, Ojo A O, Adeoyolanu O D, Are K S, Adelana A O, Oyedele A O, Adetayo A O, Oke A O. 2017. Assessment of spatial variability and mapping of soil properties for sustainable agricultural production using geographic information system techniques (GIS). *Cogent Food & Agriculture*, **3**, 1–12.

Duan L, Huang Y M, Hao J M, Xie S D, Hou M. 2004. Vegetation uptake of nitrogen and base cations in China and its role in soil acidification. *Science of the Total Environment*, **330**, 187–198.

Ferreiro J P, de Almeida V P, Alves M C, de Abreu C A, Vieira S R, Vázquez E V. 2016. Spatial variability of soil organic matter and cation exchange capacity in an Oxisol under different land uses. *Communications in Soil Science and Plant Analysis*, **47**, 75–89.

Fu W J, Tunney H, Zhang C S. 2010. Spatial variation of soil nutrients in a dairy farm and its implications for site-specific fertilizer application. *Soil & Tillage Research*, **106**, 185–193.

Fujii K, Hayakawa C, Panitkasate T, Maskhao I, Funakawa S, Kosaki T, Nawata E. 2017. Acidification and buffering mechanisms of tropical sandy soil in northeast Thailand. *Soil Tillage Research*, **165**, 80–87.

Gelaw A M, Singh B R, Lal R. 2014. Soil organic carbon and total nitrogen stocks under different land uses in a semi-arid watershed in Tigray, Northern Ethiopia. *Agriculture, Ecosystems and Environment*, **188**, 256–263.

Gruba P, Socha J. 2016. Effect of parent material on soil acidity and carbon content in soils under silver fir (*Abies alba* Mill.) stands in Poland. *Catena*, **140**, 90–95.

Guan F Y, Xia M P, Tang X L, Fan S H. 2017. Spatial variability of soil nitrogen, phosphorus and potassium contents in Moso bamboo forests in Yong'an City, China. *Catena*, **150**, 161–172.

Guo J H, Liu X J, Zhang Y, Shen J L, Han W X, Zhang W F, Christie P, Goulding K W T, Vitousek P M, Zhang F S. 2010. Significant acidification in major Chinese croplands. *Science*, **327**, 1008–1010.

Guo X, Li H Y, Yu H M, Li W F, Ye Y C, Biswas A. 2018. Drivers of spatio-temporal changes in paddy soil pH in Jiangxi Province, China from 1980 to 2010. *Scientific Reports*, **8**, 1–11.

Hanway J J, Heidel H. 1952. Soil analysis methods as used in Iowa state college soil testing laboratory. *Iowa Agriculture*, **57**, 1–31.

Hao T X, Zhu Q C, Zeng M F, Shen J L, Shi X J, Liu X J, Zhang F S, de Vries W. 2018. Quantification of the contribution of nitrogen fertilization and crop harvesting to soil acidification in a wheat-maize double cropping system. *Plant and Soil*, **434**, 167–184.

Hengl T, Heuvelink G B M, Stein A. 2004. A generic framework for spatial prediction of soil variables based on regression-kriging. *Geoderma*, **120**, 75–93.

Horswill P, O'Sullivan O, Phoenix G K, Lee J A, Leake J R. 2008. Base cation depletion, eutrophication and acidification of species-rich grasslands in response to long-term simulated nitrogen deposition. *Environmental Pollution*, **155**, 336–349.

IUSS Working Group. 2015. *World Reference Base for Soil Resources 2014, Update 2015*: *International Soil Classification System for Naming Soils and Creating Legends for Soil Maps*. *World Soil Resources Reports No. 106*. FAO, Rome.

Jones Jr J B. 1998. Soil test methods: Past, present, and future use of soil extractants. *Communications in Soil Science and Plant Analysis*, **29**, 1543–1552.

Kerry R, Oliver M A. 2007. Comparing sampling needs for variograms of soil properties computed by the method of moments and residual maximum likelihood. *Geoderma*, **140**, 383–396.

Li Q Q, Li S, Xiao Y, Zhao B, Wang C Q, Li B, Gao X S, Li Y D, Bai G C, Wang Y D, Yuan D G. 2019. Soil acidification and its influencing factors in the purple hilly area of southwest China from 1981 to 2012. *Catena*, **175**, 278–285.

Liu S L, Li Y, Wu J S, Huang D Y, Su Y R, Wei W X. 2010. Spatial variability of soil microbial biomass carbon, nitrogen and phosphorus in a hilly red soil landscape in subtropical China. *Soil Science and Plant Nutrition*, **56**, 693–704.

Liu Z P, Shao M A, Wang Y Q. 2013. Spatial patterns of soil total nitrogen and soil total phosphorus across the entire Loess Plateau region of China. *Geoderma*, **197–198**, 67–78.

Matocha C J, Grove J H, Karathanasis T D, Vandiviere M. 2016. Changes in soil mineralogy due to nitrogen fertilization in an agroecosystem. *Geoderma*, **263**, 176–184.

Mayes M, Marin-Spiotta E, Szymanski L, Akif Erdoğan M, Ozdoğan M, Clayton M. 2014. Soil type mediates effects of land use on soil carbon and nitrogen in the Konya Basin, Turkey. *Geoderma*, **232–234**, 517–527.

Mcgahan D G, Southard R J, Zasoski R J. 2003. Mineralogical comparison of agriculturally acidified and naturally acidic soils. *Geoderma*, **114**, 355–368.

Mousavifard S M, Momtaz H, Sepehr E, Davatgar N, Sadaghiani M H R. 2013. Determining and mapping some soil physico-chemical properties using geostatistical and GIS techniques in the Naqade region, Iran. *Archives of Agronomy and Soil Science*, **59**, 1573–1589.

Nsor M E, Ibanga I J. 2009. Influence of parent materials on the physico-chemical properties of soils in Central Cross River State, Nigeria. *Global Journal of Agricutural Sciences*, **7**, 183–190.

Page A L. 1965. Methods of soil analysis. Part 2. In: *Chemical and Microbiological Properties*. American Society of Agronomy, Soil Science Society of America, USA.

Pebesma E J. 2004. Multivariable geostatistics in S: The *gstat* package. *Computers & Geosciences*, **30**, 683–691.

Qu M K, Li W D, Zhang C R, Wang S Q. 2012. Effect of land use types on the spatial prediction of soil nitrogen. *GIScience & Remote Sensing*, **49**, 397–411.

R Core Team. 2017. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [2017-06-30]. https://www.R-project.org/

Ramirez K S, Lauber C L, Knight R, Bradford M A, Fierer N. 2010. Consistent effects of nitrogen fertilization on soil bacterial communities in contrasting systems. *Ecology*, **91**, 3463–3470.

Revelle W. 2018. Psych: Procedures for personality and psychological research, Northwestern University, Evanston, Illinois, USA. [2018-05-06]. https://CRAN.R-project.org/package=psych

Robert J H. 2017. Raster: Geographic data analysis and modeling. R package version 2.6-7. [2017-11-13]. https://CRAN.R-project.org/package=raster

Rosemary F, Vitharana U W A, Indraratne S P, Weerasooriya R, Mishra U. 2017. Exploring the spatial variability of soil properties in an Alfisol soil catena. *Catena*, **150**, 53–61.

Song W F, Wang C, Chen R F, Wen S L, Wang B R, Shen R F. 2017. Comparison of contribution of wheat ionic uptake to soil acidification under different long-term fertilization. *Soils*, **49**, 7–12. (in Chinese)

Sun B, Zhou S L, Zhao Q G. 2003. Evaluation of spatial and temporal changes of soil quality based on geostatistical analysis in the hill region of subtropical China. *Geoderma*, **115**, 85–99.

SSOYC (Soil Survey Office of Yujiang County). 1986. *The Soils of Yujiang County*. Office of Soil Survey in Jiangxi Province, Nanchang. (in Chinese)

Tang X L, Xia M P, Pérez-Cruzado C, Guan F Y, Fan S H. 2017. Spatial distribution of soil organic carbon stock in Moso bamboo forests in subtropical China. *Scientific Reports*, **7**, 1–13.

Tesfahunegn G B, Tamene L, Vlek P L G. 2011. Catchment-scale spatial variability of soil properties and implications on site-specific soil management in northern Ethiopia. *Soil & Tillage Research*, **117**, 124–139.

Ulrich B. 1986. Natural and anthropogenic components of soil acidification. *Journal of Plant Nutrition and Soil Science*, **149**, 702–717.

Vasu D, Singh S K, Sahu N, Tiwary P, Chandran P, Duraisami V P, Ramamurthy V, Lalitha M, Kalaiselvi B. 2017. Assessment of spatial variability of soil properties using geospatial techniques for farm level nutrient management. *Soil & Tillage Research*, **169**, 25–34.

De Vries W, Breeuwsma A. 1987. The relation between soil acidification and element cycling. *Water*, *Air*, *and Soil Pollution*, **35**, 293–310.

Wang Q, Yu H Y, Liu J F, Li F B. 2018. Attribution of soil acidification in a large-scale region: Artificial intelligence approach application. *Soil Science Society of America Journal*, **82**, 772–782.

Wilding L P. 1985. Spatial variability: Its documentation, accommodation and implication to soil surveys. In: *Soil Spatial Variability Workshop*. Wageningen, The Netherlands. pp. 166–194.

Xu S X, Shi X Z, Wang M Y, Zhao Y C. 2016. Effects of subsetting by parent materials on prediction of soil organic matter content in a hilly area using vis-NIR spectroscopy. *PLoS ONE*, **11**, 1–17.

Yang P G, Byrne J M, Yang M. 2016. Spatial variability of soil magnetic susceptibility, organic carbon and total nitrogen from farmland in northern China. *Catena*, **145**, 92–98.

Zhang H X, Zhuang S Y, Qian H Y, Wang F, Ji H B. 2015. Spatial variability of the topsoil organic carbon in the Moso bamboo forests of southern China in association with soil properties. *PLoS ONE*, **10**, e0119175.

Zhang S L, Huffman T, Zhang X Y, Liu W, Liu Z H. 2014. Spatial distribution of soil nutrient at depth in black soil of Northeast China: A case study of soil available phosphorus and total phosphorus. *Journal of Soils and Sediments*, **14**, 1775–1789.

Zhu Q C, de Vries W, Liu X J, Hao T X, Zeng M F, Shen J L, Zhang F S. 2018. Enhanced acidification in Chinese croplands as derived from element budgets in the period 1980–2010. *Science of the Total Environment*, **618**, 1497–1505.

Executive Editor-in-Chief ZHANG Wei-li
Managing editor SUN Lu-juan