Environ Geol (2008) 53:1139–1147
DOI 10.1007/s00254-007-0910-8

ORIGINAL ARTICLE

Spatial variability of soil organic matter and nutrients in paddy fields at various scales in southeast China

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Received: 6 December 2006 / Accepted: 25 June 2007 / Published online: 21 July 2007

Abstract The present study examines the spatial dependency of soil organic matter and nutrients in paddy fields at three different scales using geostatistics and geographic information system techniques (GIS). The spatial variability of soil organic matter (SOM), total nitrogen (TN) and available phosphorus (AP) has been characterized using a total of 460, 131 and 64 samples that were, respectively, collected from the Hangzhou–Jiaxing–Huzhou (HJH) Plain (10 km), Pinghu county (1,000 m) and a test plot area (100 m) within the Pinghu county, Zhejiang province of the southeast China. Semivariograms showed that the SOM and TN had moderate spatial dependency on the large scale of HJH plain and moderate scale of Pinghu county with long spatial correlation distances. At the moderate scale of Pinghu county and the small scale of a test plot area, the AP data did not show any spatial correlation, but had moderate spatial dependency in HJH plain. Spherical and exponential variogram models were best fitted to all these soil properties. Maps of SOM and TN were generated through interpolation of measured values by ordinary kriging, and AP by lognormal kriging. This study suggests that precision management of SOM and TN is feasible at all scales, and precision management of AP is feasible at large scales.

Keywords Geostatistics · Semivariogram · SOM and nutrients · Spatial variability

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Introduction

Soil nutrient level is an important indicator for soil fertility and health (General Soil Survey Office 1998). Studies have showed that there are different degrees of spatial variability in soil nutrient level. The characterization of the spatial variability of soil nutrients is essential to better understand the relations between soil properties and environmental factors. Spatial variability of soil nutrients has certain patterns (such as patchy distribution) or self-similarity. These patterns can be characterized by spatial dependency models in geostatistics. The models of spatial dependency between soil data can also be used to estimate attributes at unsampled locations. Paddy fields are widely distributed in the southeast region of China. In particular, the way paddy fields are cultivated and the growth characteristics of rice differ from that of other soils. The soil organic matter (SOM) content, total nitrogen (TN) and available phosphorus (AP) in Hangzhou–Jiaxing–Huzhou (HJH) water-net plain, one of the most developed regions in agriculture in Zhejiang province is directly connected with the crop yield and agricultural non-point source pollution (Lu et al. 2005) of the whole area. Understanding the spatial distribution of soil nutrients is necessary for increasing the efficient use of applied fertilizers and decreasing the water pollution caused by the downward movement of unused fertilizer. Geostatistics and Geographic Information System (GIS) are essential tools to analyze georeferenced information and enhance our understanding of spatial variability at various scales.

There have been growing interests in the study of spatial variation of soil properties using geostatistics since 1970s, as geostatistics techniques were well developed and successful in characterizing the spatial variations of soil properties. While many studies have been carried out at a small-scale (Webster et al. 1984; Cahn et al. 1994; Solie et al. 1999; Wilcke 2000), relatively few have been done at large-scale (Chien et al. 1997; White et al. 1997; Guo et al. 2000; Liu et al. 2004). Few studies have explicitly investigated the spatial variability of soil chemical properties in paddy field (Yanai et al. 2000, 2001). Proper agricultural and environmental management for paddy fields in South China depends greatly on the correct delineation of soil nutrients at various scales, which have not been studied well.

The primary objectives of this research were (1) to determine the structure of spatial dependency of SOM and nutrients at three different scales; and (2) to map the spatial distribution of the SOM and nutrients.

Materials and methods

Study area

The research was performed in three different areas of various spatial scales. The large-scale (1:250,000) area lies within the HJH Plain, Pinghu county. The medium-scale (1:50,000) area covers only the Pinghu county, whereas the small-scale (1:2,000) area is located within a test plot area within the northern part of Pinghu county (Fig. 1).

HJH Plain (1:250,000)

HJH water-net plain is located in the north of Zhejiang province, in the southeast part of China. It is situated at the south of the Taihu Lake. This region includes Jiaxing city, Jiashan county, Tongxiang county, Haining county, Haiyan county, Pinghu county, Huzhou city, Deqing county, Anji county, Changxing county and most part of Hangzhou city and part of Lin'an county. As typical characteristics of the regions of the South Yangtze River, numerous drainage ditches form a closely spaced waterway network in this HJH plain. HJH plain covers an area of approximately 6,390.8 km^2, and it is the major agricultural area that provides the primary food supplies of the Zhejiang province. Moreover, it is also one of the most developed areas, as to rural economy, in Zhejiang Province. Soils are mainly paddy soils, which are special hydragric anthrosols formed by long-term anthrostagnic soil formation.

Fig. 1 Sketch map of the study areas

Pinghu county (1:50,000)

Pinghu county is in the eastern HJH plain, the northeast of Zhejiang province. It borders with the Hangzhou gulf, a part of the East China Sea. In the southeast there is a coastal alluvial plain, with an altitude of 2.6–3.6 m above sea level. The northwest part is an alluvial-lacustrine plain with an altitude of 2.2–2.6 m above sea level (Liu et al. 2003). Pinghu county has a smooth landform with a slight slope to the north. Pinghu county covers 541.59 km^2, of which 71.2% is arable land. Rice (*Oryza satiya*) is the dominant crop in the area. In Pinghu, the soil is mostly paddy soil except for a small quantity of coastal saline soil with light texture, fluvio-aquic soil and yellow-red soil that are distributed in the southeast part of the county.

Test plot area (1:2,000)

The small-scale test plot area is located in the Xindai village, in the northern Pinghu county, covering an area of 400 m^2. This is a part of agricultural cropland. The plot was sown with rice and the soil is paddy soil.

Data sampling and analysis

Soil samples were taken from 460, 131, 64 locations within HJH plain, Pinghu county and the test plot area, respectively, in April 2002 based on consideration of the uniformity of soil sample distribution and soil types in the area. The locations of soil sampling points are presented in Fig. 2. All soil samples were taken within a depth range of

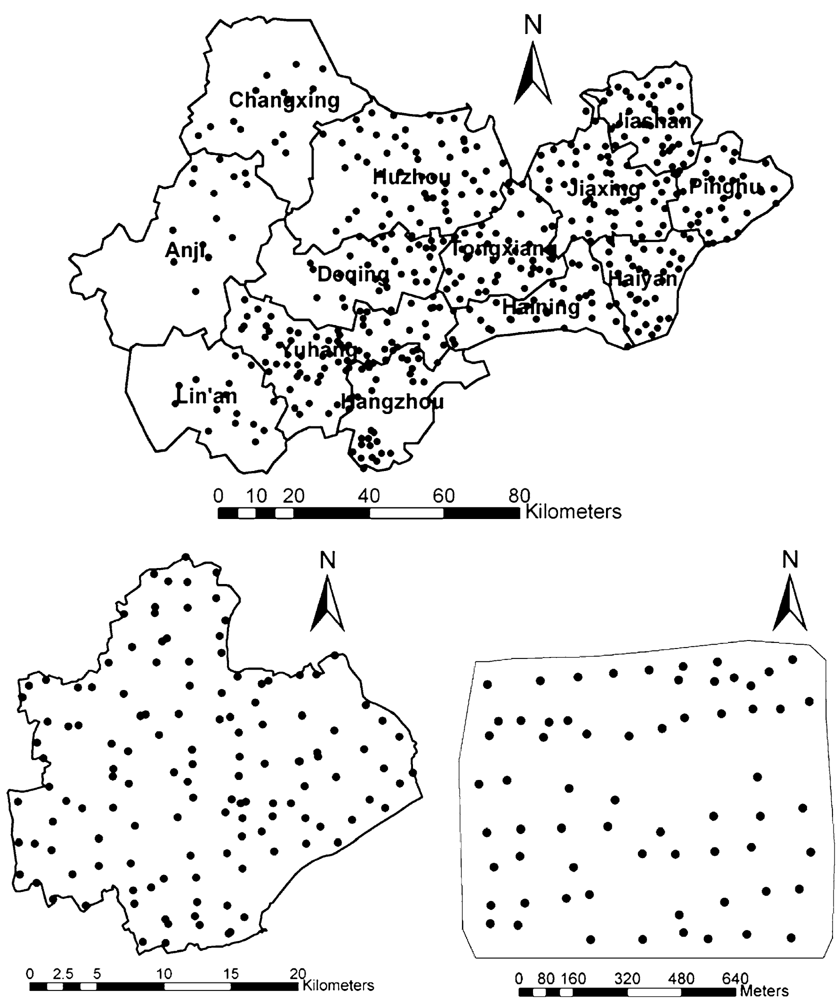
0–20 cm after removing stones and large plant root or debris by air-drying. Subsequently, each sample was thoroughly mixed and pulverized to pass through a 2-mm sieve, and stored in a plastic bag prior to the analysis of SOM, TN and AP. The SOM was determined by the potassium dichromate wet combustion procedure. The TN was measured by Kjeldahl method (Agricultural Chemistry Committee of China 1983). Soil AP (Olsen-P) was extracted using 0.5 mol l^{-1} $NaHCO_3$ (pH 8.5) and P concentration in the extract was determined using the molybdenum-blue method (Agricultural Chemistry Committee of China 1983).

Geostatistical analysis

The main application of geostatistics in soil science has been the estimation and mapping of soil attributes in unsampled areas (Goovaerts 1999). Kriging is a linear geostatistical interpolation technique that provides a best linear unbiased estimator for quantities that vary in space. Kriging estimates are calculated as weighted sums of the adjacent sampled concentrations. If data appear to be highly continuous in space, the points closer to those estimated receive higher weights than those that are farther away (Cressie 1990).

In this study, spatial patterns of the SOM and nutrients for the datasets at three scales were determined using geostatistical analysis. Semivariograms were constructed using GS+ version 7.0 (Geostatistics for the Environmental Sciences) to examine the degree of spatial continuity of soil properties among data points and to establish their range of spatial dependency. Data that were not normally distributed were logarithmly transformed in this study. Information generated through semivariogram was used to calculate sample-weighing factors for spatial interpolation by a kriging procedure (Isaaks and Srivastava 1989) in the Geostatistical Analysis extension in ArcGIS 9.0. Semivariance, $\gamma(h)$, is computed as half the average squared difference between the components of data pairs (Wang 1999; Goovaerts 1999):

Fig. 2 The distribution of sampling points at various scales



$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2. \quad (1)$$

Where $N(h)$ is number of data pairs separated by a distance h, and Z measured value for soil property, and x position of soil samples.

Ordinary kriging was used for SOM and TN prediction (Eq. 2), lognormal kriging for AP prediction (Eq. 3).

Ordinary kriging is:

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i \times Z(x_i) \quad (2)$$

where $Z(x_0)$ prediction value, n number of samples, λ weight and $Z(x_i)$ measured value for soil property at x position.

Lognormal kriging is:

$$Z_{sk}(x_0) = \exp\{Y_{sk}(x_0) + \sigma^2_{sk}(x_0)/2\}. \quad (3)$$

Where $Y_{sk}(x_0)$ is prediction value for the log-transformed sample of x_0 and $\sigma_{sk}(x_0)$ variance, $Z_{sk}(x_0)$ back-transformed prediction value.

Several standard models are available to fit the experimental semivariogram, e.g., spherical, exponential, Gaussian, linear and power models (Wang 1999). Selection of semivariogram models was made based on the regression coefficient of determination (R^2). In this study, the fitted spherical model and exponential model were mostly used.

Results and discussion

Descriptive statistics

Kolmogrov–Smirnov (K–S) test for goodness-of-fit was performed to test the normality of the selected soil property distributions. The SOM and TN at three scales were all normally distributed. AP data were not normally distributed and were further analyzed by using their logarithmically transformed values (Fig. 3). Table 1 gives the summary statistics of the datasets for SOM, TN and AP. The mean values of SOM and TN exhibited highest in test plot area, followed by Pinghu county and HJH plain. However, for AP, its mean value (25.62 mg kg^{-1}) in Pinghu was highest. Mean AP exhibited lowest (12.49 mg kg^{-1}) in HJH plain, which is half of that in Pinghu. Pinghu county has always been an area used for agricultural purpose, the content of SOM and nitrogen in soil could decrease as a result of intensive cultivation. For example, the average value of SOM in black soils in Keshan county, Heilongjiang province, decreased from 120 to 70 g kg^{-1} after 10 years of cultivation, to 45 g kg^{-1} after 20–30 years, and to 37 g kg^{-1} after 50 years (General Soil Survey Office 1998). But it is interesting that the content of the SOM and TN in paddy field remains high. This is possible because the anaerobic condition in a paddy field slows down organic matter decomposition and the nitrogen mineralization rate. Therefore, the content of SOM and TN in a paddy field should be higher than that in dry land for similar climate, geology, and fertilization. It is displayed in Table 1 that the mean values of SOM and TN in Pinghu and the test plot area are higher than that in HJH plain. Meanwhile, the mean AP displayed in Table 1 suggested an excessive P applying in Pinghu.

The coefficient of variation (CV) values of SOM, TN and AP decreased with the increase in the scale of study area, and their CV values showed highest in HJH plain and lowest in the test plot area (Table 1). At the small scale of test plot area, the soil management experience such as cultivation and fertilization was uniform and the CV values of soil properties were small. At moderate scale of Pinghu county, different agricultural management practices between farmers may have resulted in the higher CV values of soil properties. The highest CV values of SOM, TN and AP at the large scale of HJH plain, as expected, are a result of greatly variable soil management practices among different counties.

Geostatistical analysis results

The semivariograms for soil properties at three different scales were shown in Fig. 4 and their attributes are summarized in Table 2.

The Nug/Sill ratio ($C_0/C + C_0$) can be regarded as a criterion to classify the spatial dependency of soil properties. A variable has strong spatial dependency if the ratio is less than 25%, moderate spatial dependency if the Nug/Sill is between 25 and 75%, and weak spatial dependency for Nug/Sill is greater than 75% (Cambardella et al. 1994; Chien et al. 1997). Additionally, spatial dependency was defined as weak if the best-fit semivariogram model had an $R^2 < 0.5$ (Duffera et al. 2007). The spatial variability of soil properties may be affected by both intrinsic (soil formation factors, such as soil parent materials) and extrinsic factors (soil management practices, such as fertilization). Usually, strong spatial dependency of soil properties can be attributed to intrinsic factors, and weak spatial dependency can be attributed to extrinsic factors (Cambardella et al. 1994). It is shown in Table 2 that the soil properties were best fitted by a spherical model or exponential model. Both SOM and TN showed moderate spatial correlation at the large scale of HJH plain and moderate scale of Pinghu county, suggesting that the extrinsic factors such as fertil-

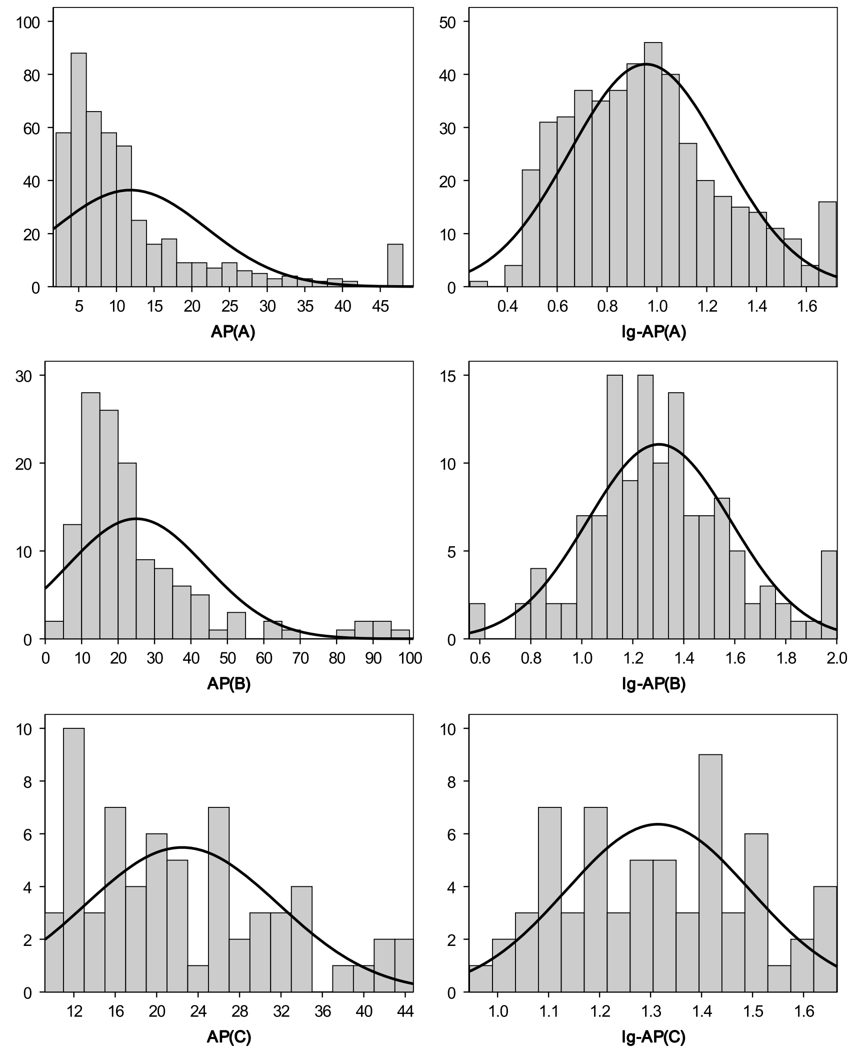


Fig. 3 The histograms of available phosphorus (AP) and log-transformed AP at the large scale of HJH plain (**a**), moderate scale of Pinghu county (**b**) and small scale of a test plot area (**c**)

Table 1 Descriptive statistical parameters of soil organic matter (SOM), total nitrogen (TN) and available phosphorus (AP)

Soil properties	Scale	Sample size	Mean	Minimum	Maximum	SD	Kurtosis	Skewness	CV (%)
SOM (g kg^{-1})	1:250,000	460	34.04	10.92	61.40	9.16	–0.05	–0.19	26.91
	1:50,000	131	35.34	17.37	62.18	8.12	–0.08	0.25	22.98
	1:2,000	64	41.08	19.90	55.90	9.41	–0.81	–0.39	22.90
TN (g kg^{-1})	1:250,000	460	2.01	0.50	3.29	0.50	–0.16	–0.22	24.92
	1:50,000	131	2.26	1.19	3.85	0.52	–0.13	0.41	23.09
	1:2,000	64	2.62	1.23	3.47	0.56	–0.58	–0.54	21.49
AP (mg kg^{-1})	1:250,000	460	12.49	2.01	97.17	12.74	12.20	3.12	102.05
	1:50,000	131	25.62	3.7	103.81	20.13	4.5	2.11	78.56
	1:2,000	64	22.47	9.33	44.09	9.31	–0.45	0.65	41.46
Logarithm of AP	1:250,000	460	0.96	0.30	1.99	0.32	0.18	0.68	33.11
	1:50,000	131	1.31	0.57	2.02	0.29	0.27	0.27	21.92
	1:2,000	64	1.31	0.97	1.64	0.18	0.98	–0.02	0.14

SD standard deviation, *CV* coefficient of variation

ization, plowing and other soil management practices weakened their spatial correlation after a long history of cultivation. At the small scale of the test plot area, the R^2 for the best-fit semivariograms of SOM and TN were all lower than that at larger scale, which showed a weak spatial dependency. Meanwhile, SOM and TN at moderate

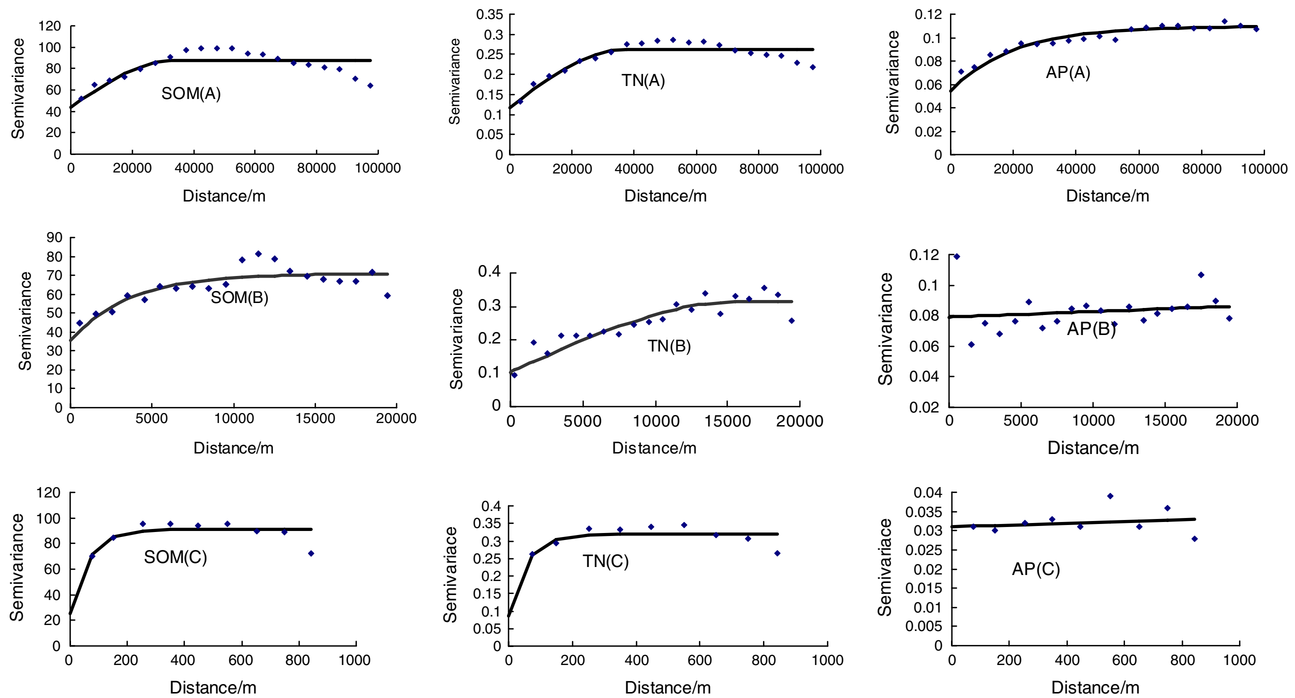


Fig. 4 The semivariograms of soil organic matter (SOM), total nitrogen (TN) and available phosphorus (AP) at the large scale of HJH plain (**a**), moderate scale of Pinghu County (**b**) and the small scale of a test plot area (**c**)

Table 2 Best-fitted semivariogram models of soil organic matter (SOM), total nitrogen (TN) and available phosphorus (AP) at three different scales

Soil properties	Scale	Model	C_0	$C + C_0$	$C_0/C + C_0$	Range (m)	R^2
SOM (g kg^{-1})	1/250,000	Spherical	43.9	87.81	0.500	33,600	0.542
	1/50,000	Exponential	35.4	70.81	0.500	10,680	0.679
	1/2,000	Exponential	25.3	90.97	0.278	186	0.456
TN (g kg^{-1})	1/250,000	Spherical	0.117	0.262	0.462	36,400	0.803
	1/50,000	Spherical	0.102	0.316	0.324	16,210	0.809
	1/2,000	Exponential	0.086	0.319	0.270	165	0.394
AP (mg kg^{-1})	1/250,000	Exponential	0.054	0.11	0.491	59,700	0.927
	1/50,000	Linear	0.079	0.086	0.918	–	0.029
	1/2,000	Linear	0.031	0.033	0.943	–	0.031

and large scale all had long spatial correlation range. The spatial ranges of SOM in HJH plain and Pinghu county were 33.6 and 10.68 km, respectively. For soil TN, its spatial correlation distances at the moderate and large scale were 36.4 and 16.21 km, respectively. This result indicates a rational sampling distance for SOM and TN within their spatial correlation ranges at the scale of Pinghu county and the HJH plain.

Soil AP also showed a moderate spatial dependency at the large scale of HJH plain with a Nug/Sill ratio of 49.1%. Its effective range value was 59.7 km, which is much longer than those of SOM and TN. However, at the scale of Pinghu county and test plot area, the semivariograms for soil AP did not show a scale of dependency, which indicated that fertilization greatly affected soil AP and reduced spatial dependency at the sampling intervals. This indicates that more samples should be taken at smaller sampling intervals in Pinghu and the test plot area to determine the spatial dependency for heterogeneous data. Therefore, it was reasonable to predict the spatial distribution of AP at large scale of the HJH plain due to their high spatial dependency. However, a more precise delineation of AP at small scale requires additional sampling.

Spatial distribution

Figure 5 presents the spatial distributions of SOM, TN and AP at three different scales of HJH plain (1:250,000), Pinghu county (1:50,000) and a test plot area (1:2,000) generated from their semivariograms. The prediction maps of SOM and TN were generated using ordinary Kriging methods with original values of SOM, TN, and the log-normal kriging on log-transformed values of AP because lognormal kriging performs better than ordinary kriging, multi-Gaussian kriging and indicator kriging when the data were skewed (Saito and Goovaerts 2000).

Figure 5 showed that SOM and TN had similar trends for high and low concentrations at three scales of study area. As is known that the soil TN is highly correlated with SOM, it is not surprising that they have similar spatial distribution patterns. Their spatial patterns had substantial geographical trends at three different scales. As shown in Fig. 5, the contents of SOM and TN in Hangzhou, Haiyan, southeast of Haining and Pinghu were low. This is as a result of different soil parent materials of these areas. These four counties are located on the coast of Hangzhou Gulf, and the soils are coastal saline soil with light soil texture. In Pinghu, the spatial patterns of SOM and TN were quite consistent with that of HJH plain: high concentration mostly distributed in northwest and central Pinghu and low concentration located in the southeast area. The test plot area is in northern Pinghu, where the highest SOM concentrations (>50 g kg^{-1}) and TN concentrations (>2.7 g kg^{-1}) are distributed. Therefore, grouping soil management could be recommended. That way, appropriate fertilizer dosage could be recommended for the

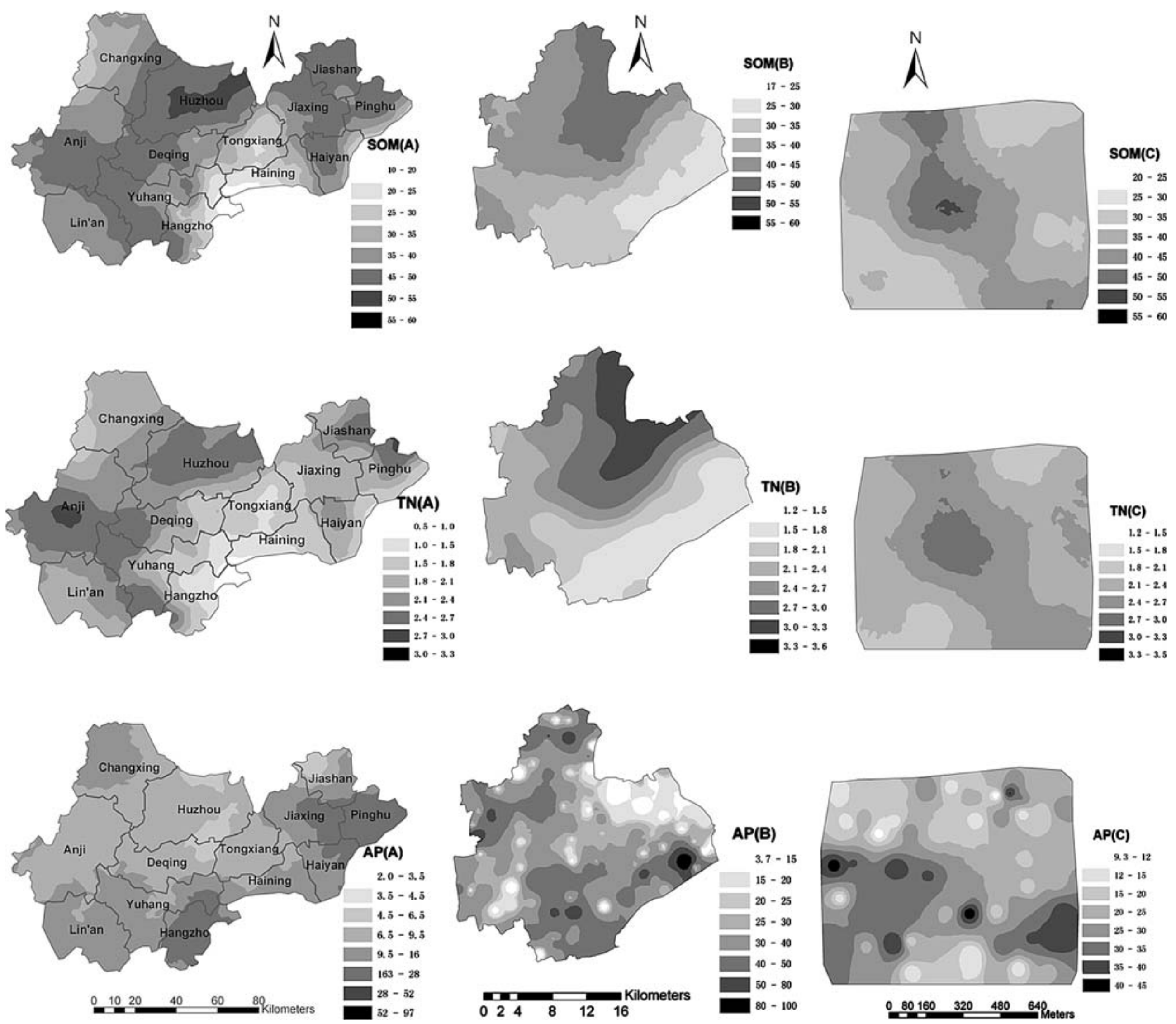


Fig. 5 The spatial distribution maps of soil organic matter (SOM), total nitrogen (TN) and available phosphorus (AP) (SOM and TN produced by ordinary kriging, AP by log-normal kriging) at the large scale of HJH plain (**a**), moderate scale of Pinghu County (**b**) and the small scale of a test plot area (**c**)

different groups with similar SOM or TN concentration thus making soil management more proper.

Soil AP concentration is greatly affected by fertilization. There were no significant geographical trends at moderate scale of Pinghu county and small scale of test plot area. However, the spatial patterns of AP in HJH plain showed a geographical trend with high concentration mainly distributed in Pinghu and Hangzhou, due to the P overfertilization in paddy field in Pinghu and the high P application dosage to satisfy the vegetable growth in Hangzhou. The result indicated that the soil AP variability at the large scale of HJH plain is mainly a result of the variability between different counties and so, grouping soil management is possible with providing information for proper agricultural management and macroscopic policy making. The variability at moderate and small scales, however, might result from the difference between various soil management strategies by farmers. Therefore, as to precise agricultural management of AP, the study at small scale was more valuable rather than at large scale because of the high variations between farmlands.

Conclusions

The results of this study showed that the soil variability increased with the increase in study scale in soil. The variability of SOM, TN and AP were scale dependent at the three different scales with an exception of AP, where semivariograms showed no significant spatial structure at the scale of Pinghu county and a test plot area.

SOM and TN showed moderate spatial dependency at the moderate scale of Pinghu county and large scale of HJH plain, because of the effect of intrinsic factors (soil formation factors, such as soil parent materials, relief and soil types) and extrinsic factors (soil management practices, such as fertilization). The large spatial correlation ranges of SOM and TN are the results of differences in parent materials and soil management between counties. That the values of R^2 between SOM and TN at small scale suggests that other processes smeared the relationship between SOM and TN. AP was moderately, spatially dependent at large scale of HJH plain and however, showed no spatial structure in Pinghu and the test plot area.

The spatial patterns of SOM and TN were apparent, especially at the scale of HJH plain and Pinghu county. Distinct geographical trends could be seen from their spatial distribution maps and the understanding such structure may provide new insights into precise agriculture by grouping soil management. The differences in soil AP among counties in HJH plain were distinct in their spatial distribution map and grouping soil management at large scale and could give a hand to macroscopic policy making for agriculture and resource managements, whereas the spatial distribution of AP in Pinghu and test plot area had no spatial continuity, owing to the different fertilization practices between farmers. So fertilization recommendation should be based on farm unit for precise agricultural management of soil AP at small scale.

Acknowledgments This research was sponsored in part by the National Natural Science Foundation project of China (40601051) and the China Postdoctoral Science Foundation (20060391061). The authors would like to thank the laboratory assistants for their analysis of soil samples. Authors appreciate the reviewers (M. Shamsudduha) and the editors for their contribution to this paper.

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