

Analysis of field-scale spatial correlations and variations of soil nutrients using geostatistics

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Abstract Spatial correlations and soil nutrient variations are important for soil nutrient management. They help to reduce the negative impacts of agricultural nonpoint source pollution. Based on the sampled available nitrogen (AN), available phosphorus (AP), and available potassium (AK), soil nutrient data from 2010, the spatial correlation, was analyzed, and the probabilities of the nutrient's abundance or deficiency were discussed. This paper presents a statistical approach to spatial analysis, the spatial correlation analysis (SCA), which was originally developed for describing heterogeneity in the presence of correlated variation and based on ordinary kriging (OK) results. Indicator kriging (IK) was used to assess the susceptibility of excess of soil nutrients based on crop needs. The kriged results showed there was a distinct spatial variability in the concentration of all three soil nutrients. High concentrations of these three soil nutrients were found near Anzhou. As the distance from the center of town increased, the concentration of the soil nutrients gradually decreased. Spatially, the relationship between AN and AP was negative, and the relationship between AP and AK was not clear. The IK results showed that there were few areas with a risk of AN and AP overabundance. However, almost the entire study region was at risk of AK overabundance. Based on the soil nutrient distribution results, it is clear that the spatial variability of the soil nutrients

differed throughout the study region. This spatial soil nutrient variability might be caused by different fertilizer types and different fertilizing practices.

Keywords Nonpoint source pollution · Soil nutrient · Geostatistics · Spatial variability · Spatial correlation coefficient

Introduction

As society continues to develop, water quality has become a topic of increasing worldwide environmental concerns (Diaz and Rosenberg 2008; Chen et al. 2009; Giri et al. 2012; Chen et al. 2012a). Generally, two types of pollution sources are defined: point source (PS) and nonpoint source (NPS) (Ritter and Shirmohammadi 2001; Liu et al. 2009). NPS pollution contributors include forestry, urban runoff, mining/construction, and agriculture. The largest contributor to NPS is agriculture. Recently, the loss of nitrogen (N) and phosphorus (P) from agricultural land via runoff has increased rapidly in comparison to that from industrial and residential lands (De Wit et al. 2000; Reungsang et al. 2005; Chen et al. 2012b). In the US, as much as 60 % of river pollution results from agriculture (Environmental Protection 2008). Pollution prevention requires a clear understanding of the impact of nutrient sources on water quality at a watershed level (Lam et al. 2010; Liu et al. 2014b).

To reduce the negative impacts of agricultural NPS pollution, Best Management Practices (BMPs) have been developed by the USA since the 1960s (Logan 1993).

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Many studies have shown that BMPs effectively reduce the NPS pollutant loads from agricultural areas (Maringanti et al. 2011; Panagopoulos et al. 2011; Liu et al. 2013). BMPs include structures, such as rain barrels or shoreline buffers, and nonstructural management practices, such as changes in land use and fertilizer application management (Lam et al. 2011; Liu et al. 2013). Unlike structural BMPs, most nonstructural BMPs are cost-effective and flexible. Therefore, land management can be applied as an effective strategy for controlling agricultural NPS pollution in many regions (Cook et al. 1996; Monaghan et al. 2007; Lee et al. 2010; McDowell et al. 2011; Thorburn and Wilkinson 2013).

Soil nutrient management is one land management strategy (Liu et al. 2013). Scientific approaches to soil nutrient management are based on the spatial variability of soil nutrients, which is obtained by analyzing soil nutrient samples. Scientific information on the spatial variability and distribution of soil properties is critical for understanding ecosystem processes and making sustainable soil, crop, and environmental management decisions (Fu et al. 2010; Tesfahunegn et al. 2011). In recent years, a mountain of work has been conducted regarding arable soils. These studies have focused on the spatial variability of soil properties, in the context of water quality protection and food security (Castrignanò et al. 2000; Tavares et al. 2008; Chaplot et al. 2010; Kerry et al. 2012).

Characterizing the spatial variability and distribution of soil properties, as well as information about soil properties, is needed at unsampled sites (Lark and Ferguson 2004). In practice, ordinary kriging is the interpolator to estimating the soil variables at unsampled sites using data at adjacent sample points. However, the spatial prediction of soil nutrients typically involves uncertainties, which must be considered when decisions regarding future management are made (Goovaerts 2001). Such management decisions are often based on the threshold values of a soil property. When a land manager interprets a kriged soil property map with respect to (a) critical threshold value(s), the uncertainty of these estimations becomes important (Lark and Ferguson 2004). Indicator kriging (IK) is used to estimate the probability of values that fall within specific class intervals by incorporating the uncertainty of the values of the variables at unsampled locations (Meirvenne and Goovaerts 2001; Triantafyllis et al. 2004; Lee et al. 2007; Arslan 2012).

Correlation is a term that refers to the strength of a relationship between two variables. A large correlation coefficient between variables may imply that these

variables come from the same pollution source (Tukura et al. 2011). However, most multivariate correlation analysis studies have focused on conventional correlation, which does not consider spatial variability (Allen et al. 2009). The results of such analyses may lead to mismanagement when the correlation varies in different areas. A new method should be developed to analyze the multivariate spatial relationship.

Based on the sampled soil nutrient data of available nitrogen (AN), available phosphorus (AP), and available potassium (AK) in a crop field near Baiyangdian Lake in 2010, the key objectives of this work were to (1) develop a method of spatial correlation analysis (SCA), (2) calculate the spatial correlation coefficient using SCA, and (3) analyze the probability of abundance using geostatistics.

Material and methods

Study region

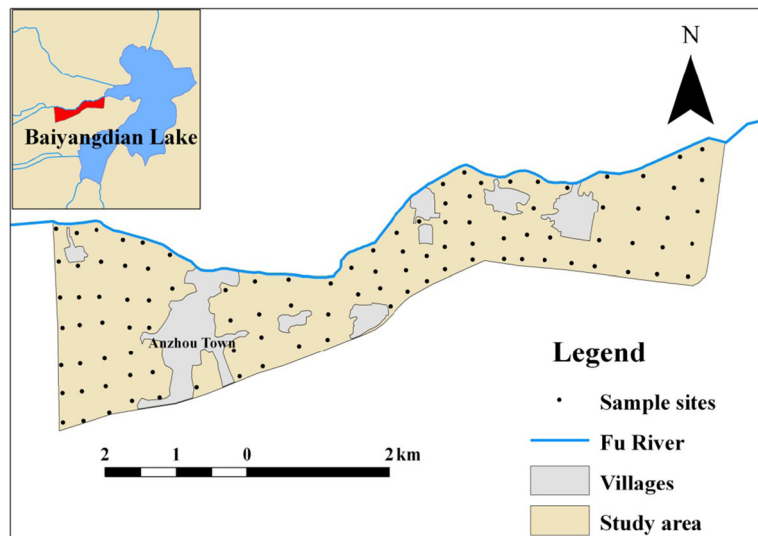
The study region covers an area of 15.33 km² near Baiyangdian Lake, which is located in the middle of the North China Plain (Fig. 1). The center coordinates of the study region are 115.85 E, 38.88 N. The region's climate is characterized by continental monsoons, and the average annual precipitation is 556 mm. There is a distinct seasonality in the annual rainfall pattern, with approximately 80% (445 mm) occurring from June to September. The mean annual air temperature is approximately 7.5 °C. The soil is calcareous cinnamon soil, which is formed by alluvial flood. The typical cropping system in the region is rotational winter wheat and summer maize cultivation (Liu et al. 2014a).

In this area, long-term human activities have led to changes in the quality and soil fertility status of cultivated land. In recent decades, the aquatic environment has changed drastically, and one of the major pollution sources is NPS (Chen et al. 2008; Zhao et al. 2010). Most studies have focused on water eutrophication, heavy metals, and organic contaminants (Dou and Zhao 1998; Zhao et al. 2011; Gao et al. 2013). Few studies have examined the impacts of soil nutrients on eutrophication.

Sample collection and analysis

A total of 105 samples were taken from the topsoil (0–200 mm) of the study region in May 2010 based on a

Fig. 1 Study area and sample sites



systematic grid (Fig. 1). The distance between each grid point is approximately 500 m. A 10 m × 10 m square field was designed to sample topsoil at each grid point. A single 5-cm-diameter core was collected at four corners and the center of each square field. Then, the five samples at each square field were mixed as the sample of the grid point. The sampling site geo-positions (latitude and longitude) in each square center were determined using GPS equipment (Garmin GPSMAP 78 s, precision: 3 m).

All soil samples were air-dried and ground to pass through a 2-mm sieve, which is necessary for available nitrogen (AN), available phosphorus (AP), and available potassium (AK) analyses. The AN was measured using the Kjeldahl method. The AP (Olsen-P) was extracted using 0.5 mol L⁻¹ NaHCO₃ (pH=8.5) and was determined using the molybdenum blue method. The AK was extracted using 1.0 mol L⁻¹ NH₄OAc (pH=7) and was measured using flame emission spectrometry. Sampling and chemical analyses were conducted based on standard methodologies (Lu 2000). Strict quality control was operated in the experiment. Quality assurance and quality control were assessed using duplicates, method blanks, and standard reference materials.

Methods

Distribution maps of the element concentrations of all species were determined by ordinary kriging (OK)

interpolation. OK provides estimation at an unobserved location of a soil variable, *z*, based on the weighted average of adjacent observed sites within a given area (Webster and Oliver 2001; Triantafyllis et al. 2004). OK has been widely used in the fields of mining, ecology, and environment science (Matheron 1965; Lloyd and Atkinson 2001; Rufino et al. 2005; Daya 2012).

Ordinary kriging is estimated by a linear combination of the observed values with weights:

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

where *Z*^{*}(*x*₀) is the estimated value of *Z* at the point *x*₀, *Z*(*x*_{*i*}) is the sampled value at the point *x*_{*i*} and λ_{*i*} is the weight placed on *Z*(*x*_{*i*}).

The weights of OK are derived from kriging equations using a semivariance function. An unbiased estimator of the semivariance function is equal to half the average squared difference between paired data values:

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

where γ(*h*) is the semivariance value at distance interval *h*; *N*(*h*) is the number of sample pairs within the distance interval *h*; and *z*(*x*_{*i*} + *h*) and *z*(*x*_{*i*}) are sample values at two points separated by the distance interval *h*.

The spatial correlation analysis (SCA) method is similar to the conventional correlation analysis, but the variables of SCA are raster data rather than

sample data. If X and Y are raster data, the spatial relationship analysis coefficient is calculated by:

$$r = \frac{\text{Cov}(X, Y)}{D(X) \times D(Y)} \quad (3)$$

where r is the correlation coefficient raster; $D(Y)$ and $D(X)$ are the variances of data X and Y ; and $\text{Cov}(X, Y)$ is the covariance of data X and Y . A 3×3 neighborhood is set in the process of the calculations. X and Y are the OK interpolation results in this study.

Indicator kriging (IK) was used to identify areas where nutrient concentrations were higher than a threshold value, Z_K . IK is a kriging analysis performed on a binary-transformed sample population (Marinoni 2003), which involves an initial reclassification of each variable, $Z(u)$, to produce binary variables (Goovaerts 1997), as follows:

$$I(u; Z_K) = \begin{cases} 1, & \text{if } Z(u) \leq Z_K, K = 1, 2, \dots, m \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

At an unsampled location, u_0 , the indicator kriging estimator is written as:

$$I^*(u_0; Z_K) = \sum_{j=1}^n \lambda_j I(u_j; Z_K) \quad (5)$$

where $I(u_j; Z_K)$ represents the values of the indicator at sampled locations, $u_j, j = 1, 2, 3, \dots, n$, and λ_j is the weight assigned to $I(u_j; Z_K)$ in the estimation of $I^*(u_0; Z_K)$.

Nutrition criteria

Crops, like all other living things, require food for growth and development. Proper nutrition is essential for satisfactory crop growth and production. Many agricultural experts have researched the impacts of different nutrient levels on the growth and production of crops, to evaluate the richness or scarcity of nutrients in relation to crop needs. Some studies have led to the establishment of nutrition criteria (Silva and Uchida 2000; Gulser 2005). Based on previous studies (Yang and Sun 2008; Zhang 2011) near our study region, the nutrition criteria of different nutrient levels in the region are listed in Table 1.

Table 1 Evaluation criteria of soil nutrients (mg/kg)

	Level 1	Level 2	Level 3	Level 4	Level 5
AN	0–30	30–70	70–90	90–120	>120
AP	0–5	5–10	10–20	20–60	>60
AK	0–40	40–80	80–100	100–150	>150
For crop	Very low	Low	Sufficient	High	Too high

Results and discussion

Basic statistical analysis

The average AN and AP contents were 75.36 and 10.45 mg/kg, respectively, indicating that AN and AP were sufficient for crop needs without considering the spatial variability (Table 2). The average AK content was 208.75 mg/kg, which is more than crop needs in the study area, without accounting for the spatial variability. The skewnesses of all the nutrients were less than 1. Therefore, all the nutrients could be regarded as normal distribution.

The basic correlation analysis results showed that there was a clear relationship between these three nutrients based on the sample data (Table 3).

Spatial variability and correlation analysis

The exploratory spatial data analysis (ESDA) was a prerequisite for carrying out the spatial analysis of nutrients by use of geostatistical analyst extension of ArcGIS. On examining empirical semivariogram, data showed spatial dependence (Fig. 2). Then the experimental variograms of these three nutrients were fitted by spherical models, and the prediction results and prediction errors were calculated. In general, the spatial distribution of soil nutrients was heterogeneity. The prediction errors were very low in the whole region. Compared with the prediction results and the prediction errors, higher values of predicted concentration were always accompanied with higher values of prediction errors.

To spatially specify whether the soil nutrients were sufficient for crop growth and production in the study region, the nutrient levels were evaluated based on the nutrition criteria and OK interpolation results (Fig. 3).

In general, the AN concentration was sufficient for crop growth and production. Level 3 AN covered more

Table 2 Descriptive statistics of soil nutrients

Soil nutrients	Min(mg/kg)	Max(mg/kg)	Mean(mg/kg)	Std. dev(mg/kg)	Skewness
AN	45.24	115.27	75.36	14.04	0.38
AP	2.54	45.10	10.45	6.94	0.85
AK	76.62	713.42	208.75	90.42	0.71

than 60.00 % of the area and was mainly distributed in the eastern and western portions of the study region. The majority of the area was categorized as level 2 AP, which was also mainly distributed in the eastern and western portions of the study region, with a proportion of 54.24 %. The majority of the region was categorized as level 5 AK, which encompassed 89.62 % of the area.

The high-concentration patterns of these three soil nutrients were mainly found near Anzhou. As the distance from the town increased, the soil nutrient concentrations gradually decreased. The high soil nutrient concentrations near Anzhou may be related to the higher incomes of farmers who live in the town, compared to farmers who live in villages. Expecting to obtain higher crop output, the higher-income farmers are willing to pay more money to buy additional fertilizer. The high concentration patterns of AN in the eastern study area may be due to the fertilizing habits of nearby farmers. Other researchers have also found that tillage and fertilizer conditions, cropping systems, and soil conservation practices can act as partial sources of spatial soil nutrient variability (Tesfahunegn et al. 2011).

Based on the OK results, the spatial correlation results of these three soil nutrients showed that the relationship between AN and AK was still positive. However, the relationship between AN and AP was negative, and the relationship between AP and AK was not clear when the spatial characteristics were considered (Table 4). The results differed from the basic results in Table 3 because the basic correlation coefficient cannot reflect spatial variations.

In addition, the spatial distributions varied (Fig. 4). The positive relationships were mainly distributed in the eastern and western portions of the study area (Fig. 4). A positive relationship means that the main fertilizer used in that region may be compound fertilizer, which contains multiple nutrients in each individual granule. These results would be helpful for site-specific soil nutrient management.

Probability analysis of abundance or deficiency

The spatial distributions of the conditional probability that the concentration of soil nutrients exceeded the upper threshold showed that the spatial distributions of the probability of overabundance were similar to the OK results (Fig. 5). A comparison of the quantiles of upper limits of level 3 in the measured nutrient concentrations frequency distributions showed that there were few areas with an overabundance of AN and AP. However, almost the entire study region exhibited an overabundance of AK.

Site-specific soil management

From the results of the soil nutrient distribution, it is clear that the spatial variability of the soil nutrients differed throughout the study region. High-concentration patterns of these three soil nutrients were mainly found near Anzhou. The spatial variety of the soil nutrients involves uncertainties, which must be considered when decisions for future management are made.

Fertilizer management was the key in the soil management. Most fertilizer was added to the soil to supply plant nutrients every year in the study region. Conservative estimates report that 30 to 50 % of crop yields are attributable to natural or synthetic commercial fertilizers (Aulakh and Pasricha 1998; Gallichand et al. 2003; Stewart et al. 2005; Bandyopadhyay et al. 2010; Ma et al. 2012). Therefore, fertilizer management should be cared in the study region.

Table 3 Conventional correlation coefficients of soil nutrients

Soil nutrients	AN	AP	AK
AN	1		
AP	0.266	1	
AK	0.416	0.394	1

$S_{0.01} = 0.25$

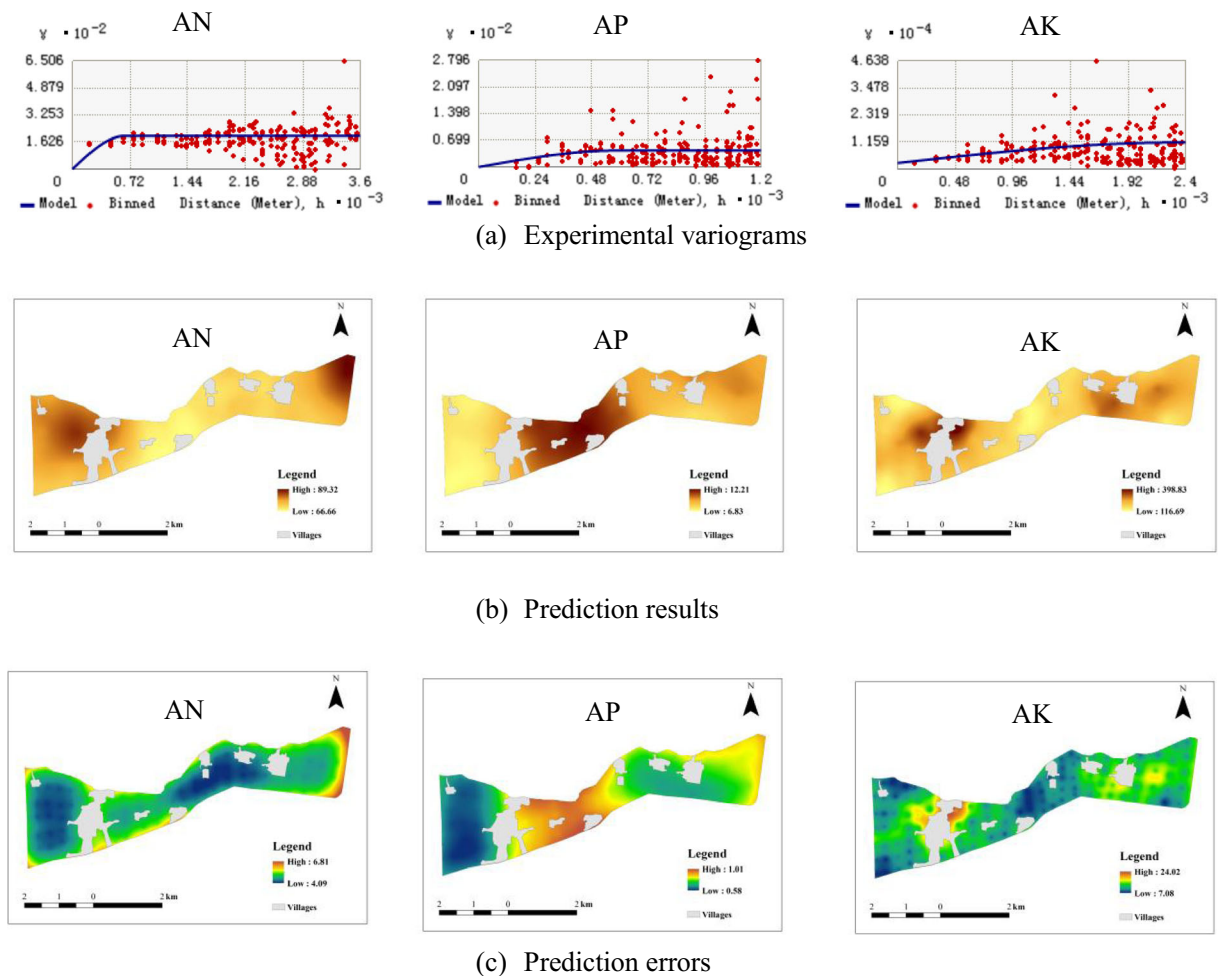


Fig. 2 a Experimental variograms, b prediction maps, and c prediction errors of soil nutrients

In the regional geochemical field, correlation analysis is generally used to identify different sources based on the correlation coefficient of sampled data (Dou and Zhao 1998). In this study, the positive relationship in eastern and western part of the study area means that the soil nutrient in these regions might come from same fertilizer, which contains multiple nutrients in each individual granule. Identification of fertilizer was the prerequisite for site-specific soil nutrient management. However, canonical correlation analysis was not appropriate here because it did not consider the spatial distribution.

Furthermore, the existing fertilizer application in the study region is identical in all fields, based on management systems, which does not consider the spatial variability of soil properties. This has resulted in under-application in areas with low nutrient levels and over-

application in areas with high nutrient levels. Thus, site-specific soil nutrient management, based on spatial variability, is considered to be the most viable approach to addressing this problem and to achieving sustainable agriculture (Fu et al. 2010; Jiang et al. 2011; Tesfahunegn et al. 2011).

Conclusion

The average contents of AN, AP, and AK were 75.36, 10.45, and 208.75 mg/kg, respectively. AN and AP were sufficient for the needs of crops and AK exceeded that need without considering the spatial variety.

In general, the spatial distribution of soil nutrients was heterogeneity and was mainly found near Anzhou. This heterogeneity of soil nutrients caused the same

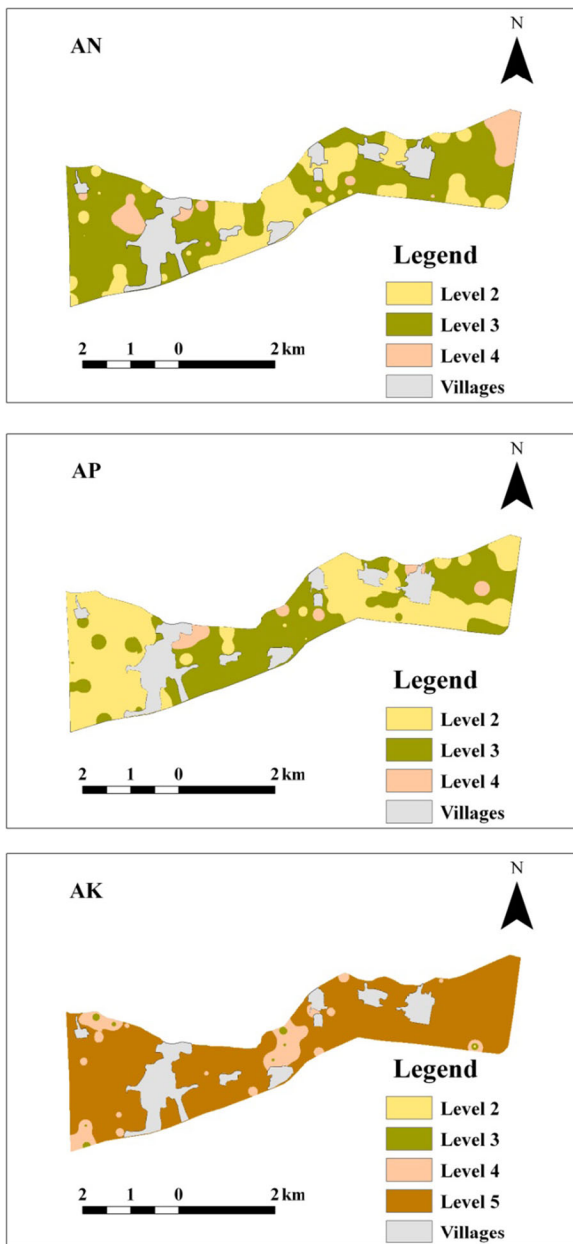


Fig. 3 Spatial distribution and evaluation patterns of soil nutrient: available nitrogen (*AN*), available phosphorus (*AP*), and available potassium (*AK*)

spatial variation of evaluation and conditional probability that the concentration of soil nutrients exceeded the upper threshold. The prediction errors were very low in the whole region. Higher values of predicted concentration were always accompanied with higher values of prediction errors. The spatial variety of the soil nutrients involves uncertainties, which must be considered when decisions for future management are made.

Table 4 Statistic results of spatial correlation coefficients

Soil nutrients	AN	AP	AK
AN	1		
AP	-0.472	1	
AK	0.446	-0.042	1

$S_{0.01} = 0.25$

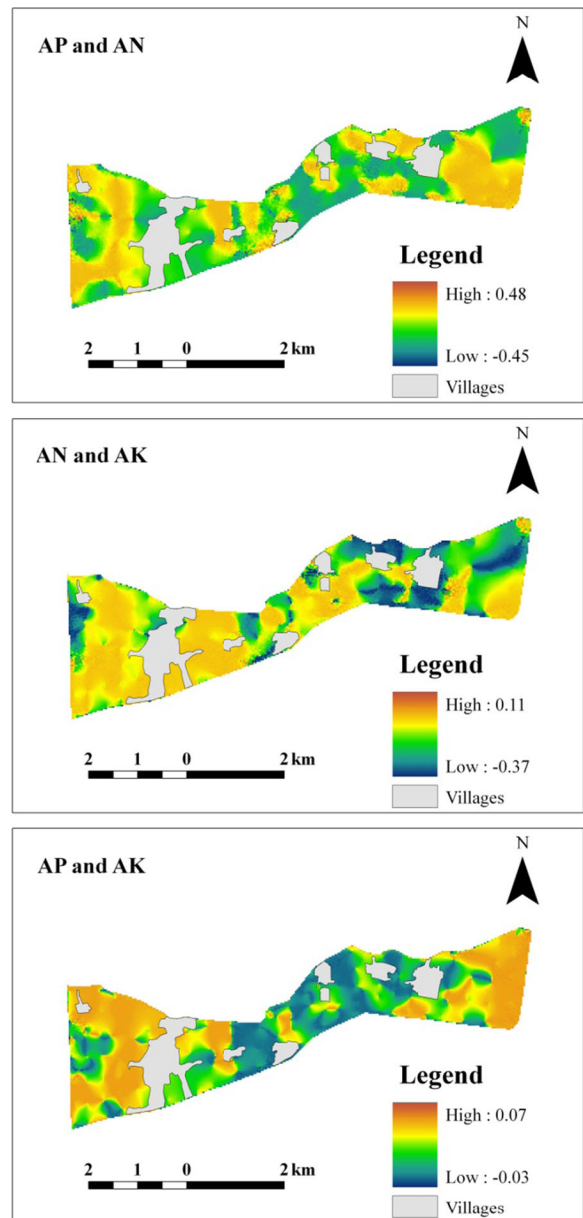


Fig. 4 Spatial distribution of correlation coefficients among available nitrogen (*AN*), available phosphorus (*AP*), and available potassium (*AK*)

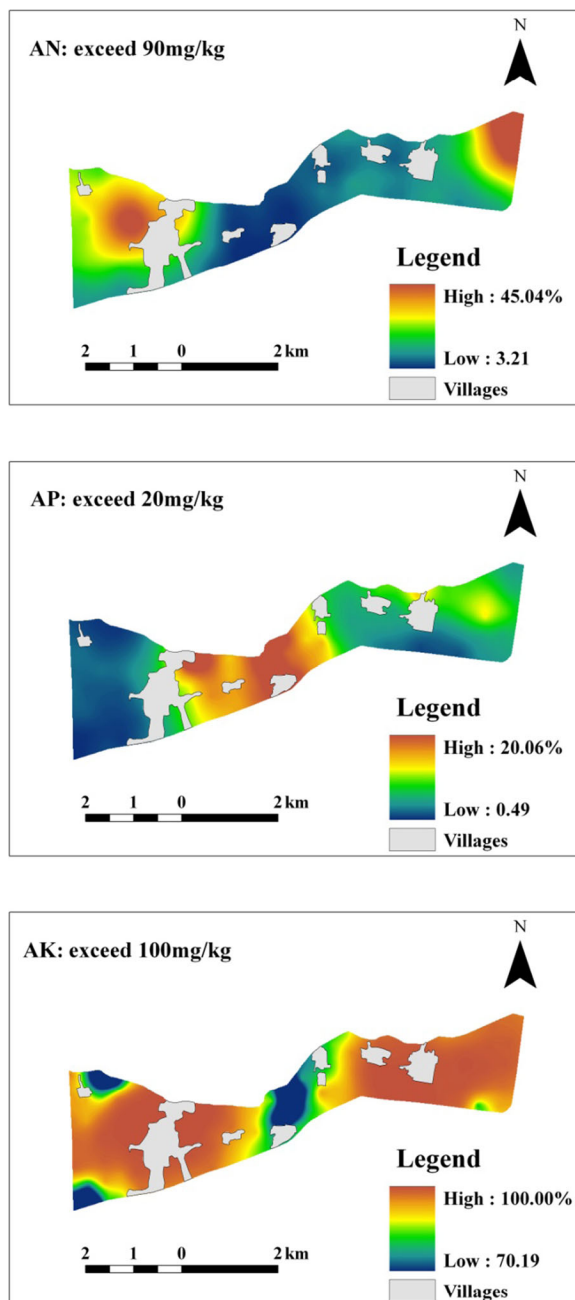


Fig. 5 The abundance probability of available nitrogen (AN), available phosphorus (AP), and available potassium (AK)

There was a clear positive relationship between these three nutrients based on the sample data. However, the spatial relationship between AN and AP was negative and the spatial relationship between AP and AK was not clear when the spatial characteristics were considered. The spatial correlation analysis could be helpful for site-specific soil nutrient management. However, canonical

correlation analysis was not appropriate here because it did not consider the spatial distribution.

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References

- Allen, R. W., Davies, H., Cohen, M. A., Mallach, G., Kaufman, J. D., & Adar, S. D. (2009). The spatial relationship between traffic-generated air pollution and noise in 2 US cities. *Environmental Research*, *109*(3), 334–342.
- Arslan, A. (2012). Spatial and temporal mapping of groundwater salinity using ordinary kriging and indicator kriging: the case of Bafra Plain, Turkey. *Agricultural Water Management*, *113*, 57–63.
- Aulakh, M. S., & Pasricha, N. S. (1998). The effect of green manuring and fertilizer N application on enhancing crop productivity in mustard-rice rotation in semi-arid subtropical regions. *European Journal of Agronomy*, *8*, 51–58.
- Bandyopadhyay, K. K., Misra, A. K., Ghosh, P. K., & Hati, K. M. (2010). Effect of integrated use of farmyard manure and chemical fertilizers on soil physical properties and productivity of soybean. *Soil & Tillage Research*, *110*(1), 115–125.
- Castrignanò, A., Goovaerts, P., Lulli, L., & Bragato, G. (2000). A geostatistical approach to estimate probability of occurrence of tuber melanosporem in relation to some soil properties. *Geoderma*, *98*, 95–113.
- Chaplot, V., Lorentz, S., Podwojewski, P., & Jewitt, G. (2010). Digital mapping of a-horizon thickness using the correlation between various soil properties and soil apparent electrical resistivity. *Geoderma*, *157*(3–4), 154–164.
- Chen, C. Y., Pickhardt, P. C., Xu, M. Q., & Folt, C. L. (2008). Mercury and arsenic bioaccumulation and eutrophication in Baiyangdian Lake, China. *Water Air & Soil Pollution*, *190*(1–4), 115–127.
- Chen, D. J., Lu, J., Shen, Y. N., Dahlgren, R. A., & Jin, S. Q. (2009). Estimation of critical nutrient amounts based on input-output analysis in an agriculture watershed of eastern China. *Agriculture Ecosystems & Environment*, *134*, 159–167.
- Chen, D., Dahlgren, R. A., Shen, Y., & Lu, J. (2012a). A Bayesian approach for calculating variable total maximum daily loads and uncertainty assessment. *Science of the Total Environment*, *430*(14), 59–67.
- Chen, Y., Liu, R., Sun, C., Zhang, P., Feng, C., & Shen, Z. (2012b). Spatial and temporal variations in nitrogen and phosphorus nutrients in the Yangtze river estuary. *Marine Pollution Bulletin*, *64*(10), 2083–2089.
- Cook, M. G., Hunt, P. G., Stone, K. C., & Canterbury, J. H. (1996). Reducing diffuse pollution through implementation of agricultural Best Management Practices: a case study. *Water Science & Technology*, *33*(4), 191–196.
- Daya, A. A. (2012). Reserve estimation of central part of Choghart north anomaly iron ore deposit through ordinary kriging

- method. *International Journal of Mining Science and Technology*, 22, 573–577.
- De Wit, M., Meinardi, C., Wendland, F., & Kunkel, R. (2000). Modelling water fluxes for the analysis of diffuse pollution at the river basin scale. *Hydrological Processes*, 14(10), 1707–1723.
- Diaz, R. J., & Rosenberg, R. (2008). Spreading dead zones and consequences for marine ecosystems. *Science*, 321, 926–929.
- Dou, W., & Zhao, Z. (1998). Contamination of DDT and BHC in water, sediments, and fish (*Carassius auratus*) muscle from Baiyangdian Lake. *Acta Scientiae Circumstantiae*, 18, 208–312.
- Environmental Protection Agency (2008). Nonpoint source pollution: the nation's largest water quality problem [online]. [Http://www.epa.gov/owow/nps/facts/point1.htm](http://www.epa.gov/owow/nps/facts/point1.htm).
- Fu, W., Tunney, H., & Zhang, C. (2010). Spatial variation of soil nutrients in a dairy farm and its implications for site-specific fertilizer application. *Soil & Tillage Research*, 106, 185–193.
- Gallichand, J., Goulet, M., Dang, T., & Huang, M. (2003). Effect of increased fertilizer applications to wheat crop on soil-water depletion in the loess plateau, China. *Agricultural Water Management*, 58(3), 267–278.
- Gao, H., Bai, J., Xiao, R., Liu, P., Jiang, W., & Wang, J. (2013). Levels, sources and risk assessment of trace elements in wetland soils of a typical shallow freshwater lake, China. *Stochastic Environmental Research & Risk Assessment*, 27(1), 275–284.
- Giri, S., Nejadhashemi, A. P., & Woznicki, S. A. (2012). Evaluation of targeting methods for implementation of Best Management Practices in the Saginaw River Watershed. *Journal of Environmental Management*, 103, 24–40.
- Goovaerts, P. (1997). *Geostatistics for natural resources evaluation* (p. 483). New York: Oxford University Press.
- Goovaerts, P. (2001). Geostatistical modelling of uncertainty in soil science. *Geoderma*, 103, 3–26.
- Gulser, F. (2005). Effects of ammonium sulphate and urea on NO₃- and NO₂-accumulation, nutrient contents and yield criteria in spinach. *Scientia Horticulturae*, 106, 330–340.
- Jiang, H. L., Liu, G. S., Wang, R., Liu, S. D., Han, F. G., Yang, Y. F., et al. (2011). Delineating site-specific quality-based management zones for a tobacco field. *Soil Science*, 176(4), 206–212.
- Kerry, R., Goovaerts, P., Rawlins, B. G., & Marchant, B. P. (2012). Disaggregation of legacy soil data using area to point kriging for mapping soil organic carbon at the regional scale. *Geoderma*, 170(1), 347–358.
- Lam, Q. D., Schmalz, B., & Fohrer, N. (2010). Modelling point and diffuse source pollution of nitrate in a rural lowland catchment using the SWAT model. *Agricultural Water Management*, 97, 317–325.
- Lam, Q. D., Schmalz, B., & Fohrer, N. (2011). The impact of agricultural Best Management Practices on water quality in a North German lowland catchment. *Environmental Monitoring and Assessment*, 183, 351–379.
- Lark, R. M., & Ferguson, R. B. (2004). Mapping risk of soil nutrient deficiency or excess by disjunctive and indicator kriging. *Geoderma*, 118, 39–53.
- Lee, J. J., Jang, C. S., Wang, S. W., & Liu, C. W. (2007). Evaluation of potential health risk of arsenic-affected groundwater using indicator kriging and dose response model. *Science of the Total Environment*, 384, 151–162.
- Lee, M. S., Park, G. A., Park, M. J., Park, J. Y., Lee, J. W., & Kim, S. J. (2010). Evaluation of non-point source pollution reduction by applying Best Management Practices using a SWAT model and QuickBird high resolution satellite imagery. *Journal of Environmental Sciences*, 22(6), 826–833.
- Liu, R. M., Yang, Z. F., Shen, Z. Y., Yu, S. L., Ding, X. W., Xing, W., & Liu, F. (2009). Estimating nonpoint source pollution in the upper Yangtze river using the export coefficient model, remote sensing, and geographical information system. *Journal of Hydraulic Engineering*, 135(9), 698–704.
- Liu, R., Zhang, P., Wang, X., Chen, Y., & Shen, Z. (2013). Assessment of effects of best management practices on agricultural non-point source pollution in Xiangxi river watershed. *Agricultural Water Management*, 117(1), 9–18.
- Liu, R., Wang, J., Shi, J., Chen, Y., Sun, C., Zhang, P., & Shen, Z. (2014a). Runoff characteristics and nutrient loss mechanism from plain farmland under simulated rainfall conditions. *Science of the Total Environment*, 468–469, 1069–1077.
- Liu, R., Zhang, P., Wang, X., Wang, J., Yu, W., & Shen, Z. (2014b). Cost-effectiveness and cost-benefit analysis of BMPs in controlling agricultural nonpoint source pollution in china based on the swat model. *Environmental Monitoring & Assessment*, 186(12), 9011–9022.
- Lloyd, C. D., & Atkinson, P. M. (2001). Assessing uncertainty in estimates with ordinary and indicator kriging. *Computers & Geosciences*, 27, 929–937.
- Logan, T. J. (1993). Agricultural best management practices for water pollution control: current issues. *Agriculture Ecosystem & Environment*, 46, 223–231.
- Lu, R. K. (2000). *Chemical analysis methods of agricultural soil (Chinese)* (pp. 45–78). Beijing: Press of China Agricultural technology.
- Ma, Q., Yu, W. T., Jiang, C. M., Zhou, H., & Xu, Y. G. (2012). The influences of mineral fertilization and crop sequence on sustainability of corn production in northeastern China. *Agriculture Ecosystems & Environment*, 158(3), 110–117.
- Maringanti, C., Chaubey, I., Arabi, M., & Engel, B. (2011). Application of a multi-objective optimization method to provide least cost alternatives for NPS pollution control. *Environmental Management*, 48(3), 448–461.
- Marinoni, O. (2003). Improving geological models using a combined ordinary–indicator kriging approach. *Engineering Geology*, 69, 37–45.
- Matheron, G. (1965). *Les variables regionalisees et leur estimation*. Paris: Masson.
- McDowell, R. W., Weerden, T. J., & Campbell, J. (2011). Nutrient losses associated with irrigation, intensification and management of land use: a study of large scale irrigation in North Otago, New Zealand. *Agricultural Water Management*, 98, 877–885.
- Meirvenne, M. V., & Goovaerts, P. (2001). Evaluating the probability of exceeding a site-specific soil cadmium contamination threshold. *Geoderma*, 102, 75–100.
- Monaghan, R. M., Wilcock, R. J., Smith, L. C., TikkiSETTY, B., Thorrold, B. S., & Costall, D. (2007). Linkages between land management activities and water quality in an intensively farmed catchment in southern New Zealand. *Agriculture Ecosystems & Environment*, 118, 211–222.
- Panagopoulos, Y., Makropoulos, C., & Mimikou, M. (2011). Reducing surface water pollution through the assessment of

- the cost-effectiveness of BMPs at different spatial scales. *Journal of Environmental Management*, 92, 2823–2835.
- Reungsang, P., Kanwar, R., Jha, M., Ahmad, K., & Saleh, A. (2005). Calibration and validation of swat for the upper maquoketa river watershed. *Center for Agricultural & Rural Development Publications*.
- Ritter, W. F., & Shirmohammadi, A. (2001). *Agricultural non-point source pollution*. New York: Lewis publishers.
- Rufino, M. M., Maynou, F., Abelló, P., Sola, L. G. D., & Yule, A. B. (2005). The effect of methodological options on geostatistical modelling of animal distribution: a case study with *Liocarcinus depurator* (crustacea: brachyura) trawl survey data. *Fisheries Research*, 76(2), 252–265.
- Silva, J. A., & Uchida, R. S. (2000). *Plant nutrient management in Hawaii's soils, approaches for tropical and subtropical agriculture* (pp. 87–89). University of Hawaii at Manoa: College of Tropical Agriculture and Human Resources.
- Stewart, W. M., Dibb, D. W., Johnston, A. E., & Smyth, T. J. (2005). The contribution of commercial fertilizer nutrients to food production. *Agronomy Journal*, 97(1), 1–6.
- Tavares, M. T., Sousa, A. J., & Abreu, M. M. (2008). Ordinary kriging and indicator kriging in the cartography of trace elements contamination in São Domingos mining site (Alentejo, Portugal). *Journal of Geochemical Exploration*, 98, 43–56.
- 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(6), 124–139.
- Thorburn, P. J., & Wilkinson, S. N. (2013). Conceptual frameworks for estimating the water quality benefits of improved agricultural management practices in large catchments. *Agriculture Ecosystem & Environment*, 180, 192–209.
- Triantafyllis, J., Odeh, I. O. A., Warr, B., & Ahmed, M. F. (2004). Mapping of salinity risk in the lower Namoi valley using non-linear kriging methods. *Agricultural Water Management*, 69, 203–231.
- Tukura, B. W., Kagbu, J. A., & Gimba, C. E. (2011). Correlation analysis of organically bound trace metals and sediment in Kubanni, Dam, Zeria, Nigeria. *Environmental Science & Technology*, 4(4), 437–443.
- Webster, R., & Oliver, M. A. (2001). *Geostatistics for environmental scientists*. Ltd, New York: John Wiley & Sons.
- Yang, L. Z., & Sun, B. (2008). *Nutrients recycling, balance and management of agricultural ecological system in China (Chinese)* (pp. 28–60). Beijing: Science Press.
- Zhang, F. S. (2011). *Fertilizing technology based on soil nutrient test (Chinese)* (pp. 11–23). Beijing: Science Press.
- Zhao, Y., Yang, Z., & Li, Y. (2010). Investigation of water pollution in Baiyangdian Lake, China. *Procedia Environmental Sciences*, 2, 737–748.
- Zhao, Y., Xia, X. H., Yang, Z. F., & Xia, N. (2011). Temporal and spatial variations of nutrients in Baiyangdian Lake, north China. *Journal of Environmental Informatics*, 2, 102–108.