Spatial Estimation of Soil Total Nitrogen Using Cokriging with Predicted Soil Organic Matter Content

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Accurate measurement of soil total N (TN) content in agricultural fields is important to guide reasonable application of nitrogenous fertilizer. Estimation of soil TN content with limited in situ data at an acceptable level of accuracy is important because laboratory measurement of N is a time- and labor-consuming procedure. This study was conducted to evaluate cokriging of soil TN with predicted soil organic matter (SOM) content as auxiliary data. The SOM content was predicted by cokriging with a digital number (DN) of Band 1 of Landsat Enhanced Thematic Mapper (ETM) imagery. Soil TN content was estimated by using 88 soil samples for prediction and 43 soil samples for validation in a study area of 367 km^2 in Haining City, China. Field-measured soil TN content ranged from 0.47 to 2.48 g kg^{-1}, with a mean of 1.25 g kg^{-1}. Soil TN content of all 131 soil samples including samples for prediction and validation was highly correlated with measured ($r = 0.81$, $p < 0.01$) and predicted ($r = 0.81$, $p < 0.01$) SOM content in paddy fields. Then, the predicted SOM content was used as auxiliary variable for the prediction of soil TN content. By using the 43 samples for validation, we had a mean error (ME) of 0.03 g kg^{-1} and a root mean square error (RMSE) of 0.31 g kg^{-1} for kriging, and a mean error of 0.00 g kg^{-1} and a root mean square error of 0.25 g kg^{-1} for cokriging, respectively. Our results indicate cokriging with predicted SOM content data was superior to kriging. In addition, predicted data of the auxiliary variable have the potential to be useful for cokriging when the predicted auxiliary data have high prediction accuracy.

Abbreviations: DN, digital number; ETM, (Landsat) Enhanced Thematic Mapper; GPS, global positioning system; ME, mean error; RMSE, root mean square error; SOM, soil organic matter; TN, total nitrogen.

SOIL FERTILITY & PLANT NUTRITION

Nitrogen is an important nutrient in soil, a basic resource for maintaining the Earth's ecosystems, and a primary restrictive factor for crop production. To improve crop production, nitrogenous fertilizers are applied to arable land. During the last 50 yr, global nitrogenous fertilizer applications have increased steadily, rising almost 20-fold to the present rate of ~10^{11} kg yr^{-1} (Glass, 2003). Soil TN content often exceeds plant growth requirements that results in surpluses of nitrogenous fertilizer in soil. High N fertilization rates generally result in low N use efficiency and high N loss (Li and Zhang, 1999). Effective use of N can improve crop production, while excessive application of nitrogenous fertilizers leads to negative impacts on surrounding environments, especially the aquatic environment (Carpenter et al., 1998; Smith et al., 2001; Lu et al., 2007). Understanding the spatial distribution of soil TN is necessary to increase the efficient use of applied fertilizers and to decrease water pollution potential resulting from off-site transport of excess fertilizer.

Since the 1970s, geostatistics have served to advance analytical methodology for spatial interpolation and to facilitate quantification of spatial features of soil properties (Burgess and Webster, 1980). Geostatistical estimation makes it possible to predict values at unsampled locations by taking spatial correlation into account between estimated and sampled points (i.e., spatial variability). In addition, geostatistical estimation minimizes the variance of estimation error. The above two characteristics of geostatistical estimation are critical for improving the accuracy of spatial prediction (Saito et al., 2005).

Soil Sci. Soc. Am. J. 73:1676-1681
doi:10.2136/sssaj2008.0205
Received 10 June 2008.

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Geostatistics, especially kriging, has been used widely in soil nutrient studies (Burrough, 1983; Zhang et al., 1992; Cambardella et al., 1994; Yanai et al., 2003; Gallardo, 2003; Ouyang et al., 2006). Cokriging is an extended technique of kriging. The technique is used to estimate a primary variable that is difficult to measure using variables that are more easily determined and correlated with the primary variable. Many studies have demonstrated superiority of cokriging to kriging when auxiliary variables were more densely sampled and highly correlated to primary variables (Stein et al., 1988; Stein and Corsten, 1991; Zhang et al., 1992, 1997; Istok et al., 1993; Wu et al., 2003). Cokriging has been used extensively in soil nutrient studies in recent years and has been demonstrated as a valid method that is useful for increasing the precision of prediction (Yates and Warrick, 1987; Zhang et al., 1999; Han et al., 2003; Wu et al., 2003).

Many easily measured variables, such as soil properties and remotely sensed imagery, are often highly correlated with SOM. However, these variables are often poorly correlated or uncorrelated with soil TN. For example, many studies have shown that SOM has unique spectral reflectance characteristics in the visible and near infrared (NIR) region, and correlates significantly with soil reflectance (Al-Abbas et al., 1972; Mulders, 1987; Schulze et al., 1993; Chen et al., 2000). To our knowledge, however, no unique spectral reflectance characteristic correlates significantly with soil TN. Since soil TN is highly correlated with SOM (Osterhaus et al., 2008), SOM has the potential to be a good auxiliary variable for soil TN prediction by using a cokriging approach. From our literature search, all auxiliary data used for cokriging in previous studies were measured data, not predicted data. The objectives of this study were to investigate the use of predicted SOM content data as an auxiliary variable for improved estimation of soil TN, and to compare soil TN predictions by kriging and by cokriging using the predicted SOM content data. One of the potential applications of this technique is to reduce the cost of soil nutrient analysis by improving the efficiency of the field-related soil sampling component of nutrient management programs.

MATERIALS AND METHODS

Description of Study Area

The study area is part of Haining City located on the Hang-Jia-Hu Plain in the northeastern region of Zhejiang Province, China (Fig. 1). It is bounded by longitude 120°18' to 120 °45' east and latitude 30°22' to 30 °31' north with a total area of 367 km^2. The area is in the northern subtropical zone of monsoonal climate with a temperate and humid climate throughout the year and four distinct seasons. The average annual temperature is 15.9°C and the mean annual precipitation is approximately 1190 mm. Paddy field is the dominant land use/land cover of arable land and paddy soil (Gleysols) is an anthropic soil that is dominant in the study area.

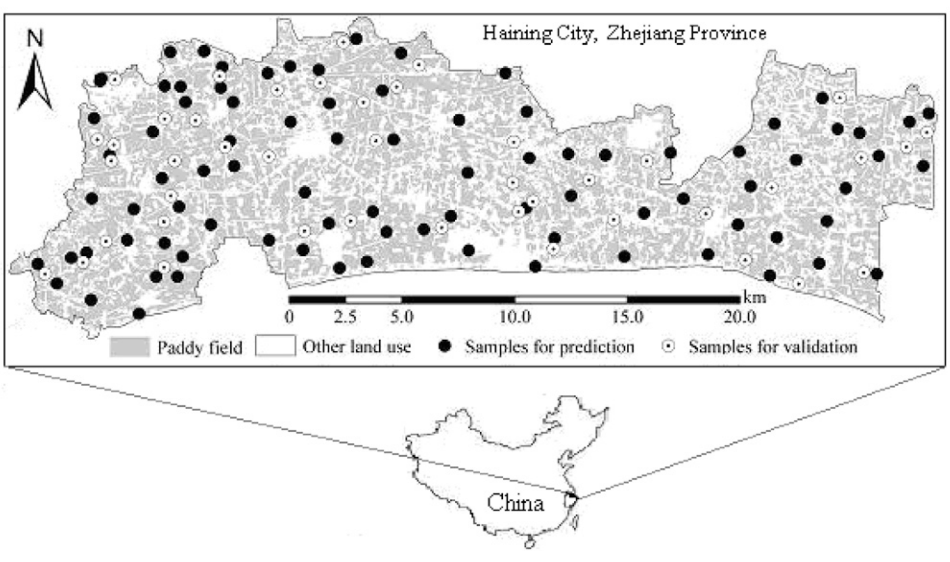

Fig. 1. General location of study area, soil sample distribution, and dominant land use (Other land uses include water bodies, orchards, built-up land, and upland crops).

Sampling Design and Soil Analysis

A total of 131 topsoil (0–15 cm) samples were collected in November 2003 according to land use and soil type in the study area (Fig. 1). Of the 131 samples, 88 soil samples (2/3) were used for soil TN prediction and the remaining 43 soil samples (1/3) were used for validation. When selecting soil samples for prediction, we ensured these selected samples were distributed uniformly to reduce the influence of uneven distribution of the samples used for assessing the accuracy of TN prediction. When sampling, surface soil of approximately eight points in each site of the same plot were collected, fully mixed, and then divided into portions of 1 to 2 kg each. Only one of the portions was packed with a bag and brought back to the laboratory for analysis. The positions of all sample sites were georeferenced using a hand-held global position system (GPS). Samples were air-dried, sieved at a diameter of 2 mm, and then analyzed in laboratory for two variables: SOM (dry ash method), soil TN (Kjeldathl method digested with $H_2SO_4 + H_2O_2$).

Previously, we analyzed the relationship between SOM content and soil TN content of 131 soil samples with corresponding ETM spectral data that were acquired on 23 Dec. 2003. Output from the correlation analysis between the six independent spectral variables (DN, of Band 1–5 and Band 7 of Landsat ETM imagery) and SOM content and between the six independent spectral variables and soil TN (Table 1) revealed negative correlation coefficients except the DN of Band 4, having low to moderate positive correlation between independent spectral variables and the dependent variable. All the absolute correlation coefficients between soil TN and the six independent spectral variables were less than that between SOM and the six independent spectral variables (all < 0.5). The absolute correlation was the strongest between SOM and the DN of Band 1 ($r = -0.587$, $p < 0.01$). After natural logarithmic transformation of SOM content (lnSOM) and the DN values, stronger correlations were found between SOM content and the spectral reflectance, that is, the correlation coefficient between lnSOM and the natural logarithmic transformation of the DN values of Band 1 (lnETM 1) was −0.629 ($p < 0.01$). Yates and Warrick (1987) found that cokriging gave better predictions than kriging when sample correlation coefficients exceeded 0.5 and when the auxiliary variable was more densely sampled. For our study area, Landsat ETM spectral data are not good

Table 1. Pearson correlation coefficients between soil organic matter content (SOM) of 131 soil samples and the digital number of Landsat Enhance Thematic Mapper (ETM) imagery† and between soil total nitrogen content (TN) of 131 soil samples and the digital number of Landsat ETM imagery.

	ETM 1	ETM 2	ETM 3	ETM 4	ETM 5	ETM 7
SOM	−0.587‡	−0.532‡	−0.547‡	0.273‡	−0.271‡	−0.431‡
TN	−0.435‡	−0.420‡	−0.415‡	0.160	−0.190	−0.331‡
	lnETM 1	lnETM 2	lnETM 3	lnETM 4	lnETM 5	lnETM 7
lnSOM	−0.629‡	−0.574‡	−0.597‡	0.235‡	−0.290‡	−0.454‡
lnTN	−0.476‡	−0.459‡	−0.459‡	0.140	−0.197	−0.336‡

† ETM 1, ETM 2,…, ETM 7, the digital number of Band 1, Band 2, …, Band 7 of Landsat ETM imagery; lnSOM, the natural logarithm of soil organic matter content, lnTN, the natural logarithm of total nitrogen content; lnETM 1, lnETM 2, …, lnETM 7, the natural logarithm of ETM 1, ETM 2, …, ETM 7.

‡ All correlation coefficients listed are significant at $p < 0.01$ level (2-tailed).

auxiliary variables for soil TN prediction; however, such data have the potential to be good auxiliary variables for SOM prediction.

To improve the accuracy of SOM prediction in the study area, the natural logarithmic transformation of the DN values of Band 1 (lnETM 1) was used as auxiliary variables in SOM prediction (Fig. 2). We also predicted SOM in the area by kriging. Then, we compared the reliability in SOM estimation by the methods of kriging and cokriging based on the maps of kriging standard deviations, and validated them by using cross-validation. The detail processes and results are described in another paper (Wu et al., 2009). The results indicate that cokriging significantly improved the precision and reliability of SOM prediction. To use predicted SOM content data as an auxiliary variable for soil TN prediction, we sampled 555 pixels, 467 pixels were sampled based on a grid-based sampling scheme with a spacing of 1 km (east-west) and 0.75 km (north-south), and the other 88 pixels were sampled based on the corresponding location of 88 soil samples for TN prediction.

Kriging and Cokriging

Kriging and cokriging are two typical geostatistical prediction methods. The semivariogram or cross-semivariogram is one main component of kriging or cokriging and serves as an effective tool for evaluating spatial structure and variability (Boyer et al., 1991; Cahn et al., 1994). The estimator for the semivariogram and cross-semivariogram is

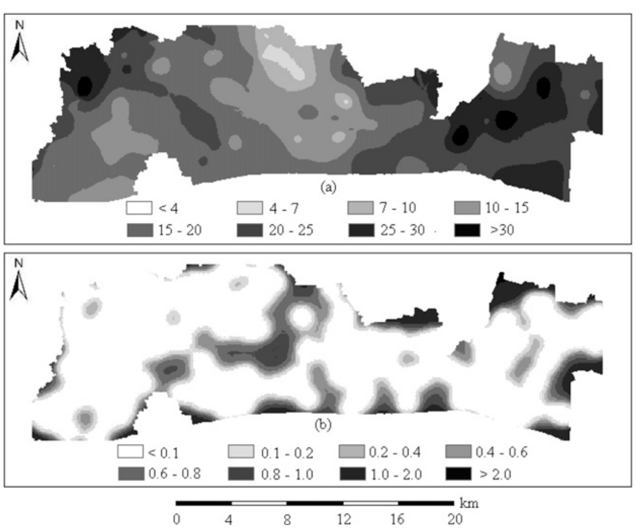

Fig. 2. Predicted soil organic matter content (g kg^{-1}) by (a) cokriging with remotely sensed data and (b) cokriging prediction error map of soil organic matter content (g kg^{-1}).

$$\gamma_{ij}(h) = \sum_{k=1}^{n(h)} \{[z_i(x_k+h) - z_i(x)][z_j(x_k+h) - z_j(x)]\} / 2n(h)$$

where γ_{ij} is the semivariance (when $i = j$) with respect to random variable z_i, h is the separation distance (lag), $n(h)$ is the number of pairs of $z_i(x_k)$ and $z_j(x_k)$ in a given lagged distance interval of (h + dh).When $i \neq j$,γ_{ij} is the cross-semivariogram, which is a function of h(Yates and Warrick, 1987). In this study, anisotropy of variograms was not founded. All the semivariograms in isotropic form were fitted to linear model, spherical model, exponential model, or Gaussian model, and chose its best fitting semivariogram model that had relatively higher coefficient of determination and lower residual sum of square for geostatistical prediction (Wang, 1999).

Soil TN content of 88 soil samples used for prediction had high skewness and were transformed using the natural logarithm form before kriging. The exponential model was used to back-transform the natural logarithm soil TN content. Other studies have shown that logarithm transformation and back-transformation may have other side effects that are difficult to interpret or may add uncertainty (Armstrong and Boufassa, 1988; Roth, 1998; Goovaerts, 1999). We did not consider the effect of logarithm transformation and back-transformation in this study given their difficulty to assess and they were used in the two predictions. In this study, kriging and cokriging were chosen to estimate and map the spatial distribution of SOM and soil TN. We used the nearest 16 sampling points and a maximum searching distance equal to the range distance of the variable. Semivariograms and cross-semivariograms were constructed using GS+ version 7.0 (Geostatistics for the Environmental Sciences).

Evaluation of Soil Total Nitrogen Predictions

To evaluate the performance of the two spatial interpolation methods, kriging and cokriging with predicted SOM content data, descriptive statistics were used to compare true (measured) soil TN content of 43 soil samples for validation with the predictions based on the two spatial interpolation methods. In addition, we computed the ME and RMSE. The ME and RMSE are defined based on Isaaks and Srivastava (1989):

$$ME = \frac{1}{n}\sum_{i=1}^{n}[z(u_i) - z^*(u_i)]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[z(u_i) - z^*(u_i)]^2}$$

where $z(u_i)$ is the measured value of z at location u_i and $z^*(u_i)$ is the predicted value at the same location. The ME provides a measure of bias; and the RMSE provides a measure of accuracy.

Cross-validation is used as another way of validating kriging predictions (Cressie, 1993; Myers, 1997). We removed one sample from the data set, used the remaining samples for prediction in each iteration, and repeated the process until all samples had been removed individually. Then, we calculated the mean of predictions as the last prediction for each sample in the process of cross-validation.

RESULTS

Soil Nutrient Level and Their Correlation

The soil TN contents of the 131 soil samples ranged from 0.47 to 2.48 g kg^{-1}, with a mean of 1.25 g kg^{-1} and a standard deviation of 0.39 g kg^{-1}. The mean soil TN content of the 88 soil samples used for prediction was equal to that of the 43 soil samples for validation (Table 2). The SOM contents of 131 soil samples ranged from 5.7 to 36.4 g kg^{-1} with a mean of 19.5 g kg^{-1} and a standard deviation of 6.36 g kg^{-1}. The predicted SOM by cokriging ranged from 5.9 to 36.2 g kg^{-1}, with a mean of 19.1 g kg^{-1} and a standard deviation of 5.39 g kg^{-1}. Predicted SOM content of 88 soil samples (Fig. 1) used for prediction was also very close to the measured values. The predicted SOM content were also close to the measured SOM contents of 131 soil samples in descriptive statistics. These results indicated that the spatial prediction of SOM could accurately describe the spatial variability of SOM in the area.

Table 2. Statistical summary† for soil total nitrogen (TN) content (g kg^{-1}) and soil organic matter content (SOM, g kg^{-1}) in the study area.

		N	Min	Max	Mean	SD	CV(%)	Skew	Kurt
TN	All soil samples	131	0.47	2.48	1.25	0.39	31.2	0.64	0.76
	Samples for Pred	88	0.56	2.48	1.25	0.37	29.6	0.82	1.14
	Samples for Valid	43	0.47	2.35	1.25	0.42	33.6	0.38	0.16
SOM	All soil samples	131	5.7	36.4	19.5	6.36	32.6	0.17	−0.08
	Measured‡	88	5.7	33.4	19.4	5.82	30.0	−0.10	−0.29
	Predicted1§	88	5.9	33.2	19.4	5.74	29.6	−0.11	−0.25
	Predicted2#	555	5.9	34.1	19.2	5.51	28.7	0.07	−0.44

† Skew, skewness; Kurt, kurtosis; TN, soil total nitrogen content; SOM, soil organic matter content; Pred, prediction; Valid, validation.

‡ Measured, measured SOM values of 88 soil samples for prediction.

§ Predicted1, predicted values of corresponding 88 soil samples for prediction.

Predicted2, predicted values extracted from the prediction map of SOM in the study area.

The TN contents of soil samples were highly correlated with measured and predicted SOM contents. The correlation coefficient between the soil TN contents of all measured soil samples and measured SOM contents was 0.81 (n = 131, p < 0.01), the coefficient between the soil TN content of all measured soil samples and predicted SOM content was 0.81 (n = 131, p < 0.01), the coefficient between the soil TN content of 88 soil samples for prediction and measured SOM content was 0.78(n = 88, p < 0.01), and the coefficient between the soil TN content of 88 soil samples for prediction and predicted SOM content was 0.78 (n = 88, p < 0.01), respectively. The correlation coefficient between soil TN and predicted SOM was almost equal to that between soil TN and measured SOM.

Spatial Prediction of Soil Total Nitrogen

The transformed soil TN contents of 88 soil samples for prediction were fitted well with a normal distribution (skewness = −0.13, kurtosis = 0.10) and predicted SOM content of 555 samples for cokriging were also fitted well with a normal distribution (skewness = 0.07, kurtosis = −0.44). In our study, both the transformed soil TN and predicted SOM passed the Shapiro-Wilk's normality test (S-K p > 0.05). The semivariogram of transformed soil TN provides a clear description of its spatial structure with some insight into possible processes affecting its spatial distribution. A spherical model fit the semivariogram well, with a high coefficient of determination (R^2 = 0.818), moderate nugget/sill ratio [$C_0(C+C_0)$] of 0.496, and effective range of 30 km. The semivariogram of predicted SOM was also fitted well by a spherical model, with a high coefficient of determination (R^2 = 0.982), moderate nugget/sill ratio [$C_0(C+C_0)$] of 0.490 and effective range of 29 km. The cross-semivariogram was fitted well by an exponential model, with a high coefficient of determination (R^2 = 0.906), low nugget/sill ratio [$C_0(C+C_0)$] of 0.215, and effective range of 44.5 km.

The semivariogram provides a description of the spatial structure of the predicted variable and some insight into possible processes affecting soil property distribution (Paz González et al., 2001).The nugget/sill ratio can be regarded as a criterion to classify spatial dependency of soil properties when the effect of sampling design on nugget/sill ratio was negligible. A variable has strong spatial dependency when the ratio is <25%. Comparatively, the variable has moderate spatial dependency with the ratio between 25 and 75%, and weak spatial dependency with nugget/sill > 75% (Cambardella et al., 1994; Chien et al., 1997). Additionally, spatial dependency is defined as weak if the best-fit semivariogram model has an R^2 < 0.5 (Duffera et al., 2007). From the spatial prediction maps of soil TN content by kriging and cokriging with predicted SOM content data (Fig. 3), we found that soil TN content generally had moderate spatial variability in the study area, and soil TN content in the central region was lower than that in the eastern and the western regions. However, the prediction map of soil TN content by cokriging had more classes than the prediction map by kriging, which indicated that the prediction map by cokriging was an improvement over that by kriging in describing content and spatial variability of soil TN.

Comparison and Validation of Spatial Predictions

Summary statistics for soil TN content estimated by kriging and cokriging with predicted SOM content data for the 43 validation samples are shown in Table 3. For comparison, this table also shows summary statistics of the true values of soil TN content. The ME and RMSE of cokriging for 43 validation samples were 0.00 and 0.25 g kg^{-1}, respectively; and ME and RMSE of kriging for 43 validation samples were 0.03 and 0.31 g kg^{-1}, respectively. The minimum and maximum of the prediction for 43 validation soil samples by cokriging with predicted SOM content data were 0.70 and 1.85 g kg^{-1}, respectively; and the minimum and maximum of prediction for 43 validation soil samples by kriging were 0.80 and 1.85 g kg^{-1}, respectively. The true (mea-

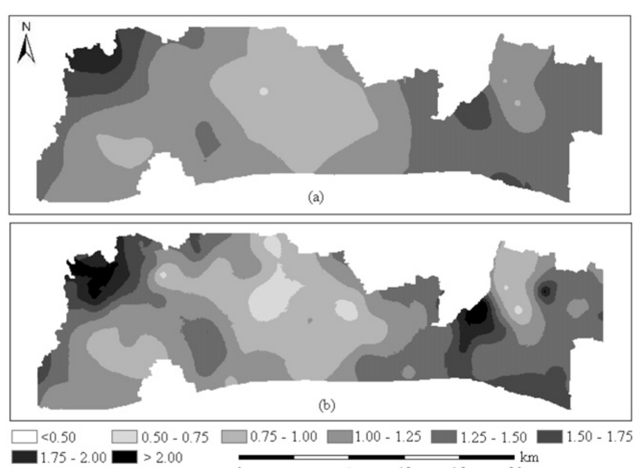

Fig. 3. Predicted soil total N content (g kg^{-1}) by (a) kriging and (b) cokriging with predicted soil organic matter data.

Table 3. Statistical summary† for measured and estimated soil total nitrogen content of 43 soil samples for validation (g kg^{-1}) and study area, kriging and cokriging with predicted soil organic matter content data were applied in the estimation.

		Min	Max	Median	Mean	ME	RMSE	r_p^2
Validation soil samples	Measured	0.47	2.35	1.27	1.25			
	Kriging	0.80	1.85	1.22	1.21	0.03	0.31	0.426
	Cokriging	0.70	1.85	1.25	1.25	0.00	0.25	0.614
Study area	Measured	0.47	2.48	1.23	1.25			
	Kriging	0.73	1.89	1.15	1.18			
	Cokriging	0.56	2.45	1.15	1.19			

† ME, mean error, RMSE, root mean square errors; r_p^2, coefficient of determination.

sured) minimum and maximum of 43 validation samples, however, were 0.47 and 2.35 g kg^{-1}, respectively (Table 3).

The minimum and maximum of prediction for entire study area by cokriging with predicted SOM content data were 0.56 and 2.45 g kg^{-1}, respectively; and the minimum and maximum of prediction for the entire study area by kriging were 0.73 and 1.89 g kg^{-1}, respectively. However, the minimum and maximum of all 131 samples were 0.47 and 2.48 g kg^{-1}, respectively (Table 3). Both the medians and means of two predictions were very similar; however, they were less than that of 131 in situ soil samples. From the results of cross-validation (Fig. 4), we found that the mean predicted soil TN content by cokriging was closer to the corresponding measured value than that by kriging to the majority of 88 soil samples for prediction. The ME and RMSE for 88 samples for prediction were 0.05 and 0.33 g kg^{-1} for kriging cross-validation and 0.02 and 0.30 g kg^{-1} for cokriging cross-validation.

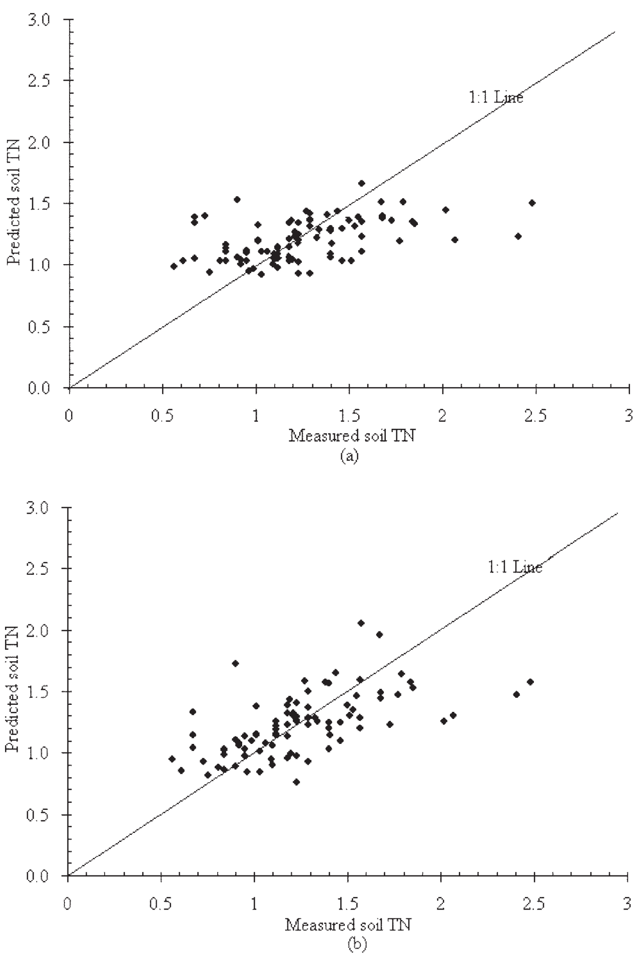

Fig. 4. Measured soil total N (TN) content (g kg^{-1}) and predicted TN content from cross-validation by (a) kriging and (b)cokriging, respectively.

DISCUSSION

Soil TN content was highly correlated with SOM content in the study area and accurate SOM content can be obtained by many approaches, such as field soil survey, remote sensing estimation, prediction by kriging with auxiliary data. Predicted SOM content has the potential to be a good auxiliary variable for soil TN content prediction when the prediction map of SOM in the study area is of high precision.

The effective range was a parameter that can reflect some information about spatial dependency of environmental variables (Journel and Huijbregts, 1978). The semivariogram of transformed soil TN had approximately 30 km of effective range, indicating that soil TN has strong spatial structure. The nugget/sill ratio of a spherical model for soil TN by lognormal kriging was between 25 and 75% with a high R^2 (0.818). This ratio indicates that soil TN content has a moderate spatial dependency in the area. The coefficient of variation of soil TN (31.2%) also indicated moderate spatial variability of soil TN.

The spatial variability of soil TN may be affected by both intrinsic (soil formation factors, such as soil parent materials) and extrinsic factors (soil management practices, such as fertilization). Generally, strong spatial dependence of soil properties can be attributed to intrinsic factors, and weak spatial dependence can be attributed to extrinsic factors (Cambardella et al., 1994). Soil TN had moderate spatial dependency in our study area. This may indicate that soil TN content was affected by both intrinsic factors and extrinsic factors in the area. This is consistent with the conclusion of Dinnes et al. (2002) that N dynamics in agricultural fields in humid regions are affected by a multitude of factors including tillage, drainage, crop type, SOM content, and weather conditions.

The prediction of soil TN content for 43 validation samples based on two kriging methods resulted in some differences from measured values. Sampling density is likely an important reason. The minimum, maximum, and mean of soil TN content predictions by cokriging were similar to all of 131 soil samples than to the predictions by kriging. This indicates that cokriging can describe better the variability of soil TN than kriging. The two parameters for validation (ME and RMSE) for cokriging were also an improvement over those parameters for kriging. This demonstrates that predicted SOM content data as auxiliary data for soil TN content prediction can improve the prediction. The ME and RMSE of cokriging for 88 samples for prediction were an improvement over that for kriging in cross-validation. This result indicates that cokriging with predicted SOM data was an improvement over kriging for soil TN prediction. All the results comparing soil TN spatial prediction and validation demonstrates that remotely sensed data such as Landsat ETM images have the potential as good auxiliary variables for improving the reliability of soil TN prediction by method of SOM prediction using cokriging.

CONCLUSIONS

The soil TN content of all 131 soil samples were highly correlated with SOM content ($r = 0.81$, $p < 0.01$), and they were also highly correlated with predicted SOM content ($r = 0.81$, $p < 0.01$), which were estimated by cokriging with remotely sensed data. The prediction of soil TN content by cokriging with predicted SOM content data was an improvement over that by kriging as measured by descriptive statistics, ME, RMSE, and cross-validation. This study demonstrates that predicted SOM content as auxiliary data improved the prediction of soil TN content and indicates that predicted data of auxiliary variables have the potential to be good sources of auxiliary data for cokriging. This is especially the case when the predicted data have been demonstrated to be of high accuracy and are highly correlated with the primary variate.

ACKNOWLEDGMENTS

This research was funded in part by the Department of Science and Technology, Zhejiang Province, China (#2006C22026), Chinese Academy of Sciences Innovative Research International Partnership Project (No.CXTD-Z2005-4) and by the National Basic Research Priorities Program (973 Program) (2002CB410810). We also acknowledge support from the China Scholarship Council and the Zhejiang University Y. C. Tang Disciplinary Development Fund. We also extend our appreciation to the journal reviewers and Dr. Raj Khosla of the Colorado State University for their valuable suggestions and constructive criticism.

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