SOIL FERTILITY & PLANT NUTRITION

Spatial Prediction of Soil Organic Matter Content Using Cokriging with Remotely Sensed Data

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Accurately measuring soil organic matter content (SOM) in paddy fields is important because SOM is one of the key soil properties controlling nutrient budgets in agricultural production systems. Estimation of this soil property at an acceptable level of accuracy is important; especially in the case when SOM exhibits strong spatial dependence and its measurement is a time- and labor-consuming procedure. This study was conducted to evaluate and compare spatial estimation by kriging and cokriging with remotely sensed data to predict SOM using limited available data for a 367-km^2 study area in Haining City, Zhejiang Province, China. Measured SOM ranged from 5.7 to 40.4 g kg^{-1}, with a mean of 19.5 g kg^{-1}. Correlation analysis between the SOM content of 131 soil samples and the corresponding digital number (DN) of six bands (Band 1–5 and Band 7) of Landsat Enhanced Thematic Mapper (ETM) imagery showed that correlation between SOM and DN of Band 1 was the highest ($r = -0.587$). We used the DN of Band 1 as auxiliary data for the SOM prediction, and used descriptive statistics and the kriging standard deviation (STD) to compare the reliabilities of the predictions. We also used cross-validation to validate the SOM prediction. Results indicate that cokriging with remotely sensed data was superior to kriging in the case of limited available data and the moderately strong linear relationship between remotely sensed data and SOM content. Remotely sensed data such as Landsat ETM imagery have the potential as useful auxiliary variables for improving the precision and reliability of SOM prediction.

Abbreviations: CV, coefficient of variation; DN, digital number; ETM, Landsat Enhanced Thematic Mapper; NDVI, normalized difference vegetation index; SE, standard error of the estimate; SOM, soil organic matter content; STD, standard deviation; TM, Landsat Thematic Mapper.

Soil organic matter is a major soil property that is extremely influential on soil physical, chemical, and biological processes, primarily soil fertility and plant growth. Water and nutrient holding capacity are enhanced and soil structure is improved with increasing SOM. Managing soil C can enhance productivity and environmental quality, and can reduce the severity and costs of natural disasters, such as drought, flood, and disease (Chen and Aviad, 1990; Stevenson and He, 1990; Blanco-Canqui and Lal, 2004). In addition, increasing SOM can reduce atmospheric CO_2 levels that contribute to climate change (Yadav and Malanson, 2007). Continued efficient use of our soils and protection of our environment requires a better understanding of SOM content and its spatial variability. To achieve this, we should know the spatial distribution and variability of SOM by means of soil survey and spatial prediction.

There have been many studies using both remotely sensed images of bare soil and spectroscopic reflectance of soil samples for soil survey, mapping, and quantitative soil property characterization (e.g., Dalal and Henry, 1986; Agbu et al., 1990; Csillag et al., 1993; Ben-Dor and Banin, 1994, 1995; Chen et al., 2008). Studies have shown that SOM correlates significantly with soil reflectance in the visible and near infrared (NIR) region (Al-Abbas et al., 1972; Mulders, 1987; Sudduth and Hummel, 1991; Schulze et al., 1993; Ben-Dor et al., 1999; Chen et al., 2000).

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Therefore, SOM content can be estimated from soil reflectance measurements if the relationship between SOM content and reflectance is strong. This approach has proven to be useful in areas with moderate to high SOM levels (about 10–50 g kg^{-1}) but is ineffective elsewhere (Sullivan et al., 2005). The relationship between reflectance and SOM is not strong over large geographic regions due to confounding effects of moisture and underlying parent material (Sudduth and Hummel, 1991; Hummel et al., 2001), extensive plant canopy over an area (Kongapai, 2007) and variations in surface roughness (Matthias et al., 2000). Although SOM can be estimated using remotely sensed image data such as Landsat Thematic Mapper (TM) imagery (e.g., Frazier and Cheng 1989; Kongapai, 2007), this approach may yield an unacceptable level of accuracy due to the phenomenon of spectral confusion where dissimilar surface features have similar spectral responses or, conversely, where similar surface features have different spectral responses (Sudduth and Hummel, 1991; Hummel et al., 2001).

Geostatistics is a powerful interpolation tool that quantifies and reduces the uncertainties of estimation and prediction and minimizes investigation costs (Ferguson et al., 1998). For over four decades, geostatistical methods, such as kriging, have been used to provide linear unbiased predictions at unsampled locations (Burgess and Webster, 1980; Odeh et al., 1995). With cokriging, additional covariates that are usually more intensively sampled can be used to assist in prediction. Studies have demonstrated the superiority of cokriging to ordinary kriging (Stein et al., 1988; Stein and Corsten, 1991; Zhang et al., 1992, 1997; Istok et al., 1993; Wu et al., 2003). Other studies have demonstrated that cokriging was only minimally superior to ordinary kriging when auxiliary variables were not highly correlated to primary variables (Shouse et al., 1990; Martinez, 1996; Triantafilis et al., 2001). This suggests that use of an appropriate auxiliary variable is important to obtain successful results from cokriging and that cokriging is most effective when the covariates are highly correlated. Yates and Warrick (1987) found that cokriging gave better predictions than kriging when sample correlations exceeded 0.5 and when the auxiliary variable was oversampled.

Spatial variability in SOM content can be predicted by kriging from limited soil samples. Moreover, SOM also can be predicted by cokriging when a strong statistical relationship exists between SOM and easily measured auxiliary variables such as cation-exchange capacity, soil texture, and remotely sensed data. Some studies found that SOM correlates with soil reflectance significantly over small to moderate geographic regions with low variation in moisture, parent material, and surface roughness (Al-Abbas et al., 1972; Mulders, 1987; Sudduth and Hummel, 1991; Schulze et al., 1993; Ben-Dor et al., 1999; Chen et al., 2000). Thus, remotely sensed data such as TM imagery may be useful auxiliary variables for SOM prediction. To our knowledge, only a limited number of studies have used geostatistical methods with remotely sensed data as auxiliary variables for predicting SOM (Bhatti et al., 1991; Ishida and Ando, 1999). The objectives of our study were to investigate the effectiveness of using remotely sensed data as auxiliary variables for SOM prediction and to compare ordinary kriging and cokriging for SOM estimation.

MATERIALS AND METHODS

Study Area Description

The study area is part of Haining City located in the Hang-Jia-Hu Plain, northeastern region of Zhejiang Province, China (Fig. 1). The study area is bounded by east longitude between 120°18′ and120 °45′ and north latitude between 30°22 ′and 30 °31′ with a total area of 367 km^2. The study area is in the northern subtropical zone of monsoonal climate with a temperate and humid climate throughout the year with four distinct seasons. The average annual temperature is 15.9°C and the mean annual precipitation is approximately 1190 mm. Paddy rice fields and bare soil are the main land use/land cover types of arable land in the area.

Sampling Design and Soil Analysis

A total of 131 soil samples (0–15 cm) were collected from paddy fields in November 2003 with consideration of land use uniformity and soil types to ensure all samples were located in paddy fields and a soil sample was collected from each soil type (Fig. 1).

Soil organic matter content was analyzed using the Dry Ash Method (Boyd, 1995). Air-dried soil samples were placed in an oven at 105°C for 24 h. After cooling the samples in a desiccator and weighing, they were placed in a muffle furnace at 305°C for 8 h and then reweighed. Finally, SOM was computed as:

$$\mathrm{SOM}=1000-10\frac{(W_F-W_T)}{(W_{TS}-W_T)} \qquad [1]$$

where SOM is soil organic matter content in g kg^{-1}, W_F, weight of crucible and soil after ashing (g), W_T, weight of crucible (g), W_{TS}, weight of crucible and oven dry soil (g).

To predict SOM in the study area using remotely sensed data as auxiliary variables, we selected a Landsat Enhanced Thematic Mapper (ETM) image acquired on 23 Dec. 2003. Normalized difference vegetation index (NDVI), a widely used indicator in remote sensing showing abundance of vegetation cover (Chen

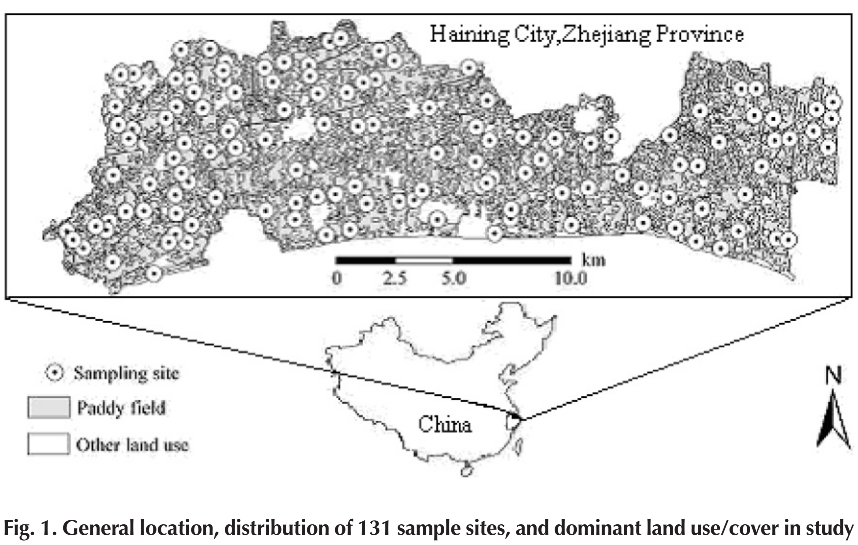

Fig. 1. General location, distribution of 131 sample sites, and dominant land use/cover in study area (Other land use types include water bodies, orchards, built-up land, and upland crops).

and Brutsaert, 1998), was calculated. Negative NDVI values were dominant in the study area indicating that the study area was comprised mostly of bare soil when the image was acquired. To use remotely sensed data as an auxiliary variable for SOM prediction, we sampled an additional 470 pixels using a grid-based sampling scheme with a spacing of 1 km (east-west) and 0.75 km (north-south) in addition to the 131 soil samples described above (Fig. 2).

Multiple Regression Analysis

The general purpose of multiple regression is to characterize the relationship between several independent or predictor variables and a dependent or criterion variable. Our goal was to estimate the correlation between SOM and remotely sensed data and build a predictive model of SOM. Multiple linear regression was conducted for SOM of the 131 soil samples with DN of Bands 1–5 and 7 of the Landsat ETM image (raw and natural-log-transformed) as the independent variables.

Kriging and Cokriging

Geostatistical methods can be used in unbiased prediction with minimum variance for the soil properties of interest (Stein and Corsten, 1991). Kriging and cokriging are two typical geostatistical prediction methods. The semivariogram and cross-semivariogram, main components of kriging or cokriging, are effective tools for evaluating spatial variability (Boyer et al., 1991; Cahn et al., 1994). The estimator for the semivariogram and cross-semivariogram is

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

where γ_{ij} is the semivariance (when $i = j$) with respect to random variable z_i, h is the separation distance, $n(h)$ is the number of pairs of $z_i(x_k)$ and $z_j(x_k)$ in a given lagged distance interval of $(h + dh)$.where γ_{ij} is the cross-semivariogram (when $i \neq j$), which is a function of h (Yates and Warrick, 1987).

The semivariogram was fit using a spherical model (Eq. [3]), and the cross-semivariogram was fit using a Gaussian model (Eq. [4]):

$$\gamma(h)=\begin{cases} C_0+C_1[1.5\frac{h}{a}-0.5(\frac{h}{a})^3] & \text{if} \quad h<a \\ C_0+C_1 & \text{if} \quad h\geq a \end{cases} \qquad [3]$$

$$\gamma(h)=C0+C_1[1-\exp(-\frac{h^2}{a^2})] \qquad [4]$$

where C_0 is the nugget variance, C_1 is the sill, a is the range, and h is the lagged distance.

The spatial distribution of SOM was predicted by applying the best-fit mathematical functions of the semivariogram and cross-semivariogram. Software version 7.0 of GS+ Geostatistics for the Environmental Sciences (Gamma Design Software, Plainwell, MI) was used to perform all the geostatistical computations and model validations.

Assessing Kriging and Cokriging Performance

Descriptive statistics and coefficient of variation (CV) were used to compare observed (measured) concentrations of all 131 soil samples with their predictions based on the two spatial interpolation methods. All the descriptive statistics were calculated using version 8.7 of ERDAS IMAGINE (Leica Geosystems, Atlanta, GA).

Maps of kriging STDs can provide information concerning the confidence associated with the kriging estimates and interpreting such maps is an important step toward quantifying reliability in spatial estimation (Olea, 1999). The larger the STD, the lower the reliability of the estimate having greater uncertainty. In this study, we compared the reliability in SOM estimation by the methods of kriging and cokriging based on maps of kriging STDs. We also used cross-validation as another method of validating kriging predictions (Cressie, 1993; Myers, 1997). We removed one sample from the data set, and used the remaining samples in the data set for each prediction, and repeated the process until all samples had been removed individually. We then calculated the mean prediction as the last prediction for each sample in the process of cross-validation.

RESULTS

Relationship between Landsat Enhance Thematic Mapping Digital Number and Soil Organic Matter Content

Output from correlation analysis between the six independent variables (Landsat ETM DN for Bands 1–5 and Band 7) and the dependent variable SOM content revealed low to moderate negative correlation except for the DN of Band 4, which may have been influenced by the presence of vegetative cover in some regions of the study area (Table 1). The absolute correlation was the strongest between SOM and the DN of Band 1 ($r = -0.587$). After natural logarithmic transformation of SOM content (lnSOM) and the DN values (lnETM1...), stronger negative correlations were found between SOM content and Landsat spectral reflectance with the exception of lnETM4 which resulted in a slightly lower positive correlation with lnSOM compared with ETM4 with SOM. The correlation between lnSOM and lnETM 1 remained the highest among all spectral bands at −0.629 (Table 1).

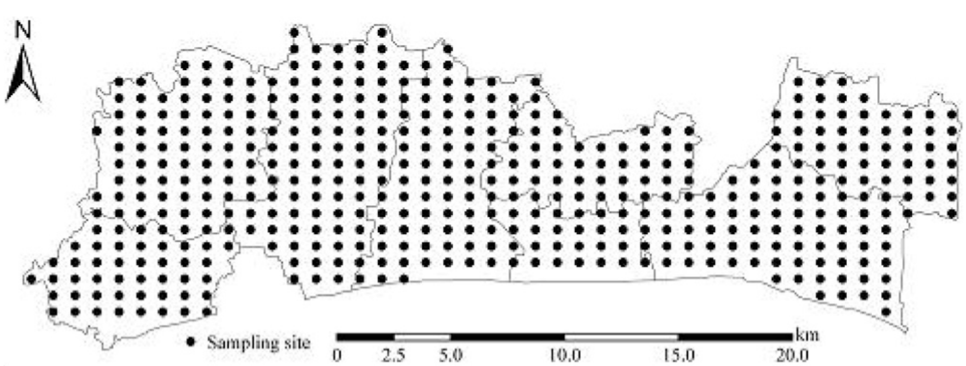

Fig. 2. Distribution of 470 auxiliary remotely sensed data locations in the study area (location of associated 131 soil samples not shown).

When the independent variables were used in a multiple stepwise regression analysis, the results indicated that only ETM1 remained as a statistically significant predictor variable ($P < 0.05$):

$$\ln SOM = 27.62 - 5.421 \ln ETM1 \quad [5]$$

(R^2 = 0.396, SE = 0.287)

where lnSOM and lnETM1 are the natural logarithmic forms of SOM and ETM1, respectively. The coefficient of determination (R^2) of the model was 0.396, and the standard error of the estimate (SE) was 0.287, which means that only 39.6% of the variation of SOM content in the study area can be explained by ETM1 spectral reflectance with high prediction error. This high error of prediction may be due to variations in moisture, parent material, and surface roughness in the study area. Given the high error of predicting SOM with ETM spectral data, we did not directly compare this remote sensing model with the prediction of SOM using the kriging and cokriging models.

Table 1. Pearson correlation coefficients† between soil organic matter content (SOM) and the digital number (DN) 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
	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

† All correlation coefficients listed are significant at $P < 0.01$ level (n = 131).

‡ 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; lnETM 1, lnETM 2, …, lnETM 7,the natural logarithm of ETM spectral bands.

Spatial Prediction of Soil Organic Matter

The SOM content of 131 soil samples were in the range of 5.7 to 36.4 g kg^{-1}, with a mean of 19.5 g kg^{-1} and an STD of 6.36 g kg^{-1}. The data set had low skewness (0.17) and kurtosis (−0.08), thus meeting the requirement of a normal distribution for kriging and cokriging prediction. The semivariogram of SOM provided a clear description of its spatial structure with some insight into possible processes affecting its spatial distribution. The semivariograms of both SOM and DN of ETM1 were well fitted with a spherical model. The nugget/sill ratios of the fitted semivariogram models for SOM and DN of ETM1 were as low as 0.19 and 0.11, respectively. The cross-semivariogram was fitted well by a Gaussian model, with a nugget/still ratio of 0.12.

From the maps of predicted SOM content developed by both kriging and cokriging with remotely sensed data (Fig. 3), we found that the SOM content had strong spatial variability in the study area, and the SOM content in the central region of the study area was generally lower. There was a large difference in the local variability of predicted SOM content in the two prediction maps, however, with the predicted SOM map by kriging being less spatially detailed (more uniform) than that by cokriging in certain local areas such as the central part of the study area, as shown in the SOM prediction map (Fig. 3).

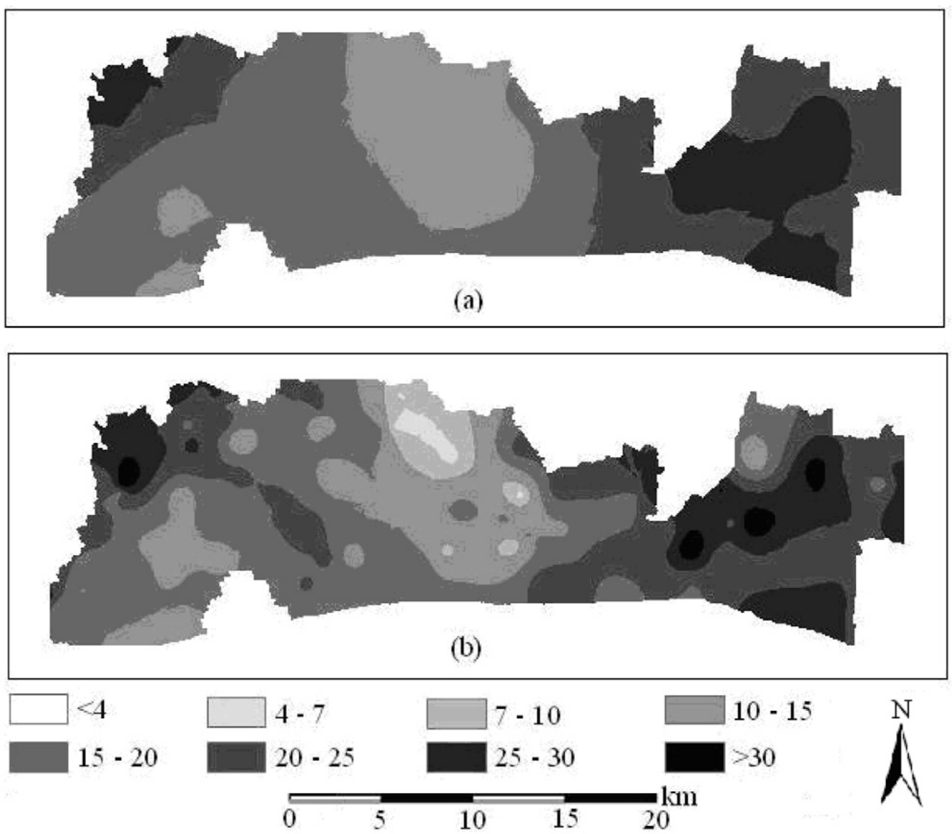

Fig. 3. Predicted soil organic matter content (g kg^{-1}) by (a) kriging and (b) cokriging.

Comparison of Spatial Predictions by Two Methods

The minimum and maximum values of SOM prediction by kriging were 10.1 and 27.3 g kg^{-1}, respectively; and the minimum and maximum values of SOM prediction by cokriging with remotely sensed data were 5.9 and 36.2 g kg^{-1}, respectively. Whereas, the minimum and maximum values of SOM derived from the 131 soil samples were 5.7 and 40.4 g kg^{-1}, respectively. The mean and CV of SOM prediction by the two methods were 19.2 g kg^{-1} and 23.4% for kriging; 19.1 g kg^{-1}and 28.2% for cokriging, respectively; and the mean and CV of SOM from the 131 soil samples were 19.5 g kg^{-1}and 32.6%, respectively. Interpreting the descriptive statistics, we found that the variances of predicted SOM by both kriging and cokriging were less than that of the 131 soil samples, and the variance of predicted SOM by kriging was less than that by cokriging.

From the kriging error maps (Fig. 4), we found that STDs of SOM by cokriging were significantly less than that by kriging throughout the study area. The range of kriging STD of SOM by kriging was 1.6 to 3.3 g kg^{-1}, with a mean of 2.2 g kg^{-1}, and the range of cokriging STD was 0.0 to 2.4 g kg^{-1}, with a mean of 0.5 g kg^{-1}.

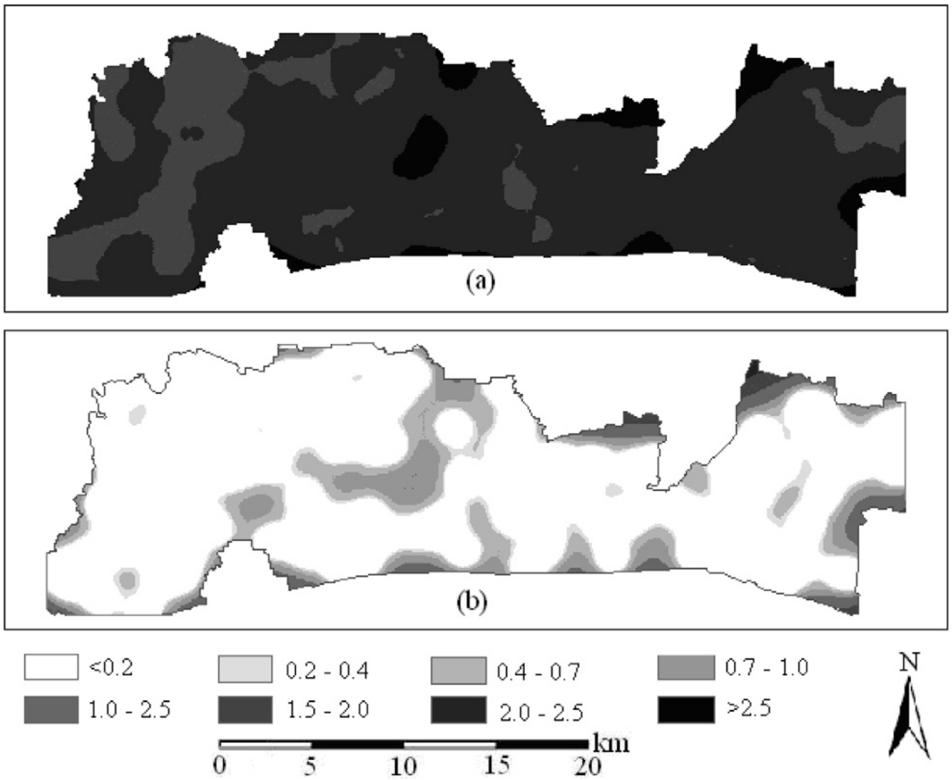

Fig. 4. (a) Kriging and (b) cokriging prediction error maps of soil organic matter content (g kg^{-1}).

The mean of predictions and mean squared prediction errors from cross-validation by the two methods were 19.5 and 4.8 g kg^{-1} for kriging and 19.5 and 2.7 g kg^{-1} for cokriging. We found that the predicted SOM content by cokriging was more similar to that of the 131 soil samples than that by kriging (Fig. 5).

DISCUSSION

The correlation coefficients between SOM and visible bands (Band 1–3) were higher than that between SOM and NIR bands (Band 4–5 and Band 7) of ETM imagery in study area. This is consistent with the results of Krishnan et al. (1980), who reported there was no absorption apex caused by organic matter in the NIR region (800–2400 nm), and SOM content was better measured with visible bands than NIR bands. Several studies (Coleman et al., 1991; Curran et al., 1990; Henderson et al., 1992) found that the reflectance of visible wavelengths (0.425–0.695 mm) had a strong correlation with SOM for soils with the same parent material. However, the correlation coefficients were only moderate in this study. This may be attributable to the differences in soil parent material, moisture, and land use/land cover conditions at the time the ETM imagery was acquired.

The remote sensing model of SOM prediction had a relatively low coefficient of determination (R^2 = 0.396) and moderate standard error (SE = 0.287). This means that SOM prediction by our remote sensing-based model had low reliability over a moderately sized geographic region, and the model did not estimate SOM with reasonable accuracy at unobserved sites in study area. The CV of soil pH and cation-exchange capacity in study area were 9 and 22%, respectively (data not presented here), which indicates some variation in soil properties related to SOM within the study area. Interpretation of soil survey and terrain maps also indicated that there are differences in parent material and surface roughness in the study area. This variation in environmental covariates may be an important factor that affected the reliability of SOM prediction using the remote sensing model.

The semivariogram and its parameters quantitatively reflect the spatial variability of SOM in the study area. The nugget/sill ratio was assumed to be a criterion to classify the spatial dependence of soil properties. Ratio values lower than 25% and higher than 75% corresponded to strong and weak spatial dependence, respectively, while the ratio values between 25 and 75% corresponded to moderate spatial dependence (Chang et al., 1998; Chien et al., 1997). In this study, both the nugget/sill ratio of the kriging semivariogram and that of the cokriging cross- semivariogram of SOM lower than 25%, demonstrating strong spatial dependence of SOM and importance of quantifying spatial variability for spatially predicting SOM in study area.

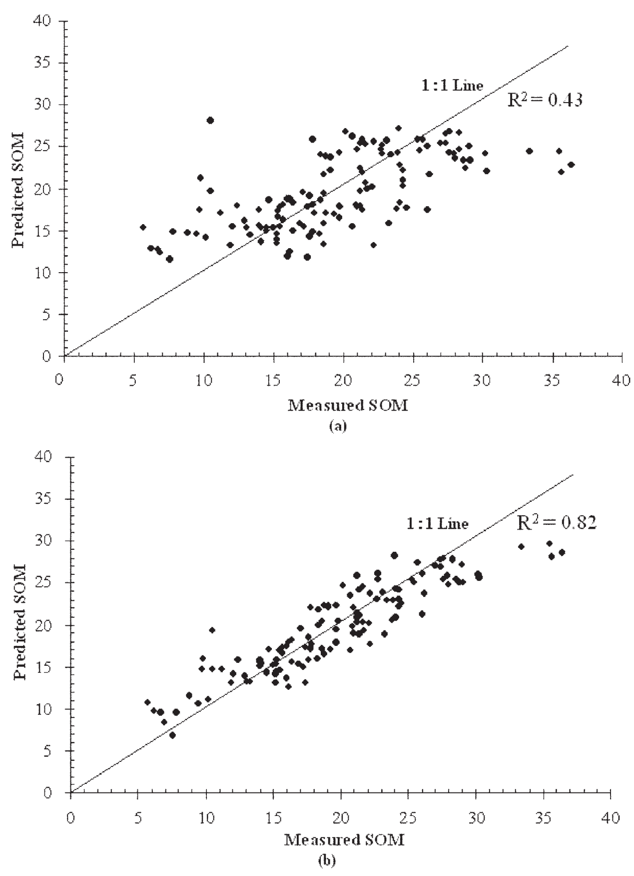

Fig. 5. Measured soil organic matter (SOM) content (g kg^{-1}) vs. the predicted SOM content from cross-validation by (a) kriging and (b) cokriging, respectively.

The minimum and maximum values of predicted SOM by cokriging were more similar to the minimum and maximum values of SOM for all 131 soil samples than the prediction by kriging. The CVs from the two prediction methods were less than that of the 131 soil samples, with cokriging CV closer in value to that of the 131 soil samples. Descriptive statistics of the two predictions methods, including minimum, maximum, and CV (exclusive of the mean value), illustrate that spatial prediction by cokriging with remotely sensed data was an improvement over spatial prediction by ordinary kriging. This demonstrates that remotely sensed data as auxiliary variables can improve the precision of SOM prediction in similar landscapes as investigated in this study.

It was difficult to assess the performance of kriging and cokriging with remotely sensed data in SOM prediction for soil samples that were sparsely distributed. Assessing the performance of kriging and cokriging with remotely sensed data, through the use of descriptive statistics, kriging STD, and cross-validation for each interpolation method had its merits and shortcoming. The predictions by kriging and cokriging had high prediction errors when samples for prediction were few and some independent samples were used for validation and not for prediction. The process of cross-validation is based on a systematic comparison of the observed and predicted values of samples calculated along with the kriging variance from a sample data set leaving one sample out for each iteration. The removal and prediction process is repeated using the remaining samples in the data. This assessment had limitations, however, due to changes in the geometry of sample locations when a point was removed for cross-validation (Davis, 1987). Given this limitation, the cross-validation result might be considered as a conservative assessment with the expectation that the final result would be an improvement when all the data points were included (Kishnė et al., 2003). Kriging STD could be a valid method for assessing the reliability of kriging predictions, though this method lacks the function of verification (Olea, 1999).

The STDs of SOM by cokriging were significantly less than that by kriging throughout the study area. The result of cross-validation also showed cokriging with remotely sensed data was better than kriging in SOM prediction. Cross-validation indicated that cokriging was better than ordinary kriging in describing spatial variability. The cross-validation also demonstrated that remotely sensed data such as Landsat ETM imagery have the potential as good auxiliary variables for improving reliability of SOM prediction.

In general, the correlation between SOM content and remotely sensed data is reduced when spatial variation of environmental covariates influences the distribution of SOM content within the area of study. This results in less accurate predictions of SOM content over moderate to large geographic region when using remote sensing-based models (Hummel et al., 2001; Kongapai, 2007; Sudduth and Hummel, 1991), which was also demonstrated in this study. Conversely, remotely sensed data have the potential to be robust auxiliary variables for improving the accuracy and reliability of SOM prediction when effort is made to reduce the influence of confounding environmental covariates such as land use/land cover conditions and soil properties that may negatively influence reflectance properties unassociated with SOM content.

CONCLUSIONS

The SOM content in our study area had moderate negative correlation in the visible spectral region (Bands 1–3) and short-wave infrared spectral region (SWIR; Bands 5,7), and low positive correlation in the NIR spectral region (Band 4) using Landsat ETM data. The correlation coefficient between the SOM and ETM Band 1 was the largest in absolute value. Although the SOM data display moderate correlation with the DN of visible, NIR, and short-wave infrared (SWIR) bands, the regression model had a low coefficient of determination (R^2 = 0.392) and moderate standard error (SE = 0.287). Thus, we were unable to obtain a satisfactory SOM prediction using a remote sensing-based model.

The predicted SOM map by cokriging with remote sensing covariates was an improvement over that by ordinary kriging and that by the remote sensing-based model in terms of describing spatial variability and reliability of the spatial estimation of SOM. The cokriging approach indicated that remotely sensed data such as Landsat ETM imagery have the potential as robust auxiliary variables for improving the accuracy and reliability of SOM prediction.

The SOM content in the study area had a strong spatial dependency, and the SOM content in the central region was generally lower (<10 g kg^{-1}) and the SOM content in the eastern region was generally higher (>20 g kg^{-1}). To improve soil quality and agricultural production, land management options should be developed to enhance SOM content in this area. Predicting and mapping SOM content based on methods used in this study can provide useful information for improving soil quality and managing nutrient budgets for agricultural production in the region.

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REFERENCES

Agbu, P.A., D.J. Fehrenbacher, and I.J. Jansen. 1990. Soil property relationships with SPOT satellite digital data in east central Illinois. Soil Sci. Soc. Am. J. 54:807–812.

Al-Abbas, A.H., P.H. Swain, and M.F. Baumgardner. 1972. Relating organic matter and clay content to the multispectral radiance of soils. Soil Sci. 114:477–485.

Ben-Dor, E., and A. Banin. 1994. Visible and near-infrared (0.4–1.1 um) analysis of arid and semiarid soils. Remote Sens. Environ. 48:261–274.

Ben-Dor, E., and A. Banin. 1995. Near-infrared analysis as a rapid method to simultaneously evaluate several soil properties. Soil Sci. Soc. Am. J. 59:364–372.

Ben-Dor, E., J.R. Irons, and G.F. Epema. 1999. Soil reflectance. p. 111–188. *In* A.N. Rencz (ed.) Remote sensing for the earth sciences: Manual of remote sensing. Wiley, Danvers, MA.

Bhatti, A.U., D.J. Mulla, and B.E. Frazier. 1991. Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. Remote Sens. Environ. 37:181–191.

Blanco-Canqui, H., and R. Lal. 2004. Mechanisms of carbon sequestration in soil aggregates. Crit. Rev. Plant Sci. 23:481–504.

Boyd, C.E. 1995. Bottom soils, sediment and pond aquaculture. Chapman and Hall, New York.

Boyer, D.G., R.J. Wright, C.M. Feldhake, and D.P. Bligh. 1991. Soil spatial variability in steeply sloping acid soil environment. Soil Sci. 161:278–287.

Burgess, T.M., and R. Webster. 1980. Optimal interpolation and isarithmic

mapping of soil properties. I. The semivariogram and punctual kriging. J. Soil Sci. 31:315–331.
Cahn, M.D., J.W. Hummel, and B.H. Brouer. 1994. Spatial analysis of soil fertility for site-specific crop management. Soil Sci. Soc. Am. J. 58:1240–1248.
Chang, Y.H., M.D. Scrimshaw, R.H.C. Emmerson, and J.N. Lester. 1998. Geostatistical analysis of sampling uncertainty at the Tollesbury managed retreat site in Blackwater Estuary, Essex, UK: Kriging and cokriging approach to minimise sampling density. Sci. Total Environ. 221:43–57.
Chen, D., and W. Brutsaert. 1998. Satellite-sensed distribution and spatial patterns of vegetation parameters over a tallgrass prairie. J. Atmos. Sci. 55:1225–1238.
Chen, F., D.E. Kissel, L.T. West, and W. Adkins. 2000. Field-scale mapping of surface soil organic carbon using remotely sensed imagery. Soil Sci. Soc. Am. J. 64:746–753.
Chen, F., D.E. Kissel, L.T. West, W. Adkins, D. Rickman, and J.C. Luvall. 2008. Mapping soil organic carbon concentration for multiple fields with image similarity analysis. Soil Sci. Soc. Am. J. 72:186–193.
Chen, Y., and T. Aviad. 1990. Effect of humic substances on plant growth. p. 161–186. *In* P. Maccarthy et al. (ed.) Humic substances in soil and crop sciences: Selected readings. ASA, Madison, WI.
Chien, Y.L., D.Y. Lee, H.Y. Guo, and K.H. Houng. 1997. Geostatistical analysis of soil properties of mid-west Taiwan soils. Soil Sci. 162:291–297.
Coleman, T.L., P.A. Agbu, O.L. Montgomery, T. Gao, and S. Prasad. 1991. Spectral band selection for quantifying selected properties in highly weathered soils. Soil Sci. 151:355–361.
Cressie, N.A.C. 1993. Statistics for spatial data. John Wiley & Sons, New York.
Csillag, F., L. Pasztor, and L.L. Biehl. 1993. Spectral band selection for the characterization of salinity status of soils. Remote Sens. Environ. 43:231–242.
Curran, P.J., G.M. Foody, K.Y. Kondratyev, V.V. Kozoderrov, and P.P. Fedchenko. 1990. Remote sensing of soils and vegetation in the USSR. Taylor & Francis, London.
Dalal, R.C., and R.J. Henry. 1986. Simultaneous determination of moisture, organic carbon, and total nitrogen by near infrared reflectance spectroscopy. Soil Sci. Soc. Am. J. 50:120–123.
Davis, B.M. 1987. Uses and abuses of cross-validation in geostatistics. Math. Geol. 19:241–248.
Ferguson, C.C., D. Darmendrail, K. Freier, B.K. Jensen, J. Jensen, H. Kasamas, A. Urzelai, and J. Vegter (ed.). 1998. Better methods for risk assessment. p. 135–146. *In* Risk Assessment for Contaminated Sites in Europe, Vol.1. Scientific Basis. LQM Press, Nottingham.
Frazier, B.E., and Y. Cheng. 1989. Remote sensing of soils in the Eastern Palouse region with Landsat thematic mapper. Remote Sens. Environ. 28:317–325.
Henderson, T.L., M.F. Baumgardner, D.P. Franzmeier, D.E. Stott, and D.C. Coster. 1992. High dimensional reflectance analysis of soil organic matter. Soil Sci. Soc. Am. J. 56:865–872.
Hummel, J.W., K.A. Sudduth, and S.E. Hollinger. 2001. Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor. Comput. Electron. Agric. 32:149–165.
Ishida, T., and H. Ando. 1999. Use of disjunctive cokriging to estimate soil organic matter from Landsat Thematic Mapper image. Int. J. Remote Sens. 20:1549–1565.
Istok, J.D., J.D. Smyth, and A.L. Flint. 1993. Multivariate geostatistical analysis of ground-water contaminant: A case history. Ground Water 31:63–74.
Kishnė, A.S., E. Bringmark, L. Bringmark, and A. Alriksson. 2003. Comparison of ordinary and lognormal kriging on skewed data of total cadmium in forest soils of Sweden. Environ. Monit. Assess. 84:243–263.
Kongapai, P. 2007. Application of remote sensing and geographic information system for estimation of soil organic matter in Nakhon Pathom Province. M.S. Diss., Mahidol Univ., Nakhon Pathom, Thailand.
Krishnan, P., J.D. Alexander, B.J. Butler, and J.W. Hummel. 1980. Reflectance technique for predicting soil organic matter. Soil Sci. Soc. Am. J. 44:1282–1285.
Martinez, C.A. 1996. Multivariate geostatistical analysis of evapo-transpiration and precipitation in mountainous terrain. J. Hydrol. 174:19–35.
Matthias, A.D., A. Fimbres, E.E. Sano, D.F. Post, L. Accioly, A.K. Batchily, and L.G. Ferreira. 2000. Surface roughness effects on soil albedo. Soil Sci. Soc. Am. J. 64:1035–1041.
Mulders, M.A. 1987. Remote sensing in soil science. Elsevier Science Publications, Amsterdam.
Myers, J.C. 1997.Geostatistical error management. Van Nostrand Reinhold, New York.
Odeh, I.O.A., A.B. McBratney, and D.J. Chittleborough. 1995. Further results on prediction from terrain attributes: Heterotopic cokriging and regression-kriging. Geoderma 67:215–236.
Olea, R.A. 1999. Geostatistics for engineers and earth scientists. p. 24–25, 303. Kluwer Academic Publishers, New York.
Schulze, D.G., J.L. Nagel, G.E. van Scoyoc, T.L. Henderson, M.F. Baumgardner, and D.E. Stott. 1993. Significance of organic matter in determining soil colors. p. 71–90. *In* J.M. Bigham and E.J. Ciolkosz (ed.) Soil color. SSSA, Madison, WI.
Shouse, P.J., T.J. Gerik, W.B. Russell, and D.K. Cassel. 1990. Spatial distribution of soil particle size and aggregate stability index in a clay soil. Soil Sci. 149:351–360.
Stein, A., and L.C.A. Corsten. 1991. Universal kriging and cokriging as regression procedure. Biometrics 47:575–587.
Stein, A., W. van Dooremolen, J. Bouma, and A.K. Bregt. 1988. Cokriging point data on moisture deficit. Soil Sci. Soc. Am. J. 52:1418–1423.
Stevenson, F.J., and X. He. 1990. Nitrogen in humic substances as related to soil fertility. p. 91–109. *In* P. Maccarthy et al. (ed.) Humic substances in soil and crop sciences: Selected readings. ASA, Madison, WI.
Sudduth, K.A., and J.W. Hummel. 1991. Evaluation of reflectance methods for soil organic-matter sensing. Trans. ASAE 34:1900–1909.
Sullivan, D.G., J.N. Shaw, D. Rickman, P.L. Mask, and J.C. Luvall. 2005. Using remote sensing data to evaluate surface soil properties in Alabama ultisols. Soil Sci. 170:954–968.
Triantafilis, J., I.O.A. Odeh, and A.B. McBratney. 2001. Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. Soil Sci. Soc. Am. J. 65:869–878.
Wu, J., W.A. Norvell, D.G. Hopkins, D.B. Smith, M.G. Ulmer, and R.M. Welch. 2003. Improved prediction and mapping of soil copper by kriging with auxiliary data for cation-exchange capacity. Soil Sci. Soc. Am. J. 67:919–927.
Yadav, V., and G. Malanson. 2007. Progress in soil organic matter research: Litter decomposition, modeling, monitoring and sequestration. Prog. Phys. Geogr. 31:131–154.
Yates, S.R., and A.W. Warrick. 1987. Estimating soil water content using cokriging. Soil Sci. Soc. Am. J. 51:23–30.
Zhang, R., D.E. Myers, and A.W. Warrick. 1992. Estimation of the spatial distribution of the soil chemicals using pseudo cross-variograms. Soil Sci. Soc. Am. J. 56:1444–1452.
Zhang, R., P. Shouse, and S. Yates. 1997. Use of pseudo-crossvariograms and cokriging to improve estimates of soil solute concentrations. Soil Sci. Soc. Am. J. 61:1342–1347.