Geostatistical Analysis of Soil Texture Fractions on the Field Scale

MASOOMEH DELBARI[1], PEYMAN AFRASIAB[1] and WILLIBALD LOISKANDL[2]

[1]Department of Water Engineering, Faculty of Agriculture, University of Zabol, Zabol, Iran;
[2]Institute of Hydraulics and Rural Water Management, Department of Water, Atmosphere and Environment, University of Natural Resources and Applied Life Sciences, Vienna, Austria

Abstract: Geostatistical estimation methods including ordinary kriging (OK), lognormal ordinary kriging (LOK), cokriging (COK), and indicator kriging (IK) are compared for the purposes of prediction and, in particular, uncertainty assessment of the soil texture fractions, i.e. sand, silt, and clay proportions, in an erosion experimental field in Lower Austria. The soil samples were taken on 136 sites, about 30-m apart. The validation technique was cross-validation, and the comparison criteria were the mean bias error (MBE) and root mean squared error (RMSE). Statistical analysis revealed that the sand content is positively skewed, thus persuading us to use LOK for the estimation. COK was also used due to a good negative correlation seen between the texture fractions. The autocorrelation analysis showed that the soil texture fractions in the study area are strongly to moderately correlated in space. Cross-validation indicated that COK is the most accurate method for estimating the silt and clay contents; RMSE equalling to 3.17% and 1.85%, respectively. For the sand content, IK with RMSE (12%) slightly smaller than COK (RMSE = 14%) was the best estimation method. However, COK maps presented the true variability of the soil texture fractions much better than the other approaches, i.e. they achieved the smallest smoothness. Regarding the local uncertainty, the estimation variance maps produced by OK, LOK, and COK methods similarly indicated that the lowest uncertainty occurred near the data locations, and that the highest uncertainty was seen in the areas of sparse sampling. The uncertainty, however, varied much less across the study area compared to conditional variance for IK. The IK conditional variance maps showed, in contrast, some relations to the data values. The estimation uncertainty needs to be evaluated for the incorporation into the risk analysis in the soil management.

Keywords: estimation uncertainty; kriging; prediction; soil texture fractions; spatial variability

In recent years, an increasing number of soil physical and chemical process models and pedotransfer functions were developed for different purposes such as modelling the water movement and solute transport in soil (GUPTA & LARSON 1979; RAWLS *et al.* 1982) or assessing soil erosion sensivity (MORGAN *et al.* 1998). A key parameter used in many soil process models and pedotransfer functions is soil texture fraction, i.e. sand, silt and clay percentages, which should be quantified accurately on the point scale. As in many cases sparse sampling is only available, some sort of spatial interpolation is required to produce a more detailed picture of the soil texture fractions. Whatever interpolation method is used, there is always some uncertainty attached to the estimates. These uncertainties cannot be neglected and need to be evaluated to assess the reliability of the estimates and the risk involved in any related decision-making process.

Geostatistics as a set of tools for spatial characterisation of the soil properties and estimation with incorporating the spatial continuity behaviour of the soil data into the estimation process has been increasingly used in the soil science over the last two decades (TRANGMAR *et al.* 1985; CAMBARDELLA *et al.* 1994; GONZALEZ & ZAK 1994;

Goovaerts 1998; Gaston *et al.* 2001, López -Granados *et al.* 2002; Nogueira *et al.* 2002; Ersahin & Brohi 2006; Delbari 2007). The most popular geostatistical interpolation method, also known as the best linear unbiased estimator (BLUE), is ordinary kriging (OK) (Journel & Huijbregts 1978; Isaaks & Srivastava 1989). OK has an extensive application in the soil science (Burgess & Webster 1980). Conventional classification methods of soil properties mapping indicate higher precision when combined with OK (Voltz *et al.* 1997). However, OK tends to smooth out the details, i.e. small values are overestimated while high values are underestimated. The smoothing effect of OK is a serious problem especially when the detection of extreme values is the main concern of the problem at hand. Therefore, OK is no longer suitable when dealing with the data of highly skewed distribution. On the other hand many soil properties in earth sciences do not follow a normal distribution due to the existence of few very small or very large values. These extreme values may affect summary statistics, e.g. the mean or variance, or spatial correlation measures of the data, e.g. the semivariogram. There are different ways to handle such extreme values. One way is to remove the extreme values from the data if, of course, their erroneousness is declared. The second way is to classify them into a separate population. This is, however, conditional on the density of the available data to allow the deviation of the reliable statistics for each subset (Goovaerts 1997). The other way is to transform the data using some transformation function, e.g. logarithmic transformation applied for a positively skewed histogram (Saito & Goovaerts 2000), since many phenomena in earth science are log-normally distributed. More generally, indicator kriging (IK) is a non-parametric (distribution-free) counterpart of OK, which can overcome the smoothing effect of OK (Journel 1983). IK is also a useful method for presenting the connectivity of extreme values in a spatial field (Goovaerts 1997).

Soil information is usually multivariate. Cokriging (COK) is a multivariate extension of OK to the situations where one or more secondary variables are spatially cross-correlated with the primary variable. In such cases, the readily available secondary information is used to improve the quality of soil properties estimates (Yates & Warrick 1987; Zhang *et al.* 1992, 1997; Vaughan *et al.* 1995; Gotway & Hartford 1996; Juang & Lee 1998). For example, Ersahin (2003) compared OK and COK for estimating the infiltration rate. He found that COK could estimate the infiltration rate more accurately than OK when the infiltration rate measurements are limited and some well-correlated secondary variable like bulk density is available. Another study conducted by Bishop and McBratney (2001) showed that in the presence of secondary information with a high or even poor correlation with the main attribute, OK is no longer suggested and hybrid methods such as kriging with external drift (KED) will result in a more precise estimation. Other researchers also suggest that the denser and less expensive auxiliary data, e.g. aerial photographs could be used to improve the prediction accuracy of the soil properties from the sparse information obtained through soil surveys (Kerry & Oliver 2003; López-Granados *et al.* 2005). There are different case studies in which various kriging methods were compared. For example, in a study conducted by Triantafilis *et al.* (2001), ordinary kriging, regression kriging, three-dimensional kriging, and cokriging were compared for predicting soil salinity. Lopez-Granados *et al.* (2002) examined the spatial patterns of seven soil chemical properties and texture fractions over two fields in southern Spain for the implementation of a site-specific fertilisation practice. Odeh *et al.* (2003) applied OK and COK to estimate soil particle-size fractions.

In spite of the main application of geostatistics for mapping the soil properties in soil science (Goovaerts 1999), it is increasingly used for assessing the uncertainty attached to the estimates. A unique feature of OK is to produce an estimation variance corresponding to each estimate, which can provide a measure of confidence on the modelled surface (Goovaerts 1997). The OK variance depends, however, on the data arrangement and model of spatial continuity only and is independent of the data values (Lloyd & Atkinson 1999). Therefore, except under homoscedaticity and normality of the distribution of the estimation errors, kriging variance cannot be used as a reliable measure of the estimation uncertainty (Goovaerts 1997). IK, in contrast, can be used for modelling local uncertainty by considering the values of actual data in addition to their configuration (Goovaerts 1997). Instead of estimating a unique value for an unsampled location, IK estimates a cumulative distribution function (cdf) corresponding to each location, which, after being post processed, different measures of local uncertainty such as conditional variance can be obtained (Goovaerts *et al.* 1997; Mohammadi *et al.* 1997).

In this study, the objectives are to predict the spatial distribution of soil texture fractions and to assess the uncertainty attached to the estimates, in particular in an erosion experiment in Lower Austria. For this purpose, the feasibility of using different kriging methods such as OK, LOK, COK, and IK is examined.

MATERIALS AND METHODS

Study area and data set

This study is conducted on a 18 ha hilly slope field (16°34' longitude and 48°34' latitude) located in a 40 ha agriculturally used watershed (Figure 1a). The field is located in Lower Austria, roughly 40 km northeast of Austria's capital Vienna and approximately 25 to 30 km from the Czech and the Slovak boarders. Geologically, the northern part of the so-called Viennese basin is alluvial deposits (Molasse zone, Zötl 1997). The landscape is characterised by gently to fairly steep slopes (5–20%). The mean annual temperature in 1994–2001 was about 9.6°C while the average annual precipitation is about 665 mm. The samples were collected from the surface layer (0–10 cm) in July 2002. A total of 136 soil samples were taken on an almost regular grid, about 30 m apart. Fine soil texture fractions (sand, silt and clay) were determined from the grain size distribution obtained through the sieving and pipette methods. Soil bulk density was also measured; the average value was 1.38 g/cm^3. The location map of the sampling points is shown in Figure 1b.

Geostatistical analysis

Geostatistical analysis usually begins with investigating the spatial continuity between the observations. The semivariogram and cross-semivariogram functions describe the spatial (cross) correlation between the data values (Isaaks & Srivastava 1989). The experimental semivariogram and cross-semivariogram are calculated using the following equation:

$$\gamma^*_{vw}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{ [Z_v(x_i + h) - Z_v(x)] [Z_w(x_i + h) - Z_w(x)] \} \quad (1)$$

where:

γ^*_{vw} – experimental semivariogram when $v = w$ and cross-semivariogram when $v \neq w$

$N(h)$ – number of pairs of random variables $Z_v(x_i)$ and $Z_w(x_i)$ at a given separation distance h

A best fit theoretical model of (cross) semivariogram is then used in kriging system to predict the spatial distribution of the soil texture fractions. The experimental semivariogram calculation and fitting models are performed using software package GS+ (Robertson 2000).

Ordinary kriging

In ordinary kriging (OK, Isaaks & Srivastava 1989), the values at the unsampled locations are

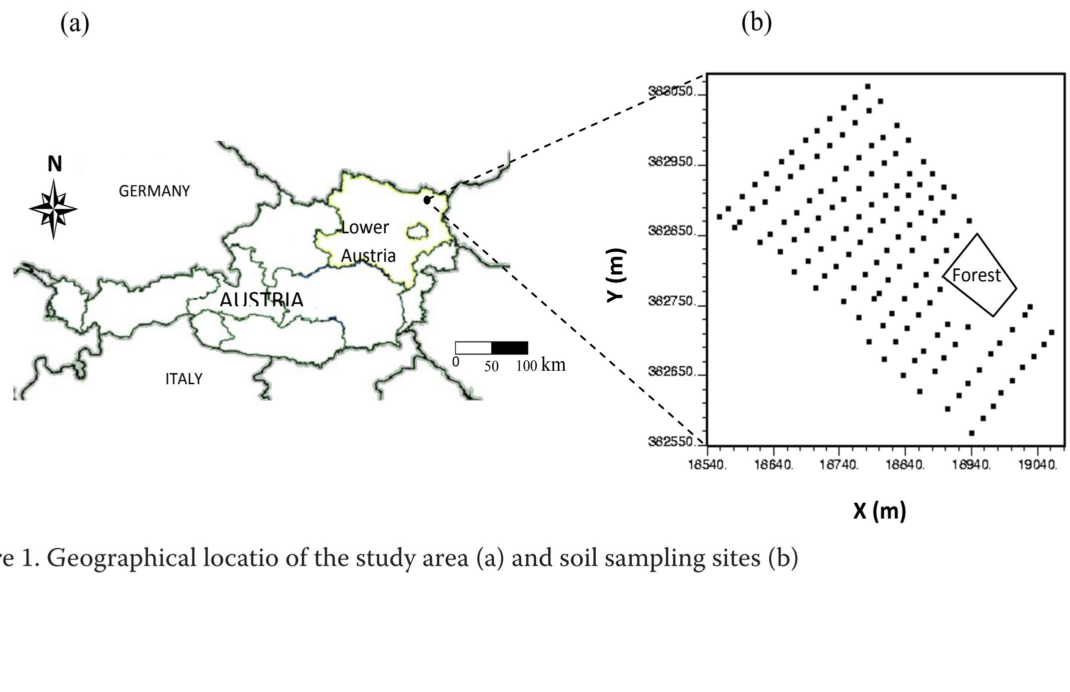


Figure 1. Geographical locatio of the study area (a) and soil sampling sites (b)

determined by a linear weighted moving averaging of the values at the sampled locations, i.e.:

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

where:

$Z^*(x_0)$ – estimated value of the variable of interest at the unsampled location x_0

λ_i – weight assigned to the known value of the variable at location x_i determined based on a semivariogram model

n – number of neighbouring observations

Allocating weights to the known locations is done in such a way that they sum to unity to provide an unbiased estimation ($E\ [Z^*(x_0) - Z(x_0)] = 0$). By minimising the kriging estimation error variance, the unknown weights are found by solving the following system of (n + 1) linear equations:

$$\begin{cases} \sum_{j=1}^{n} \lambda_j \gamma(x_i, x_j) + \mu = \gamma(x_i, x_0) \quad , \quad i = 1,\ldots,n \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \qquad (3)$$

where:

$\gamma(x_i, x_j)$ – average semivariance between all pairs of the data locations

μ – Lagrange parameter for minimisation the kriging variance

$\gamma(x_i, x_0)$ – average semivariance between the location to be estimated (x_0) and the i^{th} sample point

The OK variance is given as:

$$\sigma^2_{OK} = \sum_{i=1}^{n} \lambda_i \gamma(x_i, x_0) + \mu \qquad (4)$$

OK estimation variance corresponding to each estimate can be used to generate a confidence interval for the respective estimate assuming a normal distribution of errors (Goovaerts 1997).

Lognormal ordinary kriging

OK performed on lognormal transformed data is called lognormal ordinary kriging (LOK). The estimates have to be back-transformed to the original space at the end. This is of course a delicate issue because the antilog back-transformation of the estimates does not result in an unbiased estimate of a property in real space (Patriarche *et al.* 2005).

Cokriging

The cokriging (COK) estimator $Z_v^*(x_0)$ at the unsampled location x_0, assuming there is one auxiliary variable Z_w cross-correlated with the main variable Z_v, is given as (Isaaks & Srivastava 1989):

$$Z_v^*(x_0) = \sum_{i=1}^{n} \alpha_i \cdot Z_v(x_i) + \sum_{j=1}^{m} \beta_j \times Z_w(x_j) \qquad (5)$$

where:

α_i, β_j – weights assigned to the known values of the primary and secondary variables Z_v and Z_w, respectively

n, m – numbers of primary and secondary observations

Like for OK, to obtain an unbiased estimate of the primary variable, the sum of weights α_i should be unity while the sum of weights β_j should be zero and the COK estimation variance is minimised (Goovaerts 1997).

Indicator kriging

Indicator kriging (IK) is based on the coding of the random function $Z(x)$ into a set of K indicator random functions $I(x, z_k)$ corresponding to different cutoffs z_k:

$$I(x; z_k) = \begin{cases} 1 & \text{if } Z(x) \le z_k \\ 0 & \text{otherwise} \end{cases}, \qquad \mathrm{k} = 1, \ldots, \mathrm{K} \qquad (6)$$

After transforming the observed data to a new set of indicator variables, the experimental semivariogram is calculated for every set of indicators at each cutoff z_k as:

$$\gamma_I^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[I(x_i; z_k) - I(x_i + h; z_k) \right]^2 \qquad (7)$$

where:

$\gamma_I^*(h)$ – indicator experimental semivariogram

$N(h)$ – number of pairs of indicator transforms $I(x_i; z_k)$ and $I(x_i+h; z_k)$ at locations x_i and x_i+h, respectively,

h – separation distance vector

The conditional cumulative distribution function (ccdf) at each unsampled location, e.g. x_0, is then obtained by the IK estimator:

$$F(x_0; z_k|(n)) = I^*(x_0; z_k) = \sum_{i=1}^{n} \lambda_i I(x_i; z_k) \qquad (8)$$

where:

$I^*(x_0; z_k)$ – estimated indicator transform at the unsampled location x_0

λ_i – weight assigned to the indicator transform I at location x_i

These discrete probability functions must be interpolated within each class (between every two parts of ccdf) and extrapolated beyond the minimum and maximum values to provide a continuous ccdf covering all the possible range of the property of interest. In this study, "linear interpolation between tabulated bounds" (Deutsch & Journel 1998) provided by the sample histogram is performed to increase the resolution of the set of K estimated probabilities. IK-based ccdfs are then post processed to compute E-type estimates, which can be compared with e.g. OK estimates. Local uncertainty measures, e.g. conditional variance map, are also provided through post processing of IK-based ccdfs.

Kriging methods are performed using the software package GSLIB (Deutsch & Journel 1998). The estimation net includes a regular grid with the grid cell size of 5 × 5 m covering the study field in Lower Austria.

Validation technique and comparison criteria

The cross-validation or so-called "leave-one-out" technique (Isaaks & Srivastava 1989) is used to evaluate the utilisation of different kriging methods. The overall performance of the interpolators is compared using two statistical criteria; the root mean squared error (RMSE) and the mean bias error (MBE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left\{Z^*(x_i) - Z(x_i)\right\}^2} \qquad (9)$$

$$\mathrm{MBE} = \frac{1}{N}\sum_{i=1}^{N}\left\{Z^*(x_i) - Z(x_i)\right\} \qquad (10)$$

where:

$Z^*(x_i)$, $Z(x_i)$ – estimated and observed values at location x_i, respectively

N – number of observations

The RMSE is a measure of the accuracy of the interpolation methods; low RMSE indicates an interpolator that is likely to give reliable estimates for unknown attributes. The MBE is, on the other hand, a measure of the estimator bias; for the unbiased interpolator, the MBE should be close to zero.

RESULTS AND DISCUSSION

Characterisation of soil texture fractions

A summary statistics of clay, silt, and sand percentages in the top layer (0–10 cm depth) of soil is reported in Table 1. This information indicates that the soil texture class in the study area is generally silt loam, implying a moderate water holding capacity in the field. The susceptibility to erosion is mostly high due to the high proportion of the silt content. As seen in Table 1, both silt and sand contents have equally high variances; the greatest coefficient of variation (CV) belongs to the sand content indicating a considerable variability of the sand content in the study field. Kolmogorov-Smirnov (KS) normality test indicates that clay is almost normally distributed with a non-significant (high) P-value of 0.67. Silt and sand are strongly negatively (P = 5.17E-5) and positively (P = 1.32E-10) skewed, respectively, and can also be seen from the skewness and kurtosis coefficients and histograms of the soil texture fractions provided in Table 1 and Figure 2. This suggests

Table 1. Descriptive statistics of soil texture fractions (in %)

Variable	Minimum	Maximum	Mean	Median	SD	Variance	CV	Skewness	Kurtosis
Sand	6.91	31.97	10.31	8.81	4.51	20.38	44	3.25	10.69
ln sand	1.93	3.46	2.28	2.18	0.3	0.09	0.13	2.37	5.51
Silt	46.74	76.34	68.43	69.08	4.80	23.02	7	–2.39	7.13
Clay	15.25	26.75	21.27	21.25	2.33	5.44	11	–0.23	–0.25

SD – standard deviation; CV – coefficient of variation

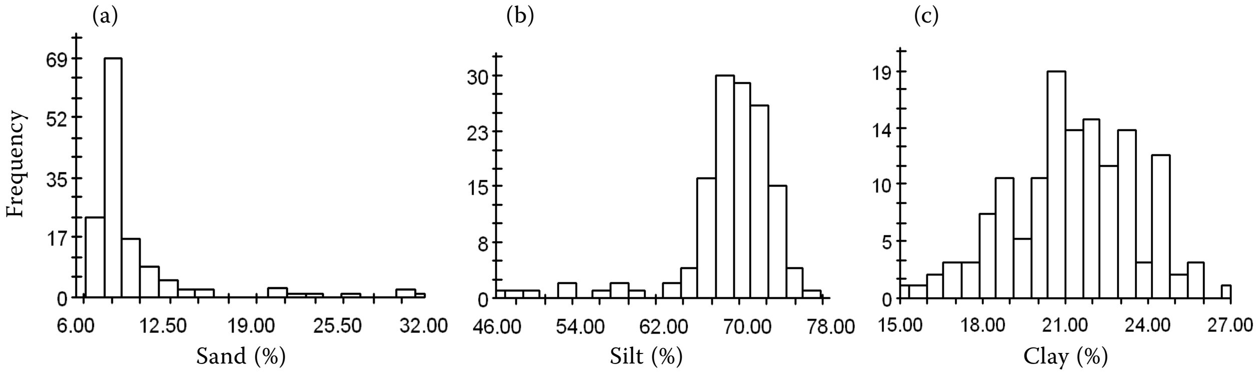


Figure 2. Histograms of sand (a) silt (b) and clay (c) contents

that the spatial distribution of the sand and silt contents in topsoil of the study area is heterogeneous. For sand with a positively skewed distribution, lognormal transformed data is also provided in Table 1. Although log-transformation reduces the skewness coefficient (Table 1) and improves the distribution of new data, it is still not able to produce a rigorously normal distribution; the distribution is closer to normal.

Pearson correlation analysis has been carried out to determine the extent of the relationship between the three soil texture fractions. The results (Table 2) reveal a strong negative correlation between the sand and silt contents (r = –0.87). Clay has a moderate negative correlation (r = –0.36) with silt and the smallest correlation (r = –0.13) exists between clay and sand contents.

Spatial correlation

The sample (cross-) semivariograms for sand, silt, and clay percentages were calculated and then fitted by the weighted least squares models. To check geometric anisotropy, directional semivariograms were calculated for four azimuths 0°, 45°, 90° and 135° with 22.5° angle tolerance. The results (not shown) did not show signs of anisotropy; hence, omni-directional (cross-) semivariograms shown in Figure 3 were only considered for further analysis. For sand, the semivariogram of logarithmic transforms was also calculated and is presented in Figure 3; it is less erratic than the semivariogram of the raw data. In Table 3, the characteristics of (cross-) semivariogram models for soil texture fraction are presented. As seen, most semivariograms include a nugget effect comprising short-range variability (spatial variation occurring at distances shorter than the smallest sampling distance) and the overall measurement error. The best fitted model to the experimental (cross-) semivariogram of the soil texture fractions in terms of the highest R^2 and lowest RSS coefficients functionally of GS+ (Robertson 2000) is generally spherical. The degree of spatial correlation is evaluated using the ratio of nugget variance (C_0) to the whole variance (Sill, Cambardella *et al.* 1994); the lower is the index C_0/Sill, the stronger is the spatial correlation. Accordingly, sand and silt having a C_0/Sill < 25% are strongly spatially correlated and clay has a moderate spatial correlation (25% < C_0/Sill < 75%). The latter is comparable with the result obtained in a study by Gallichand and Marcotte (1993) in which clay content showed a C_0/Sill of 43%. They suggest, however, a different semivariogram model and correlation distance. Since clay content does not show any strong spatial correlation, silt content having a moderate correlation with clay, is used as a secondary variable to improve possibly the estimation results. As seen in Figure 3 and Table 3, using auxiliary variable even for sand and silt contents with a relatively strong spatial dependency improves the spatial correlation results.

Table 2. Pearson correlation coefficient (r) among soil texture fractions

Texture fraction	Sand	Silt	Clay
Sand	1	–0.88*	–0.13^{ns}
Silt	–0.88*	1	–0.36*
Clay	–0.13^{ns}	–0.36*	1

*significant correlation at a significance level of $P \leq 0.05$; ^{ns}not significant

Table 3. Characteristics of (cross-) semivariogram models of soil texture fractions

Texture fraction	Structure	C_0* ($\%^2$)	Sill ($\%^2$)	Range (m)	Effective range (m)	C_0/Sill ×100	R^2	RSS
Sand	Spherical	5.01	21.03	145	145	23.82	0.785	68.7
ln sand	Spherical	0.0106	0.0942	142	142	11.25	0.894	7.9e-4
Silt	Spherical	5.86	23.85	135	135	24.57	0.885	38
Clay	Spherical	2.27	5.01	90	90	45.31	0.683	1.96
Sand-silt	Spherical	−3.91	−19.87	139	139	19.70	0.842	44.5
Clay-silt	Exponential	−0.01	−4.053	30	90	0.01	0.576	4.79

*C_0 – nugget effect of the (cross-) semivariogram

Distribution-free approach of IK was performed on the sand and silt contents, which are positively and negatively skewed, respectively. For this purpose, 6 indicator cutoffs 7.82, 8.27, 8.81, 9.89, 13.64, and 21.68% corresponding respectively to 0.10, 0.25, 0.50, 0.75, 0.90, and 0.95 quantiles of sand observations were selected. For silt 6 indicator cutoffs 57.23, 65.02, 67.38, 69.08, 71.2, and 72.62% corresponding, respectively, to 5th, 10th, 25th, 50th, 75th, and 90th percentiles of silt observations were chosen. To model the local uncertainty, IK was also performed on the clay content by choosing six threshold values 16.75, 18.25, 20, 21.25, 23, and 24.25% corresponding to 0.05, 0.10, 0.25, 0.50, 0.75, and 0.90 clay data quantiles, respectively. The characteristics of the indicator semivariograms

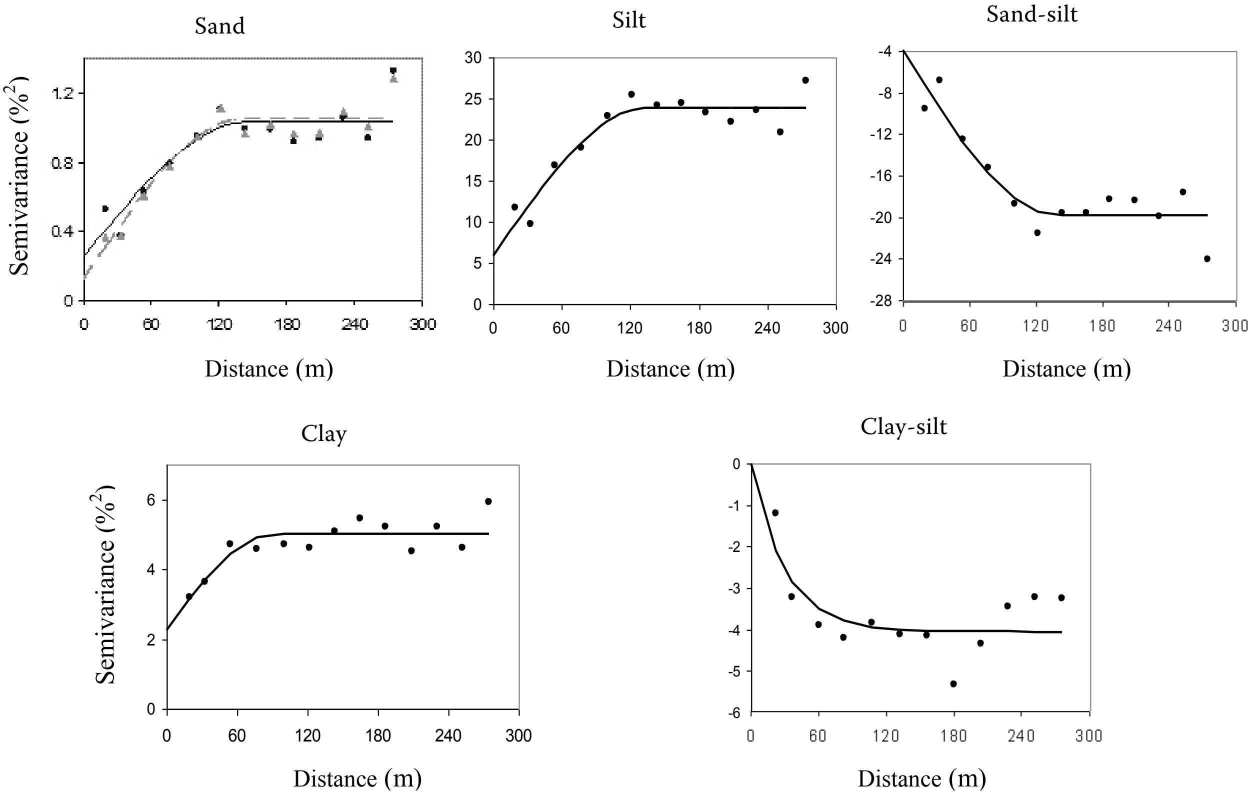


Figure 3. Experimental (cross-) semivarograms (dots) and (cross-) semivariogram models (solid line) for the sand, silt, and clay contents. For sand, the experimaental semivariogram (triangles) and semivariogram model (dashed line) of logarithmic transforms are also provided and both are rescaled by the variance of sand observations

are given in Table 4. The models are fitted using a combination of fitting by eye and the weighted least squares. Most of the indicator semivariograms show a moderate spatial correlation within the classes for the texture fractions.

Estimation and uncertainty assessment

Cross-validation results of sand, silt, and clay contents estimation using OK, LOK, COK, and full IK are presented in Table 5. The results indicated that IK is the most accurate method (RMSE = 3.12%) for estimating the sand content whereas the highest error was obtained with LOK (RMSE = 3.24%). The scatterplots of the sand observations versus the estimates from OK, LOK, and full IK are displayed in Figure 4. With all methods, the estimated mean value is similar to the actual mean value (without bias), and standard deviation (SD) of the estimated values is smaller than the sampled one (smoothness). IK, however, achieved the highest correlation coefficient between the sand observations and estimates. Surprisingly, IK smoothed out the sand estimates at the most, which may be due to an insufficient indicators selected. The smoothing effect was the least for COK, yet it gave a correlation coefficient quite similar to IK. This highlights the usefulness of the secondary variable (i.e. silt content) for improving the sand estimation results. The most accurate method for estimating the silt content appeared

Table 4. Indicator semivariogram characteristics of sand, silt, and clay contents

Texture fraction	Quantile	Structur	C_0 (%^{2})	Sill (%^{2})	Range (m)	Effective range (m)	C_0/Sill × 100	R^2	RSS
Sand	0.1	Sph.	0.04	0.098	180	180	40.82	0.682	1.92e-3
		Exp.	0.001	0.097	40	120	1.03	0.761	1.45e-3
	0.25	Sph.	0.06	0.193	85	85	31.09	0.832	1.94e-3
		Exp.	0.041	0.197	36	108	20.81	0.89	1.29e-3
	0.50	Sph.	0.18	0.256	130	130	70.31	0.673	1.96e-3
		Exp.	0.128	0.257	31	93	49.81	0.538	2.97e-3
	0.75	Sph.	0.052	0.192	105	105	27.08	0.908	1.37e-3
		Exp.	0.027	0.195	39	117	13.85	0.893	1.61e-3
	0.90	Sph.	0.026	0.095	160	160	27.37	0.881	6.7e-4
	0.95	Sph.	0.011	0.036	90	90	30.56	0.687	1.61e-4
Silt	0.05	Sph.	0.015	0.043	130	130	34.88	0.702	2.97e-4
	0.1	Sph.	0.028	0.096	160	160	29.17	0.898	5.85e-4
	0.25	Sph.	0.099	0.20	140	140	49.5	0.496	5.03e-3
	0.50	Sph.	0.17	0.26	160	160	65.38	0.780	1.96e-3
	0.75	Sph.	0.001	0.190	70	70	0.53	0.915	1.35e-3
		Exp.	0.001	0.193	28.3	85	0.52	0.873	2.20e-3
	0.90	Sph.	0.027	0.079	95	95	34.18	0.802	3.92e-4
Clay	0.05	Sph.	0.0001	0.0394	72	72	0.25	0.721	7.8e-4
	0.1	Exp.	0.0354	0.0978	42	126	36.20	0.764	7.4e-4
	0.25	Exp.	0.0001	0.1982	26	78	0.05	0.824	4e-3
	0.50	Exp.	0.0001	0.2522	22	66	0.04	0.846	3e-3
	0.75	Exp.	0.0112	0.1684	17	51	6.65	0.732	1.2e-3
	0.90	Exp.	0.0001	0.0826	15	45	0.12	0.516	6e-4

Table 5. Cross-validation results of estimating sand, silt and clay contents using different kriging methods (in %)

Method	Sand		Silt		Clay	
	MBE	RMSE	MBE	RMSE	MBE	RMSE
OK	0.03	3.19	–0.02	3.35	–0.02	1.95
LOK	–0.07	3.24	–	–	–	–
COK	0.02	3.14	–0.01	3.17	–0.01	1.85
IK	0.06	3.12	–0.04	3.46	–0.46	1.93

MBE – mean bias error; RMSE – root mean squared error; OK – ordinary kriging; LOK – lognormal ordinary kriging; COK – cokriging; IK – indicator kriging

to be COK having the lowest MBE (–0.01%) and RMSE (3.17%). The scatterplots of the estimated versus observed values of the silt content (Figure 5) also reveal that COK results in a higher correlation coefficient and a lower smoothness than the other methods. COK, which uses the cross dependency between the clay and silt contents, achieves again the highest accuracy (RMSE = 1.85%). The better performance of COK can also be observed from the scatterplots of the clay estimates versus observations (Figure 6) as it achieves the highest objectivity (the least bias), the highest correlation coefficient, and the least smoothness.

The spatial distribution of the sand, silt and clay contents over the study area are mapped using kriging methods in Figures 7–9, respectively.

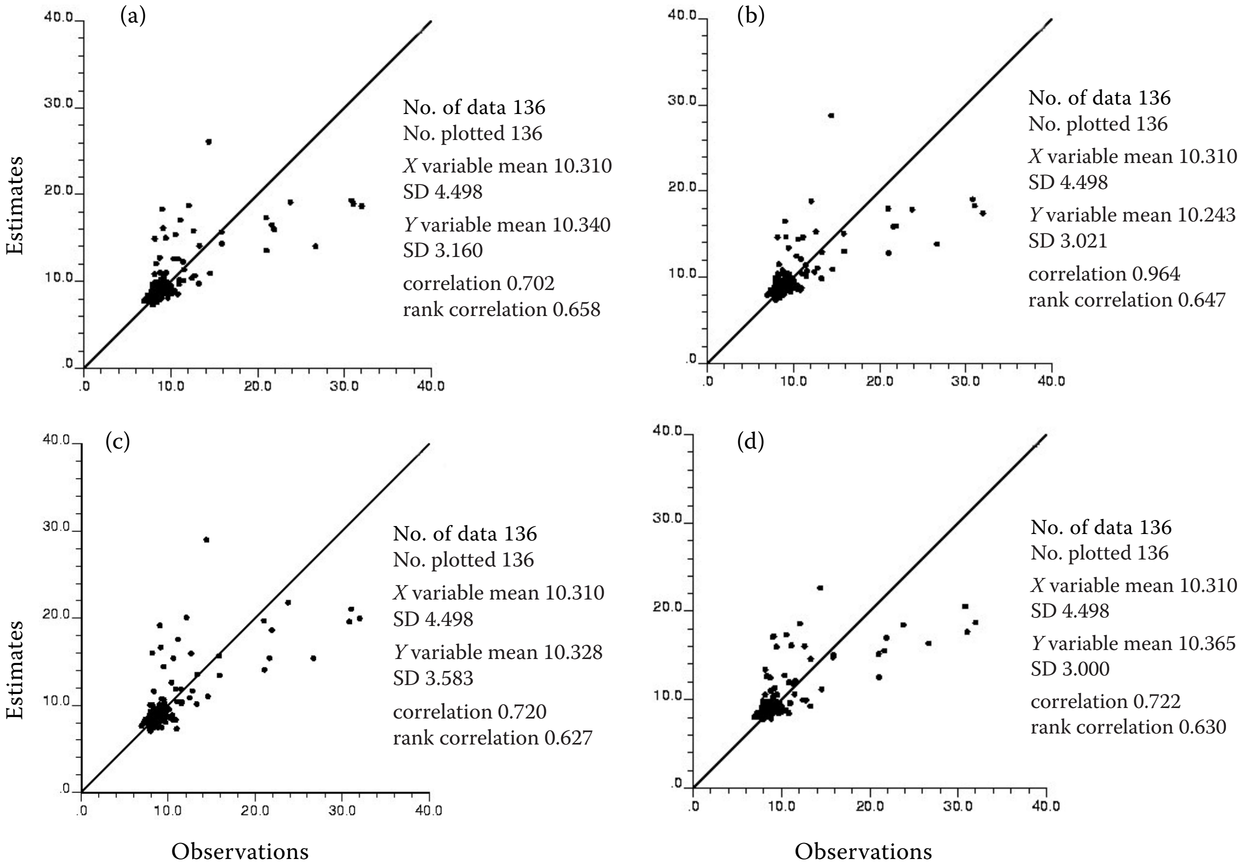
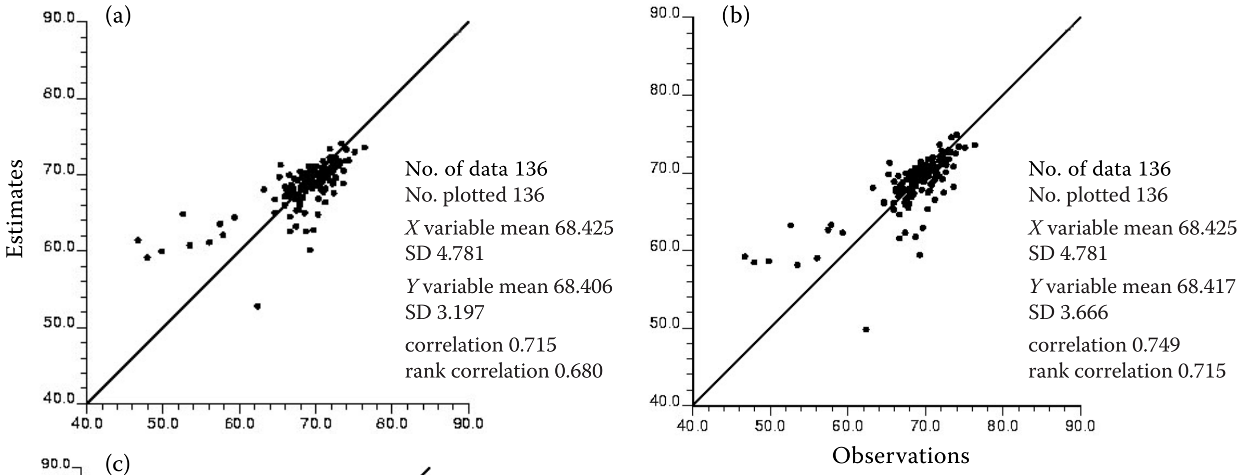


Figure 4. Scatterplot of estimated versus observed values of sand (%) obtained using ordinary kriging – OK (a), lognormal ordinary kriging – LOK (b), cokriging – COK (c), and indicator kriging – IK (d)



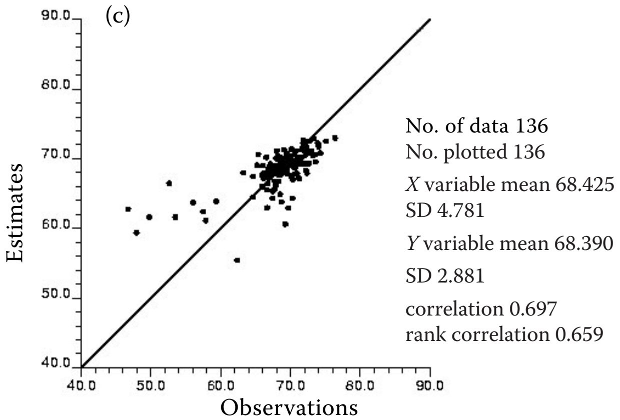
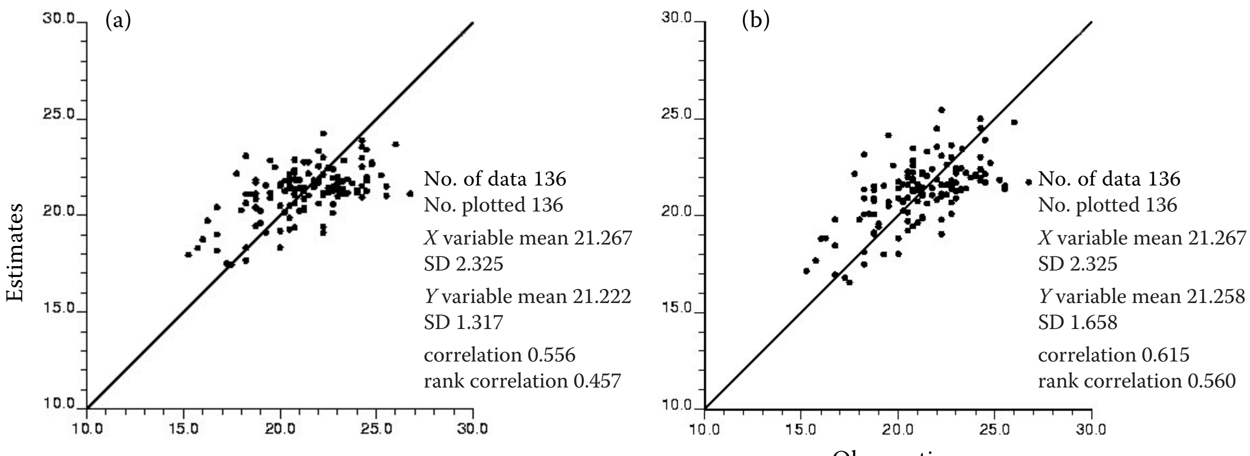


Figure 5. Scatterplot of estimated versus observed values of silt (%) obtained using ordinary kriging – OK (a), cokriging – COK (b), and indicator kriging – IK (c)



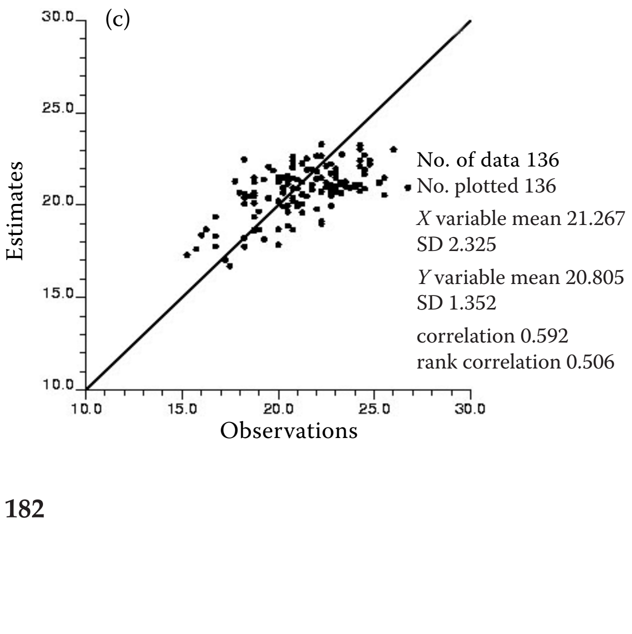


Figure 6. Scatterplot of estimated versus observed values of clay (%) using ordinary kriging – OK (a), cokriging – COK (b), and indicator kriging – IK (c)

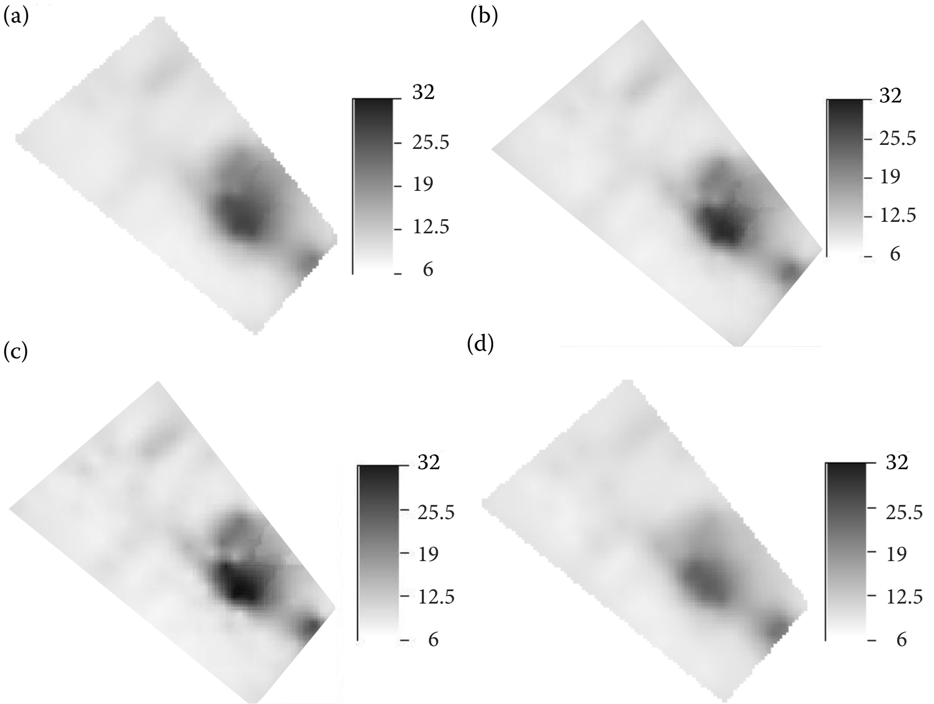


Figure 7. Mapping sand content (%) using ordinary kriging – OK (a), lognormal ordinary kriging – LOK (b), cokriging – COK (c), and indicator kriging – IK (d)

Based on the cross-validation procedure, a search circle with a radius of 100 m and a maximum of 16 neighbouring data were selected for the estimation. The higher smoothness of IK is again apparent in the estimation map of the sand content (Figure 7). All maps, however, indicate that a high sand content is mostly located in the southeast of the study area whereas low values are seen in the other regions, especially in the west and northwest of the study area. The estimation maps of the silt content (Figure 8) show the higher values are located in the western part of the study area. Again, IK represents a smaller variation over the silt content estimation map relative to the other approaches. For the clay content, the estimation maps produced by means of the three methods (Figure 9) indicate that the high values of the clay content are located mainly in the northeast corner

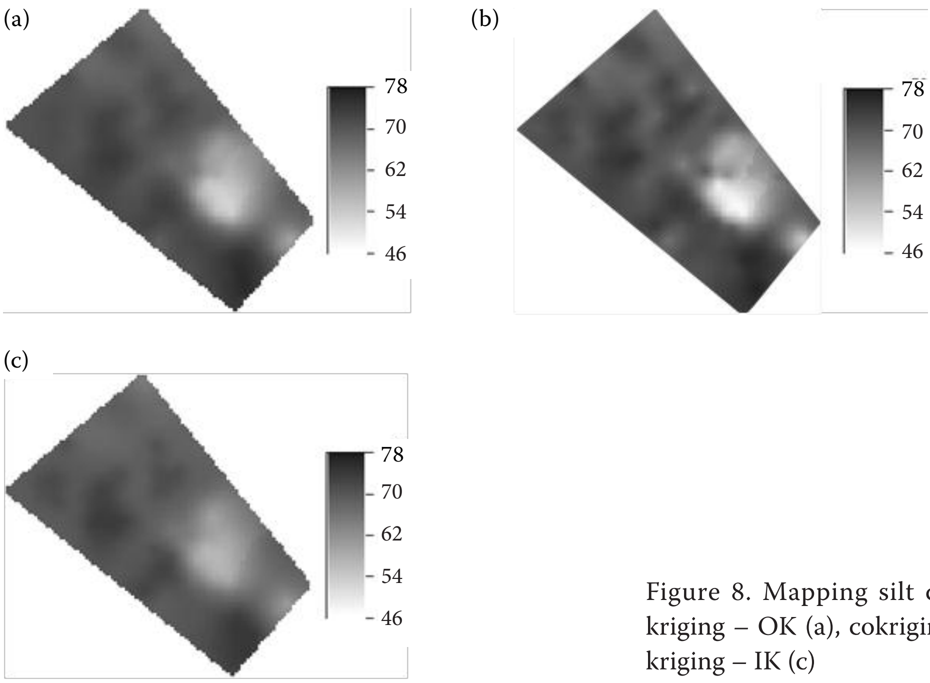


Figure 8. Mapping silt content (%) using ordinary kriging – OK (a), cokriging – COK (b), and indicator kriging – IK (c)

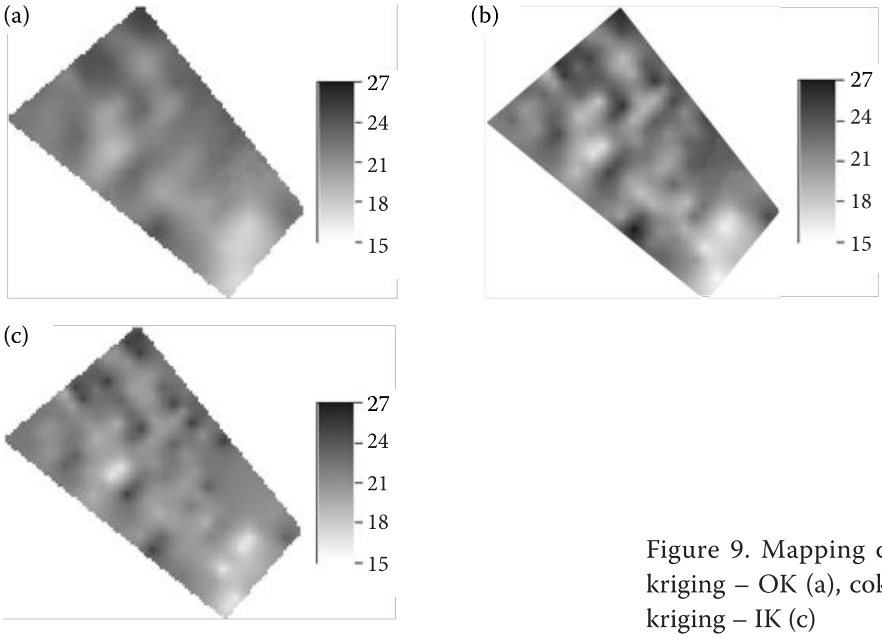


Figure 9. Mapping clay content (%) using ordinary kriging – OK (a), cokriging – COK (b), and indicator kriging – IK (c)

while the low valued-areas are mostly located in the south and southwest corners of the study area.

The estimation variance produced through OK, LOK, and COK, and IK-conditional variance of the sand estimates are mapped in Figure 10. The estimation error variance (uncertainty) provided by OK, LOK, and COK is, as expected, smaller at the sampling sites and nearby locations and it becomes higher as the distance between the observations is getting larger (south part of the study area) and where no data is available (the east and southeast parts of the study area). The conditional variances produced by IK show in contrast some relation with the sand data values in addition to the data configuration. Figure 10(d) indicates that the uncertainty of the sand estimate is smaller where the data are consistently small or intermediate (most parts of the western and northern area). The local uncertainty is larger in the high-valued areas in the south eastern area where high values are isolated, i.e. a few high values are surrounded by small values of sand. To evaluate the uncertainty model provided by OK and IK, the scatterplot of the estimation errors versus standard deviations is

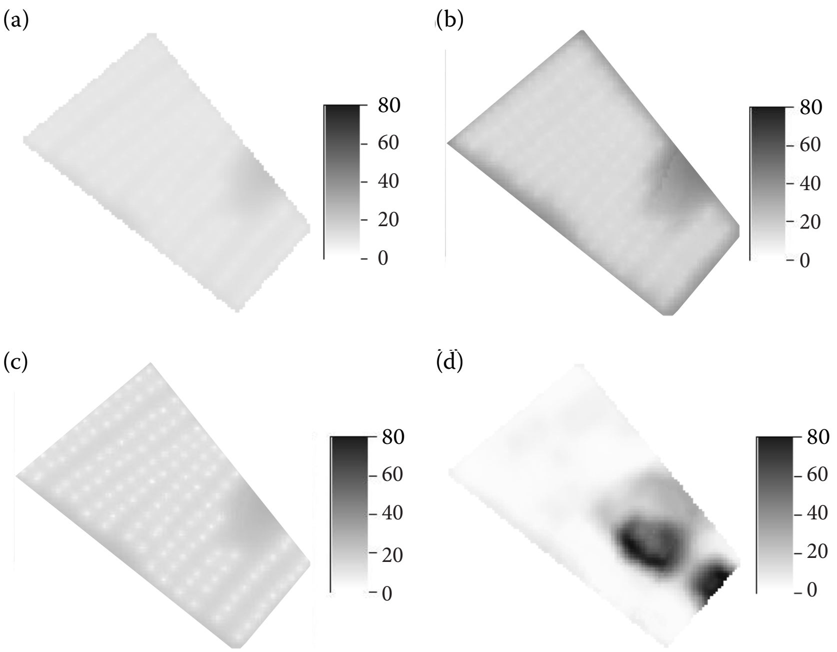


Figure 10. OK-variance (a) LOK--variance (b) COK-variance (c) and IK-conditional variance (d) of sand estimates (%)

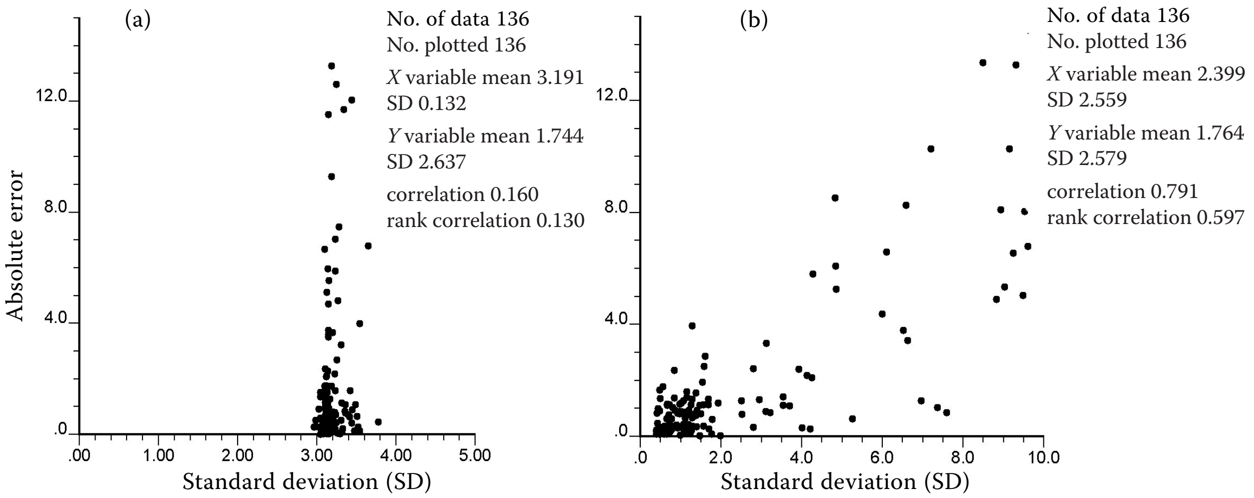


Figure 11. Scatterplot of the estimation errors versus the standard deviations of sand estimates obtained using ordinary kriging – OK (a) and indicator kriging – IK (b)

depicted in Figure 11. The results corresponding to LOK and COK are not presented due to their similarity to OK. Figure 11 shows that a poor correlation exists between the standard deviation and the magnitude of estimation errors resulting by using OK for the sand content, whereas IK-based conditional standard deviation shows a good correlation (r = 0.791) with the estimation error. This indicates that the standard deviation provided by OK in contrast to IK cannot be used as a reliable measure of the estimation precision. IK-conditional variance is also acknowledged e.g. by Goovaerts (1997) as more accurate in representing the uncertainty than OK-variance. OK (COK)-estimation variance and IK-conditional variance of the silt content are displayed in Figure 12. The relative distribution of low and high values of OK (COK)-estimation variance is similar to the sand kriging-estimation variance, due to the same configuration in both cases. COK, however, results in a smaller estimation uncertainty than OK. IK-conditional variance shows again some dependency on the

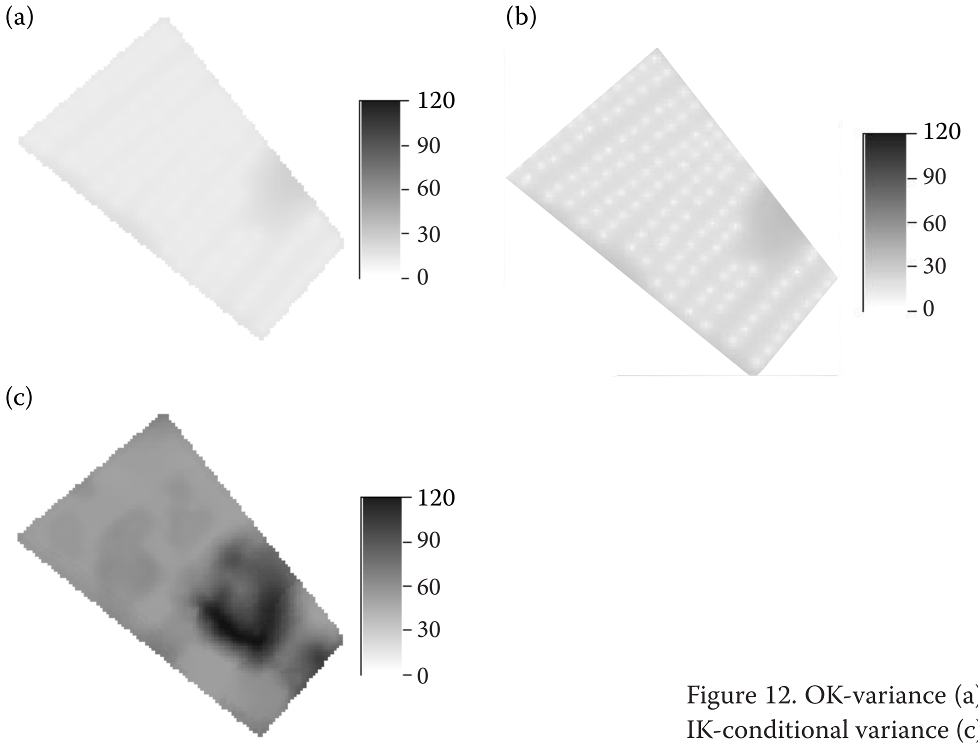


Figure 12. OK-variance (a), COK-variance (b), and IK-conditional variance (c) of silt estimates (%)

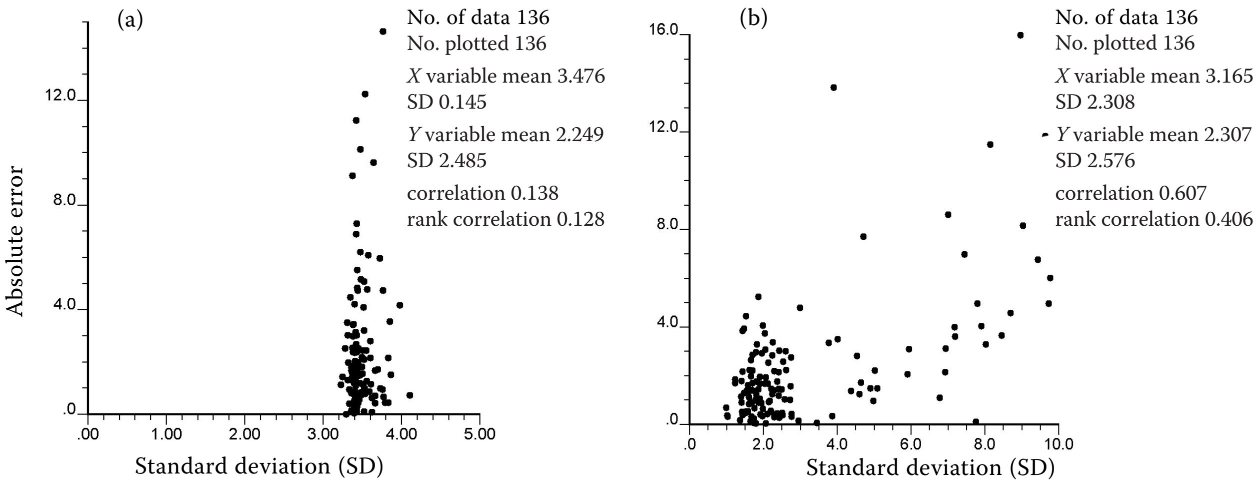


Figure 13. Scatterplot of the estimation errors versus the standard deviations of silt estimates obtained using ordinary kriging – OK (a) and indicator kriging – IK (b)

sample data. As seen also in Figure 13, a good correlation (r = 0.607) exists between the absolute error and standard deviation obtained through IK whereas the correlation for OK is quite poor. This indicates that IK-conditional standard deviation can be used as a better representative measure of the silt estimation precision. In Figure 14, the OK (COK)-estimation variance and conditional variance for the clay content estimates are presented. Again, the OK (COK)-variance maps indicate that there is a low uncertainty where the data locations are closer and a high uncertainty where they are more distant. In no similar way, IK-conditional variance map indicates that the areas of a high uncertainty (wider ccdfs) are located mostly in the north and west of the study area where the transition from the high to the low values occurs within short distances. There is a low correlation between the absolute error and standard deviation obtained through IK and no correlation for those obtained by OK for the clay content (Figure 15).

SUMMARY AND CONCLUSIONS

Geostatistical estimation methods including ordinary kriging (OK), lognormal ordinary kriging (LOK), cokriging (COK), and indicator kriging (IK)

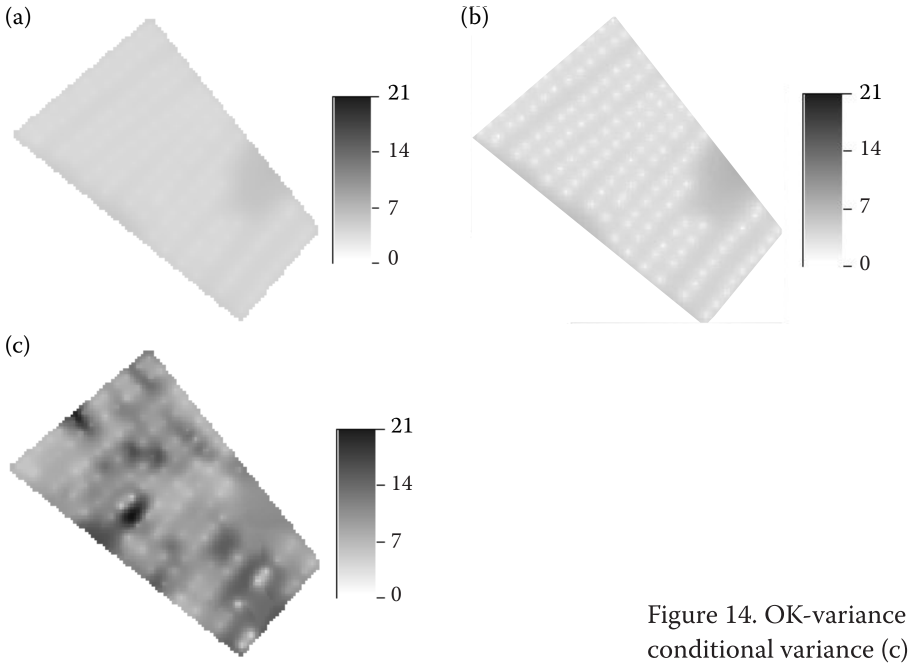


Figure 14. OK-variance (a), COK-variance (b), and IK-conditional variance (c) of clay estimates

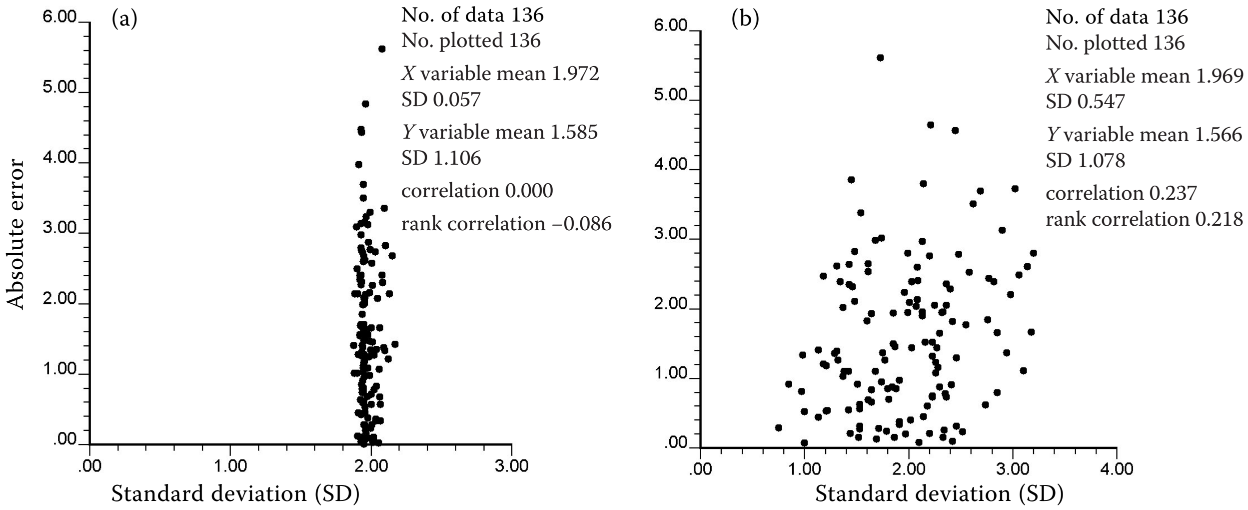


Figure 15. Scatterplot of the estimation errors versus the standard deviations of clay estimates obtained using ordinary kriging – OK (a) and indicator kriging – IK (b)

are compared for the prediction and uncertainty assessment of sand, silt, and clay proportions in a case study in Lower Austria. Statistical analysis shows that the sand content has the greatest coefficient of variation (*CV*) indicating a considerable variability of the sand content in the study field. Kolmogorov-Smirnov (KS) normality test indicates that clay is almost normally distributed whereas silt and sand are negatively and positively skewed, respectively. Thus, LOK is used for the spatial estimation of the sand content. Pearson correlation analysis reveals a strong negative correlation between the sand and silt contents and a moderate negative correlation between the clay and silt contents introducing the use of COK. The spatial correlation index C_0/Sill indicates that sand and silt having C_0/Sill < 25% are strongly spatially correlated and clay has a moderate spatial correlation (25% < C_0/Sill < 75%). The model best-fitted to the experimental auto-semivariograms of the soil texture fractions is spherical with the range of spatial correlation 145, 135, and 90 m, respectively, for the sand, silt, and clay contents. The cross-semivariogram between the clay and silt contents follows an exponential model with a correlation range of 90 m while for sand and silt contents, the cross-semivariogram has a spherical structure with a range of 139 m. Cross-validation results indicate that COK achieves the smallest error for estimating the silt and clay contents. For the sand content, while IK achieves slightly higher accuracy than COK, the latter reproduces better the extreme values in the estimation map, i.e. the smoothing effect is diminished. Overall, our results show that using the secondary variable when available will improve the estimation results considerably. The estimation uncertainty is assessed via the estimation variance maps produced by OK, LOK, and COK, and IK-conditional variance map. The estimation variance maps similarly indicate the occurrence of a lower uncertainty at the sampling sites and where the data locations are closer, and a higher uncertainty where the data are more distant. The IK-conditional variance shows, in contrast, some relation to the data values in addition to the data configuration. This indicates that the standard deviation provided by OK cannot be used as a reliable measure of the estimation precision. Therefore, in the soil science and environmental studies where the focus is on the estimation uncertainty rather than the estimation only, IK should be preferred. The estimation uncertainty needs to be evaluated for the incorporation into risk analysis in the soil management.

References

Bishop T.F.A., McBratney A.B. (2001): A comparison of prediction methods for the creation of field-extent soil property maps. Geoderma, **103**: 149–160.

Burgess T.M., Webster R. (1980): Optimal interpolation and isarithmic mapping of soil properties: I. The variogram and punctual kriging. Journal of Soil Science. **31**: 315–331.

Cambardella C.A., Moorman T.B., Novak J.M., Parkin T.B., Karlen D.L., Turco R.F., Konopka

A.E. (1994): Field-scale variability of soil properties in central Iowa soils. Soil Science Society of American Journal, **58:** 1501–1511.

Delbari M. (2007): Estimation and stochastic simulation of soil properties for case studies in Lower Austria and Sistan plain, southeast of Iran. [PhD. Thesis.] University of Natural Resources and Applied Life Sciences, Vienna.

Deutsch C.V., Journel A.G. (1998): GSLIB: Geostatistical Software Library and User's Guide. 2nd Ed. Oxford University Press, New York.

Ersahin S., Brohi A.R. (2006): Spatial variation of soil water content in topsoil and subsoil of a Typic Ustifluvent. Agricultural Water Management, **83**: 79–86.

Ersahin S. (2003): Comparing ordinary kriging and cokriging to estimate infiltration rate. Soil Science Society of American Journal, **67**: 1848–1855.

Gallichand J., Marcotte D. (1993): Mapping clay content for subsurface drainage in the Nile Delta. Geoderma, **58**: 165–179.

Gaston L.A., Locke M.A., Zablotowicz R.M., Reddy K.N. (2001): Spatial variability of soil properties and weed populations in the Mississippi delta. Soil Science Society of American Journal, **65**: 449–459.

Gonzalez O.J., Zak D.R. (1994): Geostatistical analysis of soil properties in a secondary tropical dry forest, St. Lucia, West Indies. Plant and Soil, **163**: 45–54.

Goovaerts P. (1997): Geostatistics for Natural Resources Evaluation. Oxford University Press, New York.

Goovaerts P. (1998): Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. Biology and Fertility of Soils, **27**: 315–334.

Goovaerts P. (1999): Geostatistics in soil science: state-of-the-art and perspectives. Geoderma, **89**: 1–45.

Goovaerts P., Webster R., Dubois J.-P. (1997): Assessing the risk of soil contamination in the Swiss Jura using indicator geostatistics. Environmental and Ecological Statistics, **4**: 31–48.

Gotway C.A. Hartford A.H. (1996): Geostatistical methods for incorporating auxiliary information in the prediction of spatial variables. Journal of Agricultural, Biological and Environmental Statistics, **1**: 17–39.

Gupta S.C., Larson W.E. (1979): Estimating soil water retention characteristics from particle size distribution, organic matter content, and bulk density. Water Resources Research, **15**: 1633–1635.

Isaaks E.H., Srivastava R.M. (1989): An Introduction to Applied Geostatistics. Oxford University Press, New York.

Journel A.G. (1983): Non-parametric estimation of spatial distributions. Mathematical Geology, **15**: 445–468.

Journel A.G., Huijbregts C.J. (1978): Mining Geostatistics. Academic Press, New York.

Juang K.W., Lee D.Y. (1998): A comparison of three kriging methods using auxiliary variables in heavy-metal contaminated soils. Journal of Environmental Quality, **27**: 355–363.

Kerry R., Oliver M. (2003): Variograms of ancillary data to aid sampling for soil surveys. Precision Agriculture, **4**: 261–278.

Lloyd C.D., Atkinson P.M. (1999): Designing optimal sampling configurations with ordinary and indicator kriging. In: 4th Int. Conf. GeoComputation 99. July 25–28, Fredericksburg.

López-Granados F., Jurado-Expósito M., Atenciano S., García-Ferrer A., Sánchez de la Orden M., García-Torres L. (2002): Spatial variability of agricultural soil parameters in southern Spain. Plant Soil, **246**: 97–105.

López-Granados F., Jurado-Expósito M., Pena-Barragan J.M., García-Torres L. (2005): Using geostatistical and remote sensing approaches for mapping soil properties. European Journal of Agronomy, **23**: 279–289.

Mohammadi J., Van Meirvenne M., Goovaerts P. (1997): Mapping cadmium concentration and the risk of exceeding a local sanitation threshold using indicator geostatistics. In: Soares A., Gómez-Hernández J., Froidevaux R. (eds): GeoENV I – Geostatistics for Environmental Applications. Kluwer, Dordrecht, 327–337.

Morgan R.P.C., Quinton J.N., Smith R.E., Govers G., Poesen J.W.A., Auerswald K., Chisci G., Torri D., Styczen M.E. (1998): The European Soil Erosion Model (EUROSEM): A dynamic approach for predicting sediment transport from fields and small catchments. Earth Surface Processes and Landforms, **23**: 527–544.

Nogueira F., Couto E.G., Bernardi C.J. (2002): Geostatistics as a tool to improve sampling and statistical analysis in wetlands: A case study on dynamics of organic matter distribution in the Pantanal of Mato Grosso, Brazil. Brazilian Journal of Biology, **62**: 861–870.

Odeh I.O.A., Todd A.J., Triantafilis J. (2003): Spatial prediction of soil particle-size fractions as compositional data. Soil Science, **168**: 501–515.

Patriarche D., Castro M.C., Goovaerts P. (2005): Estimating regional hydraulic conductivity fields—A comparative study of geostatistical methods. Mathematical Geology, **37**: 587–613.

Rawls W.J., Brakensiek D.L., Saxton K.E. (1982): Estimation of soil water properties. Transactions of ASAE, **25**: 1316–1320.

Robertson G.P. (2000): GS+: Geostatistics for the Environment Sciences. GS+ User's Guide Version 5. Gamma Design Software, Plainwell.

Saito H., Goovaerts P. (2000): Geostatistical interpolation of positively skewed and censored data in a dioxin-contaminated site. Environmental Science and Technology, **34**: 4228–4235.

Trangmar B.B., Yost R.S., Uehara G. (1985): Application of geostatistics to spatial studies of soil properties. Advances in Agronomy, **38**: 45–93.

Triantafilis J., Odeh I.O.A., McBratney A.B. (2001): Five geostatistical models to predict soil salinity from electromagnetic induction data across irrigated cotton. Soil Science Society of American Journal, **65**: 869–878.

Vaughan P.J., Lesch S.M., Corwin D.L., Cone D.G. (1995): Water content effect on soil salinity prediction: A geostatistical study using cokriging. Soil Science Society of American Journal, **59**: 1146–1156.

Voltz M., Lagacherie P., Louchart X. (1997): Predicting soil properties over a region using sample information from a mapped reference area. European Journal of Soil Science, **48**: 19–30.

Yates S.R., Warrick A.W. (1987): Estimating soil water content using cokriging. Soil Science Society of American Journal, **51**: 23–30.

Zhang R., Myers D.E., Warrick A.W. (1992): Estimation of spatial distribution of soil chemicals using pseudo-cross-variograms. Soil Science Society of American Journal, **56**: 1444–1452.

Zhang R., Shouse P., Yates S. (1997): Use of pseudo-crossvariograms and cokriging to improve estimates of soil solute concentrations. Soil Science Society of American Journal, **61**: 1342–1347.

Zötl J.G. (1997): The spa Deutsch-Altenburg and the hydrogeology of the Vienna basin (Austria). Environmental Geology, **29**: 176–187.

Received for publication February 26, 2010
Accepted after corrections March 10, 2011

Corresponding author:

Dr. Masoomeh Delbari, University of Zabol, Faculty of Agriculture, Department of Water Engineering, Zabol, Iran
e-mail: mas_delbari@yahoo.com