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Geostatistical Analyses of Soil Salinity in a Large Field

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Abstract. Estimating spatial variability of soil salinity is an important issue in precision agriculture. Geostatistical methods provide a means to study the heterogeneous nature of spatial distributions of soil salinity. In this study, geostatistical methods, kriging and cokriging, were applied to estimate sodium adsorption ratio (SAR) in a 3375 ha agricultural field. In cokriging, more easily measured data of electrical conductivity (EC) were incorporated to improve the estimation of SAR. The estimated spatial distributions of SAR using the geostatistical methods with various reduced data sets were compared with the extensive salinity measurements in the large field. The results suggest that sampling cost can be dramatically reduced and estimation can be significantly improved using cokriging. Compared with the kriging results using total SAR data, cokriging with reduced data sets of SAR improves the estimations greatly by reducing mean squared error and kriging variance up to 70% and increasing correlation of estimates and measurements about 60%. The sampling costs for SAR estimation can be reduced approximately by 80% using extensive EC data together with a small portion of SAR data in cokriging.

Keywords: soil salinity, spatial variability, geostatistical analyses

Introduction

Precision agriculture practices in arid and semiarid areas require periodic information on soil salinity. Excessive soil salinity may cause crop loss and, eventually, land degradation (Lesch *et al.*, 1992). Soil salinity problems appear worldwide during irrigation practices (Ballantyne, 1963; Bettenay *et al.*, 1964; Greenlee *et al.*, 1968; Halvorson and Rhoades, 1976). High saline areas often distribute randomly within non-saline and low saline irrigation fields, therefore, receive the same inputs of tillage, water, fertilizer, and seed as non-saline soils, even though no crop is produced. Soluble salts affect the productivity of soils in two principal ways: changing the osmotic potential of soil solution and increasing the content of exchangeable sodium, which produces in most soils an unfavorable physical conditions (Richards *et al.*, 1956). The attempts are made to remediate high saline areas by biological methods and by site-specific irrigation (Szabolcs, 1989; Ismail *et al.*, 1991; Malcolm, 1991; Mankin *et al.*, 1997). Excess salinity of soil solution can be corrected by leaching with water of good quality. The removal of excess exchangeable sodium requires an application of gypsum amendment. Therefore, development and maintenance of reclamation and irrigation projects on saline soils require accurate and updated information about spatial distributions of soil soluble salts, especially the exchangeable sodium.

Assessing soil salinity is complicated by the nature of its spatial and temporal variability (Rhoades and Ingvalson, 1971). Conducting soil salinity measurements at high sampling density is costly and time-consuming. Fortunately, it is possible to use quick in-situ methods of electrical conductivity (EC), which is related to soil salinity, to evaluate salinity. The relationship between EC and soil salinity is complicated by other factors influencing measured conductivity in the field, such as soil texture, water content, and bulk density (Rhoades *et al.*, 1976; Banton *et al.*, 1997). Thus, in situ measurements of electrical conductivity require calibration for a certain field (case) to be suitable to monitor and map soil salinity. Such calibration usually is conducted using common statistical methods of correlation and regression (Halvorson and Rhoades, 1976; Chang *et al.*, 1983; Rhoades *et al.*, 1989b).

Geostatistical methods, kriging and cokriging, are becoming commonly used estimation techniques to generate soil maps. Kriging has been applied to quantify variability of various spatial variables in soil science. For example, Tabor *et al.* (1984, 1985) used variograms and kriging to determine the spatial variability of nitrates in cotton petioles and analyzed spatial variability of soil nitrate and correlated variables. Istok and Cooper (1988), Cooper and Istok (1988 a,b) applied kriging to study groundwater contamination. Yates *et al.* (1993) used geostatistics in the description of salt-affected soils. Samra and Gill (1993) used kriged results to assess variations of pH and sodium adsorption ratio associated with tree growth on a sodium-contaminated soil. Using disjunctive kriging, Yates *et al.* (1986 a,b) presented spatial distributions and corresponding conditional probability maps of soil electrical conductivity.

Whereas kriging is used to evaluate the spatial distribution of a variable based on sampled data of the variable itself, cokriging is applied to improve estimation of undersampled variables using abundant data of other variables. Yates and Warrick (1987) applied cokriging to estimate soil water content with the auxiliary data of bare soil surface temperature and sand content. Using kriging and cokriging, Zhang *et al.* (1995) estimated trace elements in soils and plants. Zhang *et al.* (1992a, 1997) used cokriging with pseudo-cross-variograms to estimate spatial distributions of soil chemicals.

Geostatistical methods can be powerful tools for characterizing large-scale spatial distributions of soil properties for precision agriculture. In this study, kriging and cokriging were utilized to estimate spatial distributions of soil salinity and sampling strategies. We used cokriging and electrical conductivity data to improve the estimation of sodium adsorption ratio (SAR). The estimated results were compared with extended salinity measurements in a large agricultural landscape.

Materials and methods

To determine the spatial distribution of salinity, a 3375 ha area of irrigated farmland within South-Fork Kings River Watershed in central California was investigated in summer of 1987 (Rhoades *et al.*, 1988). The study area is located in northern Kings County, east of the Kings River, and in the LeMoore, Hanford, Guernsey, and Stratford quadrangles. The site was selected because irrigated agriculture predominates and a cross-section of agricultural crops and management practices is well represented within the area. Well-managed large corporate farming units, small family farms, and abandoned parcels of land occur randomly within the area. The area also contained a wide distribution of soil types with texture ranging from loam sand to clay (Rhoades *et al.*, 1989a). The water table in the area was located at a depth ranging from less than one to greater than three meters below the soil surface. The whole area was divided with a 200 × 200 m grid. Within each grid one soil sample was taken at random resulting in total 898 soil samples. To evaluate salinity, sodium adsorption ratio (SAR) was measured in samples following conventional methods (U.S. Salinity Laboratory Staff, 1954; Munk, 1992). In-situ electrical conductivity (EC) data were collected at the same locations using the four-electrode technique (Rhoades *et al.*, 1990). Statistical and geostatistical analyses of soil salinity were conducted using all 898 data points of EC and various reduced data sets randomly selected from the total 898 points of SAR. The data were analyzed using descriptive statistics (STATISTICA, Statsoft Inc., 1993) and geostatistical methods of kriging and cokriging (GSLIB, Stanford University, 1997).

The ordinary kriging estimator, $Z^*(x_0)$, of an unsampled site is a linear sum of weighted observations within a neighborhood:

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

where $Z^*(x_0)$ is the estimate of Z at x_0, λ_i is the weight assigned to the ith observation, and n is the number of observations within the neighborhood. The weighing factors of λ_i's are determined based on a variogram of Z. Cokriging is a method for estimating one or more variables of interest using data from several variables by incorporating not only spatial distribution, but also intervariable correlation. A cokriging estimate is a weighted average of available data with weights chosen so that the estimate is unbiased and has minimum variance, analogous to ordinary kriging (Myers, 1982, 1984).

Cross-validation is used to evaluate the accuracy of the variogram and cross-variogram models for kriging and cokriging. In this procedure, every known point is estimated using the values at the neighborhood around it, but not itself. The summary statistics from the cross validation includes mean error, mean squared error, mean kriging variance, reduced kriging variance, correlation between estimates and error, and correlation between estimated and actual values (Isaaks and Srivastava, 1989). Mean error, mean squared error, correlation between estimates and error, and mean kriging variance should be as small as possible. Reduced kriging variance and correlation between estimated and actual values should be as close to unit as possible. After trial and error process of the cross validation a variogram (cross-variogram) model with the best summary statistics is chosen.

The following methods are used to compare results estimated with kriging and cokriging. Relative improvement, or relative reduction of estimation accuracy, is defined by

$$R_E = 100\%(|MSE_R| - |MSE_E|)/|MSE_R| \quad [2]$$

where MSE_E and MSE_R are the mean squared errors for evaluated and reference methods, respectively. For example, comparison between the estimation accuracy of cokriging using a reduced data set of SAR and the EC data versus the accuracy of kriging using the total SAR data is obtained using the mean squared error of cokriging (MSE_E) and the mean squared error of kriging (MSE_R). If R_E is positive, estimation accuracy for the evaluated method is better than the reference method. If R_E is negative, the evaluated method is worse than the reference method. The relative improvement or reduction of accuracy based on the mean kriging variance is defined in the same way by replacing MSE_E and MSE_R in Eq. 2 with respective values of the mean kriging variance. The relative improvement or reduction of correlation between estimated and actual values is defined by

$$R_r = 100\%(|1 - r_R| - |1 - r_E|)/|1 - r_R| \quad [3]$$

where r_E and r_R are the correlation coefficients between estimated and actual values for evaluated and reference methods, respectively.

Results

Table 1 lists the descriptive statistics of the raw and log-transformed EC and SAR data, including mean, median, coefficient of variation (CV), skewness, and kurtosis. The descriptive statistics of the data suggest that both electrical conductivity and sodium adsorption ratio are lognormally distributed variables. Therefore, the log-transformed data of SAR and EC were used for geostatisical analyses. This transformation not only modified variable distribution to normal, but also improved the correlation coefficient (r) between EC and SAR from 0.61 to 0.82. To study advantages of cokriging and sampling strategies, 11 reduced data sets of SAR with 50, 75, 100, 200, 300, 400, 500, 600, 700, 800, and 850 data points were randomly selected from the original data set. Locations of the original data and some of the randomly selected data sets are shown in Fig. 1. All of these reduced data sets are normally distributed after log-transformation and have a correlation coefficient (r) with EC about 0.8.

Table 1. Summary statistics for experimental data.

Variable	N	Mean	Median	CV	Skewness	Kurtosis
EC (dS m^{-1})	898	6.675	3.560	1.37	3.318	15.564
log(EC)	898	0.527	0.551	0.98	0.142	−0.846
SAR	898	22.447	7.710	2.35	8.397	96.081
log(SAR)	898	0.916	0.887	0.66	0.188	−0.375

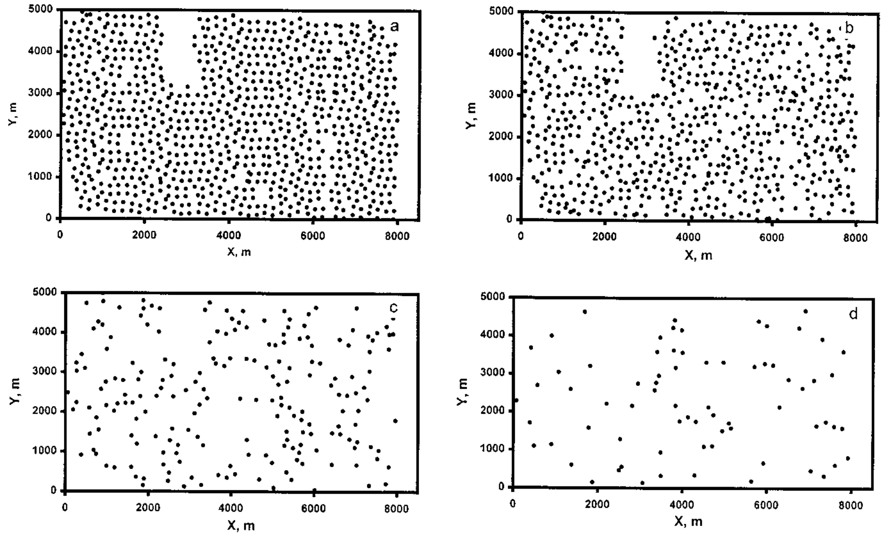

Figure 1. Spatial location of the (a) total 898 and randomly selected (b) 700, (c) 200, and (d) 100 data points of SAR.

Variograms and cross-variograms were calculated for the data sets. Preliminary calculations of variograms in different directions showed that all variograms were isotropic. Therefore, the omnidirectional variograms were used for analyses. Sample variograms of all the data sets show that the spatial structures of SAR and EC can be well characterized by the spherical model:

$$\gamma(h) = \begin{cases} C_0 + C_1\left[1.5(h/a) - 0.5(h/a)^3\right] & h \le a \\ C_0 + C_1 & h > a \end{cases} \qquad [4]$$

where h is the lag distance, C_0 is the nugget, $C_0 + C_1$ is the sill, and a is the range. The parameters of variogram models for each data set were chosen through cross validation. The parameters of the models for the different data sets of SAR were very similar (Table 2 and Fig. 2). Therefore, an average spherical model with range, nugget, and sill equal to 700, 0.14, and 0.33, respectively, was used for all the data sets of SAR. These parameters were obtained based on the cross validation for the 100-point data set of SAR (Table 2 and Fig. 2b) and used for each data set of SAR in kriging and cokriging. The summary statistics of cross validation using this variogram model with the different reduced data sets are listed in Table 3.

Cokriging was conducted for each reduced data set of SAR based on the three variograms: the variogram for the reduced data set of SAR, a variogram for total EC data, and a variogram of the sum of SAR and EC (EC + SAR) at the common locations (Zhang *et al.*, 1997). The variogram of the EC data was also spherical with nugget, sill, and range equal to 0.14, 0.26, and 700, respectively (Table 2). Using the same variogram model for the different reduced data sets of SAR and

Table 2. Parameters of variogram models.

Variable,	Variogram			Variogram of sum EC + SAR		
number of data points	Nugget	Sill	Range (m)	Nugget	Sill	Range (m)
SAR, 100	0.14	0.33	700	0.57	1.1	950
SAR, 200	0.16	0.35	700	0.58	1.1	850
SAR, 300	0.14	0.33	800	0.57	1.1	950
SAR, 400	0.15	0.33	700	0.57	1.1	1000
SAR, 500	0.14	0.32	700	0.57	1.1	950
SAR, 600	0.15	0.32	500	0.57	1.1	950
SAR, 700	0.14	0.34	600	0.57	1.1	950
SAR, 800	0.14	0.33	700	0.56	1.1	900
SAR, 850	0.14	0.33	700	0.57	1.1	950
SAR, 898	0.14	0.33	700	0.57	1.1	950
EC, 898	0.14	0.26	700			

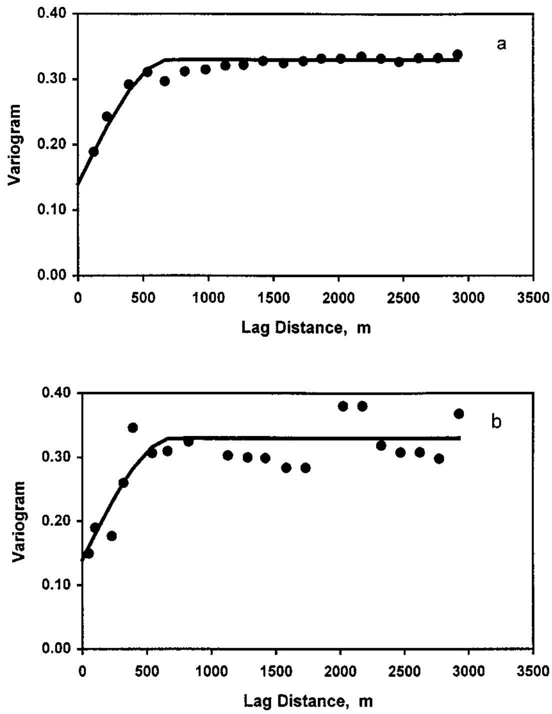

Figure 2. Sample variogram (circles) and model (solid line) of the (a) total 898 and (b) 100 randomly selected SAR data.

Table 3. Summary statistics of kriging for different data sets.

Variable, number of data points	Statistics*					
	ME	MSE	MKV	RKV	r_e	r_a
SAR, 50	0.039	0.349	0.331	1.055	0.115	0.208
SAR, 75	0.030	0.364	0.318	1.173	0.116	0.234
SAR, 100	0.010	0.303	0.328	0.903	0.139	0.318
SAR, 200	0.008	0.371	0.291	1.269	0.135	0.383
SAR, 300	−0.021	0.316	0.307	1.042	0.286	0.460
SAR, 400	0.000	0.286	0.271	1.059	0.180	0.442
SAR, 500	−0.010	0.259	0.261	0.990	0.149	0.490
SAR, 600	−0.005	0.287	0.253	1.138	0.151	0.48
SAR, 700	−0.001	0.275	0.247	1.114	0.117	0.532
SAR, 800	0.000	0.263	0.242	1.085	0.095	0.539
SAR, 850	0.000	0.259	0.237	1.095	0.072	0.550
SAR, 898	−0.001	0.257	0.235	1.096	0.060	0.549
EC, 898	0.000	0.189	0.206	0.918	0.022	0.538

*ME is mean error. MSE is mean squared error. MKV is mean kriging variance. RKV is reduced kriging variance, which is MKV divided by MSE. r_e is correlation coefficient between estimated value and error. r_a is correlation coefficient between estimated and actual values.

the model of EC, variograms of EC + SAR for each data set were selected through cross validation. The variogram models of EC + SAR for the reduced data sets were also spherical and have slightly variable parameters (Table 2). Therefore, a spherical variogram model of EC + SAR with nugget, sill, and range equal to 0.57, 1.1, and 950, respectively, was applied for conducting cokriging with each reduced data set of SAR and the whole data of EC. The cross-variogram was calculated using (Zhang *et al.*, 1992b):

$$\gamma_{12} = 0.5(\gamma_{12}^{+} - \gamma_{11} - \gamma_{22}) \qquad [5]$$

where γ_{12} is the cross-variogram of EC and SAR, γ_{11} is the variogram for SAR, γ_{22} is the variogram for EC, and γ_{12}^{+} is the variogram for EC + SAR. The cross-variogram of EC and SAR satisfies the Cauchy-Schwartz inequality (Myers, 1982; Zhang *et al.*, 1997). This condition guarantees that the cokriging coefficient matrix is positive definite and the variance of the estimated variables is positive. The summary statistics for cokriging results with the different reduced data sets of SAR are shown in Table 4.

The summary statistics for kriging (Table 3) and cokriging (Tables 4) show that cokriging provides much better estimation results for SAR than kriging. On average, for kriging of the reduced data sets the mean squared error is 0.276, the mean kriging variance is 0.255, the correlation coefficient of estimation and error is 0.124, and the correlation coefficient of estimated and actual values is 0.399 (Table 3). For cokriging, the same average statistics are 0.100, 0.099, 0.042, and 0.770, respectively (Table 4). The accuracy of kriging and cokriging increases with increasing number of the used data points. The mean kriging variance decreases from 0.331 to 0.237 when the number of data points used for kriging increases from

Table 4. Summary statistics of cokriging for different data sets of SAR and total 898 EC data

Variable, number of data points	Statistics*					
	ME	MSE	MKV	RKV	r_e	r_a
SAR, 50	0.057	0.143	0.176	0.860	0.230	0.794
SAR, 75	0.055	0.125	0.155	0.837	0.116	0.826
SAR, 100	0.003	0.117	0.143	0.827	0.008	0.804
SAR, 200	0.009	0.153	0.119	1.334	0.010	0.802
SAR, 300	−0.007	0.123	0.115	1.091	0.009	0.818
SAR, 400	−0.002	0.097	0.098	1.102	0.008	0.848
SAR, 500	−0.003	0.080	0.088	0.963	0.038	0.872
SAR, 600	−0.002	0.094	0.080	1.214	0.018	0.861
SAR, 700	−0.002	0.090	0.075	1.210	0.008	0.874
SAR, 800	−0.001	0.090	0.070	1.303	0.028	0.869
SAR, 850	0.000	0.090	0.068	1.345	0.034	0.871

*Abbreviations as in Table 3.

50 to 850 (Table 3). For cokriging, this statistic decreases more quickly from 0.176 to 0.068 for the same range of data points (Table 4). The correlation between estimated and actual values only increases slightly with number of data points for cokriging, and shows relatively stable increase for kriging (Tables 3 and 4).

We calculated the relative improvement or reduction in estimation accuracy based on some kriging and cokriging statistics for the different reduced data sets of SAR (Eqs. 2 and 3). Kriging with all 898 SAR data is used as a reference method both for kriging and cokriging (Fig. 3, the dashed line). Whereas kriging conducted with any reduced data sets of SAR shows a reduction in accuracy (negative values) for all statistics compared with kriging using all SAR data, cokriging reveals stable improvement in prediction accuracy (Fig. 3a, b, c). Cokriging with only 50 SAR values and all 898 EC data gave even better estimation than kriging with 898 SAR data. The relative improvement in the mean squared error and mean kriging variance increases with the number of data points and shows a 40 to 70% improvement for cokriging of data sets with 100 or more SAR measurements and all 898 EC data compared with kriging of all SAR data (Fig. 3a, b). The improvement in correlation between estimated and actual values for cokriging is better than 60% for any reduced data set of SAR. The correlation only improves slightly with increasing number of SAR data (Fig. 3c). The vertical distance between the best fitting lines in Fig. 3 is used to show the improvement in accuracy of cokriging versus kriging for the same data sets of SAR. The improvement in estimation accuracy based on the mean cokriging variance or the mean squared error does not vary much with the number of data points and ranges from 60 to 80% (Fig. 3a, b). The improvement in estimation accuracy based on the correlation between estimated and actual values is up to 140% (Fig. 3c). In summary, all the statistics are highly improved by cokriging using the reduced data sets of SAR and all 898 EC data compared with kriging using all SAR data. The improvement increases slightly as the number of SAR measurements increases. Comparing cokriging results with kriging using the same reduced data sets of SAR, the improvement in mean

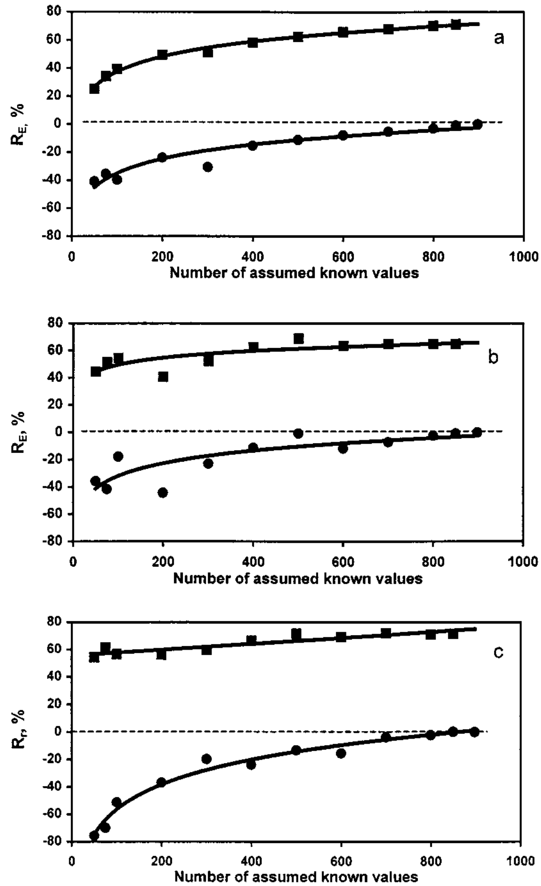

Figure 3. Relative improvement (+) or reduction (−) of estimation accuracy based on (a) mean kriging variance, (b) mean squared error, and (c) correlation of estimated and actual values for kriging (circles) and cokriging (squares) using randomly selected data sets of SAR, compared with kriging using the total SAR data.

squared error and mean kriging variance remains almost constant for any data set. Therefore, increasing the number of SAR measurements does not significantly influence the accuracy of estimation with cokriging.

Spatial patterns of SAR estimated by different mapping strategies are shown in Fig. 4. Although almost all the territory is saline with EC of saturated soil extract more than 2 dS m^{-2}, only small area is with high exchangeable sodium (Fig. 4a). The high SAR area is relatively well delineated by cokriging using 200 SAR data with the total EC data (Fig. 4b). The cokriging results adequately represent both the spatial patterns and range of SAR values. Kriging with 200 SAR data tends to overestimate the areas with SAR greater than 60 and spread the areas with SAR from 15 to 30 on the non-sodic area (Fig. 4c). Both kriging and cokriging methods using 100 SAR data failed to outline the high SAR area adequately (Fig. 4d). Thus,

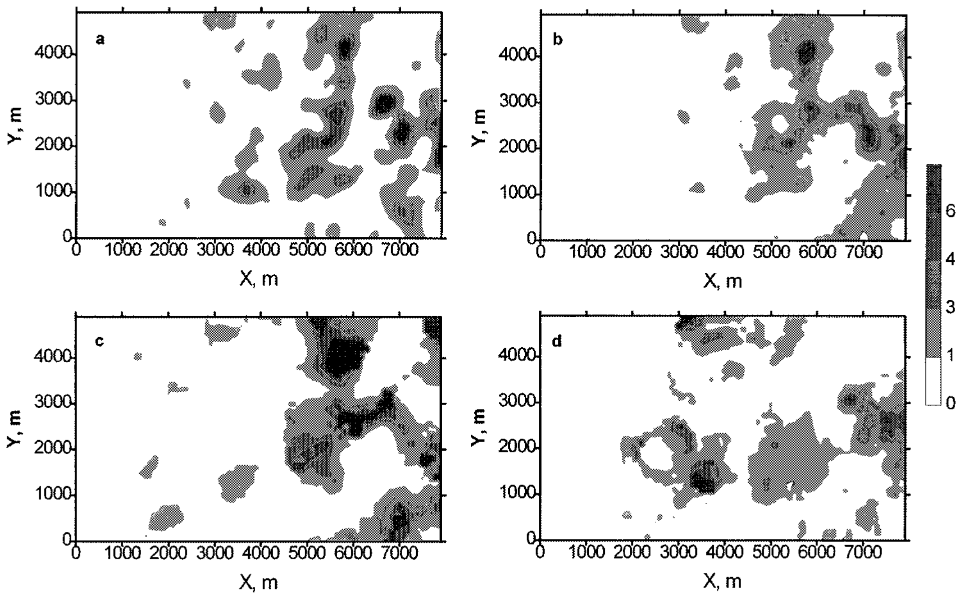

Figure 4. Contour maps of SAR estimated by (a) kriging with 898 SAR data, (b) cokriging with 200 SAR and 898 in-situ EC data, (c) kriging with 200 SAR data, and (d) cokriging with 100 SAR and 898 in-situ EC data.

cokriging using reduced data sets of SAR with 200 and more data points well characterizes the spatial distribution of SAR. Cokriging conducted using data sets of 100 and less SAR data, although still improves estimation accuracy, does not represent the spatial pattern of SAR adequately.

Cokriging with reduced data of SAR and extensive in-situ EC data has been shown to improve estimation of SAR significantly compared with kriging using only extensive SAR data. To conclude that cokriging is a better estimator than kriging, the sampling cost for the methods needs to be considered together with the estimation accuracy. In terms of sampling cost, electrical conductivity is very easy to obtain. Hundreds of the data points can be measured directly in the field during one day without actual sampling and analyzing soil samples in the laboratory. On the other hand, soil adsorption ratio analysis requires soil sampling and laboratory measurement of Ca, Mg and Na in each sample, therefore, is very costly and time consuming. Relative cost of in-situ EC measurements versus SAR analysis is approximately 1:60. The relative improvement in estimation accuracy for cokriging using reduced data sets for SAR and all EC data was compared with the relative sampling cost for the same data sets in Fig. 5. The sampling cost linearly increases with the number of data points. However, the improvement in estimation accuracy is almost constant (60%) for 200 and more data points of SAR. The sampling cost for 200 SAR and 898 EC data is about one forth of the sampling cost for 898 SAR data. Reducing SAR measurements to less than 200 points is not recommended, since it would be difficult to obtain adequate spatial pattern of SAR distribution.

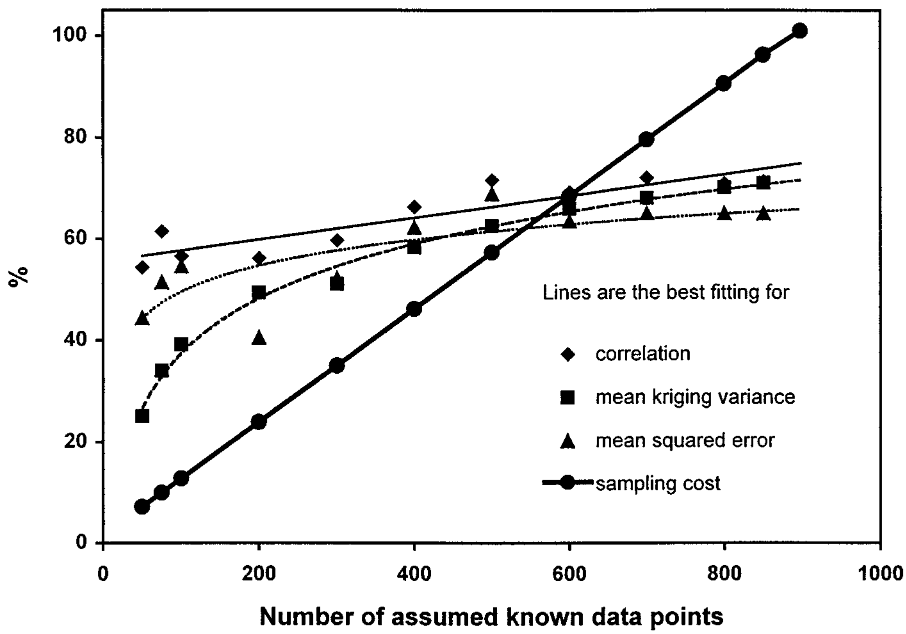

Figure 5. Relative sampling cost and relative improvement of prediction accuracy based on mean kriging variance, mean squared error, and correlation between estimated and actual values for cokriging using various reduced SAR data sets and 898 EC data compared with kriging using the 898 SAR data.

Therefore, the optimal sampling strategy for this example is to measure randomly about 200 locations for SAR and about 4 to 5 times as many locations for EC.

Conclusions

In this study, kriging and cokriging were used to estimate the soil salinity, including electrical conductivity (EC) and sodium adsorption ratio (SAR), over a 3375 ha area of irrigated farmland. Geostatistical analyses were conducted for the reduced data sets containing 6 to 90% of the original SAR data. The analyses show a great potential for reducing sampling costs and increasing prediction accuracy using cokriging. Using only 22% of the SAR data, cokriging improves the prediction of SAR significantly by incorporating the information of EC. Compared with the kriging results using all 898 SAR data, cokriging using 200 SAR and 898 EC data improved the mean squared error and mean kriging variance by 40 to 50%, and the correlation between estimated and actual values by 60%. In addition, the sampling cost was reduced up to 5 times. Cokriging is shown to be an accurate, yet economic, method for evaluation of spatial distributions of soil salinity in large fields.

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