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GEOSTATISTICAL ANALYSIS OF SOME SOIL PHYSICAL PROPERTIES USING COLLOCATED COKRIGING FOR ABO-MONQAR VILLAGE, FARAFRA OASIS, EGYPT.

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ABSTRACT

Measuring available water (AW) and saturated hydraulic conductivity (Ks) within a landscape are important because there are key attributes controlling water budget which is important for the agricultural production and transport processes in the soil. Estimation of these attributes at an acceptable level of accuracy is important, especially in the case when they exhibit high variability, since their measurements are a time- and labor-consuming procedure. This study was conducted to evaluate and compare kriging and cokriging to estimate AW and Ks using clay content data on 2147-ha of sand to sandy clay loam soils. Kriging techniques rely on the spatial dependence between observations to predict attribute values at un-sampled locations. Cokriging on the other hand, utilizes the spatial correlation between two variables to map the primary one, which is under-sampled, using information content of the secondary variable. Collocated cokriging is used when the primary and the secondary variables are sampled at the same location. The present study aimed for applying collocated cokriging to map topsoil AW and Ks (primary variable) measured in 26 samples, using the information content of topsoil clay (secondary variable) measured in 46 samples. Topsoil AW ranged between 33.52 and 127.34 mm m^{-1} with a mean of 71.54 mm m^{-1} and Ks ranged from 0.11 to 5.17 md^{-1} with a mean of 2.52 md^{-1}, whereas topsoil clay varied from 0.80 to 20.20 % with a mean of 7.25 %. The correlation coefficients, (r), between

clay and AW and Ks were 0.94 and -0.93 respectively, and, therefore, helped estimation of AW and Ks values at unobserved locations and satisfies the most important criteria for carrying out cokriging. The fitted semivariogram for clay and AW were Spherical, were it was Gaussian for Ks. The cross-semivariogram between clay, AW and Ks were Exponential. The cokriged spatial distribution of topsoil AW and Ks were mapped and compared to kriged AW and Ks. The cokriging results were cross-validated and the standard error of estimation was lower in cokriging than in kriging. The study showed the superiority of cokriging upon kriging as a spatial mapping method, especially if the primary variable is under-sampled.

Keywords: Geostatistical analysis, Collocated cokriging, Kriging, Clay content, available water saturated hydraulic conductivity, Cross-semivariogram and Semivariogram.

INTRODUCTION

Knowledge about the maximum water conducting capacity of soils is crucial in understanding and modeling several surface and subsurface processes. The partitioning between infiltration and runoff, temporary water logging in the root zone, rate of solute transport, and several other agricultural and environmental processes are dependent on the soil's saturated hydraulic conductivity (Ks). Also water budgets for the agricultural production, transport processes and crop water requirements are reliant on available water content (AW). However, obtaining sufficient and reliable Ks and AW data for large-scale process modeling remains a challenge. Inherent soil heterogeneity and extrinsic factors cause orders of magnitude variability in spatial distribution of Ks and AW (Wilson *et al*., 1989; Bosch and West, 1998; Ersahin, 2003; Sobieraj *et al*., 2004; Iqbal *et al*., 2005 and Gupta *et al*. 2006).

Geostatistical analysis has been widely applied in soil science for assessing spatial patterns of variation of a number of soil properties at a range of scales and with different sizes of sampling grids. Spatial interpolation is a procedure for estimating the value of a variable at unsampled locations. The interpolation techniques commonly used in earth sciences include linear regression, ordinary kriging and co-kriging (Kollias *et al*., 1999). The cokriging technique provides more accurate estimation than the ordinary kriging method, if the cross–semivariogram function estimation accuracy is expected when a higher sampling density is used. The cross-correlation between variables is utilized to improve these estimates, and to reduce the variance of the estimation error (Isaaks and Srivastava, 1989). Yates and Warrick (1987) estimated soil water content using a cokriging procedure in which the bare soil surface temperature and the sand content were used to supply additional information. Stein *et al*. (1988) used cokriging to increase computation precision in moisture deficit maps. Ersahin (2003) showed that cokriging provided no advantage over kriging when data were sufficient. With kriging, 45 observed Infiltration Rate (IR) values were sufficient to obtain the same information as 50 observations. However, using cokriging with 120 bulk density values, 40 observed values of IR were sufficient to obtain the same information from that obtained with 50 field measurement of IR. This indicates that cokriging was more successful than kriging when IR is under-sampled.

The objectives of this study were (i) to describe spatial variability of AW, Ks and clay, (ii) to assess the spatial relationship between both AW and Ks and clay, and (iii) to evaluate and compare the geostatistical procedures (kriging and cokriging) in estimating Aw and Ks at unobserved sites using limited available data of AW or Ks.

MATERIALS AND METHODS

The Study Site

The study site is located at 95 km northern- west of Farafra City - Farafra oasis. It comprises part of the newly reclaimed sandy soils in a new valley. The total acreage of the studied area is about 2147 hectares (map 1).

Sampling Scheme

Forty-six soil observations were collected over the study area. The observations were analyzed for clay percentage (Gee and Bauder, 1986). These soil observations were used as a secondary data for interpolating of Available Water (AW) in mm m^{-1} and saturated

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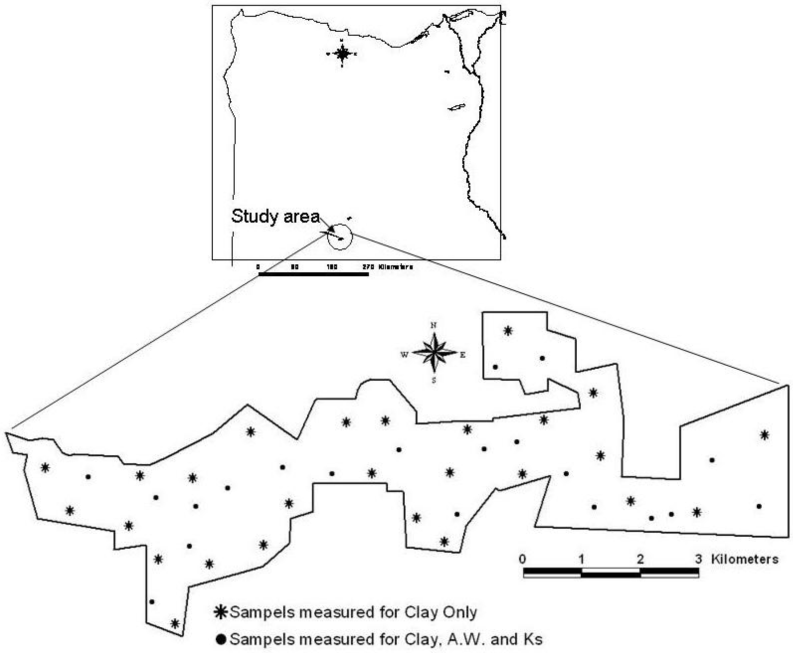
hydraulic conductivity (Ks) in md^{-1}. Twenty-six soil observations were taken randomly as a subset of the original data and analyzed for AW (Klute, 1986) and Ks (Klute and Dirksen 1986), which are considered as the primary variables. The samples locations were georeferenced to the UTM coordinate system. The spatial configuration of the soil observations used for AW and Ks are shown in map (1).

Descriptive Statistical Analysis

The data for clay, AW and Ks were analyzed for basic statistics including mean, variance, standard deviation, minimum, maximum, skewness, and kurtosis. The histogram for both variables was obtained, and the correlations between the variables were calculated.



Map (1): Location of the study area and observation sites.

Semivariogram and Cross-semivariogram Analysis

The semivariogram is defined as half of the average squared difference between two attribute values separated by vector **h**, for one variable (Burrough and McDonnell, 1998):

$$\gamma(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{Z(x_i) - Z(x_i + h)\}^2$$

where $N(h)$ is the number of pairs at lag **h**, $Z(x_i)$ is the value of the attribute at location (x_i) and $Z(x_i + h)$ is the value of the attribute at location (x_i + h) separated by distance **h**. The separation vector **h** is specified with some direction and distance (lag) tolerance. This semivariogram is used to model PWP and Ks with clay and then fitting them to one of the known semivariogram functions (Gaussian, Exponential, and Spherical). In case of using two variables (cokriging) the cross-semivariogram is calculated as follows:

$$\gamma_{UV}(\mathrm{h}) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \{Z_U(x_i) - Z_U(x_i + h)\}\{Z_V(x_i) - Z_V(x_i + h)\}$$

where Zu (AW and Ks) and Zv (clay) are the two variables. This equation is used to model AW or Ks using the information of clay content, and then fitting the obtained model to one of the known cross-semivariograms represented by Gaussian, Spherical, or Exponential functions as follows:

The exponential model:

$$\gamma(h) = C_0 + C_1\left(1 - \exp\left(\frac{-h}{A_0}\right)\right)$$

The Gaussian model:

$$\gamma(h) = C_0 + C_1\left(1 - \exp\left(\frac{3h^2}{A_0^2}\right)\right)$$

The spherical model:

$$\gamma(h) = C_0 + C_1\left\{1.5\left(\frac{h}{A_0}\right) - 0.5\left(\frac{h}{A_0}\right)^3\right\} \qquad for \quad h < A_0$$

Where C_0 is the nugget, C_1 is the sill, h is the separation distance (lag) in meters, and A_0 is the range.

Cokriging

A cokriged estimate is a weighted average in which the value of U at location x_o is estimated as a linear weighted sum of co-variables V_k. If there are k variables k = 1, 2, 3,. . .V, and each variable is measured at n_v places, x_{ik} = 1, 2, 3.... N_k, then the value of one variable U at x_o is predicted by (Burrough and McDonnell, 1998):

$$z'_U(x_o) = \sum_{k=1}^{V}\sum_{i=1}^{n_v} \lambda_{ik} Z(x_{ik}) \qquad \text{for all } V_k$$

where λ_{ik} is the weight assigned to variable k and $Z(x_{ik})$ is the value of the variable at location i.

To avoid bias, i.e. to ensure that:

$$E[z_u(x_o) - z'_u(x_o)]=0 \text{ and}$$
$$\text{the sum of weights } \lambda_{ik} = 1 \text{ for } U = V \text{ and}$$
$$\text{the sum of weights } \lambda_{ik} = 0 \text{ for } V_k \neq U$$

The first condition (sum of weights λ_{ik} = 1) implies that there must be at least one observation of U for cokriging to be possible. The interpolation weights are chosen to minimize the variance:

$$\sigma^2_u(x_o) = E[\{z_u(x_o) - z'_u(x_o)\}^2]$$

There is one equation for each combination of sampling site and attribute, so for estimating the value of variable j at site x_o, the equation for the g^{th} observation site of the k^{th} variable is:

$$\sum_{j=1}^{V}\sum_{i=1}^{n_v} \lambda_{ij}\gamma_{ij}(x_{ij}, x_{gk}) + \Phi_k = \gamma_{uv}(x_o, x_{gk})$$

for all g=1 to n_v and all k=1 to V, where Φ_k is the Lagrange's multiplier. These equations together make-up the cokriging system.

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Cross Validation

Cross validation is a technique used to compare estimated and true values using the information available in the data set. In cross validation, the estimation method is tested at the locations of existing samples. The sample value at a particular location is temporarily discarded from the sample data set; the value at the same location is then estimated using the remaining samples. Once the estimate is calculated, it is compared to the true sample value that was initially removed from the sample data set. This procedure is repeated for all samples. This could be expressed as (Isaaks and Srivastava, 1989):

$$Error = r = v' - v$$

Where *v'* is the estimated value and *v* is the true value. Mean square error (MSE) is calculated from the formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} r^2$$

Coupling Geostatistics to GIS

The estimates from cokriging and kriging (GS+, Version 7.0, Gamma Design Software, Plainwell, MI 2006) were formatted, then exported to Arc View GIS software (ESRI, 1997) for better visualization and output.

RESULTS AND DISCUSSION

Description of Spatial Patterns:

The analysis of spatial data starts with posting the data values. Map (1) shows the spatial distribution of soil surface clay, available water, and saturated hydraulic conductivity, sampled at 26 and 46 locations, respectively. The observations were chosen to cover the variations in the area under investigation.

Descriptive Statistical Analysis

The statistical analysis of the clay, AW and Ks are illustrated in Table (1). It is clear that clay and Ks have more variability than available water as the CV% is almost more than doubled. This is attributed to the greater number of soil samples with low clay content, which lowered the mean compared to the standard deviation. Variance indicates that AW has spread on a wide range contrary to clay, which is distributed around a high number of samples with low values.

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Table 1: Descriptive statistical parameters for clay (%), AW (mm/m) and Ks (m/d).

Statistical Parameter	Clay	A.W.	Ks
Mean	7.25	71.54	2.53
Standard Deviation	7.08	28.11	1.88
CV,%	97.63	39.29	74.16
Variance	50.10	790.22	3.52
Minimum	0.80	33.52	0.11
Maximum	20.20	127.34	5.17
Skewness	0.72	0.49	-0.12
Kurtosis	-1.27	-1.22	-1.62
No. of sample	46	26	26

Regression analysis of clay, AW and Ks indicated highly correlated variables, which satisfies the need to carry out cokriging analysis of AW and Ks using the information content of clay. The correlation coefficient for this analysis are 0.94 and -0.93 for clay and both AW and Ks, respectively. Yates and Warrick (1987) showed that if the correlation coefficient between a primary variable and the covariable exceeds 0.5, then the inclusion of the covariable is favorable, and cokriging performs better than kriging. The following equation represents the regression analysis of AW and Ks with clay:

$$AW_{(mm/m)} = 44.50 + 3.73\,(clay,\ \%) \qquad r^2 = 0.94$$

$$Ks\ (m/d) = 7.26\,(clay,\ \%)^{-1.153} \qquad r^2 = -0.93$$

Semivariograms for Clay, AW and Ks

The parameters of the fitted semivariograms for clay, AW and Ks are shown in Table (2), and the semivariograms are shown in Figure (1). The formulated equations for these three variables are as follows:

$$\gamma Clay\,(h) = 25.90 + 112.80\left\{1.5\left(\frac{h}{24390.0}\right) - 0.5\left(\frac{h}{24390.0}\right)^3\right\}$$

$$\gamma AW(h) = 403.0 + 1910.0\left\{1.5\left(\frac{h}{25820.0}\right) - 0.5\left(\frac{h}{25820.0}\right)^3\right\}$$

$$\gamma Ks(h) = 1.89 + 8.79\left\{1 - \exp\left(\frac{-3h^2}{(9500.0)^2}\right)\right\}$$

Table 2: Semivariogram types and parameters for properties.

Variable	Best fit model	Nugget (C_0)	Sill (C_1)	Range (A_0)	R^2
Clay, %	Spherical	25.90	112.80	24390.0	0.88
AW, mm/m	Spherical	403.00	1910.00	25820.0	0.90
Ks, m/d	Gaussian	1.89	8.79	9500.0	0.94

It is clear that the coefficient of determination (R^2) for all models exceeds 0.80, which indicates the goodness of the estimation. Moreover, the fitted Gaussian semivariogram indicates a smoothly varying pattern for both variables (Burrough and McDonnell, 1998).

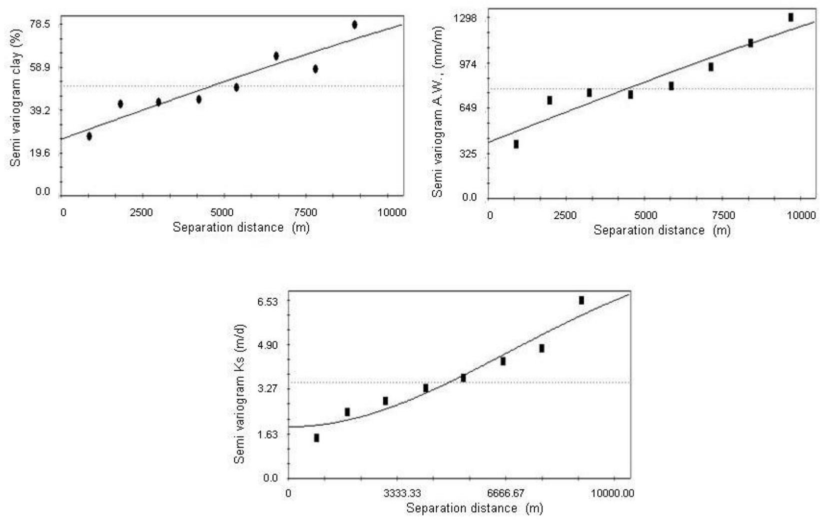


Figure (1): The semivariograms for clay (upper left), A.W. (upper right) and Ks (below).

The Cross-semivariogram (Collocated semivariogram)

The cross-semivariogram of clay with AW and Ks are of the collocated type, which means that the estimation was performed using variables measured at the same location. Table (3) and Figure (2) indicate the parameters of the fitted positive Exponential cross-semivariogram between clay with AW and negative exponential cross-semivariogram between clay and Ks.

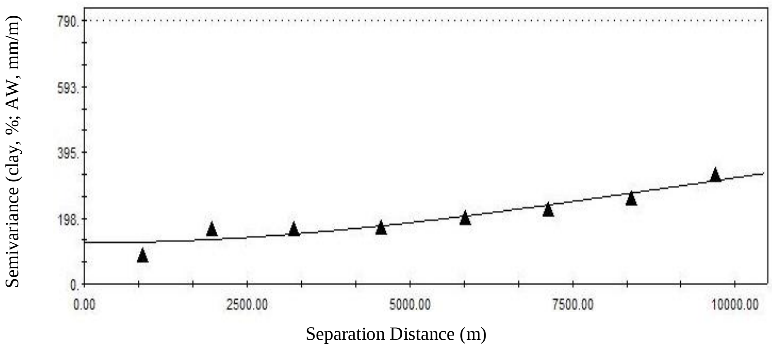
$$\gamma_{AW\text{ - }Clay}(h) = 82.5 + 342.5\left(1 - \exp\left(\frac{-8590.0}{A_0}\right)\right)$$

$$\gamma_{Ks-Clay}(h) = -4.69 - 29.5\left(1 - \exp\left(\frac{-12240.0}{A_0}\right)\right)$$

Table 3: Cross-semivariogram parameters of clay with AW and Ks.

Variable	Best fit model	Nugget (C_0)	Sill (C_1)	Range (A_0)	R^2
AW and clay	Exponential	82.5	342.5	8590.0	0.88
Ks and clay	Exponential	-4.69	-29.5	12240.0	0.93

The most important parameter in this estimation is the high R^2 (0.88) and (0.93) for clay with AW and Ks obtained from the fitting process, respectively. This high estimation regression coefficient comes very close to that of the simple linear regression (0.88) and (0.94) between AW and Ks with clay. The advantage of cokriging over linear regression is that it takes into consideration the spatial variability of the surrounding points, rather than performing blindly the linear regression, which lacks this improvement.



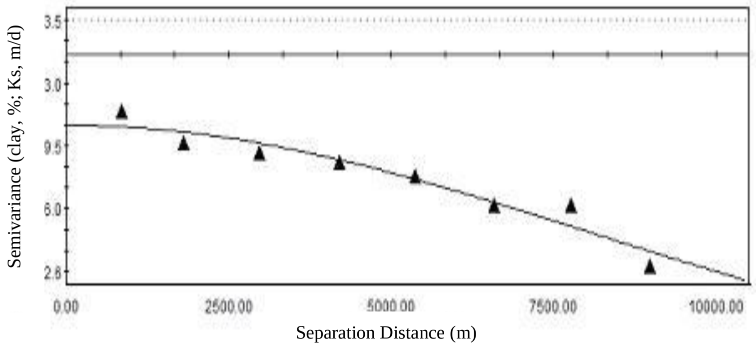


Figure (2): The cross-semivariogram between clay and A.W. (above), clay and Ks (below)

Cokriging Compared to Kriging

The output from cokriging process is a map of the spatial distribution of AW and Ks based on the information content and the high correlation with clay (Map 2 and 3). It is clear that the cokriged AW and Ks are smoothed out, because estimated values are less variable than actual values. This is expressed by an overestimation of small values while large values are underestimated; however the smoothing depends on the local data configuration (Goovaerts, 1999). Topsoil AW and Ks were kriged in order to compare with the cokriging results.

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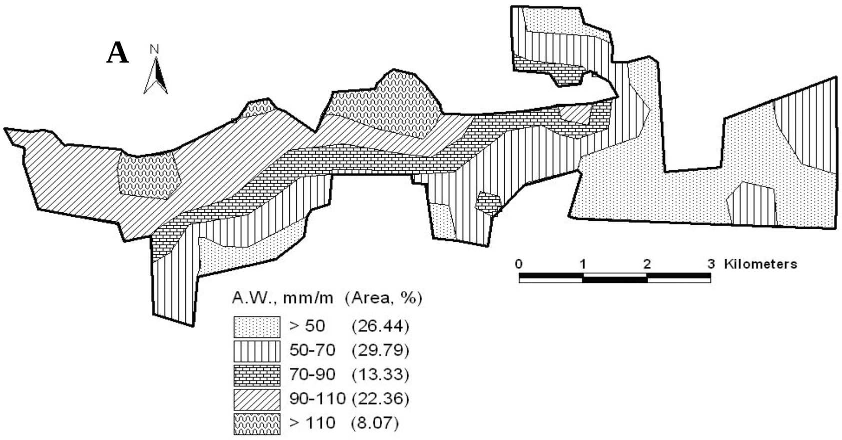

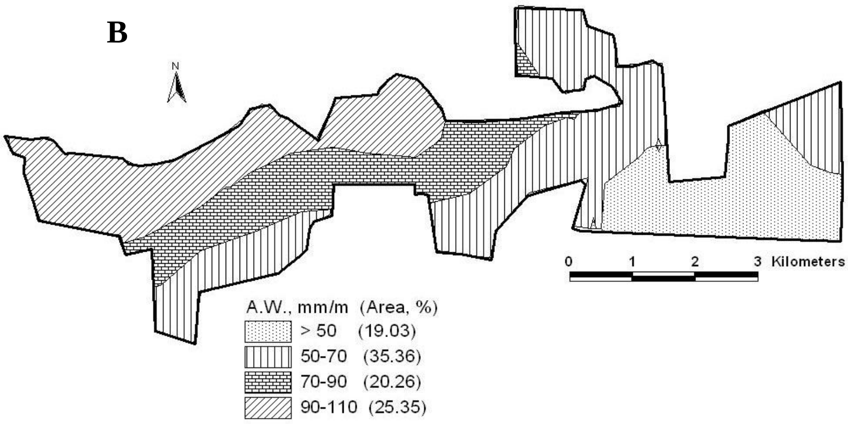

Map (2): Cokriged (A) and kriged (B) of available water.

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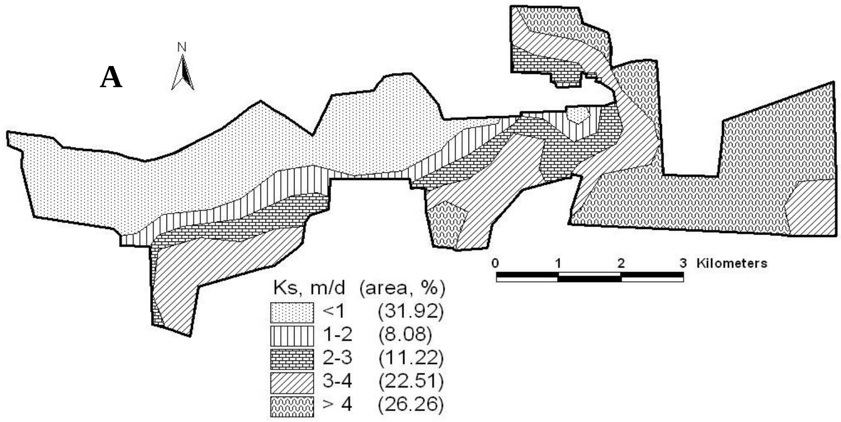

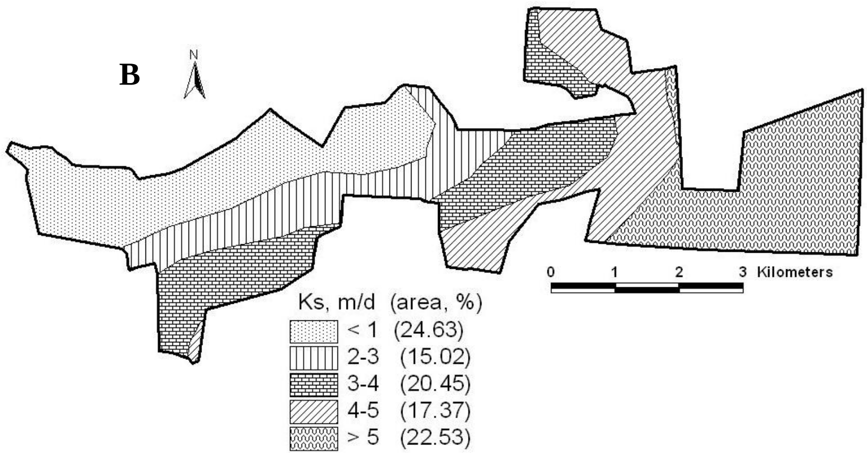

Map (3): Cokriged (A) and kriged (B) of saturated hydraulic conductivity.

The kriged maps (2B and 3B) are more segregated than the cokriged ones (maps 2A and 3A) due to the limited numbers of available data points for interpolation (26 points), compared to the number of available points for cokriging (46 points). Moreover, the standard error of estimation is much higher in kriging (0.166 for AW and 0.130 for Ks) in contrast to cokriging (0.114 for AW and 0.108 for Ks), as kriging behaves irregularly near to the boundaries, where

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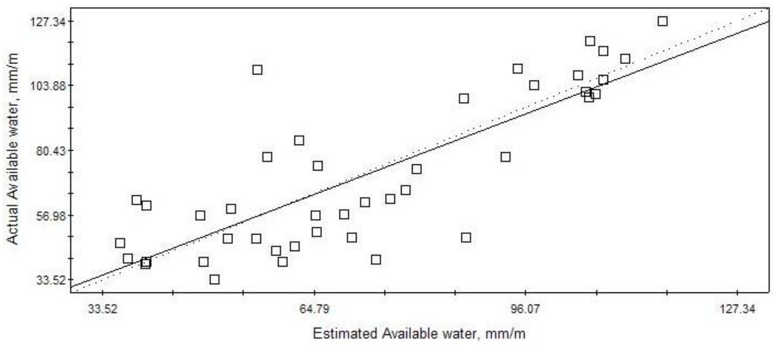
data points are absent. For these reasons, cokriging is much preferred over kriging, especially if the primary variable is under-sampled, as in the case of topsoil AW and Ks (26 samples spread over an area of 2147.59 ha). This data agreed with Elmenshawy and yehia (2006) and contrary to what Bahnassy (2002) was concluded, where he utilized about 21% of the total data points (28 points) to cokrige SAR using the information content of EC.

Cross Validation of Cokriging and Kriging

The process of cross validation between the estimated and the true value permits the evaluation of cokriging performance. Figure (3) shows the linear regression between the cokriged and actual values of AW. The regression equation resulted from the cokriging cross validation for AW is as follows:

Cokriged AW (predicted) = 3.77 + 0.936 AW (measured)
r = 0.807 *SE prediction = 0.108*



Figur (3): Cross validation between cokriged and actual values of AW. (The solid line is the regression line, the dot-dash line is for r = 1)

For Ks Figure (4) shows the linear regression between the cokriged and actual values of Ks. The regression equation resulted from the cokriging cross validation for Ks is as follows:

Cokriged Ks (predicted) = 0.25 + 0.877 Ks (measured)
r = 0.82 *SE prediction = 0.099*

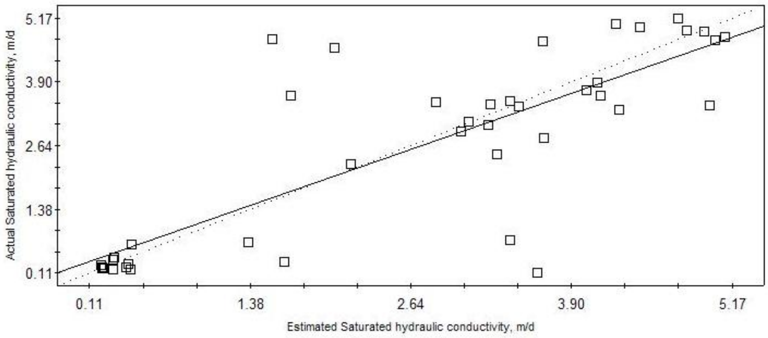


Figure (4): Cross validation between cokriged and actual values of Ks.
(The solid line is the regression line, the dot-dash line is for r = 1)

For comparison sake, both kriged AW and Ks were cross validated to see how the standard error (SE) of prediction behaves (Figures 5 and 6) and check the results with cokriging estimates.

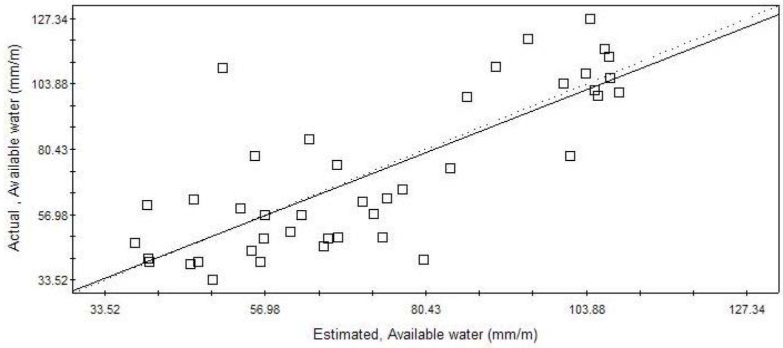


Figure (5): Cross validation between kriged and actual values of AW.
(The solid line is the regression line, the doted line is for r = 1)

Figure (5) shows the linear regression between the kriged and actual values of AW. The regression equation resulted from the kriging cross validation is as follows:

Kriged AW (predicted) = -14.055 + 1.192 AW (measured)
r = 0.78 *SE prediction = 0.121*

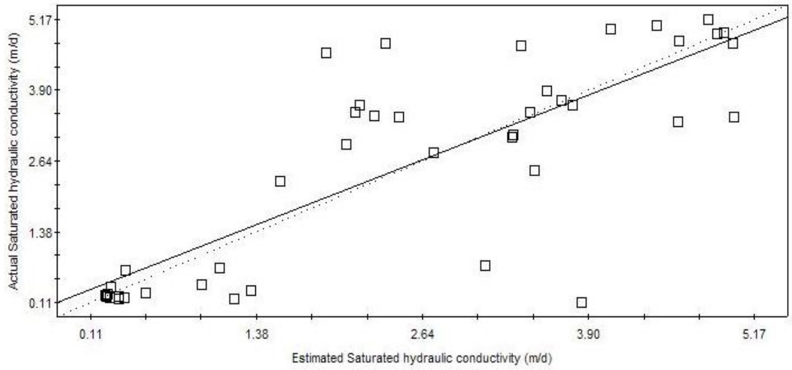


Figure (6): Cross validation between kriged and actual values of Ks.
(The solid line is the regression line, the doted line is for r = 1)

For Ks Figure (6) shows the linear regression between the kriged and actual values of Ks. The regression equation resulted from the kriging cross validation is as follows:

Kriged Ks (predicted) = 0.25 + 0.914 Ks (measured)

r = 0.80 SE prediction = 0.106

The standard error of kriging prediction of AW and Ks are relatively higher (0.121 and 0.106) than that of cokriging (0.108 and 0.099) respectively. While, the kriging correlation coefficients for Aw and Ks are relatively less (0.75 and 0.80), as compared to the cokriging (0.81 and 0.82), respectively. For these reasons, cokriging is preferred over kriging, especially in the case of under-sampling the variable of interest. Moreover, there must be an intensely sampled covariable, which is correlated with the variable of interest.

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CONCLUSIONS

Spatial variability in measured AW and Ks has significant spatial correlation to study predictions of AW and Ks from clay using kriging and cokriging procedures. The data of AW and Ks in topsoil were significantly correlated to clay. The results also showed that using cokiging with 46 clay values, 26 observed values of AW and Ks were sufficient to obtain the same information from that obtained with 46 measurements of AW and Ks. The results of cross validation standard error of cokriging and kriging indicate that cokriging was more successful than kriging when AW or Ks are under-sampled. Ks and AW are widely used in modeling of water and chemical transport in soils and irrigation practices. The spatial variability of this process on a landscape is important, affecting the accuracy of the modeling work and efficiency of the irrigation practices. However, measuring AW and Ks are time- and labor consuming. Therefore, estimation of this process with a reasonable accuracy given a minimal observed values using kriging and cokriging is very important.

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الملخص العربى

تحليل جيواحصائي لبعض خصائص الارض الفيزيائية لقرية أبو منقار بواحة الفرافرة – مصر باستخدام طريقة حساب التواجد المشترك

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يعتبر تقدير الماء المتاح ومعامل التوصيل الهيدروليكى المشبع فى الاراضى مهم حيث يعتبرا من المقاييس المهمة التى تتحكم فى الميزان المائى للانتاج الزراعى وعمليات الانتقال فى داخل التربة. التنبؤ بهاتان الخاصيتان بمستوى دقة مقبول ذو اهمية خصوصا فى حالة وجود اختلافات كبيرة فى التقدير وان خطوات تقديرها يستهلك وقت ومجهود. تم من خلال هذه الدراسة تقييم ومقارنة كل من kriging و cokriging فى التنبؤ بالماء المتاح والتوصيل الهيدروليكى المشبع باستخدام قيم نسبة الطين لمساحة 2147 هكتار لارض رملية الى لومية رملية طينية. تعتمد طرق kriging على الارتباط الفراغى بين العينات للتنبؤ بقيم الخاصية تحت الدراسة فى مواقع لم يؤخذ منها عينات. من جانب آخر، فان cokriging يستفيد من الارتباط الفراغى بين خاصيتين لرسم خريطة توزيع الصفة الأساسية تحت الدراسة (والتى يؤخذ منها عينات قليلة) باستخدام المحتوى المعلوماتى للمتغير الثانوى (والذى يؤخذ منه عينات كثيرة). تستخدم طريقة collocated cokriging عندما يتم جمع عينات المتغير الأساسي و المتغير الثانوى من نفس المكان.

تهدف الدراسة الحالية إلى استخدام طريقة cokriging لرسم خريطة توزيع كلا من الماء المتاح ومعامل التوصيل الهيدروليكى (المتغير الاساسى) للطبقة السطحية و المقاسة فى 26 عينة بمعلومية نسبة الطين (المتغير الثانوى) والمقاسة فى 46 عينة. وقد تراوحت قيم الماء المتاح فى الطبقة السطحية بين 33.52 الى 127.34 مم/م بمتوسط 71.54 مم/م والتوصيل الهيدروليكى المشبع من 0.11 الى 5.17 م/يوم وبمتوسط 2.52م/يوم، فى حين اختلفت قيم نسبة الطين فى الطبقة السطحية بين 0.80 و 20.20 % بمتوسط 7.25%. وقد كان معامل الارتباط r بين نسبة الطين والماء المتاح والتوصيل الهيدروليكى المشبع 0.94 & -0.93 على التوالى مما يوفى أهم شرط لاستخدام cokriging وهو وجود معامل ارتباط عالى بين المتغيرين. وقد تم عمل fitting لشكل توزيع الاختلافات semivariogram لكل من الماء المتاح ونسبة الطين وقد كان يتبع نموذج Sphericalاما بالنسبة لمعامل التوصيل الهيدروليكى فكان يتبع نموذج Gaussian وكذلك التصاحب بين الخاصيتين cross-semivariogram كان يتبع نموذج Exponential. وقد تم رسم خريطة توزيع ا لماء المتاح والتوصيل الهيدروليكى المشبع باستخدام cokriging و مقارنتها بخريطة توزيع ا لماء المتاح والتوصيل الهيدروليكى المشبع باستخدام kriging. بالإضافة إلى أن القيم المقدرة بكل من الطريقتين قد تم عمل cross-validation لها ووجد ايضا ان الخطأ القياسى للقيم المتنبأ بها بطريقة cokriging اقل من قيمته فى طريقة kriging. وقد أوضح هذا البحث أفضلية استخدام الـ cokriging عن استخدام kriging كأحد طرق رسم الخرائط، خاصة إذا تم تجميع عينات قليلة للمتغير تحت الدراسة، مع وجود متغير آخر له علاقة ارتباط قوية مع المتغير الأساسى .