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ORIGINAL ARTICLE

Spatial information of soil hydraulic conductivity and performance of cokriging over kriging in a semi-arid basin scale

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Abstract Unlike the studies in small parcels by systematic measurements, the spatial variability of soil properties is expected to increase in those over relatively large areas or scales. Spatial variability of soil hydraulic conductivity (K_h) is of significance for the environmental processes, such as soil erosion, plant growth, transport of the plant nutrients in a soil profile and ground water levels. However, its variability is not much and sufficiently known at basin scale. A study of testing the performance of cokriging of K_h compared with that of kriging was conducted in the catchment area of Sarayköy II Irrigation Dam in Cankırı, Turkey. A total of 300 soil surface samples (0–10 cm) were collected from the catchment with irregular intervals. Of the selected soil properties, because the water-stable aggregates (WSA) indicated the highest relationship with the hydraulic conductivity by the Pearson correlation analysis, it is used as an auxiliary variable to predict K_h by the cokriging procedure. In addition, the sampling density was reduced randomly to $n = 175$, $n = 150$, $n = 75$ and $n = 50$ for K_h to determine if the superiority of cokriging over kriging would exist. Statistically, the results showed that all reduced K_h was as good as the complete K_h when its auxiliary relations with WSA were used in cokriging. Particularly, the results of the "Relative Reduction in MSE" (RMSE) revealed that the reduced data set of $n = 75$ produced the most accurate map than the others. In this basin-scaled study, there was a clear superiority of the cokriging procedure by the reduction in data although a very undulating topography and topographically different aspects, two different land uses with non-uniform vegetation density, different parent materials and soil textures were present in the area. Hence, using the statistically significant auxiliary relationship between K_h and WSA might bring about a very useful data set for watershed hydrological researches.

Keywords Water-stable aggregates · Soil hydraulic conductivity · Kriging · Cokriging · Basin scale

Introduction

Hydraulic conductivity has a great influence on controlling environmental, hydrological and erosional processes, and may be significantly affected by soil properties, topography and land use and management. Because of the variability in chemical and physical soil properties, soil hydraulic conductivity may considerably vary in a field. Öztekin and Ersahin (2005) found that the saturated hydraulic conductivity (K_s) of a cultivated soil was 2.5 times greater than the adjacent virgin soil, and also significant K_s differences existed between sample locations within rows of each cultivated location. Mohanty et al. (1991) conducted a study in a no-till field with a loam soil of glacial till in the central Iowa, and reported that coefficient of variation (CV) of K_s was 90%. On the other hand, CV of K_s was found as 112.3% in the Virginia by Albrecht et al. (1985). According to Hillel (1982), total porosity, distribution of pore

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sizes, and pore geometry of soil pores are the soil characteristics that primarily affect K_s. Mason et al. (1957) found that bulk density was a poor indicator for K_s while Bouma and Hole (1971) reported a reduction in K_s with increases in soil bulk density.

The interpolation of spatially referenced data is generally performed by geostatistical methods (Ripley 1981) and such geostatistical approaches as kriging and cokriging have been recently used by scientists, environmentalists and decision makers to determine and assess spatial characteristics of environmental processes. Although kriging is statistically related to regression analysis closely, and its ability to describe spatial dependence is directly a function of the quantity and quality of the sample data (Miller et al. 2007), cokriging makes use of correlation between the variable of interest and other more easily measured variables (Odeh et al. 1995). In the general theory of cokriging, secondary variable (covariate) describes behavior of primary (Chiles and Delfiner 1999; Goovaerts 1997; Journel and Huijbregts 1978; Isaaks and Srivastava 1989; Wackernagel 1995), and it has been used widely in soil science (Vauclin et al. 1983; Trangmar et al. 1987; Yates and Warrick 1987).

There are some studies of determining the superiority of cokriging over kriging to more effectively monitor environmental processes with limited data as its sampling procedure costs less and takes less time (Vauclin et al. 1983; Vaughan et al. 1995). Ersahin (2003) compared ordinary kriging with cokriging to estimate infiltration rate (IR) on an 8.5-ha alluvial field. The author reported that the bulk density of subsoil was significantly related to IR, and therefore, they successfully used it for estimating the IR values at unobserved locations. The cokriging was consequently superior to the kriging in estimating IR in the case of limited available data. Yates and Warrick (1987) evaluated gravimetric water content as a primary variable, and bare soil temperatures and sand contents as auxiliary variables. It is found that the cokriging resulted in better predictions than the kriging when the correlations between the primary and the auxiliary variables exceeded 0.5 and when the auxiliary variable over sampled.

Spatially using some soil physical properties, Baskan et al. (2009) compared the efficiency of ordinary kriging and cokriging to estimate the Atterberg limits, and concluded that cokriging with the reduced data set was better for estimating the liquid limit and the plastic limit values than kriging; however, this was not the case for the prediction of the plastic index. Triantafilis et al. (2001) performed an assessment for ordinary kriging, regression kriging, three-dimensional kriging and cokriging on the basis of accuracy and bias in soil salinity estimates. Although regression kriging worked best overall, cokriging showed the highest rank for these criteria when the mean and standard deviation (SD) of ranks were considered. In the study of predicting soil salinity by satellite images, Eldeiry and Garcia (2009) found that regression techniques had an advantage over cokriging techniques, since they captured the small variations in estimating soil salinity. Knotters et al. (1995) also made a comparison of kriging, co-kriging and kriging combined with regression for spatial interpolation of horizon depth with censored observations. Kriging combined with regression gave better results than co-kriging. Furthermore, in kriging combined with regression, fewer model parameters needed to be estimated. This would be even advantageous if two or more auxiliary variables were used.

Spatial characteristics of the hydraulic conductivity (K_f) were investigated in a 1.2 ha texturally uniform soil with a stable structure, using the cokriging (Reynolds and Zebchuk 1996). Spatial relationships between the auxiliary variables of soil texture, organic carbon and surface topography and K_f were tested in the research. K_f was mainly affected by the stable soil structure and not by the texture, organic carbon or surface topography. Shouse et al (1990) and Martinez-Cob (1996) indicated that cokriging was only minimally superior to the ordinary kriging when auxiliary variables were not highly correlated to primary variables. Literature also suggests that cokriging could provide a better prediction for a soil variable when the best auxiliary variable was selected. Indeed, Goovaerts (1997) noticed that the contribution of the secondary information to the cokriging estimate depended not only on the correlation between the primary and secondary variables, but also on their patterns of spatial continuity. Similarly, Baskan et al. (2009) also accentuated that, for a successful analysis in cokriging, in addition to the high correlation coefficient, it was necessary to have sufficient sample numbers that could better represent the spatial structure.

The objectives of this study were to determine the spatial variability of K_h, to test spatial relationships between K_h and selected soil properties of topsoil (0–10 cm) and to compare successes of both cokriging and kriging for the cases of limited data of K_h collected in a basin.

Materials and methods

Study area

The study area, about 28 ha, is located in the catchment area of the Sarayköy II Irrigation Dam in Cankırı, Turkey, and, approximately 110-km northeast of Ankara (Fig. 1). The climate is terrestrial, and the temperature of the region ranges from −6.2 to 25.8°C and the annual precipitation is nearly 500 mm as the long-term average values of

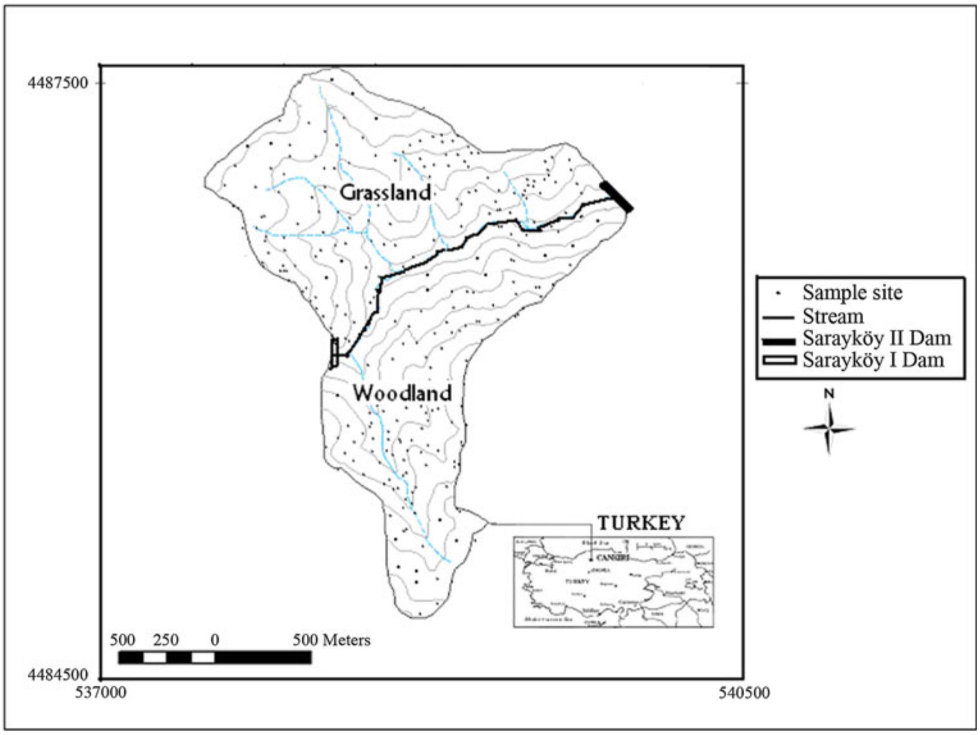


Fig. 1 Map of the study area

40 years. In the area elevations vary from 751 to 1,225 m above the sea level. The catchment mostly has the relatively steep hill slopes between 12 and 36%. Soil depths are generally shallow to moderately deep and with a texture of sandy clay loam. The calcareous and andesitic formations dominantly exist in the northern part of the area while, principally, the serpentine formation is in the southwest side of the area.

In fact, the catchment area of the Sarayköy II Irrigation Dam contains two adjacent land use types, which are grassland in the southern part of the region and mixed woodland in the northern part of the region where undulating hills with severe and long slopes are prevailing. About 40 years ago, Sarayköy I Irrigation Dam was constructed at the upper part of the Sarayköy basin, totally covering the water collection area of 12.8 km^2 (Fig. 1). Unfortunately, the dam lake has already been filled by sedimentation and now not in use for irrigation purposes.

Soil sampling and analysis

A total of 300 soil samples were collected from the grassland and mixed woodland in May 2006 with irregular intervals from the mineral soil layer of 0–10 cm. A very rough topography of the study area did not allow collecting soil samples with regular intervals at the grid base. Variations in the soil color, topography and vegetation density were taken into consideration in selecting the sampling sites (Fig. 1), the coordinates of which are located with the global position system (GPS).

According to the Soil Survey Staff (1996), soil samples were analyzed for clay (C), silt (Si) and sand (S) contents, and the amounts of coarse and fine sands (CS and FS, respectively) were further determined by sieving through 0.100-mm screen openings. The method of Nelson and Sommers (1982) was used for determination of soil particulate (>0.053 mm) and mineralogical organic matter (<0.053 mm) fractions (POM and MOM, respectively). Tests of the saturated hydraulic conductivity were performed by the method of Klute and Dirksen (1986).

Soils samples were analyzed for aggregate stability using wet sieving analysis, and the percent of water-stable aggregates (WSA) in 1–2 mm size was calculated by

$$\mathrm{WSA} = \frac{\left(M_{(a+s)} - M_s\right)}{\left(M_t - M_s\right)} \times 100 \qquad (1)$$

where $M_{(a+s)}$, M_s and M_t are the mass of the resistant aggregates plus sand (g), the sand fraction alone (g) and the sieved oven-dried soil (g), respectively.

Descriptive statistical analysis

Values of mean, SD, minimum, maximum, CV, skewness and kurtosis were calculated for the variables of each land use. The Kolmogorov–Smirnov (K–S) test and the

Pearson's correlation analysis were, respectively, performed for the conformance to a normal distribution for full and reduced data and for the examination of relationships between the selected soil properties (cS, fS, Si, C, POM, MOM and WSA) and the hydraulic conductivity. The correlation coefficients were as well calculated between WSA and each reduced data set of K_h (SPSS-10).

Geostatistical analysis

Experimental semivariogram and cross-semivariogram for the separation distance (lag) h were calculated, respectively, by Eqs. 2 and 3 (Matheron 1965; Journel and Huijbregts 1978; Burgess and Webster 1986a, b; Trangmar et al. 1985):

$$\gamma*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x)_i - z(x_i + h)\right]^2 \quad (2)$$

$$\gamma_{uv}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z_u(x)_i - Z_u(x_i + h)\right]\left[Z_v(x_i) - Z_v(x_i + h)\right] \quad (3)$$

where $z(x_i)$ was the value of the measured soil properties at spatial location x_i and $N(h)$ was the number of pairs with a distance of (lag)h. In Eq. 3, lowercase letters u and v indicate the primary and secondary variables, respectively. The spherical models were fitted to the experimental semivariograms and cross-semivariograms. All geostatistical computations were conducted by the software package GS + 5 (Gamma Design Software).

Mean square error (MSE) was used to validate the error estimations, where $z(x_i)$ and $z^*(x_i)$ are the true and estimated values, respectively (Eq. 4), and subsequently, relative reduction in MSE (RMSE) was described in Eq. 5, where $\mathrm{MSE_k}$ and MSE_{ck} are the MSE values of kriging and cokriging, respectively.

$$\mathrm{MSE} = \frac{1}{N} \sum_{i=j}^{n} \left[z(x_i) - z*(x_i)\right]^2 \quad (4)$$

$$\mathrm{RMSE} = 100(\mathrm{MSE}_k - \mathrm{MSE}_{ck})/\mathrm{MSE}_k \quad (5)$$

Results and discussion

Descriptive statistics of soil properties

The mean, SD, CV, minimum and maximum values, skewness and kurtosis and the coefficient of the K–S test for each soil property are shown in Table 1. The mean values were 243 ± 102, 170 ± 69, 256 ± 64, 329 ± 100, 12.10 ± 11.08 and 14.29 ± 10.02 for clay (C), silt (Si), coarse sand (cS), fine sand (fS), particular organic matter content (POM) and mineralogical organic matter content (MOM) in the unit of g $\mathrm{kg^{-1}}$, respectively. Those of saturated hydraulic conductivity (K_h) and WSAs were 8.04 ± 6.47 and 73.37 ± 21 in the units of cm $\mathrm{h^{-1}}$ and percent, respectively. The K_h, POM and MOM had relatively higher variations than those of C, Si, cS, fS and WSA (≥70 and ≤42%, respectively). Although the POM had the highest CV (91%), the smallest CV was obtained for cS (25%). Unless they differed intrinsically, it could particularly be expected that cS of the surface soil was not as variable as Si, which is more susceptible to the erosion, transportation and deposition processes in any slope (Basaran et al. 2008), and higher variation in POM could be explained depending on the land use change and management. The CV of K_h is noticeably higher (81%) as usually acknowledged by the review of the related literatures (Mohanty et al. 1991; Albrecht et al. 1985).

The analysis of the Pearson correlation coefficients summarizes the relationships among the measured soil properties (Table 2). Statistically, the values of WSA, POM and MOM are significantly correlated with K_h at the

Table 1 Descriptive statistics of the soil properties (n = 300)

Soil properties	Mean	SD	CV	Min.	Max.	Skewness	Kurtosis	K–S coefficients
C	243	102	42	48	657	1.03	1.8	0.034
Si	170	69	41	30	477	0.69	1.39	0.468
cS	256	64	25	90	409	−0.12	0.47	0.868
fS	329	100	30	3.1	602	−0.85	1.05	0.001
K_h	8.04	6.47	81	0.3	33	1.48	2.11	0.001
POM	12.10	11.08	91	0.3	77	2.04	5.02	0.001
MOM	14.29	10.02	70	0.9	58	1.5	2.98	0.001
WSA	73.37	21	29	10	99	−0.75	−0.30	0.001

C clay (g $\mathrm{kg^{-1}}$), *Si* silt (g $\mathrm{kg^{-1}}$), *cS* coarse sand (g $\mathrm{kg^{-1}}$), *fS* fine sand (g $\mathrm{kg^{-1}}$), *POM* particular organic matter content (g $\mathrm{kg^{-1}}$), *MOM* mineralogical organic matter content (g $\mathrm{kg^{-1}}$), *WSA* water-stable aggregates (%), K_h saturated hydraulic conductivity (cm $\mathrm{h^{-1}}$), *SD* standard deviation, *CV* coefficient of variation, *K–S* coefficient of Kolmogorov–Smirnov test level of $P < 0.001$. The highest correlation coefficient was obtained between the WSA and K_h ($r = 0.541$). The results indicated that WSA might more favorably be used as an auxiliary variable to predict K_h by cokriging when compared with the respective correlation coefficients of other soil properties with K_h. For the cokriging resulted in better predictions than the kriging when the correlations between the primary and the auxiliary variables exceeded 0.5 and when the auxiliary variable was sampled in great numbers (Yates and Warrick 1987; Goovaerts 1997; Baskan et al. 2009), WSA was selected as auxiliary variable since correlation coefficient was bigger than 0.5.

The K–S tests for the data of K_h and WSA showed that they were not normally distributed ($P < 0.001$). Therefore, it meant that transformations should be used for increasing the applicability and usefulness of the statistical techniques based on the normality assumption (Fenton and Griffiths 2008). Figures 2 and 3 show the frequency distributions of the raw and transformed data for K_h and WSA, respectively. It appeared that the natural logarithmic (Ln) and inverse sinusoidal transformations (ArcSin) of the data of K_h and WSA, respectively, decreased the non-normality significantly. The distribution of K_h was initially right skewed (1.48) and kurtotic (2.11) while tailing and peaking of the LnK_h distribution were considerably smaller (−0.44 and 0.09, respectively) (Fig. 2a, b). The ArcSin transformation for WSA particularly provided a better value for the skewness when compared with that of the distribution of the raw data (−0.12 and −0.75, respectively). On the other hand, it was not as good as in improving the kurtosis (−0.30 and −0.83, respectively). Since the left tailing is significantly reduced (Fig. 3a, b), the transformed data, rather than the raw data was chosen for the spatial analyses.

Table 2 Correlation between measured soil properties and hydraulic conductivity ($n = 300$)

	Soil properties						
	WSA	*C*	Si	cS	fS	POM	MOM
K_h	0.541*	n.s.	n.s.	n.s.	n.s.	0.381*	0.341*

C clay (g kg^{-1}), *Si* silt (g kg^{-1}), cS coarse sand (g kg^{-1}), *fS* fine sand (g kg^{-1}), K_h saturated hydraulic conductivity (cm h^{-1}), *POM* particular organic matter content (g kg^{-1}), *MOM* mineralogical organic matter content (g kg^{-1}), *WSA* water-stable aggregates (%), *SD* standard deviation, *n.s.* insignificant

* $P < 0.001$

Geostatistical analysis

Geostatistical parameters for the complete data of LnK_h and ArcSinWSA are shown in Table 3 ($n = 300$). The directional semivariograms calculated at the angles of 0° (N–S), 45° (NE–SW), 90° (E–W) and 135° (SE–NW) for the measured variables indicated no severe anisotropy. Therefore, omni-directional semivariograms were obtained using the cross-validation method, and the data were modeled with isotropic functions to determine the spatially dependent variance within the catchment area of the Sarayköy II Irrigation Dam. The values for each property at observation points were used for estimating values at unknown points by the ordinary block kriging and using parameters of the semivariograms generated.

Exponential and Gaussian semivariogram models provided the best fits for LnK_h and ArcSinWSA, respectively, and a spherical cross semivariogram led to the best fit for LnK_h/ArcSinWSA (Table 3). The nugget effects caused either by the measurement error or by the variation of the property were determined as 0.352, 0.0244 and 0.0462 for LnK_h, ArcSinWSA and LnK_h/ArcSinWSA, respectively. Because of the positive linear correlation between K_h and WSA ($r = 0.541$) (Table 2) and since the high values of LnK_h matched with those of ArcSinWSA by modeling the cross-semivariogram for LnK_h/ArcSinWSA, the nugget effect decreased and a maximum spatial correlation of LnK_h/ArcSinWSA (1,123 m) was found greater than those of LnK_h and ArcSinWSA alone (251 and 485 m,

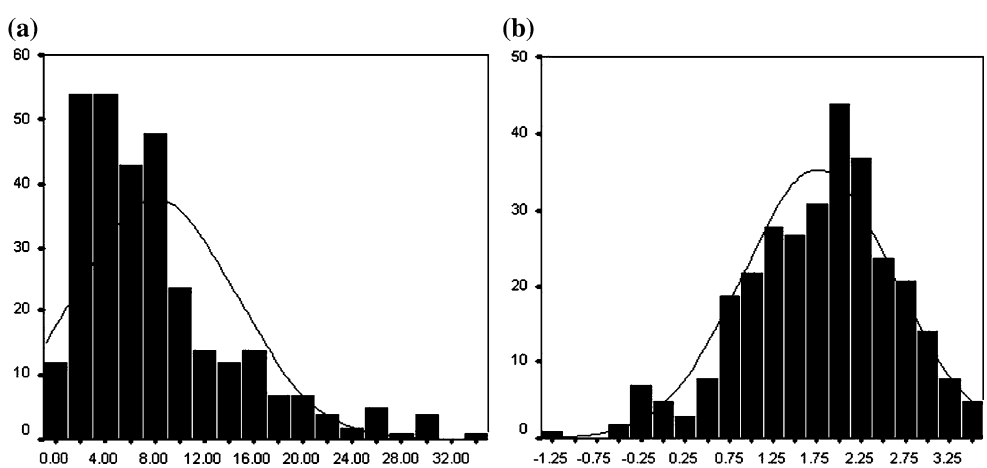


Fig. 2 The frequency distributions of the raw and transformed data of K_h. **a** Raw data, **b** LnK_h

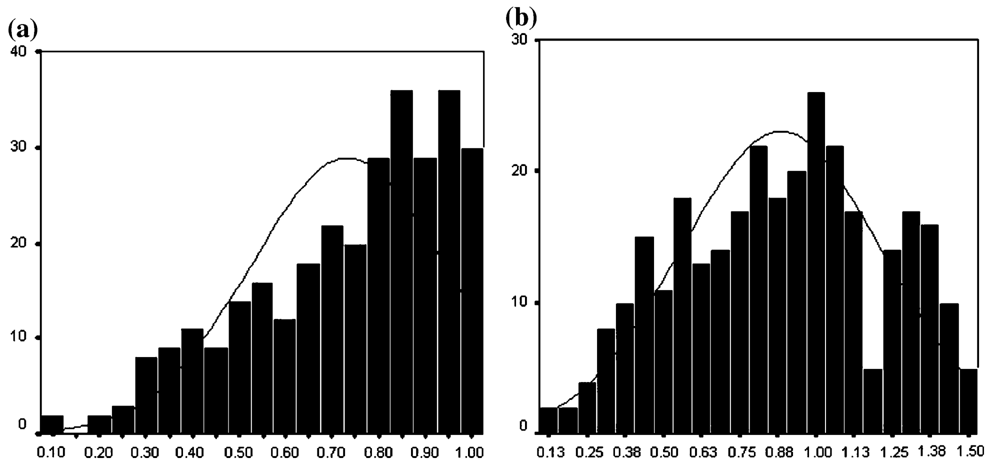


Fig. 3 The frequency distributions of the raw and transformed data of WSA. **a** Raw data, **b** ArcSinWSA

Table 3 Semivariogram models and parameters for LnK_h and ArcSinWSA and a cross semivariogram model for LnK_h and ArcSinWSA for complete data set

Variable	Semivariogram model	Nugget (C_0)	Sill ($C_0 + C$)	$C_0/(C_0 + C)$ (%)	Range (m)	r^2
LnK_h	Exponential	0.359	0.768	47	251	0.932
ArcSinWSA	Gaussian	0.0244	0.0489	50	485	0.965
Variable	Cross-variogram model	Nugget (C_0)	Sill ($C_0 + C$)	$C_0/(C_0 + C)$ (%)	Range (m)	r^2
LnK_h/ArcSinWSA	Spherical	0.0462	0.1184	39	1,123	0.986

LnK_h Ln-transformed hydraulic conductivity values, *ArcSinWSA* ArcSin-transformed water-stable aggregates

respectively) (Table 3). With respect to their nugget-to-sill ratio ($C_0/(C_0 + C)$, LnK_h, ArcSinWSA and LnK_h/ArcSinWSA had moderate spatial dependences (Chien et al. 1997), and the values were 47, 50 and 39%, respectively. However, LnK_h/ArcSinWSA had a relatively stronger spatial dependence than both LnK_h and ArcSinWSA.

Spatial patterns of WSA and K_h are given in Fig. 4a and b, respectively. The lower K_h and WSA values were distributed on the northern and northeastern part of the study area, while the higher K_h and WSA values were on the southern and southwestern parts. The effects of land use and topography on the spatial pattern of WSA were discussed in detail by Basaran et al (2008) for the same area. The catchment has two different land uses, grassland and woodland and two main topographical aspects, northern and southern. Basaran et al. (2008) indicated that lower organic matter contents of the grassland, regardless of the organic matter fractions (POM and MOM) could be a result of overgrazing effects on soil quality and vegetation density. Moreover, micro-climatic conditions resulted from topographical discrepancies in the watershed were also expected to have an influence on varying organic matter contents. For example, the northern aspect of the catchment, where grassland is located, is characterized by a lower annual vegetation cover, and therefore, the sources of organic matter are rather limited as the micro-climatic conditions considerably restrict the soil moisture and soil temperature. The southern aspect of the study site, where woodland is located, is characterized by higher vegetation cover, organic matter content and soil moisture because of the micro-climatic conditions. Dahlgren et al. (1997), Smith and Smith (2000) and Tsui et al. (2004) explained that topography influences the local and regional microclimates by changing pattern of precipitation, temperature, solar radiation and relative humidity.

The performance of kriging and cokriging with the reduced data set

The ordinary cokriging procedure was used along with the isotropic semivariograms and cross-semivariograms for the LnK_h and ArcSinWSA variables to estimate K_h at the unobserved points. Furthermore, to determine the advantages of cokriging over kriging, the sampling density was reduced randomly to $n = 175$, $n = 150$, $n = 75$ and $n = 50$ for K_h (R1K_h, R2K_h, R3K_h and R4K_h, respectively). The analysis of the Pearson's correlation coefficients among the four reduced K_h values and WSA are given in Table 4. Statistically, there were significant positive correlations between the values of R1K_h, R2K_h, R3K_h and R4K_h and WSA at the level of $P < 0.001$ and the correlation coefficient values were 0.545, 0.550, 0.559 and 0.532, respectively. These values demonstrated that all of

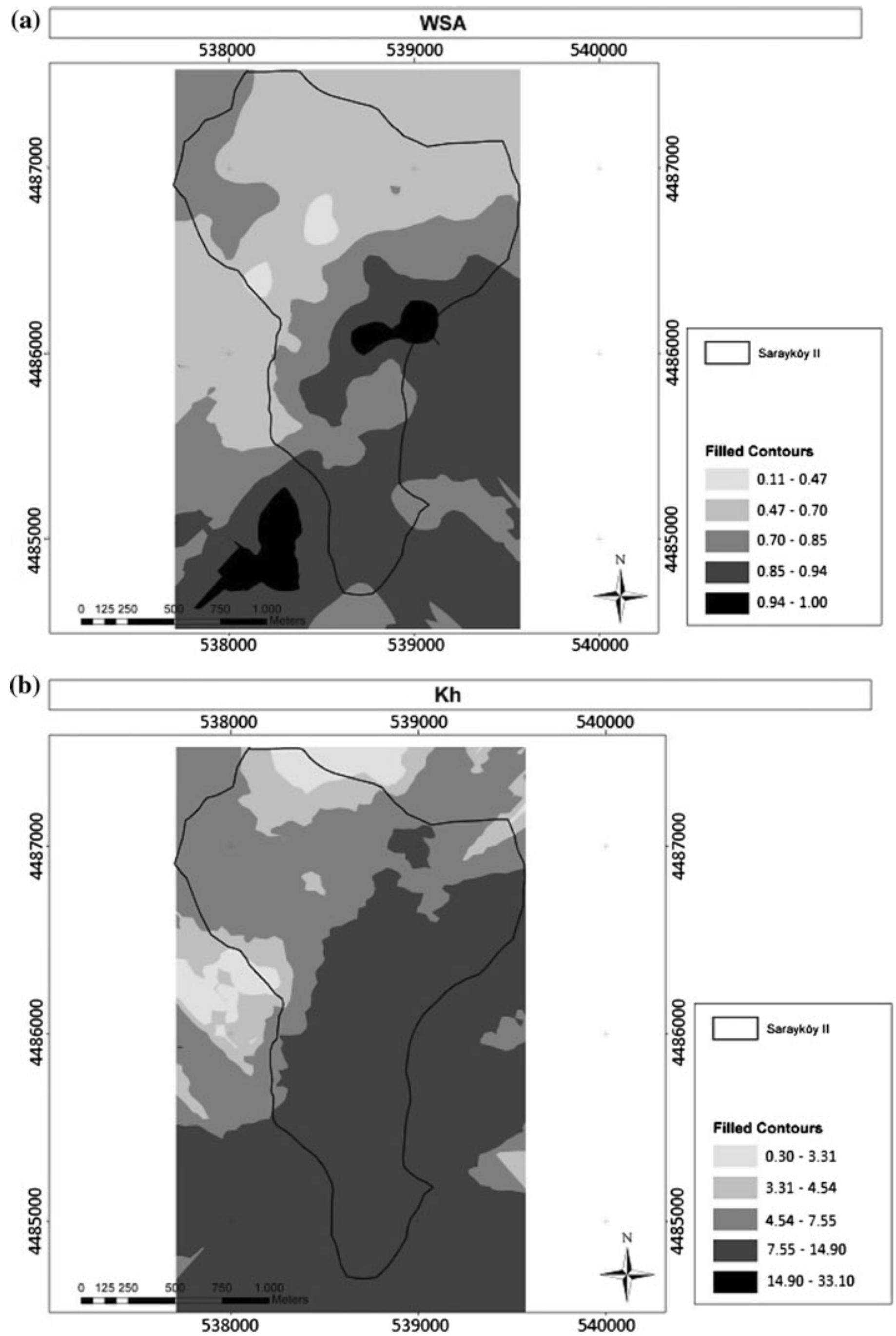


Fig. 4 Spatial patterns of K_h and WSA for full data set, **a** WSA (%), **b** K_h (cm h^{-1})

Table 4 Correlation coefficient between WSA and the reduced data set of K_h ($n = 175$, $n = 150$, $n = 75$ and $n = 50$ for K_h, $P < 0.001$)

	R1LnK_h	R2LnK_h	R3LnK_h	R4LnK_h
ArcsinWSA	0.545	0.550	0.559	0.532

R1LnK_h, R2LnK_h, R3LnK_h and R4LnK_h are reduced data sets for the saturated hydraulic conductivity (K_h) with $n = 175$, $n = 150$, $n = 75$ and $n = 50$, respectively, in comparison to the complete data set with $n = 300$

LnK$_h$ Ln-transformed hydraulic conductivity values, *ArcSinWSA* ArcSin-transformed water-stable aggregates

the reduced K_h were as good as the complete K_h in the relation with WSA (Yates and Warrick 1987). Similarly, Ersahin (2003) reported that using cokriging with 120 bulk density values, 40 observed values of infiltration rate (IR) were sufficient to obtain the same information as that obtained with 50 field measurement of IR and concluded cokriging was more successful than kriging when infiltration rate is undersampled.

The cross-semivariograms of R1LnK_h (a), R2LnK_h (b), R3LnK_h (c) and R4LnK_h (d) and ArcSinWSA are given in

Fig. 5 and the related geostatistical parameters are listed in Table 5. For all of them, exponential models provided the best fits for cross-semivariograms. The lowest nugget variances were found for R3LnK_h/ArcSinWAS and R4LnK_h/ArcSinWAS (0.0001) while those of R1LnK_h/ArcSinWAS and R2LnK_h/ArcSinWAS were relatively higher (0.0201 and 0.0177, respectively). This fact, although the sill values ($C_0 + C$) did not change among them (0.143, 0.142, 0.125 and 0.147, respectively), resulted in lower unexplained variability ([$C_0/(C_0 + C)$]), which could be caused by measurement error or micro-variability less than the shortest sampling distance for R3LnK_h/ArcSinWAS and R4LnK_h/ArcSinWAS (0.07 and 0.07, respectively) (Table 5). Small [$C_0/(C_0 + C)$] values for these data sets indicated that a higher accuracy could be achieved in mapping K_h using WSA as an auxiliary variable (Isaaks and Srivastava 1989) and all had strong spatial dependences (Chien et al. 1997).

On the other hand, the highest spatial correlation was for R2LnK_h/ArcSinWSA (1,078 m) while those of R1LnK_h/ArcSinWSA, R3LnK_h/ArcSinWSA and R4LnK_h/ArcSinWSA did not vary noticeably (545, 512 and 540 m, respectively). The highest spatial correlation for R2LnK_h/ArcSinWSA (1,078 m) could be related to performance of data reduction procedure.

The isotropic cross-semivariograms models and parameters are used for the cokriging procedure to estimate the spatial variability of K_h from each reduced data set with the secondary variable of WSA in the catchment of the Sarayköy II Irrigation Dam (Fig. 6). A similar spatial pattern was found for R1LnK_h, R2LnK_h and R3LnK_h while the spatial pattern of R4LnK_h was different from the other reduced data sets.

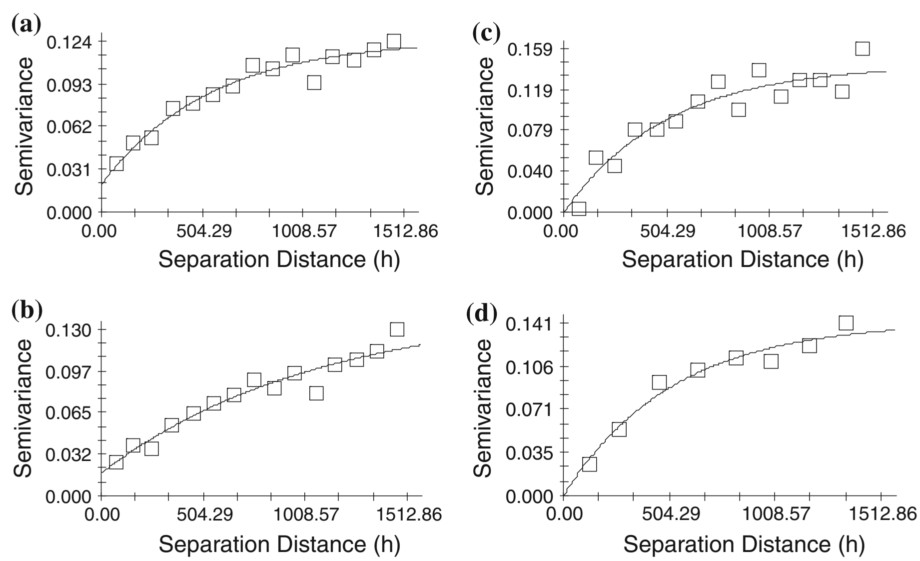


Fig. 5 Cross-variograms of R1LnK_h, R2LnK_h, R3LnK_h and R4LnK_h and ArcSinWSA (**a**–**d** respectively)

Table 5 Semivariograms and cross-semivariograms models and parameters for the reduced data

Variable	Semivariogram model	Nugget (C_0)	Sill ($C_0 + C$)	$C_0/(C_0 + C)$ (%)	Range (m)	r^2
R1*LnK_h	Exponential	0.249	0.81	31	164	0.872
R2LnK_h	Exponential	0.158	0.77	21	176	0.952
R3LnK_h	Exponential	0.121	0.791	15	243	0.902
R4LnK_h	Exponential	0.372	0.745	50	405	0.814
Cross-semivariogram						
R1LnK_h/ArcSinWAS	Exponential	0.0201	0.125	16	545	0.952
R2LnK_h/ArcSinWAS	Exponential	0.0177	0.147	12	1,078	0.936
R3LnK_h/ArcSinWAS	Exponential	0.0001	0.143	0.07	512	0.889
R4LnK_h/ArcSinWAS	Exponential	0.0001	0.142	0.07	540	0.965

R1K_h, R2K_h, R3K_h and R4K_h are reduced data sets for the saturated hydraulic conductivity (K_h) with $n = 175$, $n = 150$, $n = 75$ and $n = 50$, respectively, in comparison to the complete data set with $n = 300$

LnK_h Ln-transformed hydraulic conductivity values, *ArcSinWSA* ArcSin-transformed water-stable aggregates

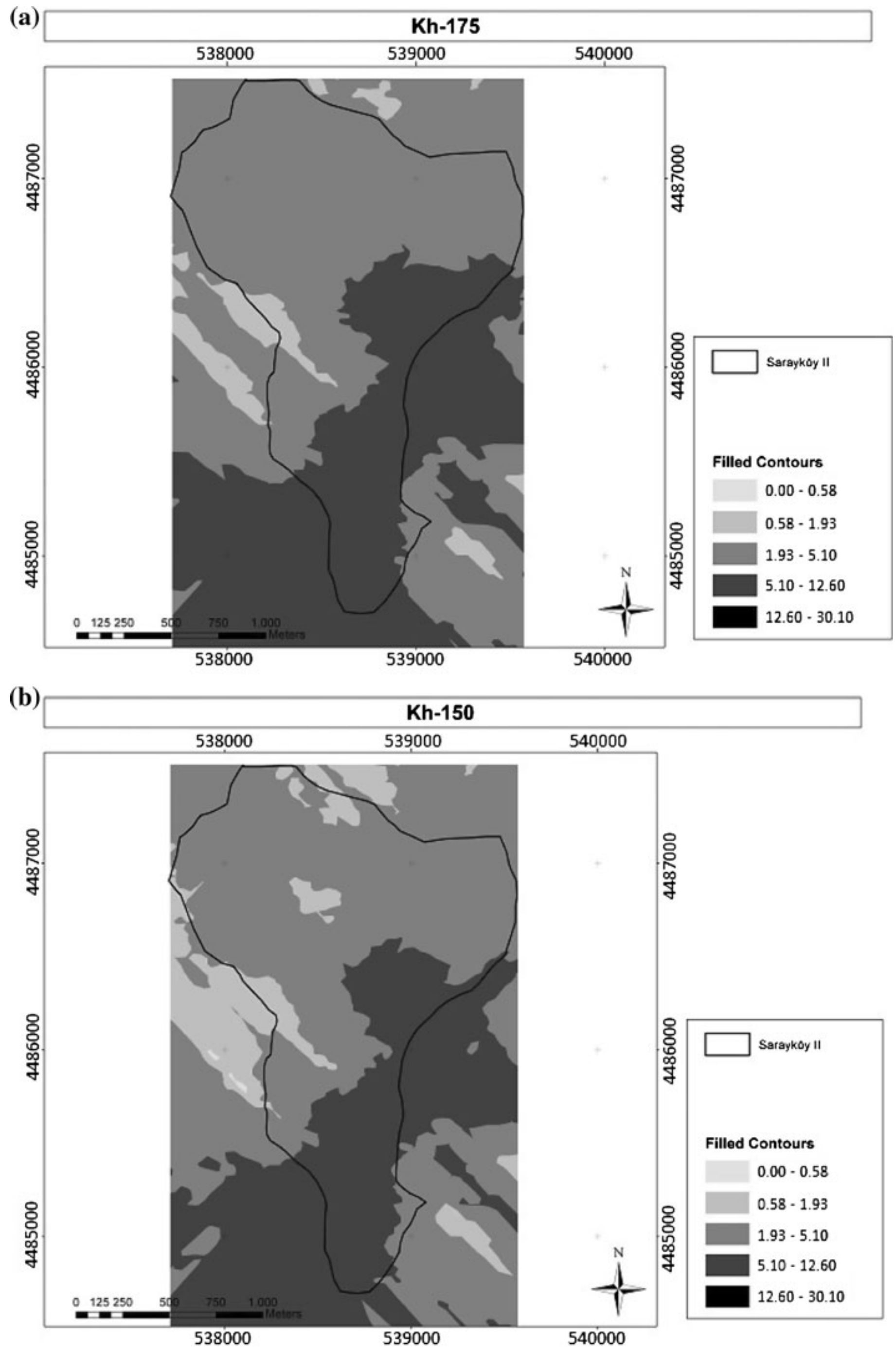
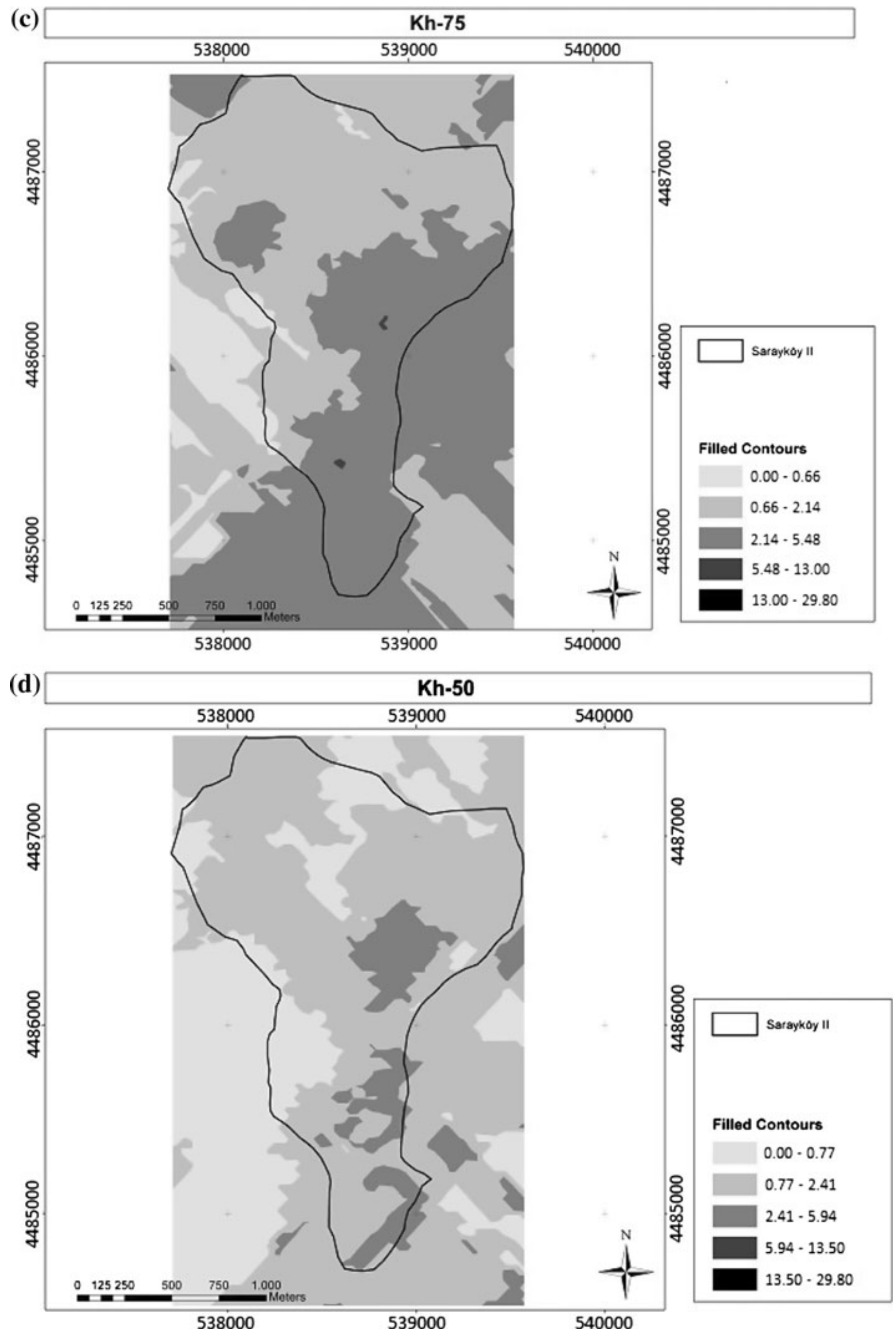


Fig. 6 The cokriging maps of K_h (cm h^{-1}) for each reduced data set: **a** 175, **b** 150, **c** 75 and **d** 50, respectively

The cross validation of residuals and the correlation coefficients between the measured and predicted values are used to assess the performance of each data set (Voltz and Webster 1990; Laslett 1994; Gotway et al. 1996; Ersahin 2003; Baskan et al. 2009). The cross validation results of the kriging and cokriging maps for the reduced sampling density are shown in Table 6. The MSE values showed that map accuracy was almost the same for the reduced models of kriging (34.59, 36.53, 39.16 and 38.99 for R1K_h, R2K_h, R3K_h and R4K_h, respectively) while the MSE values of cokriging maps decreased by R4K_h, for which MSE started increasing again after a certain degree of the fall-off. The values were 11.39, 5.84, 4.95 and 14.79 for R1K_h, R2K_h, R3K_h and R4K_h, respectively, and the lowest MSE value was observed with R3K_h.

Superiority of cokriging over kriging was determined for all of the reduced data (Table 6). The RMSE values showed that map accuracies were increased by cokriging which relatively reduced the MSE values by 67, 84, 87 and 62% for R1K_h, R2K_h, R3K_h and R4K_h, respectively, and

Fig. 6 continued



the cokriging map of R3K_h was the most adequate map. The map of R3K_h clearly indicated that a 75 sampling density and a related sampling distance were sufficient for obtaining the best spatial information on K_h of the catchment of the Sarayköy II Irrigation Dam in this research. The correlation coefficients between the measured and predicted values are another validation method for evaluating the map accuracy. The kriging maps had much lower correlation coefficients (0.461, 0.445, 0.317 and 0.285 for R1K_h, R2K_h, R3K_h and R4K_h, respectively) than those of cokriging (0.954, 0.971, 0.981 and 0.932 for R1K_h, R2K_h, R3K_h and R4K_h, respectively). In addition, *r* values of kriging decreased with the reduction in data while those of cokriging increased as the reduction in data proceeded by R4K_h, for which *r* started declining again, but being still much higher than that of kriging (0.285 and 0.932, respectively).

Although the selected research area has a very undulating topography and topographically different aspects, two different land uses with non-uniform vegetation density,

Table 6 Results of the ordinary kriging and cokriging estimations calculated from the results of the cross-validation of the reduced data of K_h

Variable	Mean	Estimated mean		r^2		MSE		RMSE
		Kriging	Cokriging	Kriging	Cokriging	Kriging	Cokriging	
R1K_h	7.85	6.31	6.57	0.461	0.954	34.59	11.39	67
R2K_h	8.13	6.63	7.08	0.445	0.971	36.53	5.84	84
R3K_h	8.21	6.64	7.34	0.317	0.981	39.16	4.95	87
R4K_h	8.11	6.36	6.61	0.285	0.932	38.99	14.79	62

R1K_h, R2K_h, R3K_h and R4K_h are reduced data sets for the saturated hydraulic conductivity (K_h) with $n = 175$, $n = 150$, $n = 75$ and $n = 50$, respectively, in comparison to the complete data set with $n = 300$

r correlation coefficient, *MSE* mean square error, *RMSE* relative reduction in MSE

different parent materials and soil texture, there was a superiority of the cokriging procedure by the reduction of data. Martinez-Cob (1996) tested the ordinary kriging, cokriging and modified residual kriging to interpolate long-term mean total annual reference evapo-transpiration (AETO) and long-term mean total annual precipitation (APRE) in a mountainous region. The researcher did not recommend one method for AETO, but reported superiority of cokriging to kriging for APRE. Spatial continuity of WSA could be another determining factor in terms of the cokriging accuracy in our study. Therefore, the accuracy of cokriging was closely related both to the correlation between primary and secondary variables and to their patterns of the spatial continuity (Goovaerts 1997; Baskan et al. 2009).

The secondary variable has to maintain the primary variable to obtain more reliable maps; therefore, performance of the cokriging certainly depended on high correlation between primary and secondary variables. Despite the non-uniform condition in the study area, high correlation between reduced data set of K_h and WSA provided superiority of the cokriging over the kriging. In the most of the studies on performance of the cokriging, highly correlated variable(s) were selected on uniform small parcels. Yates and Warrick (1987), Stein et al. (1988), Zhang et al. (1992, 1997), Istok et al. (1993) and Ersahin (2003) found superiority of cokriging over kriging in generally uniform small parcels with respect to soil properties and a systematic sampling scheme was used in their studies that could provide the same degree of effects of intrinsic or extrinsic factors on primary and secondary variables. With this study, the cokriging superiority was tested over the kriging in a very complex basin scale with respect to geology, land use, slope, texture, aspect, vegetation density and management.

Conclusion

The study compared the performance of cokriging of K_h to that of kriging in a basin scale. The cokriging technique, which used WSAs as an auxiliary parameter to predict the soil hydraulic conductivity (K_h) with a reduced data set, generated a better map than that of the kriging. It was tested by the "Relative Reduction in MSE" (RMSE) which indicated that the map accuracies were increased by the cokriging which relatively reduced the MSE values by 67, 84, 87 and 62% for the reduced data sets for K_h with $n = 175$, $n = 150$, $n = 75$ and $n = 50$, respectively. In addition, when the correlation coefficients between the measured and predicted values were investigated, for the mentioned order of the reduced data sets of K_h, the cokriging had much greater values (0.954, 0.971, 0.981 and 0.932) than those of the kriging (0.461, 0.445, 0.317 and 0.285). Despite studying in a larger scale, characterized by more complicated elements than those of small parcels, a clear advantage of the cokriging procedure by reducing data was observed.

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