Trends in
Soil Science
Vol. 2, (1997)

Applications of geostatistics in soil science

R. Zhang[1], P. Shouse[2], S. Yates[2] and A. Kravchenko[1]
[1]Department of Plant, Soil and Insect Sciences, University of Wyoming, Laramie, WY 82071-3354, USA. [2]U.S. Salinity Laboratory, USDA-ARS Riverside, CA 92507-4617, USA

ABSTRACT

Soil spatial variability and heterogeneity is a frustrating but important issue in the field-scale description of soil physical, chemical, and hydrological parameters. Geostatistics is a useful tool to study spatial distributions of soil properties. Geostatistics provides efficient and accurate methods for estimating soil variables, designing optimum sampling strategies, and simulating stochastic transport processes in heterogeneous soils. In this paper, the commonly used geostatistical methods and their applications in soil science are reviewed and summarized from over 140 publications.

INTRODUCTION

The fundamentals of geostatistics were developed empirically by Krige and others during the 1950's to assist in assessment and management of gold ore reserves in South Africa ([1, 2, 3, 4]). A coherent body of theory was developed by Matheron ([5]) for solving ore estimation problems associated with spatial variations. The theory embraces a set of specific statistical techniques to quantify the correlation of spatially distributed random variables, and perform spatial interpolation of these variables ([6, 7, 8]).

Geostatistical techniques provide a means for describing the spatial variability of soil properties by considering spatial distributions and inter-variable correlations, provide optimum interpolation schemes for soil mapping, and provide methods for improving estimates of soil properties ([9]). In soil science, geostatistical methods have been used to estimate soil properties such as water content ([10 - 12]), soil temperature ([13 - 15]), soil-water pressure head ([16 - 18]), various soil chemical properties ([19 - 29]), soil texture and structural stability ([19, 30 - 33]), mechanical impedance ([34]), infiltration rate ([35-38]), water retention properties ([20, 30, 39, 40]), soil salinity ([41 - 43]), and soil surface topography ([44]). Geostatistics is also used to study spatial scales and patterns of soil variation to improve sampling efficiency ([45 - 51]).

As a general trend, geostatistics is being increasingly used as an advanced tool to solve problems in soil science, for example, large-scale soil mapping, non-point source pollution, and precision agriculture. The main issue of all the problems is how to deal with spatial variability and heterogeneity of random variables involved. Therefore, in this paper we briefly reviewed the commonly used geostatistical methods. Applications of the methods in soil science were summarized, which may provide the insight of geostatistics use.

VARIOGRAMS

Soils are heterogeneous and spatially variable. Spatial variations with independence are commonly characterized with a variogram (also called semi-variogram) in geostatistics ([8]). Any set of n values, $Z(x_1)$, ..., $Z(x_n)$, of a measured soil property, Z, is called a regionalized or spatial random variable ([52]). The collection of random variables for all points in the field is the random function $Z(x)$. With n measurements of a soil property, $Z(x_1)$, ..., $Z(x_n)$ its sample variogram is estimated as ([6, 53])

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

where $N(h)$ is the number of sample pairs separated by a lag distance h. Two types of estimation errors occur when calculating the true variogram from a single realization ([6]). The first is called the variance of estimation and a consequence of using a limited number of sample measurements to estimate the variogram. This error is inversely proportional to the number of sample pairs $N(h)$ at a given lag distance ([52, 54]). The second type of error is a manifestation of local fluctuations in the mean value of $Z(x)$. These fluctuations cause estimates of the variogram to vary from point to point in the field. This source of error is called the fluctuation variance related to the distribution of the separation distances between sample pairs ([52, 54]). Two practical rules for calculating the experimental variogram

follow directly from these analyses: $N(h) > 30$, and $|h| < L/2$, where L is the longest possible distance in the sampled field ([6, 9, 52]).

After computing sample variograms, variogram models should be chosen to represent the spatial structures. Any mathematical function for variograms must be conditionally positive-definite, (i.e., increasing or constant with increasing h, and non-negative) ([9, 55, 56]). In the literature, functions which meet these criteria are called authorized functions ([1, 2, 6, 56]). The best advice is to choose appropriate functions from authorized models. Several authorized models frequently used in analyses of spatial variations of soil properties are listed as follows:

1. Spherical model

$$\gamma(h) = C_0 + C_1[1.5(h/a) - 0.5(h/a)^3], \quad 0 \le h \le a$$
$$= C_0 + C_1, \quad h > a \qquad [2]$$

where C_0 is called the nugget, $C_0 + C_1$ is the sill, and a is the range.

2. Exponential model

$$\gamma(h) = C_0 + C_1[1 - \exp(-h/a)] \qquad [3]$$

3. Gaussian model

$$\gamma(h) = C_0 + C_1\{1 - \exp[-(h/a)^2]\} \qquad [4]$$

4. Power model ($0 < \lambda < 2$)

$$\gamma(h) = C_0 + C_1 h^{\lambda} \qquad [5]$$

If $\lambda = 1$ we have the linear model.

5. DeWijsian model

$$\gamma(h) = C_0 + C_1 \log h \qquad [6]$$

The procedure for fitting an appropriate mathematical model to sample variogram values usually consists of the following steps: 1) choosing candidate models from the authorized models; 2) estimating the model parameters (sill, nugget, range) either by the eyeball method ([1, 2]) or by using more objective weighted least squares ([57]) or maximum likelihood methods ([58, 59]); and 3) choosing the "best" model among the reasonable candidate models.

Choosing the "best" model among the reasonable candidate models can be difficult because there is rarely any theoretical ground for choosing a particular model ([60, 61]). Nevertheless, there are some statistical criteria that can be employed to pick the "best" model. One such method is the Akaike information criterion (*AIC*), which helps to find the "best" fitted model with the minimum parameters. The unbiased estimate of the *AIC* is calculated by

$$AIC^* = n \ln(R) + 2p \qquad [7]$$

where n is the number of sample variogram values, p is the number of independent parameters in the model, and R is the residual sum of squares of deviations from the fitted model. The model having the lowest *AIC* is judged "best" ([22, 56, 59]).

Another method for deciding the best model from a set of candidate models is by means of cross-validation ([62]). This procedure has been misnamed "jackknifing" in the literature ([63]) and is in reality a "leave-one-out" method. In this method, sample values are deleted one at a time and then kriged (described later) to estimate the missing data point from the remaining sample values. Statistical analyses of the kriging errors (differences between estimated and measured values) and the standardized mean-squared errors (the average of the kriging errors divided by their respective kriging variances) determine if a bias is present in the estimation and if the estimation errors are consistent with the kriging variances. The average kriging error should be close to zero for a model to produce unbiased estimates. For kriging errors to be consistent with the kriging variances, the standardized errors should be normally distributed with a mean of zero and a variance close to one ([12, 63]). The use of cross-validation for model discrimination has been suggested for applications involving kriging, while the *AIC* method has been preferred for cases where it is necessary to describe the main characteristics of the spatial variability ([56]).

APPLICATIONS OF GEOSTATISTICAL METHODS

Kriging

The prime use of geostatistical methods is to estimate soil properties at unsampled sites so that spatial distributions of the properties within the field can be determined. The estimation method is known as kriging ([64, 65]). Kriging is essentially a means of weighted local averaging based on the variogram model, which provides the required spatial information ([66, 67]). Kriging has the advantage over regression methods by considering the spatial correlation during the estimation process. Kriging provides both unbiased estimates with minimum variance and a measure of the estimation variance. As such, kriging is superior to other interpolation methods ([9, 67]). There are several forms of the linear and nonlinear kriging equations such as simple kriging, ordinary kriging, block kriging, universal kriging, and disjunctive kriging.

Simple kriging assumes that the mean value of the

random variable is known *a priori*. This assumption limits the use of this technique for general estimation problems. Simple kriging is not be discussed in detail here. Interested readers can consult Journel and Huijbregts ([6]) for a detailed explanation of the kriging equations.

Most often the mean value of a random variable is unknown. The kriging equations can be written so that the mean value becomes part of the solution. The ordinary kriging estimator, $Z^*(x_0)$, of an unsampled site is a linear sum of weighted observations within a given neighborhood and expressed in a mathematical form as ([68]):

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \qquad [8]$$

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. An unbiased estimate of $Z(x_0)$ (i.e., $E[Z^*(x_0) - Z(x_0)] = 0$) requires that a constraint be placed on the weights, λ_i's, such that

$$\sum_{i=1}^{n} \lambda_i = 1 \qquad [9]$$

The best linear unbiased estimate of the conditional expectation of $Z(x_0)$ is obtained by using the Lagrangian technique to minimize the estimation variance. The ordinary kriging equations result from minimizing the estimation variance and the unbiased condition of Eq. 9. The kriging system is a set of n+1 linear equations obtained by setting each partial derivative equal to zero:

$$\frac{\partial}{\lambda_i}\left\{E\left[Z(x_0) - Z^*(x_0)\right] - 2\mu \sum_{i=1}^{n} \lambda \right. \qquad [10]$$
$$\left. = 0 \quad i = 1, 2, \ldots, n \right.$$

where μ is the Lagrange multiplier, plus Eq. 9. The system of equations can be written in terms of the variogram function as follows:

$$\sum_{j=1}^{n} \lambda_j \gamma(x_i - x_j) + \mu = \qquad [11]$$
$$\gamma(x_0 - x_i) \quad i = 1, 2, \ldots, n$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad [12]$$

The system of equations is easily solved using Gauss elimination and the solution yields the n weights and the Lagrange multiplier ([9, 52, 54]). The minimum estimation variance, or kriging variance, is obtained from

$$\sigma_K^2 = E\left\{\left[Z(x_0) - Z^*(x_0)\right]^2\right\} = \sum_{i=1}^{n} \lambda_i \gamma(x_i - x_0) + \mu \qquad [13]$$

Although a contour map drawn from point data and estimates is the most accurate map, local discontinuities can obscure longer range trends in soil variables. Also, the positions of the discontinuities depend on the locations of particular data points, and a shift in the orientation of an observation grid can result in a substantially different map. This is an artifact caused primarily by sampling ([68]). The shortcomings of point kriging can be avoided by using a procedure known as block kriging. Block kriging can be regarded as a more general kriging method of which point kriging is a special case ([9]). Instead of interpolating between points, block kriging considers a region with its center. The variogram values between observed data points and the interpolated point are replaced by the average values between the observed points and all points in the region.

In the cases of soil properties exhibiting non-stationary behavior called drift ([69]), the mean values of soil properties are not constant even within small neighborhoods but depends on position within the field ([70]). Universal kriging provides an unbiased linear estimator when a drift is present. The universal kriging variance is usually larger than that with ordinary kriging because of the uncertainty associated with modeling the drift functions ([66]). The detailed mathematical explanation of universal kriging is referred to Webster and Burgess ([66]) and Bregt et al. ([71]).

Disjunctive kriging represents a form of nonlinear kriging which offers an improvement over linear kriging methods ([65, 72]). For disjunctive kriging unknown functions must be determined that may or may not be linear. When these functions are linear and the random function is multivariate normal, the disjunctive kriging method is identical to ordinary kriging. One important advantage the disjunctive kriging method has over ordinary kriging is that an estimate of the conditional probability that the value at an estimation site is greater than an arbitrary critical value, can be calculated ([6, 73, 74]). This conditional probability is a useful means for determining the risk of various management alternatives and plays an important role when the user is interested in determining the chances that a variable is above some threshold level.

Kriging has been applied to quantify variabilities of various spatial variables in soil science. Yost et al. ([22, 23]) used variograms and kriging for geostatistical analyses of soil chemical properties in large land areas. Vauclin et al. ([13]) and ten Berge et al. ([14]) utilized kriging to analyze spatial variability of soil surface temperature. Using kriging Vauclin et al. ([30]) estimated available water content and water

content at 1/3 bar. Kitanidis and Vomvoris ([75]) used kriging and inverse methods to identify permeability distributions in groundwater modeling. Tabor et al. ([76]) used variogram and kriging to determine the spatial variability of nitrates in cotton petioles. They ([77]) also analyzed spatial variability of soil nitrate and correlated variables: contents of sand, silt, and clay, pH, electric conductivity, sodium, potassium, and phosphorus in an irrigated cotton field. Xu and Webster ([78]) applied kriging to study of top soil properties in Zhangwu County, China. By minimizing kriging variance, Webster and Burgess ([79]) described sampling and bulking strategies soil properties. Davidoff et al. ([15]) presented a method to verify the presence of a trend in studying spatial variability of soil temperature. Ahmed and Marsily ([80]) estimated transmissivity in an area 80 x 40 km using kriging combined with linear regression, kriging with an external drift, and kriging with a guess field. Webster and McBratney ([26]) developed maps of soil fertility at Broom's Barn by simple kriging. Wilson et al. ([81]) performed universal kriging to study spatial dependence of soil-water potentials associated with septic systems. Stein et al. ([82]) predicted 30-year average moisture deficits by means of kriging. Mulla ([83]) used kriging to estimate spatial patterns in clay and sand contents at 5-m spacing along two 660-m transects. Then spatial distributions of soil matric suction and hydraulic conductivity were estimated. Istok and Cooper ([84]), Cooper and Istok ([52, 54]) applied kriging to study groundwater contamination. Voltz and Webster ([85]) compared kriging, cubic splines and soil classification for predicting topsoil clay content. Bregt et al. ([71]) constructed isolinear maps of soil water deficit with empirical confidence limits using ordinary and universal kriging. Gallichand et al. ([86, 87]) showed that kriging improved the representation of hydraulic conductivity for subsurface drainage design. Kriging allowed clear identification as contour maps that could be used to determine homogeneous block hydraulic conductivity. Gallicharnd et al. ([87, 88]) presented a procedure to consider uncertainty of hydraulic conductivity and water depth into drainage design, suing block kriging to estimate the effective hydraulic conductivity of square blocks with sides equal to the lateral drain spacing. Using kriging technique, Bregt et al. ([89]) produced the conditional probability maps of the depth from the surface to the pyritic layer in a study area of 410 ha. Samra and Gill ([90]) used kriged results to assess variations of pH and sodium adsorption ratio in a sodium-contaminated soil and associated tree growth. Kravchenko et al. ([91]) applied variograms and kriging to estimate spatial variability of soil hydraulic properties in Russia. Using disjunctive kriging, Yates et al. ([92, 93]) presented spatial distributions and corresponding conditional probability maps of soil electrical conductivity. In the context of viral contamination, Yates and Yates ([94]) used disjunctive kriging as an approach to management decision making. Webster ([95]) used disjunctive kriging to estimate the likelihood of copper and cobalt in the soil.

Cokriging

Cokriging, which has been introduced into the soil sciences more recently ([12]), uses two or more regionalized variables simultaneously, and in such a manner that the spatial correlation information from each variable aids in the interpolation process. The theory and practice of cokriging is a logical extension of kriging to situations where two or more variables are spatially interdependent. Cokriging is preferable to kriging in the cases of: i) the under sampled problem -- where one variable is more costly or more difficult to obtain than the other; and ii) sparse apparent sampling density -- where variables are sampled at different locations with only minimal coincident sampling necessary to calculate the cross-variograms. Theoretically, if regionalized variables are correlated with one another, there should be an overall improvement in the quality of the estimate based on the comparison between the kriging and cokriging variances. Also, there is often a great potential for reducing the sampling density required for appraising and mapping soil properties by using an under-sampling strategy. Cokriging allows an improvement in the estimation of the variable of primary interest without additional sampling. This may translate into a more efficient sampling scheme.

When two spatially random variables $Z_1(x)$ and $Z_2(x)$ are sampled, and a significant correlation between the two variables exists, the added information due to this correlation can be used to improve the estimate at an unsampled location ([12, 30, 80]). The added information enters the interpolation through the cross-variogram function which gives the correlation between two variables as a function of separation distance. The cross-variogram function is analogous to the variogram function and is a measure of the correlation in space between two regionalized variables. The moment estimator of the cross-variogram is given by

$$\gamma^{*}_{12}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z_1(x_i) - Z_1(x_i + h) \right] \left[Z_2(x_i) - Z_2(x_i + h) \right] \quad [14]$$

To properly execute cokriging, it is necessary to have two variograms (one for each variable) and one cross-variogram for every pair of correlated regionalized variables in the cokriging system.

A cokriging estimate is a weighted average of the available data with weights chosen so that the estimate is unbiased and has minimum variance, analogous to ordinary kriging. The cokriging estimator for two variables is in the

form of ([96, 97])

$$Z_1^*(x_0) = \sum_{i=1}^{k} \lambda_{1i} Z_1(x_i) + \sum_{j=1}^{k'} \lambda_{2j} Z_2(x_j) \quad [15]$$

$$\sum_{i=1}^{k} \lambda_i = 1 \qquad \sum_{j=1}^{k'} \lambda_j = 0 \quad [16]$$

where k and k' are the numbers of samples of $Z_1(x)$ and $Z_2(x)$ used to estimate the unsampled point, x_0, and λ_1 and λ_2 are the associated weighing factors for $Z_1(x)$ and $Z_2(x)$, respectively. Although in most cases estimates of only one of the random functions is desired, such as in the under-sampled problem, the complete cokriging solution will enable estimation of all correlated functions simultaneously ([96 - 98]). In theory it is possible to use an unlimited number of variables in the cokriging system, in practice however, three or four is the most that can be handled efficiently.

The key step in cokriging is to formulate cross-variograms of random variables. Standard approaches for modeling cross-variograms are usually based on sums or differences of two random variables that are measured at the same locations. One disadvantage to standard cokriging is that only common locations can be used to estimate the cross-variogram. Estimating cross-variograms requires a large number of locations where data are collected for both variables, a condition that is usually not satisfied in practice. Clark et al. ([99]) presented a variation of cokriging, using pseudo-cross-variograms. The approach does not require a large number of common locations where data are available for all variables. Myers ([100]) gave a general definition of the pseudo-cross-variogram as

$$\gamma_{12}(h) = \gamma_{21}(-h) = \frac{1}{2} Var[Z_1(x) - Z_2(x+h)] \quad [17]$$

The sample pseudo-cross-variograms for variable 1 (Z_1) and variable 2 (Z_2) are computed by means of

$$\gamma_{12}^*(h) = \frac{1}{2N} \sum_{i=1}^{N} [Z_1(x_i) - Z_2(x_i+h)]^2 \quad [18]$$

and

$$\gamma_{21}^*(h) = \frac{1}{2N} \sum_{i=1}^{N} [Z_2(x_i) - Z_1(x_i+h)]^2 \quad [19]$$

Replacing cross-variograms in the cokriging estimator with pseudo-cross-variograms yields the pseudo-cokriging equations ([100]).

Cokriging was applied to interpolate and map the silt content of topsoil, taking account of the co-regionalized silt and sand contents of the subsoils by McBratney and Webster ([48]). Vauclin et al. ([30]) estimated available water content and water content at 1/3 bar using cokriging with measured data of sand, silt and clay contents. Ahmed and Marsily ([80]) estimated transmissivity in a large field using cokriging with data on transmissivity and specific capacity. Utilizing cokriging, Hoeksema et al. ([101]) estimated water table elevation at unsampled locations based on values of water table elevation and ground surface elevation measured at wells and at points along flowing streams. Using simulations of 500 observations in an area of 404 ha of sandy soils, Stein et al. ([10, 11, 82, 102]) predicted 30-year average moisture deficits by means of kriging and cokriging. In general, soil surface temperature is much less time consuming and labor intensive than measurements of water content. Mulla ([83]) used measured data of surface temperature at 5-m spacing and soil water content at 20-m spacing along with cokriging techniques to estimate water content at 5-m spacing on two 660-m transects. Yates ([103]) utilized disjunctive cokriging to assess soil salinity. Yates and Warrick ([12]) estimate soil water content using cokriging with the auxiliary data of bare soil surface temperature and sand content. Zhang et al. ([33]) improved soil textural estimates using spectral properties and cokriging. Using kriging and cokriging, Zhang et al. ([104]) estimated trace elements in soils and plants. Zhang et al. ([28]) used cokriging with symmetric pseudo-cross-variograms to estimate the spatial distribution of soil chemicals, NO_3 and Ca. Applying cokriging with non-symmetric pseudo-cross-variograms, Zhang et al. ([29]) determined solute mass and distribution computations in a large soil field.

Other Applications

Based on the spatial structure, the variogram, sampling strategies have been developed to maximize sampling accuracy, while minimize sampling number therefore sampling costs ([33, 105]). McBratney and Webster ([47, 48]) described a geostatistical method for designing optimal sampling schemes for local estimation and mapping of regionalized variables of soils. Russo ([106]) and Warrick and Myers ([107]) presented methods for optimizing the selection of sampling locations for variogram calculations. Flatman and Yfantis ([108]) developed geostatistical strategy for soil sampling. Through geostatistical analyses, Zhang et al. ([50]) developed relationships of variance as a function of sample support sizes. Hardy et al. ([109]) initiated a geostatistical analysis using regraded spoil sampling data to design optimal sampling strategies for spoil characterization. Zhang et al. ([51]) related plot shape effect and optimum plot sizes to soil

heterogeneity and spatial variability.

Monte Carlo simulations are powerful tools for stochastic modeling of water flow and chemical transport in heterogeneous soils. The first step of Monte Carlo simulations is to generate random fields of hydraulic properties (such as soil hydraulic conductivity) and chemical properties (such as dispersivity and adsorption coefficient for adsorbing chemicals). Based on knowledge of the mean, variance, and variogram of physical and chemical parameters, their random distributions can be generated using unconditional or conditional simulations. Random field generators based on geostatistical methods include the turning bands method ([110, 111]) and the fast Fourier transform method (FFT) ([111, 112]). Zhang and Yang ([113]) developed an iterative solution to solve a stochastic differential equation and provided an efficient method for simulating soil variability.

Dagan ([114]) conducted stochastic modeling of water flow and solute transport in groundwater by unconditional and conditional simulations of hydraulic conductivity and transmissivity. Russo and Bresler ([39, 40]) treated soil hydraulic properties as stochastic processes and analyzed their spatial variability and estimate errors in heterogenous fields. Morkoc et al. ([115]) analyzed sorghum yield related to soil heterogeneity using a stochastic approach. Silliman and Wright ([116]) applied conditional simulations for stochastic analysis of the paths of high hydraulic conductivity in porous media. Graham and McLaughlin ([117]) used geostatistical methods to produce random velocity fields for stochastic analysis of nonstationary subsurface solute transport. Using conditional simulations of the log transmissivity, Rubin and Dagan ([118]) studied impact of transmissivity measurements on solute travel time in heterogeneous formations. Bellin et al. ([119]) simulated dispersion in heterogeneous porous formations using stochastic modeling with random distributions of the log transmissivity generated with the FFT method. To simulate field measurements of hydraulic conductivity in unsaturated heterogeneous soils, Russo ([120]) and Tseng and Jury ([121]) used the turning band method to generate random fields of a scaling factor which was used to describe soil heterogeneity. Polmann et al. ([122]) applied geostatistical methods to characterize spatial variability and heterogeneity of soil retention and hydraulic functions and generated random space functions of the hydraulic properties for stochastic modeling of large-scale flow in heterogeneous unsaturated soils. Yang et al. ([123, 124]) conducted stochastic analyses of adsorbing solute transport in two- and three-dimensional, heterogeneous, unsaturated soils, using unconditional simulations to characterize random fields of soil retention and hydraulic conductivity functions as well as adsorption coefficient for adsorbing chemicals.

Through theoretical analyses of hydraulic head variograms, Chirlin and Dagan ([125]) provided the insight of the head spatial variations for steady flow in statistically homogeneous aquifers. Sisson and Wierenga ([35]) and Vieira et al. ([36]) studied spatial variability of field infiltration rates. Other geostatistical analyses of infiltration rates include Bautista and Wallander ([37]), Cressie and Horton ([38]), and Berndtsson and Larson ([126]). Hoeksema and Kitanidis ([127]) applied the geostatistical approach to estimate transmissivity from hydraulic head and transmissivity measurements for two-dimensional groundwater modeling. Russo ([128]) presented a geostatistical approach to the trickle irrigation design in heterogeneous soils. He ([129]) also utilized a geostatistical approach to investigate the spatial variability of three soil properties: the saturated hydraulic conductivity, the soil characteristic parameter, and the dispersivity, as well as the initial salinity for solute transport in heterogeneous fields. Conditional simulations were conducted to analyze the salinity profile and its spatial distribution during leaching in a 187-ha plot of land and applied for salinity management. Yeh et al. ([18]) estimated spatial variability of soil-water pressure in a field soil. Cohen et al. ([130]) used variograms of digital imagery for evaluating conifer canopy structure. Using fractal and geostatistical analyses of over 130 longitudinal dispersivities, Neuman ([131]) proposed a universal scaling rule for hydraulic conductivities and dispersivities. He concluded that log hydraulic conductivities constitute a self-similar random field with homogeneous increments characterized by a variogram $\gamma(s) = cs^{1/2}$. Mohanty et al. ([132]) proposed a robust-resistant geostatistical approach to interpret spatial behavior of saturated hydraulic conductivity of a glacial till soil under no-tillage system. Mohanty and Kanwar ([133]) analyzed spatial variability of residual nitrate-nitrogen under tillage systems, using a composite three-dimensional resistant and exploratory approach. Woodbury and Sudicky ([134]) performed geostatistical characterization of hydraulic conductivity at the Borden aquifer in Canada. Desbarats and Srivastava ([135]) applied a geostatistical framework to characterize the heterogeneous transmissivity field and corresponding steady-state head and discharge fields. Woldt and Bogardi ([136]) described a methodology for groundwater monitoring network design using multiple criteria decision making and geostatistics. Miyamoto and Cruz ([42]) assessed spatial variability of soil salinity in furrow-irrigated soils. Yates et al. ([43]) used geostatistics to describe chemical distributions of salt-affected soils. Using geostatistical and stochastic analyses, Dagan ([137]) related the scale-dependent transport processes to soil heterogeneity. Neuman ([138]) studied scale-dependent permeability and flow velocity fields through fractal and geostatistical analyses. Zhang et al. ([139]) analyzed spatial and temporal distributions of precipitation in Wyoming using geostatistics. Rahman et al. ([140]) evaluated spatial variability of Rocky Mountain forest soils using conventional statistics and geostatistics. Di Federico and Neuman ([141]) developed scaling methods for random fields of hydraulic conductivities and dispersivities by means of truncated power variograms and associated spectra.

SUMMARY

In this paper, we briefly reviewed several geostatistical methods commonly used in soil science: variogram construction, simple kriging, ordinary kriging, block kriging, universal kriging, disjunctive kriging, cokriging, and pseudo-cokriging. During the past two decades, geostatistics has been applied in soil science to study spatial variability and heterogeneity, estimate spatial and temporal distributions, design optimum sampling strategies of soil properties, and conduct stochastic modeling of water flow and chemical transport in heterogeneous soils. Geostatistical analyses have been used to study numerous properties and transport processes in soil science, such as soil texture, structure, soil water content, soil water retention, soil hydraulic conductivity, transmissivity, permeability, dispersivity, infiltration rate, pressure head, groundwater depth, soil temperature, soil chemicals, pH, electric conductivity, soil salinity, soil adsorbing coefficient of reactive chemicals, trace elements in soils and plants, crop yields, and precipitation. As a continuing trend, geostatistics is being combined with other advanced techniques, such as geographic information system and numerical modeling ([142]), and becoming a powerful tool for studying large-scale problems in agriculture and the environment.

REFERENCES

[1] David, M., 1977, Geostatistical Ore Reserve Estimation. Elsevier Scientific Publ. Co., Amsterdam, The Netherlands.

[2] Clark, I., 1979, Practical Geostatistics. Applied Science Publ., London, U.K.

[3] Henely, S., 1981, Nonparimetric geostatistics. Applied Science Publ., Halsteaad Press, John Wiley and Sons, New York, NY.

[4] Isaaks, H. E., and Srivastava, R. M., 1989, An introduction to applied geostatistics. Oxford University Press Inc., Oxford, UK.

[5] Matheron, G. 1963, Econ. Geol. 58, 1246-1266.

[6] Journel, A. G., and Huijbregts, C. J., 1978, Mining Geostatistics. Academic Press, London, U.K.

[7] Warrick, A. W., and Nielsen, D. R., 1980, Spatial variability of soil physical properties in the field, D. Hillel (Ed.), Applications of soil physics. Academic Press, New York, p. 319-344.

[8] Warrick, A. W., Myers, D. E., and Nielsen, D. R., 1986, Geostatistical methods applied to soil science, A. Klute (Ed.) Methods of soil analysis. Part 1. 2nd ed. Agronomy, p. 53-82.

[9] Webster, R., 1985, Adv. Soil Sci. 3, 1-70.

[10] Stein, A., Hoogerwerf, M., and Bouma, J., 1988, Geoderma, 43, 163-177.

[11] Stein, A., van Eijmsbergen,A. C., and Barendregt, L. G., 1991. Math. Geol., 23, 703-719.

[12] Yates, S. R., and Warrick, A. W., 1987, Soil Sci. Soc. Am. J., 51, 23-30.

[13] Vauclin, M., Vieira, S. R., Bernard, R., and Hatfield, J. L., 1982, Water Resour. Res. 18, 1677-1686.

[14] ten Berge, H. F. M., Stroosnijder, L., Burrough, P. A., Bregt, A. K., and de Heus, M. J., 1983, Agric. Water. Manage, 6, 213-226.

[15] Davidoff, B., Lewis, J. W., and Selim, H. M., 1986, Soil Sci. Soc. Am. J., 50, 1122-1127.

[16] Saddiq, M. H., Wierrenga, P. J., Hendrickx, J. M. H., and Hussain, M. Y., 1985, Soil Sci., 140, 126-132.

[17] Hamlett, J. M., Horton, R., and Cressie, N. A. C., 1986, Soil Sci. Soc. Am. J., 50, 868-875.

[18] Yeh, T. C. J., Gelhar, L. W., and Wierrenga, P. J., 1986, Soil Sci., 142, 7-12.

[19] Campbell, J. B., 1978, Soil Sci. Soc. Am. J., 42, 599-620.

[20] Gajem, Y. M.,Warrick, A. W., and Myers, D. E., 1981, Soil Sci. Soc. Am. J., 45, 709-715.

[21] McBratney, A. B., Webster, R., McLaren, R. G., and Spiers, R. B., 1982, Agronomie, 2, 969-982.

[22] Yost, R. S., Uehara, G., and Fox, R. L., 1982, Soil Sci. Soc. Am. J., 46, 1028-1032.

[23] Yost, R. S., Uehara, G., and Fox, R. L., 1982, Soil Sci. Soc. Am. J., 46, 1033-1037.

[24] van der Zaag, P., Yost, R. S., Trangmar, B. B., Hayashi, K., and Fox, R. L., 1984, Geoderma, 34, 293-314.

[25] Trangmar, B. B., Yost, R. S., and Uehara, G., 1985, Adv. Agron., 38, 45-94.

[26] Webster, R., and McBratney, A. B., 1987, J. Sci. Food Agric., 38, 97-115.

[27] Samra, J. S., Sharma, K. N. S., and Tyangi, N. K., 1988, Soil Sci., 145, 180-187.

[28] Zhang, R. Myers, D. E., and Warrick, A. W., 1992, Soil Sci. Soc. Am. J., 56, 1444-1452.

[29] Zhang, R., Shouse, P., and Yates, S., 1997, Soil Sci. Soc. Am. J., (in press).

[30] Vauclin, M., Vieira, S. R., Vachaud, G., and Nielsen, D. R., 1983, Soil Sci. Soc. Am. J., 47, 175-184.

[31] Ovalles, F. A., and Collins, M. E., 1988, Soil Sci. Soc. Am. J., 52, 1702-1707.

[32] Shouse, P. J., Gerik, T. J., Russell, W. B., and Cassel, K. D., 1990, Soil Sci., 149, 351-360.

[33] Zhang, R., Warrick, A. W., and Myers, D. E., 1992, Geoderma, 52, 223-234.

[34] Selim, H. M., Davidoff, B., Flühler, H., and Schulin, R., 1987, Soil Sci., 144, 442-452.

[35] Sisson, J. B., and Wierenga, P. J., 1981, Soil Sci. Soc. Am. J., 45, 699-704.

[36] Vieira, S. R., Nielsen, D. R., and Biggar, J. W., 1981, Soil Sci. Soc. Am. J., 45, 1040-1048.

[37] Bautista, E., and Wallender, W. W., 1985, Trans.

ASAE, 28, 1846-1851.
[38] Cressie, N. A. C., and Horton, R., 1987, Water Resour. Res., 23, 911-917.
[39] Russo, D., and Bresler, E., 1981, Soil Sci. Soc. Am. J., 45, 682-687.
[40] Russo, D., and Bresler, E., 1982, Soil Sci. Soc. Am. J., 46, 20-26.
[41] Hajrasulliha, S., Baniabbassi, N., Metthey, J., and Neilsen, D.R., 1980, Irr. Sci., 1, 197-208.
[42] Miyamoto, S., and Cruz, I., 1987, Soil Sci. Soc. Am. J., 51, 1019-1025.
[43] Yates, S. R., Zhang, R., Shouse, P. J., and van Genuchten, M. Th., 1993, Use of geostatistics in the description of salt-affected soils, D. Russo and G. Dagan (Ed.), Water flow and solute transport in soils. Springer-Verlag, New York, p. 283-304.
[44] Mulla, D. J., 1988, USA. Earth Surf. Proc. and Landforms, 13, 389-405.
[45] Burgess, T. M., Webster, R., and McBratney, A. B., 1981, J. Soil Sci., 32, 643-659.
[46] McBratney, A. B., and Webster, R., 1981, Computers Geosci., 7, 335-365.
[47] McBratney, A. B., and Webster, R., 1983, Soil Sci., 135, 177-183.
[48] McBratney, A. B., and Webster, R., 1983, J. Soil Sci., 34, 137-162.
[49] McBratney, A. B., Webster, R., and Burgess, T. M., 1981, Computers Geosci., 7, 331-334.
[50] Zhang, R., Warrick, A. W., and Myers, D. E., 1990, Math. Geol., 22, 107-121.
[51] Zhang, R., Warrick, A. W., and Myers, D. E., 1993, Geoderma, 62, 183-197.
[52] Cooper, R. M., and Istok, J. D., 1988, J. Env. Eng., 144, 270-286.
[53] Rendu, J. M., 1978, An introduction to geostatistical methods of mineral evaluation. South Africa Instit. Min. and Metal., Johannesburg, South Africa.
[54] Cooper, R. M., and Istok, J. D., 1988, J. Environ. Engin., 114, 287-299.
[55] Armstrong, M., and Jabin, R., 1981, J. Int. Assoc. Math. Geol., 13, 455-459.
[56] McBratney, A. B., and Webster, R., 1986, J. Soil Sci., 37, 617-639.
[57] Cressie, N. A. C., 1985, J. Int. Assoc. Math. Geol., 17, 563-586.
[58] Kitanidis, P. K., 1983, Water Resour. Res., 19, 909-921.
[59] Russo, D., and Jury, W. A., 1987, Water Resour. Res., 23, 1257-1268.
[60] Cressie, N. A. C., and Hawkins, D. M., 1980, J. Int. Assoc. Math. Geol., 12, 115-125.
[61] Armstrong, M., 1984, J. Int. Assoc. Math. Geol., 16, 305-313.
[62] Delhomme, J. P., 1976, Adv. Water Resour., 1, 251-266.
[63] Davis, B. M., 1987, J. Int. Assoc. Math. Geol., 19, 241-248.
[64] Krige, D. G., 1966, J. South African Inst. Min. Metal., 66, 13-38.
[65] Matheron, G. 1976. A simple substitute for conditional expectation: The disjunctive kriging, M. Guarascia et al., (Ed.), Advanced geostatistics in the mining industry. Reidel Publ. Co., Dordrecht, The Netherlands, p. 221-236.
[66] Webster, R., and Burgess, T. M., 1980, J. Soil Sci., 31, 505-524.
[67] Oliver, M. A., 1987, Soil Use Manage, 3, 8-19.
[68] Burgess, T. M., and Webster, R., 1980, J. Soil Sci., 31, 315-331.
[69] Starks, T. H. and Fang, J. F., 1982, J. Int. Assoc. Math. Geol., 14, 309-319.
[70] Cressie, N. A. C., 1986, J. Am. Stat. Assoc., 81, 625-634.
[71] Bregt, A.K., McBratney, A. B., and Wopereis, M. C. S., 1991, Soil Sci. Soc. Am. J., 55, 14-19.
[72] Matheron, G., and Armstrong, M., 1986, J. Int. Assoc. Math. Geol., 18, 711-742.
[73] Kim, Y. C., Myers, D. E., and Knudsen, H. P., 1977, Advanced geostatistics in ore reserve estimation and mine planning (practitioner's guide). Report to the U. S. Energy Research and Development Administration, Subcontract No. 76-003-e, Phase II.
[74] Rendu, J. M., 1980, J. Int. Assoc. Math. Geol., 12, 306-321.
[75] Kitanidis, P. K., and Vomvoris, E. G., 1983, Water Resour. Res., 19, 677-690.
[76] Tabor, J. A., Warrick, A. W., Pennington, D. A., and Myers, D. E., 1984, Soil Sci. Soc. Am. J., 48, 602-607.
[77] Tabor, J. A., Warrick, A. W., Myers, D. E., and Pennington, D. A., 1985, Soil Sci. Soc. Am. J., 49, 390-394.
[78] Xu, J., and Webster, R., 1984, Catena, 11, 13-26.
[79] Webster, R., and Burgess, T. M., 1985, Soil Sci., 35, 127-140.
[80] Ahmed, S., and de Marsily, G., 1987, Water Resour. Res., 23, 1717-1737.
[81] Wilson, G.V., Scott, H. D., and Marx, D. B., 1987, Soil Sci., 144, 159-166.
[82] Stein, A., van Dooremolen, W., Bouma, J., and Bregt, A. K., 1988, Soil Sci. Soc. Am. J. 52, 1418-1423.
[83] Mulla, D.J., 1988, Soil Sci. Soc. Am. J., 52, 1547-1553.
[84] Istok, J. D., and Cooper, R. M., 1988, J. Environ. Engin., 114, 915-928.
[85] Voltz, M., and Webster, R., 1990, J. Soil Sci., 41, 473-490.
[86] Gallichand, J., Prasher, S. O., Broughton, R. S., and Marcotte, D., 1991, J. Irr. and Drain. Engin., 117, 667-

691.
[87] Gallichand, J., Marcotte, D., and Prasher, S. O., 1992, J. Irr. and Drain. Engin., 118, 744-756.
[88] Gallichand, J., Marcotte, D., Prasher, S. O.,and Broughton, R. S., 1992, Agricultural Water Management, 20, 299-312.
[89] Bregt, A. K., Gesink, H. J., and Alkasuma, 1992, Geoderma, 53, 15-29.
[90] Samra, J. S., and Gill, H. S., 1993, Soil Sci., 155, 148-153.
[91] Kravchenko, A., Shein, E., and Zhang, R., 1995, Hydrol. Sci. and Tech., 11, 175-184.
[92] Yates, S. R., Warrick, A. W., and Myers, D. E., 1986, Water Resour. Res., 22, 615-622.
[93] Yates, S. R., Warrick, A. W., and Myers, D. E., 1986, Water Resour. Res., 22:623-630.
[94] Yates, S. R., and Yates, M. V., 1989, Soil Sci. Soc. Am. J., 52, 1554-1558.
[95] Webster, R., 1991, J. Soil Sci., 42, 301-318.
[96] Myers, D. E., 1982, J. Int. Assoc. Math. Geol., 14, 249-257.
[97] Myers, D. E., 1984, Co-kriging - new developments. G. Verly et al., (Ed.) Geostatistics for natural resources characterization. Part I. Reidel Publ. Co., Dordrecht, The Netherlands, p. 295-305.
[98] Carr, J. R., Myers, D. E., and Glass, C. E., 1985, Computers and Geosci., 11, 111-127.
[99] Clark, I., K.L. Basinger and W.V. Harper. 1989. MUCK-a novel approach to co-kriging. Proceedings of the Conference on Geostatistical, Sensitivity and Uncertainty Methods for Ground-water Flow and Radionuclide Transport Modeling, B. E. Buxton (Ed.), Batelle Press, Columbus, OH. p. 473-494.
[100] Myers, D. E., 1991, Math. Geol., 23, 805-816.
[101] Hoeksema, R. J., Clapp, R. B., Thomas, A. L., Hunley, A. E., Farrow, N. D., and Dearstone, K. C., 1989, Water Resour. Res., 25, 429-438.
[102] Stein, A., Staritsky, I. G., Bouma, J., Van Eijnsbergen, A. C., and Bregt, A. K., 1991, Water Resour. Res., 27, 1963-1973.
[103] Yates, S. R., 1986, Water Resour. Res., 22, 1371-1376.
[104] Zhang, R., Rahman, S., Vance, G. F., and Munn, L. C., 1995, Soil Sci., 159, 383-390.
[105] Burgess, T. M., and Webster, R., 1984, J. Soil Sci., 35, 641-654.
[106] Russo, D., 1984, Soil Sci. Soc. Am. J., 48, 708-716.
[107] Warrick, A. W., and Myers, D. E., 1987, Water Resour. Res. 23, 496-500.
[108] Flatman, G. T., and Yfantis, A. A., 1984, Environ. Monitor. and Assess., 4, 335-349.
[109] Hardy, C. K., Dollhopf, D. J., and Quimby, W. F., 1991, Soil Sci., 151, 1-6.
[110] Mantoglou, A., and Wilson, J. L., 1982, Water Resour. Res., 18, 1379-1394.
[111] Tompson, A.F.B., Ababou, R., and Gelhar, L.W., 1989, Water Resour. Res., 25, 2227-2243.
[112] Gutjahr, A. L., Bullard, B., Hatch, S., and Hughson, L., 1994, Stoch. Hydrol. Hydr., 8, 79-108.
[113] Zhang, R., and Yang, J., 1996, Geoderma, 72, 75-88.
[114] Dagan, G., 1982, Water Resour. Res., 18, 813-833.
[115] Morkoc, F., Biggar, J. W., Miller, R. J., and Nielsen, D. R., 1985, Soil Sci. Soc. Am. J., 49, 1342-1347.
[116] Silliman, S. E., and Wright, A. L., 1988, Water Resour. Res., 24, 1901-1910.
[117] Graham, W., and McLaughlin, D., 1989, Water Resour. Res., 25, 215-232.
[118] Rubin, Y., and Dagan, G., 1992, Water Resour. Res., 28, 1033-1040.
[119] Bellin, A., Salandin, P., and Rinaldo, A., 1992, Water Resour. Res., 28, 2211-2227
[120] Russo, D., 1991, Water Resour. Res., 27, 267-283.
[121] Tseng, P., and Jury, W. A., 1993, Water Resour. Res., 29, 2087-2099.
[122] Polmann, D.J., McLaughlin, D., Luis, S., Gelhar, L. W., and Arabou, R., 1991, Water Resour. Res., 27, 1447-1458.
[123] Yang, J., Zhang, R., Wu, J., and Allen, M. B., 1996, Water Resour. Res., 32, 2747-2756.
[124] Yang, J., Zhang, R., Wu, J., and Allen, M. B., 1997, Water Resour. Res., (in press).
[125] Chirlin, G. R., and Dagan, G., 1980, Water Resour. Res., 16, 1001-1015.
[126] Berndtsson, R., and Larson, M., 1987, J. Hydrol., 90, 117-133.
[127] Hoeksema, R. J., and Kitanidis, P. K., 1984, Water Resour. Res., 20, 1003-1020.
[128] Russo, D., 1984, Water Resour. Res., 20, 543-552.
[129] Russo, D., 1984, Water Resour. Res., 20, 1260-1270.
[130] Cohen, W. B., Spies, T. A., and Bradshaw, G. A., 1990, Remote Sens. Environ., 34, 167-178.
[131] Neuman, S. P., 1990, Water Resour. Res., 26, 1749-1758.
[132] Mohanty, B. P., Kanwar, R. S., and Horton, R., 1991, Water Resour. Res., 27, 2979-2992.
[133] Mohanty, B. P., and Kanwar, R. S., 1994, Water Resour. Res., 30, 237-251.
[134] Woodbury, A. D., and Sudicky, E. A., 1991, Water Resour. Res., 27, 533-546.
[135] Desbarats, A. J., and Srivastava, R. M., 1991, Water Resour. Res., 27, 687-698.
[136] Woldt, W., and Bogardi, I., 1992, Water Resour. Bull., 28, 45-62.
[137] Dagan, G., 1994, Water Resour. Res., 30, 3327-3336.
[138] Neuman, S. P., 1995, Water Resour. Res., 31, 1455-1460.
[139] Zhang, R., A. Kravchenko, and Y. Tung, 1995. Spatial and temporal distributions of precipitation in

Wyoming. Proceeding of Fifteenth Annual American Geophysical Union, Hydrology Days, Fort Collins, Colorado, p. 377-388.

[140] Rahman, S., Munn, L. C., Zhang, R., and Vance, G. F., 1996, Canadian J. Soil Sci., 76, 501-507.

[141] Di Federico, V., and Neuman, S. P., 1997, Water Resour. Res., 33, 1075-1085.

[142] Zhang, R., Hamerlinck, J. D., Gloss, S. P., and Munn, L., 1996, J. Environ. Quality, 25, 411-418.