



Stochastic simulation of soil water status on reclaimed land in northern Alberta

¹Mapfumo E., ²Chanasyk D.S., and ³Chaikowsky C.L.A.

Abstract

Studies of spatial variability and simulation of available soil water and extractable soil water are scarce and yet such data are essential in hydrologic and solute transport modeling. A study was conducted to characterize spatial variability of available soil water and extractable soil water on a reclaimed site in northern Alberta. The vegetation on site included grasses, legumes and shrubs. The site was reclaimed and the reconstructed profile was made up of 40-100 cm of clay loam/peat material overlying fine tailings sand. Soil water was measured using neutron moisture meters on a frequency of approximately two weeks during the growing season for a 2-year period. Spatial characterizations of available soil water (ASW) and extractable soil water (ESW) on the driest and wettest measurement days were conducted using geostatistical methods. A sample semi-variogram was estimated and several permissible theoretical models fitted and the model of best fit was determined using the Akaike Information Criterion (AIC). The spherical model was found to best represent the semi-variogram for available soil water and extractable soil water. Both the available soil water and extractable soil water had very high degrees of spatial dependence (> 99%) and the range of within which sample points were auto-correlated was less than 1 m. The conditional stochastic simulation of extractable soil water at unsampled locations that were 5 m north of the sampled locations indicated a high degree of uncertainty. This implies that generation of exhaustive data sets may require more sampling points at closer spacing to reduce uncertainty.

Key words: geostatistics, spatial variability, semi-variogram, uncertainty

Introduction

Soil water may vary spatially due to variation in soil textural and structural properties as well as changes in micro-topography. Due to this variation in space, soil sampling or measurements at a finite number of places often gives incomplete pictures (Heuvelink and Webster 2001). Quite often, there is a need for us to predict between sampling points in order to construct a map of a soil property under consideration, such as soil water. Geostatistics provides a set of tools for incorporating the spatial coordinates of soil observations in data processing and thus allows description and modeling of spatial patterns and prediction at unsampled intervals (Goorvaerts 1998). Such predictions aid in generating exhaustive grid data sets that could be used in hydrologic and solute transport modeling. Spatial characterization over different scales has become invaluable in various fields of study such as soil management and soil mapping (Schloeder et al. 2001). Characterization of the spatial variability of soil properties such as available soil water, extractable soil water may be described using semi-variograms (also referred to as variograms). The semi-variogram is a standard statistical measure of spatial variability and represents a measure of the average similarity between points at a specific distance apart (Webster and Oliver 2001).

¹Soil Science and Plant Nutrition, School of Earth and Geographical Sciences, University of Western Australia, 35 Stirling Highway, Crawley 6009, Australia

^{2,3}Department of Renewable Resources, University of Alberta, Edmonton Alberta, Canada T6G 2H1

Corresponding author e-mail: emapfumo@cyllene.uwa.edu.au

Often the computation of the semi-variogram is not the final goal by itself, but is a prerequisite for the estimation of values at unsampled points through kriging and/or stochastic simulation. Ordinary kriging is an interpolation procedure that utilizes various equations to estimate values of unsampled points on a grid through minimization of the error variance. However, kriging is widely reported to overestimate small values and underestimate large values (Goovaerts 1998). Stochastic simulation, on the other hand, tends to preserve the sample variogram and may be useful in developing isarithmic maps or fine grid data sets of such variables as soil water that could be used in hydrological models. Stochastic simulation has become a popular way to apply a variability model (e.g. Gaussian, spherical, exponential models) to estimate spatial patterns of soil properties. Consequently, an image generated from stochastic simulation would have the same statistical properties that the variability model prescribes (Pachepsky and Acock 1998). The objectives of this study conducted on a reclaimed site were: i) to characterize the spatial variability in available and extractable soil water, and; ii) to evaluate the use of conditional stochastic simulation for generating extractable soil water data sets at unsampled locations during wet and dry periods.

Methodology

Site description

The study was conducted in 2001 and 2002 on the slopes of the reclaimed land on the Southwest Sand Storage Facility of Syncrude Canada Ltd. approximately 50 km north of Fort McMurray, Alberta, Canada. The tailings pond measures 25 km² and is considered to be one of the largest tailings ponds in the world. The vegetation found on site included white sweet clover (*Melilotus alba*), yellow sweet clover (*Melilotus officinalis*), white clover (*Trifolium repens*), timothy grass (*Phleum spp.*), alfalfa (*Medicago sativa*), slender wheatgrass (*Agropyron trachycaulum*), sowthistle (*Sonchus arvensis*), raspberry (*Rubus idaeus*) and strawberry blite (*Chenopodium capitatum*). The topsoil was clay loam textured ranging between 40-100 cm deep overlying tailings sand. The experimental area measured about 700 m by 400 m with an average slope of 4.5 %. The area was also terraced into benches, as a sequence of downslope and backslope separated by small waterways. The area was divided into four transects running from the first waterway upwards to the tailings pond.

Thirteen aluminum access tubes were installed in each of the four transects. Geo-referencing was conducted using a global positioning system (GPS) and coordinates of longitude and latitude were determined for each access tube. Soil water was measured every two weeks using CPN 503 neutron moisture meters starting at a 15-cm depth down to 195 cm, at 10-cm depth increments. Pressure plate analysis was conducted on soil samples collected 3 m away from access tubes in 2001 for determination of field capacity (0.033 MPa) water and wilting point (1.5 MPa) water content. Available water holding capacity (AWHC) was determined as the difference between FC and WP.

Available soil water and extractable soil water

The available soil water (ASW, in mm) and extractable soil water (ESW, in mm) on each measurement date and around each access tube were computed. Each ASW value was determined as the difference in between the field total soil water (0-40 cm interval) and wilting point (WP) soil water for that depth increment. Each ESW value was computed as the difference between the field total soil water and the minimum field soil water that was measured throughout the study period. The conversion of WP to mm for the 0-40 cm depth interval was determined as the sum of products of bulk density, gravimetric water at

WP and depth increment. ASW values for each of the 52 access tube locations were computed. Also ASW values for each slope position were determined as the average of four values representing each transect.

Spatial characterization of soil water status

To characterize the spatial variability of available soil water, extractable soil water and actual evapotranspiration geostatistical perspective was applied. This approach considered a finite domain D in space, with $D \subset R^d$. We assumed that $d = 2$; hence R^2 was the two-dimensional (horizontal) space. A spatial random variable, $Z(x)$, is a variable that takes a series of outcome values (realizations) at any location in space $x \in D$ according to a probability distribution. Thus the spatial process was represented as follows;

$$\begin{aligned} \{Z(x) : x \in D\} & \text{ where } x = \text{is a spatial element in finite domain } D, \text{ and } D \subset R^2 \\ \{x_1, x_2, \dots, x_n\} & = \text{locations} \\ \{Z(x_1), Z(x_2), \dots, Z(x_n)\} & = \text{random variables at locations.} \end{aligned}$$

The empirical semi-variogram (also referred to as experimental or sample variogram) was then computed using the classical Matheron variogram estimator (Matheron 1971) described by the following equation:

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{Equation 1}$$

where $N(h)$ = number of pairs of sample points (52 points), Z = regionalized variable (e.g. available soil water), x = sample location; h = distance between sample points (25 m). Because of the irregular distances between nearest neighbor sampling points, the separation distance (h) used in the analyses was 25 m with a tolerance of 10 m. The separation distance was estimated as the approximate average distance between nearest neighbour sample points. Because of the sampling locations were irregular, a lag distance tolerance of 5 m was imposed.

Because of the classical method of moments (Matheron) variogram estimation is sensitive to outliers, an alternative estimator, the robust variogram estimator, was also used in model fitting because it is less sensitive to the influence of outliers in the data set. The robust variogram estimator was described using the following equation (Cressie and Hawkins 1980);

$$\hat{\gamma}(h) = \frac{1}{2N(h)} \frac{\left\{ \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^{0.5} \right\}^4}{0.457 + 0.494 / N(h)} \tag{Equation 2}$$

Four permissible theoretical semi-variogram models were fitted to the experimental semi-variogram as represented below;

Spherical model:

$$\left\{ \begin{array}{l} \gamma(h) = c_0 + c_1 \left[\frac{3h}{2a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right] \\ \gamma(h) = c_0 + c_1 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq a \\ \text{for } h > a \end{array} \quad \text{Equation 3}$$

Exponential model:

$$\gamma(h) = c_0 + c_1 \left\{ 1 - \exp\left(-\frac{3h}{a}\right) \right\} \quad \text{Equation 4}$$

Gaussian model:

$$\gamma(h) = c_0 + c_1 \left\{ 1 - \exp\left(-\frac{3h^2}{a^2}\right) \right\} \quad \text{Equation 5}$$

Power model:

$$\gamma(h) = c_0 + Ah^w \quad 0 < w \leq 2 \quad \text{Equation 6}$$

where $\gamma(h)$ is semi-variogram for lag h , h is the distance between observations, c_0 is the nugget effect (i.e., the variance when the lag distance is zero), $c_0 + c_1$ is the sill (i.e. the maximum variance, σ^2), and a is the range (i.e., the lag distance at which the variogram reaches the sill, also referred to as the correlation range since it is the range at which autocorrelation becomes zero). The range marks the limit of spatial dependence, such that places further apart than the range are spatially independent.

The SAS statistical package Variogram and Mixed procedures (SAS Institute Inc., 2000) were used for determination of the empirical and robust semi-variograms and fitting permissible theoretical variogram models. For each fitted model the Akaike Information Criterion (AIC) values considered in determining the model of best fit were based on achieving convergence criteria and positive definiteness, as was required before spatial moments became utilized in stochastic simulations. The model with the smallest AIC was considered to be the best model to represent the semi-variogram. The AIC was chosen because of its ability to achieve a satisfactory compromise between goodness of fit and parsimony of the model (McBratney and Webster 1986). The nugget effect was incorporated in the model because in practice, more often than not, data suggests that a spatial process is discontinuous and have a variance that jumps from zero at lag distance of zero to positive immediately away from origin.

The semi-variogram measures the spatial dependence for the property. The covariance counterpart of the variogram measure, $\gamma(h)$ for all distance and direction vectors, h , must have the mathematical property of positive definiteness, i.e., we must be able to use the variogram or its covariance counterpart in kriging and stochastic simulation. From the semi-variogram we determined the structural variance, which is the spatially structured proportion of the sample variance that is not random noise or measurement error (also referred to as the degree of spatial dependence, SD). This is defined as;

$$SD = \left(\frac{c_1}{c_1 + c_0} \right) \times 100 \quad \text{Equation 7}$$

where $c_1 + c_0 = \text{sill}$, $c_0 = \text{nugget effect}$. The value of SD was used to evaluate the spatial dependence (or independence) of available soil water and extractable soil water.

Conditional stochastic simulation of extractable soil water

Linear prediction, such as through ordinary kriging, always results in values that are 'best' in the sense that the expected squared prediction error is minimal. However, the problem is that the field with predicted values is usually smoother than the field from which observations were obtained (Pebesma and Wesseling 1998). An alternative is stochastic simulation, whereby simulations are viewed as possible realizations of a spatially correlated random field that honor the spatial moments (mean and variogram) of the field. Different simulations may be completely independent, only sharing the spatial moments (referred to as unconditional simulation) or they may, in addition, reproduce a set of observed values (referred to as conditional simulation). A single prediction at each location within the study area is called a realization. Multiple realizations can be generated to provide a better representation of possible extractable soil water values. Multiple simulations can aid in understanding the combined effect of prediction uncertainty and spatial variation of the underlying process.

Therefore, based on the semi-variogram model, conditional stochastic simulation was used to generate a number of sets of values (realizations) that aim to reproduce each sample semi-variogram and the theoretical semi-variogram model. The technique used collected data to calculate the most likely extractable soil water at unsampled locations. The SAS statistical package (**Sim2D** procedure) was used to conduct conditional stochastic simulation of unsampled locations 5 m north of each of the 52 access tubes. Each simulation run produced 3 realizations that were used to evaluate the degree of spatial uncertainty in generating exhaustive extractable soil water data sets on driest and wettest days.

All images produced from conditional stochastic simulation are equiprobable and obey the same spatial correlation model (Pachepsky and Acock 1998). As opposed to interpolation methods, stochastic simulation does not result in a single estimated map but results in a set of maps all consistent with the data actually used and the correlation model that ties them together.

Results and Discussion

Spatial dependence of soil water

Available soil water ranged from values below wilting point up to 67 mm, whereas extractable soil water ranged between 0 and 78 mm throughout the two-year study period. Tables 1 and 2 indicate values of ASW and ESW, respectively, for data averaged across transects.

Table 1. Available soil water (TSW - WP, in mm) during measurement periods in 2001 and 2002.

Date	Available H ₂ O - Tubes												
	1	2	3	4	5	6	7	8	9	10	11	12	13
----- 2001 data -----													
June 9	32.0	49.5	33.3	52.7	33.3	54.8	16.1	20.6	54.1	22.2	24.5	32.2	57.1
June 20	25.1	43.1	24.1	43.9	29.0	47.8	9.5	6.9	44.0	19.9	44.7	28.3	56.1
July 4	-4.0	6.7	-2.9	4.0	-6.6	12.1	-8.7	-13.7	10.7	-13.4	-7.1	-6.2	19.3
July 23	7.8	15.0	4.0	10.4	7.0	38.3	9.2	1.0	16.9	3.6	10.0	6.1	49.9
Aug 14	10.6	14.5	2.4	5.4	3.7	38.0	-8.8	-6.4	21.0	1.2	6.2	0.7	49.8
Aug 27	9.5	15.0	0.7	3.1	1.3	39.1	0.9	-9.2	10.8	0.3	7.5	1.1	50.4
Sept 21	10.2	13.8	-0.9	3.7	1.4	43.2	-2.2	-12.1	6.5	-6.8	5.1	-4.5	51.9
----- 2002 data -----													
May 24	19.1	40.4	22.2	49.7	23.7	61.6	8.8	7.7	55.8	21.1	7.1	13.1	61.3
Jun 4	19.2	38.8	13.1	36.4	21.9	53.5	5.5	0.5	47.4	19.3	9.0	13.3	60.3
Jun 18	17.9	25.9	-1.5	28.7	9.8	52.6	3.6	-3.1	28.7	11.4	3.1	10.1	56.1
Jul 16	9.9	10.3	-0.6	0.5	-1.1	35.3	-3.9	-15.0	-1.8	-8.6	1.0	-0.3	44.3
Jul 29	25.2	28.9	9.2	28.8	15.6	48.5	3.1	-6.3	27.0	11.2	22.4	30.5	53.2
Aug 13	18.6	23.6	16.2	24.7	15.3	44.2	4.9	-2.8	18.8	8.7	24.2	28.5	54.7
Aug 27	18.1	21.8	8.5	23.3	28.5	66.8	7.2	-2.9	19.2	-0.5	19.7	31.4	50.0
Sept 13	29.3	31.4	18.3	30.7	23.0	51.1	8.2	5.0	34.2	9.6	29.0	35.0	60.4

Table 2. Extractable soil water (TSW - minimum TSW, in mm) during measurement periods in 2001 and 2002.

Date	Available water by tube #												
	1	2	3	4	5	6	7	8	9	10	11	12	13
----- 2001 data -----													
June 9	52.0	58.4	36.2	62.2	51.6	66.3	37.5	41.1	61.2	39.4	41.0	49.5	58.8
June 20	45.2	52.1	27.0	53.4	47.3	59.3	30.9	27.3	51.1	37.1	61.1	45.6	57.8
July 4	16.0	15.6	0.0	13.5	11.7	23.6	12.7	6.8	17.7	3.8	9.4	11.1	21.0
July 23	27.9	23.9	7.0	19.9	25.2	49.8	30.7	21.4	24.0	20.8	26.5	23.4	51.6
Aug 14	30.6	23.4	5.3	14.9	21.9	49.5	12.6	14.1	28.0	18.4	22.6	17.9	51.5
Aug 27	29.5	23.9	3.6	12.6	19.5	50.6	22.3	11.3	17.9	17.5	24.0	18.3	52.2
Sept 21	30.3	22.8	2.0	13.1	19.7	54.7	19.2	8.4	13.6	10.4	21.6	12.7	53.7
----- 2002 data -----													
May 24	39.1	49.3	25.1	59.2	41.9	73.1	30.2	28.1	62.9	38.3	23.5	30.3	63.1
Jun 4	39.3	47.7	16.0	45.9	40.2	65.0	26.9	21.0	54.5	36.5	25.5	30.6	62.0
Jun 18	37.9	34.8	1.4	38.2	28.0	64.1	25.0	17.4	35.7	28.7	19.5	27.3	57.9
Jul 16	29.9	19.2	2.3	10.0	17.2	46.8	17.5	5.5	5.2	8.6	17.4	16.9	46.1
Jul 29	45.2	37.8	12.1	38.3	33.8	60.0	24.5	14.2	34.0	28.4	38.8	47.8	55.0
Aug 13	38.6	32.6	19.1	34.2	33.5	55.6	26.3	17.6	25.9	25.9	40.7	45.7	56.4

Aug 27	38.1	30.8	11.4	32.8	46.8	78.3	28.6	17.5	26.3	16.7	36.2	48.7	51.7
Sept 13	49.3	40.3	21.2	40.2	41.3	62.6	29.6	25.4	41.3	26.8	45.5	52.3	62.1

The results of spatial analysis indicated that the best model to fit the semi-variogram data was the spherical model as indicated by the lowest AIC values in all cases and for ASW (Figure 1) and also for the ESW data.

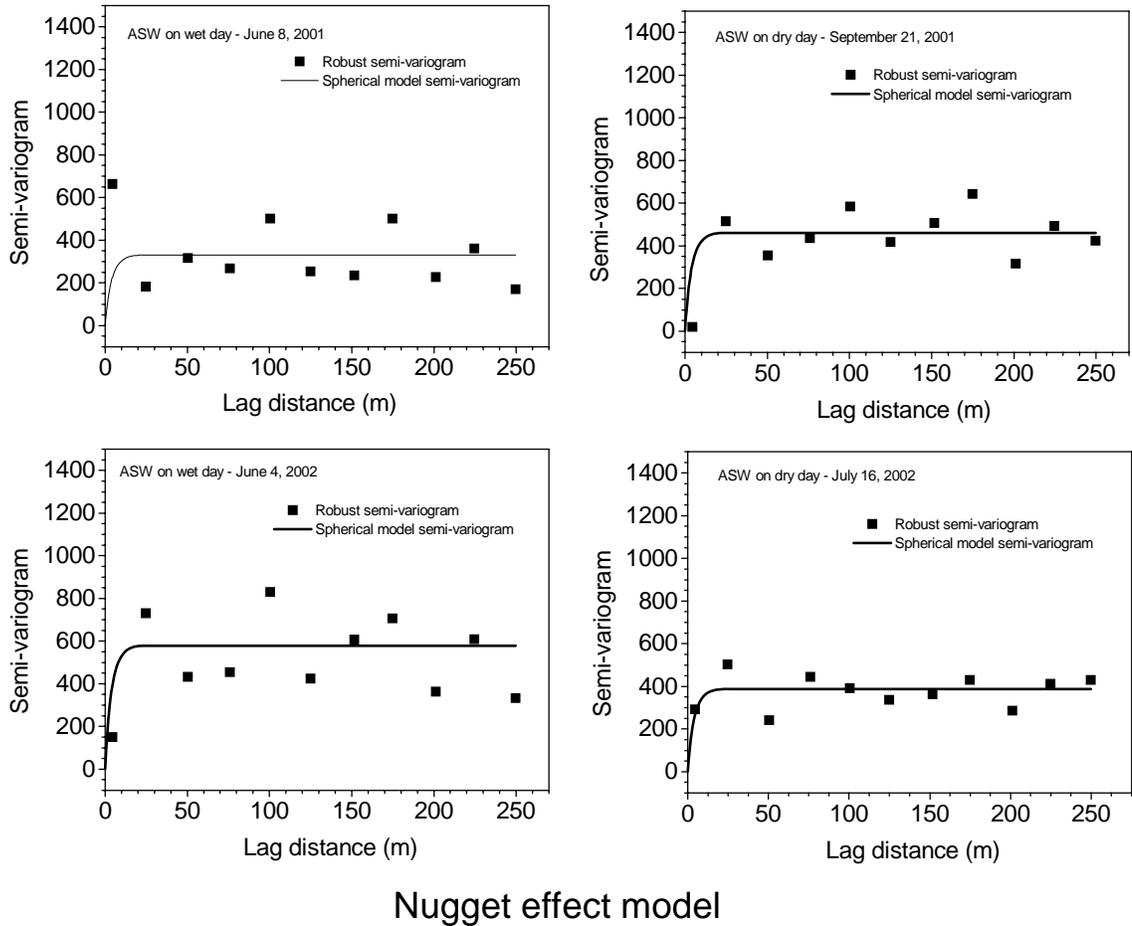


Figure 1. Robust semi-variograms for the transects of 52 available soil water values measured on wet and dry days in 2001 and 2002 on a reclaimed mined site with the spherical model fitted with nugget effect (separation distance = 25 m, lag tolerance = 5m).

The equations below indicate the fitted spherical models with their values of range, sill and nugget for available soil water and extractable soil water on wet and dry days of 2001 and 2002;

(i) Available soil water:

Wet day, June 8, 2001:

$$\left\{ \begin{array}{l} \gamma(h) = 0.63 + 535.67 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.63 + 535.67 = 536.30 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 8}$$

Dry day, Sept 21, 2001:

$$\left\{ \begin{array}{l} \gamma(h) = 0.76 + 542.58 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.76 + 542.58 = 543.34 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 9}$$

Wet day, June 4, 2002:

$$\left\{ \begin{array}{l} \gamma(h) = 0.77 + 826.15 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.77 + 826.15 = 826.92 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 10}$$

Dry day, July 16, 2002:

$$\left\{ \begin{array}{l} \gamma(h) = 0.65 + 490.00 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.65 + 490.00 = 490.65 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 11}$$

ii) Extractable soil water:

Wet, June 8, 2001

$$\left\{ \begin{array}{l} \gamma(h) = 0.55 + 329.67 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.55 + 329.67 = 330.22 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 12}$$

Dry, Sept 21, 2001

$$\left\{ \begin{array}{l} \gamma(h) = 0.77 + 458.66 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.77 + 458.66 = 459.43 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 13}$$

Wet, June 4, 2002:

$$\left\{ \begin{array}{l} \gamma(h) = 0.72 + 576.78 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.72 + 576.78 = 577.50 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 14}$$

Dry, July 16, 2002:

$$\left\{ \begin{array}{l} \gamma(h) = 0.63 + 386.08 \left[\frac{3h}{2 * 0.0001} - \frac{1}{2} \left(\frac{h}{0.0001} \right)^3 \right] \\ \gamma(h) = 0.63 + 386.08 = 386.71 \end{array} \right\} \begin{array}{l} \text{for } 0 < h \leq 0.0001 \\ \text{for } h > 0.0001 \end{array} \quad \text{Equation 15}$$

In both the ASW and ESW variogram models the range was much less than 1 cm indicating a high degree of spatial dependence as was also confirmed by the high *SD* values (> 99%). This means that for these variables values in locations that are less than 1 cm apart are highly autocorrelated and at distances further apart the values are independent. This short-range variability in ASW and ESW probably reflects the local heterogeneity of topsoil material which was composed of peat and clay loam soil in different quantities. Further, existence of a defined spatial structure at a micro-scale seems to suggest that sampling should be employed for soil water studies at that scale. However, in practice it is difficult to conduct such sampling schemes because of the nature and size of equipment used in soil water measurements. The spherical model has also been found to best describe the many soil physical properties, such as clay content, organic C, pH (Rahman et al. 1996; Gaston et al. 2001) and exchangeable cations (Schloeder et al. 2001). Also, for many soil variables an average spatial correlation range of 11 m was reported in the coastal plain of South Carolina (Lister et al. 2000). However, others have reported exponential variogram models to describe variograms for various soil properties (Ancil et al. 2002). The change of spatial structure with moisture condition (wet versus dry) observed in our study was less pronounced than that reported in other studies. For example, in a study conducted in Australia, high sills and low correlation ranges were observed during the winter wet periods, whereas during dry summer periods sills are smaller and correlation ranges longer (Western et al. 1998). The difference in the spatial structure of wet and dry periods was attributed to the dominance of lateral movement in during wet periods and dominance of vertical fluxes during dry periods.

Stochastic simulation of extractable soil water

The results of the conditional stochastic simulations indicated large uncertainty in the estimation of extractable soil water on both dry and wet days (Figure 2). The differences in the simulated extractable soil water patterns among the three realizations indicate a high degree of spatial uncertainty, because each realization had different simulated values of extractable soil water. The average of the 3 realizations minimized the variability of the simulated extractable soil water, and thus may provide better estimates for

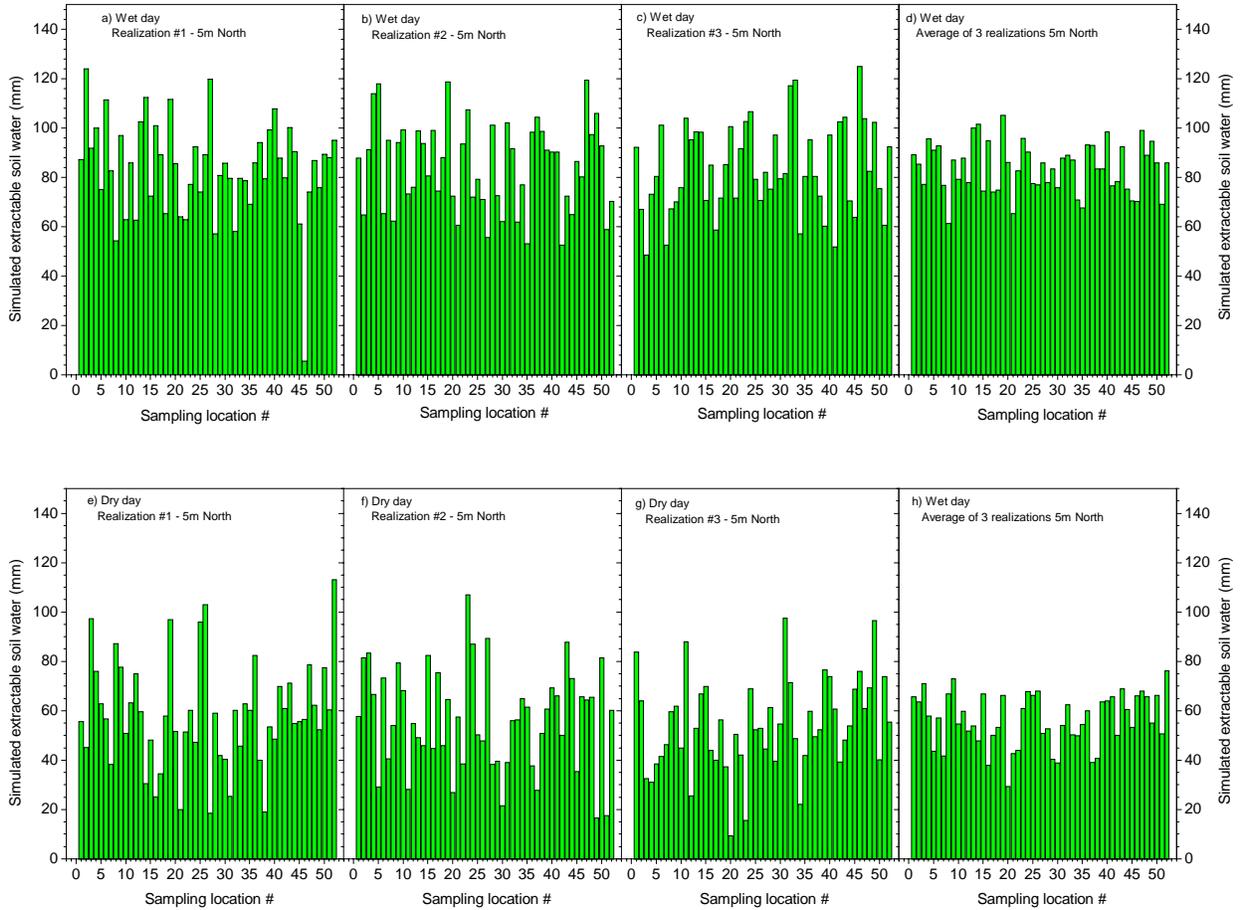


Figure 2. Stochastically simulated extractable soil water values at 52 unsampled locations that are 5 m north of sampling locations for three realizations and the average of three realizations. The top four graphs are for the wet day (a, b, c, d - June 8, 2001) and the bottom four graphs are for the dry day (e, f, g, h - September 21, 2001).

unsampled locations. Some researchers have indicated the potential use of conditional simulation in determining optimal experimental designs for future studies of soil water properties (Fagroud and van MeirVenne 2002). Furthermore, the conditional stochastic simulation provides us with a way to evaluate the risk involved in any decision-making process tied to soil water status or how prediction errors propagate through complex functions such as hydrologic models or crop growth models (Goovaerts 2001). Thus caution must be exercised in generating exhaustive available water data sets for the study area for use in hydrologic and ecosystem modeling. Multiple realizations would be required to reduce spatial uncertainty in simulated extractable soil water values for unsampled locations.

Conclusions

Characterization of spatial dependence by estimating a regular and theoretical semi-variograms indicated that the spherical model was generally the best to describe the available soil water and extractable soil water. Both the available soil water and extractable soil water had very high degrees of spatial dependence (> 99%) and the range of within which sample points were auto-correlated was less than 1 m. The stochastic simulation of extractable soil water indicated high degree of uncertainty in the simulated values, such that generation of exhaustive data sets for use in hydrologic modeling that requires data in fine grid must be exercised with caution. Any decision-making process based on soil water status should be based multiple realizations in order to ensure reduced spatial uncertainty. In our study a minimum of three realizations seemed adequate to minimize the variability of simulated soil water.

Acknowledgements

We thank Syncrude Canada Ltd. for providing the funds to conduct this research. We also thank many people that have provided assistance to this work, especially Clara Qualizza, Sabrina Rock, Noble Donkor and Sarah Wilkinson.

References

- Antil F., Mathieu R., Parent L.E., Viau A.A., Sbih M. and Hessami M. (2002) Geostatistics of near-surface moisture in bare cultivated organic soils. *Journal of Hydrology* 260(1/4), 30-37.
- Bechini L., Bocchi S. and Maggiore T. (2003) Spatial interpolation of soil physical properties for irrigation planning. *European Journal of Agronomy* 19, 1-14.
- Bertuzzi P., Bruckler L., Bay D. and Chanzy A. (1994) Sampling strategies for soil water content to estimate evapotranspiration. *Irrigation Science* 14(3), 105-115.
- Cressie N. and Hawkins D.M. (1980) Robust estimation of the variogram. *Journal of International Association of Mathematical Geology* 12, 115-125.
- Fagroud M. and Van MeirVenne M. (2002) Accounting for soil spatial autocorrelation in the design of experimental studies. *Soil Science Society of America Journal* 66, 1134-1142.
- Gaston L.A., Locke M.A., Zablotowicz R.M. and Reddy K.N. (2001). Spatial variability of soil properties and weed populations in the Mississippi Delta. *Soil Science Society of America Journal* 65, 449-459.
- Goovaerts P. (1998) Geostatistical tools for characterizing the spatial variability of microbiological and physico-chemical soil properties. *Biology and Fertility of Soils* 27, 315-334.
- Goovaerts P. (2001) Geostatistical modeling of uncertainty in soil science. *Geoderma* 103, 3-26.
- Heuvelink G.B.M. and Webster R. (2001) Modelling soil variation: past, present and future. *Geoderma* 100, 213-301.

- Lister A.J., Mou P.P., Jones R.H. and Mitchell R.J. (2000) Spatial patterns of soil and vegetation in a 40-year old slash pine (*Pinus elliotii*) forest in the Coastal Plain of South Carolina, USA. Canadian Journal of Forestry Research 30, 145-155.
- Matheron G. 1971. The theory of regionalized variables and its applications: Cahiers du Centre de Morphologie Mathematique de Fontainebleau, No. 5, 211 p.
- McBratney A.B. and Webster R. (1986) Choosing functions for semi-variograms of soil properties and fitting them to sampling estimates. Soil Science 37, 617-639.
- Pachepsky Y. and Acock B. 1998. Stochastic imaging of soil parameters to assess variability and uncertainty of crop yield responses. Geoderma 85: 213-229.
- Pebesma E.J. and Wesseling C.G. (1998) Gstat, a program for geostatistical modelling, prediction and simulation. Computers and Geosciences 24, 17-31.
- Rahman S., Munn L.C., Zhang R. and Vance G.F. (1996) Rocky mountain forest soils: evaluating spatial variability using conventional statistics and geostatistics. Canadian Journal of Soil Science 76, 501-507.
- SAS Institute 2000. SAS/STAT user's guide Version 8.1. Cary, NC.
- Schloeder C.A., Zimmerman N.E. and Jacobs M.J. (2001) Comparison of methods for interpolating soil properties using limited data. Soil Science Society of America Journal 65, 470-479.
- Webster R. and Oliver M.A. (2001) Geostatistics for environmental scientists. In Statistics in practice. Pp. 271.
- Western A.W., Bloschl G. and Grayson R.B. (1998) Geostatistical characterization of soil moisture pattern in Tarrawara catchment. Journal of Hydrology 205(1/2), 20-37.