

State Space Analysis of Soil Water Content and Textural Fractions

A.M. Al-Omran

*Soil Science Department, College of Agriculture,
King Saud University, Riyadh, Saudi Arabia*

Abstract. Soil textural fractions were measured jointly with soil water content (%) along 450 m transect in calcareous loamy (Torripasamments) at the College of Agriculture Experimental Station, Riyadh, Saudi Arabia. Soil samples were taken every 5 m along the transect. State space approach was used to analyze the two series of sand and water contents. The results indicate that the technique could be used to interpolate the sand percent values from soil water content data with very few measured data of sand percent. They indicate that 35 m distance between sand determinations can be used to interpolate sand % for distance of 5 m apart. Using the state space approach with observed values at 35 m of sand % and at 5 of soil water content resulted a correlation coefficient of 0.89 of measured vs estimated sand % at a distance of 5 m.

Introduction

The large spatial variability of textural fractions and soil water content in the fields has been reported by many investigators [1-4]. Due to the large spatial variability of textural fractions in soils investigators suggested that many observations were required to characterize the soil properties along the field. However, applying the concepts of geostatistics in analyzing the data provides mean of reducing the number of observations necessary to characterize these properties. For instance, Vauclin *et al.* [4] found that the measurements of sand, silt, clay and available water content can be taken at the range of 35-50 m rather than 10 m apart without losing the precision of the measurements using the geostatistical technique. State space model introduced by Shumway [5] provides another approach to analyze the field observations of agronomy and soil science. Morkoc *et al.* [6] showed that observations of soil temperature and incomplete observations of soil water content can be jointly used to estimate missing soil water content values. Shumway *et al.* [7] reported on the data of Morkoc *et al.* [6 & 8] using mean transect values of crop yield, water content, temperature and salt concentration at intervals of 1 m. They compared a multivariate model of state space to univariate spline model, and concluded that a multivariate model of

crop yield, temperature, water content and salt concentration does not significantly improve the crop yield estimate over that of the univariate (yield) model. However, joint analysis of correlated variables can be used to estimate the variable that is more time consuming and difficult to measure.

The objectives of this study are (1) to introduce state space technique as a new method for data interpretation to researchers in agronomy and soil science at the College of Agriculture, Riyadh; (2) to utilize the state space approach in analyzing sand % and soil water content along the transect; and (3) to demonstrate the utility of the model to interpolate the sand and soil water content along the transect.

Experimental data

The data were collected from the field at King Saud University Experimental Research Station, Riyadh. The experimental site consists of about 19 hectares in northwestern corner of the station. The soil is classified as calcareous loamy soil (Torripsamments) and was not cultivated. One transect was laid out in the experimental site and was sampled from south to north every 5 m for 450 m long. The gravimetric soil water content measurements were taken in October 1989, where soils in the region were very dry after a long hot and dry summer. Particles size distributions were estimated by hydrometer method for all the samples at the same locations on the less than 2-mm fractoin. Sand % was determined by the difference.

Theory

To achieve our objectives in determining the textural properties which are correlated with space to soil water content, state space models were used. The state space approach was introduced by Kalman [9] and Kalman and Bucy [10] in their aerospace research. The method has been applied to data in different academic fields such as economics [11], hydrology [12] and soil science [5, 6, 8, 13 & 14]. The general model as described by Shumway *et al.* [7] in details, assumes that some unobserved $px1$ vector of $X_i = (X_{i1}, \dots, X_{ip})$ can be observed through the $qx1$ observation equation:

$$Y_i = A_i X_i + V_i, \quad i = 1, 2, \dots, n \quad (1)$$

where Y_i denote the observed vector of soil parameters at spatial point i , A_i is $qxpx$ measurement matrix and v_i is a $qx1$ zero-mean vector with qxq covariance matrix, $cov(v_i) = R$. The state vector X_i satisfies the state space equation, which describes the way X_i moves through space,

$$X_i = \Phi X_{i-1} + W_i, i=1,2,\dots,n \quad (2)$$

where Φ is $p \times p$ transition matrix and w_i is the state noise vector with mean zero and covariance matrix Q . The model describes the way X_i moves through space (distance). Since there is no assumption needed to use the approach, unlike that in kriging method, measurements of sand % and soil water content do not have to be stationary as in kriging. The initial value of X_i is to X_0 with mean vector u and covariance E . In state spacing modeling u , Φ , E , Q , and R are estimated from the observed series Y_i , $i=1,2,\dots,n$ by an iterative procedure using Kalman filtering, smoothing and expectation maximization (EM) algorithm given in Shumway [15]. The procedure is repeated until we obtain stable value of -log likelihood function. The equations represent the observation and state space equation for the first order state space model which we used for our data. Higher orders models can be used as described by Shumway [15].

Results and Discussion

The data of soil water content and sand % along the transect are shown in Fig. 1(a & b). Inasmuch as only one measurement of each soil water content and sand % was made at each location, it is assumed that the local error is incorporated in each measurement along the transect. The soil of the transect was dry at the south and north section and wettest at the middle of the transect. The wettest section corresponded to lowest sand %. There was more sand % toward each end of the transect. The linear regression of soil water content versus sand % is shown in Fig. 2. The correlation coefficient of the two variables was found to be 0.69. The diagram shows the functional relationship between two properties, yet it ignores their spatial locations. The use of state space approach as suggested by Shumway [5] may provide better information by relating the two variables to each other in estimating and interpolating one variable based on information of both variables. The best suited model of state space can be determined by using Akaike's Informatin Criteria (AIC), Akaike [16], and r^2 value between observed and estimated data Shumway [7].

$AIC = -\log \text{likelihood} + 2 (\text{number of parameters})$. The best suited model can be chosen with minimum value of AIC.

The observed and estimated soil water content, using state space approach for all determined values of both sand and soil water content, are presented in Fig. 3(a & b). The r^2 value of estimated vs observed soil water content was 0.869. Fig 4 (a&b) shows the observed and estimated sand% using both variables with state space model with all observations. The r^2 value of observed vs estimated sand % was 0.997. Figures (3 & 4) show the state space models to estimate soil water content and sand

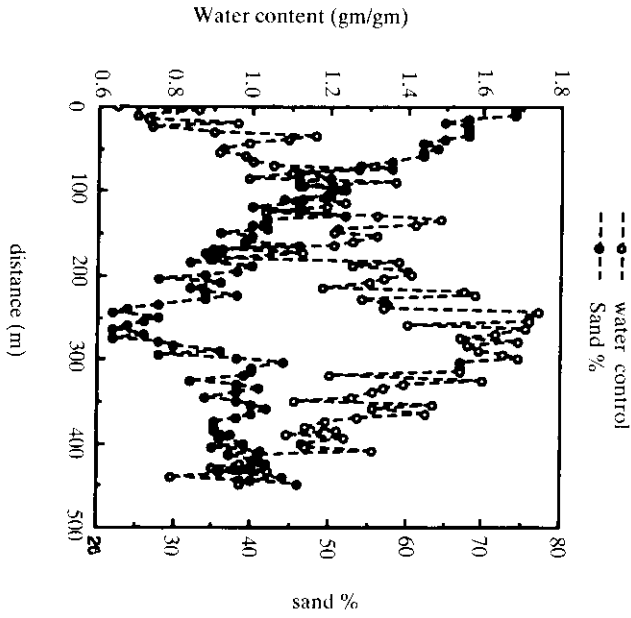


Fig. 1. Gravimetric soil water content (open circles) and sand% (closed circles) along the transect.

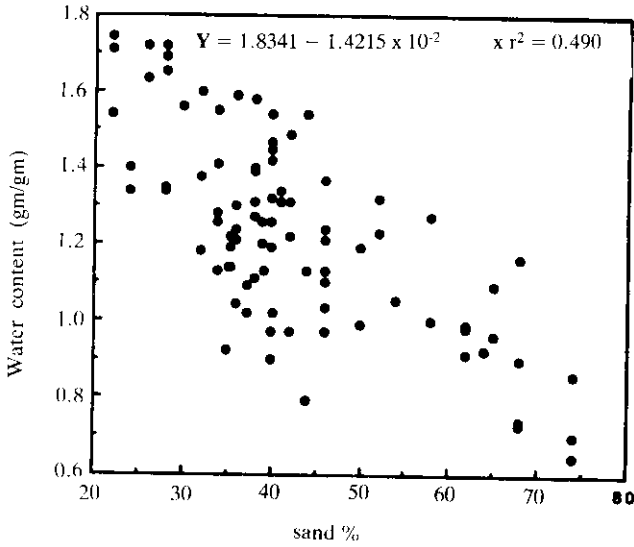


Fig. 2. Linear regression of soil water content and sand %.

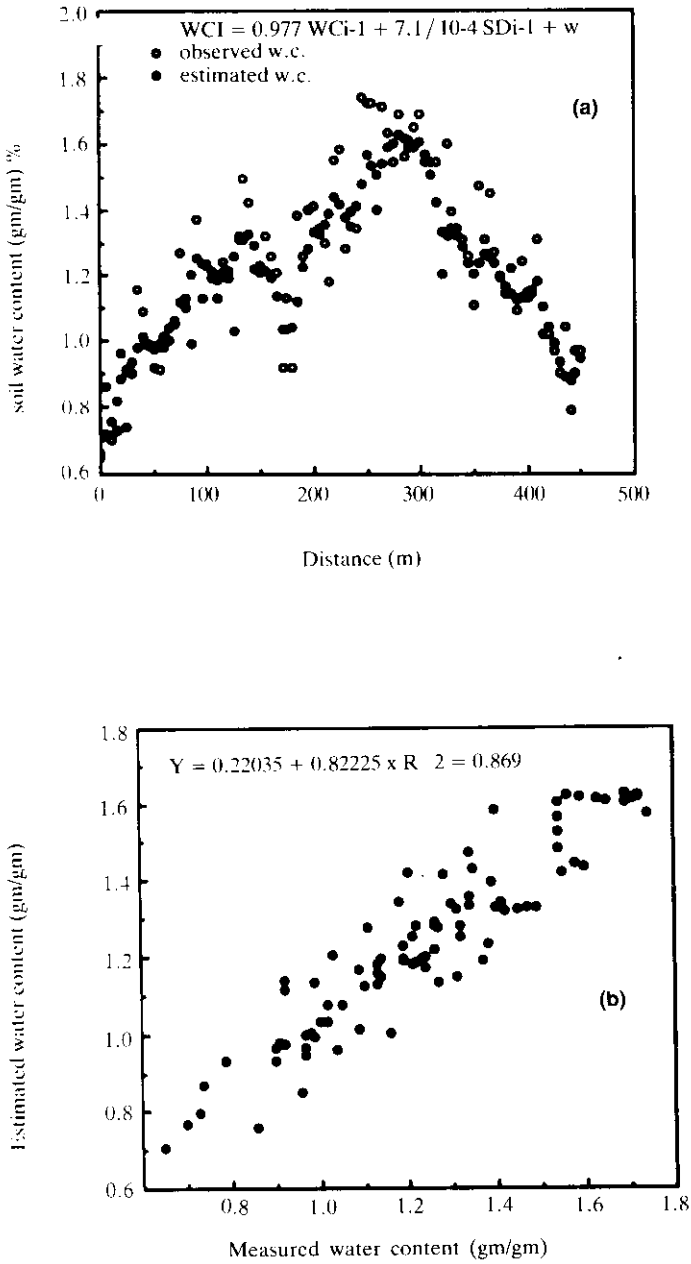


Fig. 3. Estimated and observed soil water content using all determined sand % and soil water content observations (a). Regression of estimated vs measured values of soil water content (b).

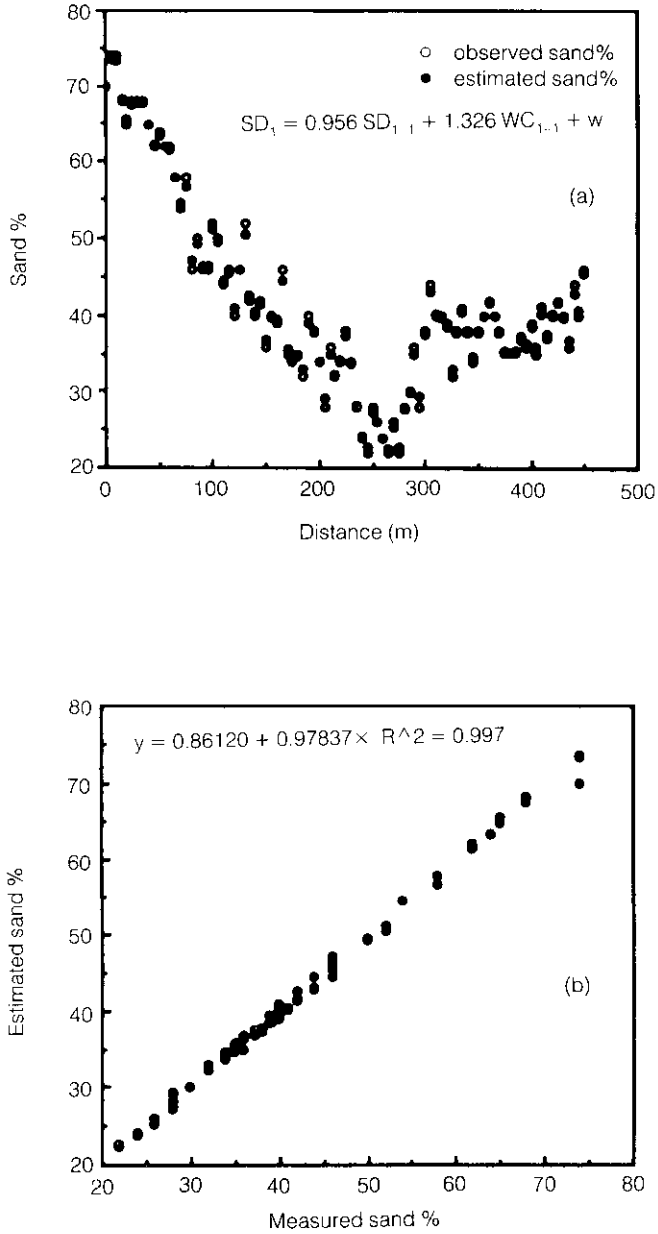


Fig. 4. Estimated and observed sand % using all sand and soil water content observations (a). Regression of estimated vs measured values of sand %.

%, respectively. The coefficients in the models of soil water content and sand % are heavily weighted on previous soil water content value and with lower weight on previous sand %. This result may indicate that soil content can be used to interpolate sand % values with high estimate of sand %.

The other objectives of state space model as noted by Morkoc *et al.* [6] and Shumway *et al.* [7] is to utilize the approach with missing observations. Thus, such approach was used to interpolate the values of sand % and soil water content at distance of 5 m from values of greater distances. Fig. (5) shows the estimated soil water content considering values of soil water content at distance of 10 m and values of sand % at distance of 5 m to interpolate soil water content values at distance of 5 m. The r^2 value of estimated vs observed is equal to 0.949. Fig. (6) shows the linear regression of estimated vs observed values of sand %, considering the value of sand % at distance of 10 m and all values of soil water content. The results clearly indicate the advantage of state space technique in interpolating missing values of variables as suggested by Morkoc *et al.* and Shumway *et al.* [6 & 7]. The results showed that state space approach is useful in estimating the missing values and interpolate the values of sand and soil water content. Thus, the joint analysis of different variables can be used to estimate the variable that is more time consuming and difficult to measure from some values of the same variable and data of relevant variable which can be easily determined.

Another attempt was made to use very few determined values of sand % and all values of soil water content to interpolate the values of sand % at distance of 5 m. The results presented in Fig. 7 show the relationship between r^2 values of measured vs estimated sand %, using all data of soil water content and few data of sand %, and the number of missing sand observations in order to estimate them at distance of 5 m. To reach this objective all measured data of two the variables were used to estimate sand %, then postulated values of sand % at given distance rather than that used for measured ones; namely at 10, 15, 20, 30, and 35 m, were used beside the use of all measured soil water content values at 5 m. The r^2 values of measured and estimated using only few values to estimate all other values along the transect is indicative of the goodness of the state space models. The results indicate that only 12 values of sand % at distance of 35 m can be used in the presence of all values of soil water content at 5 m to estimate sand % at 5 m distance. The correlation coefficient between observed and estimated values was 0.89. Thus, we may conclude that state space approach can be used with fewer values of sand % and all values of soil water content to estimate the values of sand % at closer distances.

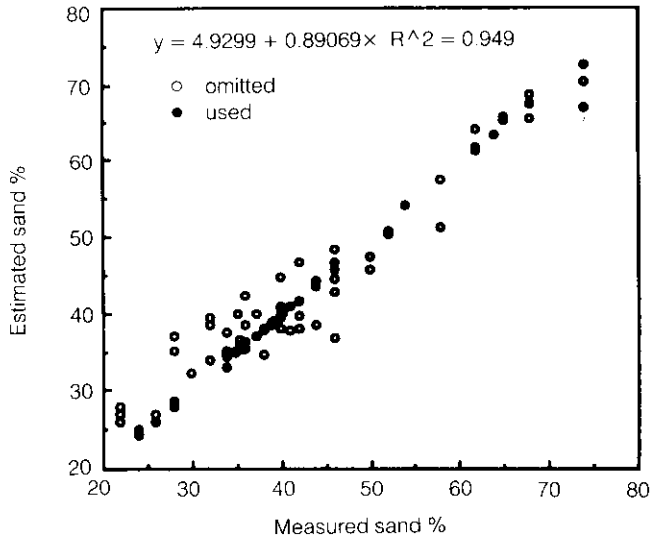


Fig. 5. Linear regression of estimated vs measured soil water content considering 50% of soil water content data and all of sand % data.

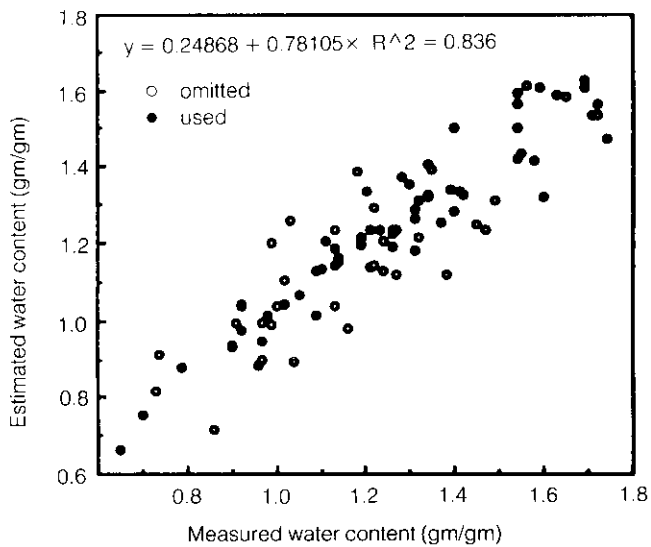


Fig. 6. Linear regression of estimated vs measured sand % considering 50% of sand % data and all of soil water content data.

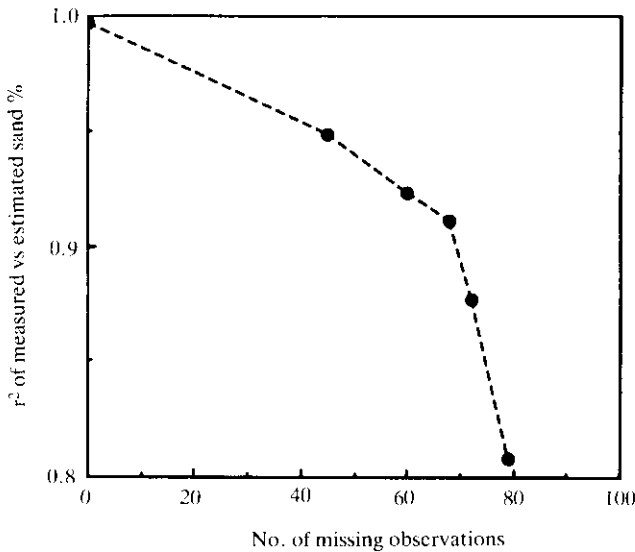


Fig. 7. Relationship between r^2 values of measured vs estimated sand % with 91, 46, 31, 23, 19, and 12 data points used in state space models with all values of soil water content.

Conclusion

The state space approach was used on jointly measured series of sand and soil water content every 5 meters along a transect. The results indicate that the technique could be used to interpolate the sand % from soil water content data with few measured sand % data. Sand % can be estimated by the state space approach at 5 m using values at 35 m of sand % and all observations of soil water content 5 m apart. The correlation coefficient of measured vs estimated sand % at this condition was 0.89 which might indicate the precision of the state space models in interpolating the data.

References

- [1] Campbell, J.B. "Spatial Variation of Sand Content and pH within Single Contiguous Delineation of Two Soil Mapping Units." *Soil Sci. Soc. Am. J.*, 42 (1978), 460-464.
- [2] Gajem, Y.M., A.W. Warrick and D.E. Meyers. "Spatial Dependence of Physical Properties of Typic Torrifluent." *Soil Sci. Soc. Am. J.*, 45 (1981), 709-715.
- [3] Van Meirvenne, M., G. Hofman, J. Van Hove and M. Van Ruymeke. "A Continuous Spatial Characterization of Textural Fractions and CaCO_3 Content of the Topsoil of the Polder Region of Northwest East-Flanders, Belgium." *Soil Science*, 150 (1990), 710-716.
- [4] Vauclin, M., S.R. Vieira, G. Vachaud and D.R. Nielsen. "The Use of Cokriging with Limited Field Soil Observations." *Soil Sci. Soc. Am. J.*, 47 (1983), 175-184.
- [5] Shumway, R.H. "Time Series in the Soil Sciences: Is There Life After Kriging?" In *Soil Spatial Variability*, Ed. J. Bouma and D.R. Nielsen. 35-60. Pudoc, Wageningen, The Netherlands. 1985.

- [6] Morkoc, F., J.W. Biggar, D.R. Nielsen and D.E. Rolston. "Analysis of Soil Water Content and Temperature Using State Space Approach." *Soil Sci. Soc. Am. J.*, 49 (1985), 789-803.
- [7] Shumway, R.H., J.W. Biggar, F. Morkoc, M. Bazza and D.R. Nielsen. "Time and Frequency-domain Analyses of Field Observation." *Soil Sci.*, 147 (1989), 286-298.
- [8] Morkoc, F., J.W. Biggar, D.R. Nielsen and D.E. Rolston. "Statistical Analysis of Sorghum Yield: A Stochastic Approach." *Soil Sci. Soc. Am. J.*, 49 (1986), 1342-1348.
- [9] Kalman, R.E. "A New Approach to Linear Filtering and Prediction Theory." *Trans, ASME. J. Basic Eng.*, 82 (1960), 35-45.
- [10] Kalman, R.E., and R.S. Bucy. "New Results in Linear Filtering and Prediction Theory." *Trans. ASME. J. Basic Eng.*, 83 (1961), 95-108.
- [11] Shumway, R.H., and D.S. Stoffer. "An Approach to Time Series Smoothing and Forecasting Using the EM Algorithm." *J. Time Ser. Anal.*, 3 (1982), 253-264.
- [12] Georgakakos, A.P., K.P. Georgakakos, and E.A. Baltas. "A State-space Model for Hydrologic River Routing." *Water Resources Res.*, 26 (1990), 827-838.
- [13] Alemi, M.H., A.S. Azari, and D.R. Nielsen. "Kriging and Univariate Modeling of Spatially Correlated Data." *Soil Technology.*, 1 (1988), 133-147.
- [14] Wendroth, O., A.M. Al-Omran, C. Kirda and D.R. Nielsen. "State-space Approach to Spatial Variability of Crop Yield." *Soil Sci. Soc. Am. J.*, (1992) (In press).
- [15] Shumway, R.H. *Applied Statistical Time Series Analysis*. N.J.: Prentice-Hall, Englewood Cliffs, 1988.
- [16] Akaike, H. "A New Look at Statistical Model Identification." *IEEE Trans. Autom. Control AC*, 19 (1974), 716-723.

تحليل الدالة المكانية للمحتوى الرطوبي وقوام التربة

عبدرب الرسول موسى العمران

قسم علوم التربة، كلية الزراعة، جامعة الملك سعود، الرياض، المملكة العربية السعودية

ملخص البحث . لقد تم قياس قوام التربة والمحتوى الرطوبي للتربة في قاطع تربة جيرية طميية في محطة الأبحاث الزراعية بكلية الزراعة، جامعة الملك سعود . حيث أخذت القياسات على أبعاد ٥ م بطول امتداد القاطع ذو الطول ٤٥٠ م . تم استخدام طريقة الدالة المكانية State space لتحليل نسبة الرمل والمحتوى الرطوبي على امتداد القاطع . دلت النتائج على أنه يمكن استخدام هذه الطريقة في التحليل للحصول على قيم المحتوى الرطوبي من عدد قليل من بيانات نسب الرمل على امتداد القاطع . وكذلك أعطت النتائج أن المسافة بين أخذ العينات يمكن أن تكون ٣٥ متراً بدلاً من ٥ أمتار .

أمكن باستخدام طريقة الدالة المكانية في التحليل استخدام عينات نسب الرمل على أبعاد ٣٥ م وعينات الرطوبة في التربة على أبعاد ٥ أمتار، تقدير نسب الرمل على مسافة ٥ أمتار، وقد كانت قيمة درجة الترابط ٠,٨٩ .

