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# Spatial and temporal variability of soil water content**

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A b s t r a c t. Soil water content was monitored at 12 cm incremental depths from the surface to a depth of 60 cm on a 0.6 ha field plot (Alfisol) with a portable hand held time domain reflectometer. Variability in soil water content was generally lowest in the surface 0-12 cm which corresponds to the plough layer, apparently as a result of homogenizing effect of ploughing. The nugget variance of soil water content generally increased with depth of sampling with lowest (2.55%, vol.) obtained at the surface 0-12 cm and highest (36%, vol.) at 48-60 cm soil depth. The topsoil water content fitted to the linear model while other depths at all sampling dates was fitted to the spherical model. The range of influence of spatial dependence of soil water content varied between 18 m at 24-36 cm depth and 27 m at 48-60 cm depth. The contour maps obtained with kriged estimate of soil water content showed more homogeneous soil water content on the surface compared with the subsurface layers. The temporal variability in soil water content with dates of sampling was found to be mainly conditioned by rainfall while the spatial variability was influenced by clay content and, subsequently, water holding characteristics of soil layers.

K e y w o r d s: water content, Alfisol, spatial variability, temporal variability

## INTRODUCTION

Soil is a product of weathering of the parent rocks that is over the earth surface which had been acted upon by climate and conditioned by both biotic factors and relief and was developed over a long period of time. The soil, therefore, inherited much of its variability from the parent rock, the constantly fluctuating climatic conditions and the dynamic nature of soil biota. In addition, land use imparts much variability on soil properties (Paz-Gonzalez *et al.*, 2000). Because of the continuously variable nature of the soil forming factors and modification by land use, soil properties also change continuously in both space and time. Variability is one of the greatest headaches in the establishment of experimental field plots. The variation in soil properties is so complex that no description of the soil can be complete (Heuvelink and Webster, 2001). Knowledge of the spatial variability of soil water properties is of great importance for determining a soil sampling strategy, for understanding and modelling of water and chemical movement, for designing field experiments and for many other investigations associated with the management of agricultural lands (Moustafa and Yomota, 1998). Standard field experimental plots are laid out in such a way as to be able to absorb the inherent variability in soil properties. Various designs are used, ranging from simple randomization with replicates to the use of split plots and incomplete blocks along with replicates, all in order to reduce the influence of variability on the result of the experiment. However, the underlying assumption of the classical experimental design is that soil properties within each treatment plot (replicate or sub-plot) are random and variations within each plot are represented by means, while the measures of dispersion such as standard error, coefficient of variation, standard deviation, confidence limits, *etc*. are used to indicate the precision of the means as an estimator. Soil properties have, however, been found not to change abruptly as the classifications would suggest, but rather to vary continuously in space (Webster and Oliver, 1990).

The desire of a soil resource manager is to know the exact properties of soil at every location and the likely change in these properties over certain period of time. Quantitative evaluation of soil resources and their responses to management requires precise information on the spatial and temporal variability of soil properties. Geostatistics, if properly applied, promises to provide this. This study was

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therefore aimed at assessing both the spatial and temporal variations in soil water content on the field plot scale, assessing the main factors controlling the pattern of the spatial variability, and examining how geostatistical tools may be used to improve precision in the evaluation of treatment effects on field scale experimental plots.

## MATERIALS AND METHOD

The experiment was carried out at Obafemi Awolowo University Teaching and Research Farm, Ile-Ife (7°25´N, and 4°39´E), Nigeria. The average annual rainfall there is 1 400 mm and has a bimodal distribution with peaks in June and September. Average annual insolation/radiation is 18.7 MJ $m^{-2}$ $day^{-1}$. The soil belongs to the Iwo soil series. It is located on a 1-3% slope. The Iwo soil is a gravelly soil derived from coarse gneiss and granite, and is classified as Alfisol (Harpstead, 1973). The soil is well drained, with the surface texture varying from sandy loam to sandy clay loam.

The field was laid out in randomised complete block design consisting of 5 different fallow treatments and four replicates per treatment. The fallow treatments imposed were: native fallow (NF), native fallow with addition of fertilizers fallow (FF), *Panicum maximum* (PN), *Euphorbia heterophylla* (EU), and *Pueraria phaseoloides* (PU). Each plot had dimensions of 10 by 15 m, with inter-row spacing of 5m among replicates and space of 3 m within sub-plots in each replicate. An electronic rain-gauge was installed in the middle of the plot to monitor the rainfall in addition to detailed weather information obtained from an automated weather station located about 150 m away from the field plot. The fallow species were ploughed-in in September in preparation for late season maize. Maize variety DMY-6 was planted on 22nd September, 2004. Access pipes made of 10 cm diameter PVC pipes were installed at two locations (5 m apart) within each treatment unit (Fig. 1) and the volumetric water content (WC) was determined with a portable Time Domain Reflectometry (TDR) device. The device is equipped with a 12 cm twin probe that is dipped into the soil and the volumetric water content read directly on a LCD display unit. The TDR was earlier calibrated with the gravimetric method and a good agreement ($R^2$ = 0.95) was recorded between the two methods. Soil water content was determined at successive 12 cm depth intervals from soil surface to a depth of 60 cm representing the rooting depth of maize. Data of soil water content were collected at weekly intervals during the early establishment till maturity and harvesting of the maize. Further descriptions of the field can be found in Tijani *et al*. (2008).

Univariate analyses were performed on the data to test for normality and variability of the samples using the SAS package (SAS Institute, 1999), while geostatistical analyses were performed on the data to determine the semivarince of the soil properties and these were fitted to the classical models using the VAR5 package (Yost *et al*., 1989). Based on the variogram parameters, interpolation of soil water content from unsampled locations was done and the contour maps of soil water content were plotted. Furthermore, the mean water content representing each experimental unit was predicted for each treatment by block kriging using the Bkrige package (Yost *et al*., 1989). The mean values obtained was subjected to analyses of variance using the PROC ANOVA subroutine of SAS (SAS Institute, 1999) and the error mean square of the analyses of variance was compared with the one obtained on the raw data.

## RESULTS AND DISCUSSION

As shown in Fig. 2, there was a significant variation in soil water content over the period of sampling. The variability, however, was more dependent on the ambient environmental conditions such as rainfall, air temperature and solar radiation (Tijani, 2007).

The classical univariate statistics show the soil water content at the surface to have the least variability while the variability of water content increased with depth of sampling (Table 1). The lower variability of soil water content on the surface soil may be ascribed to homogenization of the soil during tillage activities. There was, however, no significant difference in the magnitude of the variability in soil water content with successive dates of sampling. There was no definite trend in the variability of the soil water content with successive periods of sampling.

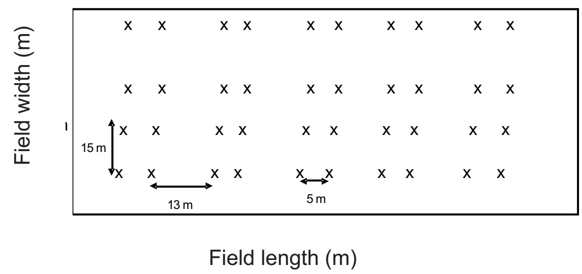


**Fig. 1.** Experimental field layout showing the sampling points.

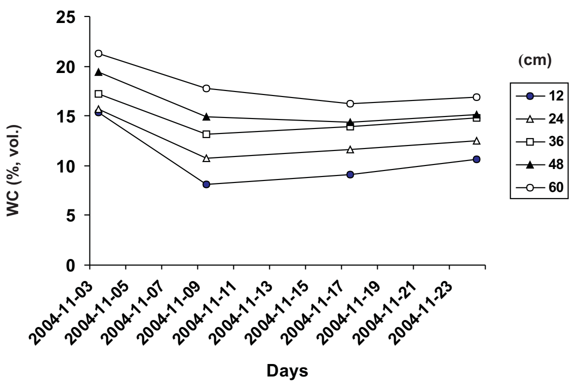


**Fig. 2.** Temporal variations in soil water content (WC) at different depths (cm) with days of sampling (November, 2004).

**T a b l e 1.** Univariate statistics of the soil water content (November, 2004)

| Date | Depth (cm) | Mean | Variance | SD | SE | Skewness | Kurtosis | Range |
|---|---|---|---|---|---|---|---|---|
| 3 | 0-12 | 15.35 | 3.4237 | 1.8503 | 0.4137 | 0.0493 | -0.4267 | 7 |
| | 12-24 | 16.03 | 5.8020 | 2.4087 | 0.5386 | 0.9671 | 1.2351 | 10 |
| | 24-36 | 17.18 | 11.6390 | 3.4116 | 0.7629 | 0.7690 | -0.1650 | 12 |
| | 36-48 | 19.40 | 10.0158 | 3.1648 | 0.7077 | 0.2055 | -0.5154 | 12 |
| | 48-60 | 21.23 | 12.7493 | 3.5706 | 0.7984 | 0.8480 | 0.1205 | 13.5 |
| 9 | 0-12 | 8.10 | 2.0684 | 1.4382 | 0.3216 | 1.1341 | 0.5797 | 5 |
| | 12-24 | 10.80 | 5.6158 | 2.3698 | 0.5299 | 0.2348 | -1.1278 | 7.5 |
| | 24-36 | 13.13 | 9.8914 | 3.1451 | 0.7033 | 1.0346 | 1.0521 | 12.5 |
| | 36-48 | 14.88 | 7.2862 | 2.6993 | 0.6036 | 0.4358 | -0.5963 | 9.5 |
| | 48-60 | 17.80 | 7.0632 | 2.6577 | 0.5943 | 0.1641 | -1.0412 | 9 |
| 17 | 0-12 | 9.08 | 4.1388 | 2.0344 | 0.4549 | 1.1350 | 0.6305 | 7 |
| | 12-24 | 11.63 | 4.9704 | 2.2294 | 0.4985 | -0.0928 | -0.8143 | 8 |
| | 24-36 | 13.90 | 5.6474 | 2.3764 | 0.5314 | 0.1382 | -0.7631 | 8 |
| | 36-48 | 14.33 | 7.2441 | 2.6915 | 0.6018 | 0.1829 | -0.7524 | 9.5 |
| | 48-60 | 16.28 | 7.6441 | 2.7648 | 0.6182 | 0.0115 | -1.0757 | 9.5 |
| 24 | 0-12 | 10.63 | 4.3125 | 2.0767 | 0.4644 | 1.0276 | 0.7673 | 7.5 |
| | 12-24 | 12.53 | 4.8283 | 2.1973 | 0.4913 | 0.1075 | -0.7305 | 8 |
| | 24-36 | 14.78 | 8.7757 | 2.9624 | 0.6624 | 0.0453 | -0.6024 | 10.5 |
| | 36-48 | 15.13 | 11.7599 | 3.4293 | 0.7668 | -0.4469 | -0.8101 | 12 |
| | 48-60 | 16.93 | 9.4283 | 3.0706 | 0.6866 | 0.2170 | -0.3963 | 11.5 |

**T a b l e 2.** Geostatistical parameters of the soil water content (November, 2004)

| Date | Depth (cm) | Nugget variance (Co) | Spatial variance (C) | Sill (C0+C) | Nugget/Sill (%) | Range | Model |
|---|---|---|---|---|---|---|---|
| 3 | 0-12 | 2.78 | 0.06 | - | - | - | Linear |
| | 12-24 | 9.40 | 3.05 | 12.45 | 75.55 | 25.11 | Spherical |
| | 24-36 | 2.74 | 13.70 | 16.20 | 16.94 | 25.168 | Spherical |
| | 36-48 | 10.46 | 7.17 | 17.63 | 59.33 | 24.3864 | Spherical |
| | 48-60 | 7.65 | 13.08 | 20.70 | 36.98 | 24.99 | Spherical |
| 9 | 0-12 | 1.56 | 0.035 | - | - | - | Linear |
| | 12-24 | 7.91 | 4.39 | 12.30 | 64.30 | 23.28 | Spherical |
| | 24-36 | 6.90 | 8.68 | 15.58 | 44.27 | 26.56 | Spherical |
| | 36-48 | 4.79 | 8.71 | 13.50 | 35.52 | 21.94 | Spherical |
| | 48-60 | 8.26 | 4.12 | 12.38 | 66.73 | 27.38 | Spherical |
| 17 | 0-12 | 2.60 | 0.08 | - | - | - | Linear |
| | 12-24 | 10.81 | 1.03 | 11.83 | 91.40 | 19.20 | Spherical |
| | 24-36 | 9.27 | 1.69 | 10.96 | 84.58 | 18.24 | Spherical |
| | 36-48 | 7.41 | 9.00 | 16.41 | 45.13 | 21.73 | Spherical |
| | 48-60 | 17.61 | 3.21 | 20.82 | 84.59 | 23.09 | Spherical |
| 24 | 0-12 | 1.37 | 4.03 | 5.40 | 25.43 | 20.45 | Spherical |
| | 12-24 | 10.17 | 3.79 | 13.90 | 73.19 | 20.82 | Spherical |
| | 24-36 | 7.91 | 6.41 | 14.32 | 55.23 | 24.56 | Spherical |
| | 36-48 | 10.69 | 12.85 | 22.94 | 46.62 | 21.86 | Spherical |
| | 48-60 | 12.61 | 9.07 | 21.67 | 58.19 | 19.78 | Spherical |

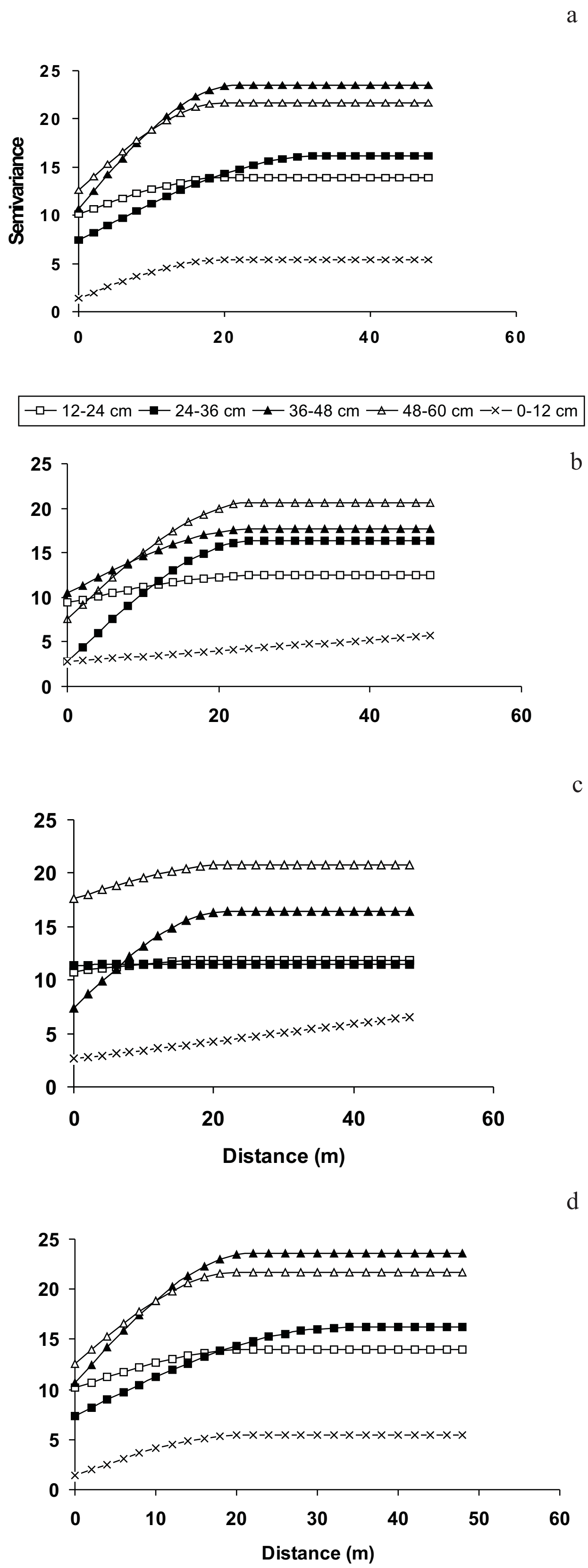


**Fig. 3.** Semivariogram plots of soil water content at different soil depths on November, 2004: a – 3, b – 9, c – 17, and d – 24.

Analysis of spatial dependence of the soil water content showed an anisotropic behaviour which was stronger on the surface, probably due to the direction of tillage operations. Semivariogram models that were best-fitted and the model parameters are given in Table 2 and Fig. 3. All soil properties showed positive nugget, which can be explained by sampling error, short range variability, random and inherent variability. The nugget-to-sill ratio can be used to classify the spatial dependence of soil properties. In this study, criteria similar to those reported by Cambardella *et al.* (1994) were used. The variable is considered to have a strong spatial dependence if the ratio is less than 25%, and a moderate spatial dependence if the ratio is between 25 and 75%; otherwise, the variable has a weak spatial dependence (Sun *et al.*, 2003). Except for the surface (0-12 cm) water content sampled on November 3, 9 and 17 which best fitted to the linear model, all other sampling depths and dates were best fitted to the spherical model. The spatial dependence of the soil water at all depths and sampling dates were moderate to weak as revealed by the nugget/sill ratio. The range of dependence of the spatial variability ranged from 18 to 27 m. Under rainfed agriculture, the capacity of soil to store water within the profile determines the amount of water that would be made available for crops between successive rainfalls. The spatial distribution of the water stored in the 0-60 cm of soil profile across the field is presented in contour maps (Fig. 4a,b,c). These shows much variability in the total amount of water stored within the profile across the field. Though there was much temporal variability in the stored water across the sampling dates, the spatial distribution was similar irrespective of the sampling dates. The spatial distribution of the percent clay content of the topsoil (0-30 cm) (Fig. 4d), when compared with the water stored in the soil profile, shows a similarity. This is an indication that the soil texture and, consequently, soil water capacity is an important underlying factor responsible for the spatial variability of the soil water on this experimental plot. This is expected, since clay is composed of very small particle sizes and large surface areas and is able to retain water, preventing them from gravitational drainage.

Parametric statistical techniques evaluate treatment significance in field experiments by comparing variability attributed to treatments to variability attributed to random error. However, in many experiments, a considerable amount of the variability attributed to random error is actually due to large-scale soil variability that cannot be accounted for by blocking (Scharf and Alley, 1993). Soil variability in field experiments causes experimental error, which is accounted for by randomization and replication. When soil variability has a spatial component, it causes correlated errors within a block, which inflates the experimental error in field experiments and masks the true treatment effects (Pan and Wang, 2009). In this study the root mean squared error (RMSE) from the analyses of variance performed on the raw

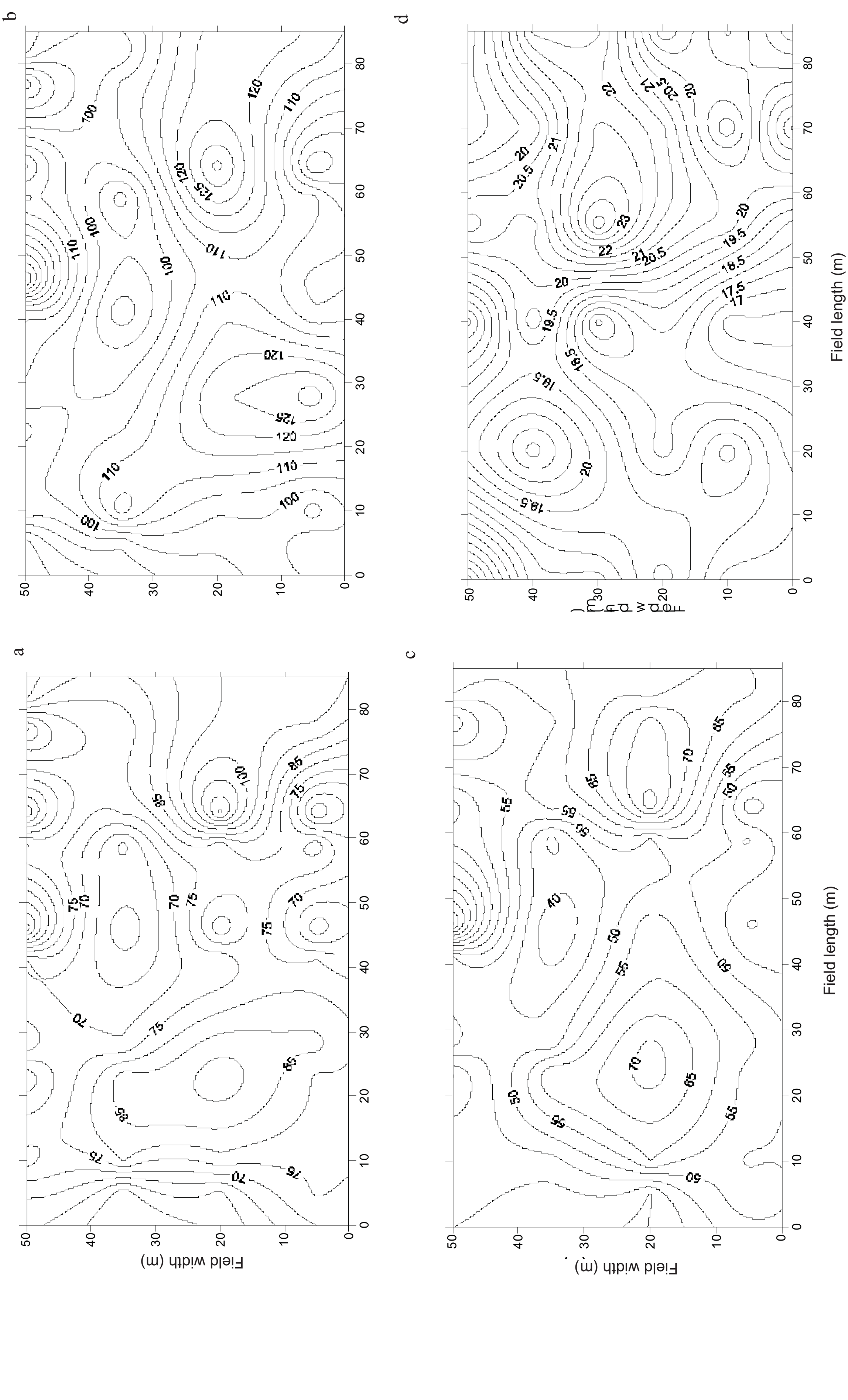


**Fig. 4.** Contour map of water stored (mm) at 0-60 cm soil depth on : a – November 3, 2004, b – November 17, 2004, and c – December 6, 2004; d – clay (%).

**T a b l e 3.** Root mean square errors (RMSE) compared between the observed and kriged interpolated values and the (ANOVA)

| Date (November, 2004) | Depth (cm) | RMSE | |
|---|---|---|---|
| | | Observed | Kriged |
| 3 | 0-12 | 1.35 | 0.91 |
| | 12-24 | 1.81 | 1.45 |
| | 24-36 | 3.07 | 2.41 |
| | 36-48 | 2.78 | 2.22 |
| | 48-60 | 2.63 | 1.99 |
| 9 | 0-12 | 1.14 | 0.66 |
| | 12-24 | 2.35 | 1.89 |
| | 24-36 | 2.98 | 2.40 |
| | 36-48 | 1.96 | 1.58 |
| | 48-60 | 2.25 | 1.85 |
| 17 | 0-12 | 1.75 | 1.31 |
| | 12-24 | 1.78 | 1.53 |
| | 24-36 | 2.29 | 1.51 |
| | 36-48 | 1.94 | 1.47 |
| | 48-60 | 2.05 | 1.78 |
| 24 | 0-12 | 2.00 | 1.46 |
| | 12-24 | 2.15 | 1.72 |
| | 24-36 | 3.16 | 2.62 |
| | 36-48 | 3.00 | 2.44 |
| | 48-60 | 2.91 | 2.19 |

data was compared with that on the kriged estimate (Table 3). The RMSE of an estimator quantifies the amount by which the estimator differs from the value of the quantity being estimated. This difference is usually either due to randomness or to the omission of some factors contributing to the variation. Thus the lower the RMSE the better is the estimate. The RMSE value was consistently lower for the data subjected to prior geostatistics (kriging) technique, in some cases by magnitude of two. Pair-wise t-test ($t = 16.11$, $P < 0.01$) showed that the RMSE for the kriged soil water content values were significantly lower than the RMSE for the raw soil water content values. Thus a consideration of the spatial nature of spatial variability of soil water content may help improve the accuracy of the determination of treatment effects on field scale experiments.

## CONCLUSIONS

1. Soil water content on the studied experimental plot showed significant spatial and temporal variation.

2. While the temporal variation in soil water content was mainly dependent on the weather, the spatial variation was found to be mainly dependent on clay content of the soil.

3. When the information on the spatial variability of the soil water content was used to estimate the mean values for each sub-plot, this gave a better precision in the analysis of variance to test the treatment effects compared to when the raw data were used as shown by lower RMSE for the former.

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