African Crop Science Journal, Vol. 14. No. 1, pp. 27-36, 2006
Printed in Uganda.
ISSN 1021-9730/2006 $ 4.00

SPATIAL VARIATION IN SOIL ORGANIC CARBON WITHIN SMALLHOLDER FARMS IN WESTERN KENYA: A GEOSPATIAL APPROACH

J.M. OKEYO, K.D. SHEPHERD[1], W. WAMICHA and C. SHISANYA[2]
Department of Environmental Science, Kenyatta University, Kenya
[1]World Agroforestry Centre (ICRAF), Nairobi, Kenya
[2]Department of Geography, Kenyatta University, Kenya

(Received 29 September, 2005; accepted 29 January, 2006)

ABSTRACT

In many farming landscapes across Sub-Saharan Africa (SSA), soil fertility has been on the decline with significant implications on crop productivity. However, even with such a decline, soil nutrient levels still differ significantly between farms, fields or within the same field. Knowledge of such spatial variability and relationships among soil properties is important in implementation of agricultural land management practices. In this study, the spatial variability of soil organic carbon (SOC) in two districts of western Kenya was modelled using the geostatistical theory of semivariography and mixed effects modeling. Soil organic C was found to be spatially correlated and the spatial structure modelled using experimental semivariograms fitted with spherical, exponential and ratio quadratic models. The nugget/sill ratios for all the three variogram models were between 50-60%, indicating moderate spatial correlation. It is suggested that future soil fertility management strategies should target individual fields, as a precision farming approach.

Key Words: Mixed effects, modeling, semivariance

RÉSUMÉ

Dans beaucoup de paysages agricoles à travers l'Afrique Subsaharienne (SSA) la fertilité du sol a connu un déclin avec des implications significatives sur la productivité des cultures. Cependant même avec un tel déclin, les niveaux de nutriments du sol varient encore significativement en fonction des fermes, des champs ou même dans un même champ. La connaissance d'une telle variabilité spatiale et des relations entre propriétés de sols est importante dans la mise en œuvre des pratiques agricoles de gestion des terres. Dans cette étude, la variabilité spatiale du carbone organique du sol (SOC) a été modélisée dans deux districts de l'Ouest kenyan en utilisant la théorie géostatistique de semivariographie et la modélisation à effets mélangés. Le sol organique C a été trouvé corrélé dans l'espace et la structure spatiale a été modelée en utilisant des semivariogrammes expérimentaux pourvus de modèles sphériques, exponentiels et à taux quadratiques. Les taux 'nuggets/sill' pour tous les trois modèles de variogrammes, étaient d'entre 50-60% indiquant une corrélation spatiale modérée. Sil est suggéré que les stratégies futures de gestion de sol doivent cibler le champ individuel comme une approche fermière de précision.

Mots Clés: Effets mélangés, modélisation, semi-variance

INTRODUCTION

One of the main factors that hinder the applicability of soil fertility management technologies over a wide area is the large spatial variability of the resource base. In Sub-Saharan Africa (SSA), where soil fertility depletion has been recognized as a principal factor limiting crop production and a threat to food security, spatial variations to be large. As more soil and environmental information becomes readily available through modern Geographical Information Systems (GIS) technology, there is opportunity for better spatial targeting of technologies in relation to variation in the natural resource base. According to Deckers (2002), targeted balanced nutrient management systems in the soilscapes of Sub-Saharan Africa are likely to be one of the cornerstones of sustainable development.

The understanding of the spatial variability of soil fertility levels between and within farms is important for refining farm management practices and for assessing the impact of agriculture on the environment. The variability of soil properties within fields is often described by a classical method, which assumes that variation is randomly distributed within mapping units. Soil variability is the outcome of many processes acting and interacting across a continuum of spatial and temporal scales and is inherently scale dependent (Parkin, 1993). In addition, soil properties frequently exhibit spatial dependency, whereby, samples collected close to each other tend to be more correlated than those collected far apart. Therefore, parametric statistics are inadequate for analysis of spatially dependent variables because they assume that measured observations are independent in spite of their distribution in space (Hamlett *et al.,* 1986).

In recent years, spatial dependence models of geostatistics have gained popularity as they allow the quantification of landscape spatial structure from point – sampled data. One such model that has received much attention and will be used in this study is the variogram (Cresse, 1993). The variogram reveals the randomness and structured aspects of the spatial dispersion of a given variable and is a plot of the average squared differences between the values of a spatial variable at pairs of points separated by a lag distance against the lag (Davidson and Csillag, 2003). The empirical variogram describes the overall spatial pattern of sample data (Fortin, 1999) and a variety of theoretical variogram models can be fitted on it to describe spatial structure of a landscape attribute. These then provide powerful capabilities which can be used to analyse realistically the complex spatial relationships in ecological systems.

The objective of the study was to quantify the variability in soil fertility level at different spatial scales from plot level to district level.

METHODOLOGY

Study area. The study was conducted in two districts, Vihiga and Siaya in western Kenya. Although, the two districts are adjacent to each, they vary distinctly climate, physical, demographic and administrative factors. Vihiga is one of the six districts in Western province, situated to the north-east of Siaya and largely covers the upper parts of the Lake Victoria Basin extending further north to boarder Kakamega forest. It lies between longitude 34° 30' east and 35° 00' east, and between latitude 00° 00' and 00° 15' north. Siaya district, on the other hand, covers the lower parts of the basin, extending to the lake. Administratively, it is located in Nyanza province, and lies between longitude 33° 58' east and 34° 33' east, and latitude 0° 26' south and 0° 18' north.

Sampling design. The study was carried out in nine sub-locations selected randomly from the two districts, five from Vihiga and four from Siaya. In each of the selected sub-locations, a Y-frame sampling design was used to select ten farms, where actual sampling was done for the various biophysical and socio-economic characteristics. Farms were located at constant lag distances along the arms of the Y. This design gave the optimal arrangement for geostatistical analysis in terms of generating a range of distances between farms with the minimum number of plots. All the fields within each farm were georeferenced by their field centres using a global positioning system (GPS) together with all the sampling points. All soil samples collected were air-dried, crushed, passed through a 2 mm sieve, and weighed before being taken to the laboratory for further analysis.

Spatial predictions. The study used regionalised variable theory, popularly known as geostatistics (Matheron, 1971), to analyse the spatial correlation of SOC. Geostatistical analysis of soil properties is based on the assumption that a variable, z, measured at a location **x**, may be treated as a realisation of a random function, denoted by Z(**x**).

The analysis is possible if the random function is intrinsic, that is if

$$E[Z(x) - Z(x+h)] = 0 \quad (1)$$

and

$$2\gamma(h) = E[\{Z(x) - Z(x+h)\}^2] \quad (2)$$

depend only on the spatial separation or lag **h**. The function $\gamma(h)$ is the variogram. An estimate of the variogram is needed in geostatistics for estimation (kriging) (Burgess and Webster, 1980), and simulation modeling. Although the classic estimator is the most commonly used and is asymptotically unbiased for any intrinsic random function (Cressie, 1993), it was not used in this study because it is very sensitive to outlying values.

The advantage of this robust estimator is that the effect of outliers is reduced, without removing specific data points from a data set. Data from each Y-frame sampling region was modeled using the above robust estimator to produce an experimental semivariogram which was then fitted with both the spherical and exponential semivariogram models.

Mixed effects modelling. A multilevel linear mixed-effects (LME) model was used to analyse the data. The model was a three-level nested model as outlined by Pinheiro and Bates (2000) and is shown in equation (3). In the 3-level model, the response for the *k*th level-3 unit within the *j*th level-2 unit within the ith level-1 unit is written as;

$$y_{ijk} = x_{ijk}\beta + z_{i,jk}b_i + z_{ij,k}b_{ij} + z_{ijk}b_{ijk} + \varepsilon_{ijk}$$

$$i=1,\dots M,\ j=1,\dots M_i,\ k=1,\dots M_{ij}$$

$$b_i \sim N(0,e1),\ b_{ij}\ N(0,\Sigma_2), b_{ijk} \sim N(0,\Sigma_3),\ \varepsilon_{ijk}\ N(0.\sigma^2 I) \quad 3,$$

where the fixed effects model matrices are $\mathbf{x}_{ijk,}$ $i=1,\dots,M$, $j=1,\dots,M_i$, and $k=1,\dots,M_{ij,}$ of size n_{ijk} x p; the first-, second-, and third-level random effects are b_i, b_{ij}, and b_{ijk} of length q_1, q_2 and $q_{3,}$ with the corresponding model matrices $\mathbf{z}_{i,jk}$, $\mathbf{z}_{ij,k}$ and $\mathbf{z}_{ijk}$ of sizes n_i x q_1, n_i x q_2, and n_i x q_3. The within-group errors ε_{ijk} are assumed to be independent for different *i*, *j* or *k* and to be independent of the random effects. The semivariogram was then modeled using the spherical, exponential and ratio-quadratic models.

RESULTS AND DISCUSSION

Estimation of soil organic carbon. Soil organic C for all fields was 0.56 ± 0.29 with a coefficient of variation of 52.2 % (Table 1). The large coefficients of variation mean that soil organic C varies widely in each of the Ys.

This variation, in turn, reflects the type and complexity of the farming systems within the study area as determined by both natural and socio-economic factors. According to Nandwa (2003), soil fertility at lower scales such as individual niches, fields in farms and village settings differ considerably due to a number of factors including differences in soil texture, landuse/fallow history, soil management, and microclimatic differences. Smallholder farmers exploit the microvariability within their farms in such a way that during the different seasons as conditioned by rainfall amounts, there are always pieces of land where crops perform well (Brouwers, 1993).

The large variability of soil organic C occurs both within fields of the same farm and among farms, with no clear cut trends or gradients, consequently posing a problem to targeted soil fertility management initiatives. According to Barrett *et al.* (2002), Sub-Saharan Africa's extraordinary biophysical variability limits the geographical scope over which any particular natural resource management (NRM) practice proves effective.

TABLE 1. Soil organic carbon in each Y design

Y	Carbon (%)	std dev
Y1	0.42	0.29
Y2	0.66	0.29
Y3	0.41	0.26
Y4	0.57	0.28
Y5	0.59	0.21
Y6	0.82	0.26
Y7	0.43	0.31
Y8	0.68	0.21
Y9	0.48	0.25

One of the reasons why nutrient depletion has been given little recognition in SSA, is that the issue has been perceived differently at various spatial scales. For example, it is difficult to convince farmers and policy makers to react proactively to agro-ecosystems with negative nutrient balances (depleted soils), which have been continuously cultivated till organic matter contents can no longer buffer nutrient depletion.

Spatial modelling. Since spatial modeling requires data from several sampling points and the basic sampling design was the Y-frame with an underlying random pattern, spatial predictions were done at the Y-level for site and regional comparisons. According to Haining (1990), data are often correlated in space creating spatial structure. When such correlation or covariance structure is evaluated, it can be used to increase the accuracy of modeling and prediction efforts. Using Equation 3, robust experimental variograms were drawn for all the Ys and then fitted with spherical and exponential models (Equations 4 and 5, respectively) as shown in Figures 1 and 2. The advantage of the robust estimator is that the effect of outliers is reduced, without removing specific data points from the data set (Kaluzny *et al.*, 1998).

The spherical models in Figure 1 show the spatial correlation of soil organic C in each of the Y-sampling sites Y1 to Y9. The models of Y1, Y4 and Y6 show that spatial autocorrelation in these sites continues beyond the maximum distance covered by the study. All the other Ys show spatial autocorrelation which ends within the maximum distance covered by the Y sites. All samples collected at distances greater than those given by the model variograms range were spatially independent. The essence of fitting empirical variograms with theoretical variogram functions was to ensure that the variance of predicted values was positive. In addition, variogram models should

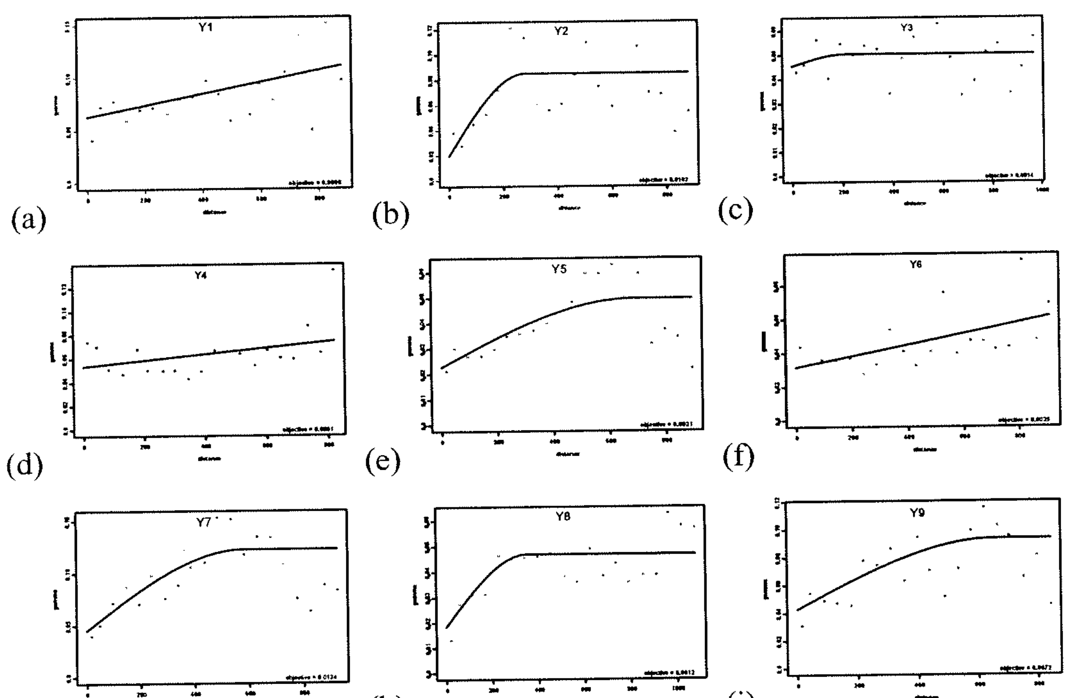

Figure 1. Spherical semivariogram models of predicted soil organic C in each of the Ys (sub-locations) (labelled a - i) showing the degree of spatial correlation.

at least have physical meaning (a random function with the given type of variogram that can exist) (Wackernagel, 1998). The models were fitted iteratively to determine the optimal distance within which spatial correlation was evident with optimum variogram parameter values, i.e., nugget effect, sill and range.

In Figure 2, the fitted exponential models show spatial structure in each of the Ys. The fitted models in Y1, Y4 and Y6 show continuous spatial structure beyond the maximum distance covered at the Y sampling design. Models in Y2, Y5, Y7, Y8 and Y9 show strong spatial structure, but whose sill is reached within the maximum distance covered. In Y3, the model shows independence of samples without any spatial structure. All the model variograms in Figures 1 and 2 exhibited large positive nugget values attributable to such variability as short scale variability (between sampling points), random and inherent variability, and sampling error.

The differences in model parameter estimates between the spherical and exponential models are shown in Table 2. In general, spherical models fitted better than exponential models as evidenced by the smaller mean squared residuals (MSR). However, both models were generally similar for all the data subsets. The nugget-to-sill ratio is used as a criterion to classify the spatial dependency of soil properties. According to Sun and Zhao (2002), a variable is considered to be having strong spatial dependence if the ratio is less than 25%, and has a moderate spatial dependence if the ratio is between 25 and 75%; otherwise, the variable has a weak spatial dependence. Both the spherical and exponential models show strong spatial dependence in Y1 and Y4, as shown in Table 2. In Y2, Y7 and Y8 the models show moderate spatial dependence, while in Y3 they show weak spatial dependency. For the remaining Y5, Y6 and Y9, the two models classify spatial variability differently. The spherical model

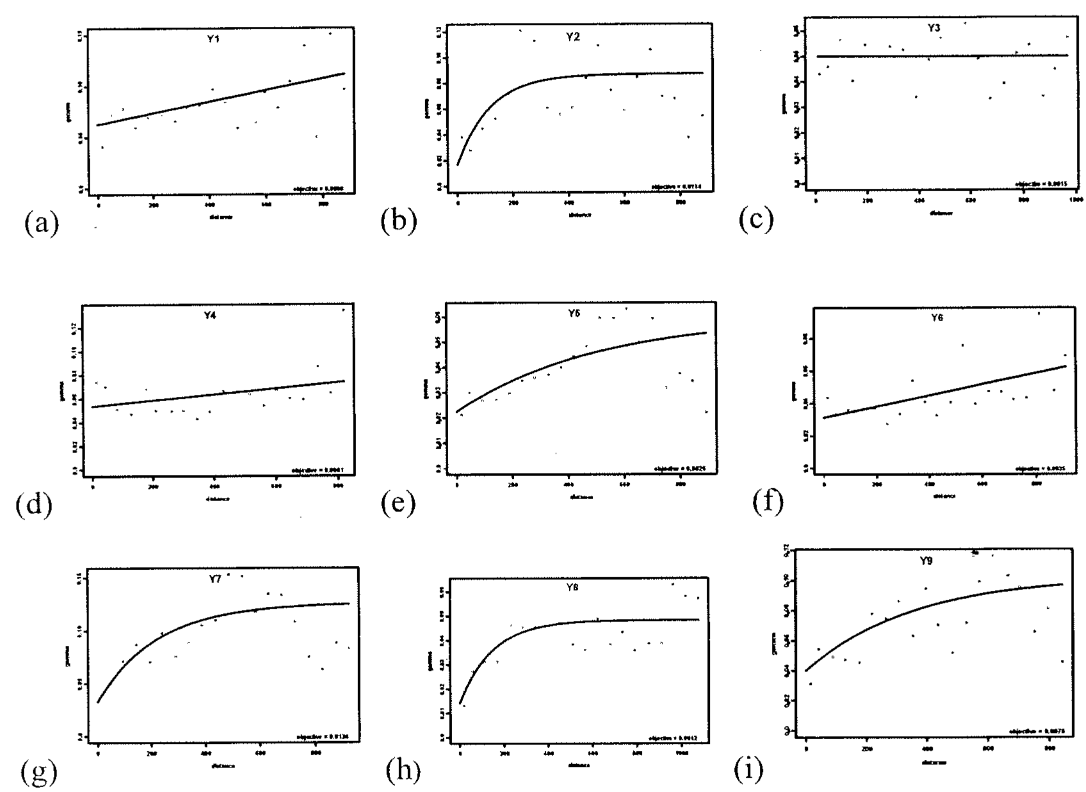

Figure 2. Exponential semivariogram models of predicted soil organic C in each of the Ys (sub-location) (labelled a - i) showing the degree of spatial correlation.

classifies the spatial dependence in Y5 and Y9 as weak (nugget/sill ratio of 0.85 in both cases), while, the exponential model classifies them as moderate (nugget/sill ratio of 0.60 and 0.64, respectively).

Analysis of the fitted variogram models for each of the data subsets indicates that the spatial autocorrelation structure of predicted soil organic carbon ranges from small distances to beyond the maximum distance of 900 metres covered by the study. In the Y1, Y4 and Y6 datasets, spatial autocorrelation structure goes beyond the maximum distance covered by the sampling design. In these three subset areas the range of spatial dependence is expected to hold up to 1.334e+08 m in Y1, 1.24e+07 m in Y4 and 2.78e+08 m in Y6. In reality, this may not be true and the large nugget effects experienced by the models indicate unexplained variance between the sampled points. Beyond these distances, the sample values are then expected to be independent and not influenced by spatial structure. According to a study carried out by Voortman *et al.*, (2002), only a small portion of the variation in crop yields was explained by soil macronutrients N, P and K, and manure application rates. A large portion of the yield differences was explained by spatial dependence or autocorrelation i.e. by the yield values of neighboring observations.

Mixed effects modelling. Linear mixed-effects models were fitted to the data as an iteration process to determine the main factors that contributed significantly to an optimal model. All the parameters that were measured in the field were treated as fixed-effects. The grouping factors; the districts, Ys within a district, and farms within a Y, were all treated as random factors, while the fields within a farm were treated as the residual variance. The Eastings and Northings represented latitudes and longitudes, respectively, and were used to account for spatial variability of the data. After several iterations, the parameter combinations shown in Table 3 were found to

TABLE 2. Models fitted to the empirical semivariograms of $\log_{10}$ organic C for each of the sublocations (Y-area), their parameter values, and the mean squared residual (MSR)

Y-	Model	co	c	a(m)	co/c	MSR
Y1	Spherical	6.20E-02	4.83E+03	1.33E+08	1.30E-05	0.0098
	Exponential	6.20E-02	1.11E+02	1.98E+06	0	0.0098
Y2	Spherical	1.90E-02	6.50E-02	2.82E+02	0.3	0.0102
	Exponential	1.60E-02	7.00E-02	1.18E+02	0.24	0.0114
Y3	Spherical	4.50E-02	4.90E-02	2.15E+02	0.92	0.0014
	Exponential	4.90E-02	0.00E+00	0.00E+00	4.52E+07	0.0015
Y4	Spherical	5.30E-02	2.10E+02	1.24E+07	0	0.0061
	Exponential	5.30E-02	4.80E+01	1.90E+06	0.001	0.0061
Y5	Spherical	2.20E-02	2.60E-02	6.84E+02	0.85	0.0021
	Exponential	2.20E-02	3.70E-02	5.00E+02	0.6	0.0026
Y6	Spherical	3.10E-02	6.14E+03	2.78E+08	5.14	0.0035
	Exponential	3.10E-02	1.53E+02	4.46E+06	0	0.0035
Y7	Spherical	4.50E-02	7.70E-02	5.84E+02	0.58	0.0124
	Exponential	3.20E-02	9.30E-02	2.21E+02	0.35	0.0136
Y8	Spherical	1.80E-02	2.80E-02	3.51E+02	0.65	0.0012
	Exponential	1.40E-02	3.40E-02	1.47E+02	0.42	0.0012
Y9	Spherical	4.20E-02	5.00E-02	6.56E+02	0.85	0.0072
	Exponential	3.90E-02	6.20E-02	3.50E+02	0.64	0.0075

c_0 = nugget effect, c = sill, a = range and MSR = mean squared residual

give better model predictions for the data. The p-values were used to eliminate the most insignificant fixed effect factors, leaving the significant ones. The model output included the values of the *Akaike Information Criterion* (AIC) (Sakamoto, Ishiguro and Kitagawa, 1986) and the *Bayesian Information Criterion* (BIC) (Schwarz, 1978), which is also sometimes called *Schwarz's Bayesian Criterion* (SBC). These were the model comparison criteria evaluated as;

$$AIC = -2\log Lik + 2n_{par}; \text{ and} \tag{16}$$

$$BIC = -2\log Lik + n_{par}\log(N) \tag{17}$$

where n_{par} denotes the number of parameters in the model and N the total number of observations used to fit the model. Under these definitions, "smaller is better". Thus, if we are using AIC to compare two or more models for the same data, we prefer the model with lowest AIC. Similarly, when using BIC we prefer the model with the lowest BIC. The model shown in Table 3 gave the lowest AIC and BIC values, meaning it was the best model obtained by the study.

Analysis of the estimated variance components (Table 3) show that the district effect accounted for a mere 2.6% of the variation in predicted organic C as compared to the Y or farm effects. The Y and farm effects account for 16.5 and 18.4%, respectively, of the total variance observed in soil organic C. Farms within a Y region exhibit between-farm variability comparable to that between Ys but with better estimates. This can be explained by the fact that farms within the same Y region show spatial autocorrelation, hence, the value of predicted soil organic C in adjacent farms can be favourably predicted with minimal standard errors.

The within-farm or between-fields (residual) variability, accounts for the greatest percentage (62.5%) of the variation associated with random effects. Thus, the deviation of an individual value of predicted soil organic C in a field is the deviation of that field from the average of the farm, Y and district where it is located. It encompasses all of the unexplained variation from field to field within a farm, such as local environmental effects (soil type, other biophysical factors not accounted for), management interventions, and measurement error. According to Voortman *et al* (2002), the causes of extreme local variability in crop growth across distances of even a few meters are still poorly understood. The variance of 0.192 means that the standard deviation of the field-to-field variation is v(0.192) = 0.438. Thus, there is more variability of predicted soil organic C within individual farms (approximately up to 63%) than the higher grouping levels.

The spatial mixed effects model. Variogram analysis in Section 3.2 showed that soil organic C displays spatial correlation structures. It's therefore necessary to account for such spatial correlation structures in the context of mixed-effects models. The semivariogram represents a decomposed (nested) random function Z(x), and according to Wackernagel (1998) a nested variogram model is a sum of spatial components characterising different spatial scales, i.e. reaching different sills of variation (b_u) at different scales, except maybe for the last coefficient (b_s), which could represent the slope of an unbounded variogram model. The semivariogram is therefore a product of several

TABLE 3. Summary of model estimates and random effects for the basic mixed effects model

Linear mixed-effects model fit by REML

AIC	BIC	logLik
1111.60	1203.44	-535.80

Random term	Std deviation	Variance comp.	% variance
District	0.090	0.008	2.6
Y	0.225	0.051	16.5
Farm	0.238	0.056	18.4
Field/residual	0.438	0.192	62.5

other individual semivariograms optimised at different lag distances.

To describe the spatial component of the experimental model, three isotropic variogram models (the exponential, spherical and rational quadratic) were fitted using REML by generalised least squares and the parameter estimates given (Table 4).

The exponential model provided the best estimates for modeling the within-group error covariance structure since it has the lowest AIC and BIC values. A comparison between the basic mixed-effects model which does not account for spatial variability, and the final mixed-effects model which does account for spatial correlation structures, indicate a strongly significant improvement of the model as shown by the anova analysis (Table 5). Thus, accounting for spatial variability improves the basic model significantly ($P<0.01$) to arrive at a more stable final model. However, when looking at the actual change in absolute values of the AIC and BIC functions, the change was minimal (Tables 4 and 5), an indication that the mixed effects model had accounted for most of the observed spatial variation. The model factored in the Y-frame sampling design used in this study as random effects, hence controlling most of the variability which would have otherwise occurred due to spatial separation of sampled areas.

The large value of the likelihood ratio (L. Ratio) test statistic gives strong evidence that spatial correlation exists and individual sample values cannot be said to be independent. This means that the influence of the fixed effects on the model with spatial correlation structures accounted for is significantly different from one in which they haven't been accounted. The nugget/sill ratio for all the three models lies between 50-60%, indicating moderate spatial correlation.

GENERAL SYNTHESIS

Soil organic carbon showed moderate spatial correlation within smallholder farms in western Kenya. However, the large variability of soil organic C observed at both within fields of the same farm and among farms, with no clear cut trends poses a big challenge in accounting for its causes. The causes of extreme local variability in crop growth, across distances of even few meters, are still poorly understood (Voortman *et al.*, 2002). It has been attributed to differences in soil chemistry (Scott-Wendt *et al.*, 1988a, 1988b; Kretschmar *et al.*, 1991; Wendt *et al.*, 1993; Stein *et al.*, 1997), but also correlates with differences in local topography (Brouwer and Powell, 1998). In Western Kenya, however, other factors such as farm size, type of management and socio-economic status of the farmer play a great role in determining soil fertility levels as well as their variability within the farm.

At the farm level, micro-scale variation is a factor of different management practices which differ from field to field, variation in biophysical aspects such as soil type and fertility, and the

TABLE 4. Model variograms fitted to the experimental semivariogram using genaralised least squares (gls)

Model	AIC	BIC	LogLik
Exponential	1089.8	1177.1	-525.9
Spherical	1090.4	1177.6	-526.2
Ratio	1094.7	1181.9	-528.3

TABLE 5. ANOVA Analysis between the fitted models

Model	df	AIC	BIC	LogLik
Basic model	1 20	1111.6	1203.4	-535.8
Final model	2 19	1089.8	1177.1	-525.9
Test	L.Ratio	p-value		
1 vs2	19.79	<.0001		

sampling error. At the Y-level micro-scale variation can only exist if sampled farms are adjacent to each other such as those around the centre of the Y. In such cases, micro-scale variation can also be a factor of different management aspects between farmers which are in turn influenced by farmers' socio-economic status. According to Fresco and Kroonenberg (1992), in ecological and geological time-scales, equilibrium situations in nutrient budgets hardly exist, as climate change, volcanism and biodiversity development all have their more or less gradual impact on agro-ecosystems. When these are coupled with variability in farmers' management, which in turn is influenced by socio-economic conditions, its not surprising that soil fertility gradients emerge at different spatial scales. Such complex interactions have led to the high variability of soil organic C observed in within and between smallholder farms of western Kenya.

Most of the observed spatial variations occurred at the field level and less at higher sampling levels. The large nugget variances observed for all semivariogram models indicate the large variability in measured soil organic C. The results concur with those of the mixed effects model which show that the residual effect associated with fields are large as compared to other random effects.

Although this study concentrated mainly on the effects of biophysical factors on the spatial variations of soil organic C, it was evident that short-term and micro-scale processes including socioeconomic endowment of the farmers have, also had a substantial impact. The net effect of these factors over the long run is a gradual build-up of nutrient rich microniches at the expense of a gradual decline in fertility over a much wider area, as already observed in western Kenya. According to Crowley and Carter (2000), such processes are easily missed in studies that aggregate data to the farm and higher system levels or assume an equal distribution of nutrients across the landscape. Therefore, it is important to note that microvariations in soil fertility and other soil properties are essential in farmers' choices of crops per locale and the variable impact of technologies in space. If this is the case, then, modeling of the spatial variations of soil fertility attributes in combination with the socioeconomic conditions of the farmers is an appropriate approach towards better targeting of ISFM technologies.

ACKNOWLEDGMENTS

Authors acknowledge the smallholder farmers of western Kenya on whose farms this research was conducted. The research funds were provided by TSBF (CIAT).

REFERENCES

Barrett, C.B., Place, F., Aboud, A. and Brown, D.R. 2002. The challenge of stimulating adoption of improved natural resource management practices in African agriculture. In: Barrett, C.B., Place, F., Aboud, A. and Brown, D.R. (Eds.). Natural Resources Management in African Agriculture. CAB International, Wallingford.

Brouwers, J.H.A.M. 1993. Rural Peoples' Response to Soil Fertility Decline: The Adja Case, Benin. PhD Thesis. Wageningen Agricultural University, Netherlands.

Brouwer, J. and Powell, J.M. 1998. Increasing nutrient efficiency in West-African agriculture: The impact of micro-topography on nutrient-leaching from cattle and sheep manure. *Agriculture, Ecosystems and Environment* 71: 229-239.

Cressie, N.A.C. 1993. Statistics for Spatial Data, revised edition. John Wiley & Sons, New York.

Crowley. E.L. and Carter, S.E. 2000. Agrarian Change and the Changing Relationships Between Toil and Soil in Maragoli, Western Kenya (1900-1994). *Human Ecology* 28:383-414.

Davidson, A. and Csillag. 2001. A comparison of nested analysis of variance (ANOVA) and variograms for characterizing grassland spatial structure under a limited sampling budget. *Canadian Journal of Remote Sensing* 29:43 - 56.

Fresco, L.O. and Kroonenberg, S.B. 1992. Time and Spatial Scales in Ecological Sustainability. *Land Use Policy* 9:155-168.

Hamlett, J.M., Horton, R. and Cressie, N.A.C. 1986. Resistant and exploratory techniques for use in semivariogram analysis. *Soil Science Society of America Journal* 50:868-875.

Haining, R. 1990. Spatial Data Analysis in the Social and Environmental Sciences. Campridge University Press, Cambridge.

Kaluzny, S.P., Vega, S.C., Cardoso, T.P. and Shelly, A.A. 1998. S+ SpatialStats, User's Manual for Windows and Unix. Insightful Corporation, New York, USA.

KARI, 2003. Soil Fertility Improvement Technologies for western Kenya. KARI Technical Note Series No. 13. KARI, Nairobi, Kenya.

Kretzschmar, R.M., Hafner, H., Bationo, A. and Marschner, 1991. Long- and short-term effects of crop residues on aluminum toxicity, phosphorus availability and growth of pearl millet in an acid sandy soil. *Plant and Soil* 136:215-223.

Nandwa, S.M. 2003. Perspectives on Soil Fertility in Africa. In: Gichuru *et al.*(Eds.). In: *Soil Fertility Management in Africa: A Regional Perspective.* Academy Science Publishers (ASP), Nairobi, Kenya.

Nandwa, S.M. and Bekunda, M.A. 1998. Research on nutrient flows and balances in east and southern Africa: state-of-the-art. *Agriculture, Ecosystems and the Environment* 71:5-18.

Ojiem, J.O.,Palm, C.A., Okwuosa, E.A. and Mudeheri, M.A. 2004. Effects of Combining Organic and Inorganic Phosphorus Sources on Maize Grain Yield in a humic-Nitisol in Western Kenya.

Parkin, T.B. 1993. Spatial variability of microbial process in soil a review. *Journal of Environmental Quality* 22:409-41.

Scott-Wendt, J., Hossner, L.R. and Chase, R.G. 1988a. Variability in pearl millet (*Pennisetum americanum*) fields in semiarid West Africa. *Arid Soil Research and Rehabilitation* 2:49-58.

Scott-Wendt, J., Chase, R.G. and Hossner, L.R. 1988b. Soil Chemical variability in sandy ustalfs in semiarid Niger, West Africa. *Soil Science* 145/6: 414-419.

Sun, B. and Zhao, Q. 2002. Spatial-temporal variability of red soil fertility in low hill region. 17[th] WCSS, 14-21 August 2002, Thailand.

Stein, A., Brouwer, J. and Bouma, J. 1997. Methods of comparing spatial variability patterns of millet yield and soil data. *Soil Science Society of America Journal* 61:861-870.

Stoorvogel, J.J., Smaling, E.M.A. and Janssen, B.H. 1993. Calculating Soil Nutrient Balances in Africa at Different Scales I. Supra-national Scale. In: Smaling EMA (Ed.), 250pp. An Ecological Framework for Integrated Nutrient Management with special reference to Kenya Agricultural University. Wageningen, Netherlands.

Tittonell, P. 2003. Soil fertility gradients in smallholder farms of western Kenya. Their origin, magnitude and importance. Msc. Thesis, Wageningen University.

Vanlauwe, B., Diels, J., Sanginga, N. and Merckx R. 2001. Integrated Plant Nutrient Management in Sub-Saharan Africa. From concepts to practice. CABI Publishing, Wallingford.

Voortman, R.L., Brouwer, J. and Albersen, P. 2002. Characterization of Spatial Soil Variability and its Effect on Millet Yield on Sudano-Sahelian coversands in SW Niger. Centre for World Food Studies, Staff Working Paper, WP – 02 – 02.

Wackernagel, H. 1998. Multivariate Geostatistics: An Introduction With Applications. 2[nd] Edition. Springer, Heidelberg.

Webster, R. and Oliver, M.A. 2001. Goestatistics for Environmental Scientists. Statistics in Practice. John Wiley & Sons, Chichester.

Wendt, J.W., Berrada, A., Gaoh, M.G. and Schulze D.G. 1993. Phosphorus sorption characteristics of productive and unproductive Niger soils. *Soil Science Society of America Journal* 57:766-773.