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Multi-scale characterization of soil variability within an agricultural landscape mosaic system in southern Cameroon

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Abstract

The characterization of soil spatio-temporal variability is essential to achieve a better understanding of complex relations between soil properties, environmental factors and land use systems. This study evaluates the sources of soil variability in an agricultural landscape mosaic system in the humid forest of southern Cameroon at four scales: (i) the regional level as affected by soil-forming factors; (ii) the local level as affected by land use; (iii) the within-plot level in shifting cultivation crop fields; and (iv) the quality control level in the laboratory. At the first three levels, the study was based on soil samples collected throughout a 2000 km^2 area, with a different sampling scheme for each level. In the laboratory, we used replicated measurements of soil chemical properties of reference samples similar to those in the study area. Analysis of variance (ANOVA), Principal Component Analysis, cluster analysis and variogram modelling were applied. Soil properties exhibit a high spatial dependence even at plot level, but there is a clear regional trend explaining 30–50% of the total variation, modelled either by elevation or geographic coordinates. Cluster analysis, landscape zoning and soil classification showed, with more than 80% coincidence between methods, that the soils of the study area can be grouped in two main classes (Ferralsols and Acrisols) and five subclasses. Soil pH (r^2=0.68) and clay content (r^2=0.51) were the best explained by regional factors of soil variation. Geostatistical analysis showed that a closer sampling density would be required to map regional variability which is not due to land use, regional trend or environmental covariates. Regional and local effects, and their interaction, accounted for 70% (clay) to 85% (pH) of the total variance. The cumulative variances from field plot and laboratory was similar to the nugget variance from geostatistical modelling. Land use practices significantly (p<0.05) influenced topsoil variation between plots at village level, but there was low variation within plots of about 1 ha. At laboratory level, all variables deviated from the ideal behaviour expected of well-mixed reference samples; however, in absolute terms both total ranges and standard deviations were quite low, except in the case of available P. Although clay content and pH have shown to vary considerably at regional level, research for appropriate management practices for

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resource use should focus chiefly on processes and factors occurring at the local level, as influenced by a dynamical land use system.

Keywords: Multi-scale characterization; Soil variability; Agricultural landscape mosaic; Rain forest; Southern Cameroon

1. Introduction

Soil heterogeneity has been recognized for many years as due to factors operating and interacting at various spatial and temporal scales (Burrough, 1993). The characterization of the spatial variability of soil attributes is essential to achieve a better understanding of complex relations between soil properties and environmental factors (Goovaerts, 1998), and to determine appropriate management practices for soil resources use (Bouma et al., 1999). It also has practical implications for sampling design for ecological, environmental and agricultural studies (Stein and Ettema, 2003). In addition, demands for more accurate information on spatial distribution of soils have increased with the inclusion of the spatial dependence and scale in ecological models and environmental management systems (Godwin and Miller, 2003). This is because the variation at some scales may be much greater than at others.

First, soils clearly differ on regional scale (Brejda et al., 2000; Guimaraes Couto et al., 1997), and a great variability can be expected as the result of widely varying soil forming factors. Yost et al. (1982) showed that soil chemical properties commonly have spatial dependence even at regional scale.

Second, it is well-known that soil properties are influenced by human activities at field level. Many studies have shown a large variation of soil properties between fields with different land uses and management strategies on the same soil type (Kotto-Same et al., 1997; Nye and Greenland, 1960). Van Es et al. (1999) showed that, under certain circumstances, tillage and temporal effects were even more significant than field-scale spatial variability.

Third, many authors (Earl et al., 2003; Godwin and Miller, 2003) have documented how spatial variability of soil properties within a single field plot affects soil performance and crop yield. However, most soils studies, including those in tropical Africa, use bulk sampling from the area analyzed or treated, e.g. the agricultural field. This leaves unanswered the question of how much soil variability is ignored by such sampling. This leads to the next question: if this variability could be mapped, how much economic benefit could there be in treating small areas of the field differently? This is the motivation for the recent interest in precision agriculture, which has resulted in much work on within-field variability, mostly in the context of high-technology farming (Godwin and Miller, 2003) but also in shifting cultivation (Mapa and Kumaragamage, 1996) and subsistence farming (Van Groenigen et al., 2000). These studies showed that physical properties are usually much less variable over short distances than chemical properties.

Finally, all of the above-mentioned studies of variability depend on the soil analytical data from the laboratory. Variation of soil analytical data from one batch treatment to another has generally been ignored by the use of check (or reference) samples in the laboratory for quality control rather than attempting to explicitly measure and model the error, which sets a lower limit on the uncertainty of all higher levels. Much work has been done on laboratory quality control (Van Reeuwijk, 1998); however, our interest here is as data users, not providers.

The fundamental question we sought to answer in this study is: at which of these scales is soil variability most significant in soils used for shifting cultivation in the humid forest zone of southern Cameroon? A related question is the degree to which the feature space of the soil-forming factors can explain variability, and how much can be explained by a model of spatial dependency in geographic space. The variation of soil properties is often described by classical statistical methods assuming independence of samples, at least within strata. However, soil properties often exhibit spatial dependence (Burrough, 1993). To determine the nature of this spatial dependence, we used geostatistical methods that have previously been successfully applied (Goovaerts, 1998); along with mixed approaches that combine stratification with local spatial dependence (Brus, 1994).

The purpose of this study was to evaluate the sources and scales of variability of soil properties in an agricultural landscape mosaic system (ALMS) from the regional to the laboratory level. Following Forman (1995) we define an ALMS as the pattern resulting from the agricultural land use system practised by small-scale farmers, which is dominated by shifting cultivation and perennial plantations (cocoa, oil palm, rubber) and where spatial and temporal heterogeneity of aggregated elements of distinct boundaries and the mixed local ecosystems are repeated in a similar form over a defined area.

2. The study site

The study was conducted in the research area of the Tropenbos Cameroon Programme (TCP), which was selected as representative of the rain forest of southern Cameroon (Foahom and Jonkers, 1992). The site covers about 200 000 ha and is located between 2°47′–3°15′ N and 10°24′–10°51′ E, within the Universal Transverse Mercator projection (UTM) zone 32N (Fig. 1). The area is part of the southern Cameroon plateau, a vast slightly undulating forested region, underlain by the Precambrian Basement Complex (Champetier de Ribes and Reyre, 1959). Fig. 2A shows the geological map of the area, as adapted from these authors. However, more detailed information on the site is provided in Yemefack et al. (in review) and Nounamo and Yemefack (2001).

The area was subdivided on physiographic basis into five landscape ecological zones (Fig. 2B) by Van Gemerden and Hazeu (1999) according to altitude and soil drainage: zone A (>700 m asl), zone B (500–700 m asl), zone C (350–500 m asl), zone D (<350 m asl), and zone E (locally important wetland valleys). The first four zones account for more than 95% of the total area. The inland valley bottom soils were not further included in this study because they are localized, easy to identify, and show clear contrasts with the upland soils. The same authors grouped the well-drained soils of the four zones in three soil types (Fig. 2B) based on soil particle size distribution and soil drainage: Nyangong soils (well-drained, very clayey from topsoil), Ebom soils (well-drained, clayey from topsoil), and Ebimimbang soils (moderately well-drained, sandy topsoil and clayey subsoil). These general soil types were named from nearby villages where the soil types were first described. Thus, they are not well-defined soil series such as defined by

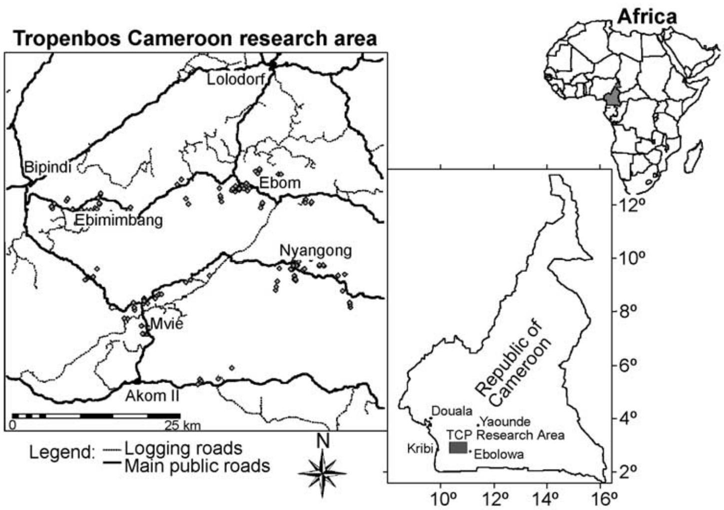

Fig. 1. Location of the study area and spatial distribution pattern of sample points (small diamonds in the sample area map).

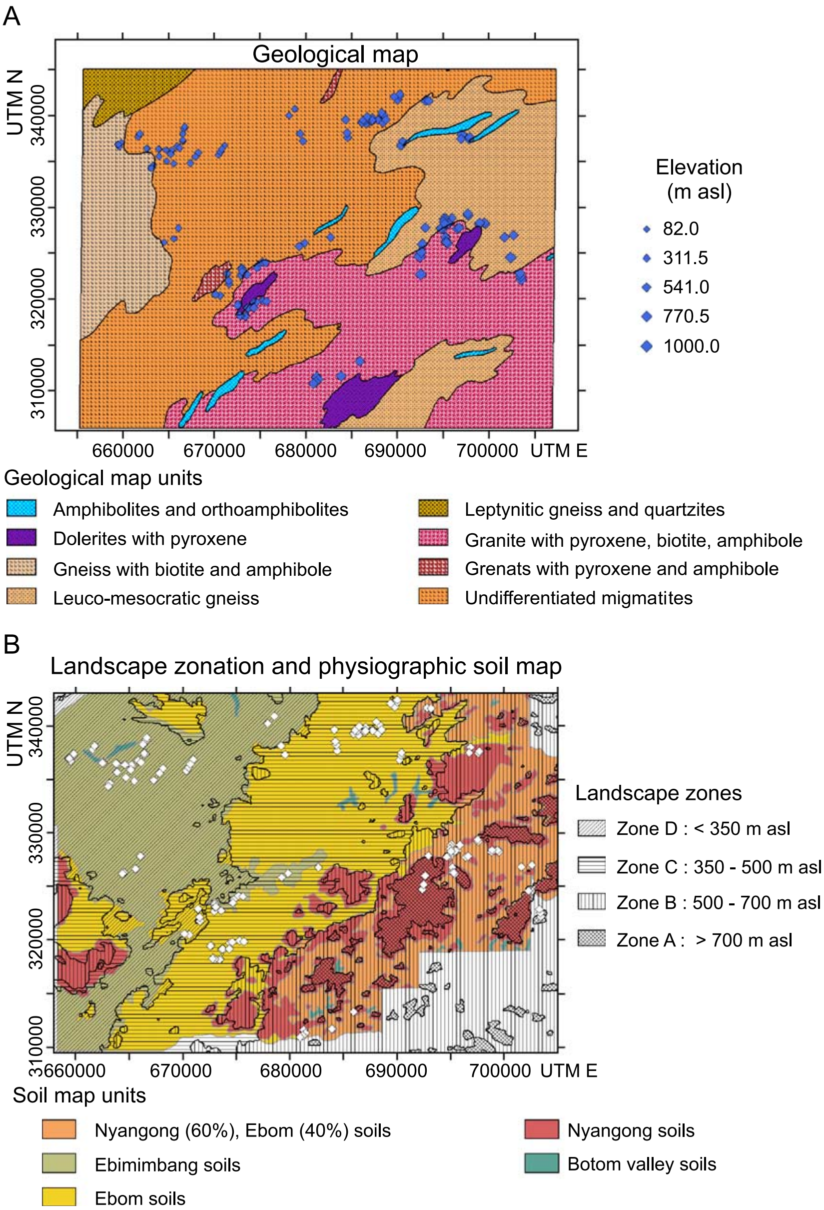

Fig. 2. Geological map and physiographic soil map as adapted from Champetier de Ribes and Reyre (1959) and Van Gemerden and Hazeu (1999), respectively.

USDA Soil Taxonomy (ST) (Soil Survey Staff, 1998), but rather loose assemblages of similar soils at approximately the family or subgroup levels of ST. These soils are classified respectively as Ferralsols and Acrisols according the World Reference Base for soil resources (WRB) (FAO-ISRIC, 1998).

3. Research design and methods

Four scales were studied: (i) the regional level of soil spatial distribution as affected by regional trend, using elevation as a proxy for soil-forming factors, and residual spatial dependence; (ii) the local level of soil variation as affected by land use; (iii) the within-plot level of soil spatial variability in shifting cultivation crop fields; and (iv) the data quality control level in the laboratory. Different sampling schemes were design for each scale. Three fixed soil layers (0–10, 10–20, and 30–50 cm) were used for all the analyses at the first three levels. Geographic analyses and visualizations were performed with the gstat (Pebesma and Wesseling, 1998) and spatial (Ripley, 1981; Venables and Ripley, 2002) packages of the R environment for statistical computing (Ihaka and Gentleman, 1996; R Development Core Team, 2002). Some visualizations were produced with the ILWIS software (ITC Unit of Geo Software Development, 2001). Cluster and Principal Components Analyses were done in the SPLUS statistical package (Lam, 2001).

3.1. Regional level

3.1.1. Field data collection and laboratory analysis

At this level, the study covered a total area of about 200 000 ha where 45 representative soil profiles were described (Van Gemerden and Hazeu, 1999) using the FAO guidelines for soil description (FAO, 1990), and sampled by genetic horizon. Soil characteristics for each of the three fixed layers were computed as weighted averages using genetic horizon thickness. In addition, 102 plots from various land use/land cover types as defined by Yemefack et al. (in review) were sampled at the three fixed depths. Each sample was a bulked composite of five sub-samples taken with an Edelman auger in a plot diagonal basis. For both data sets, samples were located purposively and subjectively to represent soil and land use types. The geographic coordinates of each sampling point were recorded using the Global Positioning Systems (GPS). The GPS was a Garmin 12XL model, with estimated precision of $\pm$100 m in 1997 when Instrument Selective Availability (SA) was still enabled. After SA was disabled in 2000 all fields were revisited with a GPS instrument precision of $\pm$10 m. These latter readings were used for adjustment and georeferencing. The elevation of each sampling point was determined from a georeferenced interpolated contour map of the area (scale 1:200 000). All the soil samples were analyzed in the IRAD Soil laboratories at Ekona and Nkolbisson, using procedures of soil analysis described in Van Reeuwijk (1993) and Pauwels et al. (1992).

3.1.2. Summary statistics

Since certain soil properties are more dynamic than others, descriptive statistics were first computed on all variables at all depths. Twelve variables showing significant variation (p<0.05) were then selected for further analyses: pH-water (code in further text pHw, units pH), organic carbon content (OC, %), available phosphorus (Pav, ppm), calcium (Ca, cmol$^+$ kg^{-1} of soil), sum of bases (SB, cmol$^+$ kg^{-1} of soil), aluminum saturation of the exchange complex (Alst, %), effective cation exchange capacity both in soil (ECEC, cmol$^+$ kg^{-1} of soil) and clay (ECECC, cmol$^+$ kg^{-1} of clay), cation exchange capacity both in soil (CEC, cmol$^+$ kg^{-1} of soil) and clay (CECC, cmol$^+$ kg^{-1} of clay), base saturation of the exchange complex (BSP, %), and clay content (Clay, %). Pairwise correlations were computed between layers for the same variable and between variables for the same layer.

3.1.3. Principal Components Analysis (PCA)

To explore the multivariate relationships between soil properties at each depth, a Principal Components Analysis (PCA) on the correlation matrix (i.e., standardized variables) was performed using the whole set of soil variables at each depth separately. The two first principal components, PC1 and PC2 were plotted on biplots (Gower and Hand, 1996). The interpretation of this biplot allowed the selection of two original soil variables (clay content and pH-water) for geostatistical and regional trend analysis.

3.1.4. Cluster analysis

Using the 12 selected soil variables at all three depths, an agglomerative hierarchical cluster analysis based on Ward's grouping method and correlation matrix (Webster and Oliver, 1990) was conducted to group the 147 regional soil observations. All depths were used in one analysis to include the effects of vertical profile differentiation. This technique arranges individuals (soil profiles) together into larger and larger groups in such a way that individuals belong to small groups, the small groups belong to larger groups, and so on. It is based on dissimilarity matrix of Euclidean distances between individuals.

3.1.5. Regional trend analysis

The aim at this level is to elucidate the spatial structure of regional soil variation, and from this to infer explanatory factors. We selected two variables (clay content and pH in water), identified as key variables by PCA, which we expected to show different structures. To minimize the effect of land use in the regional analysis, we used the deepest (30–50 cm) layer.

To determine the nature and strength of any regional trend we computed the first- and second-order linear dependence of the two variables on UTM coordinates using both ordinary (OLS) and generalized (GLS) least squares, both with the spatial R package. For GLS we fitted an approximate spatial correlation structure to a correlogram of the target variables (Venables and Ripley, 2002); this is used to determine weights, thus compensating for spatial clustering of similar values. Since calibration points were in fact clustered in villages, this weighting could result in a substantially different trend surface from OLS, especially if the observations are most dense at the highest or lowest values (Venables and Ripley, 2002). This OLS surface is effectively that used in Universal Kriging (UK) as implemented in gstat if no local neighbourhood is specified, although in UK the trend is implicit in the kriging equations and not solved for explicitly as in the trend surface analysis.

3.2. Geostatistical analyses

3.2.1. Ancillary regional variables

We computed the linear dependence of the two variables on elevation, and their categorical association with soil type, soil subtype, and landscape ecological zone, all in R using the lm() ('fit linear models') method. Such associations could be used in mapping by Kriging with External Drift (KED), given maps of these factors.

3.2.2. Variogram analysis

To test the hypothesis that values at nearby sites are more similar than those further apart, experimental variograms of the two selected variables were computed with the gstat R package using the standard Matheron estimator (Webster and Oliver, 2001). For the original variables, point pairs were grouped into bins of 750 m separation, up to a range of 15 500 m (one-third of the maximum separation in the data set); this resulted in 87–316 (median 180) point pairs per bin. Because of the clustered sampling, separations of 6–12 km had only about half the point pairs of other separations. Variograms of the residuals after removal of the regional trend showed very erratic behaviour beyond an initial sill around 5 km range, so were re-computed with that limiting distance, with narrower bins of 500 m separation to provide sufficient bins for variogram modeling; this resulted in 108–199 (median 156) point pairs per bin. Variogram model classes and initial parameters were selected by eye, and model parameters adjusted by gstat using a least-squares fit to the experimental variogram with empirical weighting proportional to the number of point pairs and inversely proportional to the square of the estimated semivariance for each (Pebesma, 2001). This gives emphasis to reliable estimation of the nugget and close-range behaviour, to which interpolation is most sensitive.

3.2.3. Kriging mapping

We mapped both target variables on a 250×250 m grid over the rectangle (658 000 E, 309 500 N) to (705 000 E, 343 000 N) in UTM zone 32N (1) from the OLS and GLS trend surfaces, (2) by ordinary kriging (OK) using the original variogram, (3) by universal kriging (UK) using the residual variogram, and (4) by regression kriging (RK) using simple kriging (SK) on the residuals from both the OLS and GLS second-order trend surfaces and the residual variogram, adding back the trend surfaces to obtain the final interpolation. Punctual kriging approximated the original support, namely small fields on the order of 50×50 m, in which short-range variability had already been removed by bulk sampling.

3.2.4. Assessing agreement between various classification techniques

The results of the hierarchical cluster and geostatistical analyses were compared to landscape ecological zoning by altitude and to the WRB soil classification, using soil profile cross tabulation in contingency matrices. To map the landscape ecological zones, a map of principal elevation contours, derived from a 1:200 000 topographic map, was interpolated and level-sliced in a Geographic Information System (GIS) according to the definitions of Van Gemerden and Hazeu (1999).

The degree of agreement between each pair of techniques was evaluated with the coefficient of contingency C (Bonham-Carter, 1994). To compute this, the cross-tabulation between soil profiles classified by a pair of methods was used as for a contingency table. Let the soil profile table between method A and method B be called matrix T, with elements T_{ij}, where there are i=1,2,. . .,n classes from method B (rows of the table) and j=1,2,. . .,m classes from method A (columns of the table). The partial totals of T are defined as T_{ir} for the sum of ith row, T_{jc} for the sum of the jth column, T_{rc} for the grand total summed over rows and columns. If the two techniques are independent of one another, with no correlation between them, then the expected overlapping class is given by the product of the partial totals, divided by grand total. Thus the expected number of profiles $T_{ij}*$ for ith row and jth column is

$$T_{ij}* = \frac{T_{ir}}{T_{rc}} T_{jc}.$$

Then the chi-square statistic is defined as:

$$X^2 = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{\left(T_{ij} - T_{ij}*\right)^2}{T_{ij}*} = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{\left(T_{ij}T_{rc} - T_{ir}T_{jc}\right)^2}{T_{ir}T_{jc}},$$

corresponding to the familiar (observed−expected)^2/expected expression, which has a lower limit of zero when there is complete agreement between the two techniques. As the observed number of cases becomes increasingly different from the expected values based on marginal totals, the chi-square increases in magnitude. One of the commonly quoted coefficients of association based on chi-square values is the contingency coefficient C, which is defined as

$$C = \sqrt{\frac{X^2}{T_{rc} + X^2}}.$$

The magnitude of C is independent of measurement units, and varies between zero (indicating no correlation) to a maximum value less than one (for strong correlation).

3.3. Local level

Four villages (Ebimimbang, Mvie, Ebom, Nyangong) were selected (Fig. 1) to represent the physiographic zones. In each village, eight land use/land cover plot types were selected with three or four different fields as replications. Land use/land cover treatments were chosen based on actual agricultural production cycles at smallholder scale and the cycling conceptual model developed by Yemefack et al. (in review). These treatments comprised three fallow types with increasing duration (CF=*Chromolaena* fallow, 3–5 years; BF=Bush fallow, 7–9 years; and FF=Forest fallow, more than 15 years), one cropland type (CL=mixed groundnut–maize–cassava crop field), one forest mixed crop field type (FCF=forest crop field), two cocoa plantations types (MCA=less than 7-year-old and OCA=more than 30-year-old), and one forest type (FV=virgin forest) as control. CL plots were resampled at the end of the cropping phase (CL2). No fertilizers were applied on any plot. A total of 155 samples were collected at each depth (FCF (12), CL1 (26), CF (12), BF (12), FF (12), FV (34), MCA (10), and OCA (12)), of which 27 were repeat samples (CL2).

The focus was on the effects of land use on soil properties because of the relative homogeneity of soils used for agriculture within each village. A one-way analysis of variance (ANOVA) and means separation (Tukey's HSD) were used to investigate the effects of land use on soil properties at each soil depth. To differentiate this effect at village level from the effect of soil type as represented by different villages, a factorial ANOVA was performed modelling villages, land use and the interaction between the two factors. The coefficient of determination (R^2) that gives the contribution of each factor to the model was calculated as follows: R^2=(Explained sum of squares of each factor)/(Total sum of squares), expressed in percentage.

3.4. Within-plot level

At this level of the study, the objective was to quantify the spatial variation of soil within an individual field plot as compared to bulked representative sample of the same plot. Three farmers' fields of 0.5–0.7 ha each were selected within a 2-km radius in Mvie village, all on Acri-xanthic Ferralsols. Two of these plots were under CL and the third under CF. In order to eliminate the effect of land use as quantified at the local level, data were standardized for certain analyses as explained below. A hierarchical nested quadrant sampling method was used to collect soil samples from each field. Each of the three field plots was divided at three stages into sampling units S_n (or quadrant) which size varied as a function of the total plot size A. The sample area at each stage S_n was defined in a geometric series $A/2^{2n}$, for n=0 ,. . ., 3 being the stage of subdivision and S_0=A, i.e. the whole plot. From each sampling unit at each stage, composite soil samples were collected at the three fixed depths with an Edelman auger from five spots in a unit diagonal basis. A total of N=75 units were then sampled at the following four stages: S_0 (N_0=3), S_1 (N_1=12), S_2 (N_2=48), and S_3 (N_3=12). These samples were analyzed in the IRAD soil laboratory at Nkolbisson for pH-water, exchangeable bases and bulk density.

Descriptive statistics were used to analyze the spread of the data. Factorial ANOVA was used to evaluate soil variability from each bulked sample within and between field plots at different depths. Nested ANOVA of the four sampling stages was carried out on standardized variables of each soil characteristic from each layer separately. Soil data from the three different fields were made comparable in each layer by adjusting the field plot mean to the mean of the whole dataset, as follows:

$$Y_i' = \left(\frac{Y_i}{\bar{Y}_i}\right) * \bar{Y},$$

where Y_i is the value of a soil variables from field i; Y-$_i$ is the within-field mean of Y_i in field i; Y- is the grand mean of Y_i between the three fields, and Y_i' is the standardized value.

3.5. Laboratory level

To evaluate baseline variation of soil analytical data, we used replicated measurements of soil chemical properties from reference batches of soils similar to those in the study area. These had been used as part of the laboratory quality control process (Van Reeuwijk, 1998) from 1992 to 2003 at IRAD Nkolbisson; period during which all the soil samples used at different scale of this study were analyzed in the same laboratory. Properties analyzed were pH-water and KCl (n=100, 3 batches); the sum of bases, Ca, Mg, K, Na, and the cation exchange capacity (CEC) of the whole soil (n=72, 3 batches); organic C (n=261, 3 batches) and total N (n=220, 3 batches); free Fe (n=20, 1 batch); and available P (n=116, 2 batches). Since absolute values were not of interest, all observations were standardized to deviations from their batch mean. The range, sample standard deviation, number of boxplot outliers defined as observations more than 1.5 times the inter-quartile range above the 3rd or below the 1st quartile (Hoaglin et al., 1983), the Shapiro-Wilk test of normality (Royston, 1982), and Bartlett's test for homogeneity of batch variances (Brownlee, 1965) were calculated with the R statistical computing environment, version 1.7.1 (Ihaka and Gentleman, 1996). For variables with non-homogenous variances, the overall sample standard deviation was computed as the square root of the average of the batch variances weighted by number of replications in each batch. In the event, these weighted standard deviations deviated by less than 1% relative to the unweighted values. To assess the contribution of laboratory variation to field studies, the laboratory standard deviation was compared to the residual root mean square from modelled experiments.

3.6. Comparing levels

According to Webster (2000) the additive nature of variances allows distinguishing variation from two or more sources and estimating their components by ANOVA. The partition of the coefficients of determination was based on the fact that factorial ANOVA partitions the total sum of squares into explained (for each factor and interaction) and unexplained sums of squares. To compare variances at the several levels, we first partitioned the multiple total coefficient of determination of factorial ANOVA model at the local level into partial coefficients of determination for the regional factor (as represented by villages), local factor (land use/land cover), and their interaction. Second, the coefficient of determination for the plot level contribution was obtained from the nested ANOVA (see Section 3.3) comparing the four stages of the nested samples. Then, we obtained the ratio of explained sums of squares (for each factor i.e. region, local, and their interaction) over the total sum of squares, as a measure of the proportion of the total variation that has been explained by each factor.

4. Results and discussion

4.1. Spatial distribution of sampling points

Fig. 1 shows the distribution of sample points within the study area. Most of the points were purposely clustered near roads and in the four selected villages. The minimum distance between sampling points was about 30 m; while the maximum distance from a point to its first nearest neighbour was about 1 km, for an average of 515 m to nearest neighbour. All the land units represented in the area were sampled, and the clusters are well distributed across the study area.

4.2. Regional variability of soils

4.2.1. Summary statistics and spatial data structure

Table 1 summarizes the statistics of the 12 soil variables studied at regional scale. All showed a positive skewness with coefficients varying between 0.08 and 2.5. So that the mean of each variable is slightly greater than the median. However, no transformation was done on the original dataset since ANOVAs are rather insensitive to slight departures from normality (Webster, 2000).

Table 1
Summary statistics of the original soil variables (sample population, n=147)

	pH	OC, %	P.av, ppm	Ca, cmol$^+$ kg^{-1}	SB, cmol$^+$ kg^{-1}	Al.st %	ECEC soil,	ECECC soil, cmol$^+$ kg^{-1}	CEC soil, cmol$^+$ kg^{-1}	CECC soil, cmol$^+$ kg^{-1}	BS, %	Clay, %
0–10 cm												
Min	3.20	1.04	2.00	0.16	0.54	0.00	2.04	8.20	2.98	10.30	3.7	9.5
Mean	4.59	2.98	7.84	2.31	3.75	19.17	6.98	27.19	11.20	40.29	38.5	31.7
Median	4.40	2.70	7.00	1.38	2.83	19.15	6.71	20.82	10.05	35.64	26.5	30.0
Max	7.60	10.90	29.00	10.71	15.89	53.00	16.21	118.31	29.00	146.2	162.4	72.0
Std Dev	0.88	1.50	4.73	2.39	3.19	13.69	2.83	19.24	5.09	20.3	33.1	13.9
SE mean	0.07	0.12	0.39	0.19	0.26	1.13	0.23	1.58	0.42	1.67	2.7	1.15
Skewness	1.17	1.92	2.06	1.75	1.73	0.25	0.89	2.32	1.15	1.84	1.4	0.96
Kurtosis	0.81	6.51	5.07	2.41	2.64	−0.55	0.84	5.80	1.58	4.94	1.7	0.01
CV%	19.20	50.20	60.40	104	85.10	72.40	40.60	70.80	45.50	50.30	86	46.50
10–20 cm												
Min	3.30	0.30	0.50	0.01	0.15	0.00	1.29	5.00	1.60	5.81	2.4	9.5
Mean	4.58	1.40	2.98	0.76	1.54	32.48	5.43	15.57	7.51	21.70	28.0	36.8
Median	4.40	1.30	3.00	0.52	1.11	31.42	5.14	14.31	7.00	19.80	16.1	36.0
Max	7.30	3.70	8.00	3.55	5.53	97.14	24.44	50.92	22.00	62.86	133.4	75.0
Std Dev	0.83	0.72	1.56	0.69	1.18	22.39	2.73	6.20	3.63	9.48	28.3	14.6
SE mean	0.06	0.06	0.13	0.06	0.10	1.84	0.23	0.51	0.30	0.78	2.3	1.2
Skewness	1.30	0.95	1.10	1.76	1.84	0.56	2.51	1.80	0.92	1.45	1.66	0.23
Kurtosis	1.21	1.02	1.16	2.79	3.02	0.35	14.97	6.76	1.028	3.54	1.29	−0.36
CV%	18.10	50.20	52.50	90.60	76.80	69	42.10	36.60	46.70	43.70	112	39.80
30–50 cm												
Min	3.50	0.20	0.00	0.01	0.13	0.00	1.30	4.42	1.00	4.00	2.4	16.0
Mean	4.75	0.81	1.34	0.57	1.20	35.07	4.76	10.95	6.93	16.1	21.9	44.7
Median	4.70	0.84	1.00	0.36	0.83	34.00	4.51	10.17	6.60	15.3	12.1	45.0
Max	6.80	1.70	3.00	2.81	5.65	120.9	12.87	22.19	14.00	31.3	106	80.0
Std Dev	0.64	0.32	0.66	0.60	1.08	23.83	1.79	3.61	2.71	6.19	22.62	12.9
SE mean	0.05	0.03	0.06	0.05	0.09	1.96	0.15	0.29	0.22	0.51	1.86	1.06
Skewness	1.05	0.08	0.99	2.13	2.33	0.92	0.99	0.98	0.30	0.59	1.74	0.16
Kurtosis	1.58	−0.44	0.67	4.00	5.34	1.29	2.01	0.98	−0.22	−0.07	2.25	−0.06
CV%	13.50	39.50	49.70	105	90.20	67.30	35.20	32.20	38.20	38.60	103	28.80

Two representative properties were selected to compare layers: clay as a percentage of total fines (physical property) and pH-water (chemical property). Coefficients of determination, calculated as the square of the correlation coefficient, are moderate (0.57–0.88) for pH and high (0.81–0.90) for clay. Adjacent layers have higher correlations than the surface and deepest layers (0.57 for pH and 0.81 for clay). This difference can be partly explained by the higher influence of land use on topsoil than the subsoil. This effect is likely greater for pH (effect of wood ash from clearing and burning) than on clay content, which is largely pedogenetic.

One-way ANOVA by depth shows a highly significant difference in clay content among layers, with the three layers averaging 31.3%, 36.8%, and 44.7%, respectively; however, pH did not differ among depths. Two-way factorial ANOVA (by depth and soil type) showed no effect of soil type on this depth relation for clay content; however for pH there was a highly significant interaction, meaning that the pH variation with depth differed among soil types. This suggests that Acrisols which have high pH values may be less sensitive to ash effects compared to acid Ferralsols, especially in the surface layer. Bartlett's test for homogeneity of variances could not reject the null hypothesis of homogeneous variances for clay content (p=0.30), but this was rejected (p<0.001) for pH; variance was significantly lower in the subsoil, most likely due to management effects in the surface soil.

Fig. 3 shows geographic postplots of clay content and pH in the 30–50 cm layer. There is a clear first-order regional trend, which was confirmed by the fitted OLS surface (multiple R^2 of 0.50 and 0.39, respectively). The principal azimuth for this trend, computed from the arctangent of the two coefficients, was approximately 125° for both variables. Clay content increases while pH decreases along this axis. Fitting a second-order OLS surface improved the goodness-of-fit to a multiple R^2 of 0.52 and 0.51, respectively. The second-order GLS trend surface, which accounts for spatial correlation between calibration points, was almost identical both in coefficients and fit (R^2=0.51) for clay content but substantially different, and with a much poorer fit (R^2=0.31) for pH. The spatial covariance structures for the GLS equations were in both cases spherical with 0.3 proportion of nugget effect and ranges of 20.5 and 15 km, respectively, at which ranges the experimental correlograms first showed no correlation. These regional trends explain only about one third to one half of the total variation, the rest to be explained by local spatially dependent processes. A mixed interpolator is indicated for mapping.

4.2.2. Principal Components Analysis (PCA)

Table 2 shows the characteristics of the first five PCs from the PCA of the standardized values of twelve soil variables for the three soil layers. In all cases these explain over 90% of the total variation. In the topsoil, the first two components explain 75%; only about 65% is explained for the deeper layers. This discrepancy indicates that management effects, concentrated in the topsoil (especially the ash effect), tend to increase the multiple correlations between soil properties.

Fig. 4 shows biplots of the first two PCs for the three layers separately. The first axis, which explains about half of the total variation, by definition shows the maximum single discrimination of the soil variables. For all three layers this axis is controlled by clay content and pH at opposite ends. On this axis, soil parameters related to soil solution and cation mobility such as soil reaction, base saturation, exchangeable bases are represented by vectors projected in the left (negative) side of the graphs. Properties related to the capacity of soil adsorption complex to retain and exchange cations with soil solution (e.g. CEC) are projected around the zero of the first axis, but dominate the second axis. Soil properties linked to the magnitude of the adsorption complexes (clay, organic carbon) are projected on the right (positive) side of the graphs. The second component, by definition orthogonal to the first, and here explaining about 20% of the total variation, explained mostly the interaction between the two main controlling factors of the first component, namely magnitude of the adsorption complex and soil solution. A number of observations plotted near the origin of the biplot are not well differentiated by the two first PCs.

4.2.3. Numerical classification of soil profiles

Cluster analysis has been successfully applied in soil survey to create classes within which the

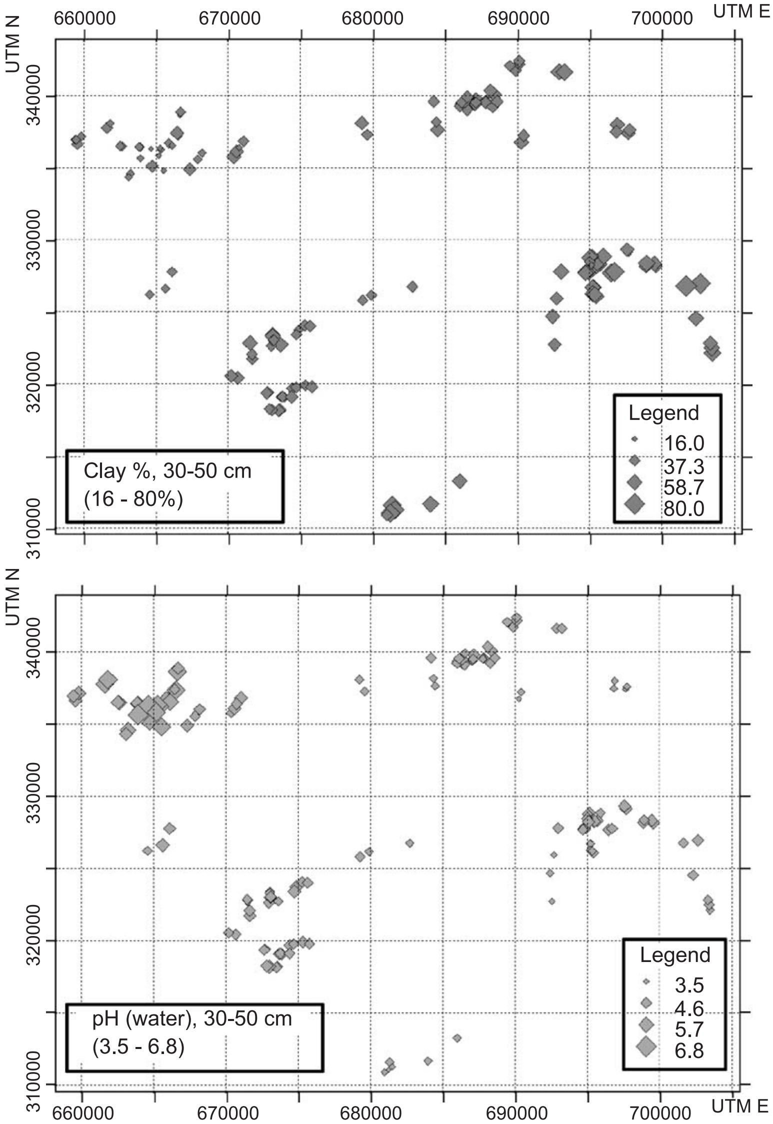

Fig. 3. Post plots of clay content and pH water at 30–50 cm depth showing regional trend.

members are generally alike and substantially different from the members of the other classes (De Gruijter, 1977; Webster and Oliver, 1990). The idea is statistically to minimize within-group variability while maximizing among-group variability, in order to produce relatively homogeneous groups. We used a hierarchical numerical classification system to reveal the various levels of similarities and allow a variable number of groupings. Fig. 5 shows the dendrogram resulting from the application of Ward's method on the correlation matrix of 12 soil parameters collected in three different soil depths. The 147 soil profiles were aggregated in two groups at the highest level. Each group was subdivided in two subgroups at the next level. Further multiple subdivisions occurred within the four subgroups as the dissimilarity decreases; however these groups show little differentiation and are hard to interpret. Classes at the first two levels showed a good correlation with the WRB groups (three, at the first level) and subgroups (seven,

Table 2
Characteristics of the first five Principal Components (PC) from the PCA of the standardized values of twelve soil variables

	PC 1	PC 2	PC 3	PC 4	PC 5
0–10 cm					
Eigenvalue	2.47	1.7	1.01	0.88	0.68
Proportion of variance (%)	50.7	23.8	8.5	6.5	3.9
Cumulative proportion (%)	50.7	74.5	83.0	89.5	93.4
10–20 cm					
Eigenvalue	2.30	1.57	1.22	1.14	0.70
Proportion of variance (%)	44.1	20.6	12.4	10.9	4.1
Cumulative proportion (%)	44.1	64.7	77.1	88.0	92.1
30–50 cm					
Eigenvalue	2.25	1.62	1.22	1.02	0.84
Proportion of variance (%)	42.1	22.0	12.4	8.6	5.9
Cumulative proportion (%)	42.1	64.1	76.4	85.0	90.9

at the third level), and landscape ecological zones (see section on the relationship between the classification techniques). Since the clusters at both levels exhibited a strong relationship with soil classification, a map of soil classes as defined by the WRB is feasible and would explain a large proportion of the total soil variation in the area. In a study in the USA, Adams et al. (1992) also found that classes formed by cluster analysis were similar to Soil Taxonomy classes. Further detailed study of cluster groupings may also reveal important pedological relationships that are not apparent when pedons are classified by landform alone (Young and Hammer, 2000).

4.2.4. Geostatistical analysis and soil mapping

4.2.4.1. Ancillary regional variables. Elevation in the study region generally increase towards the southeast (azimuth 122°, first-order surface R^2=0.90), so it is not surprising that both clay and pH are predicted from elevation with almost the same precision (R^2=0.48 and 0.44, respectively) as from UTM coordinates. However, unlike the regional trend, the relation with elevation suggests that local relief differences, which are the order of 100 m, should be associated with differences on the order of +4.5% clay and −0.2 pH units. We have no hard evidence for such relations, although soil surveyors do observe local colluviation of coarser material on toeslopes. Therefore we decided to use the best trend surface on coordinates to estimate residuals for geostatistical analysis.

4.2.4.2. Experimental variogriams. Fig. 6 shows the experimental variograms with fitted spherical variogram models and their parameters, for both original variables and residuals after removing the second-order OLS regional trend surface. The low number of points and clustered sampling resulted in erratic variograms that were difficult to model, although there is clear spatial dependency. The variogram of pH shows dependence to about 6 km, whereas that for clay shows an erratic structure, unbounded within the study area. The residual variograms from OLS were well-modelled by spherical models with dependence up to only 2.3 (clay) to 2.7 (pH) km, showing that the regional trend accounted for the long-range dependence in the original variograms. Residual variograms from the GLS surface were almost identical, although the residuals themselves were quite different especially for clay. After removal of the trend, the nugget (unexplained variance) in the residual variograms was 64% (clay) and 32% (pH) of the short-range variance. This means that kriging interpolation will have a high uncertainty even at short ranges, even for the most stable soil properties (i.e. at depth), and even on a relatively large support (farmer's field).

RK from the OLS trend surface and UK computed by gstat with no local neighbourhood gave almost identical predictions. RK from the GLS and OLS trend surfaces were very similar for clay but quite different for pH, because of the substantial difference in trend surfaces for the latter property. Fig. 7 shows interpolation maps made by OK, UK and RK from GLS, as well as the second-order GLS trend surface, for the two soil properties. The relative effects of the regional trend and local samples can clearly be seen, as well as the effect of including the trend in the interpolation, especially away from the sample points. In the case of pH, OK predicts with the global mean away from the point clusters, which is not realistic, whereas RK uses a trend but this clearly is not respected near the clusters. In the case of clay, OK gives a smooth prediction away from the clusters, because of the long-range variogram, but the apparent trend does not agree with that shown by RK. Here the RK trend is mostly respected near the clusters, with some local discrepancies. Thus, neither interpolation

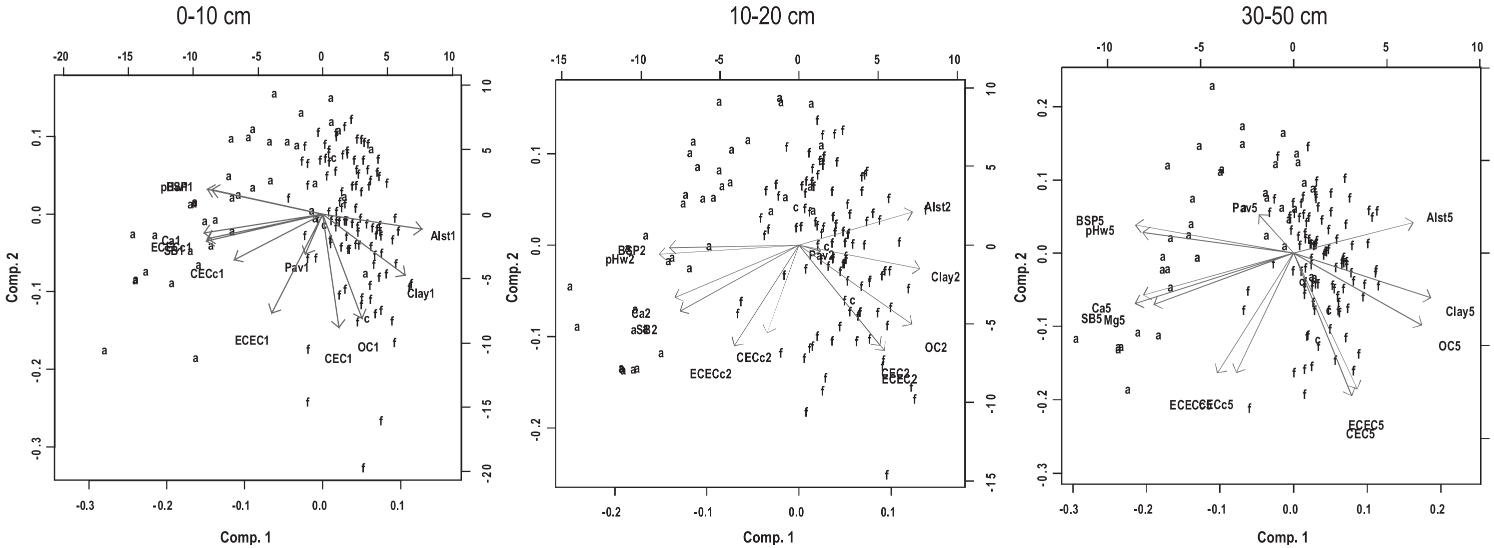

Fig. 4. Biplots of PCs 1 and 2 at the three sampling depths (a=Acrisols, f=Ferralsols).

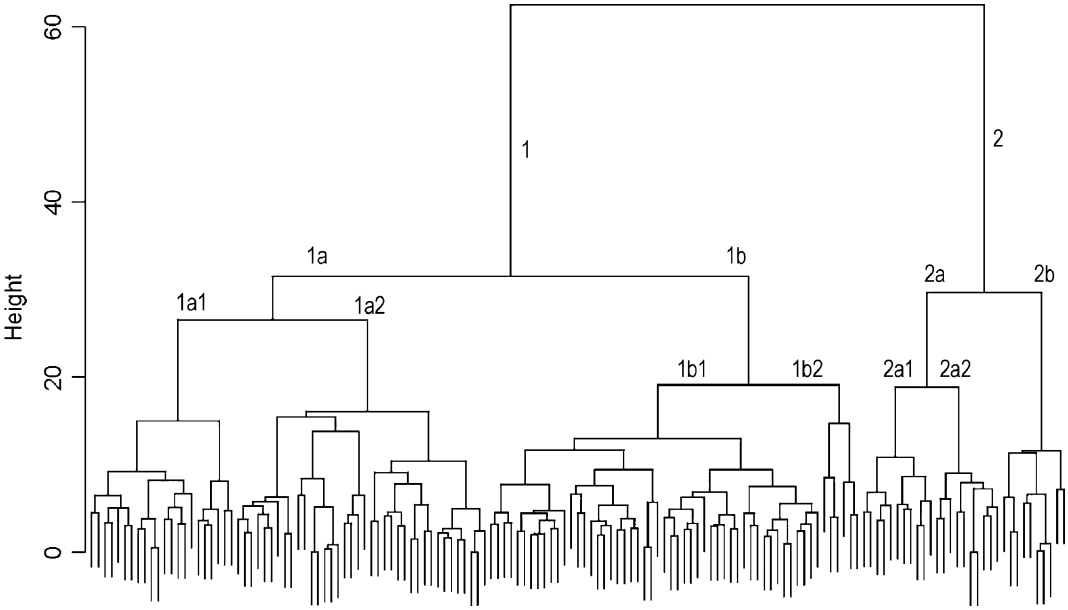

Fig. 5. Dendrogram of 147 soil profiles grouping based on 12 soil parameters measured at the three soil depths.

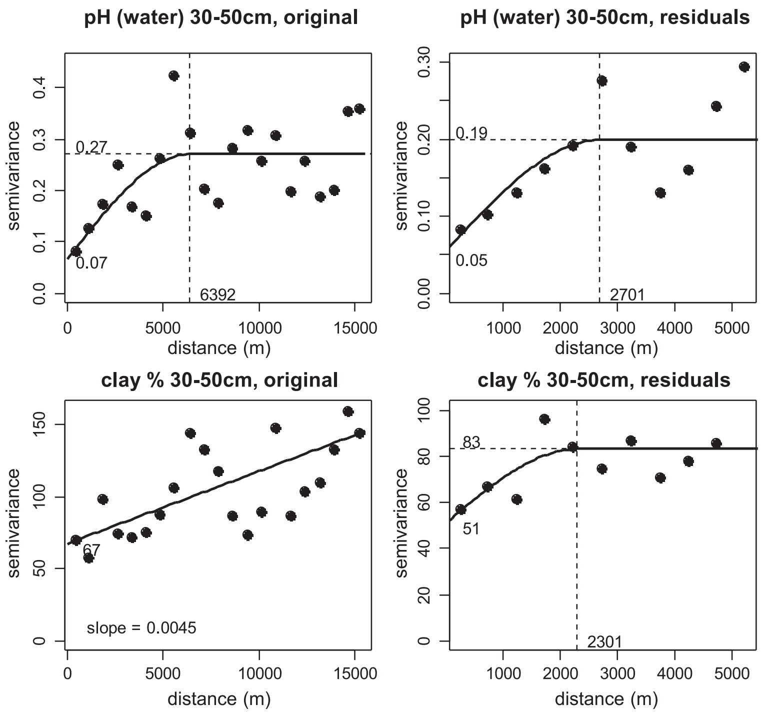

Fig. 6. Variograms modelling from the original values and residuals of clay content and pH in water within 30–50 cm soil depth. Variogram parameters on each plot; spherical models except for original clay 30–50 cm, which is unbounded linear.

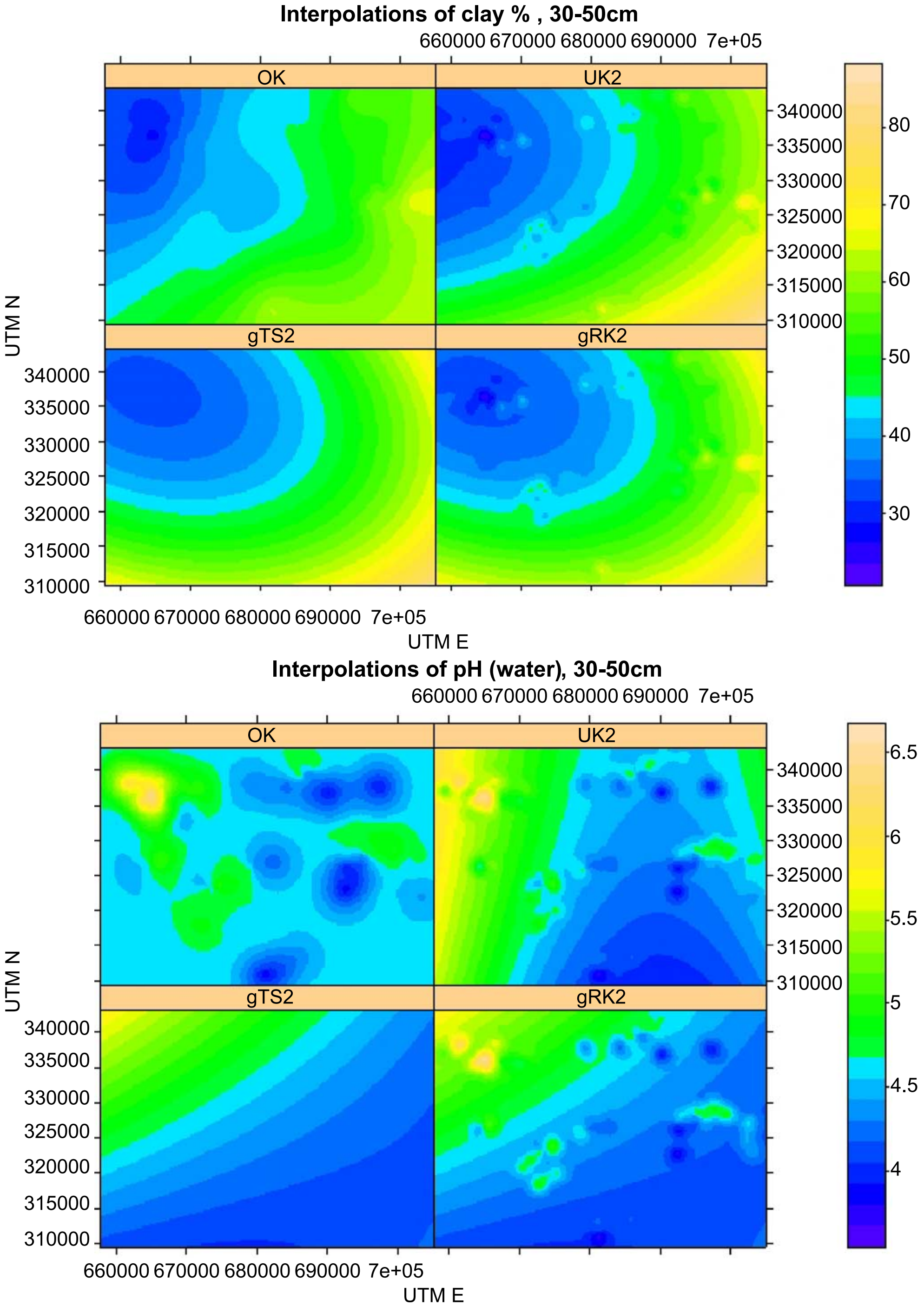

Fig. 7. Interpolations for clay content and pH of 30–50 cm layer, made by ordinary kriging (OK), universal kriging with a second-order trend (UK2), a generalised least squares second-order trend surface (GTS2), and regression kriging using residuals from this surface (GRK2).

is satisfactory away from the sampled villages; within villages the trend is minimal, so that OK is preferred.

The OK map for clay shows a clear grouping of the four villages in three soils classes related to Van Gemerden and Hazeu's classification (1999): Ebimimbang group, Ebom and Mvie groups, and Nyangong. The UK and RK maps of pH tended to group the four villages only into two classes similar to WRB classification: Ebimimbang group (Acrisols), and Mvie-Ebom-Nyangong group (Ferrasols).

These results of geostatistical analysis suggest that there is a possibility for pedometric mapping of soil of the area. However, for an accurate digital soil map, other mapping tools such factorial kriging analysis (Goovaerts, 1992), wavelet analysis, neural networks, fuzzy set, etc. (McBratney et al., 2003) may provide a better insight into the multi-scale structure of variation than revealed with our approaches (global trend and local variation). Although there seems to be no substitute for a denser sampling network, especially for variables with relative short range dependence such as pH.

4.2.5. Factors controlling soil variability at regional level

In the search of factors that control the distribution pattern of soils of the forested zone of south Cameroon, three soil forming factors (rainfall, geology and elevation) were analyzed in relation to soil variability. Rainfall analysis was based on the literature review, while geology and elevation were compared to cluster analysis and WRB soil groups using soil profile cross tabulation in contingency matrices as explained in the methodology section.

The distribution pattern of rainfall over the TCP area over a 5-year monitoring period showed a clear non-uniform pattern (Ntonga et al., 2002). The central part of the area where the altitude increases from about 200–600 m asl received a distinctly higher annual rainfall (2115–2458 mm) than the western lowlands (1816 mm) and the eastern highlands (1985 mm). They ascribed these rainfall variations to the orographic effect. The spatial pattern of this rainfall distribution is quite similar the soil distribution pattern, with more weathered and more acidic soils found at the higher elevations with greater rainfall.

The 1:500 000 geological map (Champetier de Ribes and Reyre, 1959) did not show a strong relationship with soil distribution pattern. The whole area falls into the basement complex (Fig. 2A) characterized by acid metamorphic rocks (migmatite, gneiss, micaschist) traversed by intrusions of potassic alkaline syenite and basic rock dykes. Some of the unexplained variability may be due to these local intrusions. However, the C coefficient of correlation between geological map units and the WRB soil groups was the lowest (66%). According to Zech (1993), soil formation in the humid tropics is often so advanced that the relationship between rock and soil properties are no longer clearly distinguishable, and that may be the case in this study region. However, the NNE–SSW overall orientation of boundaries between soil and physiographic zones follows the general orientation of the geological structures, having a C coefficient of 80%.

The four upland landscape ecological zones defined by altitude explained 50% and 49% of the total variance, respectively, for the two representative variables (clay content and pH in water). That is, a simple elevation zonation is more explanatory than linear regression on the continuous predictor. Separation into three WRB reference groups (Ferralsols, Acrisols, and Cambisols) was not so successful, but still explained 33% and 44% of the variance in the two properties, respectively. Separation into 11 WRB second-level groups improved the explanatory power to 50% and 51%, respectively. This shows that hierarchical soil classification was moderately successful in predicting these properties.

4.2.6. Relation between classification techniques

A global correlation of soil profile grouping between three classification methods (WRB, cluster analysis, and physiographic zoning) was used to assess the agreement of each pair of methods. Table 3 shows the different contingency tables and the coefficients C of a global correlation of each pair of techniques. The output level of each method was also assessed in order to evaluate their relative precision. The global correlation of classes between the pairs of techniques is generally high (78–89%). The highest agreement was between the WRB and the physiographic zoning of the study area, suggesting that the physiographic basis of soil inventory can be successfully applied for soil mapping in this vast forested undulating region. The numerical classification sys-

Table 3
Contingency table showing the number of soil profile classification by each pair of classification methods

		Clusters classes			
		1a	1b	2	Σ
WRB	FR	57	47	0	104
	AC	0	9	31	40
	CM	3	0	0	3
	Σ	60	56	31	147
	Coefficient C				0.78

		Physiographic zones				
		A	B	C	D	Σ
WRB	FR	5	41	58	0	104
	AC	0	0	4	36	40
	CM	3	0	0	0	3
	Σ	8	41	62	36	147
	Coefficient C					0.84

		Physiographic zones				
		A	B	C	D	Σ
CLUSTER	1a	8	31	21	0	60
	1b	0	10	41	5	56
	2	0	0	0	31	31
	Σ	8	41	62	36	147
	Coefficient C					0.82

		Cluster classes							
		1a1	1a2	1b1	1b2	2a1	2a2	2b	Σ
WRB	Axf	17	14	6	1	0	0	0	38
	Xf	5	21	37	3	0	0	0	66
	Ha	0	0	4	2	5	5	3	19
	Fpa	0	0	3	0	6	5	7	21
	Fc	0	3	0	0	0	0	0	3
	Σ	22	38	50	6	11	10	10	147
	Coefficient C								0.83

		Physiographic zones				
		A	B	C	D	Σ
WRB	Axf	5	31	0	0	36
	Xf	0	9	59	0	68
	Ha	0	0	2	17	19
	Fpa	0	0	2	19	21
	Fc	3	0	0	0	3
	Σ	8	40	63	36	147
	Coefficient C					0.89

		Physiographic zones				
		A	B	C	D	Σ
CLUSTER	1a1	5	14	3	0	22
	1a2	3	16	19	0	38
	1b1	0	8	39	3	50
	1b2	0	2	2	2	6
	2a1	0	0	0	11	11
	2a2	0	0	0	10	10
	2b	0	0	0	10	10
	Σ	8	40	63	36	147
	Coefficient C					0.83

WRB=World Reference Base for soil resources: Soil Groups (FR=Ferralsols, AC=Acrisols, CM=Cambisols), Soil Units (Axf=Acric-ferric Ferralsols, Xf=xanthic Ferralsols, Ha=Haplic Acrisols, Fpa=Ferralic and plinthic Acrisols, Fc=Ferralic Cambisols); Σ=Total.
Physiographic zones A (>700 m asl), B (500–700 m asl), C (350–500 m asl), and D (<350 m asl).
Cluster Classes (see Fig. 5); Coefficient C=Contingency coefficient.

tem correlated somewhat less with the other methods. This correlation was substantially improved by using both the lower soil unit level of WRB and the third subdivisions of cluster. The C coefficient between WRB and numerical classification increased from 0.78 (with three WRG groups and three cluster classes) to 0.83 (with five WRB units and seven cluster classes). Similarly, C coefficient between WRB and physiographic zoning (four zones) increased from 84% (with three WRG groups) to 89% (with five WRB units). However, between numerical classification and physiographic zoning, C coefficient increased only from 82% (with three cluster classes) to 83% (with five and seven clusters classes). We conclude that all three classifications give similar information at both levels of detail.

All these methods have shown that soils of the study area vary substantially and most of the variation is controlled as in many other cases (Brejda et al., 2000; Guimaraes Couto et al., 1997; Jenny, 1980; Odeh et al., 1994; Yost et al., 1982) by landscape-scale soil forming factors. This dependence suggests that (i) at semi-detailed level, soil of the area can be usefully mapped automatically by a wise integration of all the factors to regionalized variables; (ii) any soil management such as recommendations for fertilizer application and soil conservation measures should be region-specific.

4.3. Soil variability at the local level

Summary statistics for seven soil variables are shown in Table 4. Most of these soil variables showed a much higher variation at the shallowest soil depth (0–10 cm). This supports the hypothesis that the effect of land use on soil properties is most effective near the soil surface (Yemefack and Nounamo, 2000). Available P was quite variable and poorly structured, especially in the topsoil. In several cases the total variation, as measured by the sample standard

Table 4
Summary statistics of soil properties at local scale (village level)

	PH water	Total acidity ($cmol^+ kg^{-1}$)	Sum bases ($cmol^+ kg^{-1}$)	Base saturation (%)	Available phosphorus (ppm)	Clay content (%)	Bulk density (g/cm^2)
0–10 cm							
Minimum	3.2	0.04	0.6	4	2	14	0.63
Mean	4.9	2.35	5.3	53	10.5	29	1.12
Range	5.0	2.11	22.1	148	84.6	63	0.88
Maximum	8.2	9.15	22.7	152	86.6	67	1.51
Standard deviation	1.08	2.31	4.1	34	11.6	13	0.19
SE mean	0.09	0.19	0.33	2.7	0.93	1.04	0.02
Skewness	1.06	1.11	1.2	0.36	4.37	0.45	−0.34
Kurtosis	0.43	0.62	1.3	−0.83	22.26	−0.10	−0.28
CV%	22.2	98.5	77.9	64.5	110	45	17.1
10–20 cm							
Minimum	3.3	0.04	0.33	2	1	16	0.91
Mean	4.8	3.18	2.25	36	3.4	35	1.29
Range	4.5	14.14	12.65	103	11.3	64	0.77
Maximum	7.8	14.18	12.98	105	12.3	70	1.68
Standard deviation	0.92	2.4	2.05	32	1.74	14.3	0.17
SE mean	0.07	0.19	0.17	2.5	0.14	1.15	0.014
Skewness	1.22	1.03	2.59	0.95	1.94	0.08	−0.09
Kurtosis	0.78	2.54	8.92	−0.69	5.97	−0.56	−0.40
CV%	19.4	75.3	91.2	87.1	51	41.3	13.1
30–50 cm							
Minimum	37	0.08	0.33	4	1	20	Nd
Mean	4.9	2.9	1.4	27	1.6	43	Nd
Range	3.9	6.8	5.1	127	6.2	71	Nd
Maximum	7.6	6.9	5.4	131	7.2	77	Nd
Standard deviation	0.73	1.62	1.16	27	1.04	14	Nd
SE mean	0.06	0.14	0.10	2.3	0.09	1.23	Nd
Skewness	1.35	−0.35	1.82	1.7	2.48	−0.29	Nd
Kurtosis	1.68	−0.70	2.60	2.1	7.74	0.15	Nd
CV%	14.9	56	83.4	98.7	64.8	33.1	Nd

N=155 for 0–10 and 10–20 cm layers, and N=130 for 30–50 cm depth.
nd=not determined.

deviations and ranges, was higher than at regional level, probably because the local level plots included more variation in land use.

Analysis of variance and separation of significant means showed that most soil variables were sensitive to the effects of land use type. Those that showed the highest responses are presented in Table 5 as a matrix comparing on pairwise basis soil properties variations amongst land use types, for each soil depth. The number of soil variables in each cell of this table showed that most variation occur in the first soil layer and decrease with depth. Cropping treatments (FCF, CL, CL2) showed significant differences (with CL>FCF) with other treatments (FV, FF, BF, CF, MCA, OCA) for all the nine soil properties. Only those soil properties that are highly influenced by ash from burned vegetation (i.e. pH, total bases, and total acidity) showed a significant effect due to land use in the deepest layer. This suggests that the process of ash disintegration leads to rapid leaching and vertical movement of cations. Cattle et al. (1994) reported that pH, electrical conductivity, organic matter and soil acidity were the most affected by clearing and cultivation on an Rhodoxeralf in Australia. These changes, although of short duration, appear to be advantageous to improve several facets of chemical soil fertility, while creating also a more uniform environment in which to grow crops.

Table 5
Comparison matrix of significantly affected soil properties amongst land use/land cover types

0-10 cm

	Cropping phase			Fallow phase				Perennial plantation	
	FCF	CL	CL2	CF	BF	FF	FV	MCA	OCA
FCF		pH[1] Pa[1] SA[1] BS[2]	pH[3] Pav[3] Mg[3] SB[2] SA[1] Bd[3]	Pa[3]	Pa[3] Ca[1] SB[1] BS[1]	pH[2] Pa[3] Ca[3] SB[2] BS[3]	Pa[3] Ca[3] SB[2] BS[3]	Pa[3]	Pa[3] Ca[3] SB[2] BS[3] Bd[1]
CL			Mg[3] SB[3] BS[3] Bd[3]	Ca[1] BS[3]	pH[3] Pa[1] Ca[3] SB[3] SA[2] BS[3]	pH[3] Pav[1] Ca[3] SB[3] SA[3] BS[3]	pH[3] Pa[1] Ca[3] SA[3] BS[3]	Pa Ca[2] BS[3]	Pa[2] Ca[3] SB[3] BS[3]
CL2				pH[1] Ca[1] Mg[3] SB[3]	pH[3] Ca[3] Mg[3] SB[3] SA[2] BS[2] Bd[1]	pH[3] Ca[3] Mg[3] SB[3] SA[3] BS[3] Bd[3]	pH[3] Ca[3] Mg[3] SB[3] SA[3] BS[3] Clay[1] Bd[3]	Ca[2] Mg[3] SB[3]	pH[1] Ca[2] SB[3] BS[3]
CF					pH[1]	pH[3] Ca[1] SA[3] BS[3] Bd[1]	Ca[1] SA[3] BS[3]		BS[1]
BF								pH[2]	
FF								pH[3] SA[2] BS[1] Bd[2]	pH[3] SA[1] Bd[2]
FV								pH[2] SA[2] BS[2]	SA[1]
MCA									BS[1]

10-20 cm

	FCF	CL	CL2	CF	BF	FF	FV	MCA	OCA
FCF		SA[1]	pH[3] Mg[3] SB[3] BS[1] Bd[2]			pH[1]		pH[3] SA[1]	pH[2] SA[1] Bd[2]
CL			pH[3] Mg[3] SB[3] Bd[1]		BS[2]	pH[2] SA[3] BS[3]	SA[1] BS[3]	pH[3] Pa[1]	pH[3] BS[3]
CL2				Mg[3] SB[3] BS[1]	pH[3] Mg[3] SB[3] BS[3] Bd[1]	pH[3] Ca[1] Mg[3] SB[3] SA[3] BS[3] Bd[3]	pH[1] Ca[1] Mg[3] SB[3] BS[3] Bd[2]	Mg[3] SB[3]	Mg[3] SB[3] BS[3]
CF					pH[1]	pH[3] SA[1]			
BF							pH[2]	pH[3]	pH[3] Bd[1]
FF							pH[3]	pH[3] SA[3] BS[1]	pH[3] SA[3] Bd[2]
FV								pH[1] SA[1]	pH[1] SA[1] Bd[1]
MCA									

30-50 cm

	FCF	CL	CL2	CF	BF	FF	FV	MCA	OCA
FCF						BS[1]	pH[1]	pH[2] SA[2]	pH[1]
CL				BS[2]	BS[2]	SB[2] BS[3]	pH[3] BS[3]	pH[3]	pH[3] BS[3]
CL2				nd	nd	nd	nd	nd	nd
CF							pH[1]	pH[3]	pH[2]
BF							pH[1]	pH[3] SA[1]	pH[2]
FF								pH[3] SA[2]	
FV								pH[1] SA[3]	SA[1]
MCA									

FCF=Beginning of Forest crop Field; CL=Beginning of mixed food crop field; CL2=End of mixed food crop field; CF=Chromolaena Fallow=3–5 years old; BF=Bush Fallow=7–9 years old; FF=Forest Fallow>15 years old; FV=undisturbed Virgin Forest; YCA=Young mature cocoa plantation=5–7 years old; OCA=Old Cocoa plantation>30 years old. pH=pH water, Pav=Available phosphorus, Ca=Calcium, Mg=magnesium, SB=Sum of bases, SA=Total acidity, BS=Bases saturation percentage, Clay=Clay content, Bd=Bulk density, nd=not determined.

[1]=significant difference at 0.05 confidence between the two land cover types.

[2]=significant difference at 0.01 confidence between the two land cover types.

[3]=significant difference at 0.001 confidence between the two land cover types.

This larger soil variation in the surface layer was further confirmed by the results of factorial ANOVA (Fig. 8) (modeling land use and soil type at the three depths separately) from which the coefficient of determination of each soil variable was computed as the ratio between explained variance and the total variance to evaluate the contribution of land use effect on soil variability at each depth. For most soil variables, the contribution to total variance from the shallowest soil layer was 45–60%, followed by 20–35% in the second layer, and less than 15% in the deepest layer. However, for clay content, although land use showed a significant (p<0.05) effect, there was not a clear difference between the contributions of the soil depths.

The results at local level showed that traditional agricultural land use systems in southern Cameroon are also a major source of temporal variability of soil properties and processes. From clearing a portion of forest land for cropping to the formation of the secondary forest during the fallow period and/or the establishment of perennial agro-forests, soil constituents undergo important changes, especially in the topsoil. However, the magnitude of these changes varies from one property to another. Paz-González et al. (2000) reported a similar situation on an umbric topsoil horizon in Northwest Spain, and concluded that agricultural land use changes the magnitude, the diversity, and the pattern of soil spatial variability for most soil properties related to soil fertility and texture. These results may help field researchers in site selection to overcome the problem often faced with contractictory results (Van Es and Van Es, 1993) where there are clear differences in crop yields between plots but no significant treatment effect.

4.4. Sampling variability within field plots

Summary statistics are presented in Table 6 for the three properties (pH, bulk density, and bases) standardized to plot means. Frequency distributions are near-normal with close means and medians. Total variation was low compared to the regional (Table 1) and local (Table 4) levels, as shown by the standard deviation in the topsoil for bulk density (0.06 against 0.19 at local level), for pH (0.24 against 1.08 at local and 0.88 at regional levels), and for sum of bases (0.23 against 4.10 at local and 3.19 at regional level). Results are similar for the other layers. Thus the plot level is from about 5–30% as variable as the higher levels.

Factorial ANOVA showed that there were significant differences between the three soil layers and between the three field plots for all three properties. By far the largest effect was between layers; e.g. for bulk density, 86% of the total variance was ex-

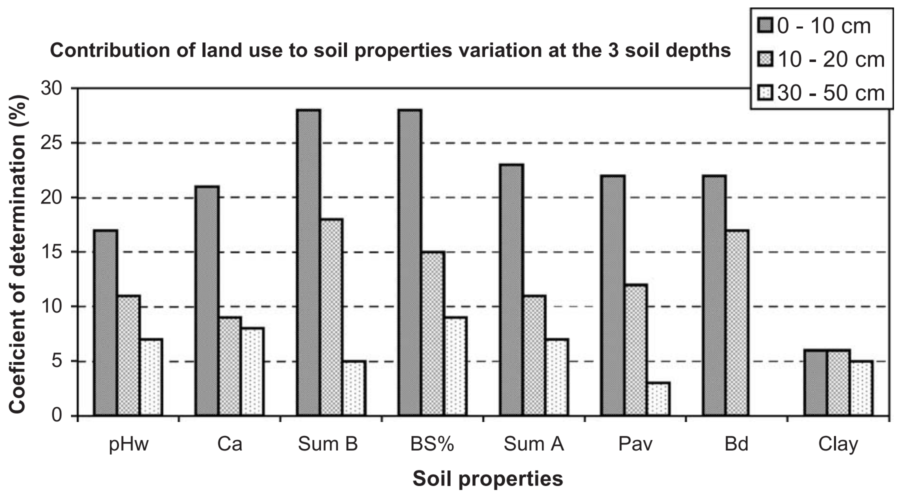

Fig. 8. Contribution (in %) of land use practices to soil properties variation for the soil variables significantly different at p<0.05 (pHw=pH in water; Ca=calcium; Sum B=total bases; Sum A=total acidity; BS%=bases saturation percentage; Pav=available phosphorus; Bd=Bulk density; Clay=clay content).

Table 6
Descriptive statistics of soil properties within the field plots (using adjusted data) (n=75)

	Min	Mean	Median	Max	Std dev	SE mean	Skewness	Kurtosis	CV%
0–10 cm									
pH Water	4.03	4.45	4.43	5.34	0.24	0.027	0.88	2.11	5.3
Sum Bases	0.95	1.56	1.56	2.11	0.23	0.26	−0.14	0.52	14.4
Bulk density	0.94	1.13	1.13	1.29	0.06	0.007	−0.24	0.70	5.5
10–20 cm									
pH Water	4.12	4.54	4.52	5.42	0.21	0.024	1.75	5.36	4.6
Sum Bases	1.06	1.91	1.88	3.35	0.45	0.052	0.87	1.19	23.5
Bulk density	1.26	1.42	1.43	1.54	0.05	0.006	−0.94	2.41	3.5
30–50 cm									
pH Water	4.41	4.70	4.61	5.69	0.23	0.026	2.12	5.41	4.8
Sum Bases	1.09	1.74	1.70	2.92	0.34	0.039	1.78	1.78	19.4
Bulk density	1.39	1.50	1.49	1.61	0.04	0.039	0.26	0.26	2.7

plained by the layers. This agrees with the results of the regional analysis (Section 4.2). Field plots explained a much smaller, but still significantly different, proportion of the variance (e.g. 2.6% for bulk density); these differences were comparable to the effect of land use as quantified in Section 4.3. The two field plots under cropping (CL) were similar and both quite different to the one under *Chromalena* fallow (CF). Because of this significant difference between the three fields, values were standardized to per-plot means as described in Section 3.3, in order to make the three fields comparable for the nested ANOVA.

The results of nested ANOVA for the three standardized soil properties at the three soil depths are given in Table 7. The largest component of variance for the surface layer (0–10 cm) derived from the 400 m^2 area (equivalent to 20 m spacing) for the three soil properties, and accounted for 40–55% of the total variance of the whole plot. The larger and smaller plot sizes (1600 and 100 m^2) accounted for about 20% each. In the lower layer of the soil profile,

Table 7
Variance components for soil properties within field plot at three soil depths, from nested analysis of variance

Stage	Plot size (m^2)	N	pH water: Variance component	pH water: % of variance	Sum bases: Variance component	Sum bases: % of variance	Bulk density: Variance component	Bulk density: % of variance
0–10 cm								
1	6400	3	0.008	5.6	0.0093	6.3	0.00022	2.4
2	1600	12	0.028	20.8	0.0296	20.1	0.00109	11.7
3	400	48	0.074	54.1	0.0586	39.9	0.00506	54.6
4	100	12	0.026	19.5	0.0493	33.7	0.00289	31.3
10–20 cm								
1	6400	3	0.070	33.0	0.0094	3.5	0.00055	8.1
2	1600	12	0.044	20.8	0.0878	32.2	0.00102	15.1
3	400	48	0.075	35.4	0.0785	28.8	0.00358	52.9
4	100	12	0.023	10.8	0.0973	35.6	0.00162	23.9
30–50 cm								
1	6400	3	0.066	39.5	0.0173	4.0	0.0002	3.2
2	1600	12	0.031	18.3	0.0979	22.6	0.0003	5.9
3	400	48	0.064	38.3	0.0895	20.7	0.0020	38.9
4	100	12	0.006	3.8	0.2288	52.8	0.0025	52.0

the variance components were approximately equal for the three largest size stages for pH. The same result was found for the sum of bases and bulk density with the three smaller size stages. In addition, the contribution of the largest plot to variance increased with soil depth (for pH) and did not change for the sum of bases and bulk density. This can best be appreciated from Fig. 9 where the accumulated variance components are plotted against spacing. The variance of bulk density, pH and the sum of bases increased substantially with spacing and leveled off (i.e. reached a sill) around 40 m (1600 m^2) for the 0–10 cm layer. This corresponds to the total variance of each soil property at this depth. Beyond the distance of 40–60 m (equivalent to the geostatistical range) the sampling units were no longer spatially correlated for bulk density and the sum of bases. For the 10–20 and 30–50 cm layers, accumulated variances for bulk density and the sum of bases followed the same pattern as for the 0–10 cm layer, whereas pH showed increasing variance with plot size, indicating spatial correlation at distances greater than the experimental area. This is in line with the results of PCA and geostatistcal analyses in Section 4.2 where pH showed with clay content the longest-range spatial dependence, with a modelled range of 6400 m.

These graphs also show that at shorter distances the variance of pH showed a slight decrease with depth (0.026 at the surface layer to 0.006 at the lowest depth), while the sum of bases showed instead an important increase with depth (from 0.05 at the surface layer to 0.23 at the lowest depth). The total variance from bulk density was in general very low in the three layers at short range. The decrease of local variation occurring at scales finer than the smallest sampling interval can be explained for pH by the relative homogeneity of the subsoil solution, out of reach of land use effects. The reverse behavior for the sum of bases is difficult to explain.

The similarity between these graphs and variograms (Davidson and Csillag, 2003; Webster and Oliver, 1990) suggests the existence of a spatial dependence in these soils at plot level, showing that precision agriculture would need to take this short-range variability into account. Subsistence farmers may already be taking this variability into account as they use surface cues (colour, amount of ash, etc.) to place individual plants within a shifting cultivation plot (Florax et al., 2002; Nounamo and Yemefack, 2001). This variance is not significant at the scale of the actual farmers' field plots treated as a whole (0.5–1.2 ha), and is minimized by the actual soil sampling procedure (composite bulk sampling) in use.

The observed low level of soil variability at field plot scale is probably due to (i) the current sampling strategies based on composite soil samples, and (ii) the plot size (around one hectare) commonly in use in the area. As the plot size may increase with changing land use practices, the within-field variance might considerably increase as well, as predicted by the regional variogram. The plot variogram can be seen as a fine resolution ('magnification') of the regional variogram; the regional nugget effect (e.g. 0.05 for pH) is resolved into a true nugget at a very short range (here, 20 m) and increasing variability at plot dimensions. We could not compute the variograms

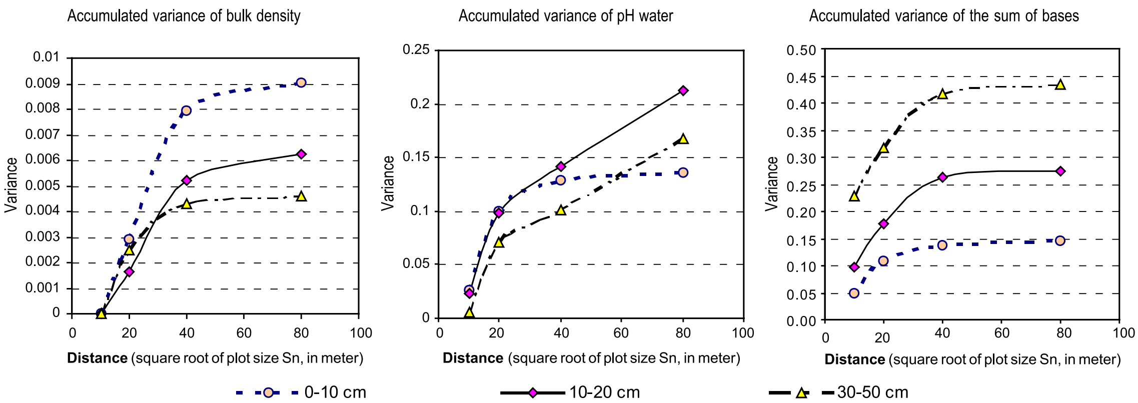

Fig. 9. Accumulated variance soil properties with the plot size plotted as a function of the square root of the plot area (m) at three depths.

for within-field plots to strengthen this link because of the limited number of available samples (25) at each single plot per depth.

4.5. Laboratory level

Table 8 summarizes the statistics of the IRAD soil laboratory quality control samples for all 11 soil properties. The standardized variables showed symmetric and compact distributions; however five had boxplot outliers representing 0.3–15% of the sample. Six variables failed the Shapiro-Wilk test of normality, and six failed Bartlett's test for homogeneity of variances of multiple batches. All variables except exchangeable Ca and K showed one or more of these deviations from the ideal behaviour expected of laboratory quality control on well-mixed samples. However, in absolute terms both total ranges and standard deviations were quite low, except for two important properties: available P and CEC. In the case of available P, the total range of 4.3 mg kg^{-1} can exceed the total amount of this nutrient in many soils of the study region. Removing the three boxplot outliers still left a range of 3.1 mg kg^{-1}. The standard deviation of 0.86 mg kg^{-1} is also fairly high; for low-P soils with an average of 4 mg kg^{-1} P this would represent a coefficient of variation of over 20%. In the case of CEC, its standardized range of 1.54 $cmol^{+}$ kg^{-1} soil is a significant fraction of critical limits used in classification of the highly weathered soils typical of the study area, e.g. the 4 $cmol^{+}$ kg^{-1} soil limit for *ferralic* properties in the WRB (FAO-ISRIC, 1998). Removing the four boxplot outliers from the total sample of 72 almost halved the range, to 0.89 $cmol^{+}$ kg^{-1} soil. Thus the quality control problem for CEC was mainly due to a few poor determinations.

4.6. Aggregated multi-scale analysis of variance components of a soil sample

This study has shown that variation in soil properties can occur over a large range of scales each with a different contributions to the total variation. Factorial ANOVA was used to differentiate the contributions of regional and local factors to soil variation. These contributions are shown in Fig. 10 for six soil variables at three soil layers. These are coefficients of determination (explained variation/unexplained variation, expressed in %) for each factor. Both regional and local factors, including their interaction, explained 60–85% of the variation at the three soil layers, except for available P, where only about 30–40% was explained. For soil chemical properties, pH was the best-explained, with 80–85% at the three layers; followed by total exchangeable bases (70–80%) but only at the two top layers. For soil physical properties, clay content and bulk density showed similar pattern at the first two layers with 65% and 70% at the third layer for clay content.

Table 8
Summary statistics of the IRAD soil laboratory quality control samples for 11 soil properties (standardized to batch means)

Variables	Units	Number of samples	Number of batches	P (variances)	Range	P (normality)	Boxplot outliers	Standard deviation
P (available)	mg kg^{-1}	116	2	0.142	4.30	0.314	3	0.863
Fe (free)	%	20	1	NA	0.46	0.228	3	0.108
C (organic)	%	261	3	0.001***	0.84	0.043*	1	0.141
N (total)	%	220	3	0.000***	0.17	0.000***	0	0.034
Ca (exchangeable)	$cmol^{+}$ kg^{-1}	72	3	0.407	0.93	0.321	0	0.183
Mg (exchangeable)	$cmol^{+}$ kg^{-1}	72	3	0.035*	0.21	0.096	0	0.045
K (exchangeable)	$cmol^{+}$ kg^{-1}	72	3	0.141	0.11	0.153	0	0.024
Na (exchangeable)	$cmol^{+}$ kg^{-1}	72	3	0.123	0.04	0.001***	0	0.011
CEC	$cmol^{+}$ kg^{-1}	72	3	0.040*	1.54	0.068	4	0.255
pH (water)	pH	100	3	0.017*	0.54	0.003**	0	0.144
pH (KCl)	pH	100	3	0.000***	0.53	0.035*	4	0.106

P (variances)=probability that rejecting the null hypothesis of equal batch variances is an incorrect decision.
P (normality)=probability that rejecting the null hypothesis of a normally distributed variable is an incorrect decision.
Probability of significance: * (0.05); ** (0.01); *** (0.001).

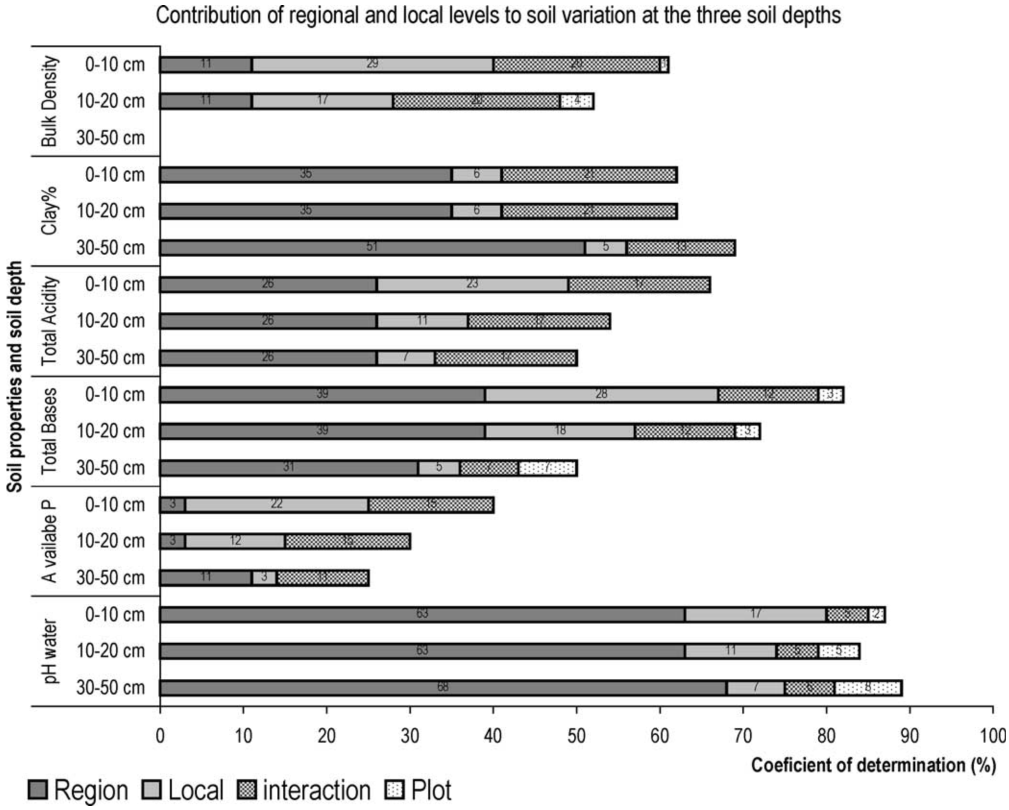

Fig. 10. Contribution (in %) of regional, local, and within plot factors to soil properties variation for the soil variables significantly different at $p<0.05$. N.B. Interaction was evaluated between regional and local factors only. Within plot variation was evaluated only for pH in water, total bases and bulk density.

Soil pH appeared to be the most affected by the regional factors (68% at 30–50 cm) of soil variation, followed by clay content (51% at the same depth). This corroborates the results of regression analysis and PCA which highlighted these two variables to be of importance in describing regional soil variability. The effect of land use at local level (in the two first soil layers) was more important for the following variables ranked in decreasing order: bulk density, total exchangeable bases, available P, and total acidity.

This strong influence of regional landscape factors and land use factors on soil variation is indeed an important conclusion of this study, which has a direct implication on sampling strategies for soil mapping and research designed to determine appropriate soil management practices (Bouma et al., 1999). The landscape regional factors appear to be a spatially coherent and permanent source of soil variation, while the land use factors constitute rather a temporal source of soil variation. Although Fig. 10 shows that the effect of land use factors is often less than that of landscape regional factors, their influences on soil management and environmental conservation are the most relevant to farmers who live in a given village. Moreover, their temporal characteristic renders their control more difficult. Research should focus more on this aspect in order to develop models that may help to understand the complex relations between land use and soil properties dynamics at this scale. The interaction between soil type and land use appeared to be also important in this study, suggesting that any management strategy should be site-specific.

In general, soil properties related to soil solution and cations mobility (pH, exchangeable cations), and those linked to soil adsorption complex (clay, organic matter) were more variable under the influence of both regional and local factors. Soil properties that are related to soil nutrient retention, including available P and CEC, were more affected by local factors, especially land use. This confirms the common opinion that tropical rainforests are dominated by nutrient-poor soils, in spite of the tremendous amount of forest biomass that they support in climax conditions. Nutrient retention of these soils is then not related to the type of soils in presence, but rather to the land use type they are being used for. In this respect, the opinion of many researchers (Sanginga et al., 2003; Van Wambeke, 1992) is that the fertility of these soils is more related to the natural fertilization system, the so-called nutrient cycle, than to soil potentialities.

At plot level, though soil properties exhibited spatial dependence, the contribution of the accumulated variance to soil variation as shown in Fig. 10, was so small (1% for bulk density, 3% for exchangeable bases, and 8% for pH-water) that this variance occurring at short distance does not significantly influence soil data at the scale of farmers' field plot, and is minimized by the actual soil sampling strategy of bulking and the actual soil management strategy of slash-and-burn ash-fertilizing on a whole-plot basis. However, any change in land use practice that tends to increase field plot size (e.g. agricultural intensification) may correlatively increase the variance of soil properties at plot level to include much of the variability found in the regional geostatistical analysis of residuals. This result corroborates however, the report from Corwin et al. (2003) who showed that the greatest plot-scale variation was for pH and clay content when portioning the plot- and local-scale variation using ANOVA on composite soil samples of a saline-sodic soil in California.

At the laboratory level, total ranges, variances and standard deviations were quite low for soil variables from repeated measurements in the laboratory, except in the case of available P where the total range was even higher than the total amount of this nutrient in many soils of the study area (especially from lower depths). The contribution of laboratory errors was evaluated to be less than 5% for many soil variables, except for available P (around 20%). This is in general in line with Webster (2000) who reported that determining the concentration of an element in the soil typically incurs a laboratory error of 2–5% of the true value. Variation due to the arbitrary choice of actual sampling locations for either single or composite samples is almost always significantly greater than this.

Although 95% of the variation in pH was explained by the three scale factors (regional, local, and within plot), for most soil variables only 75–90% were explained by these factors. Even adding the 5% soil variation due to laboratory errors, there remains 5–20% variation that could not be explain by the four scales of this study. Only pH was completely explained.

5. Concluding remarks

- At regional level, the representative variables (clay content and soil pH) at different soil depths showed a clear dependence (30–50% of the total variance) on geographic coordinates, as modelled by a second-order GLS regional trend. Because of the regional slope, elevation was an equally good continuous predictor of these properties, as was a simple zonation based on elevation, which was also reflected in the soil classification.
- Both WRB reference soil groups (Ferralsols and Acrisols) of the area showed strong spatial clustering, meaning that this classification captures important mappable differences in regional soils, leading to a sound basis for stratification for agricultural and environmental studies.
- Geostatistical analysis of the residuals from the regional trends models revealed a moderate spatial dependence at sub-regional scales, up to about 2.5 km, with a large unexplained (nugget) variance. Thus for a reliable regional map, a sampling density on the order of 1 km^2 would be required to map regional variability which is not due to land use, regional or environmental covariate. However, the results from various kriging mapping suggested that at the actual sampling scheme a mixed interpolator such as factorial kriging or a wavelet analysis may provide a better insight into the multi-scale structure of the variations, with integrated regional and local spatially dependent processes.
- Land use practices significantly influenced topsoil variation at village level (i.e. between plots); conversely there was low variation within field plots at the sizes now typical of the land use

system (1/3 to 1 ha), and the current soil sampling strategy of bulking at plot level is thus justified.

- In the laboratory, the quality control process largely minimized the treatment-induced error of soil determinations, except in the notable case of available P. This suggests that any field study on low-P soils is suspect, since laboratory variability can easily exceed treatment effects.
- This analysis was able to explain 80–95% of the overall soil variation, with 5–70% by regional factors, 3–30% by local factors, 1–10% by within-plot factors, and less than 5% by laboratory errors; however, 5–20% remained unexplained and is perhaps due to interactions between levels for which we had no experimental design, e.g. different effects of land use in different major soil.
- Further research for a better understanding of the relations between soil properties and environmental factors, and to determine appropriate management practices for resource use, should focus chiefly on processes and factors occurring at local level, as influenced by a dynamical land use system.

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