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Landscape approach to assess key soil functional properties in the highlands of Cameroon: Repercussions of spatial relationships for land management interventions

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ABSTRACT

Understanding spatial variability of soil properties is essential to support land management decisions. However, despite the growing worldwide emphasis on integrated landscape management, soil variations resulting from land use changes have rarely been documented. The study used the land health surveillance concept in combination with simple geostatistical approaches to describe key soil properties among land use types and characterize their spatial variability in the highlands of Cameroon. A total of 320 soil samples were collected in two sites with contrasting land uses (agricultural and pasture) and were analyzed for granulometric fraction, soil organic carbon (SOC), nitrogen (N), soil reaction (pH), phosphorous (P), calcium (Ca), potassium (K), magnesium (Mg), aluminum (Al) and zinc (Zn). The spatial correlations between the soil properties revealed the factors responsible for the observed differences and showed that wide ranges were obtained in agricultural site as opposed to pasture. SOC and N decreased in the order of forest > grassland > fallow > croplands > pasture due to inherent soil properties, anthropogenic activities, land cover/land use and topographic factors. Kriged maps provided detailed visualization of soil properties at landscape scale, and helped to identify critical areas for targeted land management interventions to improve land quality. The spatial distribution of selected soil properties showed a well-defined pattern of higher concentrations in the lowlands and valleys and areas with permanent vegetation cover in both sites. These results are useful for improving the efficient use of inputs such fertilizers. Context-specific land management based on spatial variability of soil properties is highly recommended and more research is required to generalize our knowledge about spatial variability of soil health indicators and the casual factors in the highlands of Cameroon.

1. Introduction

Soil formation is influenced by factors including parent material, climate, vegetation and the history of land use. Soil properties vary in space (Goovaerts, 1998) even within the homogenous layers primarily due to heterogeneity of intrinsic factors and extrinsic factors such as soil management and land use (Liu et al., 2010). Anthropogenic activities alter natural soil properties and cause changes in the edaphosystem, and can contribute to the deterioration of soil health (Zhang et al., 2011). For instance, in most agroecosystems, soil properties are generally low due to processes such as erosion, salinization, nutrient mining and leaching instigated by unsustainable agricultural practices (Batjes, 2014; Martin et al., 2014).

Soil spatial variability is a function of topography, vegetation types, land use and differences arising from land management practices such as tillage and additional inputs (Iqbal et al., 2005; Timm et al., 2006; Nanos and Rodríguez Martín, 2012; Sanchez Lizarraga and Lai, 2014). These factors are accompanied by natural process such as erosion, soil deposition methods and geological formation (Tesfahunegn et al., 2011).

Agricultural landscapes, particularly in Sub-Sahara Africa (SSA), have been managed as being homogeneous, although presenting considerable spatial variations in the level of soil properties concentrations (Wendroth et al., 2003). The current fertilizer recommendation made by extension services to small-scale farmers is uniform for the entire areas irrespective of intrinsic variations in soil, cropping history and

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previous fertilizer application. There is a risk over- or under-application of the required nutrients, and can lead undesirable environmental effects and increased in production cost. In addition, most initiatives to assess land degradation have focused on soil degradation through erosion without incorporating the impact of its processes on spatial variability of soil properties (Haregeweyn et al., 2008).

Assessment of spatial variation is critical in determining soil ecological diversity (Odumo et al., 2014a; Rodríguez Martín et al., 2014) and gauging the effects of anthropogenic activities on soil functions and associated ecosystems services (Stutter et al., 2009; Rodríguez Martín et al., 2013; Glendell et al., 2014; Rodríguez Martín and Nanos, 2016). Practically, understanding soil properties spatial variations is important for farmers attempting to enhance land productivity and to support soil management decisions such as fertilizer recommendation and appropriate fertilizer doses, application methods and frequency, irrigation rates, and soil/water conservation measures. The spatial information on soil key functional properties can be a powerful decision-making tool in achieving efficient site-specific land management practices (Guedes Filho et al., 2010), that lead to better land management decisions aimed at remedying nutrient deficiencies and maintains sustainable productivity of the soils (Özgöz, 2009).

Despite the growing worldwide emphasis on integrated landscape management with emphasis on spatial information, large investments are still being made in the highlands of Cameroon to improve soil productivity without considering soil variations. The region of highlands has experienced dramatic land use changes in the past decades due to intense agricultural activities, and soil variations resulting from such changes have rarely been documented. Fortunately, the last decades have witness the proliferation of geospatial packages used to characterize the spatial variability of soil properties due to their ability of quantifying and reducing sampling uncertainties and minimizing investigation costs (Cambule et al., 2014). There is therefore a need to use some of these techniques to quantify the changes describe earlier in order to aid accurate estimation of nutrient budgets, cycling rates and actual demand for inputs. The aims of this study were to a) quantify current soil functional properties in the highlands of Cameroon and b) display spatial variability of selected soil properties using simple l geostatistical techniques.

2. Materials and methods

2.1. Study area and soil sampling

The study area is located in the Western highlands of Cameroon, where two “sentinel sites” of 100 km^2 each with contrasting land uses were established; one dominated by agricultural activities and the other intensively used as pasture for livestock rearing (Fig. 1). The area is characterized by a tropical climate: mean daily minimum and maximum temperatures are 18 and 28 °C, respectively; mean annual rainfall ranges from 1500 to 2300 mm per year, and the rainy season extends from March to October. The topography is undulating with altitude ranging from 1000 to 1800 masl, and the vegetation is predominantly savannah with patches of gallery and montane forests. The soil is mainly composed of Ferralsols according to the World Reference Base (WRB) for soil resources classification system (IUSS, 2006). Due to anthropogenic activities, the landscape is a mosaic of land use types made up of cropland, fallow, forest, grassland, pasture and shrubland.

The study used the land degradation surveillance framework (LDSF), which is a spatially stratified, random sampling design framework based on the concept of sentinel site (Vågen et al., 2006, 2012). A sentinel site is a demarcated landscape of 100 km^2 (10 × 10 km) that is representative of a larger area, and from which in-depth data and information are gathered and the resulting analysis can be used to inform land management programs and policies. A sentinel site have 160 randomized sampling designs that allow for statistical modelling. Within each site, 16 tiles (2.5 × 2.5 km in size) are created and random centroid locations for clusters within each tile are generated. Each cluster consists of 10 plots, with randomized centre-point locations falling within a 5.64 m radius from each cluster centroid (Fig. 2a). Thus, the LDSF has two (or in some cases three) levels of randomization, which minimize local biases that may arise from convenience sampling. Each

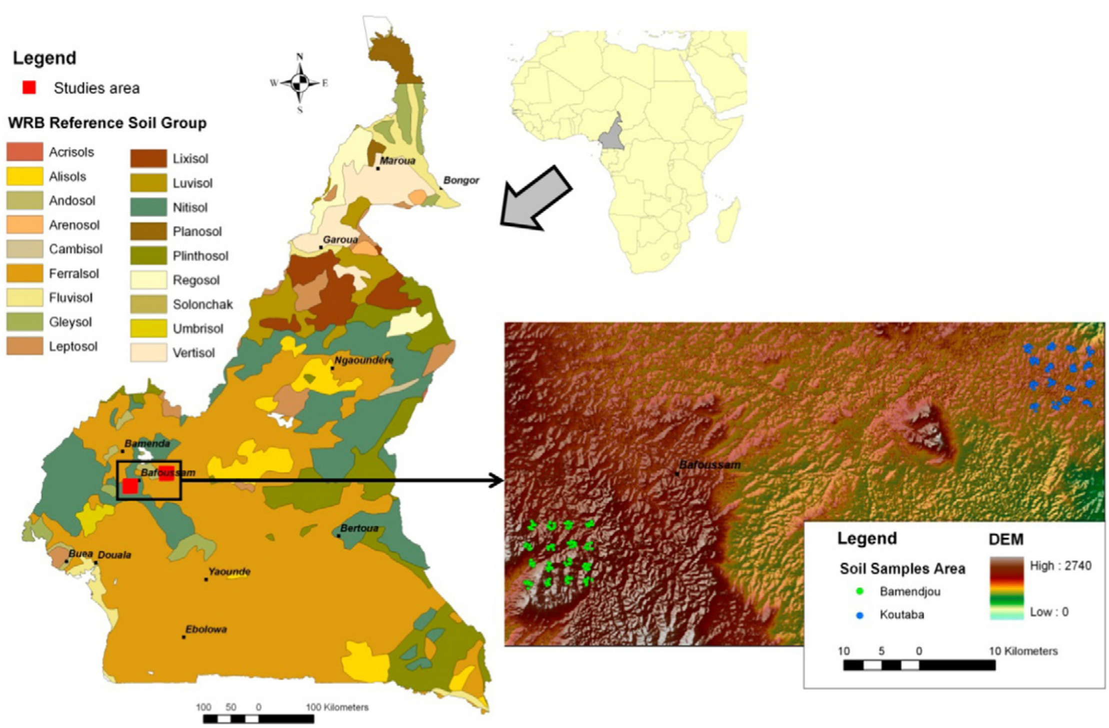

Fig. 1. Map of Cameroon showing the WRB Reference soil group and location of study areas.

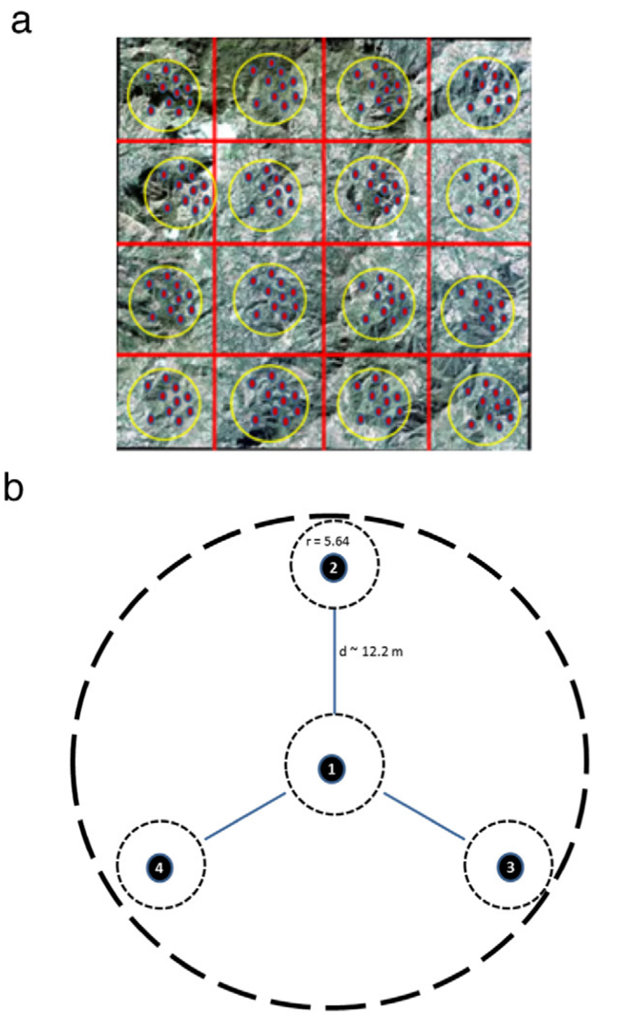

Fig. 2. a: Sentinel site of 10 × 10 km divided into a grid composed of 16 clusters. b: Sampling plot consisting of three 100 m^2 subplot within a 1000 m^2 plot.
Source (Vågen et al., 2010).

plot is 0.1 ha (1000 m^2) and consists of 4 subplots, 0.01 ha in size (Fig. 2b).The two sites were established and surveyed following procedures described in (Vågen et al., 2006, 2012). A total of 320 topsoil (0–20 cm) composite samples were collected across the two sentinel sites (160 samples per site).

2.2. Soil laboratory and spectral analyses

The soil samples ($n = 320$) were air-dried and then passed through a 2 mm sieve to remove coarse and stones prior to laboratory analysis. A subset ($n = 32$) representing ~10% of the total samples were analyzed for a range of properties at the Crop Nutrition (Cropnut) Laboratory in Nairobi using conventional wet chemistry methods. Then the 320 soil samples were ground to <100 μm using agate mortar and pestle, and were analyzed by diffuse reflectance mid-infrared spectroscopy (MIRS) using the procedure described elsewhere (Terhoeven-Urselmans et al., 2010; Vågen et al., 2013, 2016). Soil MIRS is a non-destructive, rapid, and cost-effective methodology for characterizing a large number of soil samples, and for a range of soil properties, therefore enabling landscape-level assessments of spatial variability of soil health indicators (Shepherd and Walsh, 2002; McBratney et al., 2006; Viscarra Rossel et al., 2006; Vasques et al., 2008; Zornoza et al., 2008). Regression used MIRS data as independent variables and the laboratory data as dependent variables. Then the fitted regression models were used to predict properties of all the samples based on the calibration samples (Hengl et al., 2014).

2.3. Statistical and geostatistical analysis

A standard statistical analysis (mean, median, standard deviation, coefficient of variation, etc.) was carried out to describe the soil properties involved in two sentinel sites in the highlands of Cameroon. Significant differences between land use types were assessed by non-parametric Kruskal-Wallis tests. In order to study the relationship between soils properties, canonical correlation analyses (CCorA) used considerably in ecology were applied between explanatory soil granulometric fraction, (SOC and pH) and response N, P, Ca, K, Mg, Al, Mn and Zn. The relationships between the two groups were estimated using quadrants of the CCorA (Odumo et al., 2014b). However, these classical statistical approaches ignore spatial dependence between observations (Nourzadeh et al., 2012; Nanos et al., 2015). Simple geostatistical techniques based on semivariograms have increasingly been used to analyze the spatial pattern of environmental variables (Goovaerts, 1997; Rodríguez Martín et al., 2016).

An experimental semivariogram, which is the plot of semi variance as a function of the distance, was developed to evaluate the degree of spatial continuity and to determine the range of spatial dependence for each soil property. The variogram Y was calculated as described in (Rodríguez Martín et al., 2016) and using the equation defined in Oliver and Webster (2014) as follow:

$$\gamma_{(h)} = \frac{1}{2n}\sum_{i=1}^{i=n}[Z(u_i) - Z(u_{i+h})]^2$$

where m(h) is the number of paired comparisons at lag h and ($z(u_j)$ and $z(u_{j+h})$ are sample values at two points separated by the distance h. The spherical models were used to fit the experimental semivariograms as the best model.

One of the main application of geostatistics has been the estimation and mapping of soil properties. Kriging estimates were calculated as the weighted sums of the adjacent sampled soil values. There are many different kriging algorithms, and most have been reviewed in Goovaerts (1997) with references to soil applications. In our study, SOC, N and clay percentage were mapped by ordinary kriging (OK). The most likely value R(u) that one could expect to encounter in a particular grid cell when using m nearby observations was defined as:

$$R(u) = \sum_{j=1}^{j=m}\lambda_j Z(u_i)$$

where R(u) is the estimated value and λ_j are the kriging weights; thus, λ_j values are obtained in such a way that they provide an unbiased estimator $E[R*(u) - R(u)] = 0$ and the minimum variance, $Var[R*(u) - R(u)]$. These weights are obtained by solving a system of linear equations known as an 'ordinary kriging system' (Goovaerts, 1997). This method has been previously and widely used for characterizing soil parameters. The prediction accuracy of the S SOC, N and clay percentage maps was evaluated by the cross-validation technique (Mishra et al., 2010; Meersmans et al., 2011; Rodríguez Martín et al., 2016). It removes each data location, one at a time, and predicts the associated data value. Cross-validation compares measured and predicted values (Marchant et al., 2010) which indicates that the accuracy of the Kriged results can be accepted. All the statistical analyses were carried out using the SPSS statistical package version 21.9 (SPSS Inc., Chicago, USA), XLSTAT (Addinsoft Version 2012.2.02), ISATIS V10.0 and the Geostatistical Analyst extension for ArcGis 9.3.

Table 1
Descriptive statistics of soil properties in Bamendjou site and mean values for different land uses types.

	Mean	Min	Max	CV (%)	Cropland (78)	Fallow (67)	Pasture (9)	Forest (3)	Shrubland (1)	Grassland (2)
Clay (%)	67.67	52.36	84.73	8.06	67.93 (a)	66.83 (a)	76.50 (a)	57.17 (a)	68.85 (a)	61.34 (a)
Silt (%)	21.60	9.77	51.76	17.45	20.88 (ab)	22.55 (b)	14.77 (a)	36.01 (b)	19.05 (ab)	28.22 (b)
Sand (%)	13.62	2.47	55.66	21.17	12.70 (a)	14.83 (a)	7.54 (a)	25.05 (a)	11.19 (a)	20.77 (a)
SOC (%)	3.757	0.806	7.722	27.84	3.79 (b)	3.90 (b)	1.63 (a)	5.79 (b)	3.58 (ab)	4.48 (b)
N (%)	0.262	0.051	0.589	29.30	0.260 (b)	0.274 (b)	0.107 (a)	0.439 (b)	0.262 (ab)	0.336 (b)
pH	5.893	5.107	6.563	4.00	5.905 (b)	5.903 (b)	5.559 (a)	6.181 (b)	5.818 (ab)	6.191 (b)
P (mg kg^{-1})	5.480	1.480	13.212	38.40	5.385 (b)	5.707 (b)	2.753 (a)	9.721 (b)	4.451 (ab)	8.036 (b)
Ca (mg kg^{-1})	8.313	0.704	47.694	38.47	7.753 (b)	8.819 (b)	2.353 (a)	24.349 (b)	5.231 (ab)	17.494 (b)
K (mg kg^{-1})	0.423	0.140	1.078	33.63	0.399 (ab)	0.446 (bc)	0.242 (a)	0.934 (c)	0.397 (bc)	0.685 (bc)
Mg (mg kg^{-1})	3.773	0.284	16.743	31.68	3.652 (b)	3.929 (b)	1.467 (a)	8.386 (b)	6.205 (b)	5.500 (b)
Al (mg kg^{-1})	1406	1079	1608	5.3	1420 (b)	1421 (b)	1192 (a)	1393 (ab)	1447 (b)	1319 (ab)
Mn (mg kg^{-1})	12.7	4.7	29.6	44.03	11.9 (a)	13.3 (a)	8.5 (a)	26.5 (a)	11.2 (a)	20.5 (a)
Zn (mg kg^{-1})	1.341	0.768	2.397	21.28	1.297 (a)	1.346 (a)	1.440 (a)	1.869 (a)	1.275 (a)	1.695 (a)

Total soil samples 160. Value in parentheses after the land use indicates the number of soil samples. Significant differences among the different land use types ($P < 0.05$) are indicated by different letters, based on the non-parametric Kruskal–Wallis test SD. SOC. = soil organic carbon (%).

3. Results and discussion

3.1. Descriptive statistics of soil properties

Means and coefficients of variation (CV) of soil physico-chemical properties in different land use types in Bamendjou and Koutaba sites are presented in Tables 1 and 2, respectively. Bamendjou had higher values for SOC, N, pH, Ca and sand, while Koutaba had higher value for clay and Al. Differences in essential elements (N, P and K) were also observed between the two sites. Mean P content in Bamendjou (5.48 mg kg^{-1}) was two times higher than that found in Koutaba (2.42 mg kg^{-1}), and the mean K content in Bamendjou (0.423 mg kg^{-1}) was three times higher than that found in Koutaba (0.131 mg kg^{-1}). The same trend was observed for micronutrients (Mg, Mn and Zn), with the highest levels found in Bamendjou. Textural analysis revealed that the entire study area is dominated by clay-rich soils. The soil reaction was also found to be slightly acid in both sites (pH < 6.2). The general acidity of the soils is mainly due to the chemical composition of parent materials; soils in the study area are Ferralsols according to the World Reference Base (WRB) for Soil Resources classification system (IUSS, 2006). These are strongly-weathered soils in which acidity, high exchangeable aluminum and a low ratio of basic to total cations could constitute some of the main limiting factors to permanent cropping systems.

Soil organic carbon (SOC) is considered among the most important bio-chemical parameters to assess functional capacities of soils (Rodríguez Martín et al., 2016). The SOC concentration fell within the range of 0.80–7.72% (mean = 3.75%) in Bamendjou and 1.15–5.98% (mean = 2.60%) in Koutaba. A review of critical SOC levels in soils (Loveland and Webb, 2003) has suggested that 2% SOC [ca. 3.4% soil organic matter (SOM)] is a threshold value, below which potentially serious decline in soil quality will occur. The differences observed between the two sites are ascribed to the fact that Bamendjou is dominated by agricultural activities while Koutaba is predominantly used for pasture. Bamendjou site has a long history of intense agricultural production, and most cultivated plots are managed to sustain productivity. Farmers improve soil fertility by plowing and adding organic and inorganic fertilizers (Takoutsing et al., 2013). Koutaba has been under intensive grazing for many years, and that has considerably reduced vegetation cover and has probably contributed to nutrient depletion.

The coefficients of variation (CV) helped in comparing the degree of variation within the two sites. The CV values for all soil properties ranged from 4 to 45% in Bamendjou and from 2.9 to 95% in Koutaba, which indicated low to high variation in both sites (Nielsen and Bouma, 1985). For Bamendjou, the most variable properties (CV > 38%) were P, Mn and Ca. Moderate variability (2.8% < CV < 38%) was observed for sand, SOC, N, K and Mg, while properties with very low variability (CV < 2.8%) were clay, soil pH, and Al. For Koutaba, the most variable properties were sand, Ca, K, Mg, Mn, P and Zn. N, SOC and silt were moderately variable while clay, Al and pH were the least variable. The wide range observed for most of the properties may be associated with historical land use, land cover and varying management practices. Farmers used various methods to improve the productivity of the soils and this probably has an influence on the concentration of soil nutrients. Similar findings have been reported at various scales (Di Virgilio et al., 2007; Fu et al., 2010). The majority of skewness coefficients for soil properties (not tabled) in Koutaba were positive and extremely high, while the majority of skewness coefficients in Bamendjou were moderate and negative. Highly skewed parameters indicate

Table 2
Descriptive statistics of soil properties in Koutaba site and mean values for different land uses types.

	Mean	Min	Max	CV (%)	Cropland (15)	Fallow (23)	Pasture (114)	Forest (8)
Clay (%)	78.13	58.96	99.33	7.79	71.41 (a)	73.47 (a)	80.05 (b)	76.77 (ab)
Silt (%)	14.33	5.49	33.33	24.23	19.54 (b)	17.21 (b)	12.98 (a)	15.44 (ab)
Sand (%)	4.95	1.07	22.25	42.55	7.21 (b)	7.39 (b)	4.12 (a)	5.47 (ab)
SOC (%)	2.600	1.151	5.989	20.36	3.198 (b)	3.059 (b)	2.417 (a)	2.780 (ab)
N (%)	0.143	0.065	0.410	27.22	0.185 (b)	0.179 (b)	0.129 (a)	0.153 (ab)
pH	5.298	4.870	5.921	2.9	5.327 (a)	5.435 (a)	5.273 (a)	5.222 (a)
P (mg kg^{-1})	2.423	0.883	7.787	40.28	3.108 (b)	3.242 (b)	2.170 (a)	2.397 (ab)
Ca (mg kg^{-1})	1.030	0.171	10.285	95.6	1.612 (b)	1.974 (b)	0.774 (a)	0.888 (ab)
K (mg kg^{-1})	0.131	0.060	0.578	66.92	0.185 (b)	0.193 (b)	0.111 (a)	0.130 (ab)
Mg (mg kg^{-1})	0.350	0.108	2.290	77.71	0.561 (b)	0.617 (b)	0.269 (a)	0.336 (ab)
Al (mg kg^{-1})	1467	1243	1647	2.98	1454 (a)	1480 (a)	1464 (a)	1482 (a)
Mn (mg kg^{-1})	4.99	2.02	18.12	43.55	7.24 (b)	6.87 (b)	4.30 (a)	5.15 (ab)
Zn (mg kg^{-1})	0.931	0.572	1.600	41.43	1.120 (b)	1.029 (b)	0.885 (a)	0.955 (ab)

Total soil samples 160. Value in parentheses after the land use indicates the number of soil samples. Significant differences among the different land use types ($P < 0.05$) are indicated by different letters, based on the non-parametric Kruskal–Wallis test SD. SOC. = soil organic carbon (%).

Table 3
Spearman's correlation coefficients among soil properties in Koutaba and Bamendjou areas (above and below diagonal, respectively).

	Clay	Silt	Sand	SOC	N	pH	P	Ca	K	Mg	Al	Mn	Zn
Clay		−0.942**	−0.771**	−0.762**	−0.750**	−0.191*	−0.797**	−0.544**	−0.646**	−0.467**	0.252*	−0.807**	−0.811**
Silt	−0.935**		0.739**	0.778**	0.749**	ns	0.729**	0.514**	0.619**	0.437**	−0.373**	0.824**	0.903**
Sand	−0.758**	0.884**		0.520**	0.638**	0.464**	0.882**	0.727**	0.819**	0.683**	ns	0.787**	0.515**
SOC	−0.725**	0.626**	0.309**		0.971**	0.173*	0.739**	0.669**	0.716**	0.647**	−0.290**	0.860**	0.784**
N	−0.774**	0.696**	0.402**	0.989**		0.351**	0.848**	0.811**	0.853**	0.797**	−0.164*	0.926**	0.729**
pH	−0.768**	0.608**	0.441**	0.664**	0.705**		0.652**	0.666**	0.622**	0.606**	0.341**	0.389**	ns
P	−0.937**	0.907**	0.744**	0.775**	0.838**	0.842**		0.906**	0.936**	0.824**	ns	0.907**	0.590**
Ca	−0.765**	0.731**	0.536**	0.723**	0.798**	0.811**	0.908**		0.957**	0.943**	ns	0.862**	0.453**
K	−0.851**	0.861**	0.675**	0.739**	0.822**	0.723**	0.919**	0.930**		0.942**	ns	0.928**	0.562**
Mg	−0.606**	0.587**	0.421**	0.622**	0.704**	0.596**	0.679**	0.802**	0.851**		0.156*	0.837**	0.393**
Al	−0.255**	ns	ns	0.492**	0.449**	0.230*	0.239*	ns	ns	ns		−0.212*	−0.665**
Mn	−0.839**	0.855**	0.653**	0.655**	0.733**	0.667**	0.870**	0.882**	0.967**	0.793**	ns		0.794**
Zn	−0.591**	0.684**	0.494**	0.384**	0.457**	0.380**	0.592**	0.616**	0.751**	0.614**	−0.492**	0.822**	

Sample size = 160 in each site; significant levels $^{*}P < 0.05$, $^{**}P < 0.01$, ns $P > 0.05$.

that these elements have a local distribution, that is, high values were found for these elements at some points, and low values at some other points (Grego et al., 2006).

3.2. Relationships between soil properties

There were significant positive correlations among most pairs of soil properties and some correlations (P/K, P/N, P/Ca, K/Ca, Ca/Mg, K/Mg, P/Mn or K/Mn) were very strong (Table 3). The strongest correlation was between SOC and N in Bamendjou ($r = 0.989$) and Koutaba ($r = 0.971$). These correlations were expected because the two properties are related to the amount of organic matter in the soil (Kahle et al., 2002; Takoutsing et al., 2013).

Previous studies have demonstrated the influence of N on carbon stock through plant growth and litter quantity, as well as its role in stabilizing soil carbon decomposition particularly in tropical areas (Nave et

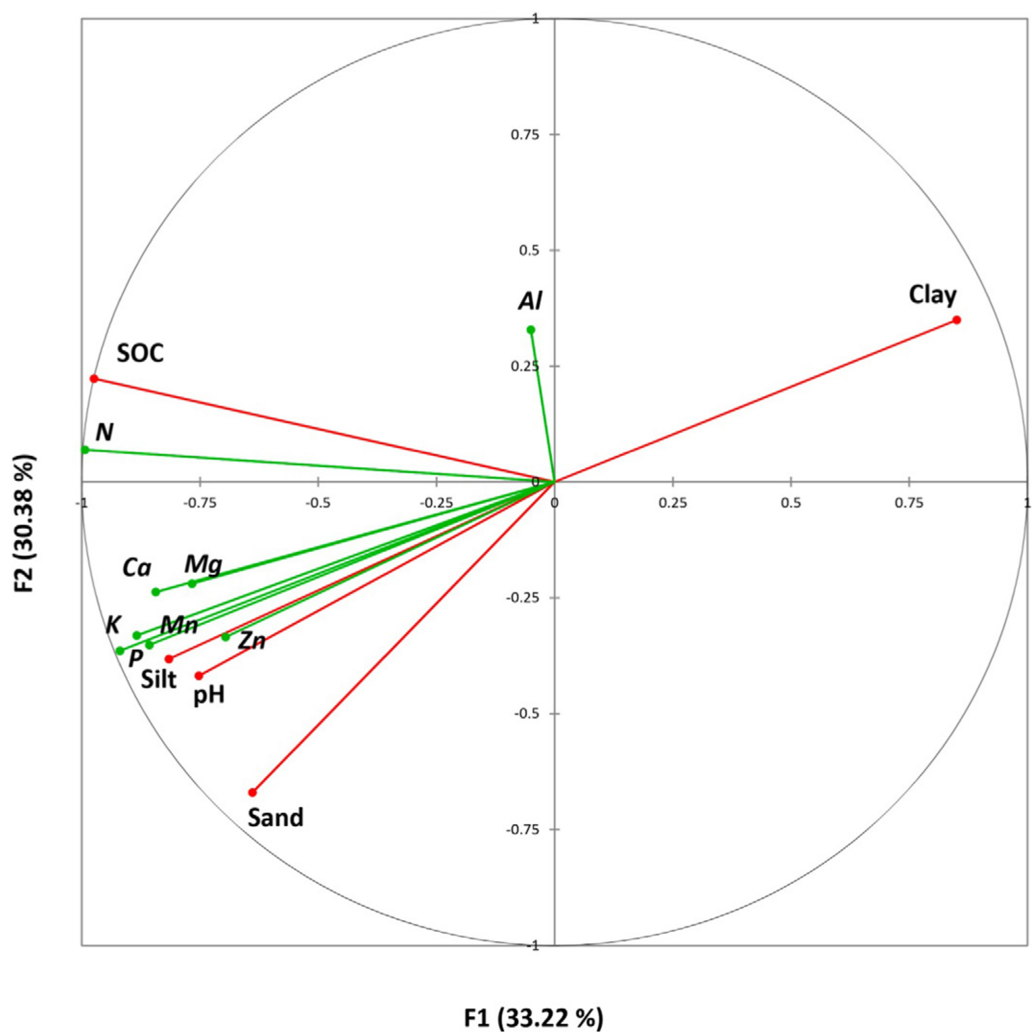

Fig. 3. CCA Ordination diagram based on the CCorA of the soil properties (soil granulometric fraction, soil organic carbon and pH) and data for soil elements contents (N, P, Ca, K, Mg, Al, Mn and Zn).

al., 2009). The dynamics of N in the soil are closely related to that of carbon: thus, any change in the level of one property may cause a change in the level of the other in the soil (Qi et al., 2007; Moges and Holden, 2008). Since the two elements are highly correlated, their concentrations in the soil will both decrease through the same processes such as erosion, crop harvesting and leaching.

Clay was negatively correlated with all the soil properties in both sites, while sand and silt showed positive and significant correlations. Most likely this is due to the differences in the controlling factors of microbial biomass, such as soil organic matter, management practices, and plant species composition, that influence the effects of clay content on soil properties. Previous studies have attributed the negative correlations of clay to soils that are well-weathered and formed under high precipitation (Côté et al., 2000; Vejre et al., 2003; McLauchlan et al., 2006). In contrast, other studies have reported positive relationships between clay content and soil properties such as N and deduced that N is protected in aggregates rich in clay, which explains the high concentrations of N on clay particles (Waswa et al., 2013).

Canonical correlation analysis (CCorA) was used to evaluate the multivariate relationships between two sets of soil variables: those that have high spatial dependence (SOC, N and clay) and the other properties (P, K, Ca, Mg, Mn, pH and Zn) (Fig. 3). Factors 1 and 2 explained 64% of the total variance in soil properties. Results showed that the concentration of nutrients and micronutrients (P, K, Ca, Mg, Mn and Zn) were positively related to SOC and pH, while P, K, Ca, Mg, and Zn content were negatively related to clay content. As expected, SOC showed a strong and positive correlation with total N.

3.3. Spatial distribution of key soil properties

A standard geostatistical analysis was carried out to describe SOC, N and clay as main soil properties to describe the spatial patterns in the two study sites. The semivariograms parameters are presented in Fig. 4 and Table 4, and suggested that the soil parameters in both sites were best fitted with the theoretical spherical isotropic model. The range (A0) is considered as the distance beyond which the value of two soil samples can be statistically independent (Goovaerts, 1997; Rodríguez Martín et al., 2009), then the correlation becomes negligible at a separation distance of about 3 km for clay in both sites (Table 4). The spatial correlation ranges were significantly wider for SOC (6 km) and N (5 km) in Bamendjou (Fig. 4a) than in Koutaba (Fig. 4b). Soil properties with wide ranges infer large area of influence and can be attributed to intrinsic factors such as soil formation (McKenzie, 2012; Liu et al., 2013; Rodriguez Martin et al., 2014; Rodríguez Martín et al., 2014). On the other hand, soil properties with short distances are associated with extrinsic factors often attributed to anthropogenic activities such as agriculture and livestock rearing (Rodríguez Martín et al., 2014). The results of this study contrasted with the general geostatistical theory. We expected shorter rather than wider ranges in Bamendjou because of the influence of human activities. This may implies that the selected properties are more influenced by intrinsic factors such as parent materials. In Koutaba however, these soil properties showed shorter ranges due to influence of grazing activities. This led to the partial conclusion that grazing has more influence on the spatial structure of soil properties than agricultural activities. The nugget was higher for clay than for N and SOC in both sites indicating that the selected sampling distance may not have well captured its spatial dependence. On the other hand, the lowest nugget observed for N attests its low spatial variability within small distances.

The moderate spatial dependence of soil properties may be also controlled by extrinsic variations such as organic and inorganic fertilizer application, grazing, tillage and soil management practices (Cambardella et al., 1994; Mueller et al., 2003). Previous studies have demonstrated that even in the case of weak spatial structure of soil properties, accurate maps are still obtainable but at the expense of intensive sampling exercises (Parfitt et al., 2009). In this context, ordinary kriging (OK) was used for the spatial interpolation and production of maps of SOC, N and clay.

Soil parameters (SOC, N and Clay) maps obtained using the ordinary kriging are presented in Fig. 5 (Bamendjou) and Fig. 6 (Koutaba). The

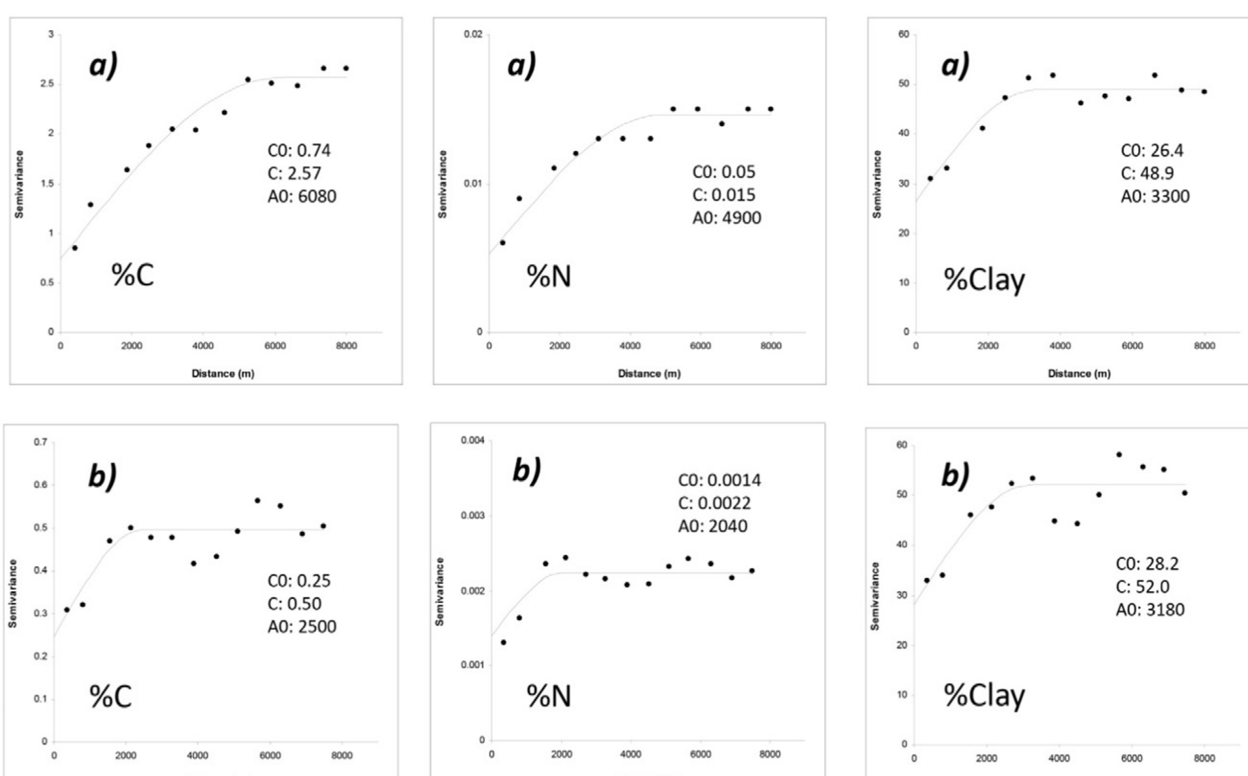

Fig. 4. Experimental variogram and spatial models for soil organic carbon (%C), soil nitrogen content (%N) and clay percentage (%Clay) in Bamendjou area (a) and Koutaba area (b).

Table 4
Parameters for semivariogram models for selected soil properties in Bamendjou and Koutaba sites.

Soil parameter	Study area	Model structure	Nugget (C_0)	Sill ($C_0 + C_1$)	Range (A_0)	DSD (%)
SOC	Bamendjou	Nugget + Spherical	0.74	2.57	6080	28%
N	Bamendjou	Nugget + Spherical	0.005	0.015	4930	36%
Clay	Bamendjou	Nugget + Spherical	26.4	48.9	3300	53%
SOC	Koutaba	Nugget + Spherical	0.25	0.50	2500	49%
N	Koutaba	Nugget + Spherical	0.0014	0.0022	2040	61%
Clay	Koutaba	Nugget + Spherical	28.2	52.0	3180	54%

DSD = degree of spatial dependence; strong DSD (DSD ≤ 25%); moderate DSD (25 < DSD ≤ 75%); weak DSD (DSD > 75%).

maps indicated areas with low SOC and N values in the central and western parts (A in Fig. 5), and high values in the eastern and southern parts (B in Fig. 5) of Bamendjou. In Koutaba, the maps indicated four areas of high concentration levels of SOC and N in the northern and eastern parts (A in Fig. 6) and low concentration in the central and southern parts of Koutaba. The low values of SOC and N in each site were found to be associated with high clay content (A in Fig. 5; B in Fig. 6), and agree with the correlation presented in Table 3 that revealed the negative relationship between clay and other soil properties. These variations in soil spatial patterns in both sites appeared to be associated with differences in land use types, landforms and vegetation cover. Changes in land use types have the potential to generate corresponding change of microenvironment and consequently influence soil nutrients (McGrath et al., 2001; Takoutsing et al., 2015). The concentrations of SOC and N were ranked as forest > grassland > fallow > cropland > pasture in both sites. The land use types with more vegetation cover exhibited the highest SOC and N values attesting that land use types had a significant impact on spatial patterns and distribution of the properties. SOC and N concentrations in the soils are influenced by above-ground biomass, ground litter accumulation and decomposition, below-ground root mass and distribution, physical and biological conditions in the soil utilization (Yong-Zhong et al., 2005; Han et al., 2008; Li et al., 2008). Additionally, the low SOC and N concentration in pastures is attributed to reduced vegetation cover following intensive grazing.

There was a smaller difference in clay content across land use types because the property is relatively little affected by changes in land

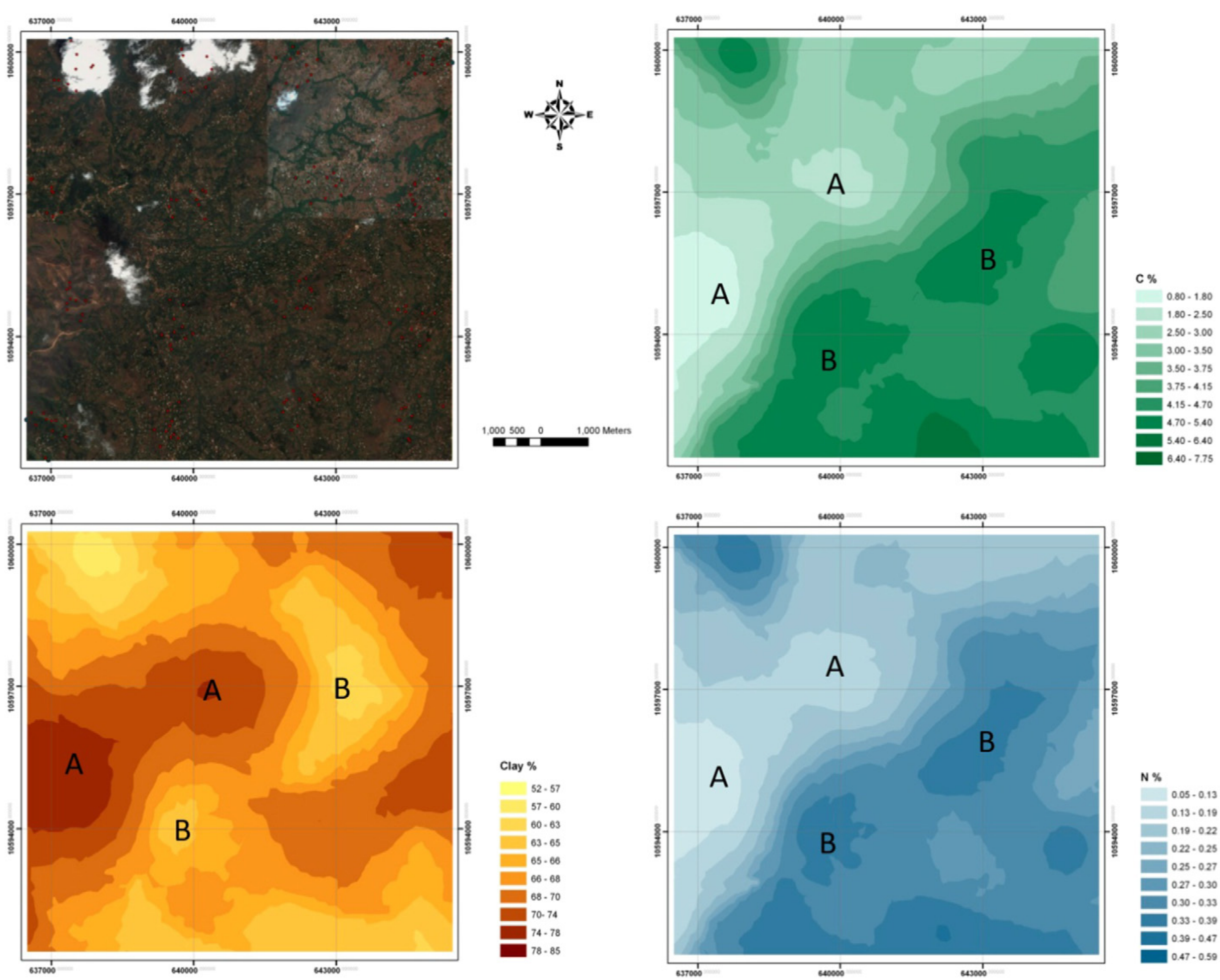

Fig. 5. Spatial distribution of C, N and clay interpolated by ordinary kriging and aerial photography showing the sampling points for the Bamendjou site.

management, supporting the assumption that soil conditions were more or less similar prior to the shifts in land use. However, clay content was found to be highest in pasture lands in both sites, because of low vegetation cover caused by overgrazing and soil compaction by animals. Our result showed that the effects of land use types, as well as their interaction on soil properties are significant, and corroborates with those previously reported under different conditions and countries (Chen et al., 2007; Meersmans et al., 2011; Meersmans et al., 2012; Berhongaray et al., 2013; Minasny et al., 2013). This implies that land use is one of the main determinant factors for the spatial distribution of soil properties.

The spatial distribution of SOC and N showed similar spatial patterns and their concentrations decreased towards the uplands. In general and from field observations, the spatial distribution of selected soil properties showed a well-defined pattern of higher concentrations in the lowlands and valleys and areas with permanent vegetation cover. This could be partly attributed to rainfall and erosion responsible for carrying nutrients from uplands to lowlands areas through runoff and leaching (Stone et al., 1985; Haregeweyn et al., 2008). With site-specific management in mind and considering the Bamendjou site, more attention should be paid to the central and western parts to increase the concentration of soil properties and to the eastern parts for protection and conservation current status of soil properties. For Koutaba, proper measures should be put in place to conserve the fertility potentials of the four key hotspot areas of high nutrient concentrations, as well as soil improvement measures to increase nutrient levels in low concentration areas. The spatial patterns of soil properties produced could be used as a guide to assess land degradation at landscape level, evaluate land suitability for crops, quantify the amount and types of fertilizers to be used by farmers and design appropriate soil and water conservation measures.

3.4. Implication of soil properties variability for smallholder farming systems

The results of the study signposted that spatial variations observed with soil properties are influenced by inherent soil differences, management practices and topographic factors. The fact that Bamendjou was dominated by agricultural activities as opposed to Koutaba dominated by pasture implies that soil properties in both sites could differ spatially. From field observations, high concentrations of soil properties were also found in croplands located close to settlement. These farms tend to be more intensively managed with additional inputs due to their ease of access, and their proximity to households.

Most soil properties that are very sensitive to management practices usually have a shorter spatial range (Özgöz et al., 2007). The differences

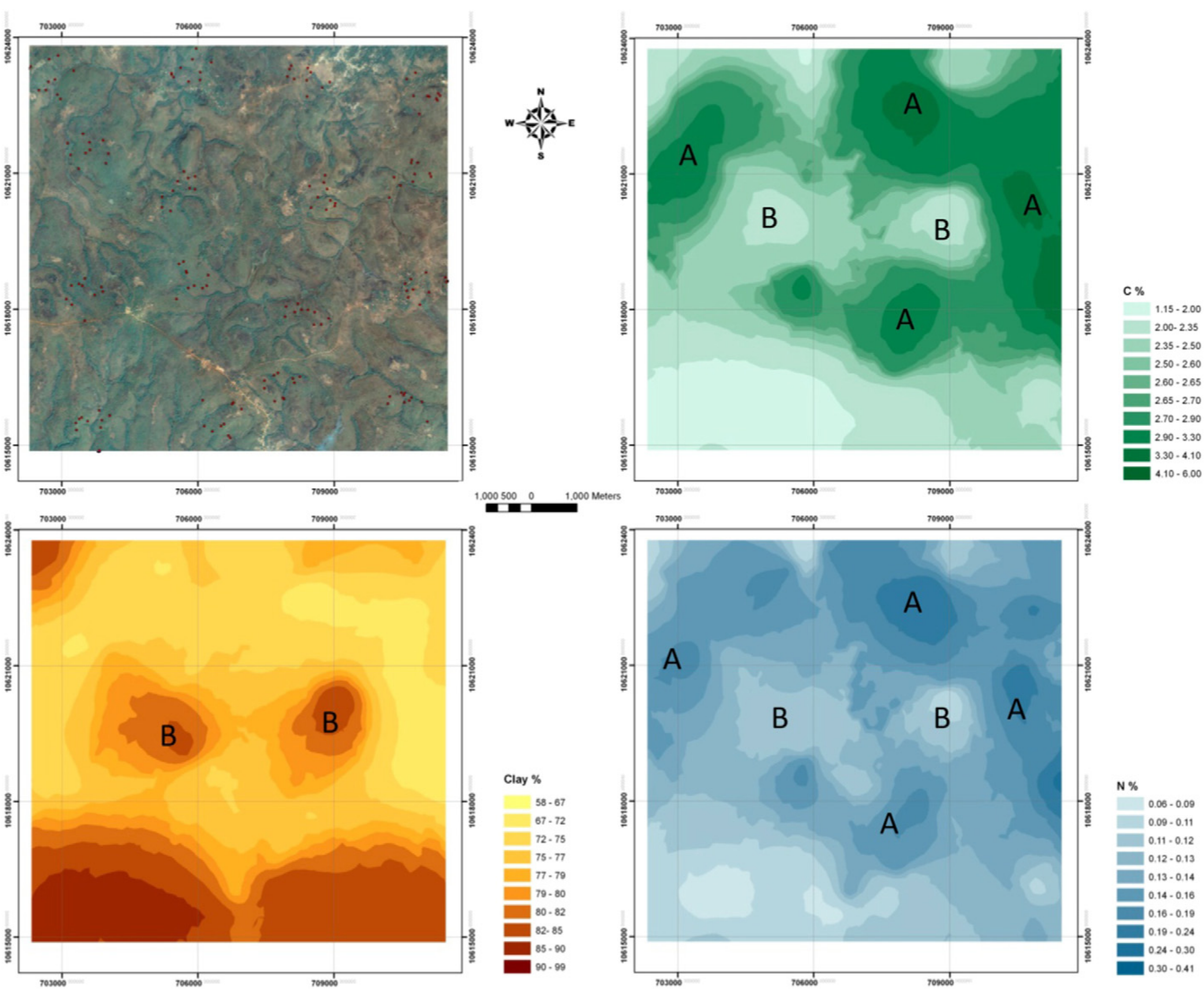

Fig. 6. Spatial distribution of C, N and clay interpolated by ordinary kriging and aerial photography showing the sampling points for the Koutaba site.

observed in the range of soil properties in this study, particularly SOC and N could therefore be attributed to both natural and anthropogenic factors (Tesfahunegn et al., 2011). Previous studies have demonstrated the influence of the two factors on spatial patterns of soil properties (Tsegaye and Hill, 1998; Özgöz et al., 2007). This implies that there is a need to develop and disseminate site-specific land management practices, instead of making blanket agronomic recommendations for all fields as it is the case now. The results of this study are very useful for smallholder farmers with low financial capacities who are called upon to improve soil productivity and crop yields using additional inputs. The findings could be used to enhance the efficient use of agricultural inputs such fertilizers by giving an indication of the concentration of nutrients (N,P and K) at precise location, or they can be used in selecting areas targeted for specific interventions such as large scale reforestation.

Across the study site, some plots may not necessarily need additional nutrients as such, but need practices that improve soil structure, water holding capacity and limit nutrient leaching. Some other plots may have deficiency in one element (N) but not in others (P and K). The current fertilizer (NPK) recommendation is uniform for all agro ecological zones in the country and has never been revised for decades with updated and reliable soil information. This has resulted in under-application in areas with low nutrient levels and over-application in areas with high nutrient levels. Areas receiving under-application of fertilizers will definitely not produce optimal crop yields; and for areas receiving over application, it is an unnecessary expense for farmers and an increase in environmental pollution (Bouma, 1997).

Sustainable intensification called for production systems that are able to increase crop yield, mitigate the risk of environmental pollution, maintain soil health and reduce cost of production for smallholder farmers. For areas in the study site with low N and SOC concentrations, appropriate N fertilizer should be applied to meet the crop nutrient requirements in order to achieve optimum yield. While for areas with high concentrations, application of N fertilizers may not be required for a period of time for both economic and environmental reasons. Management of soil nutrients based on site specific information is one of the important steps in achieving sustainable intensification of agriculture, efficient use of inputs, increased in crop yields and contribute to the fight against food insecurity at household and community levels.

4. Conclusions

Geostatistical analyses are very important for assessing the spatial structure of a given soil properties. The maps of properties revealed the variations across the study site by indicating areas of low and high nutrient concentrations. The major conclusions from this study are the following. (1) Strong and positive correlations between soil properties and nutrients were observed with the exception of clay content which negatively affects soil properties. (2) Land use types had significant effects on the concentration of soil properties, and particularly SOC and N decreased in the following order: forest > grassland > fallow > croplands > pasture land. (3) Bamendjou site had higher values for most of the soil properties compared to Koutaba. (4) a simple geostatistical analysis allowed detailed visualization and quantification of soil properties at a landscape scale and provided a baseline for the comparison and evaluation of the effectiveness of land management interventions, showing a wider ranges in Bamendjou as oppose to Koutaba despite been dominated by human activities. Therefore, management of soil nutrients based on site specific information is one of the important steps in achieving sustainable intensification of agriculture.

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