

Full Length Research Paper

# Predictor variables for soil organic carbon contents in the Miombo woodlands ecosystem of Kitonga forest reserve, Tanzania

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Few studies have established the variables which adequately predict SOC storage in the Miombo woodlands. Multiple regression analysis was used to establish the variables which could predict SOC contents in dominant soils of the Miombo woodlands of Kitonga Forest Reserve, Tanzania. Thirty soil mini-pits located at different elevations across a topographical gradient were selected, geo-referenced, excavated and samples from the natural horizons were collected for physico-chemical analysis. A total of 85 samples were collected, each representing a natural soil horizon. The results indicated that total nitrogen (TN), ( $P < 0.001$ ,  $R^2 = 0.97$ ) and TN in combination with calcium (Ca) ( $P < 0.001$ ,  $R^2 = 0.99$ ) were important predictor variables of SOC contents. The combination of cation exchange capacity, Zinc, Copper, clay and iron together with TN and Ca predicted well the SOC contents ( $P < 0.001$ ,  $R^2 = 0.999$ ). Considering time and cost implications for field and laboratory analysis in predicting SOC stocks, the combination of TN and Ca that predicted the SOC contents by 99% provided equally strong prediction when compared to the combination of all the variables. Thus, proper land management strategies which enhance conservation of TN and Ca in concert would provide adequate prediction of SOC contents in soils.

**Key words:** Miombo woodlands, predictor variables, soil organic carbon contents, multiple regressions, Kitonga Forest Reserve, Tanzania.

## INTRODUCTION

It is recognized that forest ecosystems, globally store about 40% of organic carbon, with 11% of the carbon being stored in forest soils (Negi *et al.*, 2013; Yuan *et al.*, 2013). As the largest reservoir of terrestrial carbon, soils play a role in the regulation of global warming and greenhouse gas effects (Aticho, 2013; Stockmann *et al.*, 2013; Jandl *et al.*, 2014). Globally, soils store about  $1.5 \times 10^{12}$  tons of carbon (organic and inorganic), of which about  $1.1 \times 10^{12}$  tons are found in forest soils (Aticho, 2013; Negi *et al.*, 2013). Due to the relatively long residence times provided by the humic substances found

in the SOC, soils are a potentially important long term natural sink of carbon (Lal, 2009; Bruun *et al.*, 2010; Schmidt *et al.*, 2011; Guimaraes *et al.*, 2013), thus contributing to climate change regulation.

The amounts of SOC storage across a landscape are variable among soil types, elevation, slope position, soil texture, site characteristics, soil depth, vegetation types and climate (Lal, 2005; Attua, 2009; Aticho, 2013; Hoffmann *et al.*, 2014). Due to large spatial variations of SOC contents across landscapes, assessing the current state of SOC, especially for large tracts of land, is costly and time consuming (Jha *et al.*, 2014; Nocita *et al.*, 2014). Few studies exist on the identification of variables that are likely to influence the stocks of SOC using multiple regression models (Meersmans *et al.*, 2008; Attua, 2009; Nocita *et al.*, 2014). Understanding the mec-

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mechanisms of, and the variables influencing SOC dynamics in Miombo woodland soils is important to identifying and enhancing natural sinks for C sequestration to mitigate the challenges of climate change.

The practice of identifying few variables that predict SOC stocks optimally, cost effective and time efficient would enhance the process of designing management strategies to increase SOC storage to mitigate the effects of, and to adapt to, climate change. This is important within the Miombo woodlands ecosystem, which covers about 32 million hectares, or 93% of the total forested land area and about 40% of total land, in Tanzania. Such adaptation would enhance continued provision of diverse ecosystem services to support livelihoods (Nshubemuki and Mbwambo, 2007; FAO, 2009; Woollen *et al.*, 2012). Thus, identifying a minimum set of variables that could accurately predict SOC stocks in a timely and resource-efficient manner would constitute a substantial contribution to new knowledge in this branch of science.

The overall aim of the study reported here was to identify variables which determine predictor variables of SOC contents in the dominant soil types in the Kitonga Forest Reserve (KFR), Tanzania, and select the cost effective and time saving variables which could predict the SOC contents optimally. The results would provide for extrapolation to other areas with similar soil types and similar ecological conditions. The working hypothesis of the study was that linkages between C storage and predictor variables influencing SOC in the identified soil types could be used to explain carbon stocks in other soils under similar ecological conditions.

The data obtained would provide vital information on soil carbon stocks predictor variables in Miombo woodlands in the view point of saving financial resources and time. This would be of help to policy makers and other stakeholders in designing interventions to reduce deforestation and forest degradation (REDD+), and enhance sustainable SOC storage in soils as a result of improved soil/land management practices.

## MATERIALS AND METHODS

### Study Site

Pertinent features of the KFR (07°35' - 07°43'S; and 37°07' - 37°10'E) in Kilolo District, Iringa Region, Tanzania, are summarized in Table 1. The area covers 52 km<sup>2</sup> and consists of moderate to very steep slopes, with altitude ranging from 660-1880 m above sea level. Cambisols (Inceptisols) and Fluvisols (Entisols) in the medium to steep slopes and Leptosols (Entisols) in the lower slopes are the dominant soil types of the area (Shelukindo *et al.*, 2014). Climatic data from 1981 to 2012 which shows the monthly maximum, minimum and mean temperatures, monthly rainfall and mean annual rainfall have been addressed by Shelukindo *et al.* (2014).

The dominant vegetation types across the study area are also shown in Table 1.

### Sampling Procedure

A systematic sampling method (line transect) was employed to collect soil samples by establishing plots across different elevations. All plots were located on well-drained soils across elevation gradients, taking into consideration the aspect factor.

### Soil Sampling

Within each dominant soil type a 20 x 20 square m plot was set out, and partitioned into four 10 m by 10 m quadrants. In each quadrant of 10 m by 10 m, one point was randomly selected for collecting soil samples. Soil samples from these points were collected from excavated natural horizons to a limiting layer and soils from similar horizon from the four sampled quadrant mini-pits were mixed to obtain composite samples for the different horizons. Such 20 m x 20 m square plots were replicated three times. Sub-samples from each natural horizon were mixed together to make bulk samples of about 2 kg for physical and chemical analysis in the laboratory.

### Soil Analysis

In the laboratory, soil samples were air dried to constant weight, ground and sieved through a 2 mm sieve to get the fine earth fraction ready for laboratory analysis. The bulk density was determined using the core method (Black and Hartge, 1986), and texture was determined by the hydrometer method (Day, 1965). Organic carbon was determined by the wet oxidation method (Nelson and Sommers, 1982). Total N was determined using the micro-Kjeldahl digestion-distillation method as described by Bremner and Mulvaney (1982). Extractable phosphorus was determined using filtrates extracted by the Bray and Kurtz-1 method (Bray and Kurtz, 1945) and determined by spectrophotometer (Watanabe and Olsen, 1965). The exchangeable bases (Ca<sup>2+</sup>, Mg<sup>2+</sup>, Na<sup>+</sup> and K<sup>+</sup>) were determined by atomic absorption spectrophotometer (Thomas, 1982). The micronutrients Fe, Mn, Zn and Cu were extracted using buffered 0.005M DTPA (Diethylene triamine pentaacetic acid) (Lindsay and Norvell, 1978) and their concentrations determined by an Atomic Absorption Spectrophotometer (AAS) (UNICAM 919 model). The SOC stocks were calculated based on the formula given by Spiota and Sharma (2013):

$$\text{SOC}_{\text{st}} = \% \text{SOC} / 100 \times \text{BD} \times \text{D} \times 100$$

where: SOC<sub>st</sub> is the soil organic carbon stocks (Mg C ha<sup>-1</sup>), SOC is the soil organic carbon concentration (%), BD

**Table 1.** Site characteristics of Kitonga Forest Reserve.

Item Location	Description/Value Kilolo District, Iringa Region
Latitude/Longitude	07°35' - 07°43' S - 37°07' - 37°10' E
Altitude (masl)	660- 1880
Mean Annual Rainfall (mm)	540- 734
Annual mean Temperature (°C)	12.0 - 29.0
Size of the study area (km <sup>2</sup> )	52
Parent material	In situ weathering of biotitic gneiss and muscovite quartz
* Soil type	Cambisols, Fluvisols, Leptosols
Sand (%) (surface horizon)	57 (Cambisols) - 85 (Fluvisols and Cambisols)
Silt (%) (surface horizon)	4.6 (Leptosols and Cambisols) – 10.6 (Fluvisols)
Clay (%) (surface horizon)	10.3 (Fluvisols and Cambisols) – 34.3 (Cambisols)
Bulk density (g/cm) (surface horizon)	1.0 (Leptosols) - 1.23 (Fluvisols)
pH (surface horizon)	5.1 (Fluvisols and Cambisols) - 6.2 (Fluvisols)
SOC (%) (surface horizon)	0.4 (Cambisols and Fluvisols) – 4.4 (Leptosols)
Dominant trees spp.	<i>Brachystegia</i> , <i>Julbernardia</i> , <i>Diplorhynchus</i> and <i>Condylocarpon</i>
Dominant grasses	<i>Andropogon</i> , <i>Heteropogon</i>
Dominant shrubs	<i>Fadogia</i> spp.
Dominant herbs	<i>Commelina africana</i>
* FAO classification system	

is the bulk density (g cm<sup>-3</sup>), D is the horizon thickness (cm) and 100 is the multiplication factor to convert the SOC from g cm<sup>-2</sup> to Mg C ha<sup>-1</sup>. The carbon stocks in each dominant soil type were obtained by the summation of C stocks of each natural soil horizon to the soil depth of 60 cm.

### Statistical Analysis

#### Pearson's correlation analysis

Pearson correlation (r) is a measure of the linear correlation between the SOC (%) (dependent variable, Y) and other variables (independent variables, x<sub>n</sub>), and has a value between +1 and -1 inclusive. Correlation value of 1 is total positive correlation, 0 is no correlation, and -1 is total negative correlation. These correlations are used to measure the degree of linear dependence and the strength of the relationship between variables (Kinnear and Gray, 1999; Attua, 2009).

All the soil variables (TN, Ca, CEC, Cu, Zn, Fe Mg, Mn, K, P, K, % clay, % silt, % sand and elevation) were correlated with SOC using Pearson's correlation analysis, of the model:

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2} \sqrt{n(\sum y^2) - (\sum y)^2}}$$

where:  $\sum$ : summation sign.  
 x: Predicted SOC content of a soil (dependent variable)  
 y: Predicted SOC content of a soil (dependent variable)  
 n: the number of pairs of data (x, y).  
 $\sum$ : summation sign.

The variables correlated with SOC would be used in step-wise multiple regression analysis for predicting the SOC contents. Bryman and Cramer (1997) and Kinnear and Gray (1999) similarly used Pearson's correlation matrix when sorting out suitable predictor variables for regression analysis, as well as finding inter-correlated variables to be considered in regression analysis.

#### Linear regression analysis between SOC contents and individual predictor variables

Potential predictor variables, that is, the different soil properties, in attempts at predicting SOC contents, were

**Table 2.** Pearson correlation matrix for variables which contribute to SOC.

Variable	SOC	CEC	TN	Ca	Bray-1 P	K	Mg	Na	Mn	Cu	Zn	Fe	Sand	Clay	Silt	Elevation
SOC	1															
CEC	0.97**	1														
TN	0.99**	0.96**	1													
Ca	0.99**	0.97**	0.99**	1												
Bray-1 P	0.80**	0.78**	0.82**	0.78**	1											
K	0.83**	0.85**	0.83**	0.79**	0.81**	1										
Mg	0.94**	0.97**	0.93*	0.95**	0.65**	0.79**	1									
Na	0.18 <sup>ns</sup>	0.23*	0.2*	0.26*	0.27*	-0.1 <sup>ns</sup>	0.19 <sup>ns</sup>	1								
Mn	0.82**	0.73**	0.85**	0.84*	0.64**	0.68*	0.75**	0.05 <sup>ns</sup>	1							
Cu	0.91**	0.91**	0.91**	0.92**	0.69**	0.67**	0.92**	0.34**	0.71**	1						
Zn	0.97**	0.96**	0.80**	0.98**	0.80**	0.77**	0.96**	0.27*	0.75**	0.97**	1					
Fe	0.97**	0.92**	0.98**	0.98**	0.89**	0.77	0.93**	0.17 <sup>ns</sup>	0.71**	0.88**	0.96**	1				
Sand	-0.37**	-0.5**	-0.36**	-0.35**	-0.15 <sup>n</sup>	-0.53**	-0.42**	-0.21*	-0.59**	-0.48**	0.41**	-0.26*	1			
Clay	0.44**	0.56**	0.44**	0.42**	0.18*	0.52**	0.48**	0.30**	0.64**	0.58**	0.5**	0.32**	0.98**	1		
Silt	0.63**	0.75**	0.61*	0.6**	0.33**	0.76**	0.67**	0.08 <sup>ns</sup>	0.63**	0.69**	0.67**	0.52**	0.87**	0.88**	1	
Elevation	0.3 <sup>n</sup>	0.07 <sup>n</sup>	0.02 <sup>n</sup>	-0.007 <sup>n</sup>	0.01 <sup>n</sup>	0.23*	0.04 <sup>ns</sup>	-0.22*	0.12 <sup>n</sup>	-0.04 <sup>n</sup>	-0.01 <sup>n</sup>	0.02 <sup>n</sup>	-0.3**	0.24*	0.27*	1

\* Correlation is significant at the 0.05 level

\*\* Correlation is significant at 0.01 level

<sup>n</sup> No correlation

subjected to regression analysis to study their individual contribution in predicting SOC, as indicated by R<sup>2</sup> values. The linear regression model used was:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon, \quad \text{for } i = 1, 2, \dots, n.$$

The model is valid for all n pairs of observations (X<sub>1</sub>, Y<sub>1</sub>), (X<sub>2</sub>, Y<sub>2</sub>)..... (X<sub>n</sub>, Y<sub>n</sub>)

where: Y<sub>i</sub> = Predicted SOC content of a soil (dependent variable)

X<sub>i</sub>: Predictor variable (Independent variable), i.e. TN, cation exchange capacity (CEC), and various chemical elements.

β<sub>0</sub>: = Intercept (a constant) for the relationships between X and Y

β<sub>1</sub>: Regression coefficients of the variable that influence SOC contents in the relationships between X and Y.

€ is the noise or error associated with the SOC values

The model is called linear or simple regression because there is just one predictor variable in the model with linear β<sub>0</sub> and β<sub>1</sub> parameters.

Linear regression has the limitation that it handles one dependent variable at a time. A combination of variables cannot be factored into the model. Therefore, multiple regression analysis was undertaken to evaluate the contribution of combined variables.

### Multiple regression analysis

The variables that showed significant Pearson's correlations with SOC contents were subjected to stepwise forward multiple regression analysis, using the Statistical Analysis System (SAS) version 9.2 software.

**Table 3.** Results of prediction of SOC by linear regression analysis.

Predictor variable	n	R <sup>2</sup>	Regression equation	Predicted SOC, (%)	
				Min.	Max.
Total Nitrogen (TN)	85	0.79**	Y = 0.005 + 14.22N	0.14	3.84
CEC	85	0.71**	Y = - 0.57 + 0.19CEC	0.04	3.12
Ca	85	0.62**	Y = 0.27 + 0.34Ca	0.21	3.46
Zn	85	0.58**	Y = 0.28 + 1.49Zn	0.31	3.44
Cu	85	0.20**	Y = 0.82 + 0.31Cu	0.83	2.61
Clay	85	0.03**	Y = 0.72 + 0.12Clay	0.84	1.57
Fe	85	0.22**	Y = 0.65 + 0.006Fe	0.65	2.69
Observed SOC (%)	85	-	-	0.1	4.4

\*\* Predictor variable is significant at the 0.01 level.

The SOC (%) data from eighty five soil samples, representing the natural horizons from the thirty mini-pits (up to 60 cm depth) were factored into the model for analysis. Multiple linear regressions using the stepwise method (Blanchet *et al.*, 2008; Attua, 2009; Spiota and Sharma, 2013) were used to describe the effects of various independent variables on SOC contents as the dependent variable. The model employed was as described hereunder:

$$Y_n = a + b_1 X_1 + b_2 X_2 + \dots + b_n X_n + \epsilon$$

where:  $Y_n$  = Predicted SOC content of a soil, % (dependent variable).

$X_1, X_2, X_n$  = Variables which influence SOC contents (independent variables), i.e. sand content, % slope, total nitrogen (TN), elevation, cation exchange capacity (CEC), and various chemical elements.

$a$  = Intercept (a constant) for the relationships between  $X$  and  $Y$

$b_1, b_2, \dots, b_n$  = Coefficients of the variables that influence SOC contents in the relationships between  $X$  and  $Y$ .

$\epsilon$  is the noise or error associated with the SOC values.

The goodness of fit of the model was based on  $R^2$  and probability levels.

The step-wise regression analysis was used to select significant variables, by either accepting or eliminating the respective predictor variables, based on the probability level (P-value). A predictor variable associated with a P-value less than the predetermined significance level was added; otherwise the variable was dropped. Data on SOC were first log-transformed in order to improve the normality of variables before they were factored into the model for analysis (Roberts, 2008). The model results are expected to contribute a guiding support tool for predicting SOC storage in different soil types in the Miombo woodlands with similar agro-ecological conditions.

## RESULTS AND DISCUSSION

### Pearson's Correlations between SOC contents and possible predictor variables

The results of the Pearson's correlation matrix (Table 2) showed high ( $P < 0.01$ ) positive correlation between SOC and total nitrogen (N), calcium (Ca), cation exchange capacity (CEC), zinc (Zn), iron (Fe), magnesium (Mg) and copper (Cu). In addition, relatively low positive correlation ( $P < 0.01$ ) was indicated between SOC contents and potassium (K), manganese (Mn), phosphorus (P), silt and clay, whereas low negative correlation was indicated between SOC and sand ( $P < 0.01$ ). The positive correlations imply that as the master variable of soil fertility, SOC correlates with most soil nutrients because soil organic matter (humus) adsorbs these nutrients. Metallic nutrients carry positive charges, thus are attracted to the negative charges (dissociated functional groups) of soil organic matter (Lu *et al.*, 2012; Ferreira *et al.*, 2014). The positive correlation with P is due to the fact that P can be specifically adsorbed by soil colloids, including humus (Guppy *et al.*, 2005; Criquet *et al.*, 2007).

Specific adsorption is defined as the process in which atoms, ions or molecules of a substance collect on the surface of another substance, such as a solid, without entering into the solid's minute spaces as in absorption. Those ions adsorbed below the point of zero charge are concentrated at the interface, without the participation of electrostatic forces, and are therefore considered to be specifically adsorbed (Wisniewska *et al.*, 2014). Phosphate is one of the ions that can be specifically adsorbed, hence the positive correlation between Bray-1 P and SOC (Table 2). Similar relationships, between SOC contents and some of those variables above, have also been established by others (Attua, 2009; Fu *et al.*,

2010; Tian *et al.*, 2010; Jiménez *et al.*, 2011; Chang *et al.*, 2012; Vågen and Winowieck, 2012; Laurent *et al.*, 2014).

### Predictor variables of SOC contents using linear regression analysis

The results of regression analysis for predicting SOC contents are presented in Table 3. Out of 15 predictor variables factored into the linear regression model, seven variables predicted SOC to varying degrees ( $R^2$  values). These seven variables, which were significant ( $P < 0.01$ ) in predicting the SOC contents, were TN, Ca, CEC, Zn, Cu, clay and Fe. Total N had the largest contribution ( $R^2 = 0.79^{**}$ ) in predicting SOC. This was followed by CEC ( $R^2 = 0.71^{**}$ ) and Ca ( $R^2 = 0.62^{**}$ ), with smaller contributions by each of the other metallic elements. The comparison between the observed SOC (%) (Shelukindo *et al.*, 2014) and the predicted SOC (Table 3) showed that TN had the closest values between observed and predicted SOC. The predicted values ranged from 0.14% (Profile No. 7, Cambisol) to 3.84% (Profile No. 1, Cambisol). The observed values ranged from 0.1% (Profile No. 7, Cambisol) to 4.4% (Profile No. 6, Fluvisol). Despite the relatively smaller  $R^2$  value of 0.62\*\* for the Ca compared to that of CEC ( $R^2 = 0.71^{**}$ ), Ca predicted the SOC contents slightly better than CEC, probably due to its stronger binding ability with the negatively charged functional groups of organic matter (Gallon *et al.*, 2010; Cotrufo *et al.*, 2013), with the predicted values for Ca being in the range of 0.21 to 3.45% (Table 3). The extent to which prediction could be affected by combining the variables cannot be determined by simple linear regression. This was determined by multiple regression, as discussed in the following section below.

### Predicting SOC contents using multiple regression analysis

From the results of the step-wise regression analysis, twelve equations for predicting the SOC in KFR were established as shown in Table 4. In the first equation, TN highly significantly ( $P < 0.01$ ) contributed 97% of the prediction of SOC contents, much more than was predicted by TN in linear regression. Inclusion of Ca in the model increased the prediction ( $P < 0.01$ ) of SOC contents from 97% to 99%. The combination of all seven variables (TN, Ca, CEC, Zn, Cu, Clay and Fe) predicted the SOC stocks ( $P < 0.01$ ) by 99.93%. Although the additional individual contributions of Ca, CEC, Zn, Cu, clay or Fe in the step-wise predictions of SOC contents were minimal (Table 3), their combination improved the accuracy in predicting SOC over TN alone by an additional 3.3%. These results show that TN was the strongest predictor of SOC contents, followed by TN +

Ca, with smaller contributions made by each of the other variables.

### Total N as the first predictor of SOC contents

Multiple regression analysis showed that the prediction of SOC contents was influenced highly ( $P < 0.001$ ,  $R^2 = 0.97$ ) by nitrogen. This largest contribution of TN in predicting SOC contents may be explained by the fact that in the soil, N is one among the important integral components which form the complex structure of soil humic substances such as fulvic humic acids (Stevenson 1994; Kleber and Johnson, 2010; Schmidt *et al.*, 2011; Guimaraes *et al.*, 2013). There can be no increase in soil organic carbon without first a proportionate increase in nitrogen (Chang *et al.*, 2012; Laurent *et al.*, 2014). This implies that there is a constant and close relationship between the nitrogen and organic carbon in soils. It is concluded that neither carbon and, hence, soil organic matter, nor nitrogen, can be appreciably increased or decreased without a corresponding change in the other, hence the profound contribution of N in predicting SOC. Thus, proper management of soil nitrogen eventually leads to increase in the SOC contents and stocks, which, if realized globally, will play a vital role in global climate change regulation.

The results of the present study are consistent with findings of other researchers. A study conducted by Attua (2009) in Nigeria found that TN, CEC and leaf area together predicted 95% of the SOC. The study by Fu *et al.* (2010) in China reported that TN and SOC increased uniformly along a hill slope when there was no soil erosion. Sakin (2012), in the southeast Anatolia region, Turkey, reported a very high relationship between SOC and N ( $R^2 = 0.99$ ,  $P < 0.01$ ). Cao *et al.* (2012) in China reported the transformed-log SOC of the 0-10 cm and 10-20 cm soil layers to be well predicted by total N, with  $R^2 = 0.86$  ( $P = 0.006$ ) and  $R^2 = 0.82$  ( $P = 0.007$ ), respectively. Thus, land management strategies aiming at enhancing TN will also improve the SOC contents, and this may have implications in global climate change regulation if undertaken or realized on a large scale.

### Calcium as the additional (together with TN) predictor of SOC contents

The results (Table 4) also showed that the combination of Ca with TN was also a significant ( $P < 0.001$ ,  $R^2 = 0.99$ ) SOC predictor. Of all the divalent ions in the ecosystem, calcium is the one that is strongly bound by both inorganic and organic anions (Gallon *et al.*, 2010; Cotrufo *et al.*, 2013). The stronger binding ability of calcium with organic anions makes it more superior than other divalent ions in predicting SOC contents. Chaudhari *et al.* (2012) in Haridwar, India, reported a significant ( $P = 0.01$ ) positive correlation (correlation coef-

**Table 4.** Step-wise multiple regression equations for predicting soil organic carbon contents.

Predictor variables	R <sup>2</sup>	Regression equations
Total N	0.9662**	Y = 0.11 + 11.7 TN
Total N + Ca	0.9902**	Y = 0.17 + 17.95TN – 0.29Ca
Total N + CEC	0.9705**	Y = - 0.23 + 10.47TN + 0.1CEC
Total N +Zn	0.9669**	Y = 0.01 + 14.22TN + 0.01Zn
Total N + Cu	0.9678**	Y = 0.005 + 14.22TN + 0.1Cu
Total N + Clay	0.9674**	Y = 0.01 + 14.47TN + 0.0002Clay
Total N + Fe	0.9665**	Y = 0. 0 + 14.22TN + 0.0001 Fe
Total N + Ca + CEC	0.9947**	Y = - 0.04 +15.66TN - 0.32Ca + 0.05CEC
Total N + Ca + CEC + Zn	0.9956**	Y = - 0.11+ 14.75TN - 0.21Ca + 0.05CEC - 0.21Zn
Total N + Ca + CEC + Zn + Cu	0.9974**	Y = - 0.09 + 12.55TN – 0.06Ca + 0.04CEC – 0.51Zn + 0.25Cu
Total N + Ca + CEC + Zn + Cu + Clay	0.9988**	Y = -0.05 + 13.04TN – 0.15Ca + 0.06CEC – 0.55Zn + 0.38Cu – 0.01Clay
Total N + Ca + CEC + Zn + Cu + Clay + Fe	0.9993**	Y = – 0.07 + 11.97TN – 0.17Ca + 0.07CEC – 0.56Zn + 0.37Cu – 0.01Clay + 0.0001Fe

\*\* Predictor variable is significant at the 0.01 level.

ficient ( $r = 0.70$ ) between SOC and Ca. Sapek (2013) in Poland reported that Ca uptake by plants increased with increasing concentrations of dissolved organic carbon in soil solutions, implying that the extra Ca was that bound and subsequently released by the organic matter. Thus, Ca, in combination with N, has a strong contribution in predicting SOC contents/stocks.

#### Contribution of other variables in prediction SOC contents

The results (Table 4) indicated that apart from TN and Ca, other additional variables (CEC, Zn, Cu, Clay and Fe), together with TN and Ca, contributed to improvements in SOC prediction ( $P < 0.01$ ,  $R^2 = 0.999$ ), although their incremental contributions were relatively small.

A study conducted in West Africa by Attua (2009), showing that 95% of the variability in SOC was explained by CEC, TN and leaf area (LA) has already mentioned (above). Similarly, Orgill *et al.* (2014) in Australia reported that the SOC was correlated with CEC and N, while Samarian *et al.* (2013) in Iran

showed that CEC, which was highly correlated with clay content and with soil organic matter, accounted by about 69% the SOC contents in soils.

The binding of positive metal cations such Fe ( $Fe^{3+}$ ), Cu ( $Cu^{2+}$ ) and Zn ( $Zn^{2+}$ ) to anions such as dissociated carboxyl ( $COO^-$ ) and hydroxyl ( $OH^-$ ) groups of humic substances has also been reported by other researchers (Rovira and Vallejo, 2007; Guimaraes *et al.*, 2013). Ibrahim *et al.* (2011) in Nigeria also reported a positive correlation between Cu and SOC and between Zn and SOC. This may account for the incremental contributions of these metals in predicting SOC.

Sakin (2012), in southeastern Turkey, reported a strong relationship between SOC and clay ( $P < 0.001$ ,  $R^2=0.96$ ). Plante *et al.* (2006) in Ohio and Saskatchewan found a statistically significant positive relationship ( $R^2=0.48$ ,  $P < 0.01$ ) between clay and SOC, as was similarly reported by Arrouays *et al.* (2006) in France.

The novelty of the current study was the quantification of the contributions of the metallic elements and clay to the prediction of SOC, however small the incremental contributions were.

**Table 5.** Predicted SOC (%) following step-wise multiple regression analysis.

Predictor variable	n	Predicted SOC (%)	
		Minimum	Maximum
Total N	85	0.13	3.78
Total N + Ca	85	0.06	4.27
Total N + CEC	85	0.17	3.65
Total N + Zn	85	0.16	3.15
Total N + Cu	85	0.15	3.45
Total N + Clay	85	0.16	3.20
Total N + Fe	85	0.14	3.13
Total N + Ca + CEC	85	0.09	2.98
Total N + Ca + CEC + Zn	85	0.06	3.04
Total N + Ca + CEC + Zn + Cu	85	0.11	3.58
Total N + Ca + CEC + Zn + Cu + Clay	85	0.05	3.80
Total N + Ca + CEC + Zn + Cu + Clay + Fe	85	0.13	4.63
Observed SOC (%)	85	0.1	4.4

### Predicted values of SOC from multiple regression analysis

Table 5 shows the predicted SOC (%) values using the step-wise multiple regression analysis. The observed SOC results showed that the minimum and maximum SOC (%) of the soils were 0.1 and 4.4, respectively. This was closely predicted by TN, with the minimum SOC value being 0.13% (Profile No.9, Cambisol) and the maximum being 3.78% (Profile No.6, Fluvisol). The prediction by TN + Ca ranged from 0.06% (Profile No.9, Cambisol) to the maximum value of 4.27% (Profile No.1, Cambisol).

The prediction by the combination of TN with all the other variables ranged from 0.13% SOC (Profile No.9, Cambisol) to 4.63% SOC (Profile No.1, Cambisol). However, the predicted SOC values by TN + CEC were 0.17% as the minimum (Profile No.8, Fluvisol) and 3.65% as the maximum (Profile No.1, Cambisol), which was relatively more out of range as compared to the observed values. Thus, TN in combination with Ca could be chosen as the more reliable predictor for SOC contents. The combination of all variables in the model had only a minimal improvement to the prediction of SOC contents as compared to the prediction by TN and Ca, and could be omitted without affecting the strength of the predictions. Thus, the combination of TN and Ca would save time and financial resources for the requisite field work and laboratory analysis, but would also provide equally strong SOC predictions, as it has demonstrated a strong congruence between predicted and observed SOC values (Table 5).

## CONCLUSIONS AND RECOMMENDATIONS

### Conclusions

The results of this study indicated that the combination of TN and Ca was very strong in predicting SOC contents because it accounted by 99% the OC predictions. Inclusion of the other variables (CEC, Cu, Zn, Clay and Fe) in concert improved the SOC prediction by only 0.009%. Hence, TN and Ca could be taken as the major predictors of SOC in the KFR. Table 5 showed that the predicted SOC (%) by TN in concert with Ca is closer to the observed SOC (%) values than the SOC predicted by the combination of all the variables. Therefore, these other characteristics can be omitted without affecting the strength of the predictions. Moreover, their omission will lead to a saving in time and financial costs for the field and laboratory analysis. Thus, in predicting SOC in Miombo woodlands, valuation of TN and Ca in soils could provide optimal information with the implications of saving time and financial resources.

### Recommendations

- In-depth studies on the SOC storage in Miombo woodland soils should be undertaken to broaden our understanding of the dynamics of TN and Ca as quick and reliable predictors of SOC stocks.
- It is recommended that sustainable forest and land management strategies in the KFR Miombo

woodland areas should put more emphasis on practices that may lead to the conservation and/or improvement of TN and Ca, which are the main predictors of SOC in the soils.

- It is recommended that the findings of this study be tested/demonstrated in other areas with similar soil types, ecological conditions and vegetation types so as to validate their wider application.

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