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Meta-Analysis of Long-Term Land Management Effect on Soil Organic Carbon (SOC) in Ethiopia

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ABSTRACT

The role of Soil Organic Carbon (SOC) in mitigating climate change, indicating soil quality and ecosystem function has created research interested to know the nature of SOC at landscape level. The objective of this study was to examine variation and distribution of SOC in a long-term land management at a watershed and plot level. This study was based on meta-analysis of three case studies and 128 surface soil samples from Ethiopia. Three sites (Gununo, Anjeni and Maybar) were compared after considering two Land Management Categories (LMC) and three types of land uses (LUT) in quasi-experimental design. Shapiro-Wilk tests showed non-normal distribution ($p = 0.002$, $\alpha = 0.05$) of the data. SOC median value showed the effect of long-term land management with values of 2.29 and 2.38 g kg^{-1} for less and better-managed watersheds, respectively. SOC values were 1.7, 2.8 and 2.6 g kg^{-1} for Crop (CLU), Grass (GLU) and Forest Land Use (FLU), respectively. The rank order for SOC variability was FLU>GLU>CLU. Mann-Whitney U and Kruskal-Wallis test showed a significant difference in the medians and distribution of SOC among the LUT, between soil profiles ($p<0.05$, confidence interval 95%, $\alpha = 0.05$) while it is not significant ($p>0.05$) for LMC. The mean and sum rank of Mann Whitney U and Kruskal Wallis test also showed the difference at watershed and plot level. Using SOC as a predictor, cross-validated correct classification with discriminant analysis showed 46 and 49% for LUT and LMC, respectively. The study showed how to categorize landscapes using SOC with respect to land management for decision-makers.

Key words: Discriminant analysis, land management, non-parametric test, Ethiopia, soil organic carbon

INTRODUCTION

Soil has high potential to mitigate the effect of climate change as it can be a sink or a source for one of the greenhouse gas, carbon dioxide (CO_2), because soil contains 3 times more carbon than the atmosphere and 4.5 times more than all living things (Walcott *et al.*, 2009). Soil Organic Carbon (SOC) is the largest component of terrestrial carbon pool (Chan *et al.*, 2010). The increase in SOC, with better land management, is considered as a “win-win situation” as it mitigates greenhouse gases, sustains soil ecosystem services while it increases soil quality and resilience (Chan *et al.*, 2010; Walcott *et al.*, 2009). Among other things, global climate change mitigation options can be achieved through better land management resulting in soil carbon sequestration or storage

(Zhang *et al.*, 2010). Sequestration of SOC can account for 89% of the CO_2 global mitigation for agriculture by 2030 (5.5-6.0 Gt CO_2 equivalent per year) (De Brogniez *et al.*, 2011). While mitigating the effects of climate change, SOC is also an important indicator of soil fertility because of its relationship with soil productivity reflecting agricultural sustainability (Zhang *et al.*, 2010). SOC affects several critical soil ecological functions and its physical, biological and chemical fertility (USDA., 2003; NRCS., 2004; Chan *et al.*, 2010). Soil carbon has become not only a universal indicator of soil quality but also a broader indicator of soil ecosystem functions (Janzen, 2005; Guimaraes *et al.*, 2013). So, the most practical way to improve soil quality and increase productivity is to manage SOC.

Today, there is a considerable interest to know the impact of land management on emission of greenhouse gas carbon dioxide (CO_2) by examining changes in Soil Organic Carbon (SOC). Among other things, the amount of carbon stored in the soil is influenced by the balance between inputs and outputs (Grace *et al.*, 2006) which is governed by land management. Thus, the dynamics of SOC is strongly influenced by types of land use (Barbera *et al.*, 2012; Walcott *et al.*, 2009). So, land management is a factor influencing SOC sequestration (Zhang *et al.*, 2010; USDA., 2003; Guimaraes *et al.*, 2013). Factors governing sequestration of soil organic carbon include soil type, the initial content of organic carbon, profile depth and position on the landscape (Walcott *et al.*, 2009) climatic condition (Walcott *et al.*, 2009; Zhang *et al.*, 2010). Our knowledge on how different land management affects SOC has remained far from being complete (De Brogniez *et al.*, 2011). Today, there is a critical knowledge gap in understanding the impact of land management on long-term to develop appropriate strategies (SSSA., 2010). Strategies for sustainable land management emerge from our understanding of how land management affects SOC in the long-term. In a field based experiment, if study duration extends beyond 10 years, it is a long-term study (SSSA., 2010).

SOC study requires collecting information at the point (profile) level while land management decision is required at landscape (e.g., watershed) level (Beaudette *et al.*, 2013). Decision makers do need generalization on soil information at various scales (Beaudette *et al.*, 2013). Despite the difficulty in current approaches to describe variation in soils associated with horizon boundaries, summarizing spatial soil property at watershed level is possible. Soil property aggregation of "site-wide representative soil values" for SOC is possible (Beaudette *et al.*, 2013).

A number of studies have been conducted on spatial variation of SOC beyond the national level. For example, Jobbagy and Jackson (2000) conducted global SOC analysis. There have been numerous long-term studies focused at SOC dynamics reflecting the influence of land management (Zhang *et al.*, 2010; Kapkiyai *et al.*, 1999) but field based long-term experimental studies have not been conducted in Ethiopia. In a worldwide meta-analysis of SOC change with types of land use Walcott *et al.* (2009) realized the difficulty to compare results because of methodological variation with research objectives (sampling depth, study duration, factors influencing carbon sequestration).

Examining variation in SOC under different management at various scales is important to understand the influence of agricultural practices on soil carbon. SOC variability is much influenced by the 1941 Jenny's five soil forming factors (Mzuku *et al.*, 2005). Variations in SOC from land use types or land management can be studied either using a model or long-term field studies. There are several models which are used to predict long-term changes of SOC (Grace *et al.*, 2006; Walcott *et al.*, 2009). Models, on one hand, show changes in shorter period; however, their usefulness relies on the degree of what it represents and accuracy. On the other hand, long-term studies provide better insights on the role of land management than models (Kapkiyai *et al.*, 1999).

Requirement to achieve sustainable land management differs according to specific site conditions. Such sustainability can be well examined in a long-term study by getting relevant information and establish relationship between SOC and land management (Vance, 2000; De Brogniez *et al.*, 2011). There are a number of studies conducted on SOC and land use in Ethiopia (Abera and Belachew, 2011), yet none of the studies were designed to investigate SOC in a long-term mainly based on field trial at landscape level.

The effort to overcome land degradation in Ethiopia has now shifted from mere reducing degradation to the promotion of sustainable land management. This shift calls for examining the success in land management based on key and universal indicators like SOC. Thus, this study provides summary of three case studies on the effect of long-term land management on soil carbon for the past 30 years (taking 1980s as baseline year). In this study soils were sampled form sites where type of Land Use Types (LUT) and management category were maintained for the past 30 years.

The major objective of this study was to examine variation and distribution of SOC in two long-term Land Management Categories (LMC, Better Managed (BM) and Less Managed (LM)) at a watershed level and different Land Use Types (LUT) at a plot level. Classifying landscapes into zones of management is relatively a new concept for studying soil properties (Mzuku *et al.*, 2005). The other minor objectives of the study are four fold. The first is to know the need for statistical normality test. The second is to reflect the potential role of non-parametric statistical tests in assessing the effect of land management and land use types. The third is to show how point sampling could be made useful at the landscape level for decision makers. The fourth is to reflect how SOC, as an indicator, can be used to assess long-term sustainability of management. The hypothesis of the study is that the Land Use Types (LUT) and categories of land management affect SOC variability and distribution at tillage depth (to depth of 30 cm). This study assumes that maintenance of the same type of Land Use Types (LUT) and management category (better and less managed) for the past 30 years results in to a distinct group of SOC land unit.

MATERIALS AND METHODS

Study area: The study sites are located in Southern, North-Western and North-Eastern Ethiopia. The areas were previously research sites for the Ethio-Swiss funded Soil Conservation Research Program (SCRP). Gununo is located in Wolayta Zone, 16 km WNW of Sodo Town, at 37°38'E/6°56'N (Weigel, 1986; SCRP., 2000b) in Damote-Sore district. Maybar is located in South Wello Zone, 14 km SSE of Desse Town, at 39°40'E/11°00'N (SCRP., 2000d) in Albulko District. Anjeni is located in West Gojjam Zone, Dembecha District, 15 km North of Dembecha Town at 37°31'E/10°40'N (Kejela,1995; SCRP., 2000c) (Fig. 1). Altitude of the sites varies from 1982 m above sea level (m.a.s.l) in Gununo to 2858 m.a.s.l in Maybar. Two of the sites have sub-humid climate except for Gununo with Humid climate (Thornthwaite classification).

Design and soil sampling: The study used a meta-analysis approach, where three case studies on SOC were re-analyzed at national level. The design is quasi-experimental because many of the factors which influence SOC were neither controlled nor maintained uniformly in space and time in adjacent watersheds at three sites. There are various techniques of delineating land management categories and “productivity” can be a parameter to categorize sites (Mzuku *et al.*, 2005). To categorize soils at landscape level, parameter selection depends on one’s purpose. In this study, in each site there are “twin” or adjacent watersheds grouped based on Land Management

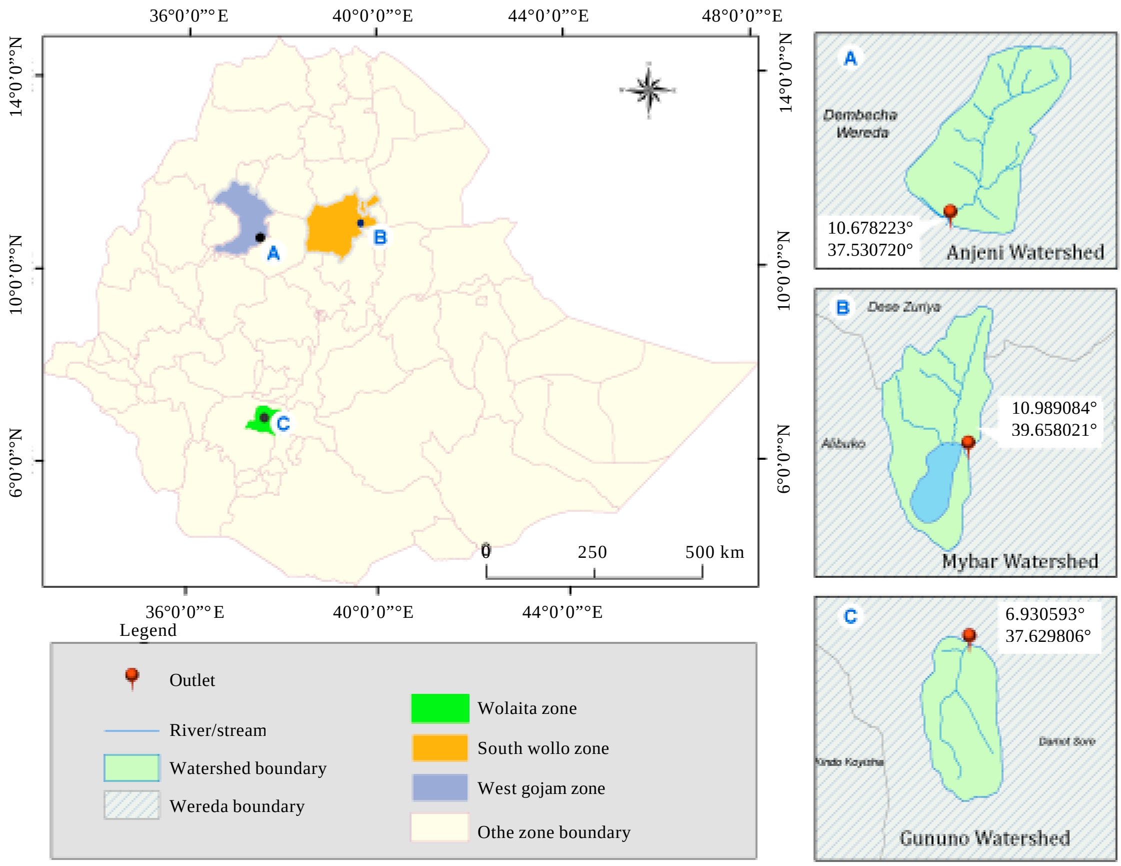

Fig. 1: Location of the study sites in Ethiopia

Categories (LMC) as Better (BM) and Less Managed (LM). The better-managed watersheds are the Soil Conservation Research Program (SCRP) sites and the less managed ones are outside SCRP sites. Better managed watersheds have longer history of land management and higher density of soil and water conservation measures (numbers or types of conservation measures/unit area of land). Within each watershed, plots were identified as major types of land use (LUT). Three LUT identified were: The Cropland Use (CLU), Forest Land Use (FLU) and Grazing Land Use (GLU). A total of 64 profiles (4 profiles per LUT) were dug in three sites and SOC data was taken form (surface and sub-surface) 128 samples. Number of profiles and soil sample density is much more intensive than what is recommended in Webster (2007) (Table 1).

Purposive sampling was used (Carter and Gregorich, 2007) to have representation Land Management Categories (LMC) and major Land Use Types (LUT). As a spatial pattern studies on SOC, stratified random samples of 4 profiles were taken for each LUT in each watershed. Before samples were taken, land use history was recorded from land owners to ensure that they have maintained the same type of land use type on each plot for the past 30 years. In 1980s, the soils of the study sites were previously described and classified using FAO-UNESCO classification (Table 1). Profile (pit) description involved recording of location, slope, position along the landscape, identifying land use type and history as described in Edmonds (1992).

Table 1: Soil types, sample numbers, land use types, profiles at the watersheds and three sites

Study site	No. of soils samples/site	Major soil types (FAO-UNESCO)*	Watersheds name	Parameters studies Water shed size (ha)*	Land management	No. of LUT	No. of soils profile/ watershed	No. of soil sample	No. of samples/ site	No. of profile	Total No. of sample
Gununo (GUN)	48	Nitosols, Acrisols,	Zerwa^{++}	72.8	BM	3	12	24	96	24	128
		Phaeozems, Fluvisols	Goppo^{+}	94	LM	3	12	24			
Maybar (MAY)	48	Phaeozems, Lithosols,	Inside kori^{++}	112.8	BM	3	12	24	81	24	
		Gleysols	Outside kori^{+}	406.9	LM	3	12	24			
Anjeni (ANJ)	32	Alisols, Nitosols,	Minchet^{++}	113.4	BM	2	8	16	62	16	
		Cambisols	Zikere^{+}	805	LM	2	8	16			

BM^{++}: Better-managed or SCRP sites, LM^{+}: Less managed or Outside SCRP, *(SCRP., 2000a-d)

Stratified depth samples were taken for each profile using the equivalent mass depth method (Walcott *et al*., 2009; Stolbovoy *et al*., 2007). Two sample depths (0-10 and 10-30 cm) were taken as a tillage layer to examine the influence of land management and land use (Guimaraes *et al*., 2013). The sample depths are as per the guideline of the Intergovernmental Panel for Climate Change (IPCC) as cited in Batjes (2010) (Table 1).

Soil and statistical analysis: Conventional soil analytical methods were used to determine soil physical and chemical properties. Air dried soil was grounded and sieved through 2 mm. Core-samplers were used for soil bulk density determination. Soil texture was determined using the Bouyoucos Hydrometer method. Soil moisture was determined using oven dry method (for 24 h at 105°C). pH (water and 0.01 M $CaCl_2$) was determined using pH meter at 1:2.5 (soil: Water/chemical) ratio. Electrical Conductivity (EC) was measured using conductivity meter using distilled water. SOC in gram per kilogram was determined using the Walkely and Black method (FAO., 1970). A conversion factor of 1.72 was used to get OM%.

Total nitrogen was determined using the Kejealdahl digestion method (Page, 1982). Available P was determined using Olsen method. CEC (Na, K, Ca, Mg) was determined using (Neutral) Ammonium Acetate method using Atomic Absorption Spectrometer (AAS) (FAO., 1970). Micro nutrients (Cu, Fe, Mn, Zn) were determined using Di ethylene Triamine Penta Acetic Acid (DTPA) method (Page, 1982).

Statistical analysis involved a test for normality and calculating the descriptive parameters. Non-parametric tests were used in this study for two reasons. First, data were non-normally distributed. Second, the design of the study was a quasi-experimental. Tests used include Shapiro-Wilk, Wilcoson or Mann-Whitney U and Kruskal Wallis, Chi-square and non-parametric discriminant analysis.

Effect of land management categories and land use on SOC were considered significant when $p<0.05$ (at $\alpha = 0.05$, confidence interval 95%). Discriminant analysis was used to know if there is any natural grouping in to LMC and LUT based on SOC data. In this study, outliers were neither removed nor were data transformed as in Strimbu *et al*. (2009) and Lauber *et al*. (2008). The statistical analyses were done using SPSS Version 20.0 (IBM SPSS statistics, Armonk, NY, US).

RESULTS AND DISCUSSION

Result of normality test: Strimbu *et al*. (2009) reviewed that 0.02% of the 420 articles in environmental science has tested for data normality. The review reflects the extent to which a test for normality may often be ignored. In a separate study Young *et al.* (1996) and Bilisoly *et al.* (1997) have also shown that the prior assumption of normality should not be taken for soil properties. Although Carter and Gregorich (2007) have indicated that commonly soils sample are skewed to the right, prior assumptions affect statistical tests. Test for normality is essential because distribution affect statistical test. Such tests are essential when dealing with soil variability in connection with land use types and management at the landscape level. When soils data are not normally distributed, non-parametric test should be used (Bilisoly *et al.*, 1997; Landau and Everitt, 2004; Strimbu *et al.*, 2009).

The SOC mean and standard deviation value for surface and sub-surface (0-10 cm and 10-30 cm) samples (n = 128) of the three sites shows 2.4 and 1.4 g kg^{-1}, respectively. The values of Standard Deviation (SD) and mean shows that the distribution is not symmetric about the mean. Index of skewedness (0.68) and kurtosis (0.25) also reflect similar fact as stated in Landau and Everitt (2004). The test and index reflected the need to go for parametric testing.

Non parametric test, Shapiro-Wilk tests, for normality was used because n<2000. The result shows p-value ($p = 0.002$, $\alpha = 0.05$) smaller than the significance level reflecting the non-normal distribution of SOC. Non-parametric tests were used in this study because of their effectiveness in examining ecological landscape (Strimbu *et al.*, 2009).

Summary of soils properties: The major types of soils in the study area were previously classified using FAO-UNESCO classification system (Weigel, 1986; SCRP., 2000a-d) (Table 1). Nitosols and Phaeozems appear to be the most common type of soils in the study areas. Soils of the study area are slightly acidic (rate) with small standard deviation for soils TN, BD and pH of the soils are noted while highest is noted for exchangeable K, CEC, base saturation and EC (Table 2).

Soil pH values (5.1) show existence of strong acidity based on Soil Survey Staff (2011) and Webster (2007) interpretation. As expected, values of pH in $CaCl_2$ are less than in water. CEC ranges from moderate to high with very high base saturation (Webster, 2007). Data on SOC shows that the 25th, 50th and 75th percentiles of SOC are 1.4, 2.3 and 3.3 g kg^{-1}, respectively. SOC value varies from 0.05 g kg^{-1} (minimum) to 6.69 g kg^{-1} (maximum). The median value for SOC is

Table 2: Descriptive statistics of soils properties (0-30 cm) in three sites (n = 128)

Soil properties	Minimum	Maximum	Mean	Std. Deviation	Range	Variance	Median
pH water*	4.04	7.07	5.6	0.6	3.03	0.4	5.7
pH $CaCl_2$$^+$	4.06	6.12	5.1	0.5	2.06	0.3	5.1
EC (μS)	4.95	71.2	21.9	11.2	66.2	127.5	19.3
CEC (meq/100 g)*,$^+$	12	58	36	13	45	169.1	37
Base Sat.*	25	299	92	54	274	3015	76
TN (%$^+$)	0.056	0.57	0.19	0.08	0.52	0.007	0.18
Av P (ppm)$^+$	0.40	23.20	2.5	2.6	22.80	6.813	1.8
K (Cmol (+)/kg)	0.07	87.4	11.5	18.7	87.4	351.0	0.6
BD (g cm^{-3})$^+$	0.96	1.62	1.26	0.13	0.66	0.02	1.2
OC (%$^+$)	0.05	6.6	2.4	1.4	6.6	1.996	2.3
OM (%$^+$)	0.09	11.5	4.2	2.4	11.4	5.906	4.0
C/N ratio	1	18	12.7	4.6	17	21	13
Moisture (%*)	16.0	61.5	29.8	7.8	45.5	61.9	28.5

Significant test ($p<0.05$, C.I = 95%, $\alpha = 0.05$) *Mann-Whitney U test for land management and $^+$Kruskal-Wallis test for land use types

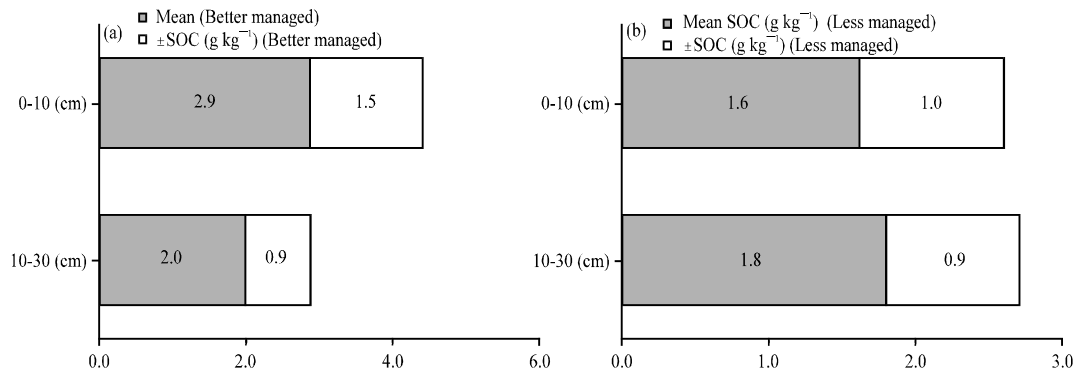

Fig. 2(a-b): SOC profile distribution (g kg^{-1}) in (a) Better-managed and (b) Less managed watersheds. Land management effect is manifested in the top layer of better managed watersheds

2.3 g kg^{-1} with a standard deviation is 1.4 g kg^{-1}. SOC coefficient of variation is 56% which is close to an average Coefficient of Variation (CV) reported for mineral soils in global study (59%) by Batjes (2010) and 64% by Jobbagy and Jackson (2000). SOC data variability is rated as high, based on Carter and Gregorich (2007) rating. The CV and total number of samples (n = 128) in this study can enable test data with 95% confidence interval with least error of 0.01 which also reflects an adequate number of sample representation for the study area.

SOC distribution at watershed and plot level: SOC distribution portrays (Fig. 2a, b) that in well-managed watershed, the SOC has better profile distribution with a contrast between surfaces reflecting the role of proper land management. Taking a median soil density of 1.2 g cm^{-3} for three areas, the stock of soil organic carbon is higher in better-managed watershed than less-managed watersheds. In less-managed watersheds, the surface (0-10 cm) profiles have depleted SOC. In the long-term, the contrast in SOC values reflect the sustainability of land management in better-managed watersheds than less-managed ones (Fig. 3a, b).

SOC variability at watershed and plot level: Comparison was made on SOC variability among the three categories of LUT (Fig. 4) and between LMC at the watersheds. Ranges of SOC values are similar to previous study (Kejela, 1995; Weigel, 1986; SCRP., 2000a-d). With two surface soil samples per profile, the total numbers of samples are 128. With a total of 64 profiles, the numbers of profiles per site are 24 for both Gununo and Maybar while it is 16 for Anjeni.

Box plot shows that the median (set as horizontal line of the box) is lowest for CLU. The FLU has highest standard deviation (1.7) followed by grasslands (1.2) and croplands (0.8). The amount of SOC variation is highest in FLU with a rank order of FLU>GLU>CLU. Variation in SOC is highest on forestland because of variability in topography and the vegetation types as reflected most in Maybar (SCRP., 2000d). The forest lands are degraded and lacked conservation measure and with no or little layer leading to small organic carbon amount compared with grasslands. On the other hand, most of the grasslands are located at the bottom lands benefiting from sedimentation and wetter condition favoring higher organic carbon content. The rank order in

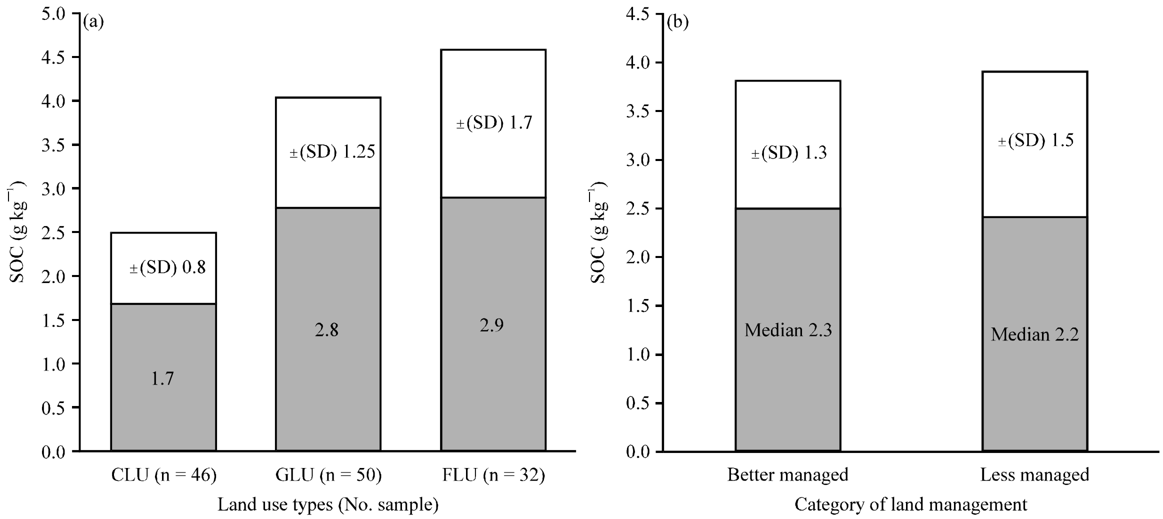

Fig. 3(a-b): (a) SOC variation (g kg^{-1}) among the LUT and (b) Watersheds with land management categories. Better managed watershed has higher mean and less variance

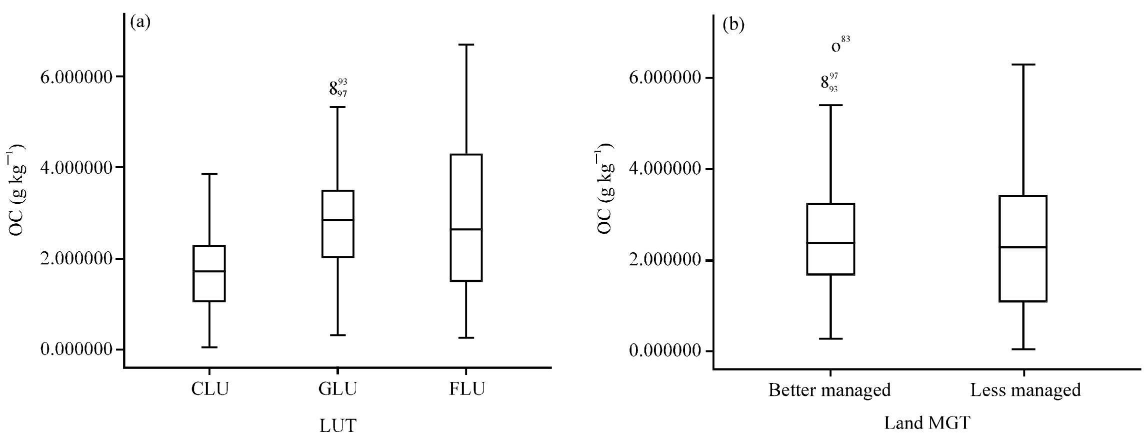

Fig. 4(a-b): Soil organic carbon (g kg^{-1}) box-and-whisker plot (a) Land Use Types (LUT) and (b) Land Management Categories (LMC). Better managed watershed has higher median and less variability reflecting effect of land management. Forests have lower median (located on steep slopes and established on degraded lands) while grasslands (located at valley bottoms at deposition sites) have higher median value

SOC variability is least in Gununo and highest in Maybar (Fig. 5, Table 3). The sub-surface (10-20 cm depth) has less median and distribution compared with the surface horizon reflecting the potential effect of land management at surface level (0-10 cm depth).

Spatial variation of SOC across sites shows that all extreme values (n = 5) of SOC were observed at Maybar. The range of variation is in rank order values for FLU (5.4-6.69 g kg^{-1}) for GLU (4.9-5.97 g kg^{-1}) for CLU (3.2-3.8 g kg^{-1}). The variations in SOC, among other things, have resulted from topographic variation of Maybar compared with the other two sites (SCRP., 2000a, d). The lowest variability in SOC value in Gununo reflects less diversity in soil

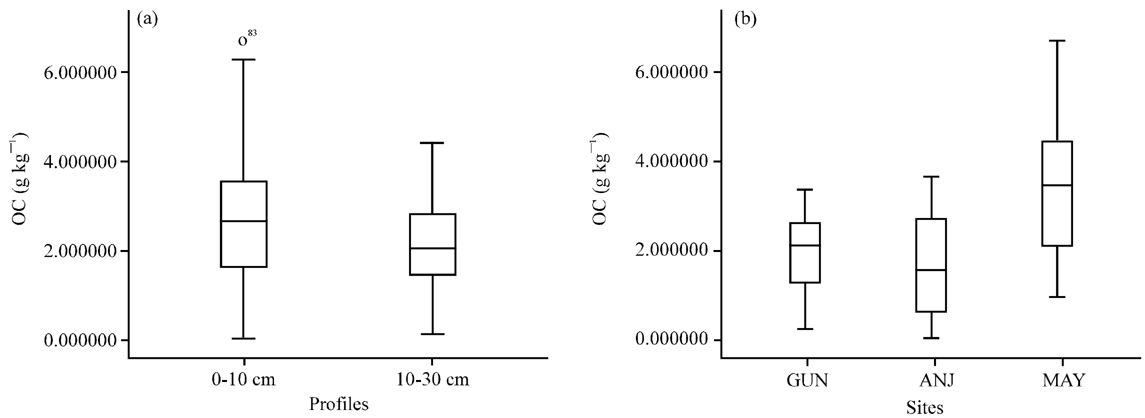

Fig. 5(a-b): Soil organic carbon (g kg^{-1}) box-and-whisker plot (a) Profile layers and (b) Three sites. Higher SOC in surface soil and higher SOC variability in Maybar resulted from its topographic variability and least median value for Anjeni contributed most by degraded Zikre watershed

Table 3: Descriptive statistics of SOC under LUT and Land Management Categories (LMC)

LUT or LMC	Sample size (n)	Mean	Median	Variance	Std. deviation	Minimum	Maximum	Std. error	95% confidence interval Lower bound	95% confidence interval Upper bound
CLU	46	1.7	1.7	0.80	0.89	0.05	3.8	0.13	1.14	1.98
GLU	50	2.8	2.8	1.58	1.25	0.31	5.0	0.17	2.53	3.24
FLU	32	2.9	2.6	3.10	1.76	0.26	6.6	0.31	2.35	3.62
BM^{++}	64	2.5	2.3	1.74	1.32	0.28	6.6	0.16	2.24	2.90
LM^{+}	64	2.4	2.2	2.26	1.50	0.05	6.2	0.18	2.03	2.78
GUN	48	2.0	2.1	0.68	0.82	0.26	3.3	0.11	1.70	2.20
ANJ	32	1.6	1.5	1.27	1.13	0.05	3.6	0.19	1.20	2.00
MAY	48	3.5	3.4	2.10	1.45	0.97	6.6	1.20	3.00	3.90

BM^{++}: Better managed, LM^{+}: Less managed, GLU: Grass land use, CLU: Crop land use, FLU: Forest land use, GUN: Gununo, ANJ: Anjeni, MAY: Maybar

types and dominance of Nitisols. The lowest extreme values (n = 5) for SOC from FLU were from Gununo and the extreme values for SOC for GLU and CLU were mixed but dominated by Anjeni. Extreme (lowest values) of CLU, SOC were (n = 5) from Anjeni which varies from 005-0.042 g kg^{-1}. The lowest value also reflects the high degree of land degradation in less managed Zikre watershed in Anjeni. This fact agrees with what is documented previously for Anjeni (OoARD., 2009). The existence of least values and high value of SOC also reflect the potential effect of management at watershed level.

Although, mean values of SOC also reflect effect of land use and management, in non-normally distributed sample, median value is the best statistically indicator reflecting effect of long-term land management. The median SOC value for better-managed is 2.38 and 2.29 g kg^{-1} for less managed watersheds.

Mann-Whitney U and Kruskal Wallis tests: Appropriate non-parametric tests were conducted (n = 128) to compare the distribution and median of SOC between the Land Management

Categories (LMC) and among Land Use Types (LUT). In this study median values were taken as a robust measure than the mean because of non-normal distribution of data (Batjes, 2010).

Mann-Whitney U test, shows significant difference in that the medians of SOC among the LUT ($p = 0.00$, confidence interval 95%, $\alpha = 0.05$) while it is not statistically significant ($p = 0.8$) across LMC. Mann-Whitney U test is not significant ($p = 0.4$, confidence interval 95%, $\alpha = 0.05$) for the distribution of SOC across land management categories. However, Kruskal-Wallis test is significant ($p = 0.00$, confidence interval 95%, $\alpha = 0.05$) for distribution of SOC across land use categories. Mann-Whitney U test is significant ($p = 0.03$, 95% confidence interval, $\alpha = 0.05$) for distribution of SOC across soil profiles (surface and sub-surface). Statistical results for SOC between soil profiles is similar to findings of (Guimaraes *et al*., 2013).

The mean rank, Mann Whitney U test, values are 67 and 62 for better and less managed watersheds, respectively. The sum of ranks is 4281 and 3975 for better-managed and less managed watersheds, respectively. The sum rank shows the difference between the two Land Management Categories (LMC) and reflecting effect of land management on SOC at land scape level.

The mean rank, Kruskal Wallis Test, (n=128 samples) shows the difference in SOC among three major land use types with value of 44, 78, 74 for CLU, GLU, FLU, respectively. The rank shows that GLU has highest values while CLU has the smallest test value of SOC.

Non-parametric discriminant analysis: Analytical methods for spatial partitioning of SOC data can be used for land management decision at landscape level. Using SOC as a predictor variable, discriminant analysis was used to group watersheds and LUT in to categories. Previous studies have shown that non-parametric discriminant analysis was used to assess the attribute difference (Strimbu *et al*., 2009). The analysis was based on 128 samples leaving out 82 with no missing. Analysis options are leave-one-out classification (cross-validated) with Wilk's Lamda method, using F value as criteria which enabled (n = 128) classification to process 210 with 128 outputs.

Canonical discriminant functions for categories of land management show an eigenvalue of 0.004 with canonical correlation (Person correlation) of 0.05. The eigenvalue is 0.20 and the conical correlation coefficient is 0.41 for LUT. The conical correlation coefficients showed that the models explained small variation (2.5%) of for LMC and (17%) for LUT. The lower value of the eigenvalues indicated the less variance explained by the discriminate function (Landau and Everitt, 2004).

The Chi-square test is statistically significant (Chi-square = 23.5, Wilk's Lambda = 0.8, $p = 0.00$) to discriminate the SOC data into three types of land uses. That is also true to test of equality of group means. However, results are not statistically significant (Chi-square = 0.44, Wilk's Lambda = 0.9, $p = 0.5$) to separate into categories of land management.

A discriminant classification was used to predict if a watershed was better or less managed and if a plot of land could belong to one of the three LUT using SOC as a predictor variable. Cross-validated result showed 46 and 49% correct classification for LUT and for land management categories, respectively. Classification result with predictive accuracy of >25% is in the acceptable range (Landau and Everitt, 2004).

CONCLUSIONS

This study shows the need to test normality of soils data when examining the SOC spatial variation and distribution. The first most important finding of the study is to show the effect of long-term land management at watershed level in median value of 2.29 g kg^{-1} for less managed and 2.38 g kg^{-1} for better-managed watersheds. Statistical results support the findings in that

Mann Whitney U test-mean values are 67 for better-managed and 62 for less managed watersheds, respectively. The sums of rank values are 4281 and 3975 for better and less-managed watersheds, respectively. Mann-Whitney U test is not significant for the medians and distribution of SOC ($p>0.05$, confidence interval 95%, $\alpha = 0.05$) across Land Management Categories (LMC) but it is significant across the soil profiles. The second most important finding of the study is to show the effect of long-term land management at plot level is reflected in the median values of 1.7, 2.8 and 2.6 g kg^{-1} for CLU, GLU and FLU, respectively. Kruskal-Wallis test, also shows significant difference in that the medians and distribution of SOC among the LUT ($p = 0.00$, confidence interval 95%, $\alpha = 0.05$). The Kruskal Wallis test shows the difference in SOC among three major land use types with value of 44, 78 and 74 for CLU, GLU and FLU, respectively. SOC variability is highest in FLU with a rank order of FLU>GLU>CLU. Among the three sites, Maybar has highest variability with more outliers while Gununo has the least variability.

Classification based on non-parametric discriminant analysis showed of 49% for categories of land management and 46% for land use types is acceptable though it is not excellent. This study also showed how SOC can be used as an indicator to show sustainability of long-term land management at both landscape (watershed) and plot level for decision makers. The study suggests undertaking additional study to get better classification result with discriminant analysis to categorize land at land scape level.

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