Landscape-scale Assessments of Soil Health: Local Determinants of Soil Organic Carbon in Ethiopia

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Soil organic carbon as an indicator of soil health

Maintaining soil organic carbon (SOC) content is recognized as an important strategy for a well functioning soil ecosystem (Palm et al. 2007; Lal, 2010; Vågen et al., 2012; Victoria et al., 2012). The UN Convention to Combat Desertification (UNCCD) recognizes that reduced SOC content can lead to land degradation, and ultimately low land and agricultural productivity. SOC is almost universally proposed as the most important indicator of soil health, not only because SOC positively influences multiple soil properties that affect productivity, including cation exchange capacity and water holding capacity, but also because SOC content reflects aboveground activities, including especially agricultural land management. Several studies have indicated that agriculture often leads to an overall decrease in SOC compared to the native land use (Schlesinger 1991; Smith, 2008; Don et al., 2010) (Figure 1). In addition, recent studies highlight that inherent soil properties (such as soil texture) form constraint envelopes which ultimately limit the soils' ability to store carbon (Winowiecki et al., 2015). Therefore, to be useful as an indicator, it is crucial to assess the importance of both inherent soil properties as well as external factors (climate, land cover, land management, etc.) on SOC dynamics across space and time.

Figure 1: Processes affecting land degradation and agricultural productivity.

Need for monitoring and assessments of soil health

Soil provides multiple ecosystem services, e.g., as a medium for plant and agricultural production, a filter for toxins and pollutants and by regulating the hydrologic cycle (Millennium Ecosystem Assessment, 2005). Since SOC is influenced by many factors, including land use and inherent soil properties, all of which vary across space, there is a great need for systematic assessments of key land health indicators across multiple scales, which helps understanding the factors drive soil health.

The Land Degradation Surveillance Framework (LDSF) is a well-established method for assessing multiple indicators at the same georeferenced location, and across landscapes (Figure 2). The LDSF is designed to provide a biophysical baseline at landscape level, and monitoring and evaluation framework for assessing processes of land degradation and the effectiveness of rehabilitation measures (recovery) over time (Vågen et al., 2013) (Figure 3). Each LDSF site has 160 – 1000 m^2 plots that are randomly stratified among 16 - 1 km^2 sampling clusters This hierarchical randomized sampling design allows for statistical modeling of key landscape variables in order to assess the health of the ecosystem including analysis on the drivers of SOC.

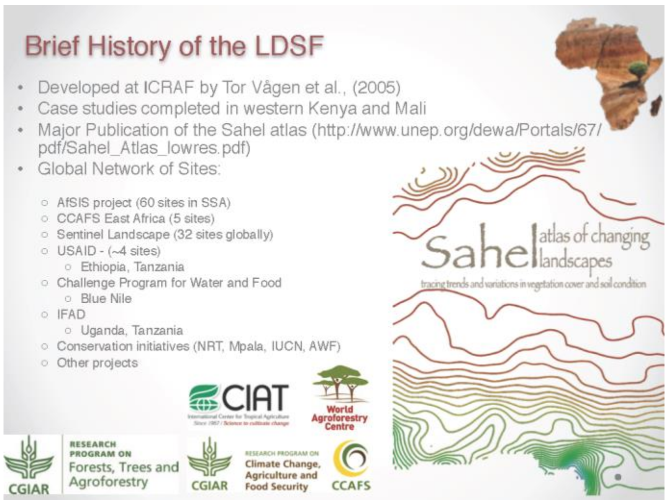

Figure 2: Brief history of the Land Degradation Surveillance Framework.

Example variables measured include: tree and shrub densities, erosion prevalence, topographic position, herbaceous layer, percent bare ground, land use history, major land use (including cultivation) and land cover. Land cover was recorded in all plots using a simplified version of the FAO Land Cover classification System (LCCS), which was developed in the context of the FAO-AFRICOVER project (http://www.africover.org).

Location of existing LDSF Sites in Ethiopia- ICRAF & CIAT

Seven LDSF surveys were conducted through two different projects in 2011-2013 (Figure 3). For example, three LDSF sites were sampled within the Blue Nile Basin for the Challenge Program for Water and Food (CPWF). Data from these sites are available online (Winowiecki et al., 2015b) and are being published (Abegaz et al., 2016). Furthermore four LDSF sites were sampled as part of the Africa Soil Information Service (AfSIS) project funded by the Bill and Melinda Gates Foundation. Results from these surveys were also published (Vågen et al., 2013a, Vågen et al., 2013b).

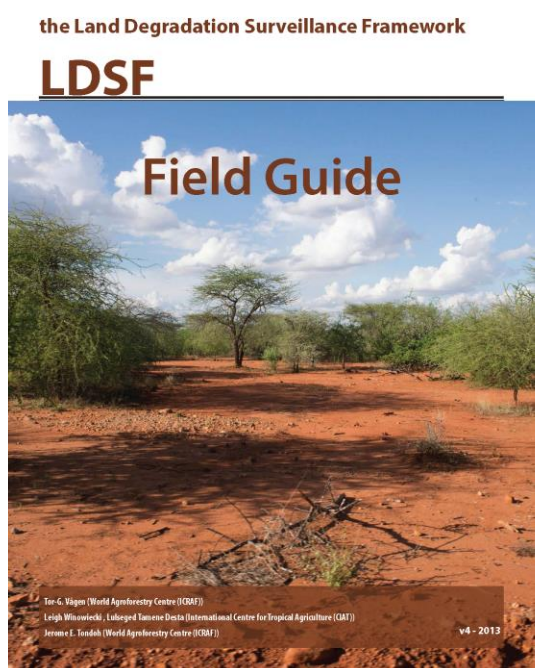

Figure 3: Land Degradation Surveillance Framework (LDSF) field guide.

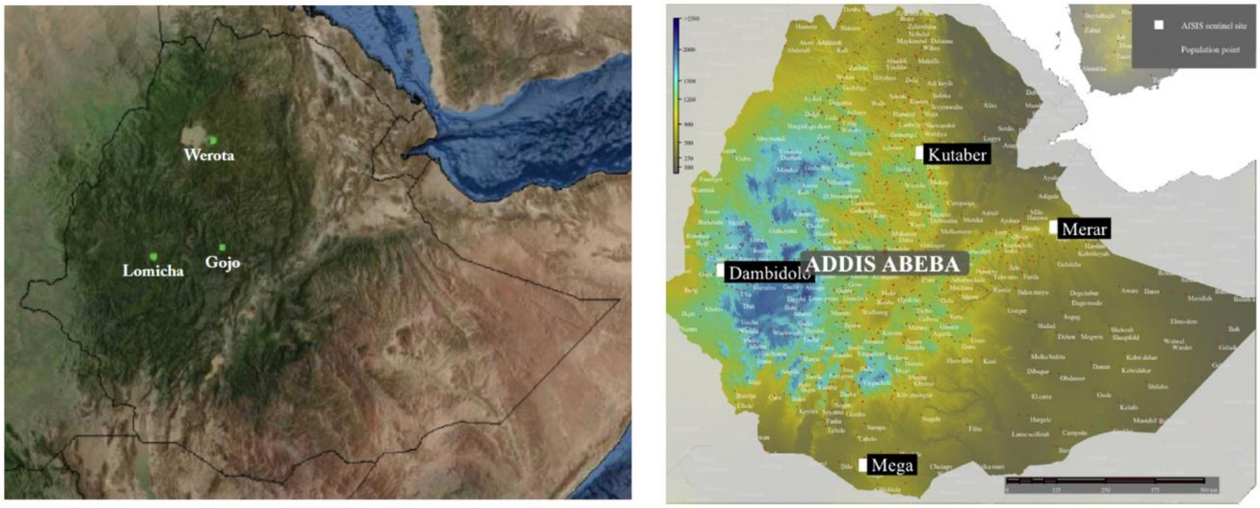

Figure 4: Location of the three LDSF sites in the CPWF Blue Nile project (left) and the four LDSF sites sampled with the AfSIS project (right) in Ethiopia.

Figure 5 shows the variation in topsoil OC content for each of the sites, using the reference plots from each cluster (n=16 samples per site). Note the higher SOC in Merar compared to the other sites and the low variability within the Werota and Mega sites.

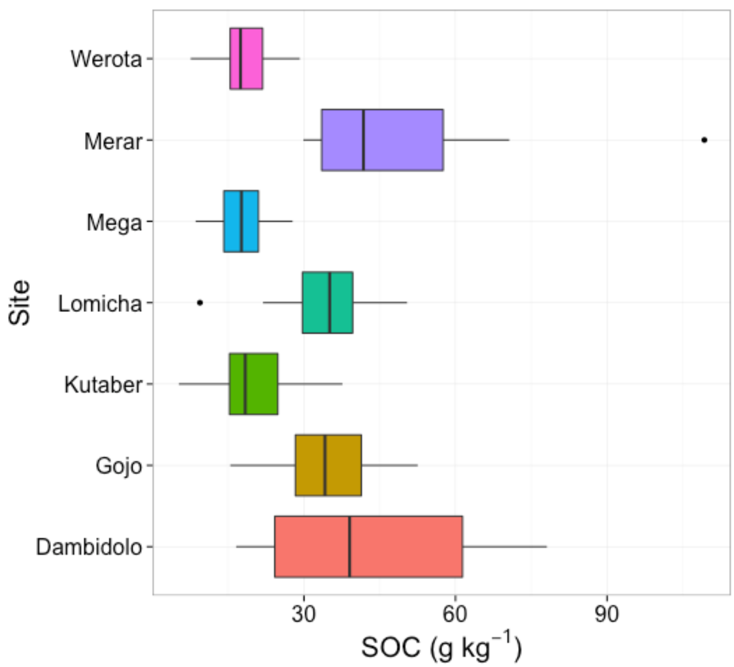

Figure 5: Variability of topsoil OC between the seven LDSF sites in Ethiopia.

Landscape-scale assessments of soil properties by mid-infrared spectroscopy (MIRS)

Soil samples ~320 per site, were analyzed for mid-infrared (MIR) spectra at the ICRAF Soil and Plant Spectroscopy Laboratory in Nairobi, Kenya (http://www.worldagroforestry.org/research/land-health/spectral-diagnostics-laboratory) (Figure 6). MIR is a well-established technique for the prediction of soil variables (Terhoeven-Urselmans et al., 2010). MIR is also rapid and cost-effective, allowing for increased sample size, which enables landscape-scale assessments. The prediction accuracy for these datasets were excellent (Vågen et al., 2013a).

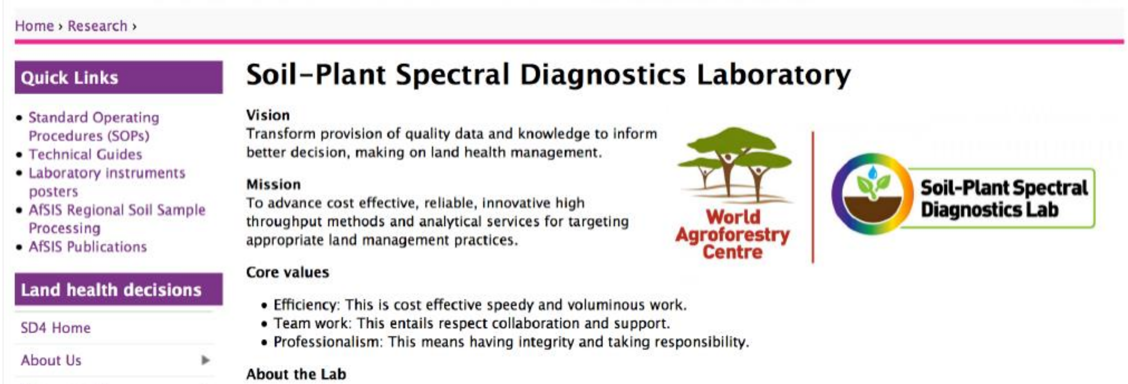

Figure 6: Soil samples were analyzed at the ICRAF soil-plant spectral diagnostics laboratory.

State Factors of Soil Formation

Hans Jenny (in 1941) published the equation of the state factors affecting soil formation, including climate, organisms, relief, topography and parent material. These factors contribute to the formation of soil and account for differences in soil types, including soil properties across landscapes. To explore the relationship between measured soil properties and state factors, we used mean annual precipitation (MAP) data obtained from the Tropical Rainfall Measuring Mission (TRMM) (1998-2011) downloaded from ICRAF's landscapeportal.org for each of the seven sites (Figure 7). Note the variation in MAP across the sites, with Mega having the lowest MAP. The other biophysical variables were collected in the field at each of the 160 LDSF plots per site, e.g., land cover, average slope and topographic position. Figure 8 shows the variation in topsoil OC content for each land cover class, per site using the MIR predicted SOC values. The average topsoil OC

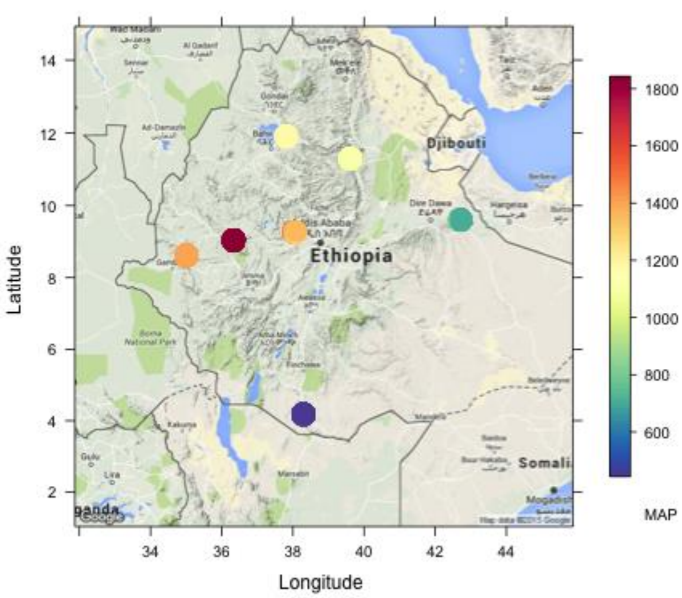

Figure 7: *Mean Annual Precipitation (MAP) in mm for each site, downloaded from landscapeportal.org, the TRMM data is from 1998-2011*

across the sites was 30 g kg^{-1}, note that the SOC content in Merar is above the average. Also note the high variability in Dambidolo grassland and cropland SOC. Overall grasslands had high variability across the sites and differences were observed between vegetation structures.

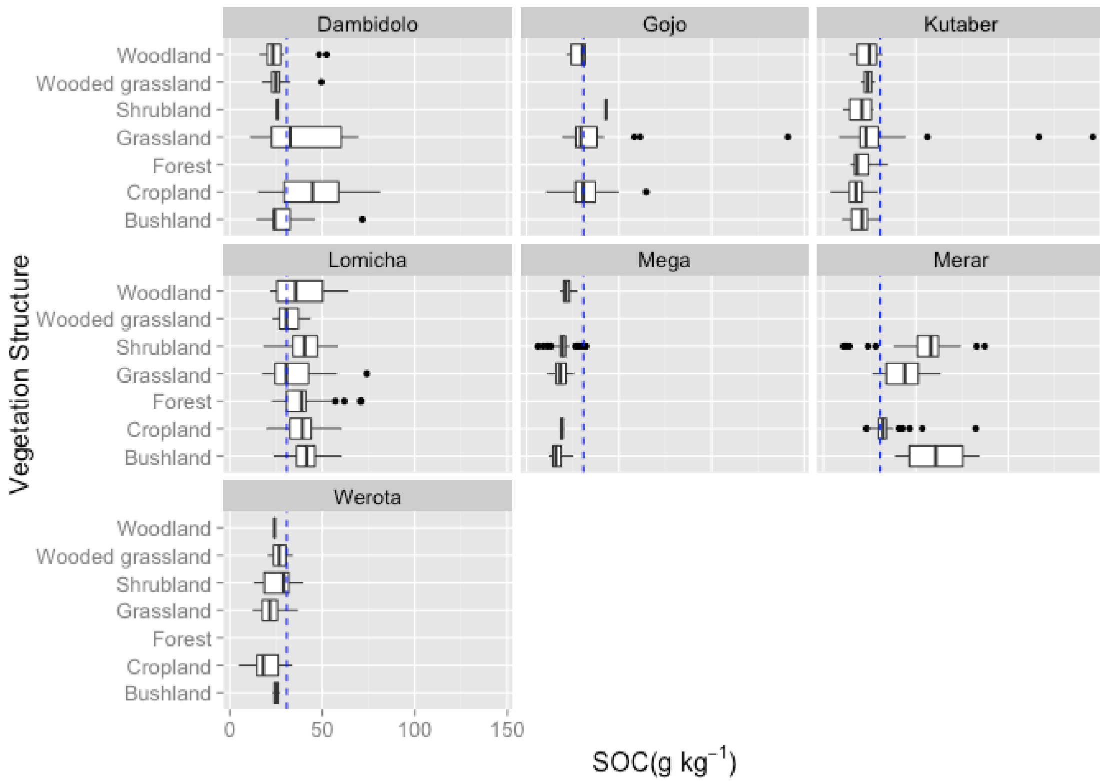

Figure 8: ***shows the variation of SOC within each site by land cover/vegetation structure class.***

Addressing Complexity: Understanding Drivers of SOC

Building on the equation derived by Jenny (1941) and using the data mentioned above, SOC was modeled using R Statistical Package to understand the factors affecting SOC dynamics in Ethiopia. Using a linear mixed model in the nlme package. Fixed effects: log(SOC) ~ MAP + avSlope + VegStructure_corr + PosTopoSeq + Sand and site as a random effect. The plots with VegStructure= "other" and "freshwater aquatic" were not included in the model and only topsoil plots were used, for a total of 1087 plots.

Table One shows the most important variables – expressed as ln SOC g kg^{-1} for modeling SOC, most notably, MAP, sand, and vegetation structure (cropland, bushland and shrubland). As also illustrated in Figure 9. There is not a noticeable difference influence of the topographic position on SOC, as confirmed in the table. These results highlight the complexity of understanding drivers and patterns of SOC, for example between the various covariate. This highlights the need to assess multiple variables, simultaneously, in order to understand spatial patterns across the landscape.

Table 1: Model results

	Value	Std.Error	t-value	p-value
(Intercept) (Bushland)	2.875929	0.2747	10.46933	0
MAP	0.000467	0.000213	2.191361	0.0286
avSlope	-0.00023	0.001541	-0.14781	0.8825
Cropland	-0.09501	0.048487	-1.95949	0.0503
Forest	0.022528	0.077271	0.291546	0.7707
Grassland	0.087536	0.050019	1.750058	0.0804
Shrubland	0.195438	0.050776	3.849049	0.0001
Wooded grassland	-0.14969	0.097642	-1.53302	0.1256
Woodland	-0.06224	0.061792	-1.00721	0.3141
Footslope	0.013222	0.041678	0.317248	0.7511
Midslope	0.029906	0.039042	0.766004	0.4438
Ridge	-0.03891	0.07715	-0.50439	0.6141
Upland	0.074997	0.038949	1.925526	0.0544
Sand	-0.00946	0.00177	-5.34697	0

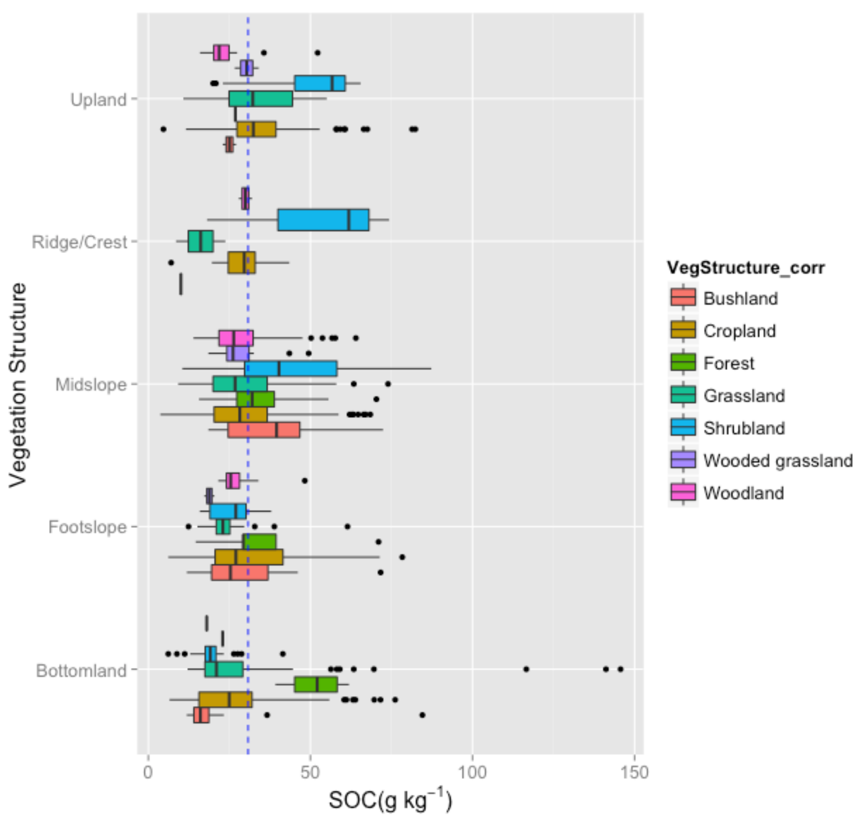

Figure 9: Boxplots of SOC by vegetation class and topographic position. Dotted line is the overall average SOC content (30 g kg^{-1}).

Effect of Cultivation & Land Degradation on SOC

Cultivation also has an effect on SOC. If we isolate cultivated and non-cultivated plots in the model, e.g., Fixed effects: log(predSOC) ~ as.factor(PlotCultMgd) and random effect: Site; we see that cultivation does have a strong effect (Table 2). There were 633 plots cultivated and 452 non-cultivated plots in the data. This analysis does not include the management of these cultivated plots nor the crops cultivated.

Table 2: Results of the model assessing the influence of cultivation on SOC. Note that cultivated plots have lower SOC content compared to non-cultivated plots, using data from all seven sites.

	Value	Std.Error	t-value	p-value
Non-cultivated	3.3737	0.1379	24.456	0
Cultivated	-0.1168	0.0264	-4.4331	0

Figure 10 shows the variation in the effect of cultivation, by site. Note that the relationship varies according to Site. For example, Dambidolo has higher SOC in cultivated plots, most likely because these plots were recently converted (<3 years ago). In addition to state factors, land degradation plays an important role in influencing SOC content (Vågen et al., 2013b, Winowiecki et al., 2016). Figure 11 is a tile graph between two different dimensions (cultivation and erosion) and shows that plots with lower erosion have higher SOC, whether that plot is cultivated or not. This analysis highlights the need to also include land degradation status when assessing SOC, in addition to the state factors. These data also highlight the complexity when assessing and predicting SOC, as well as the importance for establishing baselines for assessing the impact of interventions on SOC.

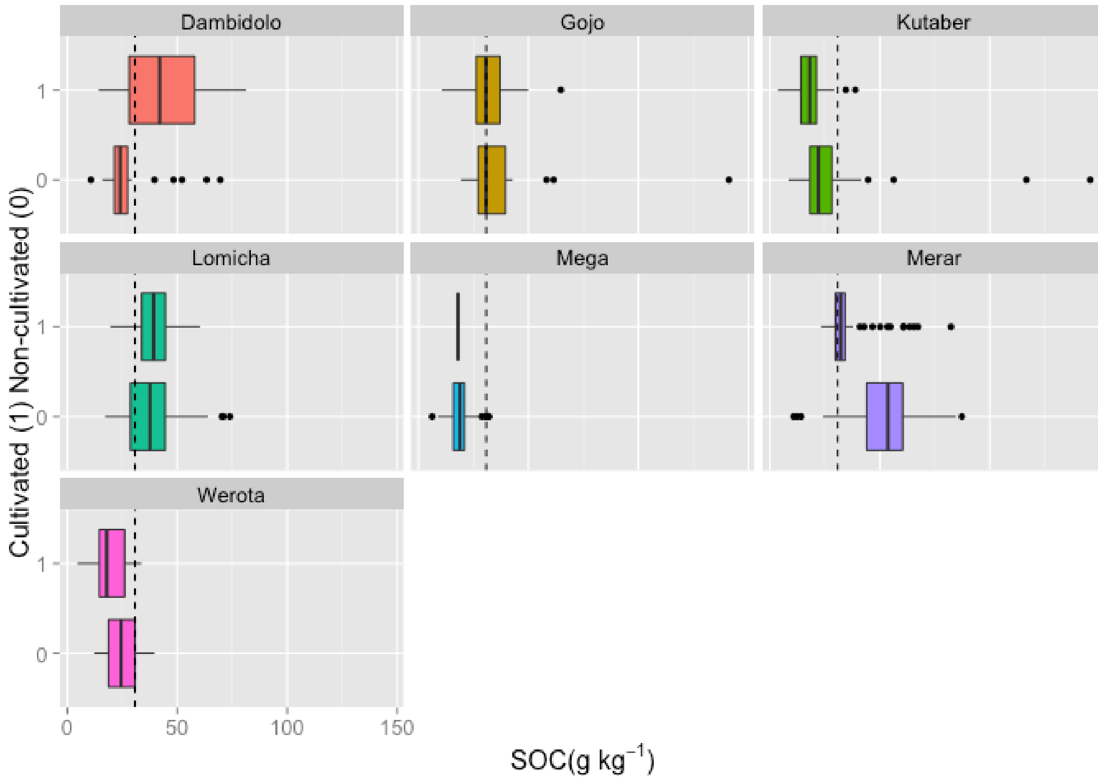

Figure 10:Boxplots showing the variability in SOC in cultivated vs non-cultivated plots in each site.

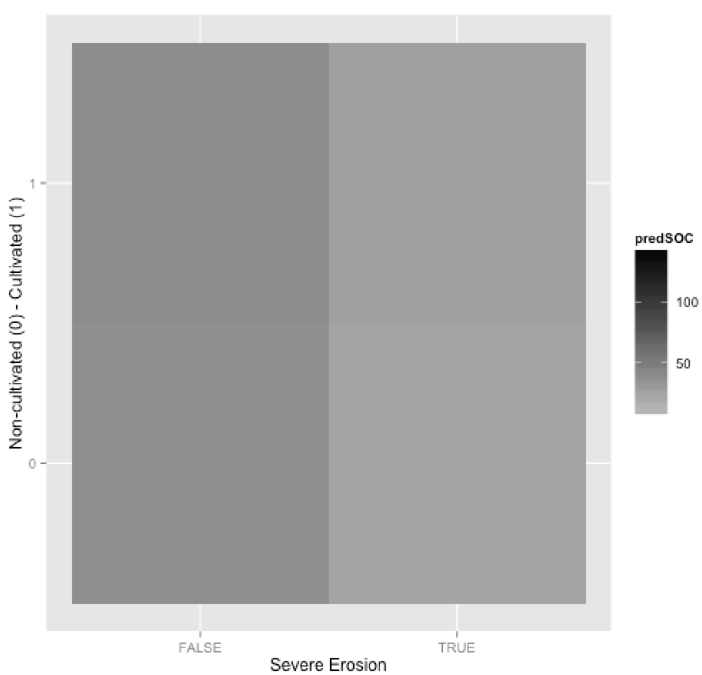

Figure 11: ***Tile graph showing the relationship between erosion and severe erosion.***

Creating a Decision Tree for SOC Dynamics

The below decision tree was developed in R Statistical Package, using the party library: A Laboratory for Recursive Partytioning (Hothorn, Hornik, and Zeileis 2006). Figure 12 shows cut-offs of MAP 1365 mm and then partitioning by vegetation structure and sand content. This tree highlights again (as in Table One) the role of MAP, sand, and vegetation structure (including crop management) in driving SOC. The boxplots at the bottom show the SOC content. Each circle also shows the level of signification for the partitioning.

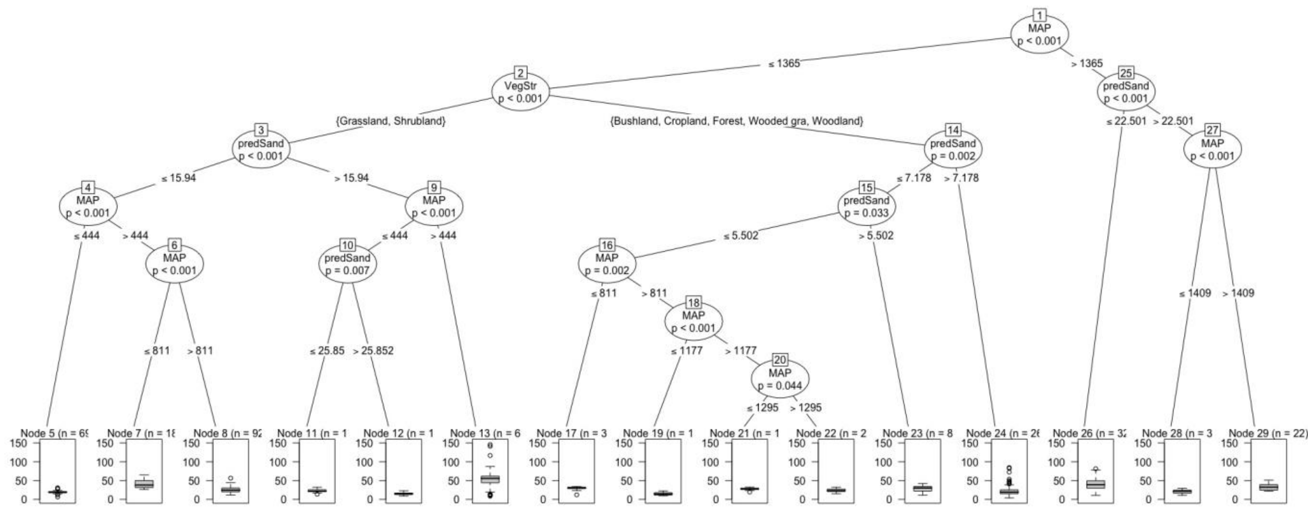

Figure 12: ***Decision tree using: MAP, vegetation structure and sand. This tree highlights the complexity of assessing SOC.***

Next Steps

Future analysis should look at the change in carbon over time, in order to better assess the trajectories of SOC. This report only focused on existing data for Ethiopia and further analysis should include more diverse datasets, including information on crop management and land-use history. In addition, the concept of regional thresholds for SOC is still needed, acknowledging variability of acceptable levels needed to maintain essential soil functions on different soil types, for example. Furthermore, understanding how SOC influences land and agricultural productivity is required in order to quantify critical ecosystem services provided by soil. Therefore, comprehensive studies that acknowledge the complexity of SOC dynamics across diverse landscapes can help better address these questions.

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