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

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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) and the UN Convention on Climate Change (UNFCC) both recognize that reduced SOC content can lead to land degradation, and ultimately low land and agricultural productivity. Degradation of soil and water resources further exacerbates the situation (Verchot et al. 2005; Vågen et al., 2012; Vågen et al. 2013). It is well documented that SOC content reflects aboveground activities, including land management, leading to potentially an overall decrease in SOC compared to the native land use (Schlesinger 1991; Smith, 2008; Don et al., 2010). 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).

Since SOC is almost universally proposed as the most important soil quality indicator, it is critical that we begin 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. In addition, 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.

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.

The Land Degradation Surveillance Framework (LDSF) is a well-established method for assessing multiple indicators at the same georeferenced location, and across landscapes (Figure Two). 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 Three). Each LDSF site has 160-1000m² plots that are randomly stratified among 16-1 km² 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.

Example variables measured include: tree and shrub densities, erosion prevalence, herbaceous layers, percent bare ground, land use history, major use and land cover. Land cover is 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).

Analysis for this report will rely on existing LDSF data collected by ICRAF and CIAT, focusing on Ethiopia.
Location of Existing LDSF Sites in Ethiopia- ICRAF/CIAT

Three sites: CPWF project

Four sites: AfSIS project

Assessing variability SOC in Seven LDSF sites in Ethiopia - Using Reference Plot Data

Seven LDSF surveys were conducted through two different projects in 2011-2013. The graphic on the right shows the variation in topsoil OC content for each of the sites, using the reference plots from each cluster (n=16 samples per site) (Figure Six). Note the higher SOC in Merar compared to the other sites and the low variability within the Werota and Mega sites.

Landscape-scale assessments: Mid-infrared (MIR) spectroscopy

All soil samples ~320 per site, were analyzed for MIR spectra at the ICRAF Soil and Plant Spectroscopy Laboratory in Nairobi, Kenya (http://www.worldagroforestry.org/research/land-health/spectral-diagnostics-laboratory). 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 are published in the publications mentioned above.
State Factors of Soil Formation

Hans Jenny (in 1941) published the equation of the state factors effecting soil formation, including climate, organisms, relief, topography and parent material. These variables contribute to the formation of soil and account for differences in soil types, including soil properties. We used data from the TRMM (1998-2011) downloaded from landscapeportal.org to obtain the mean annual precipitation for each of the seven sites (Figure Seven). The other variables were collected in the field at each of the 160 LDSF plots per site, e.g., vegetation structure, average slope and topographic position. Figure Eight shows the variation in topsoil OC content for each vegetation structure class, per site using the MIR predicted SOC values. The average topsoil OC 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 structure.

Addressing Complexity: Understanding Drivers of SOC

Building on the equation derived by Jenny 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. Figure Nine shows how the residuals are distributed, which are acceptable. Table One shows the variables of importance in modeling SOC, most notably, MAP, sand, and vegetation structure (cropland, bushland and shrubland). As also illustrated in Figure Ten, there is not a noticeable difference influence of 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 variable simultaneously in order to understand spatial patterns across the landscape.

Table One: Model results.

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std.Error</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept (Bushland)</td>
<td>2.875929</td>
<td>0.2747</td>
<td>10.46393</td>
<td>0</td>
</tr>
<tr>
<td>MAP</td>
<td>0.000467</td>
<td>0.000213</td>
<td>2.191361</td>
<td>0.0286</td>
</tr>
<tr>
<td>avSlope</td>
<td>-0.00023</td>
<td>0.001541</td>
<td>-0.14781</td>
<td>0.8825</td>
</tr>
<tr>
<td>Cropland</td>
<td>-0.09501</td>
<td>0.048847</td>
<td>-1.95949</td>
<td>0.0503</td>
</tr>
<tr>
<td>Forest</td>
<td>0.022528</td>
<td>0.077271</td>
<td>0.291546</td>
<td>0.7707</td>
</tr>
<tr>
<td>Grassland</td>
<td>0.087536</td>
<td>0.050019</td>
<td>1.750058</td>
<td>0.0804</td>
</tr>
<tr>
<td>Shrubland</td>
<td>0.195438</td>
<td>0.050776</td>
<td>3.849049</td>
<td>0.0001</td>
</tr>
<tr>
<td>Wooded grassland</td>
<td>-0.14969</td>
<td>0.097642</td>
<td>-1.53302</td>
<td>0.1256</td>
</tr>
<tr>
<td>Woodland</td>
<td>-0.06224</td>
<td>0.061792</td>
<td>-1.00721</td>
<td>0.3141</td>
</tr>
<tr>
<td>Foootslope</td>
<td>0.013222</td>
<td>0.041678</td>
<td>0.317248</td>
<td>0.7511</td>
</tr>
<tr>
<td>Midslope</td>
<td>0.029906</td>
<td>0.039042</td>
<td>0.766004</td>
<td>0.4438</td>
</tr>
<tr>
<td>Ridge</td>
<td>-0.03891</td>
<td>0.07715</td>
<td>-0.50439</td>
<td>0.6141</td>
</tr>
<tr>
<td>Upland</td>
<td>0.074997</td>
<td>0.038949</td>
<td>1.925526</td>
<td>0.0544</td>
</tr>
<tr>
<td>Sand</td>
<td>-0.00946</td>
<td>0.00177</td>
<td>-5.34697</td>
<td>0</td>
</tr>
</tbody>
</table>

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

Figure Eight: Figure Seven shows the variation of SOC within each sites by vegetation structure class.

Figure Nine: Shows the residuals for the model. While they are well spread, we can see clustering. Note fitted values are the log of SOC.

Figure Ten: Boxplots of SOC by vegetation class and topographic position.
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 Two). There were 633 plots cultivated and 452 plots not cultivated in the data. Figure Eleven shows that the relationship varies by site. For example, Dambidolo has higher SOC in cultivated plots, most likely because these plots were recently converted (<5 years ago).

In addition to state factors, land degradation plays an important role in influencing SOC content. Figure Twelve shows that lower erosion has higher SOC, whether that plot is cultivated or not. This highlights the need to also include land degradation status when assessing SOC. 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.

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 Partitioning (Hothorn, Hornik, and Zeileis 2006). Figure Thirteen 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.

Next Steps 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.
References


Hothorn, Hornik, and Zeileis 2006. Party: A Laboratory for Recursive Partytitioning. version 1.0-23


