FTA Annual Report 2016 - The Sentinel Landscapes

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RESEARCH PROGRAM ON Forests, Trees and Agroforestry

1 Introduction

Phase II of FTA (2015 to 2016) was severely affected by the funding cuts in win1/win2. Prior to the funding cuts there were plans to use a substantial amount of the win1/win2 allocation to the sentinel landscape network, specifically to facilitate place-based research activities contributing to the Flagship level IDOs within the sentinel landscapes. With the announced budget cuts in October 2014, in December it was anticipated that completion of data collection, the meta-analysis across landscapes and publishing the data sets in the open domain would approximately need 80% of the anticipated allocation for 2015. Further funding cuts through 2015 resulted in shrinkage of scientific cadres in several of the regional sentinel landscape teams and funding shortage for processing the sentinel landscape data. To ensure that regional teams were able to complete their data collection activities and complete the sentinel landscape dataset, funding cuts were absorbed by cutting allocations to the method team that is responsible for developing the indicators from the collected data. Also the two thematic sentinel landscapes could no longer be supported by the allocation to the cross cutting theme.

Despite the mentioned cuts in funding, the sentinel landscapes network has grown to 9 landscapes, with plans for an additional landscape in Miombo systems in southern Africa (Figure 1). Biophysical data collection using the LDSF has been completed in 27 LDSF sentinel sites from these 9 landscapes, the majority of the sites having completed soil analysis by June 2016. While some sites are still pending analysis due to export restrictions (e.g. India) as well as complications with customs clearance in some cases, the development of models for soil and land health mapping has been initiated and maps are being posted to the Landscape Portal for sharing after being validated against field measurements.

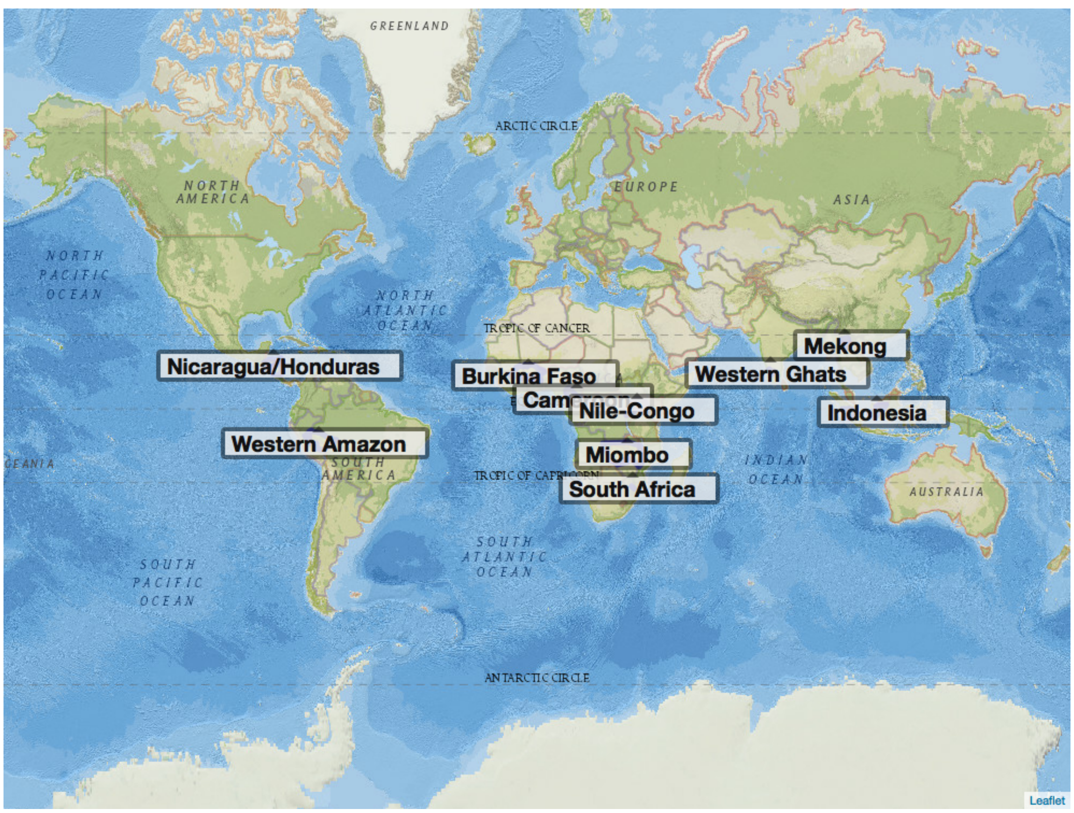

Figure 1: Map showing the network of Sentinel Landscapes by the end of 2016 (blue polygons).

2 Summary of results

2.1 Indicators of land health

One of the basic premises behind the Sentinel Landscape conceptual framework was that the landscapes needed to represent a wide range of conditions in as far as forest cover and land use was concerned. The initiative was designed around the idea of a data-driven network of landscapes representing various stages of transition from forested landscapes to more agricultural landscapes in both humid and dry ecosystems. To meet this objective, Land Degradation Surveillance Framework (LDSF) sites were established based on analyses of forest cover change between 2001 and 2012, optimizing site locations to capture gradients of land cover change. The indicator framework used in the LDSF is summarised in Figure 2.

By the end of 2016, data from 4328 plots, representing 28 sites had been collected as part of the SL network. The majority of the data collection was conducted by the end of 2015, while sites in Cameroon, India and Laos were completed later. An additional landscape (Miombo) was proposed for inclusion, but due to funding constraints activities have not commenced in this landscape. Soil analysis was still ongoing for the latter set of sites, with samples from India (Western Ghats) still pending due to complications with soil export permits. Soil samples from China were analyzed locally and have not been included in global models for prediction of soil properties from soil MIR spectroscopic measurements due to differences in laboratory procedures to the ICRAF Spectral Diagnostics Lab. Local models are being explored for these soil samples.

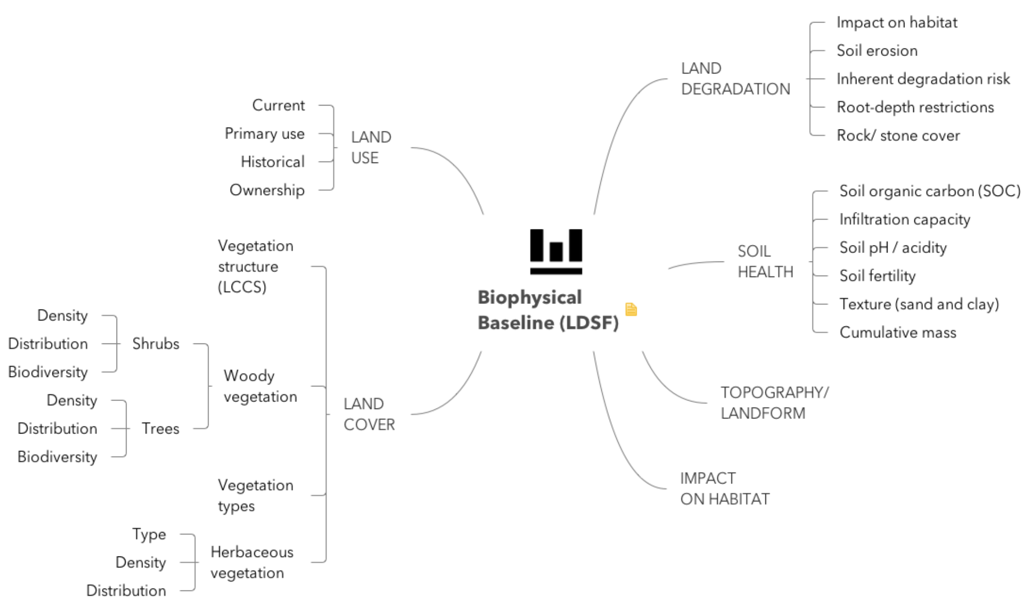

Figure 2: Schematic overview of the LDSF indicator framework that was applied in the Sentinel Landscapes for biophysical characterization of sentinel sites.

As shown in Figure 3, the LDSF sites characterized as part of the SL initiative represent a wide range of vegetation structure types (and land uses), and include both areas with natural vegetation and no cultivation (e.g. Pando in Bolivia) and intensively cultivated areas (e.g. Gishwati in Rwanda and Soralangun in Indonesia), as well as sites with a wide diversity of vegetation structure types. Figure 4 shows the intensity of cultivation for each LDSF site. If we take agroforestry (AF) to represent plots that are cultivated and where there are trees present, sites such as Madikeri in India have about 67% agroforestry, while Soralangun in Indonesia has more than 95% agroforestry (Figure 5). Madikeri is predominantly coffee agroforestry. Sites that were predominantly rangelands in drier ecosystems such as Agincourt in South Africa had very little agroforestry, based on the LDSF field surveys.

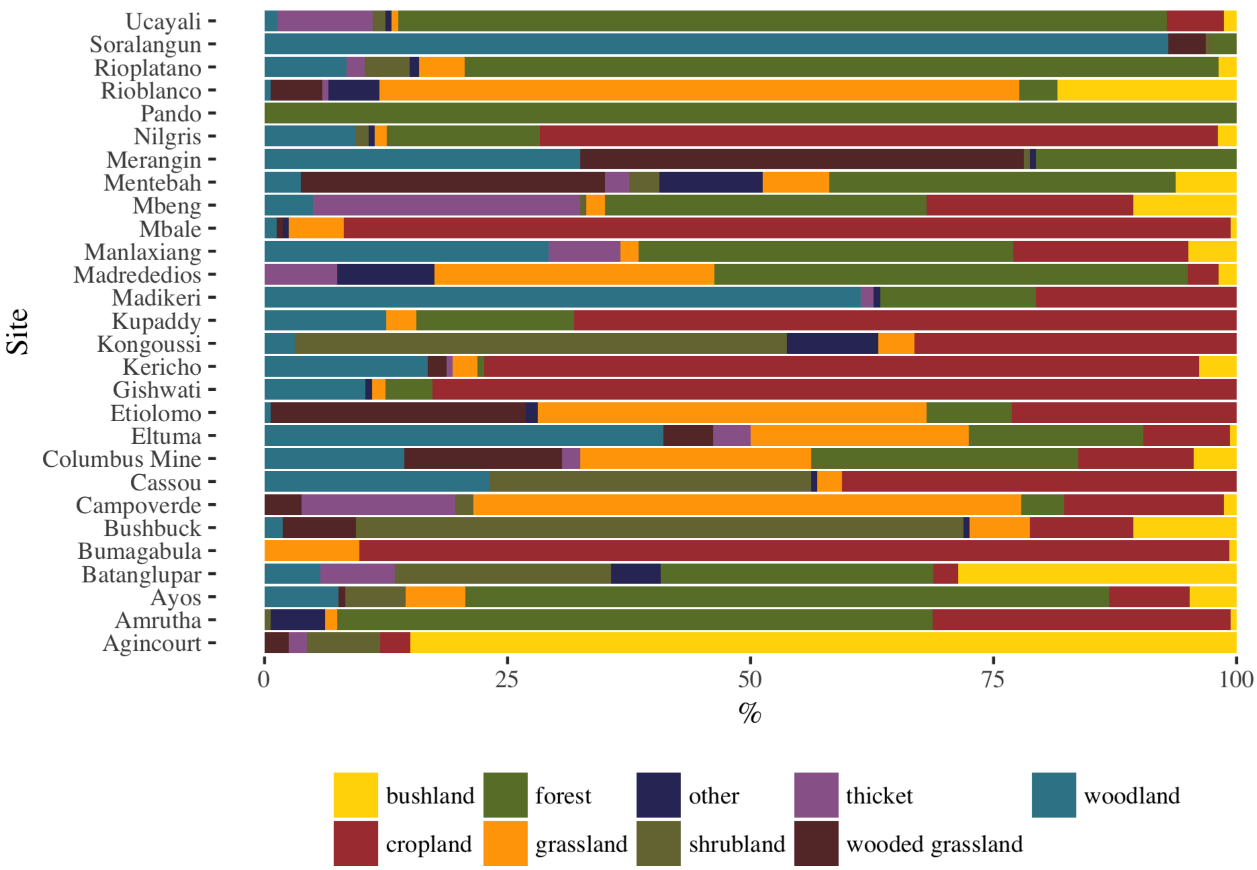

Figure 3: Distribution of vegetation structure types (classes) in each LDSF site within the Sentinel Landscapes.

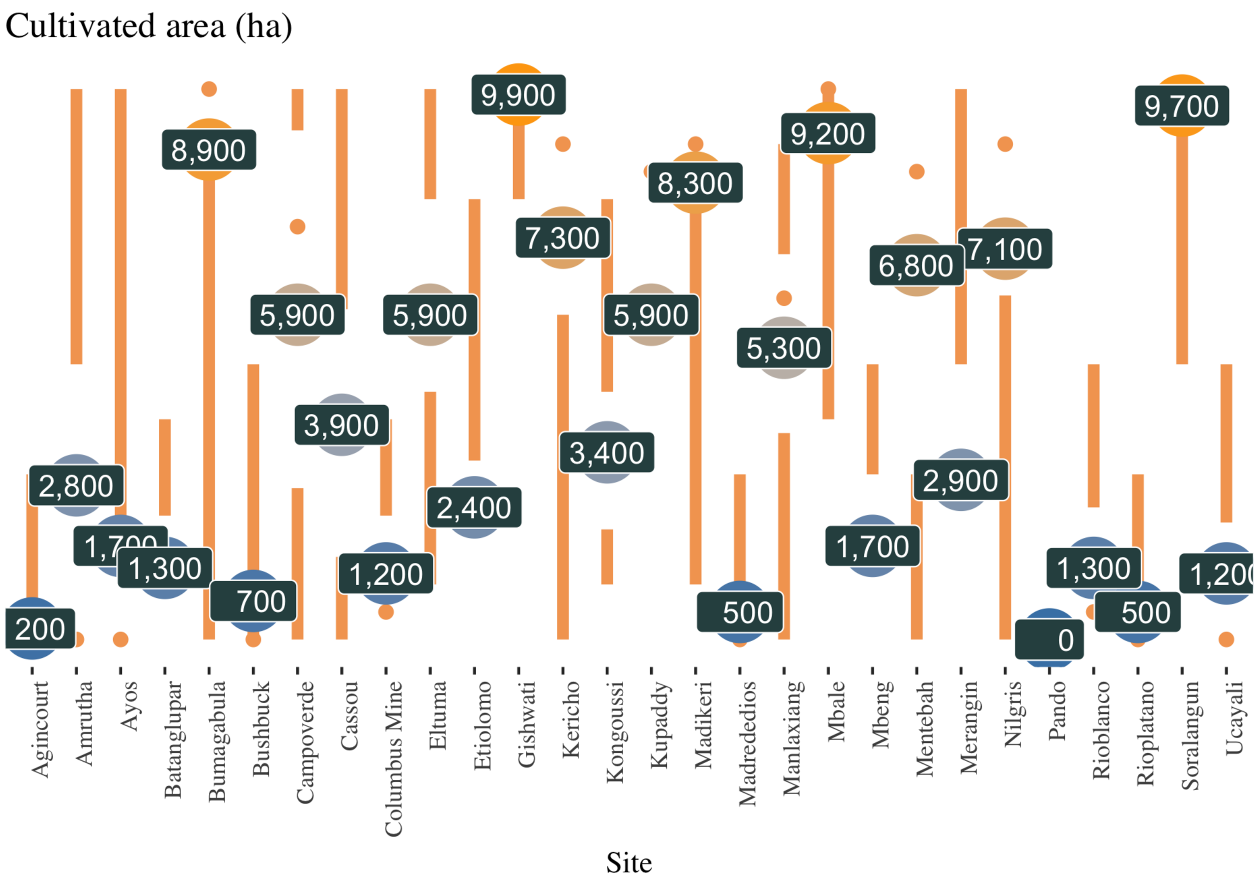

Figure 4: Area under cutlivation (ha) in each SL LDSF sentinel site.

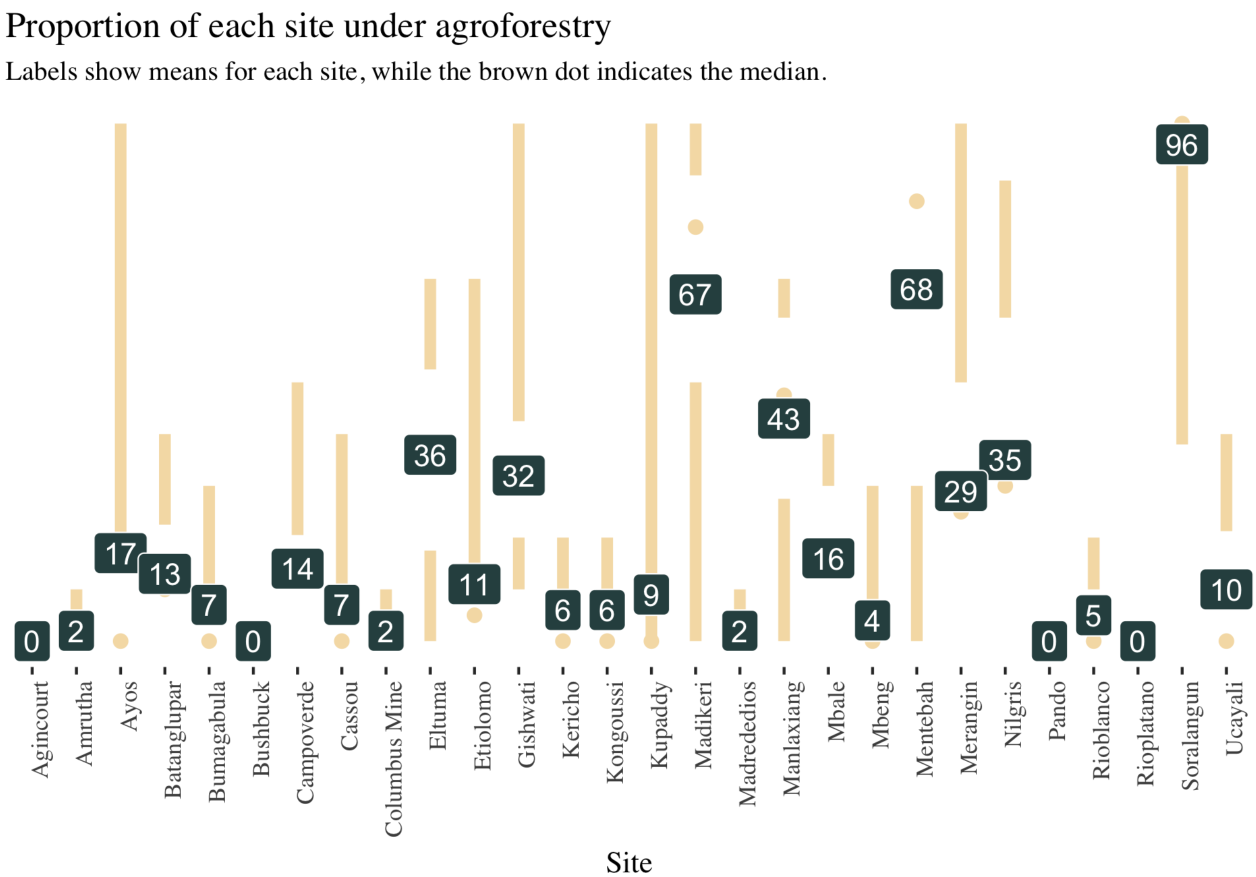

Figure 5: Area (%) under agroforestry (trees in croplands) for each SL LDSF sentinel site.

Forest cover also varied widely, from about 100% in Pando (Bolivia) to virtually no remaining forest in sites like Cassou and Kongoussi (Burkina Faso), where woodlands and croplands were the dominant vegetation structure classes. Interestingly, tree densities were relatively low in Pando (Figure 7), which had large trees and relatively low levels of disturbance.

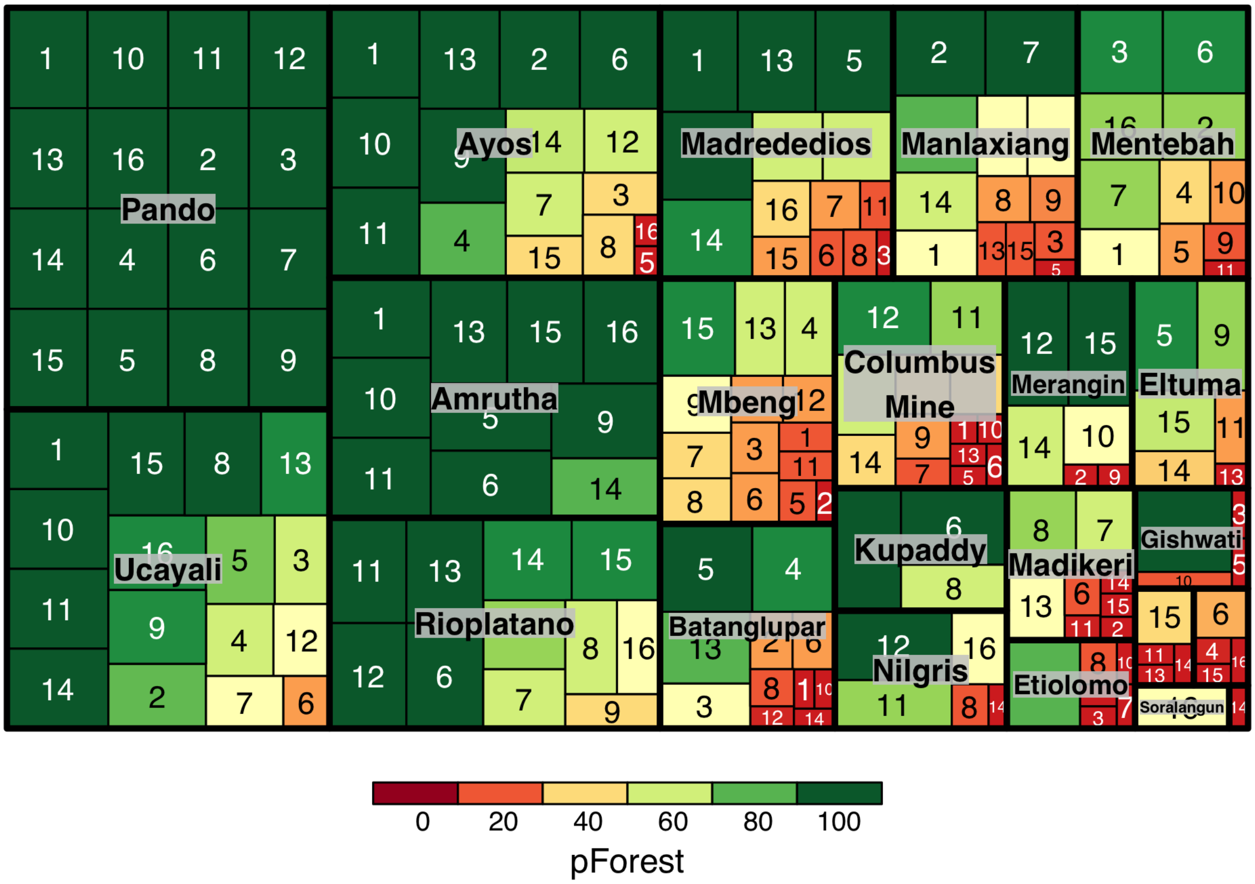

Figure 6: Visual representation of forest cover within each LDSF site, with high forest cover as green and low forest cover as yellow. The labels on each tile represent LDSF sampling clusters (i.e. range from 1 to 16) and show the variability in forest cover within each of the sites sampled as part of the SL initiative. Tile sizes are also scaled to the average forest cover in each pixel.

2.1.1 Land degradation status

Land degradation status has been mapped using predictive models for all of the sentinel landscapes sampled to date, with moderate resolution maps complete (based on MODIS) for all landscapes and high resolution mapping on-going for the LDSF sites themselves and a buffer of 20km around each site (based on RapidEye and Landsat). Erosion prevalence has been mapped for all of the sites that have RapidEye imagery available (some sites are missing due restrictions in funding or lack of available satellite imagery) and can be accessed through the ICRAF Landscape Portal. For consistency and reproducibility in ongoing meta-analyses across the SL network, maps based on MODIS and Landsat are being used.

Both LDSF data and baseline analysis results can be explored interactively online through the Sentinel Landscape Explorer (http://landscapeportal.org:3838/slExplorer/) (Figure 9). The SL Explorer also presents a brief overview of the SL framework and the kinds of analysis that are being conducted in the SL network and data can be explored interactively for a number of indicators. Maps and analytical outputs produced as part of the SL inititative are

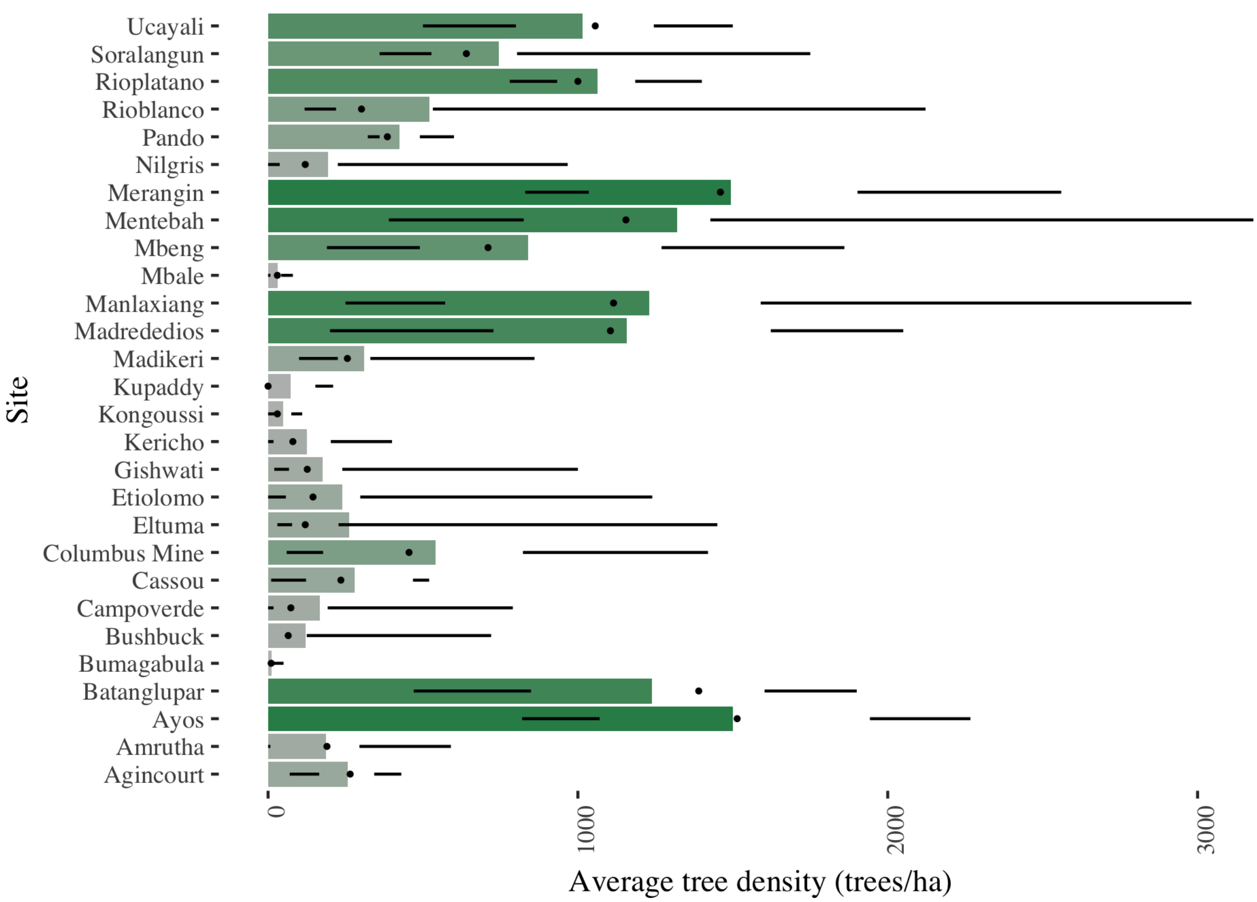

Figure 7: Average tree density by LDSF site. Bars show means, while boxplots show medians (dot) and first and third quartiles, respectively.

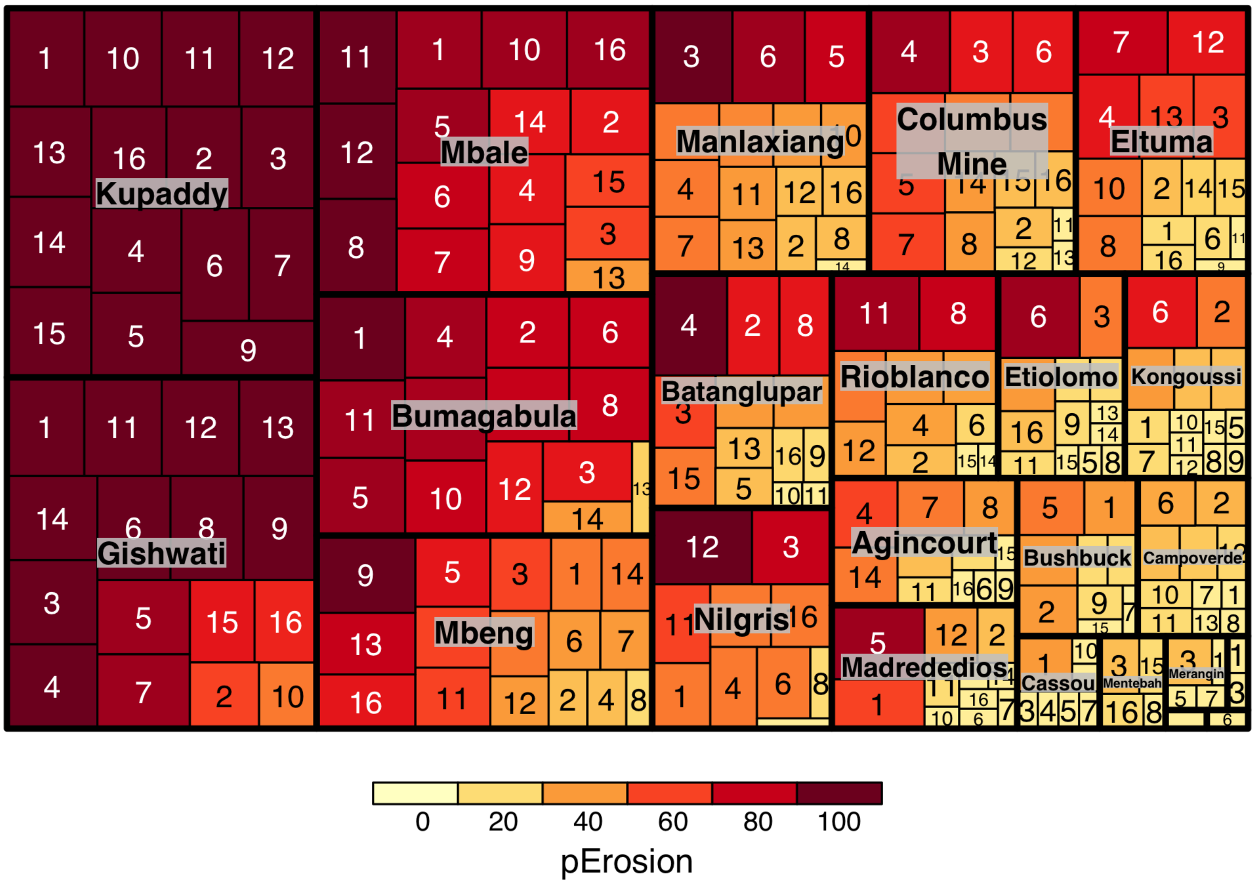

Figure 8: Visual representation of ferosion prevalence within each LDSF site, with high prevalence of erosion as red and low erosion as orange and yellow tones. The labels on each tile represent LDSF sampling clusters (i.e. range from 1 to 16) and show the variability in erosion prevalence within each of the sites sampled as part of the SL initiative. Tile sizes are scaled to the average erosion prevalence in each pixel.

presented and published on Harvard Dataverse (see link to the site on the SL explorer) and interactively on the Landscape Portal (see screenshot in Figure 10, which shows an example from Western Ghats). To register on the Landscape Portal, simply go to http://landscapeportal.org/account/signup/ and enter your registration details.

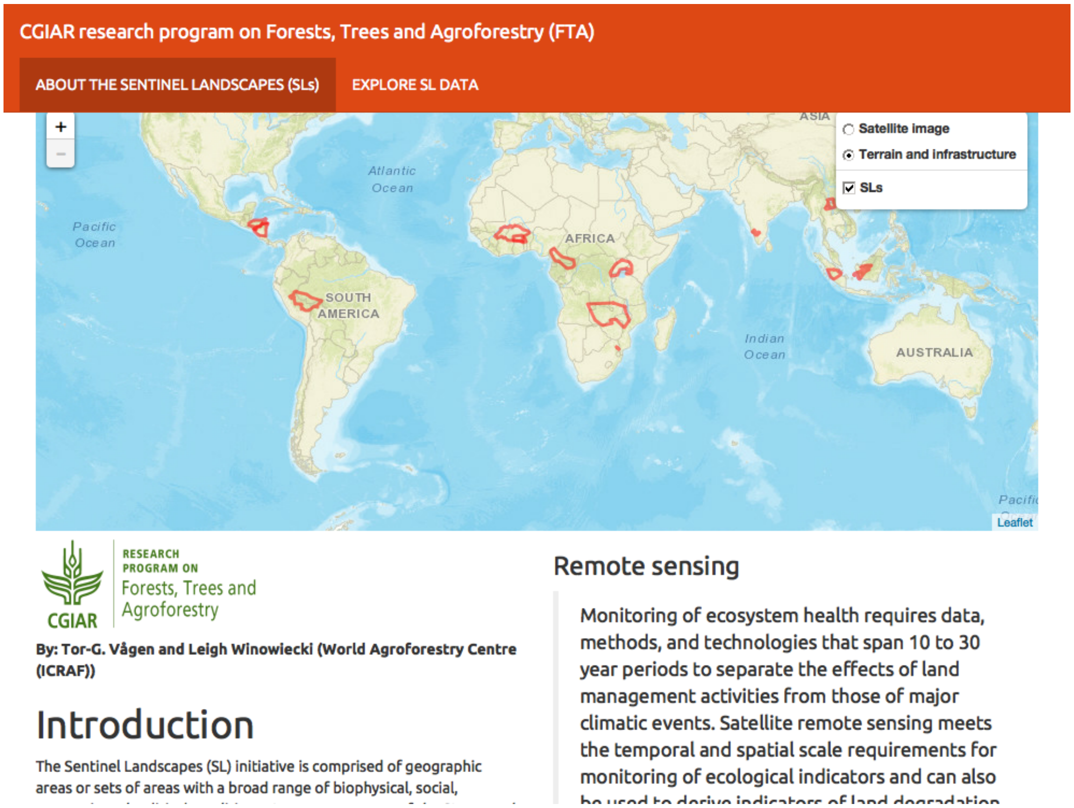

Figure 9: Screenshot of the SL explorer.

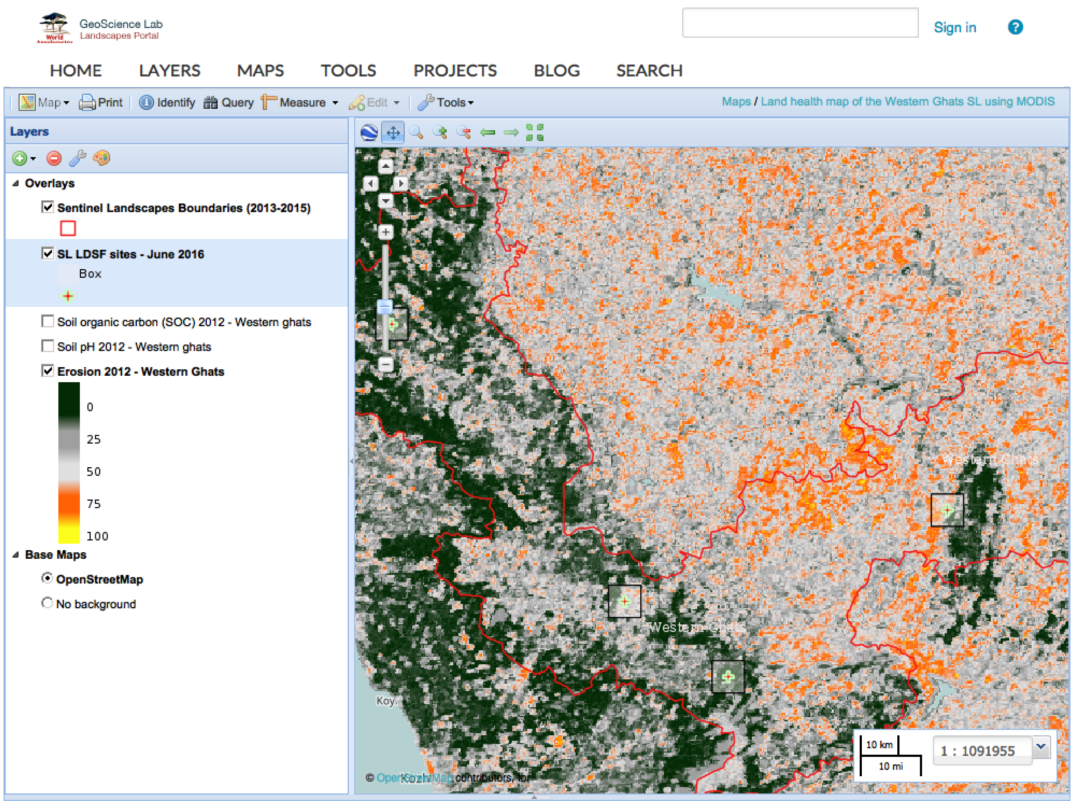

Figure 10: Screenshot showing erosion prevalence in the Western Ghats SL.

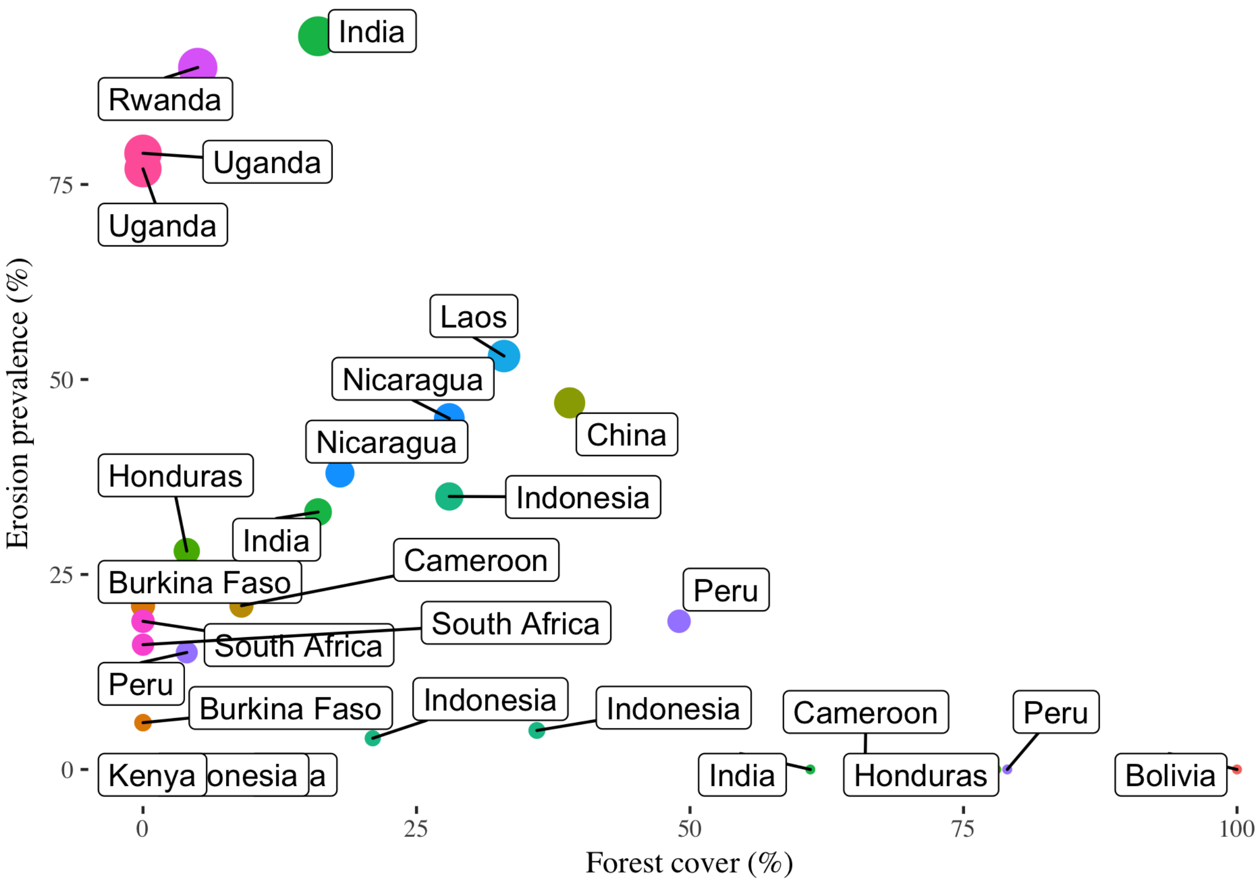

Figure 11: Erosion prevalence and % forest cover for each LDSF site, with labels showing the country that each site is located in.

2.1.2 Soil health

Soil health assessments and mapping in the SLs apply the LDSF analytical framework, which is part of ICRAF's Ecosystem Health Surveillance System (EcoHSS) to generate continuous surfaces of soil properties at several spatial scales. Given the heterogeneity of the SLs, spatial patterns of soil properties tend to be complex and assessments of the distribution of soil pH and organic carbon, as well as other soil properties, therefore need to be made at appropriate spatial scales. For example, for comparative analysis across the SLs, maps produced at moderate spatial resolution will be more appropriate as they can be produced based on remote sensing data such as MODIS that have high temporal resolution and allows for the production of estimates that are consistent globally. However, when assessing soil health at the farm scale a spatial resolution of 30m or finer is generally required in order to produce soil property maps that are sufficiently resolved to identify between-farm variation.

Most models and estimates of soil organic carbon (SOC) only allow for coarse-scale assessments of SOC sequestration potential and are not able to predict the possible fate of carbon due to land-use change at scales relevant to management interventions. The EcoHSS uses alternative approaches that enable these types of assessments to be conducted using moderate to high resolution satellite imagery to predict SOC (T.-G. Vågen et al. 2013; L. Winowiecki, Vågen, and Huising 2016; T.-G. Vågen et al. 2016), as well as cumulative soil mass (CM) measurements and direct calculations of SOC stocks (Vågen and Winowiecki 2013), without the use of bulk density, which is prone to error.

Further, the use of infrared spectroscopy is a key component of the EcoHSS approach, allowing for laboratory measurements of key indicators of soil health to be conducted for large sample sizes due to the very low costs of these measurements compared to conventional wet chemistry methods. In the SLs, 10% of the soil samples collected were analyzed using conventional methods to train predictive models for key soil properties. All samples collected and shipped to Nairobi were scanned using a mid-infrared (MIR) spectrometer in the ICRAF Spectral Diagnostics Lab in Nairobi, Kenya (see example spectral library in the top-panel of Figure 12). The ICRAF soil spectral library currently contains data for more than 100,000 soil samples from across the global tropics. As shown in the four lower panels in Figure 12, prediction accuracy for soil properties based on MIR spectra is high.

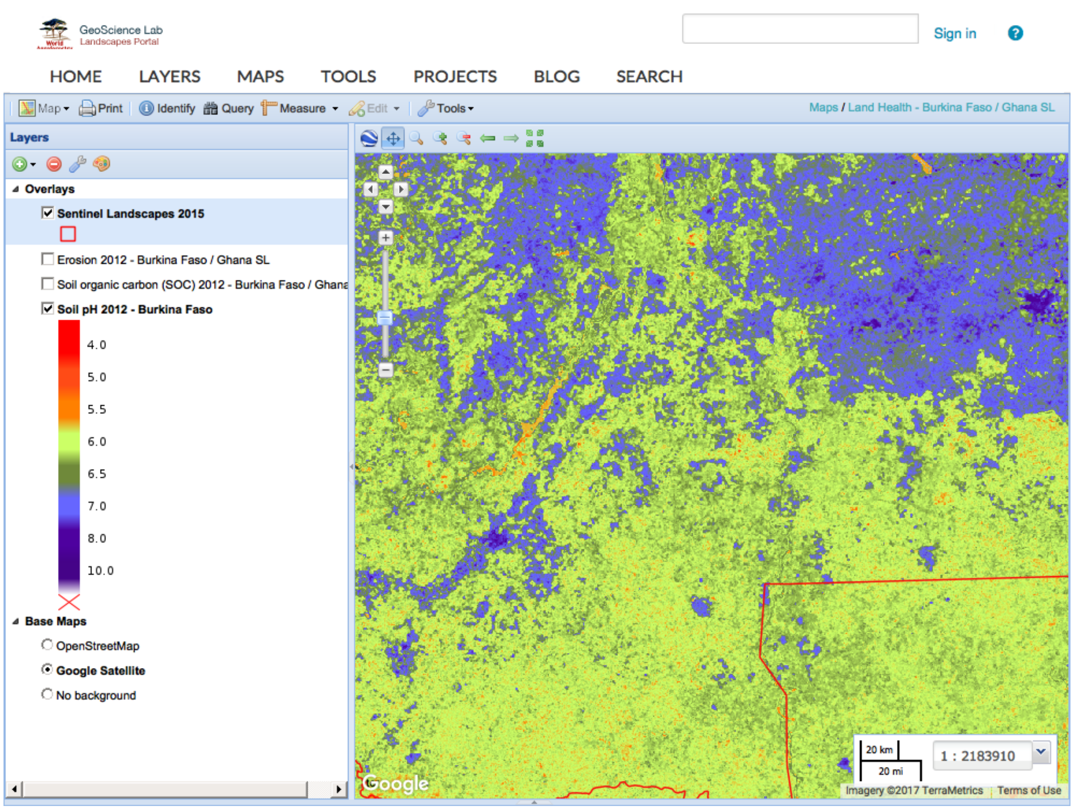

Figure 14: Screenshot showing a map of soil pH for the Burkina Faso / Ghana SL.

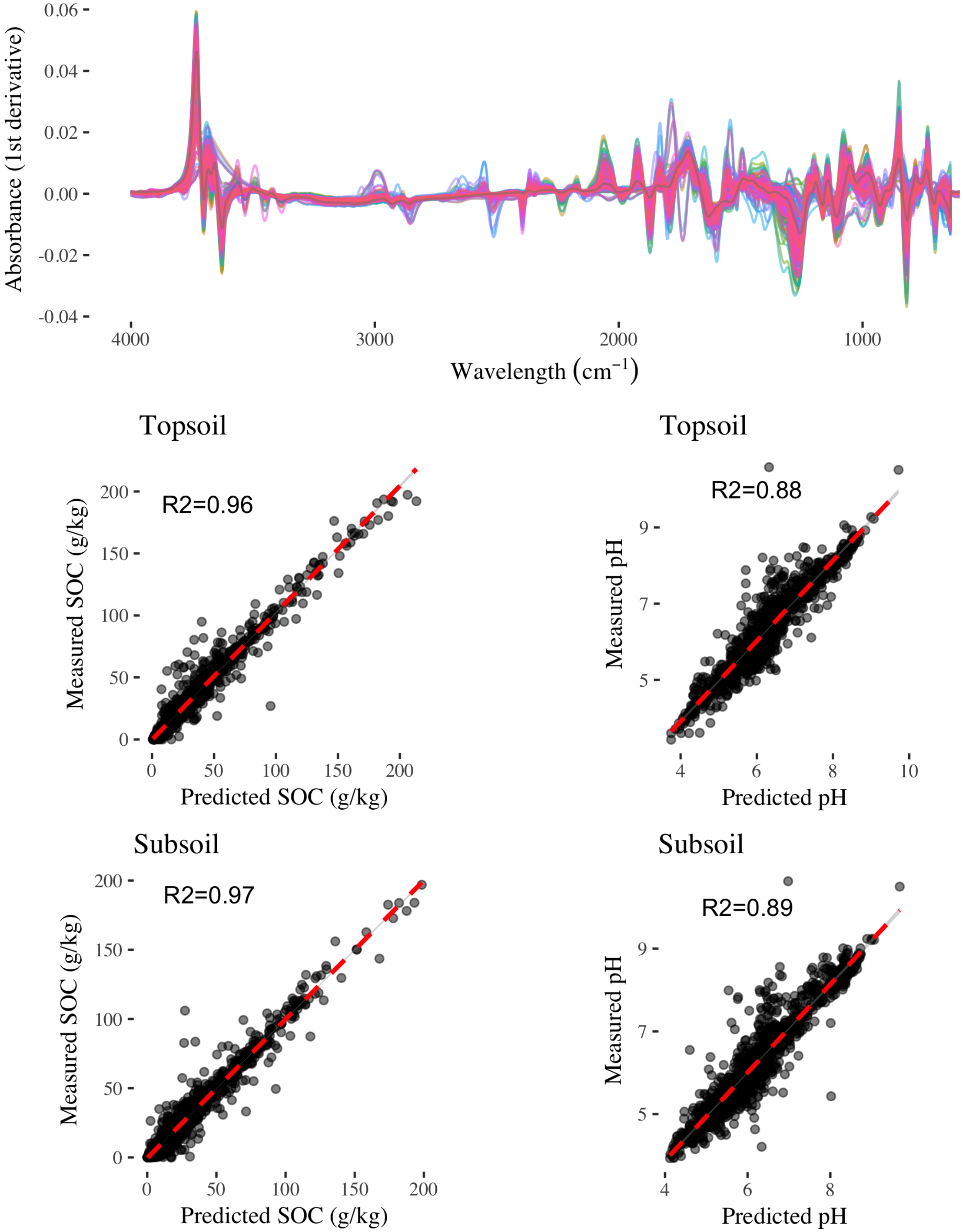

Figure 12: Soil MIR spectral library averaged by site (top) and prediction results for SOC and pH, respectively, showing predicted vs measured values for both topsoil and subsoil samples (lower panels).

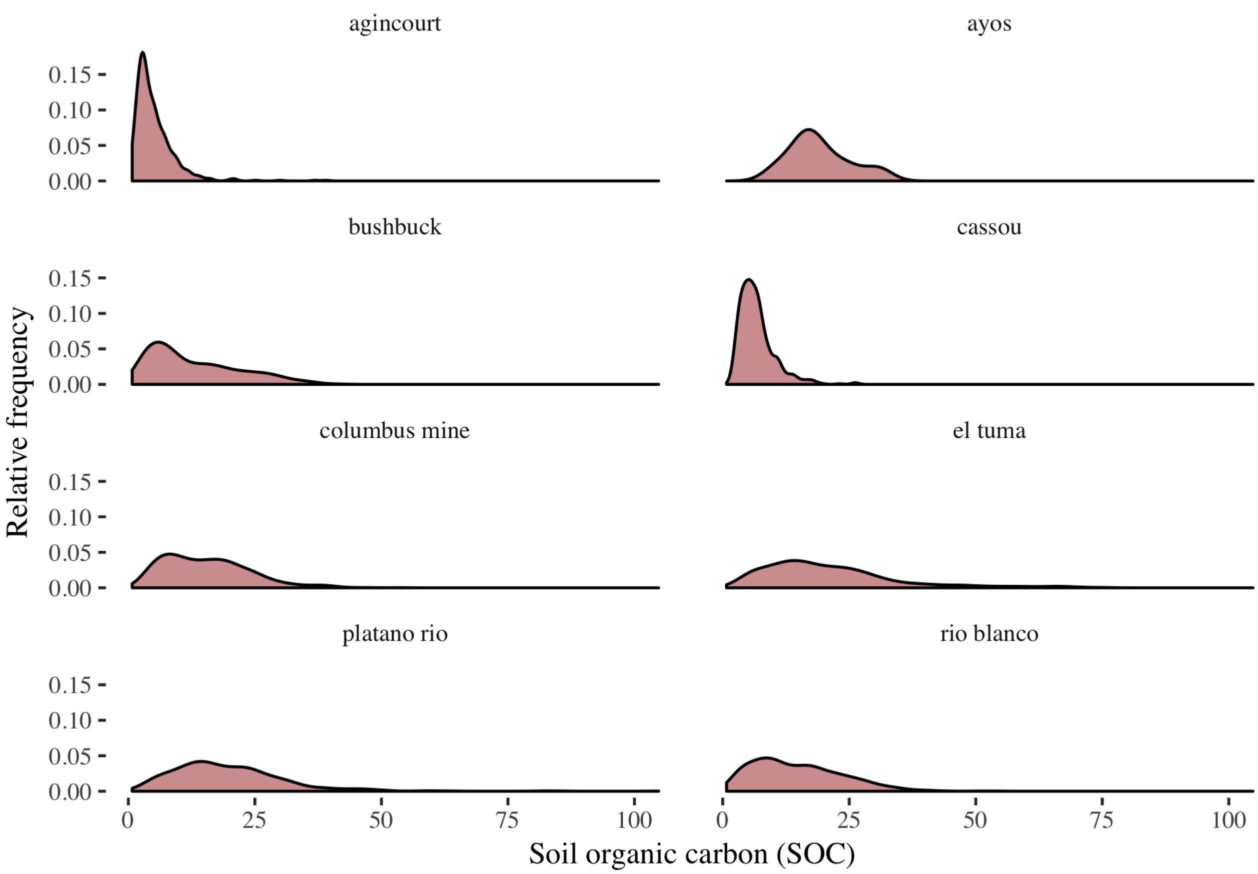

Figure 13: Distributon of soil organic carbon (SOC) for a small selection of LDSF sites from the SL initiative.

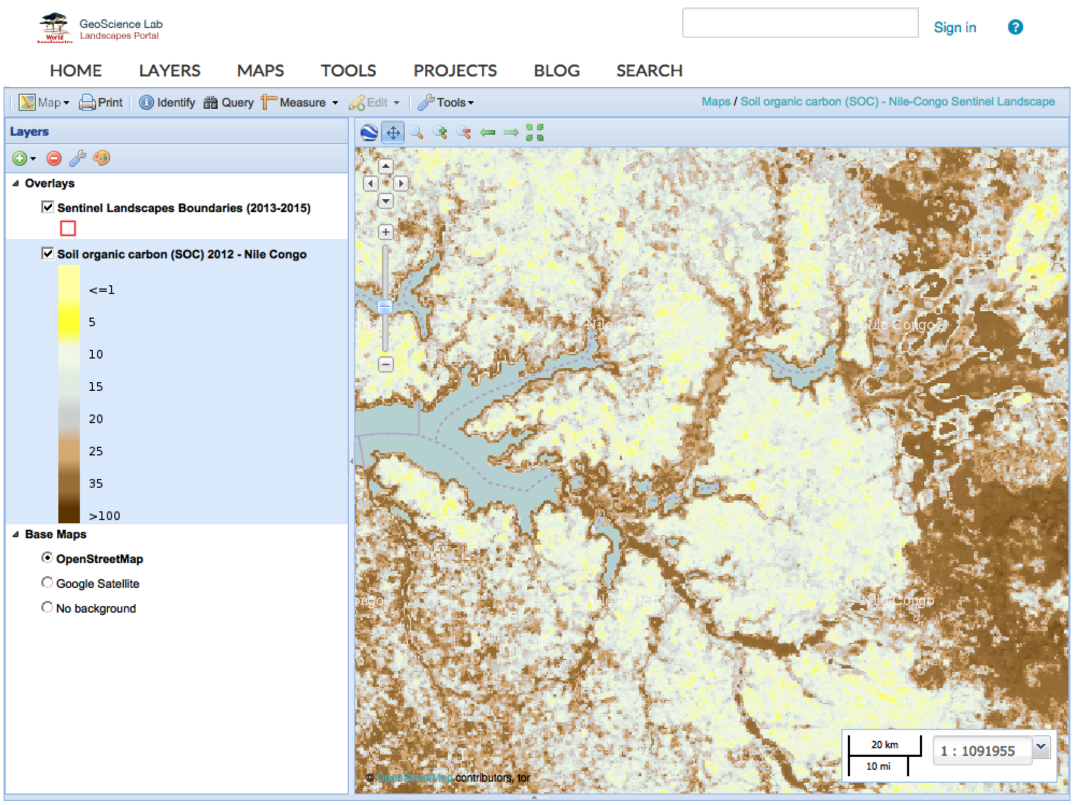

Figure 15: Screenshot showing a map of SOC for the Nile-Congo SL.

2.2 Socioeconomic surveys

Land health and socioeconomic datasets were collected using a nested, hierarchical sampling design, where household surveys and biophysical characterization were co-located in (or near) LDSF sentinel sites, which have a spatial extent of $100km^2$. Following with the SL sampling strategy, 10 villages were randomly selected in each site, from which 30 households were also randomly chosen and interviewed. Figure 16 shows the Sentinel sites where socio-economic data was collected using standardized methodologies (research design tools and instruments). In each of the sites, socio-economic surveys captured information on household demographics, migration, education, asset ownership, income sources, household food security, progress out of poverty, crop production and sales, livestock products, participation in credit markets, social networks, and natural resource use. The table below shows some of the livelihood indicators that are constructed for each site and is accompanied by a report. In summary, data was collected from:

- 8 Sentinel Landscapes
- 4 Sites per Landscapes
- 10 Villages per site
- 30 h-holds per village
- 300 h-holds per site In total, data was collected and processed from 7,039 households.

By nesting the settlements/villages within the sentinel sites, social-ecological processes can be studied in more detail and ongoing work (2017) is focusing on integrating the above land health data sets and analytical results with socio-economic indicators in order to better understand both environmental and institutional settings in the study areas, including drivers of land cover change and land degradation.

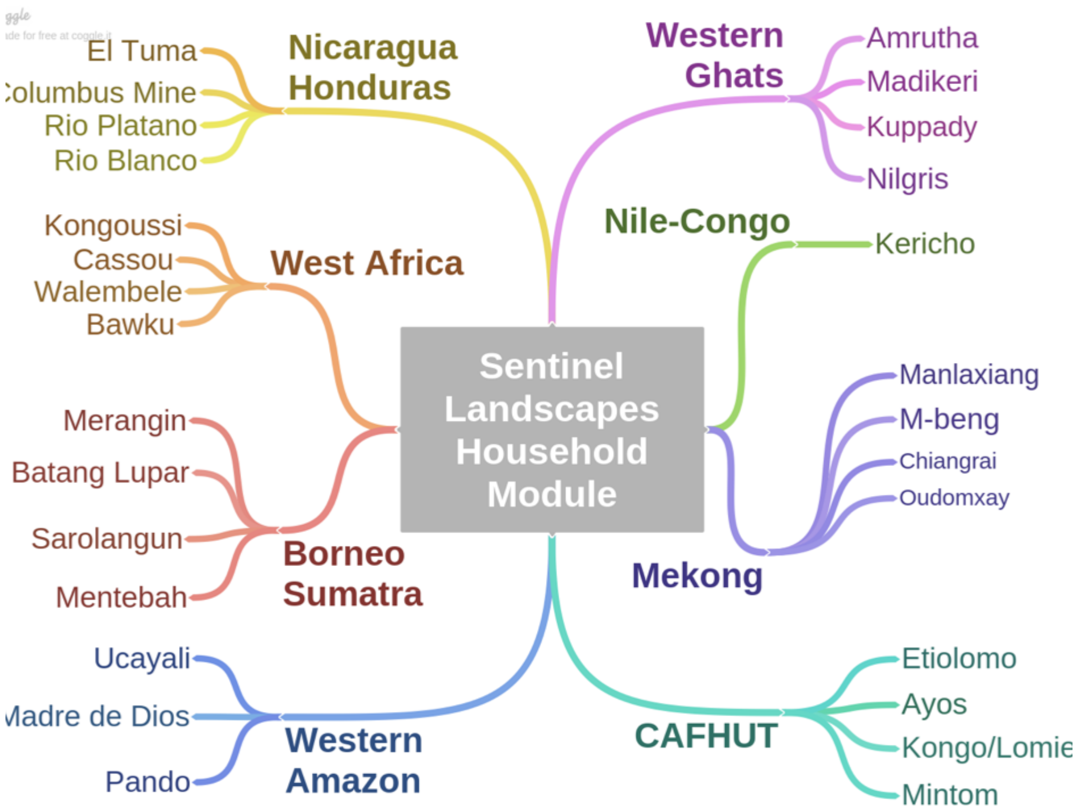

Figure 16: Sentinel sites with socio-economic data

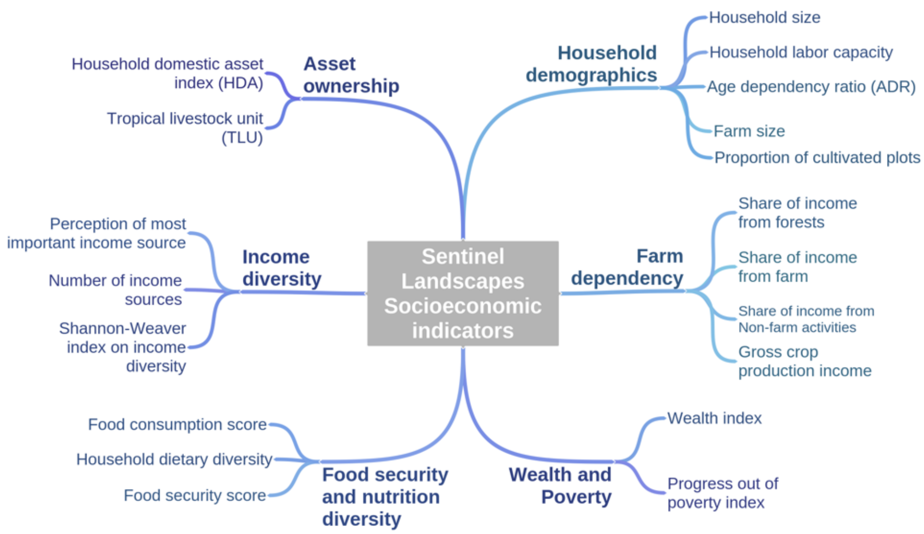

Figure 17: List of socio-economic indicators constructed

2.2.0.1 Indicator: Land ownership

This variable represents the total farm land owned by households in each site in hectares. All unstandardized units are converted into Hectares and calculated as follows:

$$\text{Size of land (ha)} = \sum_{i=1}^{5} \text{PSIZE}_i$$

The greatest variation in land ownership is found in Pando, a site in the Western Amazon SL, where the farm size ranges from as little as 1 ha or less to 800 Ha, followed by the Nicaragua & Honduras SLs. Three sites in Western Ghats, Mentebah, Sarolangun and Merangin have the lowest land ownership.

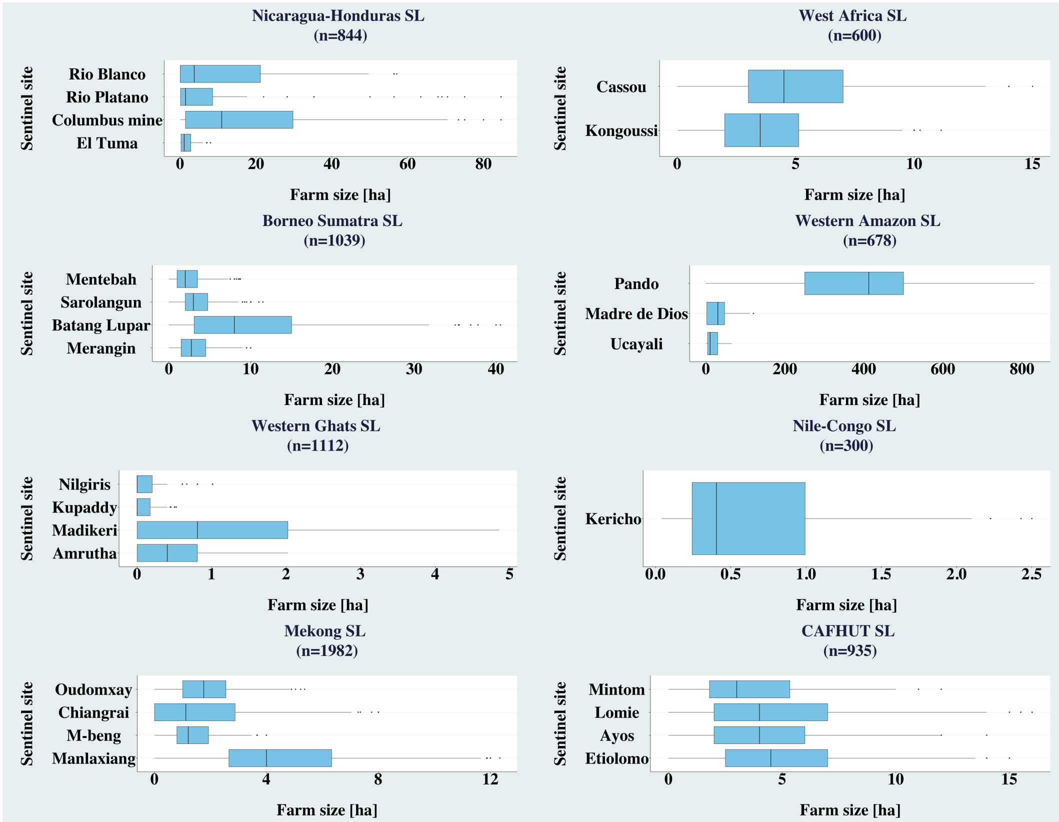

Figure 18: Farm size

2.2.0.2 Indicator: Progress out of Poverty Inde (PPI)

For more detailed information, refer to http://www.progressoutofpoverty.org/country/kenya

The Progress out of Poverty Index (PPI) is a poverty measure of the likelihood that a household falls below a certain threshold and was developed by the Grameen Foundation. It is constructed from a set of 10 questions on household socio-economic characteristics and asset ownership that are asked to the household and each item has a corresponding score. The results shows great variation of poverty when disaggregated at the country level. Households in the Peru and Bolivia sites, on average, have the lowest poverty prevalence rates at the International US$ 2.50 poverty threshold per day using the 2005 Purchasing Power Parity (PPP).

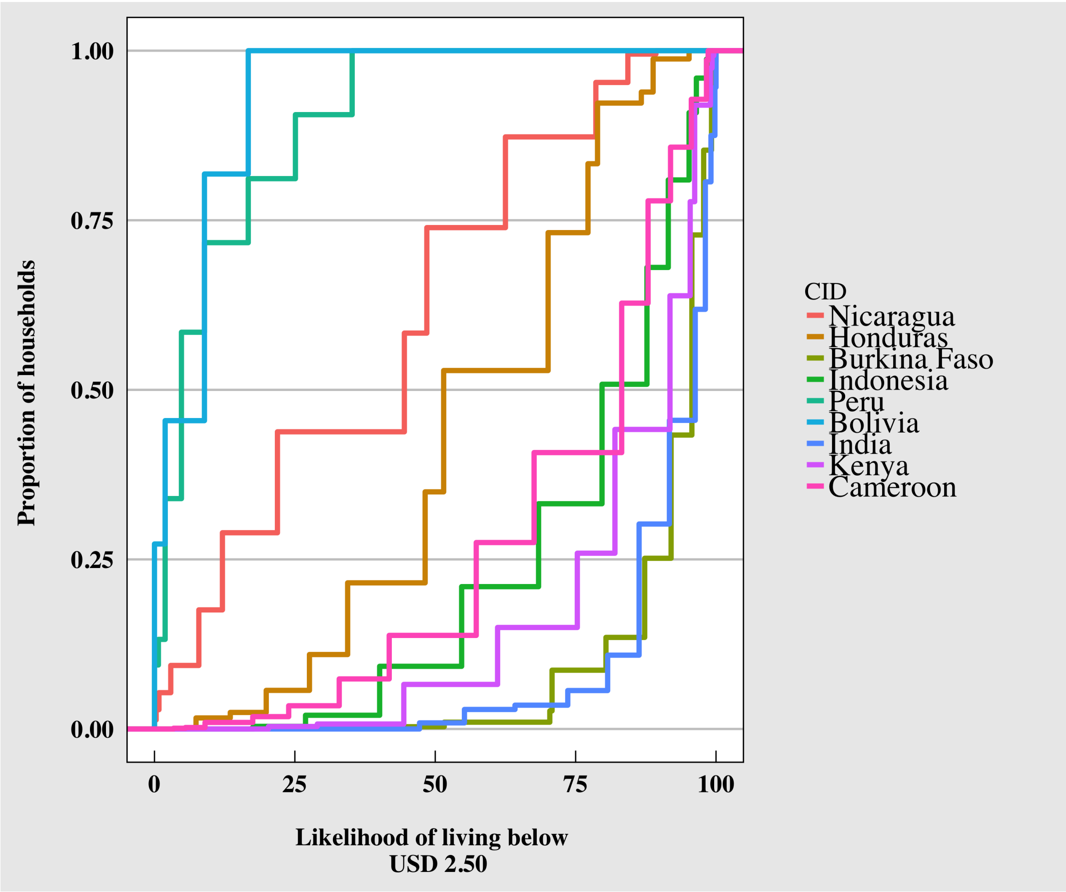

Figure 19: Progress out of poverty @USD 2.50 by country

2.2.0.3 Indicator: Food Diversity Score (FDS)

For more details see http://home.wfp.org/

Dietary diversity score is a measure of household nutrition that can be defined as number of food groups based on a 7-days recall. It is measured by simply counting the number of food or food groups consumed within the given reference period. There is great variation within and across the sentinel sites (each represented by a distinct color).

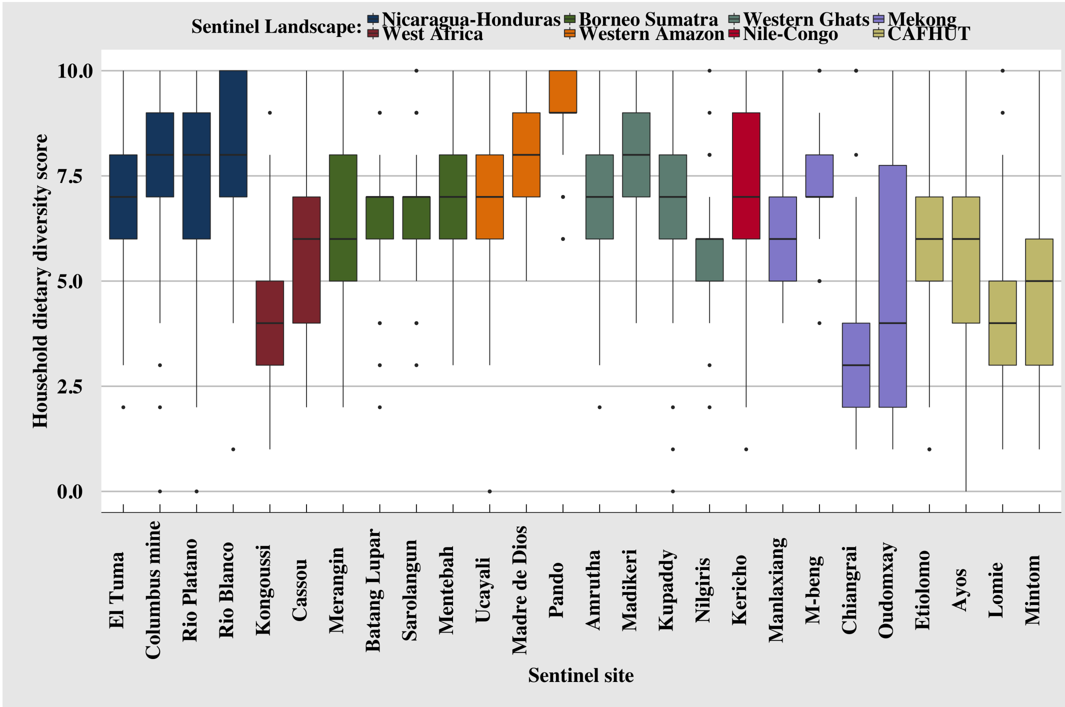

Figure 20: Food diversity score

2.2.0.4 Indicator: Gendered control of land by country

The Figure below shows the gendered control of land categorized by country. In most of the sites, men control most land For example, men have sole control of 94% of the land in the sites in Burkina Faso, while in the sites in China, 84% of the land is under joint control. In Nicaragua, 26% of the land is controlled by women (which is the highest) followed by Cameron and Kenya, respectively.

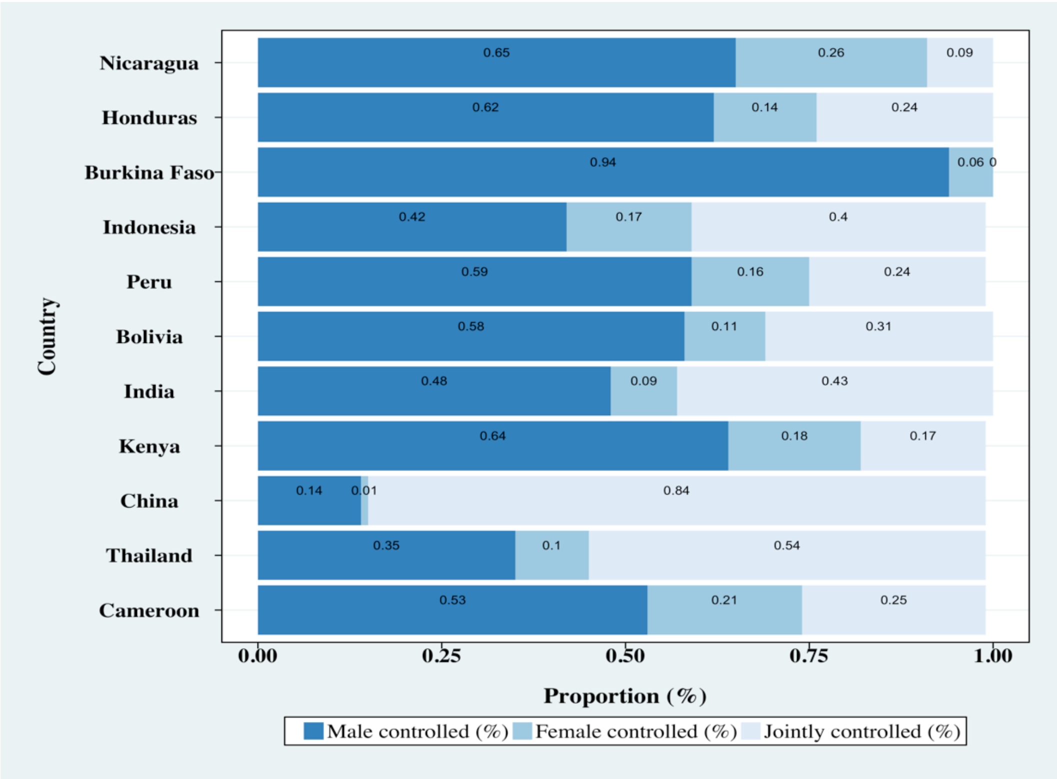

Figure 21: Gendered control of land by country

2.3 Ongoing analysis

Ongoing analysis is looking at a number of aspects of the SL network data, including integrated indicators of social and ecological aspects as outlined in Figure 22. These studies are looking at the data along three main dimensions: livelihoods, land health and institutions. One of the topics being explored is how rural people can benefit from tree resources and are willing and capable of investing in the sustainable management of these resources. Other studies are looking at soil health and land degradation in the SLs, with particular focus on drivers of changes in land cover, soil health and land degradation status. In addition, several case studies have been completed and reported for some of teh landscapes, as reflected on the FTA Sharedpoint site.

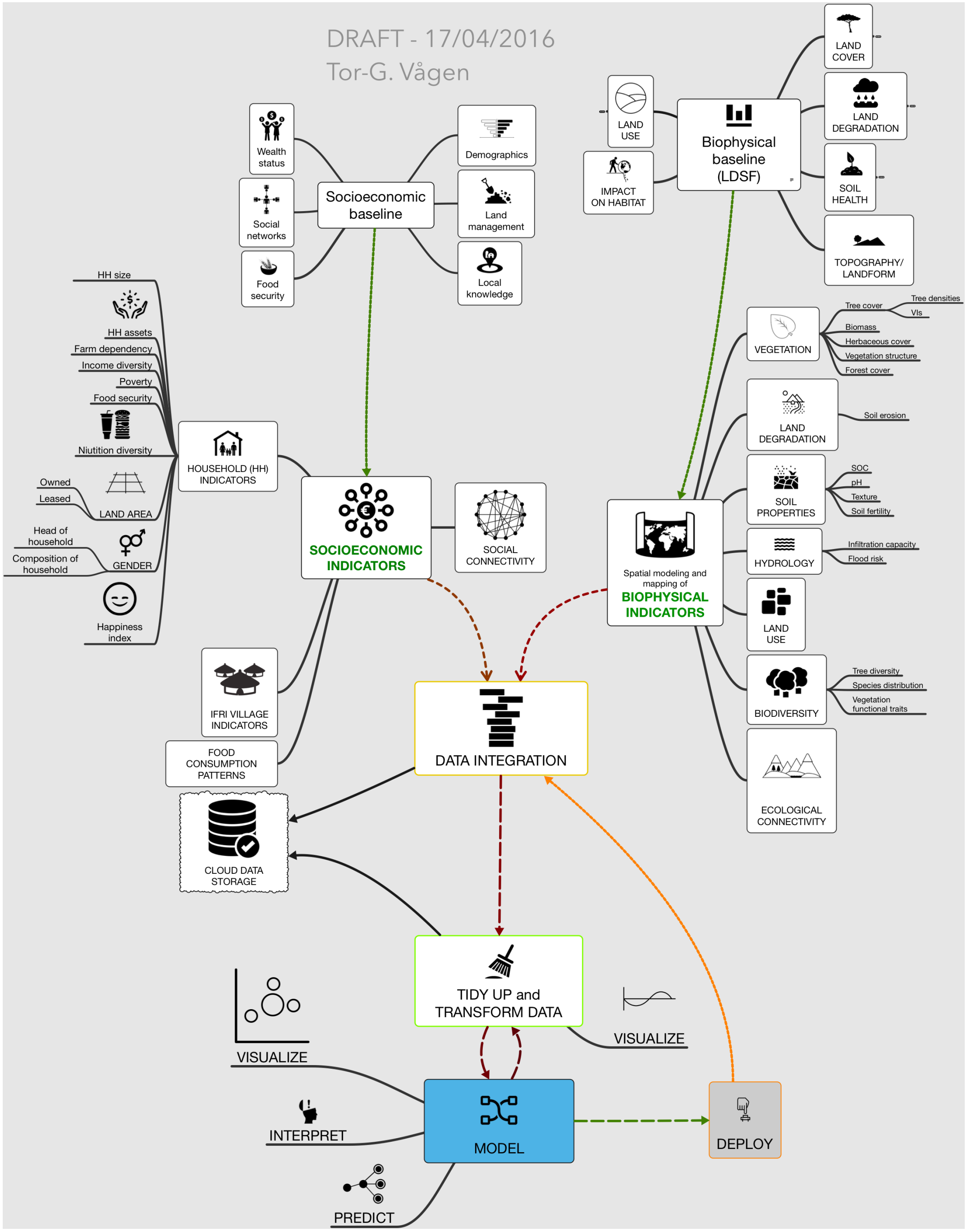

Figure 22: Outline of the conceptual framework for the integration of social and ecological indicators collected as part of the SL initiative.

3 Summary of status

			Socioeconomic			Village			LDSF			
Landscape	Country	Site	Cleaned & verified	Indicators	Dataverse	Cleaned & verified	Indicators	Dataverse	Cleaned & verified	Wet chemistry	Carbon/Nitrogen	Dataverse
Nicaragua Honduras	Nicaragua	El Tuma	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nicaragua Honduras	Nicaragua	Columbus Mine	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nicaragua Honduras	Honduras	Rio Platano	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nicaragua Honduras	Honduras	Rio Blanco	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
West Africa	Burkina Faso	Kongoussi	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
West Africa	Burkina Faso	Cassou	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
West Africa	Ghana	Walembele			✓				Omitted	Omitted	Omitted	x
West Africa	Ghana	Bawku			✓				Omitted	Omitted	Omitted	x
Borneo-Sumatra	Indonesia	Merangin	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Borneo-Sumatra	Indonesia	Batang Lupar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Borneo-Sumatra	Indonesia	Sarolangun	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Borneo-Sumatra	Indonesia	Mentebah	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Western Amazon	Peru	Ucayali	✓	✓	✓	✓	✓	✓	✓	In progress	In progress	✓
Western Amazon	Peru	Madre de Dios	✓	✓	✓	✓	✓	✓	✓	In progress	In progress	✓
Western Amazon	Bolivia	Pando	✓	✓	✓	✓	✓	✓	✓	Pending	Pending	✓
Western Ghats	India	Amrutha	✓	✓	✓	✓	✓	✓	✓	Pending	Pending	✓
Western Ghats	India	Madikeri	✓	✓	✓	✓	✓	✓	✓	Pending	Pending	✓
Western Ghats	India	Kupaddy	✓	✓	✓	✓	✓	✓	✓	Pending	Pending	✓
Western Ghats	India	Nilgiris	✓	✓	✓	✓	✓	✓	✓	Pending	Pending	✓
Nile-Congo	Kenya	Kericho	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nile-Congo	Uganda	Mt. Elgon	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nile-Congo	Rwanda	Gishwati/Begesera	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Nile-Congo	Ethiopia	Bako/Melkassa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mekong	China	Manlaxiang	✓	✓	✓	✓			✓	✓	Done locally	✓
Mekong	China	Menghan	✓	✓	✓	✓			Omitted	Omitted	Omitted	x
Mekong	Thailand	Chiangrai	✓	✓	✓	✓			Omitted	Omitted	Omitted	x
Mekong	Laos	Oudomxay/Mbeng	✓	✓	✓				✓	✓		✓
CAFHUT	Cameroon	Etiolomo	✓	✓	✓	✓	✓	✓	✓	✓		✓
CAFHUT	Cameroon	Ayos	✓	✓	✓	✓	✓	✓	✓	✓		✓
CAFHUT	Cameroon	Kongo/Lomie	✓	✓	✓	✓	✓	✓	✓	In progress		✓
CAFHUT	Cameroon	Mintom	✓	✓	✓	✓	✓	✓	✓	In progress		✓

***Sites shown as omitted were not completed due to cuts in funding.**

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