Synthesis Paper: Holistic Climate Soil Carbon Monitoring Approaches and Potentials

Content

1 Global Frame

As the global population continues to grow, so the demand for food production also increases. The interaction between food production (agriculture), climate change and land degradation is getting increasing attention due to the shared challenges and potential solutions to address multiple global challenges. Both climate change and ongoing land degradation limit global food production through rising temperatures, changes in precipitation patterns, extreme climatic events, and decreased productivity of agricultural soils due to land degradation (IPCC, 2019). These challenges especially affect many smallholder farmers in seasonally dry and tropical developing countries who produce a large share of the world's food (FAO, 2020; Thompson and Cohen, 2012). With nearly 1/4 of the world's landscapes already degraded, the ability of soils to provide ecosystem services such as providing the largest terrestrial carbon sink is severely limited (Chotte et al., 2019).

It has been widely recognized that through sustainable land management (SLM), carbon protection and sequestration in soils can contribute to climate change mitigation through negative and prevented emissions (IPCC, 2014), as well as adaptation by impeding land degradation and providing multiple co-benefits for food security and biodiversity by improving soil health and fertility (FAO, 2020; Sykes et al., 2019).

The Agriculture, Forestry and Other Land Use (AFOLU) sector is one of the biggest emitters of greenhouse gas (GHG). Unsustainable land uses contribute 10-12 $GtCO_2e$ per year, or nearly 25% of global emissions. About half of this is due to agriculture (IPCC, 2019), which is also the most vulnerable sector to climate change. Yet, the land sector, holds a large mitigation potential (Griscom et al., 2020). The global soil carbon mitigation potential from agricultural soil is estimated to be 2-5 $GtCO_2eq$ per year (Fuss et al., 2018; Smith et al., 2019), with sequestration rates due to management practices in agricultural lands estimated in the range of 0.2-0.8 t C/ha/year (FAO, 2020). A large proportion of this SOC sequestration potential lies in developing countries, especially in the tropics (Griscom et al., 2020), but also in dryland countries.

During the past five years there has been an increase in the development of an enabling political-instrumental environment that would support the adoption of SLM practices that support SOC protection and sequestration. From a climate change perspective, this is illustrated through the Paris Agreement (United Nations, 2015), the Koronivia Joint Work on Agriculture (KJWA) (UNFCCC, 2018), and the Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate and Land (IPCC, 2019) under the UNFCCC. In terms of land degradation, the UNCCD has set Land Degradation Neutrality (LDN) by 2030 as its main target. LDN is also the goal of Sustainable Development Goal (SDG) 15.3 with its indicator 15.3.1 ("proportion of land that is degraded over total land area") which consists of three sub-indicators and metrics that includes SOC (Orr et al., 2017).

Through these global conventions and mechanisms, countries have set national targets to prevent or reduce GHG emissions (through Nationally Determined Contributions to the Paris Agreement) and reduce land degradation by implementing SLM and enhancing SOC sequestration (through national LDN target setting). As a result, countries are required to monitor and report on SOC stocks and stock changes to track and report on progress in achieving their set targets.

Efficient monitoring systems are important to display both the current global and local development of land degradation and to evaluate the efficiency of undertaken actions. This is also essential for the allocation of climate finance, which can be used to overcome investment barriers in the SLM sector. Climate finance, in forms of funds or through carbon markets, must be justified by demonstrated effects on GHG emissions and/or adaptation to climate change. Furthermore, the provision of information on indicators of land degradation, like soil organic carbon (SOC), in the form of maps shows how degraded the land is and how well it can recover. This helps to prioritize land restoration over huge areas to target rehabilitation efforts efficiently with the limited financial resources (Winowiecki & Vågen, 2018).

Thus, comprehensive monitoring systems are crucial for worldwide SOC protection and enrichment.

However, efficient monitoring systems are complex and a diversity of approaches exist. In the following sections, this paper provides further information on the requirements of climate soil carbon monitoring and will provide insights on existing monitoring approaches and case studies.

2 Approaches, challenges and requirements

Under the UNFCCC, countries are required to monitor and report data on emissions, mitigation commitments and related actions and do so using a measurement, reporting and verification (MRV) framework. Essentially, MRV refers to processes whereby information is provided, examined and assessed to see whether parties meet their obligations. The process includes direct measurement or estimated calculations (M) of emissions and emission reductions, reporting (R) the measurement results through relevant documentation, and verifying (V) the quality of the data and estimates through specific procedures or expert reviews. Countries may also develop or have national MRV systems in place to support national tracking of progress towards climate-resilient and lower-carbon economies. With increased opportunity to include SOC in voluntary carbon markets (VCM), MRV has become a critical tool to assess and verify changes in SOC resulting from project implementation.

Monitoring and Evaluation (M&E) systems are used by governments, international organizations, NGOs and other project implementing agencies for their own tracking and policy purposes. These M&E systems include project-based M&E systems, as well as sectoral M&E systems that government agencies use to track the progress and outcomes of national plans and programs, including national land management, agriculture and other plans that promote SLM. Including SOC monitoring in SLM projects is essential as a tool to support adaptive management, build confidence for investments in activities that improve soil health, as well as track and account for impacts resulting from such activities that would drive subsequent investment to enhance the further adoption of SLM practices.

Together with national statistical systems, sectoral M&E systems often provide the data and assessments used to measure and report progress on mitigation and adaptation at national and international levels. International, domestic and project monitoring, evaluation and reporting processes are distinct but closely related and should ideally be integrated to ensure the all levels benefits from data generation.

The following sections provide a synopsis of the main SOC monitoring approaches, as well as important requirements for effective SOC monitoring.

2.1 SOC measurement/ monitoring approaches

Various tools and methodologies for GHG assessments exist, but in the past, many of them excluded SOC stocks and land use change (Colomb et al., 2013). SOC content is not easily measured, which presents a key barrier to implementing programmes to increase SOC at large scale and track the impact of implementation on SOC stocks (Smith et al., 2020). Due to the complex nature of SOC stock changes resulting from specific management practices such as SLM and high costs associated with direct SOC measurement, there is still a critical need for standardized, robust, reliable, cost-effective and easily applicable monitoring, reporting and verification (MRV) platforms applicable to different agricultural systems to assess SOC stocks and stock changes (FAO, 2020).

Credible and reliable MRV platforms are required for national monitoring and reporting, as well as for emissions trading to reduce the risk of investments related to SOC (Smith et al., 2020). From a climate finance and VCM perspective, donors and buyers of carbon credits require reliable proof that the required amount of carbon offsets have occurred. Such proof is essential to minimize investment risk, as well as reputational risk through the ability to show a carbon footprint with quality offsets and avoiding external criticism and concern about activities they are involved in while delivering the required amount of offset.

For SOC monitoring results to be reliable, it needs to effectively demonstrate that the adopted management practices in a specific area or project are resulting in the preservation of SOC stocks or SOC sequestration over the medium term as compared to an initial or baseline scenario. This requires the accurate and repeated measurement of SOC stock to determine the baseline stock and track stock changes over time.

SOC measurement can be done directly by taking and analyzing representative soil samples, or indirectly using activity-based, model-based, or remote-sensing based approaches (FAO, 2020; Smith et al., 2020). However, indirect approaches still require direct SOC measurement to calibrate and determine the accuracy of the respective methods. Table 1 summarizes the main characteristics, advantages and challenges associated with each approach and Table 2 provides a summary of specific examples and their key characteristics.

2.2 Key challenges

The design and implementation of SOC monitoring systems is complex and pose several scientific, technical and operational challenges at various levels (Smith et al., 2020; Wiese-Rozanova et al., 2020) as follows:

- Potentially high initialization costs associated with the development and implementation of integrated SOC monitoring systems and associated networks
- Insufficient access to appropriate measuring and monitoring technologies
- High costs of direct SOC measurement and insufficient activity data to apply accurate modelling of SOC stocks
- Insufficient accuracy, affordability and data availability for MRV and monitoring changes in SOC, especially at smallholder farmer level
- Difficulty to infer changes in SOC stocks based on the implementation of management practices
- Practices that are good for SOC sequestration may not be considered economically viable by land users, leading to low adoption
- Insufficient ability to track implementation of specific SLM practices and changes in those practices
- Increases in SOC are slow and potentially small compared to the baseline which makes it difficult to detect changes in SOC stocks
- Insufficient capacities to collect relevant data and monitor country- or project-specific emission factors and SOC changes
- The more complex the monitoring system, the more capacity development is required to apply it efficiently

2.3 Requirements

Considering the challenges associated with SOC monitoring, several requirements need to be considered when selecting developing, selecting or customizing an appropriate SOC monitoring system:

2.3.1 Reliability and scale

SOC stocks at any given time is influenced by a number of factors including plant inputs, land use and management activities, climate, and soil types. Increases in SOC generally occur over many years, and it is often difficult to identify small changes, especially if the baseline SOC content is high. Therefore, a larger change in total SOC stock, which may take several years or longer to occur, is required before a significant change could be measured with any degree of confidence. (FAO, 2020; Smith et al., 2020). To be reliable, SOC monitoring protocols therefore need to be designed to detect changes in SOC over relevant spatial and temporal scales, with adequate precision and statistical power (Smith et al., 2020).

Related to reliability of SOC monitoring is the required spatial scale at which SOC monitoring takes place (i.e. national, regional, local, or field scale), which impacts the data required to accurately quantify SOC stocks and stock changes. As a result, the SOC monitoring approach would differ when applied for national inventories compared to project monitoring, for example. Particularly at field-to-local scale there are significant challenges related to the potentially high variability in SOC stocks within a field which requires intensive sampling for accurate assessment. At regional or national level, the approach tends to be more aggregated based on potentially larger datasets which improves confidence in SOC estimates (Smith et al., 2020).

2.3.2 Practicability

A particular SOC monitoring approach must be feasible to apply in practice which requires (Mäkipää et al., 2012; Smith et al., 2020):

- **Suitability**: A particular SOC monitoring system should be suitable for the particular purpose and scale at which it is to be applied. In other words, it needs to account for the most important factors affecting SOC and changes in SOC stocks in the particular context. In order to optimize SOC monitoring for a specific purpose (i.e. a SOC project), a combination of approaches may be considered and combined to yield optimal information and results.
- **Data/information availability:** The required input information for a specific approach should be available, substitutable using default values or estimates from literature, or possible to generate as part of the SOC monitoring process
- **Cost efficiency:** The costs associated with collecting, processing and storing soil samples, as well as analysing relevant soil properties such as C content, bulk density and stone content is generally considered labour- and cost-intensive (Smith et al., 2020). Direct SOC measurement should therefore be used strategically whenever possible to determine a quality baseline and provide local data to calibrate any indirect approaches used.

2.3.3 Connectability

It is important for a SOC monitoring system process to link with other available institutional data collections and platforms. This is important to share data across locations and practices, enable the use of data for reporting at different scales and purposes, and to improve provide additional data for the continuous improvement of calculations and models at various scales.

2.3.4 Capacity development

Sufficient national and local capacities will be required to select, design or modify and implement a SOC monitoring system. Available capacities need to be considered and relevant capacity development included in the implementation process to support efficient SOC monitoring.

Table 1. Summary of SOC measurement approaches, advantages, disadvantages and examples (adapted from (Angelopoulou et al., 2019; Croft et al., 2012; Mäkipää et al., 2012; Smith et al., 2020))

	Direct measurement	Activity-based models	Remote-sensing (RS) based models
Description	Physical soil sampling for laboratory analysis	Soil organic matter (SOM) is represented using 2-5 carbon pools that differ in carbon residence time	Remote sensing data generated from satellites, aircraft, or Unmanned Aerial Systems
	Essential analyses: organic carbon, bulk density, stone content	Residence times controlled by decay rate of carbon in the different pools	Soil spectral signatures are defined by the reflectance of electromagnetic radiation by chemical substances as a function of wavelength
	Useful analyses: soil texture, inorganic carbon	Data: field areas, crops grown, crop yields of last agricultural season, types of SALM practices implemented, quantity of agricultural inputs by type, crop productivity, amount of crop residues and residue management, information on livestock to calculate manure input (number of cattle, sheep, etc.), depending on the specific model.	Soil reflectance varies according to chemical factors, such as soil mineralogy, SOM content and soil moisture, and physical structure, such as surface roughness and particle size
	Need robust study design and clear sampling protocols that account for spatial variability in SOC	Machine learning applied to predict soil properties from spectral data, libraries, and laboratory measurements based on collected data	Data: cover crop presence and patterns, tillage, residue coverage, crop type, flooding, etc.
	Requires resampling to track changes in SOC stocks		
Advantages	Relative accuracy	Makes use of measurements taken elsewhere	Non-destructive method to collect information about soil properties
	Direct measurement of SOC - no proxies needed	Increased measurements and further development continuously improve the system	Provided data covers large geographical areas
	Provides calibration data for indirect measurement approaches	Application in one country benefits from all previous system developments in other countries	Can provide information in otherwise inaccessible areas
	Sampling design and soil measurements can be coordinated with national inventories	Possibility to improve the model using direct measurements	Help to reduce the need for direct soil sampling
	Existing well-established statistical procedures to estimate uncertainties	Less expensive than soil sampling and remote sensing	SOC predictions can be continuously improved by using ancillary data, scale-specific methods, improved development of spectral libraries and better integration of RS technologies into empirical and simulation SOC models, etc.

	Trend estimates can be verified with model-based estimates	Allows a tiered approach if limited data is available	Can use a variety of RS data to monitor spatio-temporal SOC dynamics
	Other soil properties can also be determined from collected samples		Can apply direct measurement of SOC using reflectance from the bare soil surface, or indirectly by linking RS images with field data
Disadvantages	Usually measurement in top 30cm, but SOC sequestration often occurs deeper	Activity-based data still missing or insufficient	Restricted sensing in wet tropical areas due to high cloud coverage
	Laborious and expensive to collect, process, store and analyze soil samples	Data is needed to calibrate estimates across different landscapes	Negatively affected by heterogeneity of farming patterns
	Requires repeated sampling and repeated costs	Soil processes are not linear and often go beyond project duration which limits reliability of estimates	Remotes sensing techniques have low signal to noise ratio, low spectral resolution, and are subject to geometric and atmospheric distortions
	Destructive sampling method	Many models calibrated for temperate ecosystems and not as robust for tropical ecosystems with weathered soils	Remote sensing estimations are limited to the first few centimeters of topsoil
	Usually requires high number of samples to account for spatial variability	Lack of long-term datasets to text model performance	There is not yet a modeling approach that takes into account the partly complex data processing steps from RS spectrometric data and proximal soil sensing data with the influence of in situ disturbance variables
	Resulting information is not spatially continuous and requires interpolation	Estimation of plant input based on allometric relationships leads to large uncertainties	SOM content must be >2% to exert a measurable effect on soil reflectance
			SOM signal can be masked by other biochemical components e.g. iron and manganese
Considerations	Evaluate direct measurement costs against the value of SOC sequestered and search for trade-offs and alternative SOC estimation methods	Information on land use history can improve estimates	
		Need to measure the amounts of biomass entering and getting off the field to improve SOC estimates	
	Use a combination of direct measurements (at the plot scale), activity tracking, modeling and remote sensing (at larger spatial scales) for the most cost-effective and reliable estimates.		

Table 2. Examples of activity-based and remote-sensing based approaches to SOC monitoring and their main characteristics, advantages and disadvantages

Example	Description	Data and specificity
	Activity-based models	
Ex-Ante Carbon-balance Tool (EX-ACT)	• Free appraisal system developed by FAO providing estimates of the impact of agriculture and forestry development projects, programmes and policies on the carbon-balance • Land-based accounting system – relates activity data to estimated values of the five carbon pools, including SOC • **Ex ante model** that **predicts future C stock changes** based on planned management activities • Estimates C stock changes (i.e. emissions or sinks of CO_2) as well as GHG emissions per unit of land, expressed in tCO2eq/ha/yr • Helps project designers to estimate and prioritize project activities with high benefits in economic and climate change mitigation terms • Provides eight modules (Microsoft Excel sheets) for different AFOLU activity areas • Modules for SLM: Crop production and management, Grassland and livestock • Information is entered based on changes occurring *With Project vis a vis Without Project* situation – i.e. compares impacts of a planned intervention to the business-as-usual scenario • Can accommodate two levels of data specificity using a tiered approach	**Tier 1 data**: – uses IPCC recognized default values for emission factors and carbon values – includes data on wide range of land-use change activities and agricultural management practices with relatively few geographical, climatic and agro-ecological variables – **low specificity** – easiest to procure for project managers as part of standard information available in project appraisal documents **Tier 2 data:** – more complex than Tier 1 – allows for location-specific variables that provide specific carbon content and stock changes for all five carbon pools and emission factors for selected practices – example variables: SOC content, rates of SOC sequestration per land use, crop residue management, N2O and CH4 emissions from manure management, etc. – data can be difficult and expensive to collect, so it is strongly advised for core project components providing stronger GHG sources or sinks – **higher specificity** that Tier 1 with increase in location-specific data
Rothamstead carbon model (RothC)	• The only SOC monitoring system applicable in the Voluntary Carbon Standard for Sustainable Agricultural Land Management (SALM) Carbon Accounting Methodology • Freely available model developed by Rothamstead Research • Models medium to long-term turnover of organic carbon in non-waterlogged topsoils, allowing for effects of soil type, temperature, moisture content, and plant cover • Uses monthly time step to calculate total organic carbon (t/ha), microbial biomass carbon (t/ha) and changes in ^{14}C on a years to centuries timescale	**Required data:** – Monthly rainfall (mm) – Monthly open pan evaporation (mm) – Average monthly mean air temperature (^{o}C) – Clay content of the soil (as a %) – Estimate of decomposability of incoming plant material (DMP/RPM ratio) – Soil cover – is the soil bare or vegetated in a particular month? – Monthly input of plant residues (tC/ha) – Monthly input from farmyard manure (FYM) (tC/ha) if any – Depth of soil layer sampled (cm) **Higher specificity** based on localized data

	• Runs in two models: “forward” using known inputs to calculate changes in SOM and “inverse” which calculated inputs from known changes in SOM • **Ex-post model** that **models C stocks after implementation** of management activities	**Specificity may be affected** if some parameters need to be substituted from external sources e.g.: – If soil clay content is derived from literature rather than direct measurement or site-specific data – Substituting monthly open pan evaporation with potential evaporation values from literature
Remote-sensing based model		
Land Degradation Surveillance Framework (LDSF)	• Developed by World Agroforestry Centre (ICRAF) to assess soil and land health using indicators and field protocols • Indicators: vegetation cover and structure; tree, shrub and grass species diversity; current and historic land use; infiltration capacity; soil characteristics; land degradation status • Able to monitor SOC changes over a time • Data collected at multiple spatial scales to understand indicator variation across landscapes: – Random sites (10 x 10 km) across region/ watershed/ project area - Random clusters (2.5 x 2.5 km) per site - 10 plots (100 x 100 m) per cluster - 4 sub-plots (10 x 10 m) per plot • Indicators within the framework are mapped independently, but are related and relations can be modelled • Evidence is generated through systematic on the ground data collection, citizen science to crowd source data from apps and models to produce data and maps • Uses Open Data Kit for GPS field data collection • LDSF forms part of Ecosystem Health Surveillance System (EcoHSS) which uses open source tolls to apply statistical modeling and machine learning to assess processes of land degradation, soil functional properties, vegetation cover and biodiversity based on earth observation data and remote sensing • Sensors are available at 10 m (Sentinel 2) and 30 m (Landsat) spatial resolution, making it suitable for a smallholder farming context • Outputs mapped at fine resolution (5–10 m), high resolution (20-30 m) and moderate resolution (250-500 m)	**Plot-level** data collection: – Basic site characteristics described and recorded (altitude, slope, landform, presence/absence of soil and water conservation structures, vegetation cover and strata, land use, etc.) – Minimum 3 soil infiltration measurements per cluster **Sub-plot-level** data collection: – Soil surface characterization: ○ signs of visible erosion recorded and classified; percentage rock/stone/gravel cover on soil surface recorded) – Vegetation measurements: ○ (woody- and herbaceous cover ratings; woody plants, shrubs and trees counted, tree and shrub distance-based measurements taken) – Soil sampling: ○ Top- and subsoil samples collected at 0-20 cm and 20-50 cm using cumulative mass soil sampling ○ Samples pooled into 1 sample per layer per sub-plot ○ Auger depth restrictions (cm) recorded at each sub-plot if present **Earth observation** data: – Obtained from Copernicus and NASA – Sensors include Sentinels 1 and 2, Landsat and MODIS

3 Case studies and future development

3.1 Farmer-based monitoring systems in the Kenya Agricultural Carbon Project

The Kenya Agricultural Carbon Project (KACP) was initiated in 2008, and in 2009 became the first project to receive carbon credits issued under the sustainable agricultural land management (SALM) carbon accounting methodology, certified under the Verified Carbon Standard (VCS). Vi Agroforestry, a non-governmental organization, implements the project with ca. 30,000 smallholder farmers organized in 1,700 registered farmer groups[1] on 22,000 ha Based on the evaluated project successes, Vi Agroforestry scaled the project and included a dairy component with private investors. KACP provides advisory services to support farmers to adopt SLM practices, market crop produce, and manage savings and loan schemes, and also provides additional capacity building on family planning, HIV prevention, child nutrition, and other issues. SLM practices promoted by KACP include manure management, use of cover crops, composting and agroforestry. Carbon payments are one innovative element of the project. In the first ten years of the project, the average farmer sequestered about a total of 3 tCO_2 per hectare and year in the form of soil carbon and tree biomass. The carbon revenues are shared among farmer groups (60%) and used for advisory services provided by Vi Agroforestry (35%). 5% of the revenues have been used for administrative cost selling the credits. Carbon credit revenues covered only ca. 20% of the project costs. The monitoring costs are US$1.4/ha/year. However, the most important benefit for farmers is the increase in crop yields due to the combination of project interventions. Average maize yields have more than tripled from 1500 kg/ha in 2009 to more than 7,400 kg/ha in 2017. Progress in adoption of SLM measures and the resulting GHG emission reductions are tracked through an activity-based monitoring system. KACP monitors adoption of SLM practices, and a science based biophysical model (RothC) is used to estimate effects on soil carbon and GHG emissions. Supported by farmer group leaders, farmers self-report using a simple template for their agricultural crops and activities, along with land area, yield and specific SLM practices. Farmer group leaders collate the data from their members and produce a group summary that is sent to the project team via SMS. This provides the input data for estimation of carbon benefits, as well as data on adoption rates and proxy indicators of food security and other socio-economic benefits. The monitoring system is also used by farmers groups to identify training needs and priorities for advisory support. Activity monitoring engages farmers, provides crucial information to improve extension and supports self-learning by farmer groups, strengthening the commitment of farmers to the adoption of SLM activities and farmer groups' capacities. Several indicators monitored in KACP are relevant to adaptation and food security outcomes, such as numbers of beneficiaries (by gender) and crop yields. However, since funding for KACP does not explicitly target adaptation finance, the project has no separate adaptation reporting. During the scaling up of the KACP by Vi Agroforestry in another location, a tool based on the Revised Universal Soil Loss Equation was specially designed to use the activity data collected to estimate the benefits of SLM practices for soil and water conservation.

[1] Project development was initially supported and the carbon credits purchased by the World Bank BioCarbon Fund (BCF) and the Swedish International Development Agency (SIDA). The Livelihoods Funds and Brookside Dairy financed the scaling up.

3.2 Spatial assessments of soil organic carbon for stakeholder decision-making- a case study from Kenya (Vågen et al., 2018)

This case study shows the incorporation of a soil organic carbon (SOC) spatial assessment and socioeconomic data to develop an online platform, the Resilience and Diagnostic and Decision Support Tool (RDDST), which facilitates evidence-based decision making in Turkana County, Kenya. Importantly, this study points to the usefulness of SOC spatial assessments in monitoring the status of land degradation neutrality (LDN) compliance, examining how SOC dynamics can be included in decision-making.

Land degradation in Kenya costs approximately USD 1.5 Billion annually, which is close to 5% of its GDP (Munoz, 2016). Turkana County is located within the Arid and Semi-Arid Lands (ASALS) of Kenya, inhabited by about 1 million people, mostly pastoralists, and receives 250 mm of precipitation annually. Developing assessment tools for soil and land degradation is of critical importance, especially since Kenya is currently debating baseline assessments and monitoring of the Sustainable Development Goal (SDG) 15.3 targets.

Using the Land Degradation Surveillance Framework (LDSF), key indicators of land degradation risk, including soil organic carbon (SOC), soil erosion and others were assessed based on data from several LDSF conducted in the tropics. The LDSF evaluates ecological indicators at four spatial scales (100 m^2, 1000 m^2, 1 km^2 and 100 km^2) in parallel utilizing a categorized sample layout. To examine SOC and other soil indicators, LDSF employs soil infrared (IR) spectroscopic analysis, which are budget-friendly and enable scaling up. Using 10 000 georeferenced archived LDSF plots and soil samples examined for SOC at the ICRAF Soil and Plant Diagnostics Lab in Nairobi, Kenya, the SOC spatial assessments were created. This assessment is used to detect temporal changes and setting up a land and soil health monitoring schemes, which enables proactive actions that can hinder land degradation or restore degraded ecosystems (Lohbeck et al., 2018). Based on the data gathered and analytical framework, an online platform was created, using Shiny web framework for R statistics, that generates interactive graphs and data management tools to engage with stakeholders and inform country-level and global decision-making processes.

Stakeholder engagement is a critical step towards effective and accelerated implementation of the 2030 agenda. As a response, a Stakeholder Approach to Risk Informed and Evidence Based Decision Making (SHARED) was developed to incorporate land assessments within the larger decision-making context in collaboration with stakeholders in Turkana County. Using evidence-based frameworks and scientific tools customized for decision needs enables a comprehensive inter-sectoral and inter-institutional approach that recognizes the complexity of decision-making processes.

The findings estimated Kenyan SOC stocks to be about 42 Mg Carbon (C) ha^{-1} stored in the upper 30 cm segment of soil. Arid and semi-arid areas, like Turkana County, had the lowest SOC stocks (an average of <20 Mg C ha^{-1}), whereas higher amounts were found in the sub-humid and humid (see Figure 1). SOC concentration also should the same result of a higher concentration in humid and sub-humid areas as opposed to drylands. As would be expected the highest SOC stocks exist in forest areas, such as around Mt. Kenya (>100 Mg C ha−1) and others (the Aberdares, the Mau Forest Complex and Kakamega Forest). Thus, although forest areas are only a small percentage of the total lands in Kenya, they are important carbon pools. Wetlands, such as Rift Valley lakes and lacustrine on the Kenyan coast, are another key carbon pool that store between 80 and 100 Mg C ha−1 at 0 to 30 cm depth, and offer other valuable ecosystems services critical for Kenyan land health and livelihoods (Minasny et al., 2017; Saunders et al., 2007; Zedler and Kercher, 2005).

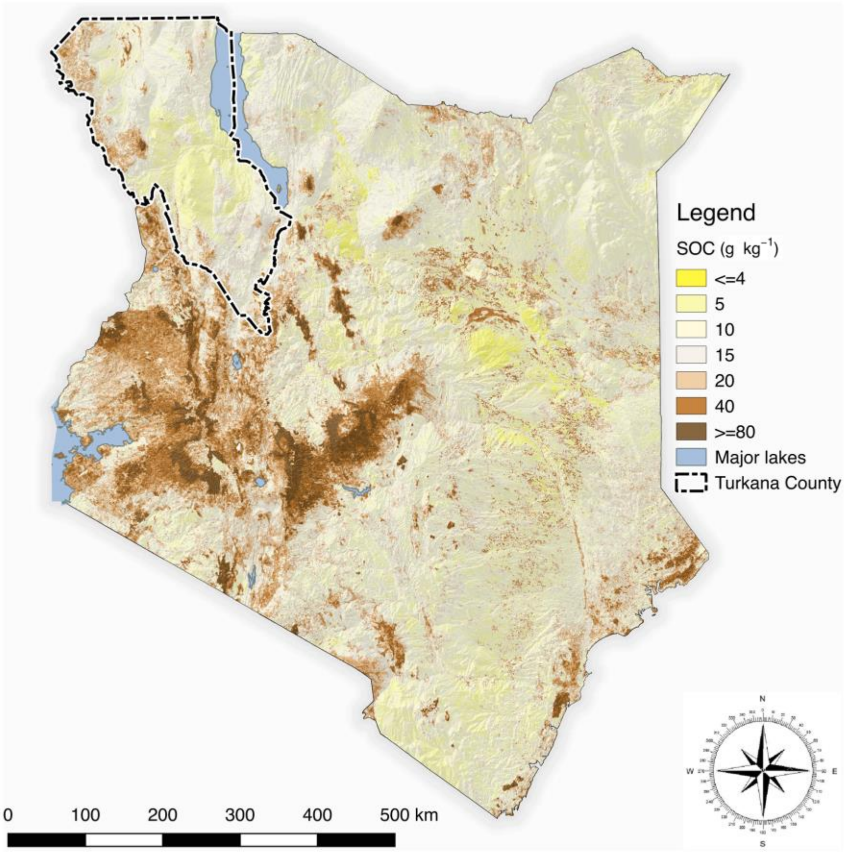

Figure 1. Soil Organic Carbon (SOC) map of Kenya with Turkana County outlined.

However, despite drylands having low SOC stocks, pockets with high SOC are exist in some areas including the Matthews Range, Ndoto, Marsabit and Kulal mountain, and the Loima Hills in Turkana County (see Figure 1, Figure 2). Thus, SOC pockets are of critical resources for pastoralists, especially for grazing during dry seasons (Oba et al., 2000), in addition to being biodiversity hotspots.

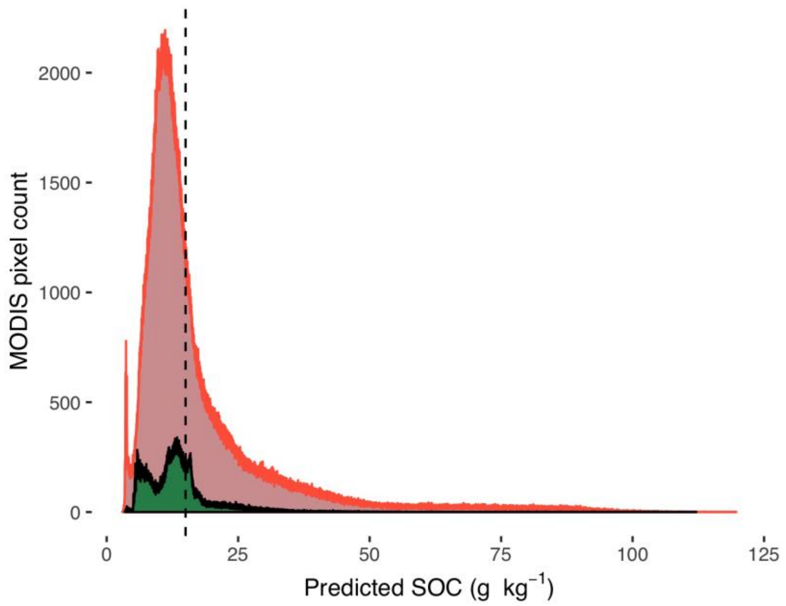

Figure 2. Histograms exhibiting SOC distribution in Turkana County (green) as opposed to the rest of Kenya (red). The vertical dashed line denotes a SOC concentration of 15 g/kg.

The RDDST tool was generated during several workshops guided through the SHARED mechanism with the participation of representatives from Turkana County government, the United Nations, and non-government organizations (NGOs). To examine resilience within Turkana County, SOC maps were integrated in the RDDST tool using data from multiple sectors including education, health, security, and environment (see Figure 3). Importantly, takeaways and recommendations from these workshops and the RDDST tool were used to the Turkana County Integrated Development Plan (CIDP) for the period 2018 to 2022. Furthermore, visualizing different land health indicators, such as vegetation cover an SOC stock, in parallel with other sectoral data resulted in a paradigm shift in decision-making that enabled identifying integrated county-integrated flagships that tackle land management and restoration while also addressing social and economic sectors.

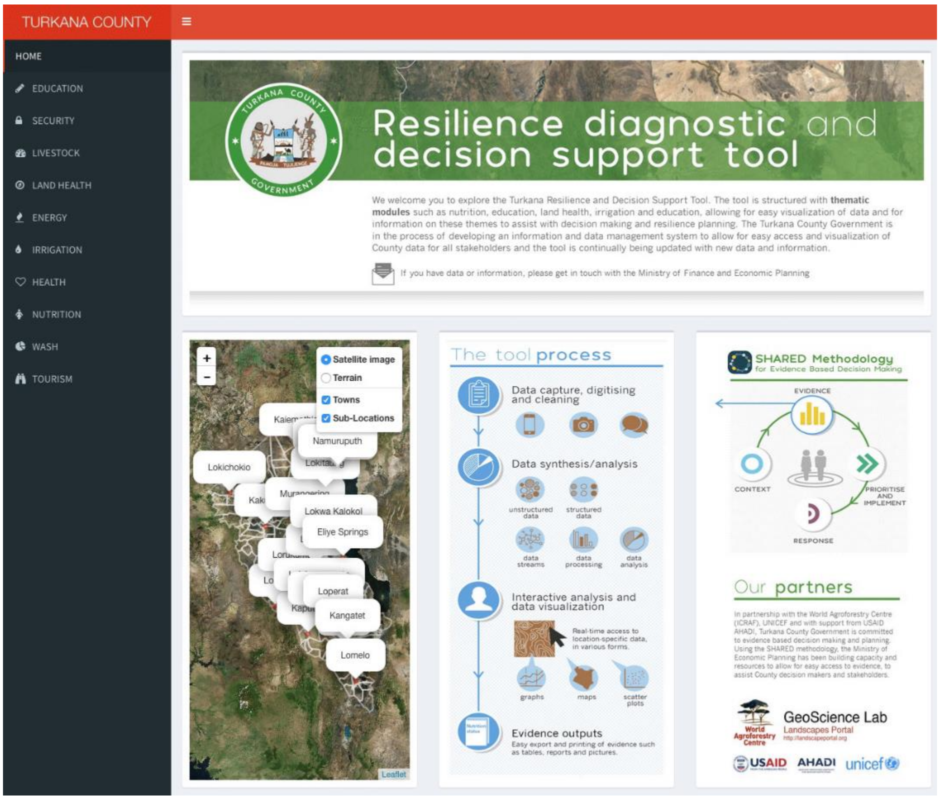

Figure 3. The main page of the Resilience Diagnostic and Decision Support Tool (RDDST) for Turkana County.

As evident from this study, spatial assessments of SOC concentration and stocks, in addition to other land and soil health indicators, are integrated into interactive dashboards that allow diverse users to consider land health indicators when identifying interventions. Additionally, the SHARED process underpinning the development of the RDDST was strengthened through organized stakeholder participation and shared learning and designing of the tools. Finally, this process proved instrumental in encouraging the uptake of land restoration interventions as well as those that increase SOC, all of which will contribute to achieving LDN and SDG 15 targets.

3.3 Links to examples of evidence from practice

- Land Degradation Surveillance Framework (LDSF):
- SALM - KACP
- FAO Ex-Ante Carbon-balance Tool (EX-ACT) – Tanzania?
- Direct sampling: Soil carbon monitoring in the United Republic of Tanzania (Mäkipää et al., 2012, chap. 5)
- Do we have an example where SOC monitoring is used for national GHG Inventories?

4 Actor and process mapping

- ICRAF
- Unique
- DLR
- FAO/GSP

5 References

Chotte, J. L., Aynekulu, E., Cowie, A., Campbell, E., Vlek, P., Lal, R., Kapović-Solomun, M., Maltitz, G. von, Kust, G., Barger, N., Vargas, R., & Gastrow, S. (2019). *Realising the Carbon Benefits of Sustainable Land Management Practices: Guidelines for Estimation of Soil Organic Carbon in the Context of Land Degradation Neutrality Planning and Monitoring. A report of the Science-Policy Interface.* Bonn, Germany. http://catalogue.unccd.int/1209_UNCCD_SPI_2019_Report_1.1.pdf

Griscom, B. W., Busch, J., Cook-Patton, S. C., Ellis, P. W., Funk, J., Leavitt, S. M., Lomax, G., Turner, W. R., Chapman, M., Engelmann, J., Gurwick, N. P., Landis, E., Lawrence, D., Malhi, Y., Schindler Murray, L., Navarrete, D., Roe, S., Scull, S., Smith, P., . . . Worthington, T. (2020). National mitigation potential from natural climate solutions in the tropics. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *375*(1794). https://doi.org/10.1098/rstb.2019.0126

IPCC. (2019). *Climate Change and Land: An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. Summary for Policymakers. Intergovernmental Panel on Climate Change. www.ipcc.ch

Jia, G., Shevliakova, E., Artaxo, P., Noblet-Ducoudré, N. de, Houghton, R., House, J., Kitajima, K., Lennard, C., Popp, A., Sirin, A., Sukumar, R., & Verchot, L. (2019). *Land–climate interactions. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. https://www.ipcc.ch/site/assets/uploads/sites/4/2020/07/05_Chapter-2-V2.pdf

Unger, M. von, & Emmer, I. (2018). *Carbon Market Incentives to Conserve, Restore and Enhance Soil Carbon*. Arlington, VA, USA. Silvestrum and The Nature Conservancy. http://4fqbik2blqkb1nrebde8yxqj-wpengine.netdna-ssl.com/wp-content/uploads/2018/09/TNC_Carbon-Market-Incentives-to-Conserve-Restore-and-Enhance-Soil-Carbon.pdf

Wiese-Rozanova, L. D., Alacantara-Shivapatham, V., Wollenberg, E., & Shelton, S. (2020). *Evaluating ambition for soil organic carbon sequestration and protection in nationally determined contributions. CCAFS Info Note.* Wageningen, the Netherlands. CGIAR Research Program on Climate Change Agriculture and Food Security (CCAFS). https://cgspace.cgiar.org/bitstream/handle/10568/108259/Info%20Note%20SOC%20in%20NDC%202020%20FINAL.pdf?sequence=1&isAllowed=y

Winowiecki, L. A., & Vågen, T.-G. (2018, August 15). Lessons from Kenya on how to restore degraded land. *The Conservation*. https://theconversation.com/lessons-from-kenya-on-how-to-restore-degraded-land-98178

Angelopoulou, T., Tziolas, N., Balafoutis, A., Zalidis, G., Bochtis, D., 2019. Remote sensing techniques for soil organic carbon estimation: A review. Remote Sens. 11, 1–18. doi:10.3390/rs11060676

Croft, H., Kuhn, N.J., Anderson, K., 2012. On the use of remote sensing techniques for monitoring spatio-temporal soil organic carbon dynamics in agricultural systems. Catena 94, 64–74. doi:10.1016/j.catena.2012.01.001

FAO, 2020. A protocol for measurement, monitoring, reporting and verification of soil organic carbon in agricultural landscapes – GSOC-MRV Protocol. FAO, Rome. doi:10.4060/cb0509en

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., de Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., Vicente, J.L.V., Wilcox, J., del Mar Zamora Dominguez, M., Minx, J.C., 2018. Negative emissions—Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13, 063002. doi:10.1088/1748-9326/aabf9f

IPCC, 2019. Climate Change and Land: An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. Summary for Policymakers. Edward Elgar Publishing.

IPCC, 2014. Summary for Policymakers, Climate Change 2014: Mitigation of Climate Change. Contribution of Work- ing Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Mäkipää, R., Liski, J., Guendehou, S., Malimbwi, R., Kaaya, A., 2012. Soil carbon monitoring using surveys and modelling: general description and application in the United Republic of Tanzania, FAO Forestry Paper.

Orr, B.J., Cowie, A.L., Castillo, V.M., Sanchez, P., Chasek, N.D., Crossman, Erlewein, A., Louwagie, G., Maron, M., Metternicht, G.I., Minelli, S., Tengberg, A.E., Walter, S., Welton, S., 2017. Scientific Conceptual Framework for Land Degradation Neutrality. A Report of the Science-Policy Interface, United Nations Convention to Combat Desertification - UNCCD.

Smith, P., Adams, J., Beerling, D.J., Beringer, T., Calvin, K. V., Fuss, S., Griscom, B., Hagemann, N., Kammann, C., Kraxner, F., Minx, J.C., Popp, A., Renforth, P., Vicente Vicente, J.L., Keesstra, S., 2019. Land-Management Options for Greenhouse Gas Removal and Their Impacts on Ecosystem Services and the Sustainable Development Goals. Annu. Rev. Environ. Resour. 44, 255–286. doi:10.1146/annurev-environ-101718-033129

Smith, P., Soussana, J., Angers, D., Schipper, L., Chenu, C., Rasse, D.P., Batjes, N.H., Egmond, F., McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J.E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A., Klumpp, K., 2020. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Glob. Chang. Biol. 26, 219–241. doi:10.1111/gcb.14815

Sykes, A.J., Macleod, M., Eory, V., Rees, R.M., Payen, F., Myrgiotis, V., Williams, M., Sohi, S., Hillier, J., Moran, D., Manning, D.A.C., Goglio, P., Seghetta, M., Williams, A., Harris, J., Dondini, M., Walton, J., House, J., Smith, P., 2019. Characterising the biophysical, economic and social impacts of soil carbon sequestration as a greenhouse gas removal technology. Glob. Chang. Biol. 1085–1108. doi:10.1111/gcb.14844

Thompson, B., Cohen, M.J., 2012. The impact of climate change and bioenergy on nutrition. The Food and Agriculture Organization of the United Nations and Springer Science+Business Media BV, Rome, Italy.

UNFCCC, 2018. Report of the Conference of the Parties on its twenty-third session, held in Bonn from 6 to 18 November 2017. Rep. Conf. Parties its twenty-third Sess. held Bonn from 6 to 18 Novemb. 2017 Add. Part two Action Tak. by Conf. Parties its twenty- third Sess.

United Nations, 2015. Paris Agreement.

Vågen, T.G., Ann Winowiecki, L., Neely, C., Chesterman, S., Bourne, M., 2018. Spatial assessments of soil organic carbon for stakeholder decision-making - A case study from Kenya. Soil 4, 259–266. doi:10.5194/soil-4-259-2018

Wiese-Rozanova, L.D., Alcantara-Shivapatham, V., Wollenberg, E.A., 2020. Evaluating ambition for soil organic carbon sequestration and protection in nationally determined contributions. CCAFS Info Note.

Lohbeck, M., Winowiecki, L., Aynekulu, E., Okia, C., and Vågen, T.-G.: Trait-based approaches for guiding the restoration of degraded agricultural landscapes in East Africa, edited by M. Isaac, J. Appl. Ecol., 55, 59–68, https://doi.org/10.1111/1365-2664.13017, 2018.

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z.-S., Cheng, K., Das, B. S., Field, D. J., Gimona, A., Hedley, C. B., Hong, S. Y., Mandal, B., Marchant, B. P., Martin, M., McConkey, B. G., Mulder, V. L., O'Rourke, S., Richer-de-Forges, A. C., Odeh, I., Padarian, J., Paustian, K., Pan, G., Poggio, L., Savin, I., Stolbovoy, V., Stockmann, U., Sulaeman, Y., Tsui, C.-C., Vågen, T.-G., Wesemael, B., and van and Winowiecki, L.: Soil carbon 4 per mille, Geoderma, 292, 59–86, https://doi.org/10.1016/j.geoderma.2017.01.002, 2017.

Munoz, P.: Land Degradation Neutrality (LDN) in Kenya, The Economic Case, UNCCD, Nairobi, Kenya, 2016.

Oba, G., Stenseth, N. C., and Lusigi, W. J.: New perspectives on sustainable grazing management in arid zones of sub-Saharan Africa, BioScience, 50, 35–51, https://doi.org/10.1641/0006-3568(2000)050[0035:NPOSGM]2.3.CO;2, 2000.

Saunders, M. J., Jones, M. B., and Kansiime, F.: Carbon and water cycles in tropical papyrus wetlands, Wetl. Ecol. Manag., 15, 489–498, https://doi.org/10.1007/s11273-007-9051-9, 2007.

Zedler, J. B. and Kercher, S.: WETLAND RESOURCES: Status, Trends, Ecosystem Services, and Restorability, Annu. Rev. Env. Resour., 30, 39–74, https://doi.org/10.1146/annurev.energy.30.050504.144248, 2005.