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# Smallholder Agriculture Takes Root in Climate Action: Evaluating soil organic carbon monitoring

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## Abstract

Voluntary carbon market (VCM) schemes facilitate funding for projects that promote sustainable land management practices to sequester carbon in natural sinks such as biomass and soil while also supporting agricultural production. The effectiveness of VCM schemes relies on accurate measurement mechanisms that can directly attribute carbon accumulation to project activities. However, measuring carbon sequestration in soils has proven to be difficult and costly, especially in the context of fragmented smallholdings predominant in global agriculture. The cost and accuracy limitations of current methods to monitor soil organic carbon (SOC) impede the participation of smallholder farmers in global carbon markets where they could potentially be compensated for adopting sustainable farming practices that provide ecosystem benefits. This study evaluates nine different approaches for SOC accounting in smallholder agricultural projects. The approaches considered involve the use of proximal and remote sensing along with process model applications. Our evaluation centers on stakeholder requirements for the Monitoring, Reporting, and Verification (MRV) system, using the criteria of accuracy, level of standardization, costs, adoptability, and the advancement of community benefits. By analyzing these criteria, we highlight opportunities and challenges associated with each approach, presenting suggestions to enhance their applicability for smallholder SOC accounting. The research gains its contextual foundation from a case study on the Western Remote sensing shows promise in reducing costs for direct and modeling-based carbon measurement. While its use is seen in certain carbon market applications, transparency is vital for broader integration. This demands collaborative work and investment in infrastructure like spectral libraries and user-friendly tools. Balancing community benefits against the detached nature of remote techniques is essential. Enhancing information access aids farmers, boosting income through improved soil and crop productivity even with remote monitoring. Handheld sensors can involve smallholders given consistent protocols. Engaging the community in monitoring can cut project costs, enhance agricultural capabilities, and generate extra income.



## Key Words

Soil organic carbon, carbon accounting, carbon farming, soil monitoring



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## 1. Introduction

Soils' capacity as a carbon sink, when properly managed, is increasingly recognized as an important strategy to fight climate change. Sustainable agricultural soil management not only aids in reversing degradation on farms but also has broader benefits for small-scale farming such as improved soil fertility and lower production input costs (Liniger et al., 2011). Sustainable land management also enhances ecosystem resilience against climate change impacts (Chenu et al., 2019; Rumpel et al., 2020). Nonetheless, most of the world's agriculture is comprised of smallholder farmers who face challenges in accessing technical knowledge and financial resources for implementing sustainable land management practices due to inadequate funding for public extension services worldwide (Wollenberg et al. 2022).

Voluntary carbon markets offer a solution to incentivize improved soil management and by this address multiple issues of food security, climate adaptation and climate mitigation in developing countries through improved soil management. Carbon sequestered on-farm through sustainable management practices can be traded as a commodity to actors aiming to offset their corporate greenhouse gas emissions. Voluntary carbon projects involving soil carbon management are emerging as a growing niche, with a tenfold increase in carbon credits issued from agricultural land management projects between 2020 to 2021 (Ecosystems Marketplace, 2022). However, effective scaling of this carbon project type to benefit smallholders in the tropics is hampered by a lack of reliable, cost-effective soil analysis methods for quantifying carbon sequestration benefits of land management practices (FAO et al., 2020; Olander et al., 2013; Berry & Ryan, 2013). This obstacle has become even more significant following the deactivation of the most utilized method for agricultural carbon projects by leading carbon standard, Verra[1].

For several reasons, smallholder carbon projects are unique to those involving commercial farms in high-income countries which have been the focus of other studies (Paul et al 2023). Importantly, smallholder fields are usually less than two hectares in size on average, so projects require aggregation of hundreds or thousands of landowners to achieve economies of scale and a tradeable amount of carbon credits. This increases the monitoring complexity and costs. Smallholder farmers also have unique needs related to project governance and adoption incentives that differ from farmers in Europe or North America who typically have larger plots, more access to information, and require less technical support. Wollenberg et al. (2022) have noted the importance of integrating the multiple needs and requirements of different stakeholders and using participatory approaches throughout such projects.

[1] Verra deactivates VM0017 methodology

Emerging technologies, like proximal and remote sensing, are promising for rapid, large-scale soil data collection and analysis. Many sources have investigated the use of such technologies for measuring soil organic carbon (SOC). However, within the context of a carbon project, technologies e.g., spectroscopy, remote sensing, and related tools e.g., handheld soil scanners are used for either data collection or analysis and applied as part of a larger monitoring approach to account for soil organic carbon content. The approach, together with monitoring approaches of other emission source/sinks and non-carbon variables, data transmission and reporting tools, makes up the MRV system of a (carbon) project. The approach considers procedure used for data collection and analysis, tools used, how often and by whom. Based on the nuances described above, it is more practical to evaluate SOC monitoring approaches for smallholder carbon projects than to assess single measurement tools. This paper takes on such a holistic systems perspective by addressing the following research questions:

1. What are the needs of different stakeholders in smallholder agricultural carbon projects in developing countries?

2. How well can existing and new SOC monitoring approaches meet the identified needs?

3. What are the challenges and benefits of available SOC monitoring approaches in the context of smallholder carbon projects in developing countries?

While questions have recently been raised about the actual effectiveness of these Agricultural Land management (ALM) projects in reaching their climate change mitigation targets (Paul et al 2023), this paper does not attempt to weigh in on this subject. Rather, considering the growing number of such projects, and the predicted exponential growth of the Voluntary Carbon Market in coming years (BCG & Shell 2022), this study takes on a functional outlook to evaluate nine different SOC monitoring approaches (Table 1), and their potential for synergizing, rather than trading off on multiple stakeholder objectives / requirements. The approaches were evaluated based on their level of accuracy, standardization, cost reduction, adoptability, and their impact on community benefits. These criteria were identified as key factors influencing the choice of monitoring approaches for carbon projects. Such an evaluation is especially timely due to increasing public scrutiny of methodologies applied by carbon projects (Miltenberger et al 2021) and a resulting evolution of smallholder methodologies within the standards.

The paper is further organized as follows: after providing some background information around the technical and operational criteria of SOC monitoring approaches we will elaborate on the nine approaches chosen for the evaluation in this paper. The methods section will provide information on the case study location in Kenya the paper connects to and will present all details on how the evaluation of SOC monitoring approaches was conducted. Finally, we highlight the main results related to the research questions and discuss further implications of the findings to provide a comprehensive conclusion.

# 2. Conceptual Background

## 2.1. Necessary elements in project MRV

In designing a monitoring approach for carbon projects, certain criteria must be borne in mind which can be classified into two categories.

**Technical criteria** are necessitated by the methodology and program requirements of carbon certification standards, following scientific best-practice. The IPCC guidelines identify completeness, accuracy, transparency, (time-series) consistency, and comparability as its foundational data quality principles. Completeness means that an inventory covers all relevant sources and sinks, and gases included in the IPCC Guidelines as well as other existing relevant source/sink categories which are specific to individual project. Most times, project boundaries include more than one carbon pool, which often require different monitoring methods. For example, a typical smallholder agricultural project might monitor above ground biomass on-farm as well as soil organic carbon pools as well as emissions from inorganic fertilizers and biomass burning. As such, it's important to note that the SOC accounting is only one aspect of the project's MRV system. Transparency means that the assumptions and methodologies used for an inventory should be clearly explained to facilitate replication and assessment of the inventory by users of the reported information. Accuracy is a relative measure of the exactness of an emission or removal estimate. Estimates should be accurate in the sense that they are systematically neither over nor under true emissions or removals, as far as can be judged, and that uncertainties are reduced as far as practicable. Consistency means that an inventory should be internally consistent in all its elements with inventories of other years. An inventory is consistent if the same methodologies are used for the base and all subsequent years and if consistent data sets are used to estimate emissions or removals from sources or sinks. Comparability means that estimates of emissions and removals reported should be comparable among projects. For this purpose, projects should use methodologies and formats agreed by standards for estimating and reporting GHG impacts. GHG Protocol and ISO 14062-2 introduce the additional principle of conservativeness. Conservative values and assumptions are those that are more likely to underestimate than overestimate GHG reductions. Where data and assumptions are uncertain and where the cost of measures to reduce uncertainty is not worth the increase in accuracy, conservative values and assumptions should be used to ensure that GHG reductions / removals are not overestimated. These principles are fundamental to provide investors and stakeholders with sufficient confidence in credits and allowing them to make decisions with a reasonable assurance as to the integrity of the reported information.

**Operational (feasibility) criteria** on the other hand are determined by the conditions under which projects remain practical and viable to their proponents. Like other projects, developers of carbon projects aim to recover expenses and ensure the ongoing viability of their operations. The approach chosen for project monitoring should be within acceptable costs and suited to the level of available data and local expertise. Monitoring also typically accounts for the non-carbon objectives of the proponents/investors and other stakeholders. For example, investors and government authorities are usually interested in a project's socio-economic and/or agronomic impacts on smallholders which tie into other Sustainable development goals. Most carbon projects therefore include this into a monitoring framework - ideally, through a mechanism that can be effectively synchronized with the project's carbon Measurement, Reporting and Verification (MRV) system.

## 2.2. SOC monitoring approaches

SOC monitoring approaches can be categorized into 2 'Domains' (Figure 1) in line with Paustian et al., (2019). Domain a involves the direct measurement of soil organic carbon through empirical observation of soil physical/chemical components while Domain b contains activity-modelling approaches which rely on the use of biogeochemical process models to estimate carbon stock changes above and below ground due to changes in land management.

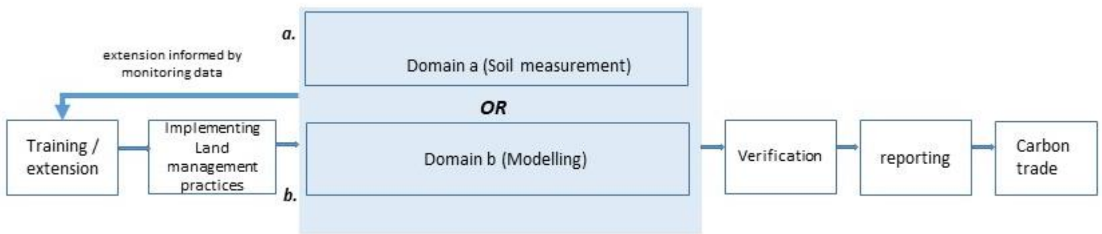


**Figure 1: Alternative SOC Monitoring Domains: a. Direct measurement and b. Activity modelling**

Domain a (measurement) approaches have 2 main sources of inaccuracy:

i.) Sampling error from biased or non-representative sampling design. This can be minimized by following best practice for soil sampling (See Annex 3 of FAO, 2020; World Bank, 2021) but often comes at additional costs,

ii.) Measurement errors due to the equipment or analytical procedures used to estimate SOC content form the sample. However, this is quite low when using conventional methods.

The accuracy of Domain b (modelling) approaches is limited due to 2 broad challenges:

i.) Leading soil models are calibrated and parameterized in temperate climates with different weather and soil properties. This limits the applicability of model parameters in tropical regions where projects are increasingly implemented. As such, suitability of activity modelling approaches for a project location can only be guaranteed through local validation of the model with long term experiments. This introduces uncertainty from the measurement and/or estimation of model input parameters.

ii.) The uncertain nature of modelling itself given that results are based on simulation of natural systems, rather than observation. Newer methods (e.g., VM0042 by VCS) now address uncertainty from model prediction error, in addition to error from model input data which was previously only accounted for.

Regardless, these approaches are less expensive and allow more frequent measurement, reporting and verification, than domain b. By contrast, Direct analysis of soil carbon using conventional laboratory methods is cost-intensive and unsuitable for large processing volumes (Angelopoulou et al., 2020; Milori et al., 2011). Therefore, many smallholder agricultural projects on the carbon market prefer activity modelling approaches. With Verra's recent inactivation of pioneer activity modelling methodology VM0017 other authors (Schilling et al., 2023) have speculated an impending shift to direct measurement for smallholder projects, reflecting the need for more rigorous methodologies for carbon projects. There is therefore a critical gap for standardized, accurate and low-cost approaches to predict and monitor changes in SOC which are suitable for smallholder projects and can enable their participation in carbon markets.

# 3. Methods

## 3.1. Study design

This study follows an iterative process of literature reviews and key informant interviews, underpinned by a case-study conducted in the Western Kenya Soil Carbon Project (WKSCP). An initial review was carried out to establish the current state of project SOC monitoring and develop a short-list of potential monitoring approaches to be analyzed. These include peer-reviewed literature on soil carbon studies, monitoring and implementation reports of carbon projects, lessons learned reports, discussion papers from project investors, and researchers as well as methodology documents from official offsetting standards. Three (3) approaches: Activity modelling 1 (AM1), Laboratory analyses (L1 and L2) as described in Table 1 were identified as the current state-of-the-art for SOC accounting. AM1 was chosen as a reference since it is the predominant monitoring approach used in existing smallholder carbon projects to monitor SOC change in croplands (So et al., 2023). The approach is characterized by modelling procedures relying on land management data, soil, and environmental parameters. On the other hand, conventional laboratory techniques including dry combustion (L1) and Ex-situ MIR spectroscopy (L2) are the widely agreed upon benchmarks for reliable SOC measurements.

From the literature (Olander et al., 2013; Saiz & Albrecht, 2016; Climate Action Reserve, 2019), desired improvements from these three approaches include simplified and less expensive data collection, reducing methodological complexity (and thus expertise requirements), while improving the scalability of SOC monitoring results over large areas. Soil spectroscopy, remote sensing and an increased integration of digital tools were identified in the literature review as components for a future vision of an improved SOC monitoring approach. Six alternative approaches (Table 1) based on these technologies were then proposed for comparison.

## Table 1: Description of the selected SOC monitoring approaches

| **Code** (Definition) | **Data collection** | | | **Analysis** | **Domain** |
|---|---|---|---|---|---|
| | **Procedure** | **Sample size** | **Frequency** | | |
|  **L1** (Laboratory Analysis 1) | Soil samples collected professionally | All participating farms | Every 4 years | Wet chemistry (Dry combustion) | a |
|  **L2** (Laboratory Analysis 2) | Soil samples collected professionally | All participating farms | Every 4 years | Dry chemistry (MIR spectroscopy) | a |
|  **PS1** (Proximal sensing 1) | Soils scanned in-field by trained farmer representatives | All participating farms | Every 4 years | In-field (Vis-NIR) spectroscopy | a |
|  **PS2** (Proximal sensing 2) | Soils scanned in-field by hired professional service | All participating farms | Every 4 years | In-field (Vis-NIR) spectroscopy | a |

| | | | | | |
|---|---|---|---|---|---|
| **RS1**<br>(Remote Sensing) | Spectral reflectance imagery from satellite data.<br>Local ‘ground-truth’ soil samples collected professionally | All participating farms | Yearly | Spectral analysis of satellite reflectance imagery | a |
| **AM1**<br>(Activity Modelling 1) | Land management data submitted by farmers and verified via random spot-checks / surveys. | All participating farms | Yearly | Tier 2 process modelling | b |
| **AM2**<br>(Activity Modelling 2) | Land management data collected **by enumerators** | All participating farms | Yearly | Tier 2 process modelling | b |
| **AM3**<br>(Activity Modelling 3) | Land management data collected **by enumerators** | **stratified random sample** of farms | yearly | Tier 2 process modelling | b |
| **AM4/RS2**<br>(Activity Modelling 4) | Land management data collected via satellite remote sensing | All participating farms | Yearly; & verified through periodic (3-5 year) field surveys | Tier 2 process modelling | b |

## 3.2. Study area and data collection

The Western Kenya Soil Carbon Project (WKSCP) was selected to provide a general context on agricultural carbon projects in developing countries. This project takes place in the counties of Bungoma, Siaya and Kakamega in Western Kenya (see Figure 2).

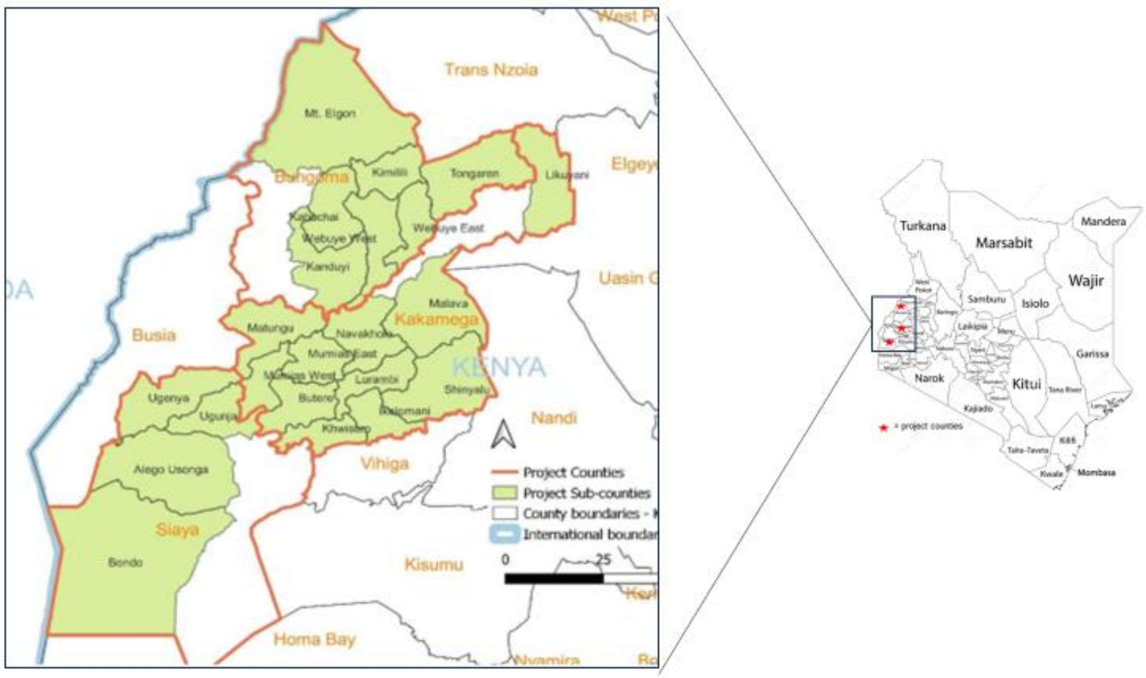


**Figure 2: Map of study area.** Source: Soil Carbon Certification Services (2023)

The project is expected to cover an area of 32,000ha at full-scale and involve about 40,000 farmer households. It has an estimated emission reduction impact of 1,873,798 tCO2e equivalent over its 20-year lifespan. WKSCP is registered with the Verified Carbon Standard using the VM0017 methodology “Sustainable Agricultural Land Management” which represents a Domain b approach. The project is currently undergoing verification for the first round of credit issuance.

The entire project area has a Tropical montane climate (IPCC, 2006). Soils are mostly clayey with high potential for storing organic matter. However, increasing human population over time resulting in land fragmentation, overutilization of the land without replenishment and recently, the misuse of inputs has led to a depletion of soil nutrients, loss of top-soil carbon and land degradation (Mburu and Kiragu-Wissler 2017; Sommer et al., 2018). Subsistence, rain-fed farming with low yields is dominant in all three project counties. The average farm size is about 1 hectare. Major crops are maize, and beans grown in two planting seasons without a fallow period. Due to a high density of poor rural, farming households (Tennigkeit et al., 2013), this region of Kenya is a hotspot for carbon and development projects with several underway and under development.

To gain more contextual information about the operational dynamics of a carbon project, soil monitoring in general and to understand the perceptions and experiences of project stakeholders about the short-listed SOC monitoring approaches, semi-structured interviews were conducted between April to May 2021 in the study area with representatives from 6 stakeholder groups. These groups were: Smallholders, Project developers and Implementing partners (IPs), Carbon certification standards, governmental/research agencies, and technical(methodological) experts. A total of 102 smallholder in all three counties and 16 expert interviews were conducted based on convenience (location, timing, and availability of the identified stakeholders to give an interview within the study timeframe). 8 of the expert interviews were conducted face-to-face while 8 were held over Zoom or Microsoft Teams. The smallholders were selected via random sampling stratified by geographical location (ward[2]) and included project participants and non-participants. All the smallholder interviews were conducted in person.

Interview questions were developed from the relevant themes in the literature and were tailored to each respondent based on their area of expertise. The questions involved querying stakeholders about their objectives in joining the carbon project, what information or results they anticipate from the monitoring process and their views on how soil monitoring tools and approaches could work in the project. The interviews were recorded, transcribed, and later analyzed as described in section 3.3.

## 3.3. Data Analysis

Figure 3 presents a conceptual framework developed to analyze the selected SOC monitoring approaches and to identify future development opportunities. At the center of the framework lies five evaluation criteria which are used to compare the proposed approaches and assess their potential benefits over conventional approaches. The criteria reflect the aforementioned project MRV needs and challenges identified in the literature search and further corroborated through key informant interviews.

[2] In Kenya, there are 47 counties which are subdivided into 290 administrative units called sub-counties. Each sub-county is further stratified into wards which contain smaller villages.

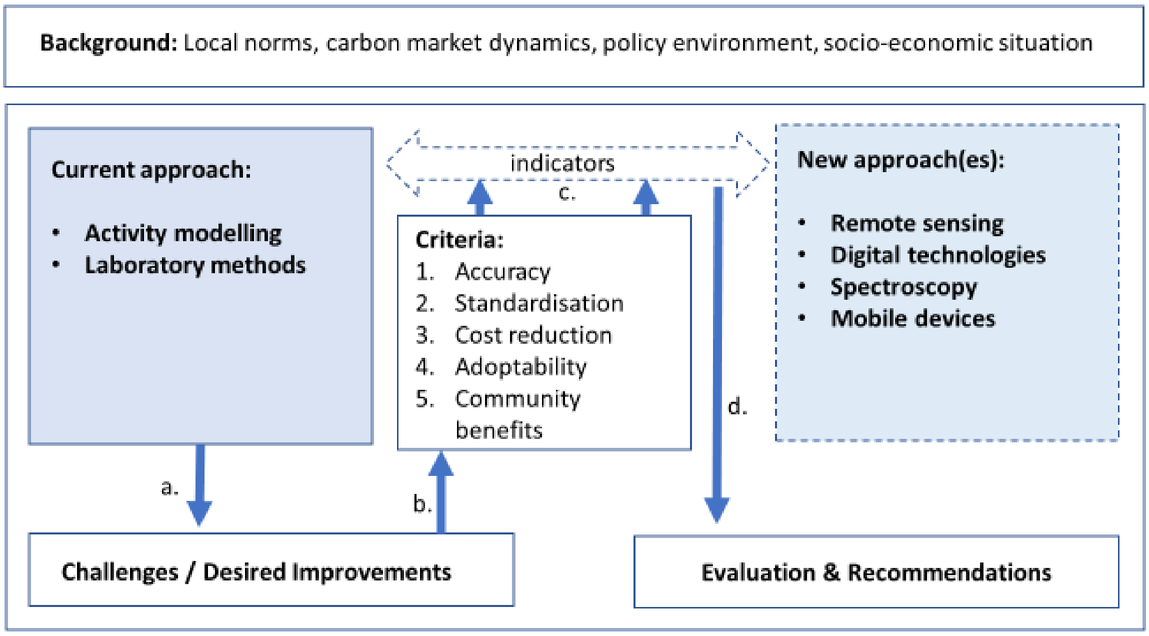


**Figure 3: Analytical framework for the evaluation of SOC Monitoring approaches.** Source: Authors own elaboration

Accuracy and standardization reflect the "technical criteria" defined by the standards while cost reduction, adoptability and community benefits reflect "operational criteria" highlighted by various project stakeholders. Using these criteria as a basis, the various approaches identified in Table 1 are then evaluated, leading to recommendations for future improvements needed for these approaches to address the multiple needs of stakeholders in smallholder soil carbon projects in low- and middle-income countries.

First, each evaluation criterion was assigned a suitable indicator (scoring mechanism) to aid objective comparison between the approaches (Table 2). Then, a deductive thematic analysis was conducted on the literature and interview data as follows.

**Table 2: Evaluation criteria and indicators for comparison**

| Evaluation Criteria | Definition and Indicator | Source of data |
|---|---|---|
| **Accuracy** | ***Definition.*** The relative ability of the underlying technology to reflect the real value of SOC stock or stock changes.<br>***Indicator.*** Mean $R^2$ values from the literature[a], scored according to the scale:<br>5 = 0.9-1.0, 4 = 0.8-0.9, 3 = 0.7-0.8, 2 = 0.6-0.7, 1 = 0.5-0.6 | **Peer-reviewed literature from validation studies** |
| **Standardization** | ***Definition.*** The presence of uniformly accepted procedures and protocols, including recognition by official carbon standards. Reflects the IPCC principles of consistency, comparability, and transparency.<br>***Indicator.*** Cumulative Yes (1) or No (0) scores to each of the following:<br>• Comparable across different sites<br>• Consistent results over time<br>• Consistent & transparent protocols for data collection<br>• Consistent & transparent protocols for data processing<br>• Consistent & transparent protocols for data analysis | **Key informant interviews, scientific peer-reviewed literature, documentation from Carbon standards[b]** |
| **Cost reduction** | ***Definition.*** The ability of the approach to reduce the amount of labor and financial investment required for monitoring.<br>***Indicator.*** Own cost estimates[c] in USD $ha^{-1}$ and year, scored according to the scale:<br>5 = \$0-1$ha^{-1}$, 4 = \$1-2$ha^{-1}$, 3 = \$2-3$ha^{-1}$, 2 = \$3-4$ha^{-1}$, 1 = \$4-5$ha^{-1}$ | **Key informant interviews, project documents** |
| **Adoptability** | ***Definition.*** Likelihood of use by farmers and Implementing organizations<br>***Indicator.*** Cumulative Yes (1) or No (0) scores to each of the following:<br>• Data collection requires low-medium effort.<br>• Data collected is perceived beneficial by users.<br>• Understood and trusted by local experts.<br>• Can be integrated with other monitoring activities e.g., other carbon pools / non-carbon variables in MRV system.<br>• Does not conflict with local practices, garners support at local and national level. | **Key informant interviews** |

| | | |
|---|---|---|
| **Community Benefits** | **Definition.** Provision of benefits and/or avoidance of negative effects for communities.<br>**Indicator.** Cumulative Yes (1) or No (0) scores to each of the following:<br>• Enables field-extension delivery.<br>• Integrates feedback loop to farmers.<br>• Increases C revenue.<br>• Empowers community through involvement in the process.<br>• Other benefit | **Key informant terviews, project documents and peer-reviewed scientific literature** |

**a See** Annex A.1
**b** Documentation from 2 standards: VCS and Gold Standard were reviewed due to their dominant share of issued VCM credits
**c See** Annex A.2

Each point raised within the literature and/or interviews was categorized into distinct thematic clusters aligning to the evaluation criteria. For example, after the approaches are explained and a respondent is asked, “which of these do you prefer and why?”, or “how do you think this will affect you or the project?”. Responses related to adoptability, influence on community benefits or standardization were then labelled and grouped as such. Sometimes, a response addressed more than one evaluation criteria.  These were then further grouped per monitoring approach. Finally, the thematic content (now grouped per approach and relevant criterion) was evaluated in relation to the scoring indicators, to derive final criteria score for each approach. The exceptions to this process were accuracy and cost reduction criteria, which were evaluated differently. Cost estimations used for comparing approaches were derived from data collected during interviews, project documents (feasibility studies) and personal communication with experts. For examining accuracy of a given approach, we compare the literature-reported coefficients of correlation (R2) between SOC values predicted by its underlying tool/technology and SOC values observed via conventional laboratory techniques (L1, L2). R2 describes the strength of linear relationship between two variables (usually observed vs predicted) and is commonly used as an indicator of model prediction accuracy. An average R2 value was taken for each technology across the different papers reviewed. This was used as a benchmark for the theoretical accuracy of each technology. In practice, however, the theoretical accuracy of a tool/technology is often different from what is achievable considering the whole approach; an observation which is explored further in the discussion. However, for this comparative analysis only the potential accuracy of the underlying tool is considered. It was noted that the concept of accuracy (the degree of a measurement representation of the true value) and precision (which concerns the repeatability of results) were sometimes used interchangeably in the project literature and in expert interviews. The concept of repeatability of results is partly captured in this evaluation under the standardization criteria.

### 3.3.1. Limitations and assumptions

Before describing the results, it is useful to highlight methodological challenges faced during this study. The first concerns the limited number of expert interviewees available to provide their perspectives on project actualities. Thus, interview findings were triangulated with the literature to enhance their credibility. Another limitation was that some of the monitoring approaches considered lacked sufficient data to develop cost estimates. As a result, some simplistic assumptions were made as described in the Annex A.2. Third, the analysis was also limited by a scarcity of validation studies on the accuracy of remote sensing for detecting land management practices (AM4/RS2). The same value for activity modelling (AM-) was therefore used on the assumption that they would be of similar value since the underlying quantification methods are the same. The comparison of R2 across different approaches also has its limitations, since R2 is a measure of correlation and high correlation values do not always mean higher prediction accuracy. For example, R2 does not account for model bias or consider random unexplainable variation. Nonetheless, R2 was chosen as an accuracy indicator as it was the most reported validation parameter across the literature reviewed. Model validation procedures in many studies, especially across different fields and purposes, are not always uniform. For instance, studies assess the accuracy of SOC predictions at differing depths; or even report on different types of error statistics making it difficult to compare. Lastly, there was often a wide range of reported R2 values for a given technology, and so the given average R2 values may be biased due to low sample sizes of available papers.

# 4. Results

In this chapter we first highlight the expectations from different project stakeholders on what the monitoring system should be able to deliver. Next, findings on how the stakeholder groups assessed the various monitoring approaches are shown, followed by an objective comparison of the approaches – given the criteria presented beforehand which integrates stakeholder perspectives and scientific literature.

## 4.1. Stakeholder Requirements for an MRV System

Table 3 provides a summary of what different stakeholders expect from a project MRV system. The most common monitoring requirements across multiple stakeholders were low process costs, high data accuracy, and the generation of useful soil, land and household information which could support decision-making on both farm and landscape levels. This corroborates with the existing literature (Schilling et al., 2023; Tennigkeit et al., 2013; Olander et al., 2013; Smith et al., 2020) and informed the criteria used in evaluating selected monitoring approaches. Accuracy is enforced by carbon standards and highly prioritized by project developers due to expectations from investors

**Table 3: Identified MRV needs of the key interviewees**

| Stakeholder group | Number of respondents | Needs from an MRV system |
|---|---|---|
| **Project proponents** | 2 | Low cost, high accuracy (to satisfy standards & buyers), generate useful information to report to stakeholders and to increase adoption |
| **Implementing organizations (usually NGOs and CBOs)** | 5 | Low field effort, low complexity |
| **Government / national research organizations** | 4 | Information which supports policymaking (e.g., landscape health, yield, socio-economic data), capacity building of local community |
| **Technical experts** | 5 | Accuracy, low cost, multipurpose data, accessibility for farmers |
| **Farmers** | 102 | Land health information, Land/farm management advice, skill acquisition |
| **Standard setting organizations** | 0 (From literature only) | Accuracy, Conservativeness, Transparency, Completeness, Consistency, Relevance, Comparability |

regarding quality and integrity of carbon credits. Researchers and technical experts require standardization of different approaches for objective comparison and time series research on project impacts. Governmental stakeholders require decision-making information. However, this also demands a certain level of standardization so that information from multiple projects within their geographic boundaries can be integrated. Project implementing organizations who are directly involved in field activities desire monitoring approaches which do not require too intensive effort in addition to other non-SOC monitoring activities. This is due to limited staff and resource capacity, which is identified by respondents as a challenge during project implementation. This is factored in to cost and adoptability considerations, under the operational criteria. The groups that hold the greatest influence on the feasibility of implementation are typically landowners and implementers. However, the design of the project MRV plan is commonly devised without taking their input into consideration. Many landowners pointed out the desire for skill development and informed land management, through participation in the project implementation and monitoring processes.

However, this was split; with much older farmers, illiterate and those with multiple livelihood sources being less inclined to participatory monitoring approaches that require specific training and/or extra data-keeping effort. Most interviewed farmers are not used to keeping farm- records and find it time-consuming to do so. This suggests that approaches which depend heavily on farm management data may place an unwelcome "data burden" on some participating landowners by imposing extra time and labor demands, in line with assertions by Schober (2021). This differs from the view of project developers and IPs who see potential community benefits in this approach to improve record keeping habits that aid farm business management. Investors in projects require the project to have additional community or biodiversity benefits to align with sustainable development goals and avoid reputational damage. Project developers also share this demand but often struggle to align practical project needs with that of local communities.

Balancing the needs and requirements of different stakeholders regarding information and level of detail from project MRV was therefore identified as a challenge in conceptualizing an 'ideal' approach.

## 4.2. Stakeholder perceptions about the monitoring approaches

Given the above needs and constraints, perceptions of project stakeholder groups on the monitoring approaches were then analyzed from the interview data. There was a consensus among respondents that conventional laboratory soil measurement is expensive, due to sampling and equipment costs. L2 (MIR spectroscopy) was notably acknowledged as less expensive than L1 even though both have almost identical data collection and preparation procedures. However, **researchers** pointed out that even conventional methods can be less than precise where quality control is lacking.

Overall, the analytical procedures behind SOC estimation were a less-understood black box for **landowners**. This group was principally indifferent to the use of any approach, on the condition that sufficient information would be offered, and the soil analysis results made accessible for their farm management decisions. The underlying concern for this group of stakeholders was the degree of accessibility to the end results of the MRV process. For this reason, approaches which include field-based data collection were preferred, as well as analytical methods yielding quick and easily interpretable results such as mobile soil scanners. When it was properly explained, landowners appreciated the potential cost and effort saving benefits of remote sensing but expressed concern over the inaccessibility of results since it involves off-farm data collection and analysis.

**Implementing organizations**, too, often rely on project developers to establish the MRV system and provide necessary training and resources for implementation. Therefore, it is unlikely that this group may be outrightly opposed to any monitoring approach. Those interviewed had limited technical understanding about carbon accounting requirements. For instance, even though they may engage in data collection for activity modelling, they lack the expertise needed to parameterize and run the carbon model. Similarly, they possessed limited knowledge about remote sensing and other soil analytical methods. Due to their preference for labor saving approaches, implementers favored data collection methods such as farmer-sourced data or approaches which group multiple plots together. They favored mobile soil scanners for the same reason since farmers could potentially be trained to use them - however some expressed skepticism about the reliability of results. This sentiment was re-echoed by **researchers and government representatives** who questioned the lack of transparency around the proprietary calibration data used in such tools.

*"The scanners you talk about on the ground that they can give you results within 2-3 minutes or 10 minutes, they use dry chemistry. Dry chemistry does not go into so many things in the soil and it's very easy for dry chemistry to give you a photocopy of another soil test. I did one. I checked on some 54 soil tests one day using dry chemistry and I was surprised when I realized that 10 soil samples had the same figures. These are different farms. Dry chemistry is cheaper, wet chemistry would be expensive, but [wet chemistry] provides very precise and dependable soil results".*

*Researcher*

The quality of collected data was of greater importance to **technical experts and project proponents** when considering the various approaches. Multiple respondents asserted that current modelling approaches were ineffective.

*'The result of an activity-based approach are theoretical results and by definition wrong and I think we shouldn't be satisfied with that. We should have higher aspirations than that'.*

*Remote sensing expert*

However, there was a general lack of consensus among experts on which data collection process or analytical methods yields best results as well as on what the required accuracy thresholds of analytical methods should be. Apart from perceived high costs, the biggest drawback of direct soil measurement approaches for **project proponents** is the fact that the observation of significant SOC stock changes over time requires long measurement intervals (3-5 years) due to the slow magnitude of change relative to stock size. Many projects require more frequent SOC quantification to generate carbon revenue which sustains project activities in cases where no other sources of funding are available. Modelling approaches have the advantage that they allow more frequent monitoring intervals and may be preferred for this reason despite limited accuracy performance.

The role of remote sensing in monitoring produced the highest split of responses within any key informant group. Several technical experts opined that remote sensing is too early-stage for use in SOC accounting due to computing uncertainties, and a widespread lack of technical expertise. Therefore, it would be better suited for the collection of readily available auxiliary data (e.g., soil texture or land use classes for stratification). One remote-sensing expert was of the contrary opinion that RS technology offers unexplored potential to improve monitoring accuracy and that the collection of auxiliary data is a sub-optimal use of remote sensing potential:

*"[Yes], it is something you can do with remote sensing. There is some ability to monitor whether a farmer has done tillage or no tillage, but not what we want to focus on, because then you're using something that can be very accurate to measure something whereby subsequently the result of that will be very inaccurate. If you want to use remote sensing to establish whether they have applied tillage or not, and then simply take a theoretical result of the application of tillage for the actual amount of carbon credits, we believe that's the wrong way around"*

*Remote sensing expert.*

## 4.3. Evaluation of Monitoring Approaches Using Selected Criteria

We evaluated the different monitoring approaches based on the selected criteria by presenting their performance in spider diagrams. For reasons of visualization we present the performances differentiated by conventional approaches, new monitoring approaches monitoring approaches based on measurements and new approaches based on modelling (see Figure 4).

### 4.3.1. Cost & Accuracy

**Impact of data collection methods**

Overall, the choice of data collection method was found to have a higher impact on total monitoring costs than the choice of data analysis method. This was especially true for activity monitoring (AM) approaches which are the current status quo for agricultural carbon projects. For example, the AM1 approach where data is collected from all participants on a yearly basis could cost up to 10 times more than AM3 where only a random sample is collected yearly with no significant difference in accuracy between both approaches. This is because statistically, beyond a certain point, only a minimal increase in accuracy is gained from increasing sample size whereas the costs continue to increase. Laboratory measurements L1 and L2 were the most expensive due to their sample collection requirements although L2 was notably less expensive due to the rapid processing of samples allowed by spectroscopic analysis.

In the case of proximal sensing, it was found that a farmer-led data collection approach (PS1) could significantly reduce costs compared to commercial mobile testing services (PS2) while providing similar potential accuracy and additional community benefits due to the participatory nature of PS1 (farmer-led) approach. 'Potential' accuracy here is emphasized because while the underlying technologies are the same, the real, achieved accuracy of the PS1 approach depends highly on the capacity of smallholders to use these devices and on the existence of standard protocols / quality control procedures to ensure consistent sample collection conditions and results.


**Figure 4: Comparison of the different monitoring approaches**

While modelling approaches are generally similar in potential accuracy, the achieved accuracy of AM1 (self-reported) approach may be lower in practice because the quality of data reported by farmers is often unsatisfactory (Schober, 2021).This is true for several reasons: non-measurement or usage of non-standard measurement units by smallholder farmers, social desirability bias in answering questions e.g., about production or fertilizer use, and lack of information that can be used to cross-check self-reported data. Because of these issues, a lot of time is spent on subsequent quality control and correction which often defeats the initial aims (convenience and cost) of farmer self-reporting. The data collection process for AM4/RS2 (modelling based on remotely sensed activity data) was also assessed to potentially impact the estimated accuracy of input data. However, the exact degree of impact was difficult to determine as this approach is not yet widely used and so available literature on this was scarce. AM3 (modelling based on a sample of farms) is currently the least expensive of the AM approaches, although AM4/RS2 (modelling based on remotely sensed activity data) provides chances to further reduce the cost and effort associated with activity data collection.

**Impact of analysis methods**

In general, the choice of analytical procedures was found to have a higher impact on the potential accuracy of a given monitoring approach than the data collection method. This is not to say that the achievable accuracy is not influenced to some degree by the data collection methods used. For example, laboratory approaches can be influenced by the sampling error and effectiveness of sample preparation steps (i.e., crushing, sieving, and drying) while the certainty of AM approaches rely heavily on the input data used for modelling. However, approaches involving laboratory-based sample analysis such as L1(dry combustion) and L2 (MIR spectroscopy) are typically the most accurate when contrasted with activity-based modelling approaches (AM-) which are generally of lower accuracy due to their indirect/theoretical nature, assuming best-practice guidelines for data collection is followed in both cases. Apart from the AM approaches and L1, other approaches considered are in fact based on spectroscopic analysis, simply used in combination with different data collection approaches. Therefore, spectroscopic analyses introduce an opportunity to maintain the accuracy of conventional lab-based analyses while driving down costs via in-situ or satellite data collection. Field-based proximal sensing tools (PS-) already show reasonable potential accuracy (Viscerra Rossel et al., 2006; Stevens et al., 2008; Sorenson et al., 2017), but lack the level of standardization to achieve consistency and comparability. Remote sensing-based monitoring (RS1, RS2) offers the best long-term cost performance, but the level of accuracy varies greatly for different studies (See Annex A.1) due to varying analytical techniques applied. No consensus exists on techniques to handle atmospheric cloud cover, the interruption of bare soil by vegetation and crop residues or to deal with varying soil conditions (e.g., moisture, texture, surface roughness) in fields during satellite or proximal data collection (van Wesemael et al., 2021).

Furthermore, as World Bank (2021) points out, most satellite sensors only measure surface (1cm) soil reflectance (the same is also true for proximal sensors) while carbon storage is usually analyzed to 30cm depth. These challenges can be overcome with specialized processing methods. For example, good results have been demonstrated for normalizing the effect of in-field moisture/texture variations using statistical techniques such as External Parameter Orthogonalization (EPO) (Nawar et al., 2020; Veum et al., 2018) and Direct Standardization (DS) (Angeloupolou et al., 2020; Ji & Viscerra Rossel, 2015). Statistical techniques can also be applied to surface spectral measurements (Kusumo, 2018; Lu et al., 2019) to correlate soil depth to carbon content, and Zepp et al., 2021 discuss an SCMap procedure to composite multi-temporal satellite imagery, allowing data to be obtained from different periods in the year where bare soil is visible. These methods, however, require high expertise.

### 4.3.2. Community benefits

PS (proximal sensing) approaches were found to provide the most positive impact on community benefits by enabling community participation, feedback, and in-field advisory, while saving costs thus allowing more carbon revenue flow to the communities. Remote sensing provided the least community benefits due to its detached, off-farm nature. For laboratory approaches, we theorize that the associated on-field benefits and greater measurement accuracy are outweighed by the high implementation costs which will take away from community benefits (if implementation costs become higher than payment from credits and therefore project is not able to self-fund or show benefits). The same may apply to other higher-cost monitoring approaches such as AM1 (self-reported) and AM2 (yearly full census), when compared to lower cost RS approaches which leave more carbon revenue available.

### 4.3.3. Standardization and adoption

As emphasized by the IPCC GHG accounting principles, standard protocols and quality control measures play a key role in aiding comparability of results over time and across projects. The Standard Operating Procedures of the Soil-Plant Spectral Diagnostics Laboratory of World Agroforestry Centre (ICRAF) provides widely adopted protocols for spectral analysis in the lab (L2). Approaches based on Proximal sensing (PS-) and Remote Sensing (RS-) were found to be less standardized than others. The use of Vis-NIR based proximal sensing has been recently endorsed by carbon certification standard, VCS under the VM0042 methodology, provided that standard measurement protocols are used such as that found in Annex B of Viscerra Rossel et al. (2016). However, this is not yet widely used/adopted. Due to a lack of sample processing when proximal sensing is used, it is important that such standardized measurement protocols are applied to minimize inconsistencies. The literature on RS-based approaches features different combinations of steps and techniques to predict SOC from remotely sensed data. No guidance exists on the selection of modelling techniques, covariates or even harmonized data sources for model input. Therefore, results from different sources are bound to provide different levels of accuracy. Error reporting is also not standardized, and many sources of uncertainty are not propagated into the results (Takoutsing et al., 2021). Moreover, these approaches are not yet endorsed by carbon standards and therefore lack precedented use in carbon projects. This was found to play an important role influencing adoption; less standardized methods were perceived with skepticism by experts and project proponents which reduces the likelihood of adoption. It follows that adoption issues are more likely to be faced by less understood technologies, since trust and transparency of monitoring approaches were found to be important factors for national and local experts. In contrast, landowners and implementers had less significant power in the adoption decision since the monitoring design is usually done by the project developer. However, if capacities are lacking, or there is a lack of synergies with other non-SOC monitoring activities, certain monitoring approaches will not be effectively adopted by those on the ground.

## 5. Discussion: Challenges, Opportunities and Recommendations

Figure 5 highlights the role of featured tools in the different monitoring approaches. Domain a (direct measurement) features conventional wet and dry laboratory methods (L1 and L2) as well as remote and proximal sensing of SOC content (RS1, PS1. PS2). Domain b (activity-based modelling) features paper, mobile or satellite-based surveys of land practices as input to models. A discussion on specific issues and recommendations related to selected approaches follows below.

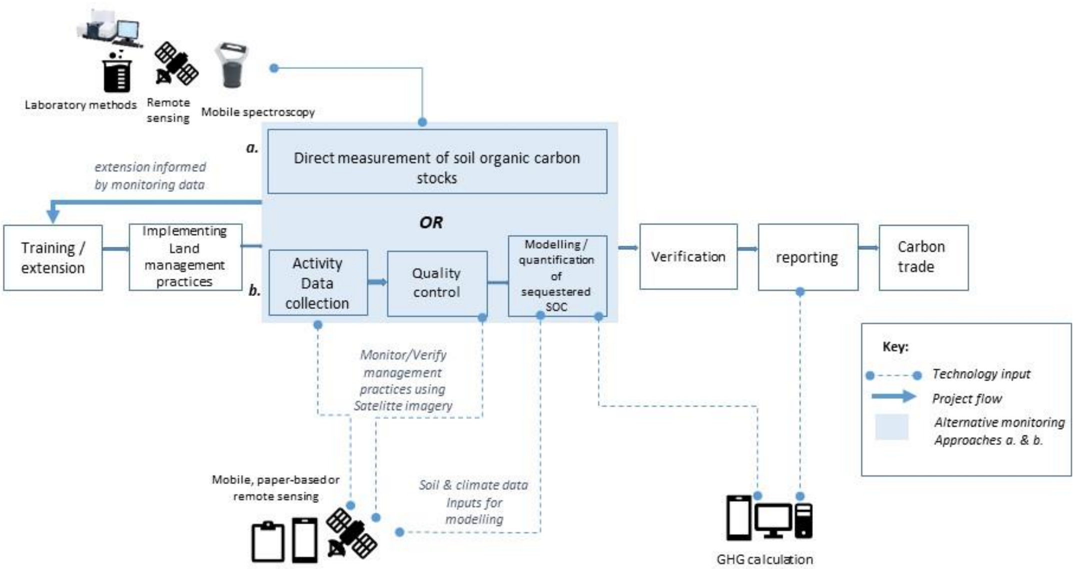

**Figure 5: Approaches and tools in the different SOC Monitoring Domains**

## 5.2. The promise of remote sensing

Indeed, the advancement of satellite imagery with high spectral resolution enables cost improvements on current data collection approaches while leveraging the accuracy potential of spectroscopic analysis. Collection and processing of plot-level soil or land management data via satellite is however still associated with several challenges.

**RS1 (Soil measurement with remote sensing)**

Technical challenges faced in collecting soil data via satellite have already been briefly discussed in the results above and in-depth in the literature (Shepherd et al., 2022; Zengh et al., 2014; van Wesemael et al., 2021). Expertise required for highly specialized processing is lacking in many developing countries and must be encouraged for adoption of this approach. This may be supported by the establishment of geostatistical toolboxes / guidelines to aid local experts in the selection of pre-processing methods, covariates, models, and validation/error accounting techniques. Overall, the lack of standardized procedures for RS-based approaches lead to conflicting reports on the accuracy of this approach in peer-reviewed studies. Some commercial organizations already market MRV solutions[3] promising accurate results with this technology. However, none of these are verified yet by a major carbon standard. Moreover, because these organizations have proprietary business models, they do not disclose their methods transparently and have not yet published scientific information that has undergone peer review. Consequently, the methods they employ lack a foundation for comparison. Not-for-profit organizations are increasingly testing and piloting such solutions[4] which may be key to democratizing the technology and making it accessible for smallholders. It is essential that carbon certification standards provide oversight on these processes for alignment market needs. Additionally, the accuracy of the RS1 approach is dependent on the soil data used for calibration. This often requires intensive field sampling efforts at the initial stage of model calibration which could be prohibitive. Collaborative effort is needed to establish sufficient soil spectral libraries in different regions for calibration of remote sensing models (Shepherd et al., 2022). Such libraries can be designed for expansion over time through the collaborative effort of crowdsourcing and communal sampling. Long-term project trials are also necessary to compare remote sensing performance across time and cropping seasons. The World Agroforestry Center (ICRAF) for example using their publicly available Land Degradation Surveillance Framework (LDSF) has been supporting satellite-based soil organic

[3] For example, Boomitra, Earthbanc.
[4] e.g., this GIZ funded project

carbon monitoring in various project contexts which could serve as the basis for such long-term comparisons.

**AM4/RS2 (remotely sensed activity modelling)**

Authors (Hagen et al., 2020; World Bank, 2021; Zheng et al., 2014) have reported the successful use of AM4/RS2 for detecting cover cropping, crop-rotation, and no-tillage practices (See Bégué et al., 2019 for an extensive review). On the carbon market, the approach is featured in protocols for detecting agroforestry practices e.g., Rabobank's Acorn methodology[5] approved under the Plan Vivo standard, and those requiring surveys of livestock numbers e.g., Verra's VM0032. More recent carbon initiatives pioneering the AM4/RS2 approach include the *Carbon Plus Grasslands Methodology*[6] developed by independent marketplace providers Regen Network Development Inc, and the CIBO Technologies program *CIBO Initiative for Scaling Regenerative Agriculture*[7]. The latter two are currently in the process of being developed under the VM0042 methodology of VCS Standard by Verra. In addition to broader remote sensing concerns already mentioned, this approach is limited by the difficulty in detecting a wider range of activities such as fertilizer use, composting or residue burning remotely. Moreover, greater variability in when and how farmers implement practices could also make remote activity monitoring more difficult, especially on smaller plots. So far, pilot trials have been done on large commercial size farms in North America and need to be conducted on smaller plots, covering a range of land use types, as typically occurring in the context of smallholders in developing countries. Further studies on the accuracy of this approach are needed to enhance the limited body of knowledge. As a Domain b approach, one important advantage of RS2/AM4 for project proponents is that it allows for more frequent MRV cycles, thereby making available cash-flow for project implementation. Activity monitoring is, moreover, essential in projects to monitor practice adoption over the project area even beyond its requirement for SOC modelling. RS2/AM4 could reduce not only the costs of activity data collection but also the risk that the process poses a data burden to certain smallholders.

A new challenge for community benefits, however, becomes the integration of feedback loops in such a system. Without ongoing advisory services, smallholders lack the technical knowledge and resources to sustain implementation of project activities and could easily revert to the baseline. Therefore, field visits remain important to sustain implementation of smallholder carbon schemes and keep the project functioning. Wehinger et al. (2023) found in a recent ELD study of WKSCP that neighboring farmers in the project area, on witnessing evidence of positive economic outcomes, have high interest to adopt the project's sustainable land management practices but are hindered by a limited availability of extension support. It is therefore worth rethinking the value of

[5] More about Acorn here
[6] Carbon Plus Grasslands Methodology here
[7] See the project listing on Verra registry here

such savings from reduced field monitoring visits since field visits are critically needed to foster adoption and optimize extension delivery. In fact, monitoring and extension are strongly intertwined in the implementation of current projects using the AM- approach (personal communication, project implementing partner). Projects using remote sensing-based approaches (RS1 and RS2/AM4) will need to carefully design feedback and advisory components which can sustain the community and environmental benefits of such projects. This may be easily addressed in regions where smartphone access is common since digital tools can be designed that recommend management practices to landowners based on remote sensing analysis. The adoption of such approaches should be tested where it is a possibility. However, in places like the case-study area where smartphone access is rare and/or internet connectivity is a challenge, this becomes more complex.

## 5.3. Proximal sensing devices

In-situ spectroscopy appears to overcome this problem by producing potentially accurate soil analysis, reducing sampling error by enabling sampling on a greater number of fields while keeping costs low and maintaining community benefits through field visits for data collection. Since field-level data collection efforts could make this technology labor-intensive across thousands of hectares, devices such as SCANS or Deep-C which can be mounted on farm vehicles (e.g., tractors) have been proposed. This approach is however not considered in this study as we consider this more feasible for larger, industrial fields where mechanization is routinely used. For smallholder farms, devolving data collection to farmers could reduce logistical costs while offering additional community benefits via participation and skills development. A few farmers can volunteer to be trained in monitoring with this device and may even offer this service to other farmers in the project area for additional income. A requirement for this is that soil scanners are easily operable by smallholder farmers and provide results that are translated for farmers into practicable advice. For example, the SoilPal (https://ujuzikilimo.com/soil-pal) scanner developed for rural farmers in Kenya which delivers SMS results in the absence of internet connectivity. Such tools could be programmed with additional features that allow the detailed soil data and GIS coordinates to be uploaded upon each scan to an external database for expert analysis – this would also rule out the possibility of biased reporting by farmers who may be incentivized to do so. Less complex Standard Operating Protocols must also be developed for the use of these devices which consider both quality requirements and ease of use by farmers. Finally, proximal sensing devices like remote sensing must find a way to control or account for soil moisture variations in field. This is already addressed above.

## 6. Conclusion

This study set out to evaluate approaches for monitoring soil carbon in smallholder agricultural projects, according to their accuracy, level of standardization, cost, adoptability, and community benefits. These criteria were identified through project stakeholder interviews and literature search as important for the success of the overall MRV system. This research investigated the use of remote sensing, soil spectroscopy, and soil models in tropical/subtropical developing countries. The current limited availability of suitable methods for smallholder agricultural carbon projects in the voluntary market underlines the study's importance.

Overall, it was found that data collection is more associated with monitoring costs while choice of data analysis methods has a greater impact on accuracy. This emphasizes the need for a systems approach, assessing the entire MRV system rather than the focus on individual technologies when considering carbon projects. Soil spectroscopy has been demonstrated as a technology which can provide rapid and accurate soil analysis at scale. Combining this with lower cost data collection such as in-field scanners or remotely sensed spectral imagery was found to offer the best cost-accuracy performance for repeated soil measurements. However, field-level data collection remains essential for monitoring adoption and supporting advisory services, which are both keys to project continuity and to delivering community benefits. The use of smartphone technology was identified as a potential tool to integrate feedback loops and bridge this gap if accessible to farmers in a project area. Practice monitoring via remote sensing can replace farm surveys and should be explored further in the context of smallholder farmers for a wider range of project land use scenarios.

Proximal sensing offers rapid data collection with high accuracy analysis and the ability to strengthen participation and capacity building of local actors e.g., via trained farmer representatives. However, this approach requires standardization through widely accepted quality control protocols. The same is true for remote sensing approaches which lack common protocols for calibration, making comparability within and among projects difficult. Moreover, the use of satellite-based spectral measurements still lacks approval by major carbon certification standards. Hence there is a basic requirement to develop clear data collection protocols for the use of in-situ and remote technologies in soil carbon monitoring, as well as performance benchmarks which are based on well-established conventional methods (‘gold standards’). These efforts should be done together with major carbon certification standards. Other techniques which are not covered in this study but should be further explored are the use of spectral sensors mounted on airborne or field vehicles.

To close initial cost/effort gaps associated with calibrating accurate spectral libraries (mainly soil sampling costs), there is a need to synergize efforts from different actors. For example, joint investment towards developing open-source libraries of soil spectral and covariate data which may be used for several purposes apart from soil carbon accounting.

Overall, the level of technical skill required to fulfil the data collection or analytical requirements of soil carbon monitoring may lead to adoption gaps for many of the newer approaches and could hinder small-scale projects which would otherwise contribute to climate action. Investing in developing countries to build local skills in new SOC monitoring approaches is crucial. The development of user-friendly decision-making tools such as automated dashboards and toolboxes[8] are also recommended to bring long-term cost savings and increased adoption.

On a final note, we highlight that the frequent focus on accuracy as the sole purpose of GHG accounting might be hindering the adoption of otherwise effective project SOC accounting approaches that fulfill various other requirements. Arguably, the principle of conservativeness if applied balances out the requirement for accuracy[9]. For instance, monitoring approaches with lower accuracy may still be suitable, if all uncertainties are properly quantified and reported to allow uncertainty deductions of final estimates. The investment decision would then hinge on whether the net value of conservative estimates justifies the effort invested in the project. Nonetheless, the principle of conservatism provides project proponents with added flexibility in selecting an appropriate monitoring approach, enabling them to strike a better balance among different requirements. It is in any case crucial, to fulfil the principle of transparency that all approaches apply appropriate error propagation techniques for uncertain data sources.

[8] Examples include the FAO Land Resource Planning Toolbox and the Climate Tool box by University of California, USA

[9] Verra in fact acknowledges that although accuracy should be pursued as far as possible, the high cost of monitoring of some types of GHG emissions and removals, and other limitations make accuracy difficult to attain in many cases. In these cases, conservativeness may serve as a moderator to accuracy to maintain the credibility of project and program GHG quantification. (Verra 2023. VCS Standard v4.4)

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## Annexes

A.1: Literature review comparing the accuracy of different methods for SOC estimation.

| **Activity modelling (Using Roth-C)** | **Authors** | **Measured Range** | **Initial stocks** | **SE** | **EF** | **MD** | **-** | **$R^2$** | **RMSE** | **Country (IPCC climatic zone)** |
|---|---|---|---|---|---|---|---|---|---|---|
| | Kamoni et al 2007 | 15-40t/ha | - | - | -0.37 | 0.06 | | 0.34[a] | 8.05t/ha | Kenya (Tropical montane) |
| | Francaviglia et al 2013 | 8.5-24.6g/kg | 15.2g/kg | 4.7 | 0.58 | - | - | 0.84 | 12.37g/kg | Italy (warm temperate moist) |
| | Lee et al 2021 | 25.39-43.55mg/ha | 35.38mg/ha | - | - | - | - | 0.98[b] | 2.45mg/ha | Australia (warm temperate dry) |
| | Mondini et al 2017 | 2.5-32g/kg | - | - | - | -1.2 | - | 0.98[c] | 4.5% | Italy and Spain (warm temperate dry) |
| | Farina et al 2013 | - | 1.7% | - | 0.42 | 1.14 | - | 0.96[d] | 5.7% | Australia (warm temperate dry) |
| | Li et al 2006 | - | 6.9g/kg | - | - | 2.22 | - | 0.78[e] | 14.27 | China (warm temperate dry) |
| | Singh & Benbi 2020 | - | 4.3g/kg | - | - | - | - | 0.94[f] | 1.07-9.86mg/ha | India (tropical dry) |
| | Studdert et al 2011 | - | 37.3g/kg | - | - | - | - | 0.59 | 4.07mg/ha | Argentina (warm / cool temperate dry) |
| | **Average** | | | | | | | **0.77** | | |
| **Ex-situ spectroscopy (in laboratory)** | **Author** | **Range** | **Mean** | **SD** | **Bands** | **Model** | **RPD** | **$R^2$** | **RMSE** | |
| | Viscarra & Rossel (2006) | 0.85-2.14 dag/kg | 1.34 | 0.25 | MIR | PLSR | - | 0.73 | 0.15dag/kg | |
| | (Reeves & McCarty, 2001) | 6130-33900 mg/kg | 13380 | 4630 | NIR | PLSR | 2.78 | 0.94 | 993mg/kg | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Peng et al 2014 | 0.79-30.73 g/kg | - | - | Vis NIR | SPA-SVMR | 1.89 | 0.73 | 2.78g/kg | |
| | Nocita et al 2013 | 9-50.2 g/kg | - | - | Vis NIR | PLSR | 2.6 | 0.87 | 3.45g/kg | |
| | Stevens et al 2008 | 5.9-22.1 g/kg | - | - | VisNIR | PLSR | 2.03 | 0.75 | 0.7g/kg | |
| | Jia et al 2017 | 0.39-130.5 g/kg | 20.05 | 19.4 | MIR | SVMR | 2.12 | 0.82 | 9.19g/kg | |
| | Jia et al 2017 | 0.39-130.5 g/kg | 20.05 | 19.4 | VNIR | SVMR | 2.41 | 0.86 | 8.06g/kg | |
| | Winnowiecki et al 2016 | 1.5-81.4 g/kg | - | - | MIR | RF | - | 0.95 | 4.3g/kg | |
| | Vagen | 1.75-30.31 g/kg | - | - | MIR | RF | - | 0.98 | 1.3g/kg | |
| | Shepard& Walsh 2002 | 2.3-55.8 g/kg | 12 | - | Vis-NIR | MARS | - | 0.8 | 3.1g/kg | |
| | Fidencio et al 2002 | 0.4-4.88 % | - | - | NIR | RBFN | - | 0.96 | 0.32% | |
| | Chang & Laird 2002 | 15.4-144.9 g/kg | 48.7 | 26.1 | Vis-NIR | PLSR | 4.2 | 0.89 | 6.2g/kg | |
| | Bai et al 2022 | 0.98-20.49 g/kg | 3.54 | 3.08 | Vis-NIR | CNN | 3.18 | 0.9 | 0.97g/kg | |
| | Gomez et al 2008a | - | - | - | MIR | PLSR | - | 0.91 | 0.15dag/kg | |
| | **Average** | | | | | | | **0.86** | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Proximal sensing** | **Author** | **SOC range** | **Mean** | **SD** | **Bands** | **Model** | **RPD** | **$R^2$** | **RMSE** | **Device** |
| | Stevens et al 2008 | 5.9-22.1 g/kg | | 2.6 | VisNIR | PLSR | 2.11 | 0.75 | 0.7g/kg | Fieldspec Pro FR |
| | Sharififar et al 2019 | 0.05-1.95 % | 0.34 | 0.35 | NIR | Cubist | 2.19 | 0.78 | 0.16% | Neospectra |
| | Sharififar et al 2019 | 0.05-1.95 % | 0.34 | 0.35 | VisNIR | Cubist | 2.92 | 0.89 | 0.12% | ASD |
| | Kusumo 2018 | 1.41-2.65 % | 1.98 | 0.40 | Vis-NIR | PLSR | 3.82 | 0.93 | 0.298% | ASD field spec 3 |
| | Gomez et al 2008 | 0.002-5.1 % | | | Vis-NIR | PLSR | 1.87 | 0.71 | 0.53% | AgriSpec portable spectrometer |
| | Bricklemyer & Brown 2010 | 6-27.2 g/kg | 12.1 | 3.20 | Vis-NIR | PLSR | 1.3 | 0.42 | - | Veris Technologies |
| | Cozzolino et al 2013 | | | | | PLSR | 1.8 | 0.81 | - | - |
| | Kodaira & Shibusawa 2013 | 3.88-10.22% | 6.59 | 1.14 | Vis-NIR | PLSR | 2.9 | 0.9 | 0.35% | RTSS (SAS 1000, SHIBUYA MACHINERY Co., Ltd.) |
| | Kweon et al 2013 | 0.4-6.9 | 2.44 | 0.81 | EC/NIR | MLR | 4.85 | 0.83 | 0.25% | Veris OpticMapper with soil EC and optical sensors |
| | Ji et al 2015 | | | | | PLSR | 1.79 | 0.7 | 0.27g/kg | |
| | Kuang et al 2015 | 0.73-17.85% | 2.32 | 2.85 | Vis-NIR | PLSR | 1.95 | 0.73 | 1.46% | AgroSpec from tec5 Technology for Spectroscopy, Germany |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Kuang et al 2015 | 0.73-17.85% | 2.32 | 2.85 | Vis-NIR | ANN | 2.33 | 0.83 | 1.22% | AgroSpec from tec5 Technology for Spectroscopy, Germany | |
| | (Viscarra Rossel et al., 2017) | 0.02-16.28% | 1.54 | 2.4 | Vis-NIR | Cubist | | 0.81 | 0.41% | SCANS | |
| | Kuhnel & Bogner 2017 | 8.3-16.9mg/G | 12.4 | | Vis-NIR | Smote/PLSR | 1.32 | 0.4 | 1.9mg/g | Agrispec portable spectrometer (PAN-alytical) | |
| | Sorenson et al 2017 | 0.25-6.14% | 1.78 | 1.28 | | Cubist | 2.2 | 0.8 | 0.6% | P4000 drill rig mounted spectrometer (Veris® Technologies) | |
| | Veum et al 2018 | 0.03-2.95 g/100g | 0.67 | 0.44 | Vis-NIR | PLSR | | 0.65 | 0.26g/100g | Veris p4000 | |
| | Nawar et al 2020 | 0.96-2.04% | 1.33 | 0.25 | VNIR | Cubist | | 0.76 | 0.12% | CompactSpec, Tec5 Technology, Germany | |
| | Shen et al 2020 | 1.15-3.589% | 2.17 | 0.49 | | PLSR | 1.71 | 0.71 | 0.28% | ASD) FieldSpec 4 High-Res | |
| | **Average** | | | | | | | **0.75** | | | |
| **Remote sensing** | **Author** | **SOC range** | **Mean** | **SD** | **Depth (cm)** | **Model** | **RPD** | **$R^2$** | **RMSE** | **Product** | **Resolution (m)** |
| | Vågen & Winowiecki, 2013 | 2-8kg/m2 | | | 30 | RF | Nil | 0.65 | - | Landsat ETM+ | 30 |
| | Winowiecki et al., 2016 | 1.5-81.4g/kg | 12.4 | | 30 | | Nil | 0.81 | 1.03kg/m2 | MODIS | 500 |
| | (Vågen et al., 2018) | 1.75-30.31 g/kg | | | | RF | Nil | 0.80 | 8.2g/kg | RapidEye | 5 |
| | Zepp et al 2021 | 0.26-18.3% | 1.9 | 1.3 | | RF | 1.77 | 0.67 | 1.24% | Landsat | 30 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (Vågen et al., 2013) | 15.5-51.5g/kg | | | 20 | RF | - | 0.79 | - | Landsat ETM+ | 30 |
| | (Dvorakova et al., 2021) | g/kg | 12.3 | | | PLSR | 2.7 | 0.78 | 0.45g/kg | Sentinel 2 | |
| | Urbina Salazar et al 2021 | 5.03-53.1 g/kg | 14.14 | 10.2 | | PLSR | 1.83 | 0.70 | 5.58g/Kg | Sentinel 2 | |
| | Gomez et al 2008a | 0.002-5.1% | | | | PLSR | 1.43 | 0.51 | 0.73% | Hyperion | 30 |
| | Ward et al 2020 | 8-134 g/kg | 15.5 | 26.02 | | PLSR | 2.19 | 0.78 | 11.88g/kg | airborne HySpex | |
| | Ward et al 2020 | 8-134g/kg | 15.5 | 26.02 | | PLSR | 2.15 | 0.77 | 12.63g/kg | simulated satellite EnMAP | |
| | (Dvorakova et al., 2020) | 7.5-19.9g/Kg | 11.6 | 2.8 | | PLSR | 1.50 | 0.59 | 1.75g/kg | APEX | 2 |
| | Žížala et al 2019 | 0.84-2.62% | 1.44 | 0.39 | | RF | 1.65 | 0.74 | 0.24% | Planetscope | |
| | Vaudour et al 2019 | 6.38-31.9g/kg | 15.08 | 4.66 | | PLSR | 1.50 | 0.58 | 3.02g/kg | Sentinel 2 | 10-20m |
| | (Ayala Izurieta et al., 2022) | Mg/ha | | | 30 | GPR | | 0.85 | 1.58mg/ha | Sentinel 2 | |
| | Bhunia et al 2019 | 0.3-9.9 | 5.02 | 2.6 | | | | 0.81 | 1.11 | Landsat 4 | |
| | **Average:** | | | | | | | **0.72** | | | |

Notes:
EF = Modelling Efficiency; CRM =Coefficient of Residual Mass; SD = Standard Deviation; SE = Standard Error; $R^2$ = coefficient of determination; RMSE = Root Mean Square Error; RPD = Residual Product D; Model = type of prediction model used for estimating SOC content from spectral data [RF: Random Forest, PLSR: Partial Least Squares Regression, GPR: Gaussian processes regression; ANN: Artificial Neural Network, Convolutional Neural Network, SPA: Successive Projections Algorithm, SVMR: Support Vector Machines Regression, MARS: Multivariate adaptive regression splines, RBFN]; Band = region of electromagnetic spectrum used for the spectral analysis

a. Originally given as r, converted to $R^2$. Averaged across 2 research sites in the paper. Estimates to 20cm depth.
b. Only the $R^2$ value reported for predicting total organic carbon in a cropping environment was taken (See Figure 3 in source)
c. Originally given as r, converted to $R^2$
d. Spearman's correlation coefficient used, results of dry and bare soil models, for all sites was taken.
e. Originally given as r, converted to $R^2$. Only results from the control (nil) treatment at Changping trial site using the Roth C M model (with input values from measured biomass) are taken.
f. Results from the independent validation are taken, averaged across 2 cropping types

**A.2: Basis and Assumptions behind cost estimates used for comparison of the MRV approaches.**

| Approach | Assumptions | Cost ($/ha/yr) |
|---|---|---|
| L1 | Laboratory analyses of soil samples is performed via wet chemistry at standard costs in Kenya ($20 per plot) for all 32,000 plots every 4 years and averaged over the 20-year project duration. | 5 |
| AM3* | Survey costs synthesized using local costs (enumerator fees and logistics) in Western Kenya for all 32,000 farmers. Assuming the survey is done yearly. | 4.4 |
| AM1 | Following estimates by experts (pers. Comm) placing farmer group monitoring costs in Kenya at $3.9/ha/yr. | 3.9 |
| L2 | Laboratory analyses of soil samples is performed via MIR-spectroscopy at standard costs in Kenya ($6.5) for all 32,000 plots every 4 years and averaged over the 20-year project duration. | 1.6 |
| PS2 | Average cost for soil analyses with soil scanner in Kenya ($6) for all 32,000 plots; performed once every 4 years and averaged over the 20-year project duration. | 1.5 |
| PS1 | Assuming the monitoring entity purchases 1 device per 500 farmers (i.e., 20 groups of 25 farmers) at the cost of an Agrocares (https://www.agrocares.com/scanners/) scanner in Kenya ($3,000). The yearly license fee of $1800 for Agrocares database is included. Total cost is then averaged over a 20-year project duration. | 0.3 |
| AM2 | Survey costs synthesized using local costs (enumerator fees and logistics) in Western Kenya for a sample size of 600 (sample size is calculated based on desired statistical accuracy level). Assuming the survey is done yearly. | 0.3 |
| RS1 | Using medium resolution imagery at cost USD 0 - 2.5/km$^2$. Assuming imagery analysis cost USD10.4/km$^2$ according to estimates by Böttcher et al. (2009) and that no additional equipment / software is purchased. Spectral analysis is carried out every 4 years at validation. One-off costs for initial collection of ground truth data (1200 soil samples) and analysis via L2 for model calibration are included in the costs. Total costs are averaged over the 20-year project duration to estimate yearly costs. | 0.2 |
| RS2/AM4 | Assumes identical cost as RS1 since the available data was not sufficient to develop cost estimates for this approach. | 0.2 |
| * Cost estimates for all AM approaches consider data collection only. QC, verification, and data analysis are not included. | | |

**A.3: Scores of the MRV approaches across performance Indicators.**

| | L1 | L2 | AM1 | AM2 | AM3 | RS2 | PS1 | PS2 | RS1 |
|---|---|---|---|---|---|---|---|---|---|
| **Accuracy (Potential)** | 5 | 4 | 3 | 3 | 3 | 3 | 3 | 3 | 2 |
| **Standardization** | 5 | 4 | 4 | 4 | 4 | 1 | 2 | 2 | 1 |
| **Cost reduction** | 1 | 4 | 2 | 1 | 5 | 5 | 5 | 4 | 5 |
| **Adoptability** | 5 | 5 | 4 | 4 | 5 | 3 | 4 | 4 | 2 |
| **Community Benefits** | 3 | 3 | 3 | 2 | 3 | 2 | 4 | 3 | 1 |

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