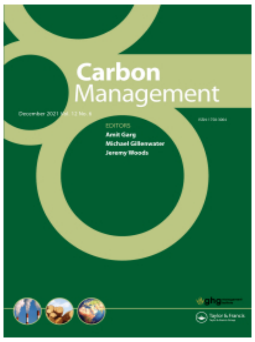
Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment

Niels H Batjes, Eric Ceschia, Gerard B M Heuvelink, Julien Demenois, Guerric Le Maire, Rémi Cardinael, Cristina Arias-Navarro, Fenny van Egmond



Carbon Management

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/tcmt20

Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment

Niels H. Batjes, Eric Ceschia, Gerard B.M. Heuvelink, Julien Demenois, Guerric le Maire, Rémi Cardinael, Cristina Arias-Navarro & Fenny van Egmond

To cite this article: Niels H. Batjes, Eric Ceschia, Gerard B.M. Heuvelink, Julien Demenois, Guerric le Maire, Rémi Cardinael, Cristina Arias-Navarro & Fenny van Egmond (2024) Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment, Carbon Management, 15:1, 2410812, DOI: 10.1080/17583004.2024.2410812

To link to this article: https://doi.org/10.1080/17583004.2024.2410812

CARBON MANAGEMENT
2024, VOL. 15, NO. 1, 2410812
https://doi.org/10.1080/17583004.2024.2410812

REVIEW ARTICLE

Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment

Niels H. Batjes[a], Eric Ceschia[b], Gerard B.M. Heuvelink[a], Julien Demenois[c,d], Guerric le Maire[e,f], Rémi Cardinael[c,d,g], Cristina Arias-Navarro[h] and Fenny van Egmond[a]

[a]ISRIC – World Soil Information, Wageningen, The Netherlands; [b]CESBIO, Université de Toulouse, CNES/CNRS/INRAE/IRD/UT3, Toulouse, France; [c]CIRAD, UPR AIDA, Montpellier, France; [d]AIDA, Univ Montpellier, CIRAD, Montpellier, France; [e]CIRAD, UMR Eco&Sols, Montpellier, France; [f]Eco&Sols, Université de Montpellier, CIRAD, INRAe, Institut Agro, IRD, Montpellier, France; [g]Plant Production Sciences and Technology, University of Zimbabwe, Harare, Zimbabwe; [h]Joint Research Centre (JRC), European Commission, Ispra, Italy

ABSTRACT
Soils are the largest terrestrial reservoir of organic carbon, yet they are easily degraded. Consistent and accurate monitoring of changes in soil organic carbon stocks and net greenhouse gas emissions, reporting, and their verification is key to facilitate investment in sustainable land use practices that maintain or increase soil organic carbon stocks, as well as to incorporate soil organic carbon sequestration in national greenhouse gas emission reduction targets. Building up on an initial review of monitoring, reporting and verification (MRV) schemes with a focus on croplands, grasslands, and forestlands we develop a framework for a modular, scalable MRV system. We then provide an inventory and classification of selected MRV methodologies and subsequently "score" them against a list of key characteristics. It appears that the main challenge in developing a unified MRV system concerns the monitoring component. Finally, we present a conceptual workflow that shows how a prototype for an operational, modular multi-ecosystem MRV tool could be systematically built.

ARTICLE HISTORY
Received 28 March 2024
Accepted 24 September 2024

KEYWORDS
Carbon sequestration; climate change mitigation; sustainable land management; carbon accounting; monitoring framework

Introduction

Soils, the largest terrestrial reservoir of organic carbon [1,2], are easily degraded when disturbed [3]. There is growing recognition of the importance of monitoring changes in soil organic carbon (SOC) stocks in the broader context of climate change mitigation ([4], Sustainable Development Goal (SDG) 13 [5]), halting and reversing land degradation (SDG 15), ensuring human livelihood/health (SDG 1,2,3) and reversing biodiversity loss ([6]; SDG 14, 15). Being able to reliably quantify the amount of organic carbon that is stored in soils and to accurately measure and model how these amounts change with management practices and land use change forms the first step towards making informed decisions about how SOC stocks can be preserved or increased and ecosystem services improved [7–11]. In this context, it is important to carefully distinguish the "sequestration of SOC in stable pools from the mere transient increases in SOC storage that follow the incorporation of manure and plant residues into soils" [12–16].

SOC refers only to the carbon component of soil organic matter (SOM) [17–19]. SOM itself is an important determinant of the quantity and quality of many ecosystem services [9, 20] and soil functioning [21,22]. It should be noted that drivers of change in SOM concentration are not exactly the same as drivers of change in SOC stock [12, 15]. For example, interventions to build up SOM quantity and quality may only lead to a reduction in carbon losses (i.e. carbon loss mitigation) rather than result in real carbon sequestration in stable pools and negative emissions [12, 16].

SOC stocks and greenhouse gas (GHG) fluxes vary with environmental conditions such as soil type and terrain (e.g. drainage, exposition), climate, and land use (e.g. agriculture, forestry, peatlands, and urban land) and management [23,24]. The overarching policy setting, such as the EU

CONTACT Niels H. Batjes niels.batjes@isric.org ISRIC – World Soil Information, Wageningen, The Netherlands.
Supplemental data for this article can be accessed online at https://doi.org/10.1080/17583004.2024.2410812.

Common Agricultural Policy (CAP) and GreenDeal [25–28], create conditions aimed at maintaining current carbon stocks in carbon-rich ecosystems (e.g. peatlands, mangroves) respectively increasing SOC stocks in, and reducing GHG emissions from, degraded ecosystems.

The European Commission [29] proposed a Framework for Carbon Removals Certification that aims to incentivise carbon removals. Alongside other removal options, this includes a specific focus on promoting "carbon farming", a category that includes nature-based solutions. The Framework establishes rules to certify and govern removals with the objective of ensuring high quality carbon removals within Europe and thereby elicit upscaling of carbon removals. The framework aims at allowing financing through various sources, for example public funding (CAP, state aid, and EU funds), food and biomass value chain (insetting), carbon credits outside the value chain (offsetting), and could entail a significant shift towards market-based incentives for mitigation in the land sector. Voluntary carbon markets are increasingly offering market-based incentives to landowners [30–32], but until now European policymakers have relied on action-based and regulatory approaches to manage the land sector, as exemplified by the CAP [29].

In data scarce countries, global default values for reference SOC stocks and emission factors are commonly used to infer changes in SOC stocks over time and variation over space, subject to defined land use and management interventions, using empirical models, i.e. Tier 1 level approaches [33,34]. The use of such default values, however, is prone to low accuracy and high uncertainty, especially when applied to estimate SOC stock change in local/landscape scale projects [35,36]. Through physical (in-situ) soil sampling combined, or not combined, with modeling researchers, project managers, and agricultural practitioners can improve estimation of current SOC stocks and changes under different land management practices. For instance, repeated measurements of SOC concentration, bulk density and proportion of coarse fragments can show how land management impacts SOC stocks over time and space, provided they are based on a strategic research/experimental design [37]. When paired with sustainable soil management and agricultural practices, the information can be used in financing frameworks to promote carbon sequestration while supporting livelihoods through increased soil health and possibly agricultural yields, as well as addressing climate change. In practice, however, the cost of taking sufficient soil samples to reliably monitor changes in carbon farming projects can be prohibitive, hence the need for developing novel approaches (e.g. hybrid modeling). For such practices to be rewarded, the reported SOC gains need to be verified by a third party. Importantly, the experts or companies that are in charge of carrying out monitoring and reporting should not also carry out the verification, due to a possible conflict of interest; see for example the independent review of Australian carbon credit units (ACCUs) [38].

Consistent and accurate monitoring of changes in SOC stocks and net GHG emissions, reporting, and their verification, is key to facilitate investment in sustainable land use practices that maintain and increase SOC, as well as to incorporate SOC sequestration in GHG emission reduction targets at the international and national level (e.g. Nationally Determined Contributions, NDC) [39]. Yet, according to Wiese et al. [40], only 28 out of 184 countries in the Paris Climate Agreement referred to SOC, peatlands or wetlands in their NDCs: "to increase country commitments and attention to managing SOC, there is a need for improved SOC measurement and monitoring, for better evidence on the impacts of management practices on SOC, and for incentives for farmers to change practices and overcome barriers."

The short- and longer-term socio-economic perspective of farmers versus the long-term perspective of SOC sequestration projects needs to be considered too [41–44]. Soil management interventions aimed at increasing organic matter (i.e. SOC) levels in soil and to decrease organic carbon loss in soils of different agro-ecological and urban systems, and their possible co-benefits, have been described elsewhere [24, 45–50].

While most Monitoring, Reporting and Verification (MRV) schemes focus on total SOC, it should be noted that the carbon in soils consists of different forms that are chemically varied and have specific turnover times [51]. The complex biological basis of SOC sequestration has recently been reviewed by Lavelle [52], while Doetterl et al. [53] focused on the effects of biotic and abiotic factors controlling SOC dynamics at continental to global scales. Potential, actual and attainable SOC sequestration rates are determined by defining factors, such as clay mineralogy, limiting factors (e.g. climate) and reducing factors (e.g. erosion, residue removal, soil fertility decrease, land mismanagement) or increasing factors (e.g. improved land management, crop rotation, cover crops, additional C inputs) [54]. Further, there may be stoichiometric [55–58] and microbiological limitations [59–61], as well as often overruling social and economic limitations to attainable SOC gains [42, 62–65].

Although soils are a promising reservoir to store carbon, long time scales are required to sequester amounts of (stable) carbon of relevance to mitigate climate change [66–68]. Alternatively, particulate organic matter (POM) defined as the "0.053–2 mm size fraction" of SOM [69], can also play a role in climate change mitigation. Part of it can persist over longer time scales as it can be trapped within soil aggregates where it is not available for soil microbes to cycle [70,71]. For the fast-decomposing POM, the stock and carbon accrual can be high, but management needs to be maintained to be relevant for climate change mitigation [72] as there is a high risk of reversal (hence a percentage of credits is held in a buffer pool to mitigate this risk).

Possible gains in SOC are considered to be finite [73,74] and are reversible upon changes in land management practices [75,76]. The validity of the widely accepted assumption of "possible stable SOC gains being finite due to the limited mineral surface available" (i.e. saturation concept) has recently been questioned and remains an issue of scientific debate [77–79]. In this context, it is important to differentiate between the concepts of C-saturation versus C-equilibrium, which is based on inputs/outputs of C for a given system [16].

Importantly, interventions that are focused on SOC sequestration may not be as efficient for climate change mitigation as anticipated [80–83]. Also they might not always lead to increased crop productivity [13,14, 84,85], and often operate on longer time scales than many smallholder farmers can accept financially [42]. A recent study [86] found that the main incentives for smallholder farmers to participate in carbon payment schemes are non-monetary. These include improved yields, building soil resilience and limit erosion, increasing soil organic matter as a source of nitrogen (N) in "low soil fertility regions" [87–89] or, alternatively, to reduce the application of inorganic N fertilizers in parts of the world with N-related environmental problems [81, 90]. Further incentives include access to financial advisory services and credit, investments in local infrastructure, and the development of income-generating activities. Such co-benefits play a central role in carbon payment projects as they can enhance the likelihood of permanence of practices to sustain SOC stocks, a central issue related to the credibility of SOC credits [86]. In this context, it is also important to be aware of the risk of land grabbing associated with some "carbon credit oriented" projects and large-scale investments in farmland [91–94].

The abbreviation MRV, as used in this review, stands for Monitoring, Reporting and Verification. The monitoring activities under consideration are related to national scale, landscape, plot and/or project scale inventories, and those focusing on the carbon markets (e.g. voluntary and compliance), as well as "insetting." The economic considerations of carbon market-oriented MRV systems, i.e. underpinning business models, are intricate [95–97]. Payment models can focus on preserving or increasing forest biomass, conserving SOC, reducing net emissions from soil, increasing sequestration of carbon into soils or a combination thereof. Most voluntary carbon market schemes in agriculture work on the basis of "Net Abatement," i.e. SOC stock increases plus soil derived GHG emission reductions (i.e. consider net GHG emission changes expressed as CO_{2eq}). For some MRV systems, however, measuring SOC change is not required (i.e. "action-based" verification), but this precludes the scope for true verification (i.e. "result-based"). In this context, some groups prefer to use "Measurement, Monitoring, Reporting and Verification" (MMRV) to show the importance of field measurements, rather than MRV alone [98]. Many MRV guidelines and approved methodologies have been proposed, yet their differences remain unclear. In this study, we compared 17 of these guidelines using 26 criteria including the ecosystems covered, geographic scope, tier level and reporting frequency.

The WorldBank [7] identified three broad types of payment systems applicable to projects sequestering SOC in agricultural land. These were ranked according to cost of implementation, confidence of atmospheric impact, and degree of complexity: a) Payment for practice (input-based system); b) Payment for practice with performance dividend; and c) Payment for performance (output-based system, e.g. carbon-market, voluntary or compliance). For the first payment system, it is sufficient to implement an eligible practice to get paid. Alternatively, for the last payment system (c) an assessment of the impact is compulsory and the payment itself can be modulated based on the performance. The second payment system (b) is a blend of systems "a" and "c," with a fixed payment plus a bonus based on the performance.

Although much progress in national and sub-national level MRV systems for SOC has been achieved over the last two decades [11, 66, 99–103], a recent poll of staff working in environmental organizations, businesses, academic researchers and government entities identified MRV as "one of the largest challenges by entities developing carbon farming schemes" [104]. This has partly to do with the scale at which the MRV system is needed when referring to carbon farming, i.e. farm or plot scale, which may involve approaches that differ from those commonly used for national or sub-national inventories (i.e. Tier 1 and Tier 2) and make more systematic use of Tier 3 approaches, with exhaustive management and farm data collection for GHG emissions assessment. The most common challenges according to the poll were the lack of robust monitoring, reporting and verification systems as well as knowledge about the relevant costs. This is surprising considering that UNFCCC [105] principles indicate that MRV systems should be "transparent, complete, consistent, comparable and accurate" and also consider the common sense principles of being "pragmatic, cost-effective, scalable, timely, and operational." Importantly, safeguards against "greenwashing" [106,107], and the often associated "land grabbing" [92,93], through uncertainty quantification and solid verification by independent suitably experienced and qualified third parties will be essential [108–111]. Yet, verifiers may not have the right expertise, and many will not have the modeling experience, pointing at a need for training capacity [112].

The primary objective of this study, carried out in the framework of the EU ORCaSA project [113], is to propose an approach for a modular, integrative, and multi-ecosystem MRV framework for SOC stock changes. First, we carried out an in-depth literature search using the Web of Science platform to retrieve studies that examined SOC and MRV systems focusing on croplands, grasslands and forest lands. Additional articles were identified from personal research libraries (For URLs see Supplementary information S4). Based on this, in Section " Components for a modular MRV framework", we propose a conceptual, modular, and scalable MRV framework. Subsequently, we provide an inventory and classification of current MRV methodologies and subsequently "score" them using a list of key characteristics (Section "Inventory and classification of current MRV approaches"). Thereafter, in Section "Towards an operational, integrative, and multi-ecosystem MRV approach for SOC stock changes", we build on this and provide an outlook on how an operational, modular multi-ecosystem MRV system could be systematically built in the next phase of the ORCaSa project.

Components for a modular MRV framework

Smith et al. [114] discussed a conceptual MRV framework for cropland dedicated to NDCs. They described how different "building blocks" (e.g. field measurements, datasets, models) could contribute to the three components of an MRV system for SOC changes. The study also provided a methodological basis for the ground monitoring, modeling, and verification of SOC stock changes. It requires to combine different datasets (e.g. input for models, calibration and validation data), together with models (e.g. empirical, soil process-based models, coupled soil-crop process-based models, carbon balance models), embedded in a spatial data infrastructure (SDI) allowing for handling of databases, intensive computing, decision support systems, and verification and distribution of results/reporting. It is important to note that when process-based models simulate only the soil compartment they require external information on biomass inputs to the soil, while coupled soil-vegetation models directly estimate biomass inputs. Therefore, the choice of modeling approach will have important consequences when the calculation of net SOC stock changes is operationalized.

A "building block," is one of the separate parts that are combined to make an operational MRV system. Examples are spatial data layers (e.g. maps of soil properties, land management and activity data), modeling approaches (e.g. process-based soil, vegetation or coupled soil-vegetation models, or data-driven models), or the combination of Earth Observation (EO) data and radiative transfer models that can produce biophysical data from EO to be assimilated in process-based models. The building blocks themselves, many elements of which already exist as loose modules [115–117], need to be assembled in an operational processing chain to be applied in one or several contexts of applications (e.g. CAP, Carbon market, or NDC) [118–120]. Note that the same building blocks (and their constituting parts) can be used in one or several components of an MRV system. For example, both the Comet Farm Tool [121] and the DayCent model [122,123] are Tier 3 approaches (and even include the same model), but their use and role in MRV systems is completely different.

A different conceptual MRV framework has been presented by Paustian et al. [124]. It includes components similar those proposed by Smith et al. [114], as well as a scalable quantification platform (which is not detailed in the paper itself), and further considers the different communities that should be served by an MRV system (e.g. national policies, carbon finance market and supply chains).

Depending on the size of the area to be monitored, the availability/accuracy of the input data, protocols for sampling/measurement, monitoring frequency, scale of interest and purpose, different MRV approaches and associated methodologies (e.g. Tiers as in Bockstaller et al. [119] for the CAP), will be needed.

Based on the above, and discussions during two international stakeholder workshops, we pictured a scalable, modular MRV framework (Figure 1):

a. Monitoring (M), which includes experiments or observatories (e.g. long-term soil observations, flux tower networks), direct (soil) measurements, activity data, spatial data layers, Earth Observation (see M1 to M5 in Figure 1) aimed at developing and/or applying models (M6 to M8). The gear wheel in the green monitoring box (M) serves to illustrate that these activities are performed within the context of a scalable quantification platform.
b. Reporting (R), which includes rules and procedures (R1 and R2).
c. Verification (V), which includes rules and procedures, verification itself, proof of adoption of practice, and data (soil and/or EO) for verification (V1 to V4).

The three components and their building blocks, as well as their practical application, have been discussed in detail in Batjes et al. [125]. Landscape-scale assessment of SOC stock changes in agriculture and forestry, for example, can present a number of practical problems. Data are needed from heterogeneous areas, often for multiple points in time, and the collection and laboratory analyses of these samples can be expensive and time consuming [126]. However, time and costs can be reduced by taking composite samples and using proximal sensing techniques, such as MIR/NIR spectroscopy, and developing soil spectral calibration libraries and estimation services [100, 127–131]. Overall, field measurements (even when considering the associated uncertainties [132,133]) are still considered the best option to quantify and verify SOC content and SOC changes. They are also needed for model development and calibration as well as verification. The use of field measurements, modeling and remote sensing for MRV purposes is often complementary [134,135].

Broadly speaking, three types of models are used to predict SOC stocks and SOC stock changes: a) process-based (M6 in Figure 1) or mechanistic models [114, 124, 136,137]; b) data-driven (M7, or

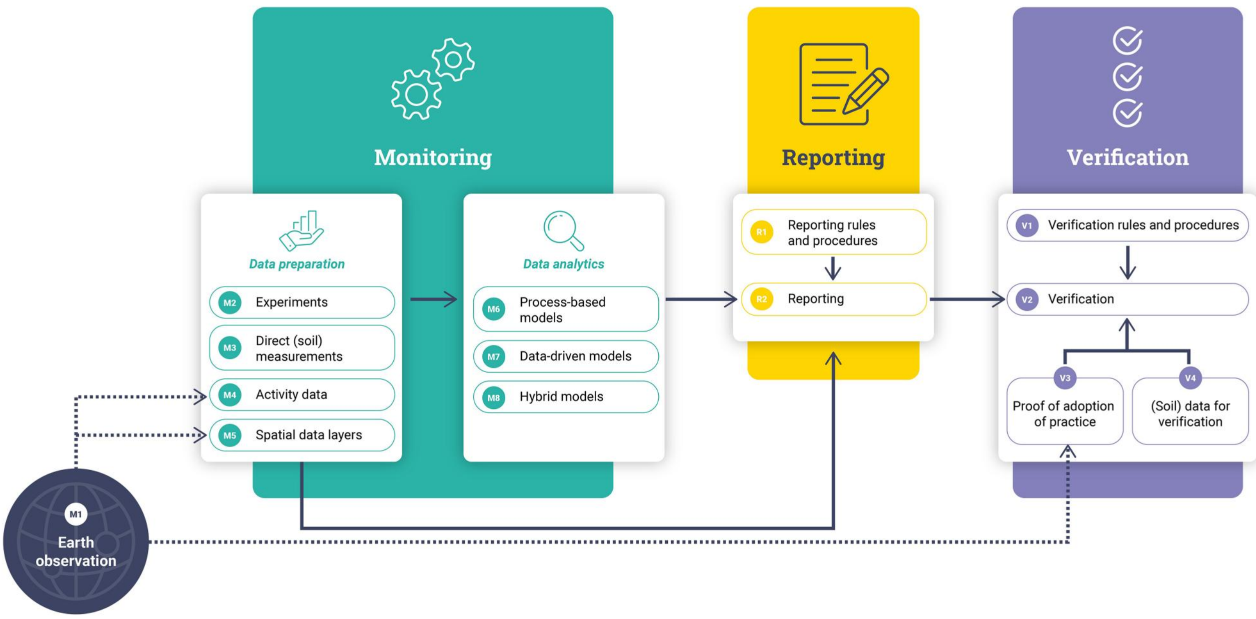


Figure 1. Schematic representation of components, building blocks, and information flow for a modular, scalable MRV system. (the dotted lines illustrate that Earth Observation can provide activity and spatial data for monitoring and reporting, respectively independent input for verification).

empirical) models [138,139]; and c) hybrid models (M8, [140–142]). The second type of model is based on statistical relationships derived directly from field (experiment) observations, while process-based models consider algorithms that are founded on more general scientific understanding. The latter is derived from laboratory- and field-based experiments, as well as a variety of field-based observations of SOC distribution along climatic, vegetation, topographic and geological gradients. Data-driven (M7) and process-based models (M6) can be combined in hybrid models (M8).

General specifications for the different model categories mentioned earlier, and their main characteristics, are presented in Table 1. A critical discussion of the differences between the applied methods, such as quality/differences of measuring protocols, remote sensing approaches (e.g. what is measured and how (SOC, biomass, Net Primary Production), model structures and data requirements, local or off-site calibration, use of measured or map-based (aggregated) data for driving modeling, and accounting for the associated uncertainty) is considered beyond the scope of this review as these have been addressed elsewhere [37, 99, 101, 118, 125, 141, 143–147]. However, such methodological differences are crucial and will have a major impact on the quality of the actual MRV system.

A fairly recent development has been the development of "hybrid models" that combine multiple data sources and modeling techniques [148]. For example, these can comprise a combination of "field data – remote sensing – machine learning" [149,150], "field data – remote sensing – ecosystem models" [151–157], or "field data – remote sensing – machine learning – ecosystem models" [120]. The combination of field measurements, remote sensing and ecosystem carbon models can be used for upscaling plot data for carbon accounting to larger areas (e.g. regional, country or global scale). However, the approach can also be used for downscaling: in that case, large scale data or model output (e.g. from a Dynamic Global Vegetation Model) are combined with remote sensing data to refine ecosystem or data-driven model outputs at smaller spatial scales, thus capturing local variations in carbon dynamics [158]. Another recent development has been the use of geostatistical approaches for assessing space-time changes in SOC stocks using machine learning that draws on large soil databases and environmental covariates [138, 159]. Le Noë et al. [160] provided a comprehensive review of ~250 SOC models, spanning 90 years of model development history, and concluded that combining independent validation based on observed time series and improved information flow between predictive and conceptual models is needed to increase reliability in predictions. Different sources of uncertainty associated with MRV systems, and steps towards their quantification, are discussed elsewhere (see Section "Reporting and verification").

Decision support tools provide information on the quantification of SOC stock changes, GHG emissions, or both. They mainly use IPCC Tier 1 (i.e. consider default or country-specific emission factors) and Tier 2 (i.e. consider more detailed and region-specific data and models) approaches but can also include a module for Tier 3 (most comprehensive and site-specific methodologies) [156, 161,162]. Tier 3 type approaches, the most demanding ones, are run using spatially explicit inputs and farm/region-specific model parameters. Tier 3 is considered to be the most accurate approach [33]. Operational tools (in particular Tier 3 type) depend on several of the building blocks described in Figure 1 (e.g. spatial data for climate

Table 1. Examples of different model categories and current decision support tools and their characteristics[a].

	Models			Decision support tools
Characteristics	Data-driven	Process-based	Hybrid	
Data requirement	Low	High (environmental data)	High (environmental data)	High (farm specific data)
Calibration requirement	Low	High	High	Low
Required expertise	Low	Medium-high	High	Medium
Management options	Medium (categories)	No-high	High	Medium-high
Targeted scale	Country and larger	Point, country and larger	Point, country and larger	Field-farm
Uncertainty/expected error for field scale	High	Medium-low	Medium-low	Medium-high
Examples	IPCC and UNFCC (Tier 1 and Tier 2); Machine learning[b]	Roth C (Tier 3), EPIC, CENTURY, DAYCENT, DNDC (Tier 3)	AgriCarbon-EO[b]	Cool Farm Tool (Tier 1), Comet Farm (Tier 1 and 2), CPB tools (Tier 1 and 2), SIMEOS-AMG (Tier 3)

[a]Adapted from Kuhnert et al. [94]. Note that some process-based models only consider C (e.g. RothC); whereas others consider C, N, P etc dynamics (e.g. DayCent) and these are often termed 'biochemical models'. Some process-based models have no plant/crop component (e.g. RothC), while others have (e.g. DayCent). All have biochemical pathways related to the cycling of incoming C using defined conceptual pools with varying decay rates.

[b]Machine-learning based models and hybrid models seldom have clear abbreviations; for examples see text.

or activity data as input, in-situ soil data for verification).

Inventory and classification of current MRV approaches

Inventory

National scale

Different MRV systems will be needed depending on their projected applications. National MRV frameworks under the UN Framework Convention on Climate Change (UNFCC) [28] focus on "what is measured, what is reported, and what is verified." The adopted IPCC methodologies are intended to yield national GHG inventories that are transparent, complete, accurate, consistent over time and comparable across countries (i.e. compliance oriented).

Smith et al. [114] reviewed MRV methods in use in countries participating in the Global Research Alliance on Agricultural Greenhouse Gases (GRA). All countries that are parties to the UNFCCC need to deliver national inventories of emissions and removals of GHG associated with human activities. Since different countries have different capacities to produce inventories, the IPCC guidelines lay out tiers of methods for each emission source. They [114] reported that countries listed as "non-annex 1" (i.e. mostly developing countries that have ratified or accepted the UNFCCC and are not included in Annex 1 of the Kyoto Protocol) face major challenges due to a paucity of data respectively limited technical capacity to collect the data necessary for the inventories. For instance, in sub-Saharan Africa, countries often lack activity data in addition to specific emission factors [163]. As a result, most GRA countries use a Tier 1 approach to report SOC changes associated with areas defined as cropland, while industrialized (Annex I) countries such as Australia, Canada and Denmark use a Tier 3 approach, respectively based on FullCAM, Century and C-Tool models. Further, specificities on methodologies and models used in selected GRA countries are provided in Smith et al. [114].

Subnational to project scale

More recently, Oldfield et al. [164] prepared an overview of SOC estimation and sampling methods, listing main issues and approaches to be considered in an MRV framework. Their study considered twelve published MRV "protocols" for SOC credits generated on cropland and rangeland. They assessed over forty characteristics for each protocol. Unsurprisingly, these protocols take different approaches to quantifying SOC and net GHG removals, often building upon national conventions. While some use soil sampling only, others combine sampling with process-based modeling, or use only modeling and remote sensing. These differences as well as the way issues such as permanence (i.e. consider the sustained climate mitigation effect in the long-term) and additionality (i.e. consider if the reported emission reductions and/or carbon removals associated with the adoption of new land management practices (i.e. project scenario) would be greater than under the "business-as-usual" scenario (i.e. without the carbon finance or incentive)) are accounted for may create the risk of generating credits that are not equal or comparable [94, 103, 165]. Furthermore, it should be noted that some of the protocols reviewed in Oldfield et al. [164] have since been retracted by the certifying agencies as some of the claims for carbon offsets made could not be substantiated due to "greenwashing" [106,107].

According to Arcusa and Sprenkle-Hyppolite [115], based on an analysis of the carbon dioxide removal (CDR) certification and standards ecosystem for the year 2021–2022, there are at least thirty standard developing organizations. These propose at least 125 standard methodologies for carbon removal from 23 different CDR activities. Further, they identified 27 different versions of certification instruments in voluntary and compliance markets. In practice, again, this diversity makes it cumbersome to determine whether net climate benefits have been achieved or not. This shows the importance of developing an operational unified, modular, multi-ecosystem MRV "tool" for SOC and ecosystem carbon stocks (see Section "Towards an operational, integrative, and multi-ecosystem MRV approach for SOC stock changes").

Black et al. [103] presented an innovative global comparative analysis of farmland SOC "programmes or standards", abbreviated below as "codes", providing novel insights into the range of approaches governing this global marketplace. For this, they elaborated an analytical framework for the systematic comparison of "codes." They used this to identify commonalities and differences in approaches, methods, administration, commercialization, and operations for twelve publicly available "codes" from around the world. These "codes" used a range of mechanisms to manage additionality, uncertainty and risks, baselines, measurement, reporting and verification, auditing, resale of carbon units, bundling and stacking, stakeholder engagement, and market integrity. They concluded that adapting or translating existing "codes," or developing new approaches, to a workable farm level carbon "code" in a new country or region is not trivial, since these must address local economic, environmental, and social factors, including farming systems, soil and climatic conditions, regulations, social norms and values.

For France, Yogo et al. [166] proposed three possible options for carbon balance evaluation and monitoring with different methodologies, tools and data that can be mobilized, as well as recommendations for the specific case of croplands, and pointed at the advantage of moving towards methods that include remote sensing for a territorial deployment. Their comprehensive assessment included a review of twenty different methodologies, and tools, to assess at least one of the three main GHGs (CO_2, N_2O and CH_4) and/or carbon sequestration in soil and above-ground biomass. The underlying calculations include IPCC Tier 1 or Tier 2 emission factors, but also a range of models and use of satellite data.

For the Netherlands, Lesschen et al. [117] developed an elaborate "rating" system. It considers criteria and describes characteristics for twelve selected models and tools, to identify their suitability for application by farmers in the Netherlands. Criteria for selection include public availability, licensing, validation, accessibility of input data, applicability to cropland and grassland under climatic conditions similar to those in the Netherlands, as well as other characteristics, such as whether models are maintained, the number of C-pools, temporal scale and temporal resolution, spatial resolution, soil depth and number of layers, consideration of water balance and nitrogen interactions. On the basis of their inventory, Lesschen et al. [117] selected four potentially suitable soil C-models. Subsequently, they identified the data requirements of these models in terms of soil parameters, weather data, kind, and type of organic materials (manure) applied, soil management, information on crop type, etc. After a qualitative comparison, the four models were compared quantitively using datasets for two long-term experiments in the Netherlands. It followed that there are substantial differences between the models – this made the comparison of SOC changes uncertain. While some models simulated the same trends, changes in SOC levels varied substantially between models. Several studies [167–169] indicated that a multi-model analysis reduced the uncertainty in simulated SOC stocks, which would suggest that MRV systems should not rely on one model only. All of this will have implications for the verifiability of modelled SOC stock changes, or net GHG emissions, at an accepted confidence level (e.g. 90%). In this context, it should be noted that carbon markets do not look for change in SOC stocks over time, but rather at additionality or the difference in estimated GHG emissions under the "project" scenario versus GHG emissions that would have occurred under the "business-as-usual" scenario (i.e. net abatement).

Similarly, different MRV approaches and methodologies are used in the forest sector [170–173]. Differences in statistical sampling design, for example, as well as field sampling techniques and subsequent laboratory analyses will impact on the predictive quality of different monitoring networks [99, 174,175], making inter-comparison of results derived from various monitoring systems problematic [147, 176]. According to Olsson [177], unmeasurable uncertainties, such as political issues and economic rebound effects potentially leading to carbon "leakages," tend to be neglected in inventories. Importantly, different certification schemes can result in different prices being paid per net tonne of CO_{2eq} sequestered. These prices, in turn, will among others influence land use and crop management decisions [178–180] hence achievable carbon sequestration.

Reviewed guidelines and approved methodologies

From the above it follows that many different guidelines and methodologies relating to MRV exist and that the terms used are not always clear-cut with a diverse range of associated certification schemes. In this context, Demenois et al. [94] referred to a "jungle of certification schemes". For this review, as indicated earlier, we considered a selection of guidelines recognized as being most relevant based on the expertise of the writing team, and subsequent feedback during two international stakeholder workshops (Table 2). Succinct descriptions thereof are provided in Supplementary Information S2.

Typically, each approved methodology is based on one, or several, standards. These are often documented in a central registry which lists whether methodologies are accepted, in (scientific)

Table 2. List of reviewed guidelines and approved methodologies (listed in alphabetical order of their abbreviation).

Abbreviation	Name
AU-CFIDV	Carbon Farming Initiative—Estimating Sequestration of Carbon in Soil Using Default Values https://www.dcceew.gov.au/climate-change/emissions-reduction/emissions-reduction-fund/methods/estimating-sequestration-of-carbon-in-soil-using-default-values
AU-CFMM	Carbon Farming Initiative—Estimating soil organic carbon sequestration using measurement and models method https://www.cleanenergyregulator.gov.au/ERF/Choosing-a-project-type/Opportunities-for-the-land-sector/Agricultural-methods/estimating-soil-organic-carbon-sequestration-using-measurement-and-models-method
BC-SCM	BCarbon Soil Carbon Protocol https://static1.squarespace.com/static/611691387b74c566a67f385d/t/63483a986a24ac421c4f4414/1665677979013/2022-10-13-BCarbon-Soil-Carbon-Protocol-V2.pdf
CARSSE	Climate Action Reserve Soil Enrichment Protocol v 1.0 https://www.climateactionreserve.org/wp-content/uploads/2020/10/Soil-Enrichment-Protocol-V1.0.pdf
DE-MOOR	Moor Futures https://www.moorfutures.de/downloads/
FR-LBC	Label Bas Carbone (There are six approved methodologies for SOC, see below for details). https://label-bas-carbone.ecologie.gouv.fr/quest-ce-que-le-label-bas-carbone
Gold Standard	Soil Organic Carbon Framework Methodology https://globalgoals.goldstandard.org/
GSOC-MRV	FAO GSOC MRV Protocol https://www.fao.org/documents/card/en/c/cb0509en
IPCC	IPCC guidelines for national greenhouse gas inventories https://www.ipcc.ch/site/assets/uploads/2019/12/19R_V0_01_Overview.pdf
NL-SNK	Stichting Nationale Koolstofmarkt https://nationaleco2markt.nl/ https://nationaleco2markt.nl/methoden/
Nori	Nori Croplands Methodology, v 1.3 https://nori.com/resources/croplands-methodology
Plan Vivo	Plan Vivo standard methodology https://www.planvivo.org/standard-documents
Regen	Regen Network Methodology for GHG and Co-Benefits in Grazing Systems https://registry.regen.network/v/methodology-library/published-methodologies/carbonplus-methodology-for-grazing-systems-v1.0-and-credit-class
UK-PC	IUCN-UK Peatland Code https://www.iucn-uk-peatlandprogramme.org/peatland-code-0
US-ACR	American Carbon Registry (There are four methodologies for SOC, see 3.2.2) https://americancarbonregistry.org/carbon-accounting/standards-methodologies
VM0006	Methodology for Carbon Accounting for Mosaic and Landscape-scale REDD Projects, v2.2 https://verra.org/methodology/vm0006-methodology-for-carbon-accounting-for-mosaic-and-landscape-scale-redd-projects-v2-2/
VM0042	VM0042 Methodology for Improved Agricultural Land Management, v2.0 https://verra.org/methodologies/vm0042-methodology-for-improved-agricultural-land-management-v2-0/

[a]Listed in alphabetical order of abbreviations (all URLs last accessed 5 July 2024). Short descriptions are provided as Supplementary Information S1.
[b]These guidelines include several approved methodologies, see Supplementary Information S1 for additional information.

peer review or open for public comment. Further, registries list inactive (or repealed) methodologies and their version. Major registries in the voluntary carbon offset market include the American Carbon Registry (ACR) [181], Verified Carbon Standard (VERRA) [182], Climate Action Reserve (https://www.climateactionreserve.org/) and Gold Standard Impact Registry (https://www.goldstandard.org/).

Classification characteristics

We defined a list of main characteristics that should be considered when comparing the guidelines and approved methodologies considered in Table 2. This list (Table 3) considers characteristics such as purpose of the MRV system, ecosystem(s) covered, Tier level, geographic scope, scope of monitoring as well as verification requirements such as "additionality" and "permanence."

For each characteristic, either one or several answers are possible. For example, for the classification characteristic "Ecosystem(s) covered," there are nine options, and one could answer "Croplands," "Grasslands" or "Wetlands/peatlands." Alternatively, for the characteristic "Leakage requirement" only two answers are possible (Yes or No). During the "scoring" it proved cumbersome to unmistakably assign a class for some characteristics in view of the overall diversity/complexity of the considered MRV guidelines/methodologies, such as consideration of multiple Tiers. In such instances, pragmatically, "best appraisals" were provided considering the available "multi-faceted" information. This level of "uncertainty" has been expressed under "Confidence in ratings," which was assessed as: High (5 times), Medium (8 times) and Low (4 times). Results of the assessments were stored in a spreadsheet with eighteen rows and twenty-seven columns (see Supplementary Information S3) of which only the first eight columns and rows are shown in Table 4 in view of space. As indicated, in some cases, we only assessed one specific methodology whereas there can be more (e.g. six for Label Bas Carbone (FR-

Table 3. **List of characteristics for classification of guidelines and approved methodologies.**

Classification characteristic	Answer 1	Answer 2	Answer 3	Answer 4	Answer 5	Answer 6	Answer 7	Answer 8	Answer 9
Purpose of MRV system	Compliance market (National inventories, CAP)	Corporate Supply Chain (insetting)	Voluntary carbon market (offsetting)						
Ecosystem(s) covered	Croplands	Grasslands	Forestlands[a]	Woodland/ Shrubland	Wetlands/ peatlands	Urban land	Agric. land and agro-forestry	Agric. land and woody vegetation	Forestland, grassland & cropland[b]
Geographic scope	Specific country	Multiple countries							
Aggregation (bundling) of farms	Allowed	Not allowed							
Tier level	1	2	3	All					
Scope of monitoring	SOC stock change	GHG accounting	All						
GHGs targeted	CO_2	CH_4	N_2O	All					
Baseline setting	Soil measurements	Historic land management data	Modelled	Hybrid					
Dependence on Earth Observation data	No	Partly	Fully						
Requires ground truth SOC observations in reporting phase	No	Yes, at start date	Yes, at final date	Yes, at start and final date	High frequency				
Probability-based (soil) sampling	No[c]	Yes							
Target depth interval	Topsoil	Topsoil and subsoil							
Method of soil analysis	Wet/dry chemistry	Proximal-sensing derived	NA						
Quality assurance during successive stages of measurement / monitoring	No	Yes							
Modelling in reporting stage	Not applied	Data-driven models	Process-based models	Hybrid models					
Reporting periods	Pre-implementation	During monitoring round	Final reporting	All					
Frequency of reporting	$<$ 5 years	5 - 10 year	10-15 year	$>$ 15 years					
Verification approach	Action-based: proof of adoption of practice	Result-based: convenience sampling[c]	Result-based: probability sampling						
Uncertainty quantified in reporting stage	No	Yes							
Defines acceptable level of uncertainty in verification stage	No	Yes							
Transparency and reproducibility requirements	Low	Moderate	High						
Leakage requirement	No	Yes							
Additionality requirement	No	Yes							
Permanence requirement	No	Yes							
Reversal requirement	No	Yes							
Data retention/ sharing policy	No	Yes							

[a]No differentiation is made here for Forestland, which may include Afforestation and Reforestation.
[b]These ecosystems and not listed in any particular order.
[c]Non-probabilistic sampling.

Table 4. Scoring of MRV guidelines and approved methodologies[a].

Abbreviation	Purpose of MRV	Ecosystem(s) covered	Geographic scope	Aggregation (bundling) of farms	Tier level	Scope of monitoring	GHGs targeted
AU-CFIDV	Voluntary carbon market	Agricultural land and woody vegetation	Specific country	Allowed	1	GHG accounting	All
AU-CFMM	Voluntary carbon market	Agricultural land and woody vegetation	Specific country	Allowed	3	SOC stock change	CO_2
BC-SCM	Voluntary carbon market	Croplands	Specific country	Allowed	3	SOC stock change	CO_2
CARSSE	Voluntary carbon market	Croplands	Specific country	Allowed	All	All	All
DE-MOOR	Voluntary carbon market	Wetlands/ peatlands	Specific country	Not allowed	1	GHG accounting	N_2O
FR-LBC[b]	Voluntary carbon market	Croplands	Specific country	Allowed	All	All	All
Gold Standard	Voluntary carbon market	Agricultural land and agro-forestry	Multiple countries	Allowed	All	SOC stock change	All
GSOC-MRV	Voluntary carbon market	Agricultural land and agro-forestry	Multiple countries	Allowed	All	All	All

[a]Only the first eight columns are shown here in view of the length of the full table (see Supporting Information S2 for the full set of ratings).
[b]For abbreviations see Table 2. Note that several guidelines, such as FR-LBC, consider different methodologies and only one or two of these are assessed here (*in casu*, 'Field crops' for FR-LBC). Details are provided in Supporting Information S1.

LBC), see Supplementary Information S2 and footnote to Table 4).

Characterization of reviewed MRV systems and methodologies

In view of the large number of characteristics involved, it would be helpful to reduce the multidimensional space in which the MRV approaches are scored to only two dimensions. As a result, each MRV approach would be situated in a two-dimensional plane, where MRV approaches that have similar characteristics are close to each other, while those exhibiting distinct features are positioned farther apart. This dimension reduction can be achieved with a statistical technique known as multidimensional scaling [MDS, see 183,184]. Here we applied MDS using the "*cmdscale*" function of the "*cluster*" package of the R software for statistical computing [185]. This approach differs from the one adopted by Demenois et al. [94], who used multiple correspondence analysis (MCA) to assess main differences between SOC standards. An important difference between MDS and MCA is that a characteristic that is systematically isolated from all the other characteristics (and hence considered "very particular") will always appear on the first dimension of the MCA plot, but not necessarily on the MDS plot [186].

Multidimensional scaling requires a dissimilarity matrix as input. This is a square matrix that has as many rows and columns as there are MRV approaches, and whose value at row *i* and column *j* stores the dissimilarity between the *i*-th and *j*-th MRV approach. The dissimilarity between two MR approaches is derived from the characteristics of the two MRV approaches. Since the characteristics of MRV approaches listed in Table 2 are measured on a nominal scale, common Euclidean distances cannot be computed. We therefore used the Gower metric [187]. This simply assigns distance 0 if the two MRV approaches have the same value for the characteristic, and distance 1 if they are not the same. This was done for all characteristics and the average of all distances was taken to define the dissimilarity between two MRV approaches. It is possible to assign weights to the characteristics and thus allow some characteristics to have more influence on the final dissimilarity metric than others. We did not do this here and assumed that all characteristics are equally important, which is a simplification. Furthermore, we treated all characteristics as nominal variables, even if the reported classes are on an ordinal scale. This means that for "Transparency and reproducibility of requirements," for example, the distance between two MRV approaches that score "low" and "high" is the same as that between two MRV approaches that score "low" and "moderate" or "moderate" and "high".

Results of the multidimensional scaling are shown in Figure 2. The MRV approaches are fairly uniformly distributed in the two-dimensional space and there are no clear clusters or extremes, although some patterns can be observed. MRV approaches in the lower right (LR) quadrant, for

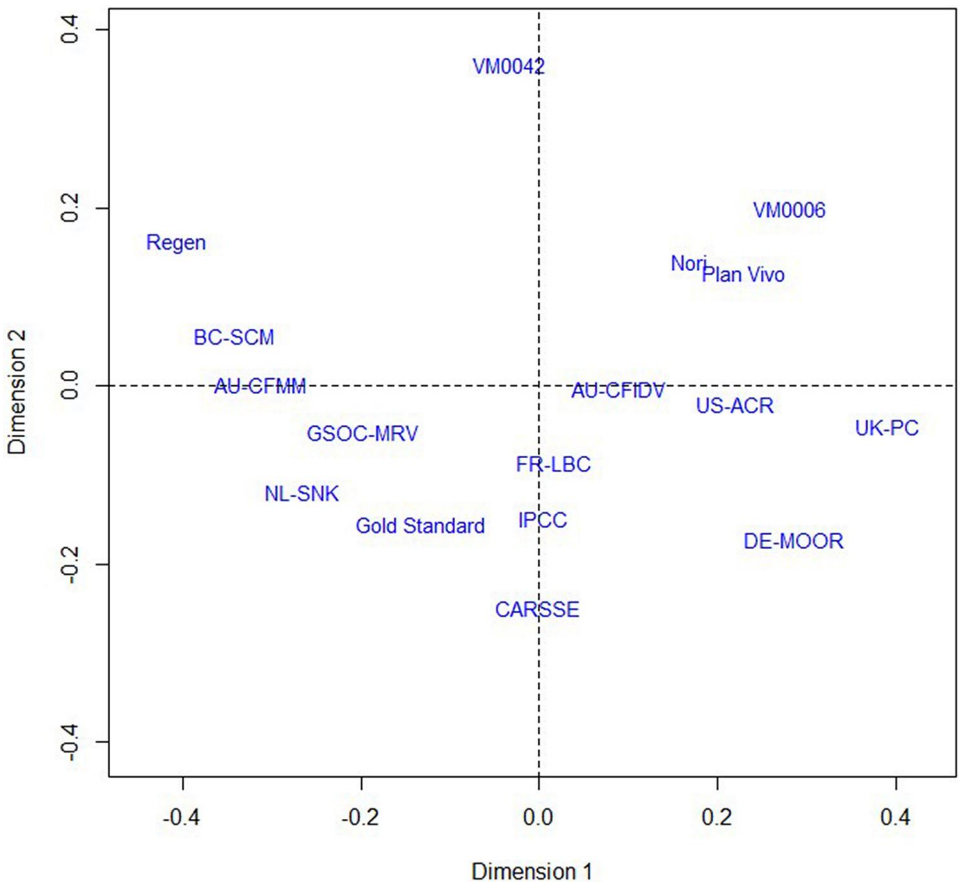


Figure 2. Position of considered MRV guidelines and approved methodologies in a two-dimensional space after application of multidimensional scaling to MRV characteristics.

example, all relate to a specific country and most follow a Tier 1 approach. While they focus on different ecosystems, they mainly have "moderate" or "high" transparency requirements, and most score yes for "additionality", "permanence," "leakage," "reversibility," and "data retention" requirements. Verification for all is action-based and transparency requirements are mostly assessed as "moderate." All methodologies are aimed at the compliance market in the LR quadrant. In the lower left quadrant (LL), Gold Standard and GSOC-MRV are quite close indicating that they share key characteristics. Indeed, both MRV approaches aim at the voluntary carbon market, are applied in multiple countries, also consider Tier 3 level approaches, predominantly are result-based and agree on many of the requirements, yet not in a systematic way. Alternatively, IPCC is focused on the compliance market, considers all ecosystems (e.g. forestlands, grasslands, and croplands), all three Tier levels, yet can follow different verification pathways. Other clusters of apparently similar MRV approaches are AU-CFMM, BC-SCM, NL-SNK and Regen; all four are developed for a specific country or countries, make use of process-based models except for Regen, consider soil measurements, have similar reporting frequency, are result-based, and have a data retention/sharing policy. They all occur in the UL quadrant and mainly are for agricultural land, i.e. grassland and/or cropland. In the upper right quadrant (UR) all MRV approaches focus on the voluntary carbon market. VM0006, Nori and Plan Vivo all focus on SOC stock change and are applicable in multiple countries, use historic land management as baseline setting and do not require ground truth SOC observations (i.e. verification is action-based), but have different frequencies and periods of reporting. VM0042 is somewhat "isolated" in Figure 2 in the sense that it occurs at the top of the central vertical axis, but no clear explanation for this can be found. Filtering the considered MRV approaches by axis (i.e. "LL-LR" for Dimension 1 resp. "LL-UL" for Dimension 2) does not provide any clearcut "messages" for possible captions. Possibly, the main conclusion that can be drawn from Figure 2, considering the simplifications involved, again is that the landscape of MRV guidelines and applied methodologies is quite diverse.

It should be noted that five out of the twenty-six characteristics are related to a verification "requirement" (e.g. absence of leakage or reversal requirement). Since no weights were applied these characteristics together have a strong effect on the outcome of the multidimensional scaling, for example five times stronger than "Purpose of MRV" or "Ecosystem(s) covered." There is much to say for reducing their influence by assigning weights. Likewise, many users might wish to assign a higher weight to characteristics such as "requires ground truth SOC observations" and "Target depth interval (for soil sampling)," or "Tier level" than to characteristics such as "Reporting periods" and "Frequency of reporting." Assigning weights involves subjective choices but so does the a priori decision about which characteristics are included in the analysis. A sensitivity analysis on a few characteristics could show which characteristics are more important and how the results would be affected. Alternatively, it could be worthwhile to organize stakeholder workshops to jointly define and refine key characteristics of MRV guidelines and methodologies, assign associated weights, and evaluate the sensitivity of the multidimensional scaling results to choices made. Finally, it should be noted that the reduction to a two-dimensional space caused a significant loss of information, indicating that Figure 2 should only be used in an indicative way.

Towards an operational, integrative, and multi-ecosystem MRV approach for SOC stock changes

General considerations

MRV frameworks typically comprise several "building blocks" (see Figure 1) that consider various levels of complexity, as shown in Table 1 for modeling approaches. Building on the present review, and recommendations made by the International Consortium on Soil Carbon Sequestration in Agriculture [188], we highlight the need to develop a methodological framework and prototypes for operational multi-ecosystem monitoring tools for net SOC stock changes. Ideally, this modular tool (preferably web-based) would:

a. define the project's name, boundaries, duration, scope (e.g. NDC or insetting), and ecosystem(s) under consideration;
b. permit uploading of activity data and of other relevant spatial data layers, with preference for local data when available (e.g. soil data, climatic data, aboveground biomass data);
c. define the relevant method for designing the baseline (e.g. project specific, generic) and test different scenarios (e.g. type of land use conversion, recommended management practices) to increase SOC stocks and reduce GHG emissions (decision tool);
d. produce biophysical products derived from EO data that will eventually be assimilated in Tier 3 modeling approaches or used in ML (machine learning) and AI (artificial intelligence) approaches.
e. utilize a decision tree to select and run the appropriate methodology for monitoring (e.g. Tier 1 to Tier 3 with or without assimilating EO data, AI or hybrid). One of the criteria for building the decision tree itself is the context of MRV (e.g. NDCs, voluntary carbon market, insetting) that defines the duration and frequency of monitoring (e.g. annually estimates for insetting prevent the use of in-situ soil sampling approaches), while other considerations such as data availability, technical expertise, costs and project scope will also be accounted for.

To guide the development of such operational tools, we propose a methodological framework presented in Figure 3. However, there are several limitations to this framework: it is not yet adapted to situations involving land use change, does not account for non-CO_2 greenhouse gas emissions and climatic (e.g. albedo changes) and environmental effects, and it does not consider the trade-off between cost and accuracy in monitoring approaches. Further, Figure 3 does not visualize the various levels of maturity, accuracy or scalability of the different methods available for monitoring or verifying SOC stock changes.

Monitoring

It appears that the main challenges in developing a unified, operational MRV system concern the monitoring component. As shown in Figure 3, this component can rely on various approaches the choice of which may depend on the previously mentioned decision tree (their spatial arrangement in Figure 3 is arbitrary);

a. Soil MRV approaches that combine SOC stock change with consideration of field measurements,
b. Tier 1 or Tier 2 approaches, for instance when there is no process-based model calibrated and validated for the local context;

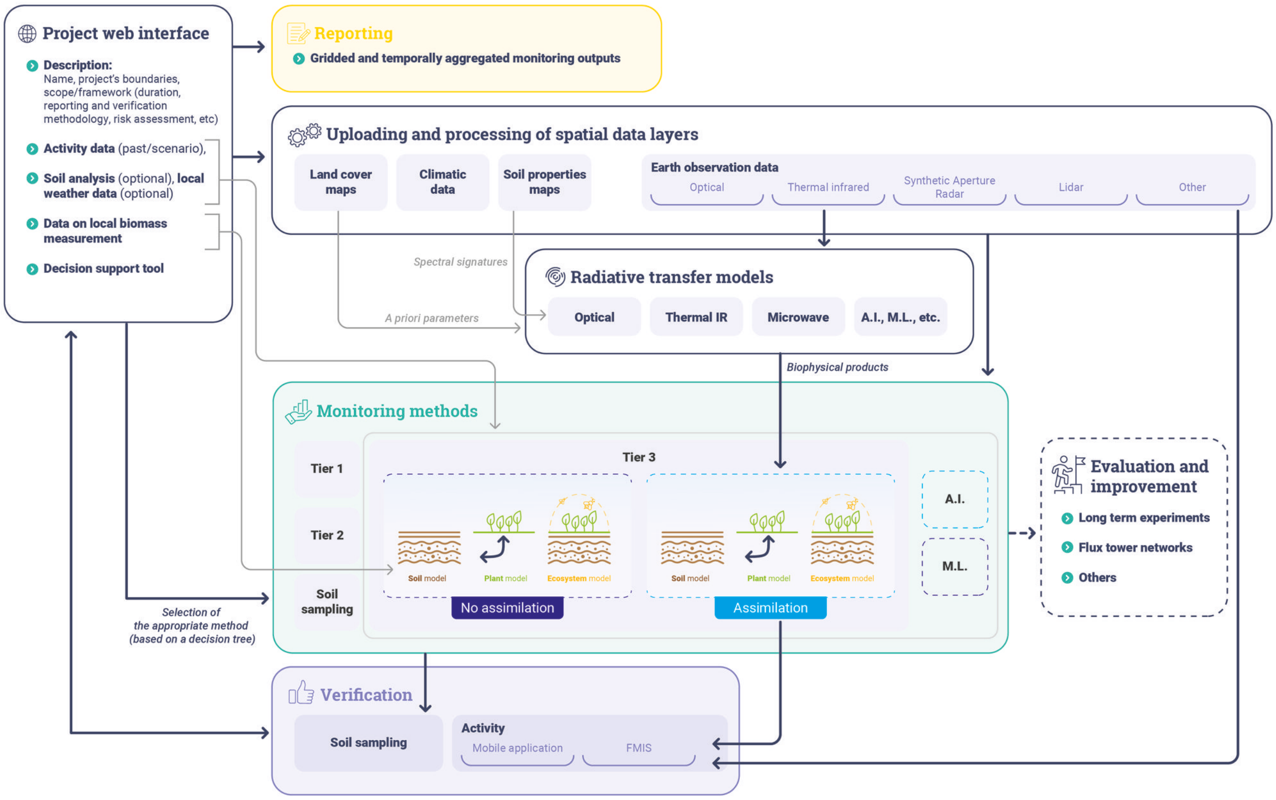


Figure 3. Proposition for a multi-ecosystem methodological framework depicting a modular flowchart for building an operational MRV tool for assessing net SOC stock changes (abbreviations: A.I., artificial intelligence; M.L., machine learning; IR, infrared; FMIS, Farm Management Information system).

c. Tier 3 approaches which may or may not: assimilate remote sensing, be based only on soil modelling, use independent soil and vegetation models (e.g. biomass estimates being used as input in the soil model), or use ecosystem models that assess the full ecosystem carbon budget, sometimes with limited field validation. Alternatively, emerging AI [189,190] and evolving ML-based SOC MRV approaches [138, 191] may be considered.

In the French LBC methodology for arable land, for example, a Tier 3 approach with a focus on soil was chosen. There are no clear guidelines for modelling or measuring crop or cover crop biomass in the field or by satellite, and no field-measured SOC changes over time are considered for local validation [192,193]. However, large uncertainties in SOC stock change estimates can result from rough biomass estimates. Wijmer et al. [120], for example, showed that assimilating averaged LAI (leaf area index) at plot level instead of using high-resolution LAI products (10 m) can result in a significant underestimation of the winter wheat biomass. Overall, very few guidelines, methodologies or tools rely on biomass quantification by remote sensing (or by hybrid modeling approaches such as remote sensing data assimilation) to map its spatial variability in an attempt to provide the soil models with more accurate estimates of biomass carbon inputs.

Assimilation of remote sensing data in plant or ecosystem models can correct the model's trajectory [194]. Such models assimilate biophysical products (e.g. LAI, aboveground biomass) derived from radiative transfer models and remote sensing products (corrected for atmospheric effects with orthorectification) that may be built on sensors with different wavelengths [195–198] as shown in Figure 3. Such radiative transfer models can be integrated in the monitoring tool as in Wijmer et al. [119]. However, as shown for croplands [188] and forestlands [199,200], upscaling process-based models initially developed for local applications by assimilating remote sensing data is challenging as they need much data for model evaluation and calibration. Based on these considerations, Tier 3 type estimation methods for current carbon stocks may benefit from assimilation of remote sensing data. However, a dedicated new generation of models such as SAFYE-CO_2 [154,155], tailored to upscaling the carbon budget components, would have to be developed for this. Meanwhile, another approach may consist in correcting the model's output based on the analysis of the vegetation's spatial variability by using spectral indices such as the Normalized Difference Vegetation Index or LAI maps derived from remote sensing [201].

Alternatively, a combination of Tier 3 approaches could be used. For example, a single vegetation model, with or without remote sensing data assimilation, may provide biomass input data to one or several soil models (e.g. for an ensemble approach). Further, for Tier 3 methods EO assimilation may not always be possible (e.g. for very small plots, or optical EO data in very cloudy areas) or relevant (e.g. in hilly areas where the limited accuracy of biophysical products may result in a high uncertainty on the final estimates). It should be noted also that several biophysical products, such as LAI and superficial soil water content, could be assimilated in a specific process-based model and that several radiative transfer models could be used to derive a specific biophysical variable in an ensemble approach. As such, each methodology should be regularly evaluated and whenever possible improved based on *in situ* data collected at long-term experimental sites or from flux tower networks as shown in Figure 3.

Implementation of a Tier 3 approach, however, may not always be relevant or possible for example when process-based models are not calibrated or validated for the project's local context. We refer to the prototype quantification platform developed for croplands in France as an example. It considers the joint use of NIVA's [195] algorithms for Tiers 1 and 2 and the SAFYE-CO_2 model [154,155] for Tier 3. Alternatively, for Tier 3 a hybrid modeling approach could be used for an area defined by land use type, building for instance on Wijmer et al. [120]. Depending on the context and scale of monitoring, soil data to run the soil module may be obtained from local sources, respectively from appropriately scaled soil products (e.g. SoilGrids [196], LUCAS [197] or national soil databases) complemented with in-situ field measurements for validation.

Each ecosystem has its specificities, therefore some "building blocks" (or modules) will have to be designed, added or implemented in a context-specific way [198, 202–204]. For instance, monitoring SOC stock changes for peatlands (highly organic soils) would require adapted SOC models [205] and an adapted framework that considers seasonal fluctuations of the water Table [206,207], and may require coupling with a hydrological module [208]. Likewise, specific approaches would be needed to model net SOC stock changes in other ecosystems such as forestland [31, 170, 173, 199] or in urban environments [209,210].

Reporting and verification

Reporting requirements are fully linked to the objectives of the applied methodologies (e.g. national GHG inventories or carbon farming), the stakeholder responsible for the reporting (e.g. a state, a farmer) and the nature of the payment systems (i.e. payment for practice, payment for performance, or payment for practice with performance dividend). Generally, the more complex the methodologies are, the more demanding the reporting will become. For example, reporting on the implementation of a practice might be straightforward for a farmer, but this will be far more challenging if a farmer aims for a payment for performance derived from model-based approaches. Therefore, it is essential to consider the heterogeneity of capacities (e.g. reliable access to Internet for online reporting) and expertise of the stakeholder responsible for the reporting.

CIRCASA [211] made recommendations for cropland that could be used for or adapted to other ecosystems. The CIRCASA team suggested that reporting should primarily be through gridded data extraction (e.g. of the modelled outputs) for any spatially defined area (e.g. a field, farm, small region, sourcing area of an industry, given crop type, or country) and any time period (e.g. one year for CAP or insetting programs up to several years or decades for NDCs or offsetting projects). Inherently, all SOC stock change estimates should be provided with the same unit (e.g. g C m^{-2} or g CO_{2eq} m^{-2} per time period considered); any claims put forth by projects must always be substantiated by statistically rigorous evidence and be independently verified by a third party.

Concerning baseline setting, we recommend an adaptative framework, with supporting guidelines/tools, that would accommodate both generic (i.e. calculated for a given type of pedoclimatic conditions × crop rotation × practices) and project-specific baselines. The operational processing chain described above would allow both. First, it could produce information on several years prior to implementation of, for instance, a carbon farming program but also during the project's life cycle. Second, because the proposed approach is based on remote sensing and hybrid modeling it will allow to simulate scenarios for plots/farms in the same pedoclimatic region (or landscape) that consider the adoption level of recommended carbon farming practices, and this for a range of crop rotations.

Verification of the practices implemented during performance-based projects could benefit from modern technologies. For instance, activity data could be collected through mobile phones [212,213], online portals [214] or connection to Farm Management Information Systems (FMIS) [215,216] with application programming interfaces (APIs) [217]. Yet, our own recent experience has shown that activity data in FMIS may lack reliability/consistency and may require to be checked by a third party (e.g. an agricultural council).

For verification of SOC stock changes, we recommend an approach based on soil re-sampling (e.g. surveys, grids, demonstration farms) and remote sensing using standardized protocols. To optimize the cost/accuracy ratio of verification, well-designed initial and final soil sampling schemes are needed [37, 218,219]. Further, the process should be based on consistent sampling procedures and comparable analytical methods [147, 220–224]. A principal decision is whether to adopt a design-based or model-based statistical inference for output-based verification. The important advantage of design-based statistical inference (i.e. statistical sampling theory) is that it is entirely model-free, hence makes no assumptions [225,226]. It yields unbiased estimates of SOC stock change for an area of interest while the associated estimation accuracy is quantified. However, it requires a probability sample from the area of interest, with all inclusion probabilities known and greater than zero. Model-based approaches essentially rely on statistical regression (e.g. machine learning [227] or kriging [228]. They may also use uncertainty propagation methods [229,230] when outputs of process-based models are used to infer the SOC stock change and uncertainties in model inputs, parameters and structure need to be accounted for. It is important to note that, due to an averaging out effect, uncertainty decreases when spatial averages of SOC stock change are computed [159, 219]. The uncertainty decrease is largest when errors have a low spatial correlation. More information about design-based and model-based statistical inference for verification of output-based projects is provided elsewhere (Supplementary Information 1).

For verification of results emanating from "advanced" Tier 3 approaches, pluri-annual high-resolution maps of biomass and SOC stock changes produced by hybrid modeling approaches (e.g. AgriCarbon-EO) could be useful as these will provide insights into spatio-temporal dynamics of C stock changes, for instance to help identify areas that preferentially store or lose C. Such an integrated approach would allow for a substantial reduction in the number of soil samples required to detect significant SOC stock changes (at a predefined confidence level), ultimately providing more representative and accurate estimates.

Conclusions

Current MRV systems use a diversity of guidelines and approved methodologies. These consider a wide range of procedures to manage, for example, additionality, uncertainty, persistence, baselines, measurement, reporting and verification. A selection of current MRV guidelines and approved methodologies, as applied to various ecosystems in defined geographies, was characterized according to twenty-six "key characteristics" using a pre-defined number of classes/options for each characteristic. Subsequent multi-dimensional scaling showed that the considered MRV methodologies are fairly uniformly distributed in the two-dimensional space and that there are no clear clusters or extremes, and some patterns were observed. The assessment, however, was not unambiguous as it required simplifications. In retrospect, having a binary categorization of characteristics like leakage, permanence, and additionality could not capture the nuance as to how the different protocols actually account for those "complex" issues. Although a protocol can set these requirements, this does not mean that they actually do a "sufficient job at" accounting for them [231]. In the future, it could be worthwhile to organize regional stakeholder workshops to jointly revise the list of key characteristics while also assigning weights to each characteristic with a view to evaluate the sensitivity of the results of the multidimensional scaling procedure to various choices.

As a follow up to this review, building on the elements shown in Figure 3, the next phase of the ORCaSa project will be to develop a prototype for an operational, modular and multi-ecosystem MRV system that would be applicable in different contexts (e.g. national or subnational reporting, CAP, voluntary carbon market, insetting/supply chain) and at different levels of complexity (i.e. Tier 1 to 3), depending on the context of application and the availability/accuracy of input data. An important element of that work will be to develop decision trees to guide the choice of MRV system components that will be proposed by ORCaSa.

There are still numerous research and governance issues to consider with respect to improving MRV approaches [232,233]. These are being addressed in the framework of the Soil Carbon International Research Consortium (IRC) which aims to provide better access to research, methods and practices for soil carbon (see https://www.impact4soil.com/), and a strategic research agenda is currently being developed.

Acknowledgements

This study was carried out in the framework of the EU ORCaSa project (https://irc-orcasa.eu). We thank the participants of two international stakeholder workshops for their valuable contributions. Our special thanks go to the anonymous reviewers whose insightful comments and suggestions helped us to improve the original submission.

Disclosure statement

The authors have no financial or non-financial competing interests associated with this research or the publication of this manuscript.

Funding

The ORCaSa project has received funding from the Horizon Europe Programme under grant agreement n° 101059863.

Data availability statement

The materials and data that support the findings of this study are available at https://doi.org/10.17027/isric_e6dasc18.

References

1. Batjes NH. Total carbon and nitrogen in the soils of the world. Eur J Soil Sci. 1996;47(2):151–163. doi:10.1111/j.1365-2389.1996.tb01386.x.
2. Friedlingstein P, O'Sullivan M, Jones MW, et al. Global carbon budget 2022. Earth Syst Sci Data. 2022;14(11):4811–4900. doi:10.5194/essd-14-4811-2022.
3. FAO, ITPS. Status of the world's soil resources (SWSR) - Main report. Rome: Food and Agriculture Organization of the United Nations and Intergovernmental Technical Panel on Soils; 2015. p. 650.
4. IPCC. Climate change 2022: impacts, adaptation and vulnerability. In: Pörtner H-O, Roberts DC, Tignor M, et al, editors. Cambridge (UK) and New York (NY, USA): UNEP, WMO; 2022. p. 3068.
5. UNEP. UNEP and the Sustainable Development Goals; 2023 [cited 2023 07 june]. Available from: https://www.unep.org/explore-topics/sustainable-development-goals.
6. IPBES. Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science- Policy Platform on Biodiversity and Ecosystem Services. Brondizio ES, Settele J,Díaz S, Ngo HT, editors. Bonn (DE); 2019.
7. WorldBank. Soil organic carbon (SOC) MRV sourcebook for agricultural landscapes. Washington: The World Bank Group; 2021.
8. FAO-GSP. Unlocking the potential for soil organic carbon - Outcome document. Global Symposium on soil organic carbon (21-23 March 2017). Rome (Italy): FAO; 2017. p. 36.
9. UNEP. The benefits of soil carbon - managing soils for multiple, economic, societal and environmental benefits. UNEP Yearbook - Emerging issues in our global environment 2012. Nairobi: United Nations Environmental Programme; 2012. p. 19–33.
10. Banwart SA, Noelmeyer E, Milne E, editors. Soil carbon: science, management and policy for multiple benefits. Wallingford (UK): CABI; 2015.
11. Rumpel C, Amiraslani F, Bossio D, et al. Studies from global regions indicate promising avenues for maintaining and increasing soil organic carbon stocks. Reg Environ Change. 2023;23(8):1–4.
12. Baveye PC, Berthelin J, Tessier D, et al. Storage of soil carbon is not sequestration: straightforward graphical visualization of their basic differences. Eur J Soil Sci. 2023;74(3):e13380. doi:10.1111/ejss.13380.
13. Janzen HH. The soil carbon dilemma: shall we hoard it or use it? Soil Biol Biochem. 2006;38(3):419–424. doi:10.1016/j.soilbio.2005.10.008.
14. Moinet GYK, Hijbeek R, van Vuuren DP, et al. Carbon for soils, not soils for carbon. Glob Chang Biol. 2023; 29(9):2384–2398. doi:10.1111/gcb.16570.
15. Chenu C, Angers DA, Barré P, et al. Increasing organic stocks in agricultural soils: knowledge gaps and potential innovations. Soil Tillage Res. 2019;188: 41–52. doi:10.1016/j.still.2018.04.011.
16. Don A, Seidel F, Leifeld J, et al. Carbon sequestration in soils and climate change mitigation—Definitions and pitfalls. Glob Chang Biol. 2023;30(1): e16983. doi:10.1111/gcb.16983.
17. Pribyl DW. A critical review of the conventional SOC to SOM conversion factor. Geoderma. 2010;156(3-4): 75–83. doi:10.1016/j.geoderma.2010.02.003.
18. Lettens S, Vos BD, Quataert P, et al. Variable carbon recovery of Walkley-Black analysis and implications for national soil organic carbon accounting. Eur J Soil Sci. 2007;58(6):1244–1253. doi:10.1111/j.1365-2389.2007.00916.x.
19. De Vos B, Lettens S, Muys B, et al. Walkley-Black analysis of forest soil organic carbon: recovery, limitations and uncertainty. Soil Use Manage. 2007;23(3):221–229. doi:10.1111/j.1475-2743.2007.00084.x.
20. Bouma J. Soil science contributions towards Sustainable Development Goals and their implementation: linking soil functions with ecosystem services. Z Pflanzenernähr Bodenk. 2014;177(2):111–120. doi:10.1002/jpln.201300646.
21. Creamer RE, Hagens M, Baartman J, et al. Editorial for special issue on "understanding soil functions –

from ped to planet". Eur J Soil Sci. 2021;72(4):1493–1496. doi:10.1111/ejss.13099.

22. Nannipieri P, Ascher J, Ceccherini MT, et al. Microbial diversity and soil functions. European J Soil Science. 2003;54(4):655–670. doi:10.1046/j.1351-0754.2003.0556.x.
23. Wiesmeier M, Urbanski L, Hobley E, et al. Soil organic carbon storage as a key function of soils - A review of drivers and indicators at various scales. Geoderma. 2019;333:149–162. doi:10.1016/j.geoderma.2018.07.026.
24. Beillouin D, Corbeels M, Demenois J, et al. A global meta-analysis of soil organic carbon in the Anthropocene. Nat Commun. 2023;14(1):3700. doi:10.1038/s41467-023-39338-z.
25. Bouma J, Pinto-Correia T, Veerman C. Assessing the role of soils when developing sustainable agricultural production systems focused on achieving the UN-SDGs and the EU green deal. Soil Systems. 2021;5(3):56. doi:10.3390/soilsystems5030056.
26. European Commission. Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the regions - The European Green Deal. Luxembourg ; 2019. p. 24.
27. European Commission. Proposal for a Directive of the European Parliament and of the Council on Soil Monitoring and Resilience. European Commission; 2023. p. 22.
28. United Nations. Handbook on measurement, reporting and verification for developing countries. Bonn: Framework Convention on Climate Chage, United Nations Climate Change Secretariat; 2014. p. 56.
29. European Commission. Proposal for a regulation of the european parliament and of the council establishing a union certification framework for carbon removals. Brussels: European Commission; 2022. p. 52.
30. Mooney S, Janoski K. Economic considerations for the development of a carbon farming scheme. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 809–827.
31. Haya BK, Evans S, Brown L, et al. Comprehensive review of carbon quantification by improved forest management offset protocols. Front For Glob Change. 2023;6(6):9588. doi:10.3389/ffgc.2023.958879.
32. Tamme E. Financing engineered carbon removal with the voluntary carbon markets - synergies with public funding and a look beyond double claiming. Tallinn (Estonia): Climate Principles OU; 2022. p. 10.
33. IPCC. 2019 refinement to the 2006 ipcc guidelines for national greenhouse gas inventories: overview. Buendia EC Guendehou S Limmeechokchai B, et al. Geneva: IPCC; 2019. p. 15.
34. UNCCD.; 2017 Good Practice Guidance SDG Indicator 15.3.1: proportion of land that is degraded over total land area (ver. 1.0). p. 115.
35. Cardinael R, Umulisa V, Toudert A, et al. Revisiting IPCC Tier 1 coefficients for soil organic and biomass carbon storage in agroforestry systems. Environ Res Lett. 2018;13(12):124020. doi:10.1088/1748-9326/aaeb5f.
36. Batjes NH. Soil organic carbon stocks under native vegetation - revised estimates for use with the simple assessment option of the Carbon Benefits Project system. Agriculture Ecosyst Environ. 2011;142(3-4):365–373. doi:10.1016/j.agee.2011.06.007.
37. Brus DJ. Statistical sampling approaches for soil monitoring. European J Soil Science. 2014;65(6):779–791. doi:10.1111/ejss.12176.
38. Australian Government. Independent review of australian carbon credit units canberra: department of climate change, energy, the environment and water, australian government; 2023; [cited 2023 20 October]. Available from: https://www.dcceew.gov.au/climate-change/emissions-reduction/independent-review-accus.
39. Bellassen V, Angers D, Kowalczewski T, et al. Soil carbon is the blind spot of European national GHG inventories. Nat. Clim. Chang. 2022;12(4):324–331. doi:10.1038/s41558-022-01321-9.
40. Wiese L, Wollenberg E, Alcántara-Shivapatham V, et al. Countries' commitments to soil organic carbon in nationally determined contributions. Climate Policy. 2021;21(8):1005–1019. doi:10.1080/14693062.2021.1969883.
41. Wander MM, Ugarte CM. Understanding the value of and reasoning behind farmer adoption of carbon centric practice. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Doods Science Publishing; 2022.p. 829–850.
42. Funk R, Pascual U, Joosten H, et al. From potential to implementation: an innovation framework to realize the benefits of soil carbon. In: Banwart SA, Noelmeyer E, Milne E, Management and policy for multiple benefits. Wallingford (UK): CABI. Soil carbon Science; 2015. p. 47–59.
43. Rumpel C. Benefits and trade-offs of soil carbon sequestration. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 183–207.
44. Buck HJ, Palumbo-Compton A. Soil carbon sequestration as a climate strategy: what do farmers think? Biogeochemistry. 2022;161(1):59–70. doi:10.1007/s10533-022-00948-2.
45. FAO, ITPS. Recarbonizing global soils - A technical manual of recommended management practices. Voume 1: introductioin and methodology. Rome: Global Soil Partnership; 2022. p. 52.
46. Lal R. Managing soils for negative feedback to climate change and positive impact on food and nutritional security. Soil Sci Plant Nutr. 2020;66(1):1–9. doi:10.1080/00380768.2020.1718548.
47. Mora de la Luz M, Medina J, Poblete-Grant P, et al. Innovative agriculture management to foster soil organic carbon sequestration. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 271–301.

48. Paul S, Leifeld J. Management of organic soils to reduce soil organic carbon losses. In Rumpel C, editor. Optimizing forest management for soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 617–679.
49. Dick D, Bayer C, Dieckow J. Fostering carbon sequestration in humid tropical and subtropical soils. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing ; 2022. p. 681–706.
50. Khangura R, Ferris D, Wagg C, et al. Regenerative agriculture - a literature review on the practices and mechanisms used to improve soil health. Sustainability. 2023;15(3):2338. doi:10.3390/su15032338.
51. Baldock JA, Sanderman J, Macdonald LM, et al. Quantifying the allocation of soil organic carbon to biologically significant fractions. Soil Res. 2013;51(8):561–576. doi:10.1071/SR12374.
52. Kyker-Snowman E, Lombardozzi DL, Bonan GB, et al. Increasing the spatial and temporal impact of ecological research: a roadmap for integrating a novel terrestrial process into an Earth system model. Glob Chang Biol. 2022;28(2):665–684. doi:10.1111/gcb.15894.
53. Doetterl S, Abramoff R, Cornelis J-T, et al. Understanding soil organic carbon dynamics at larger scales. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Buddleigh Dodds Science Publishers; 2022. p. 115–182.
54. Ingram JS, Fernandes ECM. Managing carbon sequestration in soils: concepts and terminology. Agriculture Ecosyst Environ. 2001;87(1):111–117. doi:10.1016/S0167-8809(01)00145-1.
55. Bertrand I, Viaud V, Daufresne T, et al. Stoichiometry constraints challenge the potential of agroecological practices for the soil C storage. A review. Agron Sustain Dev. 2019;39(6):54. doi:10.1007/s13593-019-0599-6.
56. de Vries W. Soil carbon 4 per mille: a good initiative but let's manage not only the soil but also the expectations: comment on Minasny. Geoderma. 2017;309:111–112. Geoderma. 2017. doi:10.1016/j.geoderma.2017.05.023.
57. Xu X, Thornton PE, Post WM. A global analysis of soil microbial biomass carbon, nitrogen and phosphorus in terrestrial ecosystems. Global Ecol Biogeogr. 2013;22(6):737–749. doi:10.1111/geb.12029.
58. Kirkby CA, Richardson AE, Wade LJ, et al. Nutrient availability limits carbon sequestration in arable soils. Soil Biol Biochem. 2014;68:402–409. doi:10.1016/j.soilbio.2013.09.032.
59. Ulrich S, Tischer S, Hofmann B, et al. Biological soil properties in a long-term tillage trial in Germany. Z Pflanzenernähr Bodenk. 2010;173(4):483–489. doi:10.1002/jpln.200700316.
60. Berner D, Marhan S, Keil D, et al. Land-use intensity modifies spatial distribution and function of soil microorganisms in grasslands. Pedobiologia. 2011;54(5-6):341–351. doi:10.1016/j.pedobi.2011.08.001.
61. van Diepeningen AD, de Vos OJ, Korthals GW, et al. Effects of organic versus conventional management on chemical and biological parameters in agricultural soils. Appl Soil Ecol. 2006;31(1-2):120–135. doi:10.1016/j.apsoil.2005.03.003.
62. Izac AMN. Developing policies for soil carbon management in tropical regions. Geoderma. 1997;79(1-4):261–276. doi:10.1016/S0016-7061(97)00044-X.
63. Keel SG, Bretscher D, Leifeld J, et al. Soil carbon sequestration potential bounded by population growth, land availability, food production, and climate change. Carbon Manage. 2023;14(1):2244456. doi:10.1080/17583004.2023.2244456.
64. Batjes NH. Technologically achievable soil organic carbon sequestration in world croplands and grasslands. Land Degrad Dev. 2019;30(1):25–32. doi:10.1002/ldr.3209.
65. Demenois J, Torquebiau E, Arnoult MH, et al. Barriers and strategies to boost soil carbon sequestration in agriculture. Front Sustain Food Syst. 2020;4(37):1–14. doi:10.3389/fsufs.2020.00037.
66. Sierra CA, Crow SE. Modeling soil organic carbon dynamics, carbon sequestration and the climate benefit of sequestration. Understanding and fostering soil carbon sequestration; 2022. p. 351–374.
67. Amundson R. The Pandora's box of soil carbon. Proc Natl Acad Sci U S A. 2022;119(11):e2201077119. doi:10.1073/pnas.2201077119.
68. Smith P. How long before a change in soil organic carbon can be detected? Glob Chang Biol. 2004;10:1878–1883.
69. Cambardella CA, Elliott ET. Particulate soil organic-matter changes across a grassland cultivation sequence. Soil Sci Soc Am J. 1992;56(3):777–783. doi:10.2136/sssaj1992.03615995005600030017x.
70. Six J, Conant RT, Paul EA, et al. Stabilization mechanisms of soil organic matter: implications for C-saturation of soils. Plant Soil. 2002;241(2):155–176. doi:10.1023/A:1016125726789.
71. Bossuyt H, Six J, Hendrix PF. Aggregate-protected carbon in no-tillage and conventional tillage agroecosystems using carbon-14 labeled plant residue. Soil Sci Soc Am J. 2002;66(6):1965–1973.
72. Angst G, Mueller KE, Castellano MJ, et al. Unlocking complex soil systems as carbon sinks: multi-pool management as the key. Nat Commun. 2023;14(1):2967. doi:10.1038/s41467-023-38700-5.
73. Hassink J. Preservation of plant residues in soils differing in unsaturated protective capacity. Soil Sci Soc Am J. 1996;60(2):487–491. doi:10.2136/sssaj1996.03615995006000020021x.
74. Cotrufo MF, Ranalli MG, Haddix ML, et al. Soil carbon storage informed by particulate and mineral-associated organic matter. Nat Geosci. 2019;12(12):989–994. doi:10.1038/s41561-019-0484-6.
75. Noordwijk M, Goverse T, Ballabio C, et al. Soil carbon transition curves: reversal of land degradation through management of soil organic matter for multiple benefits. Wallingford: CABI Books; 2015.
76. Zomer RJ, Bossio DA, Sommer R, et al. Global sequestration potential of increased organic carbon

in cropland soils. Sci Rep. 2017;7(1):15554. doi:10.1038/s41598-017-15794-8.
77. Begill N, Don A, Poeplau C. No detectable upper limit of mineral-associated organic carbon in temperate agricultural soils. Glob Chang Biol. 2023;29(16):4662–4669. doi:10.1111/gcb.16804.
78. Cotrufo MF, Lavallee JM, Six J, et al. The robust concept of mineral-associated organic matter saturation: a letter to Begill et al., 2023. Glob Chang Biol. 2023;29(21):5986–5987. doi:10.1111/gcb.16921.
79. Poeplau C, Begill N, Don A. Response to: "The robust concept of mineral-associated organic matter saturation: a letter to Begill et al. (2023)". Glob Chang Biol. 2023;29(21):e4–e6. doi:10.1111/gcb.16920.
80. Lugato E, Leip A, Jones A. Mitigation potential of soil carbon management overestimated by neglecting N2O emissions. Nature Clim Change. 2018;8(3):219–223. doi:10.1038/s41558-018-0087-z.
81. Kanter DR, Bartolini F, Kugelberg S, et al. Nitrogen pollution policy beyond the farm. Nat Food. 2019;1(1):27–32. doi:10.1038/s43016-019-0001-5.
82. Gerber JS, Carlson KM, Makowski D, et al. Spatially explicit estimates of N2O emissions from croplands suggest climate mitigation opportunities from improved fertilizer management. Glob Chang Biol. 2016;22(10):3383–3394. doi:10.1111/gcb.13341.
83. Pique G, Carrer D, Lugato E, et al. About the assessment of cover crop albedo potential cooling effect: risk of the darkening feedback loop effects. Remote Sens. 2023;15(13):3231. doi:10.3390/rs15133231.
84. Keenor SG, Rodrigues AF, Mao L, et al. Capturing a soil carbon economy. R Soc Open Sci. 2021;8(4):202305. doi:10.1098/rsos.202305.
85. Oldfield EE, Bradford MA, Wood SA. Global meta-analysis of the relationship between soil organic matter and crop yields. SOIL. 2019;5(1):15–32. doi:10.5194/soil-5-15-2019.
86. Tamba Y, Wafula J, Magaju C, et al. A review of the participation of smallholder farmers in land-based carbon payment schemes. Nairobi: TMG (Think Tank for Sustainability) and ICRAF. 2021 (ICRAF Working Paper).
87. Falconnier GN, Cardinael R, Corbeels M, et al. The input reduction principle of agroecology is wrong when it comes to mineral fertilizer use in sub-Saharan Africa. Outlook Agric. 2023;52(3):311–326. doi:10.1177/00307270231199795.
88. Vanlauwe B, Amede T, Bationo A, et al. Fertilizer and soil health in Africa: the role of fertilizer in building soil health to sustain farming and address climate change. Muscle Shoals, AL, USA: International Fertilizer Development Center (IFDC); 2023. p. 82.
89. Giller KE, Kanampiu F, Hungria M, et al. The role of nitrogen fixation in African smallholder agriculture. Agricult Ecosyst Environ. 2019;285:106601. doi:10.1016/j.agee.2019.106601.
90. Sonneveld MPW, Bouma J. Methodological considerations for nitrogen policies in the Netherlands including a new role for research. Environ Sci Policy. 2003;6(6):501–511. doi:10.1016/j.envsci.2003.08.005.
91. Lorenzo C, Vermeulen S, Leonard R, et al. Land grab or development opportunity? Agricultural investment and international land deals in Africa London/Rome: International Institute for Environment and Development, Food and Agricultural Organization of the United Nations, and International Fund for Agricultural Development; 2009. p. 120.
92. De Schutter O. How not to think of land-grabbing: three critiques of large-scale investments in farmland. J Peasant Stud. 2011;38(2):249–279. doi:10.1080/03066150.2011.559008.
93. Yang B, He J. Global land grabbing: a critical review of case studies across the world. land. Land. 2021;10(3):324. doi:10.3390/land10030324.
94. Demenois J, Dayet A, Karsenty A. Surviving the jungle of soil organic carbon certification standards: an analytic and critical review. Mitig Adapt Strateg Glob Change. 2022;27(1):1–17. doi:10.1007/s11027-021-09980-3.
95. Soil EJP. Inventory of the use of models for accounting and policy support (soil quality and soil carbon); 2021. p. 34.
96. Cevallos G, Grimaut J, Bellassen V. Domestic carbon standards in Europe: overview and perspectives. I4KCE Institute for Climate Economics; 2019. p. 44.
97. Nogues M, Husson M, Paul G, et al. Framework of possible business models for the implementation of a carbon demonstrator - Territorial demonstrators of soil carbon sequestration. INRAE, LISIS and NATAÏS; 2021.
98. Shrestha G, Cooley S, Larson L, et al. Report for the Carbon Dioxide Removal (CDR): towards a Unified Monitoring, Measuring, Reporting and Verification (MMRV) Framework Workshop; 2023. p. 36.
99. Batjes NH, van Wesemael B. Measuring and monitoring soil carbon. In: Banwart SA, Noelmeyer E, Milne E, editors. Soil carbon: science, management and policy for multiple benefits. Wallingford (UK): CABI; 2015. p. 188–201.
100. Kuhnert M, Vetter SH, Smith P. Measuring and monitoring soil carbon sequestration. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge (UK): Burleigh Dodds Science Publishing; 2022. p. 305–321.
101. Aitkenhead M. Digital tools for assessing soil organic carbon at farm and regional scale. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 395–419.
102. Wang Y, Qi Q, Zhou L, et al. Recognition of potential outliers in soil datasets from the perspective of geographical context for improving farm-level soil mapping accuracies. Geoderma. 2023;431:116374. doi:10.1016/j.geoderma.2023.116374.
103. Black HIJ, Reed MS, Kendall H, et al. What makes an operational farm soil carbon code? Insights from a global comparison of existing soil carbon codes using a structured analytical framework. Carbon Manag. 2022;13(1):554–580. doi:10.1080/17583004.2022.2135459.
104. European Commission (Directorate-General for Climate Action). Reviewing the contribution of the land, land-use change and forestry sector of the

green deal. Workshop IV Carbon farming in the CAP strategic plans; 2021.
105. UNFCC. Handbook on measurement, reporting and verification for developing country parties. Bonn: United Nations Climate Change Secretariat; 2014. p. 56.
106. Popkin G. Shaky ground. Science. 2023;381(6656): 369–373. doi:10.1126/science.adj9318.
107. West TAP, Börner J, Sills EO, et al. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. Proc Natl Acad Sci U S A. 2020;117(39):24188–24194. doi:10.1073/pnas.2004334117.
108. Yang Z, Nguyen TTH, Nguyen HN, et al. Greenwashing behaviours: causes, taxonomy and consequences based on a systematic literature review. J Business Econ Manag. 2020;21(5):1486–1507. doi:10.3846/jbem.2020.13225.
109. Trouwloon D, Streck C, Chagas T, et al. Understanding the use of carbon credits by companies: a review of the defining elements of corporate climate claims. Glob Chall. 2023;7(4):2200158. doi: 10.1002/gch2.202200158.
110. Montgomery AW, Lyon TP, Barg J. No end in sight? A greenwash review and research agenda. Organ Environ. 2023;37(2):221–256. doi:10.1177/10860266231168905.
111. Miltenberger O, Jospe C, Pittman J. The good is never perfect: why the current flaws of voluntary carbon markets are services, not barriers to successful climate change action. Front Clim. 2021;3: 686516. doi:10.3389/fclim.2021.686516.
112. Rabobank. Carbon sequestration in agricultural soils: how to unlock the green potential of the agricultural sector. Amsterdam: Economic Research, Rabobank; 2021. p. 31.
113. ORCaSA. ORCaSa because soil organic matters - A Horizon Europe initiative that aims to bring together international stakeholders working on techniques for capturing and storing carbon in the soil; 2023 [cited 2024 15 February]. Available from: https://irc-orcasa.eu/.
114. Smith P, Soussana J-F, Angers D, et al. 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. 2020;26(1):219–241. doi:10.1111/gcb.14815.
115. Arcusa S, Sprenkle-Hyppolite S. Snapshot of the carbon dioxide removal certification and standards ecosystem (2021–2022). Climate Policy. 2022;22(9-10): 1319–1332. doi:10.1080/14693062.2022.2094308.
116. FAO-GSP. A protocol for measurement, monitoring, reporting and verification of soil organic carbon in agricultural landscapes – GSOC-MRV Protocol. Rome: FAO, ITPS, GSP; 2020. p. 140.
117. Lesschen JP, Hendriks C, van der Linden A, et al. Ontwikkeling praktijktool voor bodem C (in Dutch). Wageningen: Wageningen Environmental Research; 2020. p. 52.
118. Nevalainen O, Niemitalo O, Fer I, et al. Towards agricultural soil carbon monitoring, reporting, and verification through the Field Observatory Network (FiON). Geosci. Instrum. Method. Data Syst. 2022; 11(1):93–109. doi:10.5194/gi-11-93-2022.
119. Bockstaller C, Sirami C, Sheeren D, et al. Apports de la télédétection au calcul d'indicateurs agri-environnementaux au service de la PAC, des agriculteurs et porteurs d'enjeu. Innovations Agronomiques. 2021; 83:43–59.
120. Wijmer T, Al Bitar A, Arnaud L, et al. AgriCarbon-EO v1.0.1: large-scale and high-resolution simulation of carbon fluxes by assimilation of Sentinel-2 and Landsat-8 reflectances using a Bayesian approach. Geosci Model Dev. 2024;17(3):997–1021. doi:10.5194/gmd-17-997-2024.
121. Paustian K, Schuler J, Killian K, et al. COMET2.0-Decision support system for agricultural greenhouse gas accounting. Managing Agricultural Greenhouse Gases; 2012. p. 251–270.
122. Del Grosso SJ, Mosier AR, Parton WJ, et al. DAYCENT model analysis of past and contemporary soil N2O and net greenhouse gas flux for major crops in the USA. Soil Tillage Res. 2005;83(1):9–24. doi:10.1016/j.still.2005.02.007.
123. Mathers C, Black CK, Segal BD, et al. Validating DayCent-CR for cropland soil carbon offset reporting at a national scale. Geoderma. 2023;438:116647. doi: 10.1016/j.geoderma.2023.116647.
124. Paustian K, Collier S, Baldock J, et al. Quantifying carbon for agricultural soil management: from the current status toward a global soil information system. Carbon Manage. 2019;10(6):567–587. doi:10.1080/17583004.2019.1633231.
125. Batjes NH, Ceschia E, Heuvelink GBM, et al. International review of current MRV initiatives for soil carbon stock change assessment and associated methodologies. Wageningen: ISRIC, INRAE and CIRAD; 2023. (ORCASA Deliverable 4.1)
126. Arias-Navarro C, Díaz-Pinés E, Klatt S, et al. Spatial variability of soil N2O and CO2 fluxes in different topographic positions in a tropical montane forest in Kenya. JGR Biogeosci. 2017;122(3):514–527. doi: 10.1002/2016JG003667.
127. Poeplau C. Advances in measuring soil organic carbon stocks and dynamics at the profile scale. In: Rumpel C, editor. Understanding and fostering soil carbon sequestration. Cambridge: Burleigh Dodds Science Publishing; 2022. p. 323–350.
128. Shepherd KD, Ferguson R, Hoover D, et al. A global soil spectral calibration library and estimation service. Soil Security. 2022;7:100061. doi:10.1016/j.soisec.2022.100061.
129. Viscarra Rossel RA, Behrens T, Ben-Dor E, et al. Diffuse reflectance spectroscopy for estimating soil properties: a technology for the 21st century. Eur J Soil Sci. 2022;73(4):e13271. doi:10.1111/ejss.13271.
130. McBride MB. Estimating soil chemical properties by diffuse reflectance spectroscopy: promise versus reality. Eur J Soil Sci. 2022;73(1):e13192. doi:10.1111/ejss.13192.
131. Cécillon L, Barthès BG, Gomez C, et al. Assessment and monitoring of soil quality using near-infrared reflectance spectroscopy (NIRS). Eur J Soil Sci. 2009; 60(5):770–784. doi:10.1111/j.1365-2389.2009.01178.x.

132. Bünemann EK, Bongiorno G, Bai Z, et al. Soil quality – a critical review. Soil Biol Biochem. 2018;120:105–125. doi:10.1016/j.soilbio.2018.01.030.
133. van Leeuwen CCE, Mulder VL, Batjes NH, et al. Effect of measurement error in wet chemistry soil data on the calibration and model performance of pedotransfer functions. Geoderma. 2024;442:116762. doi:10.1016/j.geoderma.2023.116762.
134. van Wesemael B, Chabrillat S, Sanz Dias A, et al. Remote sensing for soil organic carbon mapping and monitoring. Remote Sens. 2023;15(14):3464. doi:10.3390/rs15143464.
135. McKenzie N, Henderson B, McDonald W. Monitoring soil change: principles and practices for Australian conditions. CSIRO Land & Water, CSIRO Mathematical & Information Sciences, National Land and Water Resources Audit; Black Mountain (AU): CSIRO; 2002. p. 112.
136. Smith P, Smith JU, Powlson DS, et al. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. Geoderma. 1997;81(1-2):153–225. doi:10.1016/S0016-7061(97)00087-6.
137. Parton WJ, Schimel DS, Cole CV, et al. Analysis of factors controlling soil organic matter levels in Great Plain grasslands. Soil Science Soc Am J. 1987;51(5):1173–1179. doi:10.2136/sssaj1987.03615995005100050015x.
138. Heuvelink GBM, Angelini ME, Poggio L, et al. Machine learning in space and time for modelling soil organic carbon change. Eur J Soil Sci. 2021;72(4):1607–1623. doi:10.1111/ejss.12998.
139. De Rosa D, Ballabio C, Lugato E, et al. Soil organic carbon stocks in European croplands and grasslands: how much have we lost in the past decade? Glob Chang Biol. 2024;30(1):e16992. doi:10.1111/gcb.16992.
140. Soussana JF, Allard V, Pilegaard K, et al. Full accounting of the greenhouse gas (CO2, N2O, CH4) budget of nine European grassland sites. Agriculture Ecosyst Environ. 2007;121(1-2):121–134. doi:10.1016/j.agee.2006.12.022.
141. Tziolas N, Tsakiridis N, Chabrillat S, et al. Earth observation data-driven cropland soil monitoring: a review. Remote Sens. 2021;13(21):4439. doi:10.3390/rs13214439.
142. van der Voort TS, Verweij S, Fujita Y, et al. Enabling soil carbon farming: presentation of a robust, affordable, and scalable method for soil carbon stock assessment. Agron Sustain Dev. 2023;43(1):22. doi:10.1007/s13593-022-00856-7.
143. Perugini L, Pellis G, Grassi G, et al. Emerging reporting and verification needs under the Paris Agreement: how can the research community effectively contribute? Environ Sci Policy. 2021;122:116–126. doi:10.1016/j.envsci.2021.04.012.
144. Nieto L, Houborg R, Tivet F, et al. Limitations and future perspectives for satellite-based soil carbon monitoring. Environ Challenges. 2024;14:100839. doi:10.1016/j.envc.2024.100839.
145. Lark RM. Some considerations on aggregate sample supports for soil inventory and monitoring. Eur J Soil Sci. 2012;63(1):86–95. doi:10.1111/j.1365-2389.2011.01415.x.
146. Arrouays D, Marchant BP, Saby NPA, et al. Generic issues on broad-scale soil monitoring schemes: a review. Pedosphere. 2012;22(4):456–469. doi:10.1016/S1002-0160(12)60031-9.
147. Saby NPA, Bellamy PH, Morvan X, et al. Will European soil-monitoring networks be able to detect changes in topsoil organic carbon content? Global Change Biol. 2008;14(10):2432–2442. doi:10.1111/j.1365-2486.2008.01658.x.
148. Schauberger B, Jägermeyr J, Gornott C. A systematic review of local to regional yield forecasting approaches and frequently used data resources. Eur J Agron. 2020;120:126153. doi:10.1016/j.eja.2020.126153.
149. Odebiri O, Mutanga O, Odindi J. Deep learning-based national scale soil organic carbon mapping with Sentinel-3 data. Geoderma. 2022;411:115695. doi:10.1016/j.geoderma.2022.115695.
150. Vaudour E, Gholizadeh A, Castaldi F, et al. Satellite imagery to map topsoil organic carbon content over cultivated areas: an overview. Remote Sensing. 2022;14(12):2917. doi:10.3390/rs14122917.
151. Ovando G, Sayago S, Bocco M. Evaluating accuracy of DSSAT model for soybean yield estimation using satellite weather data. ISPRS J Photogramm Remote Sens. 2018;138:208–217. doi:10.1016/j.isprsjprs.2018.02.015.
152. Jin X, Kumar L, Li Z, et al. A review of data assimilation of remote sensing and crop models. Eur J Agron. 2018;92:141–152. doi:10.1016/j.eja.2017.11.002.
153. Bandaru V, Yaramasu R, Jones C, et al. Geo-CropSim: a Geo-spatial crop simulation modeling framework for regional scale crop yield and water use assessment. ISPRS J Photogramm Remote Sens. 2022;183:34–53. doi:10.1016/j.isprsjprs.2021.10.024.
154. Pique G, Fieuzal R, Debaeke P, et al. Combining high-resolution remote sensing products with a crop model to estimate carbon and water budget components: application to sunflower. Remote Sens. 2020;12(18):2967. doi:10.3390/rs12182967.
155. Pique G, Fieuzal R, Al Bitar A, et al. Estimation of daily CO2 fluxes and of the components of the carbon budget for winter wheat by the assimilation of Sentinel 2-like remote sensing data into a crop model. Geoderma. 2020;376:114428. doi:10.1016/j.geoderma.2020.114428.
156. Clivot H, Mouny J-C, Duparque A, et al. Modeling soil organic carbon evolution in long-term arable experiments with AMG model. Environ Model Softw. 2019;118:99–113. doi:10.1016/j.envsoft.2019.04.004.
157. Guan K, Jin Z, Peng B, et al. A scalable framework for quantifying field-level agricultural carbon outcomes. Earth Sci Rev. 2023;243:104462. doi:10.1016/j.earscirev.2023.104462.
158. Ciais P, Bastos A, Chevallier F, et al. Definitions and methods to estimate regional land carbon fluxes for the second phase of the REgional Carbon Cycle Assessment and Processes Project (RECCAP-2).

Geosci Model Dev. 2022;15(3):1289–1316. doi:10.5194/gmd-15-1289-2022.
159. Szatmári G, Pásztor L, Heuvelink GBM. Estimating soil organic carbon stock change at multiple scales using machine learning and multivariate geostatistics. Geoderma. 2021;403:115356. doi:10.1016/j.geoderma.2021.115356.
160. Le Noë J, Manzoni S, Abramoff R, et al. Soil organic carbon models need independent time-series validation for reliable prediction. Commun Earth Environ. 2023;4(1):158. doi:10.1038/s43247-023-00830-5.
161. Milne E, Sessay M, Paustian K, et al. Towards a standardized system for the reporting of carbon benefits in sustainable land management projects. Integrated Crop Management. 2010;11:105–117.
162. Del Grosso S, Ojima D, Parton W, et al. Simulated effects of dryland cropping intensification on soil organic matter and greenhouse gas exchanges using the DAYCENT ecosystem model. Environ Pollut. 2002;116 Suppl 1: S75–S83. doi:10.1016/s0269-7491(01)00260-3.
163. Rosenstock TS, Wilkes A. Reorienting emissions research to catalyse African agricultural development. Nat Clim Chang. 2021;11(6):463–465. doi:10.1038/s41558-021-01055-0.
164. Oldfield EE, Lavallee JM, Kyker-Snowman E, et al. The need for knowledge transfer and communication among stakeholders in the voluntary carbon market. Biogeochemistry. 2022;161(1):41–46. doi:10.1007/s10533-022-00950-8.
165. Paul C, Bartkowski B, Dönmez C, et al. Carbon farming: are soil carbon certificates a suitable tool for climate change mitigation? J Environ Manage. 2023;330:117142. doi:10.1016/j.jenvman.2022.117142.
166. Yogo WIG, Clivot H, Wijmer T, et al. Evaluation and monitoring methodologies for soil carbon balance and recommendations for drafting a low carbon label method. ADEME Report. no. 18-03-C0034. INRAe; 2021.
167. Riggers C, Poeplau C, Don A, et al. Multi-model ensemble improved the prediction of trends in soil organic carbon stocks in German croplands. Geoderma. 2019;345:17–30. doi:10.1016/j.geoderma.2019.03.014.
168. Couëdel A, Falconnier GN, Adam M, et al. Long-term soil organic carbon and crop yield feedbacks differ between 16 soil-crop models in sub-Saharan Africa. Eur J Agron. 2024;155:127109. doi:10.1016/j.eja.2024.127109.
169. Farina R, Sándor R, Abdalla M, et al. Ensemble modelling, uncertainty and robust predictions of organic carbon in long-term bare-fallow soils. Glob Chang Biol. 2021;27(4):904–928. doi:10.1111/gcb.15441.
170. Mäkipää R, Abramoff R, Adamczyk B, et al. How does management affect soil C sequestration and greenhouse gas fluxes in boreal and temperate forests? – a review. For Ecol Manage. 2023;529:120637. doi:10.1016/j.foreco.2022.120637.
171. Oliver GR, Beets PN, Garrett LG, et al. Variation in soil carbon in pine plantations and implications for monitoring soil carbon stocks in relation to land-use change and forest site management in New Zealand. For Ecol Manage. 2004;203(1-3):283–295. doi:10.1016/j.foreco.2004.07.045.
172. Lacarce E, Le Bas C, Cousin JL, et al. Data management for monitoring forest soils in Europe for the Biosoil project. Soil Use Manage. 2009;25(1):57–65. doi:10.1111/j.1475-2743.2009.00194.x.
173. ICP Forests. ICP Forests monitoring Manual Eberswalde (Germany); 2021.
174. Louis BP, Saby NPA, Orton TG, et al. Statistical sampling design impact on predictive quality of harmonization functions between soil monitoring networks. Geoderma. 2014;213:133–143. doi:10.1016/j.geoderma.2013.07.018.
175. van Wesemael B, Paustian K, Andrén O, et al. How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO_2 fluxes in agricultural soils? Plant Soil. 2010;338(1-2):247–259. doi:10.1007/s11104-010-0567-z.
176. Bispo A, Andersen L, Angers DA, et al. Accounting for carbon stocks in soils and measuring GHGs emission fluxes from soils: do we have the necessary standards? Front Environ Sci. 2017;5(41):1–12. doi:10.3389/fenvs.2017.00041.
177. Olsson A. Assessing Carbon Dioxide Removal methods amid uncertainty: soil carbon sequestration, biochar and harvested wood products as methods for climate change mitigation. School of Engineering Sciences in Chemistry, Biotechnology and Health (CBH), Chemical Engineering, Energy Processes. Stockholm: KTH; 2023.
178. Lehmann N, Briner S, Finger R. The impact of climate and price risks on agricultural land use and crop management decisions. Land Use Policy. 2013;35(0):119–130. doi:10.1016/j.landusepol.2013.05.008.
179. Sperow M. Marginal cost to increase soil organic carbon using no-till on U.S. cropland. Mitig Adapt Strateg Glob Change. 2018;24(1):93–112. doi:10.1007/s11027-018-9799-7.
180. D'Arcangelo FM, Pisu M, Raj A, et al. Estimating the CO2 emission and revenue effects of carbon pricing. Paris: OECD Economics Department; 2022. p. 52.
181. ACR. American Carbon Registry; 2023 [cited 2023 15 October]. Available from: https://www.offsetguide.org/understanding-carbon-offsets/carbon-offset-programs/voluntary-offset-programs/american-carbon-registry/.
182. VCS. VCS standard - a VERRA verified standard. Washington, DC: Verra; 2023. p. 74.
183. Borg I, Groenen PJF. Modern multidimensional scaling. Theory and applications.New York: Springer; 2005.
184. Cox TF, Cox MAA. Multidimensional scaling. 2nd ed. Boca Raton: Chapman & Hall/CRC; 2020.
185. R Core Team. R: a language and environment for statistical computing. Vienna: R Foundation for Statistical Computing; 2021.
186. Cadoret M, Lê S, Pagès J, et al. Multidimensional scaling versus multiple correspondence analysis when analyzing categorization data. In Fichet B, Piccolo D, Verde R, editors. Classification and multivariate analysis for complex data structures. Vol. Studies in

classification, data analysis, and knowledge organization. New York: Springer-Verlag; 2011. p. 301–308.
187. Gower JC. A general coefficient of similarity and some of its properties. Biometrics. 1971;27(4):857–871. doi:10.2307/2528823.
188. Castaldi F, Chabrillat S, Jones A, et al. Soil organic carbon estimation in croplands by hyperspectral remote APEX data using the LUCAS topsoil database. Remote Sens. 2018;10(2):153. doi:10.3390/rs10020153.
189. Sabine G. Artificial intelligence and soil carbon modeling demystified: power, potentials, and perils. Carbon Footprints. 2022;1(1):5.
190. Liu L, Zhou W, Guan K, et al. Knowledge-guided machine learning can improve carbon cycle quantification in agroecosystems. Nat Commun. 2024;15(1):357. doi:10.1038/s41467-023-43860-5.
191. Stockmann U, Padarian J, McBratney A, et al. Global soil organic carbon assessment. Global Food Secur. 2015;6:9–16. doi:10.1016/j.gfs.2015.07.001.
192. Weiss M, Jacob F, Duveiller G. Remote sensing for agricultural applications: a meta-review. Remote Sens Environ. 2020;236:111402. doi:10.1016/j.rse.2019.111402.
193. Blackmore S, Godwin RJ, Fountas S. The analysis of spatial and temporal trends in yield map data over six years. Biosyst Eng. 2003;84(4):455–466. doi:10.1016/S1537-5110(03)00038-2.
194. Ferrant S, Gascoin S, Veloso A, et al. Agro-hydrology and multi temporal high resolution remote sensing: toward an explicit spatial processes calibration. Hydrol Earth Syst Sci. 2014;18(12):5219–5237. doi:10.5194/hess-18-5219-2014.
195. NIVA. Carbon farming, Result-based schemes and NIVA indicators; 2023. p. 16.
196. Poggio L, de Sousa L, Batjes NH, et al. SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. SOIL. 2021;7(1):217–240. doi:10.5194/soil-7-217-2021.
197. Ballabio C, Lugato E, Fernández-Ugalde O, et al. Mapping LUCAS topsoil chemical properties at European scale using Gaussian process regression. Geoderma. 2019;355:113912. doi:10.1016/j.geoderma.2019.113912.
198. Yu Y, Saatchi S. Sensitivity of L-Band SAR backscatter to aboveground biomass of global forests. Remote Sens. 2016;8(6):522. doi:10.3390/rs8060522.
199. Le Maire G, Davi H, Soudani K, et al. Modeling annual production and carbon fluxes of a large managed temperate forest using forest inventories, satellite data and field measurements. Tree Physiol. 2005;25(7):859–872. doi:10.1093/treephys/25.7.859.
200. Le Maire G, Marsden C, Nouvellon Y, et al. MODIS NDVI time-series allow the monitoring of Eucalyptus plantation biomass. Remote Sens Environ. 2011;115(10):2613–2625. doi:10.1016/j.rse.2011.05.017.
201. Fowler A, Basso B, Maureira F, et al. Spatial patterns of historical crop yields reveal soil health attributes in US Midwest fields. Sci Rep. 2024;14(1):465. doi:10.1038/s41598-024-51155-y.
202. Revill A, Sus O, Barrett B, et al. Carbon cycling of European croplands: A framework for the assimilation of optical and microwave Earth observation data. Remote Sens Environ. 2013;137:84–93. doi:10.1016/j.rse.2013.06.002.
203. Fieuzal R, Sicre CM, Baup F. Estimation of sunflower yield using a simplified agrometeorological model controlled by optical and SAR satellite data. IEEE J Sel Top Appl Earth Observ Remote Sens. 2017;10(12):5412–5422. doi:10.1109/JSTARS.2017.2737656.
204. Baup F, Ameline M, Fieuzal R, et al. Temporal evolution of corn mass production based on agro-meteorological modelling controlled by satellite optical and SAR images. Remote Sens. 2019;11(17):1978. doi:10.3390/rs11171978.
205. Premrov A, Wilson D, Saunders M, et al. CO2 fluxes from drained and rewetted peatlands using a new ECOSSE model water table simulation approach. Sci Total Environ. 2021;754:142433. doi:10.1016/j.scitotenv.2020.142433.
206. Renou-Wilson F, Byrne K, Flynn R, et al. Peatland properties influencing greenhouse gas emissions and removal (AUGER Project). Dublin: University College Dublin; 2021. p. 197.
207. Crezee B, Dargie GC, Ewango CEN, et al. Mapping peat thickness and carbon stocks of the central Congo Basin using field data. Nat. Geosci. 2022;15(8):639–644. doi:10.1038/s41561-022-00966-7.
208. Minasny B, Berglund Ö, Connolly J, et al. Digital mapping of peatlands – a critical review. Earth-Sci Rev. 2019;196:102870. doi:10.1016/j.earscirev.2019.05.014.
209. Edmondson JL, Davies ZG, McHugh N, et al. Organic carbon hidden in urban ecosystems. Sci Rep. 2012;2(1):963. doi:10.1038/srep00963.
210. Vasenev VI, Smagin AV, Ananyeva ND, et al. Urban soil's functions: monitoring, assessment, and management. In: Rakshit A, Abhilash PC, Singh HB, editors. Adaptive soil management: from theory to practices. Singapore: Springer; 2017. p. 359–409.
211. CIRCASA. Strategic Research Agenda on soil organic carbon in agricultural soils. INRA; 2020. p. 30.
212. Baumüller H. The Little We Know: An Exploratory Literature Review on the Utility of Mobile Phone-Enabled Services for Smallholder Farmers. J Intl Dev. 2018;30(1):134–154. doi:10.1002/jid.3314.
213. Herrick JE, Beh A, Barrios E, et al. The Land-Potential Knowledge System (LandPKS): mobile apps and collaboration for optimizing climate change investments. Ecosyst Health Sustain. 2016;2(3):e01209. doi:10.1002/ehs2.1209.
214. Fritz S, See L, Carlson T, et al. Citizen science and the united nations sustainable development goals. Nat Sustain. 2019;2(10):922–930. doi:10.1038/s41893-019-0390-3.
215. Fountas S, Carli G, Sørensen CG, et al. Farm management information systems: Current situation and future perspectives. Comput Electron Agric. 2015;115:40–50. doi:10.1016/j.compag.2015.05.011.
216. Melzer M, Bellingrath-Kimura S, Gandorfer M. Commercial farm management information systems - a demand-oriented analysis of functions in practical use. Smart Agricultural Technol. 2023;4:100203. doi:10.1016/j.atech.2023.100203.

217. Arroqui M, Mateos C, Machado C, et al. RESTful Web Services improve the efficiency of data transfer of a whole-farm simulator accessed by Android smartphones. Comput Electron Agric. 2012;87(0):14–18. doi:10.1016/j.compag.2012.05.016.
218. de Gruijter JJ, McBratney AB, Minasny B, et al. Farm-scale soil carbon auditing. Geoderma. 2016;265:120–130. doi:10.1016/j.geoderma.2015.11.010.
219. Wadoux A-C, Heuvelink GBM. Uncertainty of spatial averages and totals of natural resource maps. Methods Ecol Evol. 2023;14(5):1320–1332. doi:10.1111/2041-210X.14106.
220. Batjes NH. Options for harmonising soil data obtained from different sources. Wageningen: ISRIC - World Soil Information; 2023. p. 21.
221. Bispo A, Arrouays D, Saby N, et al. Proposal of methodological development for the LUCAS programme in accordance with national monitoring programmes. Towards climate-smart sustainable management of agricultural soils (EU H2020-SFS-2018-2020/H2020-SFS-2019). Brussels: EJP Soil. 2021. p. 135.
222. van Leeuwen C, Mulder VL, Batjes NH, et al. Statistical modelling of measurement error in wet chemistry soil data. Eur J Soil Sci. 2022;73(1):13137. doi:10.1111/ejss.13137.
223. Fernandez-Ugalde O, Scarpa S, Orgiazzi A, et al. LUCAS soil il module - Presentation of dataset and results. Luxembourg: Publications Office of the European Union; 2022, p.128.
224. d'Andrimont R, Yordanov M, Martinez-Sanchez L, et al. Harmonised LUCAS in-situ land cover and use database for field surveys from 2006 to 2018 in the European Union. Sci Data. 2020;7(1):352. doi:10.1038/s41597-020-00675-z.
225. De Gruijter JJ, Brus DJ, Bierkens MFP, et al., editors. Sampling for natural resource monitoring. Heidelberg: Springer; 2006.
226. Brus J. Spatial sampling with R. New York: Chapman and Hall R/C; 2022.
227. James G, Witten D, Hastie T, et al. An introduction to statistical learning. New York: Springer New York; 2021.
228. Webster R, Oliver A. Geostatistics for environmental scientists (2nd ed.). Chichester: Wiley; 2007.
229. Taylor JR. An introduction to error analysis: the study of uncertainties in physical measurements (2nd ed.). Mill Valley University Science Books; 1982.
230. Heuvelink GBM. Error Propagation in Environmental Modelling with GIS. Boca Raton: CRC Press; 1998.
231. Anderegg WRL, Trugman AT, Badgley G, et al. Climate-driven risks to the climate mitigation potential of forests. Science. 2020;368:1327. doi:10.1126/science.aaz7005.
232. Soussana JF, Arias-Navarro C, Bispo A, et al. Strategic Research Agenda (SRA) on Soil Carbon. European Union's Horizon 2020 research and innovation programme grant agreement No 774378 - Coordination of International Research on Soil Carbon Sequestration in Agriculture (CIRCASA); 2020. (CIRCASA Deliverable 3.1).
233. Bray AW, Kim JH, Schrumpf M, et al. The science base of a strategic research agenda - Executive Summary . European Union's Horizon 2020 research and innovation programme grant agreement No 774378 - Coordination of International Research Cooperation on soil CArbon Sequestration in Agriculture (CIRCASA); 2019. (CIRCASA Deliverable D1.3)