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INTERNATIONAL REVIEW OF CURRENT MRV INITIATIVES FOR SOIL CARBON STOCK CHANGE ASSESSMENT AND ASSOCIATED METHODOLOGIES

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INTERNATIONAL REVIEW OF CURRENT MRV INITIATIVES FOR SOIL CARBON STOCK CHANGE ASSESSMENT AND ASSOCIATED METHODOLOGIES

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1. Introduction

1.1 Background

Soils are the largest terrestrial reservoir of organic carbon (Batjes 1996; Friedlingstein *et al.* 2022), yet great uncertainty remains in estimates of soil organic carbon (SOC) and changes therein at global, continental, regional and local scales. There is growing recognition of the importance of monitoring changes in SOC stocks in the broader context of climate change mitigation ((IPCC 2022), SDG 13 (UNEP 2023)), halting and reversing land degradation (SDG 15), ensuring human livelihood/health (SDG 1,2,3) and reversing biodiversity loss ((IPBES 2019); 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 soil carbon stocks can be preserved or increased and ecosystem services improved (UNEP 2012; Banwart *et al.* 2015; FAO-GSP 2017; WorldBank 2021; Rumpel *et al.* 2022). In this context, it is important to very carefully distinguish the "sequestration of SOC from mere transient increases in SOC storage that follow the incorporation of manure and plant residues into soils" (Janzen 2006; Chenu *et al.* 2019; Baveye *et al.* 2023; Moinet *et al.* 2023).

Generally, it is assumed that soil organic matter (SOM) consists of about 58% organic carbon, and this factor is then used to convert soil organic matter into estimates of soil organic carbon, which is a simplification (e.g., De Vos *et al.* 2007; Lettens *et al.* 2007; Pribyl 2010). SOM itself is an important determinant of the quantity and quality of many ecosystem services (e.g., UNEP 2012; Bouma 2014) and soil functioning (e.g., Nannipieri *et al.* 2003; Creamer *et al.* 2021). Importantly, drivers of change in SOM are not exactly the same as the drivers of change in the SOC stock (e.g., Banwart *et al.* 2015).

Soil carbon stocks and GHG (greenhouse gas) fluxes vary with environmental conditions such as soil type and terrain (e.g., drainage, exposition), climate, and land use and management (e.g., agriculture, forestry, peatlands, and urban land) (Wiesmeier *et al.* 2019; Beillouin *et al.* 2023). The overarching policy setting, such as the EU CAP/GreenDeal (Bouma *et al.* 2021), European Parliament Directive on 'Soil Monitoring and Resilience' (European Commission 2023), and United Nations Framework on Climate Change (United Nations 2014), create conditions aimed at maintaining current carbon stocks in carbon-rich ecosystems (e.g., peatlands, mangroves) as well as increasing SOC stocks and reducing GHG emissions. These complex ecosystems will respond differently to defined anthropogenic land use activities and environmental change.

The EU Commission's proposed Framework for Carbon Removals Certification[1] (30 November 2022) aims to incentivise increased carbon removals. Alongside other removals 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 stated aim of ensuring high quality carbon removals within Europe and thereby trigger upscaling of carbon removals. Central to the Framework's approach are the so-called four

[1] https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7156

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QU.A.L.ITY criteria that define certification requirements related to quantification (QU), additionality (A), long-term storage (L), and sustainability (ITY). The Framework mainly intends to mobilise additional funding for carbon farming activities 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 but until now, European policymakers have predominantly relied on action-based and regulatory approaches to manage the land sectors, as exemplified by the EU Common Agriculture Policy (CAP).

In data scarce regions, 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 (e.g., UNCCD 2017; IPCC 2019b). The use of such default values, however, is prone to little accuracy and high uncertainty when applied to estimate soil carbon stocks in local/landscape scale projects. Through physical (*in-situ*) soil sampling combined with modelling (data-driven and process-based) and remote sensing (hybrid approach), researchers, project managers, and agricultural practitioners can estimate current SOC stocks and changes under different land management practices. For instance, repeated measurements of soil carbon concentration, bulk density and proportion of coarse fragments show how land management impacts SOC stocks over time and space. 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 samples to reliably monitor changes in carbon farming projects can be prohibitive, hence the need for developing new (e.g., hybrid) approaches as discussed later in this report. Ultimately, for such practices to be rewarded the reported SOC gains need to be verified by a third party. Importantly, the experts or companies who 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)[2].

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 soil carbon, as well as to incorporate soil carbon sequestration in GHG emission reduction targets at the international and national level (e.g., Nationally Determined Contributions, NDC) (Bellassen *et al.* 2022). Yet, according to Wiese *et al.* (2021), 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 (Funk *et al.* 2015; Buck and Palumbo-Compton 2022; Rumpel 2022; Wander and Ugarte 2022). 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

[2] https://www.dcceew.gov.au/climate-change/emissions-reduction/independent-review-accus

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systems have been described elsewhere (Lal 2020; Dick *et al*. 2022; FAO/GSP 2022; Mora *et al*. 2022; Paul and Leifeld 2022; Beillouin *et al*. 2023; Khangura *et al*. 2023).

While most MRV schemes focus on total organic carbon, it should be noted that the carbon in soils consists of different forms that are chemically varied and have characteristic turnover times (Baldock *et al.* 2013). The complex biological basis of SOC sequestration has recently been reviewed by Lavelle (2022), while Doetterl *et al*. (2022) focused on the effects of biotic and abiotic factors controlling soil organic carbon dynamics at continental to global scales. Potential, actual and attainable SOC sequestration are determined by defining factors, such as clay mineralogy and soil aeration, limiting factors (e.g., climate) and reducing (e.g., erosion, residue removal, soil fertility decrease, land mis-management) or increasing (e.g., improved land management, crop rotation, cover crops, additional C inputs) factors as visualised in Figure 1 (Ingram and Fernandes 2001). Further, there may be stoichiometric (Xu *et al*. 2013; Kirkby *et al*. 2014; de Vries 2017; Bertrand *et al*. 2019) and microbiological limitations (van Diepeningen *et al*. 2006; Ulrich *et al*. 2010; Berner *et al*. 2011), as well as often overruling social and economic limitations to attainable SOC gains (Izac 1997; Funk *et al*. 2015; Batjes 2019; Keel *et al*. 2023).

Although soils are a promising reservoir to store carbon, long time scales are generally required to sequester amounts of (stable) carbon of relevance to mitigate climate change (Amundson 2022; Sierra and Crow 2022). Alternatively, labile carbon (particulate organic matter) can also play a role in climate change. Some particulate organic matter (POM) can persist over longer time scales, as it can be trapped within soil aggregates where it is not available for soil microbes to cycle (Bossuyt *et al*. 2002; Six *et al*. 2002). For the fast decomposing POM, this is a dynamic stock, the stock and C accrual can be high, but management needs to be maintained to be relevant for climate change mitigation (Angst *et al*. 2023) as there is a high risk of reversal.

Possible gains in SOC are considered to be finite (Hassink 1996; Cotrufo *et al*. 2019) and are reversible upon changes in land management practices (Noordwijk *et al*. 2015; Zomer *et al*. 2017). The validity of the widely accepted assumption of 'possible SOC gains being finite' has recently been questioned by Begill *et al*. (2023) and subsequently rebutted by Cotrufo *et al*. (2023).

Importantly, interventions that are focused on SOC sequestration and climate change mitigation may not lead to increased crop productivity (Janzen 2006; Moinet *et al*. 2023), and often operate on longer-time scales than many smallholder farmers can 'stomach' financially (Funk *et al*. 2015). Recently, Tamba *et al*. (2021) found that the main incentives for smallholder farmers to participate in carbon payments schemes are non-monetary. These include improved yields, building soil resilience, increasing soil organic matter as a source of N aiming to cut down the inorganic N fertiliser application, 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, a central issue related to the credibility of soil carbon credits (Tamba *et al*. 2021). In this context, it also important to be aware of the risk of land grabbing associated with some 'carbon credit' and 'biofuel' projects and large-scale investments in farmland (Lorenzo *et al*. 2009; De Schutter 2011; Yang and He 2021).

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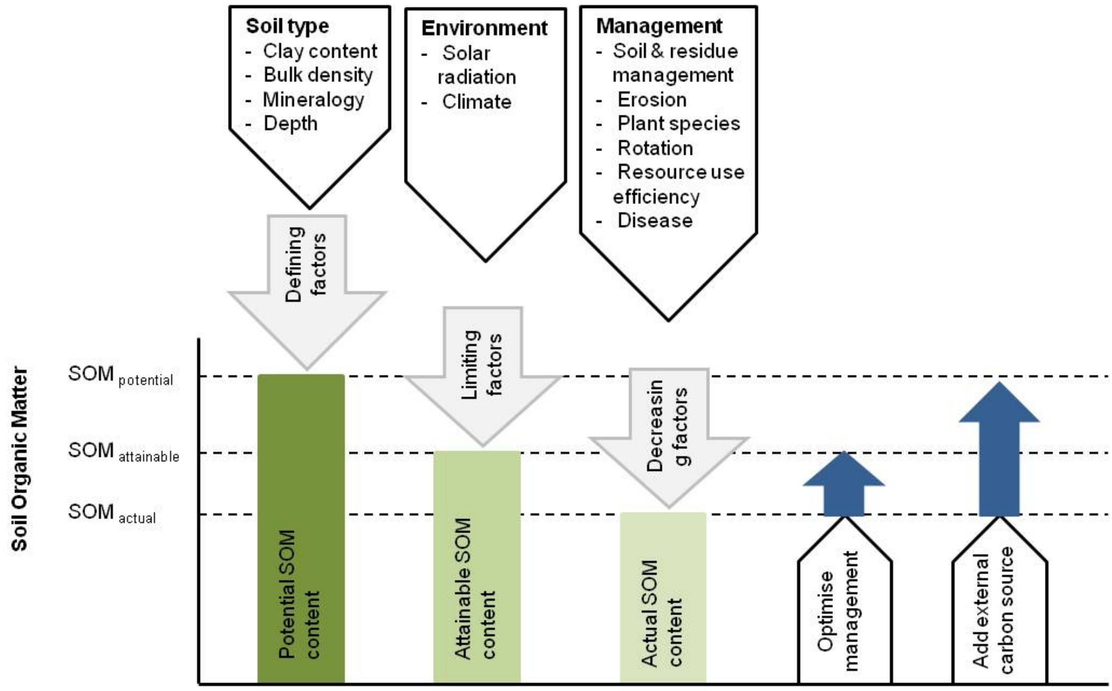

Figure 1. Effects of soil type, climate and management factors on the retention of SOM in soils (Ingram and Fernandes 2001).

The abbreviation MRV, as used in this review, stands for Monitoring, Reporting and Verification[3]. The monitoring activities under consideration are related to national scale inventories, landscape and/or project scale inventories, and those focusing on the carbon markets (e.g., voluntary and compliance). The economic considerations of carbon market-oriented MRV's, i.e. underpinning business models, are intricate and discussed elsewhere (see for example the EJP Soils Road4Schemes4 project, Cevallos et al. (2019) and Nogues et al. (2021)). Payment models can focus on conserving soil carbon, reducing net emissions from soil, or increasing sequestration of carbon into soils. Most voluntary carbon market schemes work on the basis of 'Net Abatement', i.e. soil C stock increases plus soil derived GHG emissions reductions. Ultimately MRV use soil C stock data in different ways, and it is not simply measuring change in soil C stock. In fact, for some MRVs change is not required, as discussed later in the document.

Four broad types of payment systems applicable to projects sequestering soil carbon in agricultural settings have been identified by the WorldBank (2021). Listed in order of increasing complexity, cost to implement, and confidence of atmospheric impact, these are: a) Payment for practice (input-based system); b) Payment

[3] In the UNFCC Bali Action Plan 2007 (paragraph 1bii), the term MRV first was coined as follows: "Nationally appropriate mitigation actions by developing country Parties in the context of sustainable development, supported and enabled by technology, financing and capacity-building, in a *measurable, reportable and verifiable* manner" (see UNFCC 2014. *Handbook on Measurement, Reporting and Verification for developing country parties*, United Nations Climate Change Secretariat, Bonn, 56 p. United Nations Climate Change Secretariat). In the context of national MRV systems and their purpose, however, it often turned out in practice that a broader sense as reflected by the term 'Monitoring' might be more appropriate (Wartmann S, Larkin J, Eisbrenner K and Jung M *Elements and Options for National MRV Systems*, International Partnership on Mitigation and MRV, 37 p. https://carbon-turkey.org/files/file/docs/Elements_and_Options_for_National_MRV_Systems.pdf). Throughout the present review we use 'M' for 'Monitoring' when dealing with national and sub-national level MRV systems.
[4] https://ejpsoil.eu/soil-research/road4schemes

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for practice with performance dividend, c) Payment for performance (output-based system), and d) Carbon-market, voluntary or compliance.

Although much progress in national and sub-national level MRV has been achieved over the last two decades (Batjes and van Wesemael 2015; Aitkenhead 2022; Black *et al.* 2022; Kuhnert *et al.* 2022; Rumpel *et al.* 2022; Sierra and Crow 2022; Wang *et al.* 2023), a recent poll of staff working in environmental organisations, businesses, academic researchers and government entities identified MRV as “one of the largest challenges by entities developing C farming schemes” (European Commission 2021). 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 revealing considering that UNFCC (2014) principles indicate that MRVs should be “transparent, complete, consistent, comparable and accurate” and also consider the *common sense* principles of being “pragmatic, cost-effective, scalable, timely, and operational”.

1.2 Aims of review

An MRV framework provides a theoretical description or concept of a comprehensive MRV system, as generically outlined for example in Paustian *et al.* (2019) and Smith *et al.* (2020). The framework is defined by the context of the MRV, for example ‘assess changes in SOC stock over time in croplands subject to defined land use/management interventions or changes in policies’. The framework itself consists of various components:

- Methodologies for monitoring (e.g., protocols for soil sampling, description of the modelling approach), reporting (e.g., which farm management data to provide and when) and verifying (e.g., take soil samples for a part of the carbon estimation area or use of remote sensing to verify changes in management) aimed at quantifying and verifying SOC change over time *vis a vis* a baseline and intervention scenario. These are described in protocols that provide a step-by-step procedure on how to solve an issue, following a uniform set of standards (Stanley *et al.* 2023).
- Rules (e.g., soil depth and period to be considered for assessing SOC stock changes, carbon farming practices considered or not, verification procedure) for establishing and implementing carbon farming (CF) projects from project plan to certification.
- Guiding principles: These concern for example additionality, permanence, double counting, carbon leakage or the management of uncertainty and risk associated with carbon farming projects, and how carbon discounts are applied.

The primary aim of this review is to provide an inventory of current MRV initiatives with a focus on croplands, grasslands and forests, and to evaluate their main characteristics along the lines recommended by the CIRCASA project (Smith *et al.* 2020). This will serve to identify possible ‘building blocks’ and associated methodologies for a ‘cookbook’ (blueprint) towards an MRV framework applicable to different contexts (e.g.,

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national and subnational reporting, CAP, voluntary C market, insetting/supply chain) and at different levels of complexity (Tiers) depending on the context of application and the availability/accuracy of input data.

The review consists of five chapters, one appendix, and a glossary of commonly used terms. The introductory chapter, which sets the context, is followed by a description of the main MRV components and associated methodologies (Chapter 2) considering the frameworks developed by 1) the CIRCASA project (Smith *et al.* 2020), focussed on Nationally Determined Contributions (NDCs), and 2) by Paustian *et al.* (2019) with greater focus on farm level carbon farming projects. Building upon this, in Chapter 3, we provide an inventory and classification of current MRV methodologies and subsequently 'score' them using characteristics first defined by the writing team itself and thereafter discussed/refined during two international 'stock-taking' workshops and one 'stakeholder' webinar. The fourth chapter identifies knowledge gaps and provides an outlook on what directions Task 4.2 ('Cookbook for a blueprint of an MRV framework for croplands SOC stock changes') and Task 4.3 ('Building an integrative and multi-ecosystem MRV framework for SOC stock changes') might take. Conclusions are presented in Chapter 5.

2. Description of main MRV components

2.1 Context

As an output of the CIRCASA project, Smith *et al.* (2020) have proposed an MRV framework for cropland dedicated to NDCs (Figure 2). This figure presents how different building blocks (e.g., datasets, models) could contribute to the three components of MRV (Monitoring, Reporting and Verification) of SOC changes. The study also provided a methodological basis for the ground monitoring, for modelling and for the 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 models, crop 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 MRV results/reporting.

A 'building block,' in Figure 2, is one of the separate parts that can be combined to make the MRV itself. For example, spatial data layers (e.g., soil properties, land management), process-based models, data-driven models, and Earth Observation (EO) data). The building blocks themselves can be assembled in an operational processing chain to be applied in one or several contexts of applications (e.g., CAP, Carbon market, NDC). Note that the same building blocks (and their constituting parts) can be used in one or several components of an MRV.

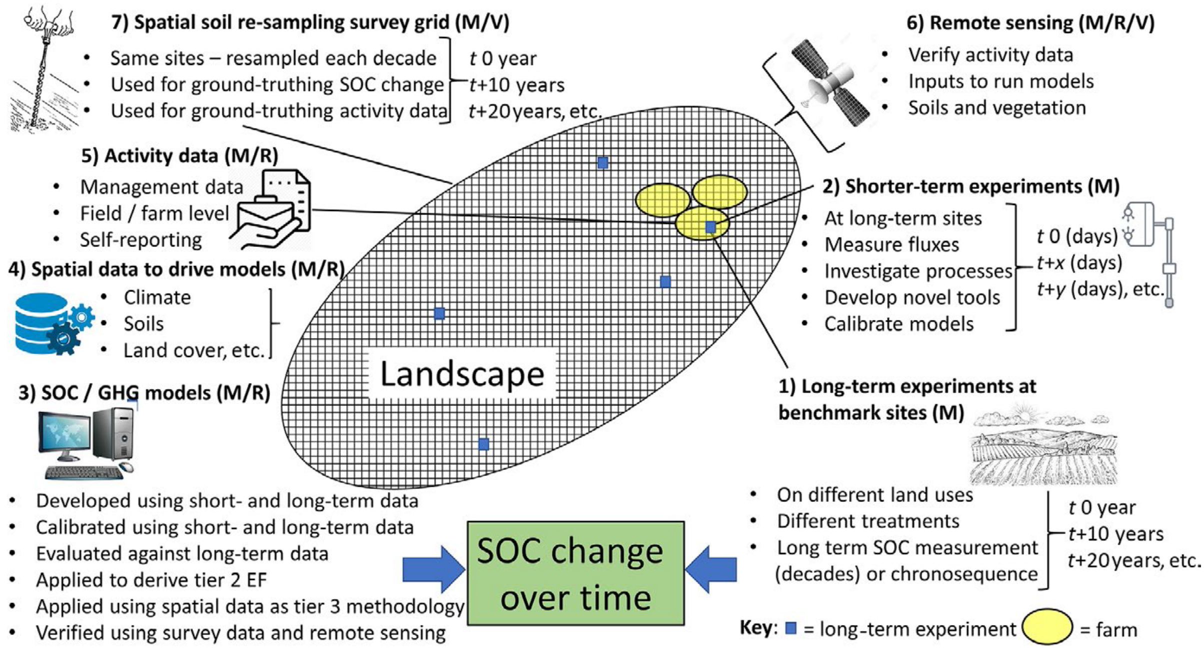

Figure 2. Building blocks of a soil monitoring, reporting and verification framework. The letters M, R, V, indicate to which component(s) each building block could contribute (Source: Smith et al. 2020).

A different framework (Figure 3) has been presented by Paustian *et al.* (2019). It includes components similar to the one proposed by Smith *et al.* (2020), as well as a scalable quantification platform (which is not really detailed in the paper itself), and further considers the different communities that should be served by an MRV (e.g., national policies, carbon finance market, and supply chains). Further, unlike the figure extracted from the Smith *et al.* (2020) paper, Figure 3 visualises a clear flow order from left to right.

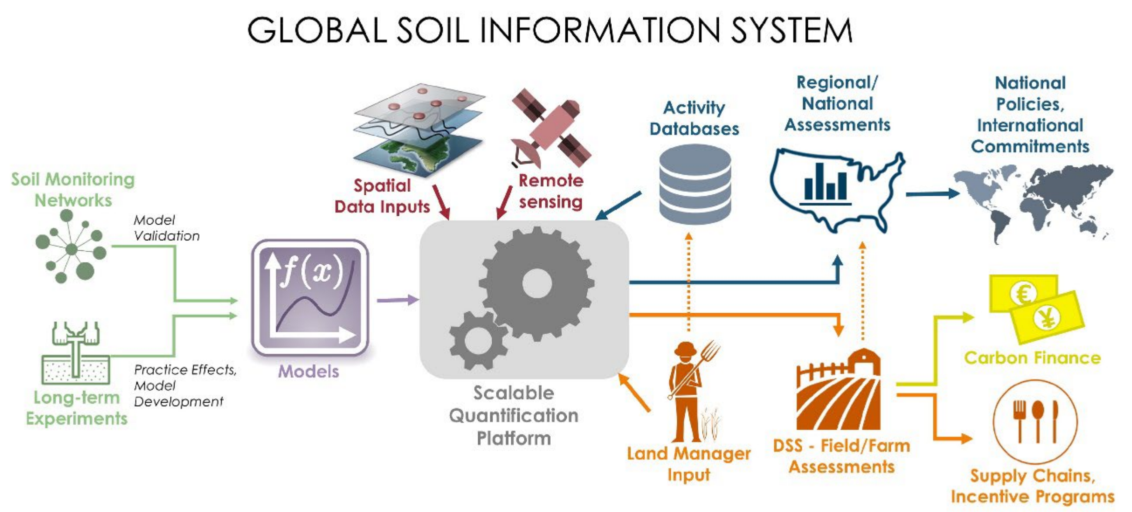

Figure 3. Schematic representation of components and information flow for an approach to quantify soil carbon stock changes (and net GHG emissions) from field to national scales, aimed at supporting different implementation policies to remove atmospheric CO2 and sequester soil carbon (From: Paustian et al. (2019)).

Depending on the size of the area to be monitored, the availability/accuracy of the input data (e.g., climate, remote sensing, soil properties or activity data), protocols for sampling/measurement, monitoring frequency, scale of interest (e.g., farm/plot level, landscape level, subnational, national and international) and purposes (e.g., carbon farming, insetting, CAP, NDCs), different MRV approaches, and associated methodologies, will be needed.

Based on the above and related discussions three components for an MRV framework were defined (Figure 4); these will be discussed in the following (sub)sections:

- Monitoring, which includes experiments, direct (soil) measurements, activity data, spatial data layers, Earth Observation (M1 to M5) 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.
- Reporting, which includes rules and procedures (R1 and R2).
- Verification, which includes rules and procedures, verification itself, proof of adoption of practice and, data (soil and/or EO) for verification (V1 to V4).

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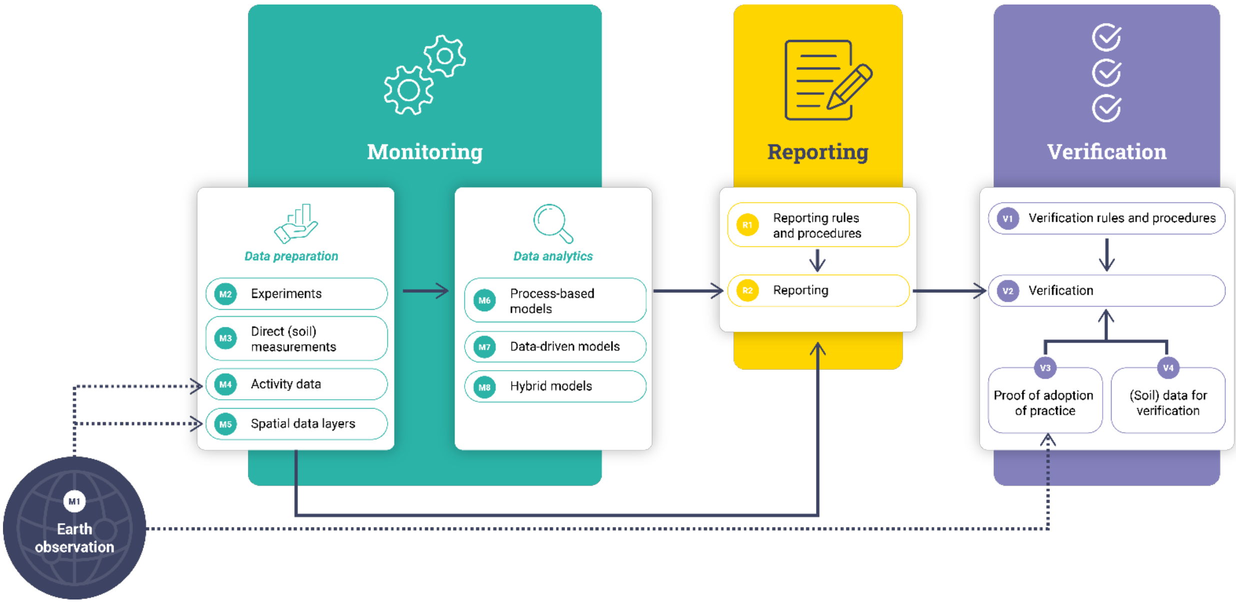

Figure 4. Schematic representation of components, building blocks, and information flow for a generic, scalable MRV system.

As indicated earlier, a building block is one of the separate parts that can be combined to make the MRV itself; note that the same building blocks (and their constituting parts) can be used in one or several components of an MRV.

2.2. Monitoring

2.2.2 Data Preparation

2.2.2.1 General considerations

This section addresses building blocks M1 to M5 of Figure 4.

Differences in how protocols for the carbon market (e.g., ERF (Emission Reduction Fund), NDC, CAP, C market, insetting) estimate SOC stock changes and net GHG reductions, as well as differences in context of their application, may create the risk of creating credits that are not equivalent or even comparable (Demenois *et al.* 2021; Oldfield *et al.* 2021; Arcusa and Sprenkle-Hyppolite 2022; Tamme 2022; Paul *et al.* 2023). This diversity makes it cumbersome to determine net climate benefits that have been achieved, unless verified by soil sampling and/or modelling based on harmonised measurement and modelling approaches. As soils are characterised by high spatial variability, direct (in situ) measurement requires an appropriate sampling design and sampling protocols (Minasny and McBratney 2006; Tirez *et al.* 2014; FAO-GSP 2020; Brus 2022; Buenemann

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et al. 2023). Alternatively, experiments are needed to determine the short- and long-term relationships between environmental (e.g., ENSO (El Nino Southern Oscillation) and management factors and SOC dynamics (Gardi *et al.* 2009; van Wesemael *et al.* 2010; Arrouays *et al.* 2018; Arrouays *et al.* 2021).

2.2.2.2 Earth observation

Earth observation from satellites and remote sensing can provide a valuable and timely source of data across countries and regions on natural resources and ecosystems. These data can be combined with other geo-referenced socio-demographic, economic and public administration data, for example to model changes in GHG emissions (e.g., Stevens *et al.* 2012; Tziolas *et al.* 2021; Dvorakova *et al.* 2022; van Wesemael *et al.* 2023). Vaudour *et al.* (2022) reviewed recent satellite-based spectral approaches for SOC assessment with several satellite sensors for different study scales and geographical contexts. Most approaches that rely on purely spectral models have been carried out since 2019 and these mostly considered temperate croplands in Europe, China and North America at the scale of small regions (some hundreds of km^2.) These studies mainly considered SOC content in the uppermost layer of mineral soil, and often included limited calibration against field measurements.

Most satellite-derived SOC spectral prediction models use limited pre-processing and are based on bare soil pixel retrieval after Normalised Difference Vegetation Index thresholding (Vaudour *et al.* 2022). Many models used partial least squares regression to predict SOC content and SOC stock from the spectra, while random forest and other machine learning algorithms such as support vector machines are also frequently used. Vaudour et al (2022) did not find any studies on deep learning methods, or on all-performance evaluations and uncertainty analysis of spatial model predictions. Nonetheless, their review identifies satellite-based spectral information, especially derived under bare soil conditions, as a promising approach that deserves further investigation. The ongoing ESA WORLDSOILS[5] project will take the analysis a step further by: a) modelling soil organic carbon for permanently vegetated soil; b) integrating models for bare and permanently vegetated soil; c) prototyping up-scaled predictions, and d) developing a data dissemination platform. Ultimately, the ESA WORLDSOILS project aims to develop an operational Soil Monitoring System to provide yearly estimations of SOC at global scale, exploiting space based Earth observation data leveraging large soil data archives and modelling techniques to improve the spatial resolution and accuracy of SOC maps. Earlier, Vaudour *et al.* (2019), based on a Sentinel-2 time series for the Versailles Plain (France), analysed the impact of acquisition date, and related weather and soil surface conditions on the prediction performance of topsoil SOC content (plough layer), and found that the best performing dates were spring dates characterised by both lowest soil surface roughness and moisture content. Many of the studies, focus on possible changes in topsoil organic carbon content only, not on SOC stock changes themselves.

Earth observations missions for biomass mapping have recently been reviewed by Duncanson *et al.* (2021). Several current and upcoming missions (e.g., GEDI[6] (Global Ecosystem Dynamics Investigation), EU-

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[5] https://world-soils.com/
[6] https://gedi.umd.edu/

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BIOMASS[7], NISAR[8] (NASA-ISRO Synthetic Aperture Radar)) should provide improved data for biomass mapping compared to those obtained with earlier sensors, as these were designed with a primary science goal of mapping forest biomass. Being of a publicly available nature, these mission datasets are anticipated to form the basis for other new biomass products through data fusion and alternative algorithms (Duncanson *et al.* 2021). An important issue is that there are discrepancies between forest components estimated from field survey (ground truthing) and remote sensing approaches; field measurements are generally 'trunk-based' (i.e., consider a tree only if at least half the trunk base section is within the plot) while RS sensors measure forests from an area- or volume-based perspective (i.e., consider only the plant material having a ground projection within the plot) (Mascaro *et al.* 2011).

Spatial data layers derived from remote sensing are often used as input for models (e.g., assimilation and forcing) as discussed by Padarian *et al.* (2022) and Wijmer *et al. (2023)*.

Earth observation is often used to monitor activity on forest and agricultural ecosystems. For croplands, this includes crop rotations, cover crops, harvesting (e.g., silage maize), mechanical or chemical destruction, soil work (i.e., tillage practices), handling of straw residues (fraction of soil coverage) and irrigation. For grasslands, this includes cutting/grazing and ploughing. For forest, it can be used to monitor harvesting and degradation/rehabilitation activities. Recent examples of use of EO derived data in applications relating to land management, regenerative agriculture and SOC monitoring are given elsewhere (e.g., le Maire *et al.* 2005; Bartholomeus *et al.* 2007; Soudani *et al.* 2008; Serbin *et al.* 2009; le Maire *et al.* 2011; Siegmann *et al.* 2012; Biney *et al.* 2021; Fayad *et al.* 2021; Zhang *et al.* 2021; Gasmi *et al.* 2022). Overall, EO/RS-derived information on activity data is often used as input for Tier 3 type models (i.e., soil/plant/coupled models).

2.2.2.3 Experiments and flux measurements

This section addresses building blocks M2 and M3 of Figure 4.

Field experiments

Results of short-term (<5 yr) and long-term (>10 yr) field experiments are needed for developing and calibrating process-based SOC-models (Janzen *et al.* 1992; Smith *et al.* 1997a; Rasmussen *et al.* 1998; Parton *et al.* 2000; Falloon and Smith 2002), see for example the Broadbalk and Highfield long-term experiments at Rothamsted (Jenkinson 1990; Poulton *et al.* 2003; Gregory *et al.* 2009). Traditionally, most agricultural long-term field experiments are located in Europe and North America (see ISCN[9] website), with an increasing number of sites located in the Global South (see GLTEN website[10]). Examples of the later include long-term experiments described by Kamoni *et al.* (2007), Cardinael *et al.* (2022), and Laub *et al.* (2023). Alternatively, results of in-situ measurements via soil monitoring networks (SMN), such as Australia's Terrestrial Ecosystem

[7] https://earth.esa.int/eogateway/missions/biomass
[8] https://nisar.jpl.nasa.gov/
[9] https://iscn.fluxdata.org/network/partner-networks/ltse
[10] https://glten.org/

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Research Network (TERN[11]) or LUCAS[12] topsoil database, are mainly used as input for models and model output validation; they also permit to directly calculate SOC stock changes over time at defined locations.

There is also a need for new types type of studies as discussed by Li et al. (2023) with respect to a new Rothamsted long-term field experiment. Soil carbon projects struggle to provide the scientific evidence to justify the potential increases in soil carbon that they expect to find because most of the literature is geared towards single management practices. However, modern farming does not work like this and moves towards sustainable farming which is characterised by a whole 'systems' change, not just a single practice change.

Chronosequence studies

Chronosequence studies, a surrogate for long-term (>10 yr) field experiments, assume space-for-time substitution to infer temporal dynamics from measurements at sites of different ages but similar land-use histories (Cerri *et al.* 2003; Costa Junior *et al.* 2013; Macdonald *et al.* 2013; Manu *et al.* 2014; Resende *et al.* 2017; Ma *et al.* 2018; Wang *et al.* 2022). They are particularly useful when investigating post-disturbance recovery of systems that take decades to centuries to recover (Walker *et al.* 2010), such as forests. However, as discussed by de Palma *et al.* (2018) there is a need for well-defined studies.

Direct (flux) measurements

Short to long-term (>20 yr) flux sites are equipped with eddy covariance setups that measure continuously net CO_2 ecosystem exchanges (NEE) with the atmosphere and monitor other carbon cycle components (gross primary production (GPP), plant and soil respiration, SOC stock changes) and other GHGs fluxes between ecosystems and atmosphere. Standardised networks, such as ICOS[13] for Europe, NEON[14] for the USA and OZFlux[15] for Australia and New Zealand are registered in the worldwide FLUXNET[16] network.

There are various issues of and needs for scaling from chambers to fields and systems with flux towers as discussed elsewhere (e.g., Soussana *et al.* 2007). Most studies have provided flux measurements from static chambers (e.g., Carnol *et al.* 2002; Riveros-Iregui *et al.* 2008; Premrov *et al.* 2021; Barthel *et al.* 2022; Busman *et al.* 2023) which will need to be upscaled to the region under consideration (e.g., Xiao *et al.* 2012; Ran *et al.* 2016; Davidson *et al.* 2017), with associated uncertainties.

[11] https://www.tern.org.au/
[12] https://esdac.jrc.ec.europa.eu/projects/lucas
[13] https://www.icos-cp.eu/
[14] https://www.neonscience.org/data-collection/meteorology/
[15] https://www.ozflux.org.au/
[16] https://fluxnet.org/about/

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2.2.2.4 Direct (soil) measurements

This section addresses building block M3 of Figure 4.

*Planning in-*situ (soil*) measurements*

Diverse protocols for site location, soil sampling and analysis are available for agricultural landscapes (McKenzie *et al.* 2002; Scott *et al.* 2002; Ravindranath and Ostwald 2008; Nayak *et al.* 2019; FAO-GSP 2020; Mudge *et al.* 2020; Bispo *et al.* 2021; Huising *et al.* 2022; GLOSOLAN 2023), forest land (Jolivet *et al.* 2006; GOFC-GOLD 2009; ICP Forests 2021b; FAO 2022; Verkerk *et al.* 2022; Mäkipää *et al.* 2023), peatlands (FAO 2020), and urban soils (Vasenev *et al.* 2017). These approaches often differ in terms of sampling design, frequency of observation and depth of sampling, as well as the analytical methods themselves (e.g., 'wet and dry' chemistry or spectroscopy-derived data), pointing at a need for international harmonisation (e.g., Morvan *et al.* 2008; Baritz *et al.* 2014; Louis *et al.* 2014; Bispo *et al.* 2021; Shamrikova *et al.* 2022). For example, sampling the topsoil only (e.g., 0-20 or 0-30 cm) rather than a greater depth of soil (say up to 50 or 100 cm), as well as the SOC stock calculation method itself (e.g., fixed depth versus equivalent mass basis (e.g., Ellert and Bettany 1995; Wendt and Hauser 2013)), can result in significantly underestimating, and even potentially negating, SOC stock change (Batlle-Bayer *et al.* 2010; Amundson *et al.* 2022; Skadell *et al.* 2023).

Sampling design

When planning and implementing a field monitoring programme, as indicated, numerous aspects have to be considered: for example, the sampling area (point or block support), number and kind of (sub)samples, depth of sampling (i.e., nominated depth (e.g., 0-30 cm) or actual depth (i.e, 0-90 cm)), range of soil parameters to be measured (e.g., organic carbon content, moisture content, bulk density, and coarse fragments) and analytical methods for their measurement (McKenzie *et al.* 2002; Morvan *et al.* 2007; GOFC-GOLD 2009; Lark 2012; Louis *et al.* 2014; Munera-Echeverri *et al.* 2021; Sanderman *et al.* 2023). The representativeness of samples and confidence in the final data produced after analysis are linked; the key points mentioned in Pierre Gy's Theory of Sampling (Petersen 2005) can be inspiring for MRV. The objective (context) of the MRV and its complexity will largely determine which statistical methodology should be used, as there are trade-offs between the different classes of design. Broadly, sampling schemes can be classified as design-based (probabilistic) and model-based (non-probabilistic) (De Gruijter *et al.* 2006). Detailed description of statistical approaches for random, grid-based, and stratified monitoring schemes may be found in De Gruijter *et al.* (2006), Brus et al (2022), Allen et al (2010) and Heuvelink (2022). The statistical inference method will vary depending on the type of sampling design (Karunaratne *et al.* 2014).

Traditional field measurements versus proximally-sensed data

Overall, traditional field measurements (e.g., based on random sampling) are impractical for a generic implementation of an MRV (i.e., too costly and labour intensive), and other solutions that replace or at least reduce the sampling intensity in the fields and reduce the cost of sample analysis in the laboratory are required, see Kuhnert (2022), Poeplau (2022), Shepherd et al. (2022) and Viscarra Rossel et al. (2022). At

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present, lab-based spectral measurements are considered more precise than field-based spectral measurements (Reeves 2010; McBride 2022). The development of a global soil spectral calibration library and estimation service appears promising (Cécillon et al. 2009; Shepherd et al. 2022), as long as the spectral datasets and models can be harmonised to local conditions.

Specific chemical bonds that characterise the organic matter have strong absorbance peaks at defined wavelengths in the visible (VIS), near (NIR) and mid-infrared (Mir) spectral regions. This aspect has been successfully used to qualify and quantify SOC contents and related properties in a large variety of contexts, climates, and agroecosystems (Viscarra Rossel *et al.* 2006; Gholizadeh *et al.* 2013; Soriano-Disla *et al.* 2014). SOC models combined with NIR/MIR models for soil bulk density have been used to assess SOC stocks using pedotransfer functions (Moreira *et al.* 2009) and machine learning algorithms (Shi *et al.* 2023). NIR/MIR models for assessing soil bulk density or SOC stocks may be representative of the 'black box modelling' that "has been used to estimate (i.e., basically using SOC content and particle size analysis) secondary properties indirectly using 'surrogate' calibration because there is sometimes a correlation of spectral features to another (primary) soil property which presents some ability to predict the soil property in question" (McBride 2022). Considering both the advantages and the recognised limitations of these spectral techniques (see Nduwamungu *et al.* 2009; Stenberg *et al.* 2010; Gobrecht *et al.* 2014) they seem appropriate to generate sufficiently reliable data for MRV purposes. The 'lower' costs associated with spectrally and proximally-derived data, as a rapid and high throughput measurement technology for numerous soil properties, make it possible to base interpretations on a greater number of soil samples, given that appropriate prediction models are calibrated, albeit with lower accuracy (Leenen *et al.* 2022).

Both MIR and VIS-NIR estimates are accepted as appropriate methods to measure SOC concentrations for large scale monitoring programmes such as the Rapid Carbon Assessment Project in the USA (Wijewardane *et al.* 2016), the Australian Carbon Farming Initiative (Sanderman *et al.* 2023), and present EU LUCAS topsoil sampling rounds (Jones *et al.* 2021; Leenen *et al.* 2022). An important aspect here is that the wet chemistry-derived data (e.g., SOC) used for the calibration itself should be analysed using the same analytical procedures, and this preferably in a single reference laboratory (e.g., van Leeuwen *et al.* 2022). Overall, the issue of calibration and uncertainties in calculating soil C stock gains should not be underestimated.

Summarising, there is a need for a 'more balanced and contemporary approach' which emphasises the need for direct measurement with the need to reduce costs; sensors offer a way to reduce costs further - but only if they have the direct measurement at the right spatial scales. Basically, we need direct measurement to support cost-effective MRV whether by measurement or sensors.

Examples of soil monitoring networks

As indicated, there is an increasing demand for up-to-date soil organic carbon data for national, continental and global environmental and climatic modelling. Within the 'EU Land Use/Cover Area frame Survey', LUCAS Soil provides a harmonised collection and analysis of soil samples from across the EU based on a uniform standardised soil monitoring methodology (Fernandez-Ugalde *et al.* 2022; Orgiazzi *et al.* 2022). The topsoil (0-20 cm) data obtained from revisited locations during the 2009-2015-2018 campaigns can be used to quantify changes of SOC content, though not necessarily SOC stock, in view of the shallow depth of sampling and

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limited number of bulk density data. Initially, the focus of LUCAS Soil was on characterising changes in agricultural land but, apparently, this is changing in the ongoing '2020 monitoring' round with the inclusion of forest land. Since 1995, a monitoring framework for forest soils in Europe has been implemented by ICP Forest (ICP Forests 2021a, b). It monitors forest (and soil conditions, every 10 yr) at two levels of thematic detail.

LUCAS and ICP Forest use somewhat different approaches, for example for site selection and soil sampling, while the soil analytical methods are largely similar (ISO standards). In this context, Bispo *et al.* (2021) discussed a proposal for methodological development for the LUCAS programme in accordance with national monitoring programmes. Alternatively, for Finland, the Field Observatory Network (FiON) has established a unified methodology towards monitoring and forecasting agricultural carbon sequestration by combining offline and near-real-time field measurements, weather data, satellite imagery, modelling, and computing networks (Nevalainen *et al.* 2022) .

For Australia reference can be made to the Soil Carbon Research Program (SCaRP[17]) programme (2009-2012), the Soil Organic Carbon Monitoring (SOC-M[18]) programme on improving soil carbon storage and measurement, as well as the recent National the Australian Soil Strategy (Australian Government 2021) which outlines priority actions over the next 5 years to improve Australia's soil health and long-term security. Similarly, in 2021, for the USA the US Department of Agriculture has launched the first phase of a national soil carbon monitoring programme in the framework of its Conservation Reserve Program (CRP[19]) initiative.

Overall, soil monitoring networks should consider a soil depth of at least 100 cm (and include the organic top layer), and measure SOC content, bulk density and proportion of coarse fragments (using harmonised methods), to allow calculations of SOC stock changes on an equivalent mass basis.

2.2.2.5 Activity data

This section addresses building block M4 of Figure 4.

Activity data are data on the level of an activity that causes direct GHG emissions (e.g., use of machines) but that may also affect (increase or reduce) SOC stocks and biogenic GHG fluxes (e.g., livestock numbers affect methane emissions, N fertilisers impact N2O emissions). The activities causing direct GHG emissions are multiplied by emissions factors for GHG accounting purposes (Tier 1 approach, based on global default values). Area-specific activity data are needed for Tier 2 level calculators (e.g., Milne *et al.* 2007) and Tier 3 level process-based models (e.g., FullCAM[20]) for the land sector accounting as part of national annual reporting under UNFCCC, for example.

Activity data are dramatically missing for large sections of the world, especially in sub-Saharan Africa. Rosenstock and Wilkes (2021) suggest investments in activity data for monitoring should be prioritised as

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[17] https://csiropedia.csiro.au/soil-carbon-research-program/
[18] https://www.dcceew.gov.au/climate-change/emissions-reduction/agricultural-land-sectors/soil-carbon-storage-measurement
[19] https://www.nrcs.usda.gov/programs-initiatives/crp-conservation-reserve-program
[20] https://www.dcceew.gov.au/climate-change/publications/full-carbon-accounting-model-fullcam

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they can also provide benefits to the governments in terms of investment in planning or monitoring national development policies. For small and heterogenous fields, as widely occurring in SSA and other regions, accurately identifying land cover quickly and inexpensively is now possible using high resolution EO data (e.g., ESA Sentinel 2 satellite); these resources are freely available through open-source tools such as Collect Earth Online (CEO[21]). Nonetheless, the lack of systematic activity data collection even in developed countries is considered one of the main barriers to systematic direct and undirect GHG emission and SOC stock change estimates at plot to farm level (e.g., for the CAP eco-schemes in Europe).

Land management activities can typically be obtained by surveys, and in the future, survey with door-to-door data collection could be replaced by new mobile phone technologies and citizen data (Fritz *et al.* 2019). In the Global North, a lot of farmers now use Farm Management Information Systems (FMIS) to reduce production costs, for precision agriculture, to comply with agricultural standards (Fountas *et al.* 2015) or even to comply to carbon farming programmes. Provided access to the data is facilitated, FMIS could be an important source of detailed farm management activities.

Some of farmer and forester activity can be detected and mapped from high spatial and temporal resolutions remote sensing data (e.g., Sentinel –1 and –2 constellations), now freely available in platforms such as Collect Earth Online, even if the spatial resolution can still be a challenge for smallholder farms. However, new private satellite constellations like Planet[22] or EarthdailyAgro[23] with higher spatial resolution may solve this issue. The temporal resolution may also be limiting for detecting some activities (e.g., irrigation with thermal infrared satellites) and long periods of cloudiness can prevent detection of practices (e.g., harvest). This limitation, however, can be lifted in some cases through the use of radar remote sensing (e.g., Synthetic Aperture Radar like Sentinel-1) that allow to observe the surface despite any cloud cover. Last, many practices (e.g., pesticide applications) cannot yet be detected by remote sensing or at least not in an operational manner; others practices may strongly affect SOC stocks remain challenging to monitor (e.g., mineral or organic fertilisation, and export of straw).

Practices that are usually monitored by remote sensing for cropland include: crop types and crop rotations, cover crops, tillage or ploughing, harvesting, and encroaching salinisation (e.g.Serbin *et al.* 2009; Waldhoff *et al.* 2017) (Lawes *et al.* 2022; Zhou *et al.* 2022). For forest, the main practices monitored by remote sensing are tree species, partial or total harvest (clear-cut), planting, rotation length, and degradation (e.g., le Maire *et al.* 2011; Ose and Cresson 2019; Gao *et al.* 2020). JRC-TMF[24], 'Tracking long-term (1990-2022) deforestation and degradation in tropical moist forests', is as an example of available product.

2.2.2.6 Spatial data layers

This section addresses building block M5 of Figure 4.

[21] https://www.collect.earth/
[22] https://www.planet.com/
[23] https://earthdailyagro.com/
[24] https://forobs.jrc.ec.europa.eu/TMF

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Changes in soil properties, such as soil organic matter content/quality, are determined by the interaction of five soil forming factors: climate (Cl), organisms and biosphere (O), relief or topography (R), parent material (P) and time (T) (Jenny 1941). Point and spatial data layers (i.e., environmental co-variates) representing these factors as well as activity data at an appropriate scale (e.g., Malhotra *et al.* 2019; Zeraatpisheh *et al.* 2023), will be needed to run (and evaluate) a range of data driven and ecosystem models (e.g., Luo *et al.* 2016; Heuvelink *et al.* 2020; Smith *et al.* 2020). Typically, these include terrain parameters derived from a digital elevation model, land cover maps, climatic maps, vegetation indices or spectral reflectance obtained from Earth observation imagery, maps of climate variables and soil class, geological or geomorphological maps (see van Egmond *et al.* 2023). A requirement for selecting covariates for a given SOC stock change project or GHG inventory is that these cover the entire area under consideration, which may be at the plot/site, landscape, national and regional scale. Therefore, it is important that the resolution of the selected covariates is appropriate for the target resolution of the MRV assessment (e.g., Poggio *et al.* 2021; Fendrich *et al.* 2023; Wijmer *et al.* 2023; Zhou *et al.* 2023).

Covariate layers can be obtained for free from various sources (see van Egmond *et al.* 2023) such as the Earth Engine Data Catalogue, Microsoft Planetary Computer and Copernicus Global Land Service, and the CGIAR Consortium for Spatial Information platform. Sentinel products are available via the Sentinel hub, while thousands of datasets are available through metadata hosted by NASA's Open Data Portal[25]. A wide range of environmental data can be accessed, and submitted, through the European Open Science[26] Cloud, such as Corine Land Cover. Similarly, historical climate data are available on-line from various organisations, such as NOAA[27] which provides quality controlled daily, monthly, seasonal, and yearly measurements of temperature, precipitation, wind, and degree days. When more spatial and temporal detail is required, for example for some hybrid Tier 3 level applications, a range of national meteorological institutes can be approached.

In the next two paragraphs, we pay greater detail to soil data and land use/cover maps.

Soil type and soil properties data

Overall, there are two types of soil property maps can be divided into two broad categories, those derived from traditional soil survey and those created using digital soil mapping (Dai *et al.* 2019). At global scale, examples of traditional soil maps include the Harmonised World Soils Database (HWSDv2) (Nachtergaele 2023), which builds on the WISE30sec database (Batjes 2016). Well-known examples of digital soil mapping products include SoilGrids250m (Poggio *et al.* 2021) and GlobalSoilMap (Arrouays *et al.* 2020). By their nature, such 'global' scale products are not meant for local applications as clearly indicated by Poggio *et al.* (2021) and others.

It should be noted that there are large differences in global and regional predictive maps of soil carbon stocks as compiled by GSP-ITPS (2018, GSOCmap) or with 'S-World' (Stoorvogel *et al.* 2017), and estimates based on SoilGrids and HWSD (e.g., Tifafi *et al.* 2018; Stoorvogel and Mulder 2021). In this context, it is important to consider how well predictive mapping can represent soil geography (or soil landscapes), at a given scale level

[25] https://data.nasa.gov/
[26] https://eosc-portal.eu/
[27] https://www.ncei.noaa.gov/cdo-web/

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(Rossiter *et al.* 2021; Han *et al.* 2022). For sub-national and local scale assessments of SOC stock change, spatially detailed soil maps (or GIS layers), based on environmental co-variates and soil data reported/measured at a fine scale, will be required (e.g., Grunwald *et al.* 2011; Piikki *et al.* 2017; Venter *et al.* 2021; Dandabathula *et al.* 2022). The following webpage[28], compiled by David A. Rossiter, attempts to catalogue all freely available primary soils information usable in a geographic information system (GIS), either as points, lines, polygons or grids ('rasters'). Many point data, however, are not freely accessible in a digital format yet (Arrouays *et al.* 2017; Batjes *et al.* 2020; Cornu *et al.* 2023).

In this respect, there is a need to have a global soil resources centre to bring together old (i.e., legacy) and newly collated soil data in a uniform, harmonised way for the benefit of the international community, following FAIR principles (Mons *et al.* 2019). Mechanisms should be developed through which data held by private organisations as well as commercial companies can be accessed freely through a federated, global soil information system, using open standards, with the (non-harmonised) source data themselves remaining with the respective data providers (e.g., van Egmond *et al.* 2018; Batjes *et al.* 2020; de Sousa *et al.* 2021; Van Egmond and Fantappiè 2021; de Sousa 2023).

Land Use maps

Besides edaphic and environmental factors, soil management such as crop rotation and land use change play a key role in determining the magnitude and direction of changes in SOC stocks. Recent development in SOC modelling frameworks at pan-EU scale investigated the effect of land use change on SOC stocks. Information of land use change at pan-EU scale is generally obtained from satellite imagery or products derived from these images such as the CORINE[29] Land Cover. However, land use change information at pan-EU scale obtained from satellite imagery is affected by a relatively high temporal and spatial uncertainty. Therefore, including accurate spatial and temporal information of land use into SOC modelling frameworks could reduce overall uncertainty.

For agricultural land, for example, accurate spatial time series of land use change in Europe can be obtained from IACS[30] (Integrated Administration and Control System). IACS is a system to support the implementation of a uniform Common Agricultural Policy (CAP) in the EU Member States. The Identification System for Agricultural Parcels (LPIS - Land Parcel Identification System) and the Aid Applications and Payments Claims (GSAA - GeoSpatial Aid Application) subsystems of IACS contain the spatial data components themselves.

The inclusion of complete time series information (IACS data) for model training is likely to improve model performance and reduce the uncertainty in model predictions when a model is employed at pan-EU scale. This would not only reduce the uncertainty in model estimates, but could also facilitate MRV processes supporting carbon sequestration initiatives.

[28] https://www.isric.org/explore/soil-geographic-databases\
[29] https://land.copernicus.eu/pan-european/corine-land-cover
[30] https://agriculture.ec.europa.eu/common-agricultural-policy/financing-cap/assurance-and-audit/managing-payments_en

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Satellite imagery, as discussed earlier, will be used increasingly for verification of management continuity and monitoring of permanence.

2.2.3 Data analytics

This section addresses building blocks M6 to M8 of Figure 4.

2.2.3.1 General considerations

Landscape-scale assessment of SOC stock changes in agriculture and forestry 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 data can be expensive and time consuming. The use of field measurements, modelling and remote sensing for MRV is often complementary (van Wesemael *et al.* 2023). Broadly speaking, three types of models are used to predict SOC stock changes: a) process-based (M6, or mechanistic) models (Parton *et al.* 1987; Smith *et al.* 1997b; Paustian *et al.* 2019; Smith *et al.* 2020), b) data-driven (M7, or empirical) models, and c) hybrid models (M8, Soussana *et al.* (2007), Tziolas *et al.* (2021), van der Voort *et al.* (2023)). The second type of model is based on statistical relationships derived directly from field (experiment) observations, while process-based (or mechanistic) models consider algorithms that are founded on more general scientific understanding. This knowledge 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). A recent development has been the use of geo-statistical approaches for assessing space-time changes in SOC stocks using machine learning that draws on large point (soil) databases and environmental co-variates (Heuvelink *et al.* 2021). Recently, Le Noë *et al.* (2023) published 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.

All models are based on a set of assumptions about a system and as such give an approximation of the actual situation. They therefore have an inherent level of uncertainty, which can be quantified with appropriate statistical methods (e.g., Larocque *et al.* 2008; Nol *et al.* 2010; Ogle *et al.* 2010; Portner *et al.* 2010; Wang and Chen 2012; Brus 2014; Jandl *et al.* 2014; Feng *et al.* 2016; Keel *et al.* 2017; Heuvelink *et al.* 2021; Poggio *et al.* 2021). This should be kept in mind when deciding whether a model, or base map, should be used for an assessment. As indicated by Milne *et al.* (2012) and others, the purpose for which a SOC/GHG assessment is being carried out (for example, a report to a funding agency, an inventory, or a project to gain certification from a carbon market) and the desired level of accuracy and precision, will determine whether a particular model should be used at all. See, for example, the elaborate selection procedure developed for the Netherlands (Lesschen *et al.* 2020) as discussed below (Section 2.2.3.5).

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Models can contribute to MRV in various ways. As described by Kuhnert *et al.* (2022), they can: a) provide estimates for baselines, b) interpolate measurements (in time and space), c) extrapolate measurements for projections for an ex-ante assessment, d) estimate SOC changes, and e) provide information for optimised measurement plans. General specifications for different model categories as elaborated by Kuhnert *et al.* (2022) are presented in Table 1, with some modifications.

Table 1. Specifications for different model categories.

	Decision support tools	Models		
		Empirical	SOC models	Biochemical
Data requirement	High (farm specific data)	Low	High (environmental data)	High (environmental data)
Calibration requirement	Low	Low	High	High
Required expertise	Medium	Low	High	High
Management options	Medium-high	Medium (categories)	No-high	High
Targeted scale	Field-farm	Country and larger	Point, country and larger	Point, country and larger
Uncertainty/expected error for field scale	Medium-high	High	Low	Low
Examples	Cool Farm Tool (Tier 1), Comet Farm (Tier 1 and 2), CPB tools (Tier 1 and 2), SIMEOS-AMG (Tier 3)	IPCC and UNFCC models (Tier 1 and Tier 2)	Roth C (Tier 3)	EPIC, CENTURY, DAYCENT, DNDC (Tier 3)

* Adapted from Kuhnert *et al.* (2022). Note that models such as RothC and DayCent are process-based models. Some only consider C (e.g., RothC); others consider C, N, P etc dynamics (e.g., DayCent) and these are termed 'biochemical models' here. 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.

2.2.3.2 Process-based models

This section addresses building block M6 of Figure 4.

Mechanistic SOC and biogeochemical models (i.e., process-based models), that consider country specific model parameters and are spatially explicit, correspond with IPCC's Tier 3 approaches. As defined here, they only consider SOC dynamics (yet some, such as DayCent, also consider N and P dynamics) while biochemical models also consider processes such as N and P cycle as well as plant growth. Both types of ecosystem models provide a mathematical representation of ecological processes, interactions, and feedbacks within a defined ecosystem. By simulating the dynamic of forests, grasslands and crops, ecosystem models can provide insights into carbon stocks and GHG flux change over time (Smith *et al.* 2020). The models encompass various components that capture the complexity of forest, grasslands and crop ecosystems. Examples of such components are vegetation growth, carbon allocation, photosynthesis, respiration (from plant and soil), nutrient cycling, and soil-climate interactions.

As indicated earlier, process-based models can be categorised into different types, based on their complexity and focus (Mäkelä *et al.* 2000). For instance, biogeochemical models that emphasise the cycling of carbon, nitrogen, and other nutrients (Goll *et al.* 2017; Cornut *et al.* 2022), models that focus on forest, crop and grasslands growth and specifically simulate phenology, biomass accumulation, crops yield, crop residue decomposition (Brisson *et al.* 2003; Dufrêne *et al.* 2005). By simulating carbon stocks and fluxes in crops, these new generation models can provide insights into the impacts of agricultural or sylvicultural practices on carbon sequestration and GHG emissions; importantly, they can easily be adapted for application to different ecosystems, management regimes and (changing) climate conditions.

To ensure the accuracy and reliability of ecosystem models, calibration/parameterisation and validation using field measurements are necessary. Field data on e.g., plant morphology or density, biomass inventories, yield or CO_2 flux measurements, and soil (i.e., physical and chemical properties) are critical for model calibration/validation. By comparing model outputs with field data, ecosystem models can be refined and adjusted to accurately represent the specific characteristics of forests and agricultural ecosystems. However, these elaborate ecosystem models are 'data hungry' so that data availability and quality can present major challenges, particularly in heterogenous agricultural landscapes. Important uncertainties are associated with parameterisation, data inputs, and the simplification of complex ecological processes that are represented in these models; current research is addressing these issues. For example, one way to reduce uncertainty is to assimilate observations (e.g,. from remote sensing) in to the model to force it, or to better calibrate some parameters (Pique *et al.* 2020b; Pique *et al.* 2020a). At the moment, further parameterisation/calibration and validation are required before this type of complex and data demanding models can be used widely for MRV applications (Clivot *et al.* 2019). Therefore, at the moment, consideration of 'simpler' models may be preferred in the context of many area/ecosystem-specific MRVs.

As indicated earlier, regionally calibrated/validated ecosystem models describe the complex dynamics of carbon in defined ecosystems, potentially enabling the estimation of carbon stocks, fluxes, and changes over time. For forest ecosystems, such models presently account for tree growth, mortality, and carbon dynamics (Dufrêne *et al.* 2005); in cropland and grassland they consider crop biomass accumulation and carbon allocation to the different plant components as well as harvest (Brisson *et al.* 2003). This present advantages for MRV in the sense that these models capture ecological processes, thereby facilitating a better understanding of carbon dynamics, which is not the case when MRT approaches rely on field measurements only (Smith *et al.* 2020). In particular, they allow for scenario analysis, such as simulating the impacts of various driving factors on forest or crop/grassland carbon stocks in above-ground biomass and the soil, to identify possible management strategies for carbon sequestration (Karjalainen *et al.* 2003).

Models dedicated to upscale carbon budget components using remote sensing data were originally developed for application at the field scale. However, they are increasingly used to assess the impact of climate and/or agronomic practices on SOC dynamics or GHG emissions, yield changes, and water dynamics at larger scales (e.g., Nevalainen *et al.* 2022). As discussed by Ojeda *et al.* (2021), this raises the question of how data aggregation approaches and model formulation affect outputs when such models are applied at

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large spatial scales, for short and long-term forecasting, and how uncertainty is propagated (Liu *et al.* 2011; Weng and Luo 2011; Luo *et al.* 2016; Liu and You 2021; Liu *et al.* 2023); validation studies still largely focus on the global North. Garsia *et al.* (2023) pointed at the increasingly large number SOC simulation models, which vary considerably in their formulation, applicability and sensitivity, as well as data requirements. Consequently, practitioners and certificate providers are confronted with the critical challenge of selecting the models that are appropriate to the specific conditions in which they will be applied. To date, however, uniform guidelines for model selection are lacking and they could be considered in the upcoming 'MRV cookbook' (i.e., ORCaSa Deliverable D4.2).

2.2.3.3 Data-driven models

This section addresses building block M7 in Figure 4.

Data-driven models primarily rely on historical data collected throughout a system's or process's lifetime to establish relationships between input and output variables. They are commonly used for IPCC Tier 1 and 2 type calculations of carbon stock change (IPCC 1996, 2019c). In their simplest form (Tier 1), for mineral soils, the calculations consider default/reference soil organic carbon stocks, three default stock change factors (i.e., for type of land use/land-use change, management regime, and input of organic matter), land area under consideration, and length of the inventory period (20 year by default). Region-specific emission factors, as well as climate and soil data, can be considered in IPCC Tier 2 calculations, which would reduce uncertainty (e.g., Batjes 2011; Maia *et al.* 2013). Increasingly, data driven models are embedded in calculators used for 'Scope 3' reporting by companies (see Greenhouse Gas Protocol 2023), see for example NIVA below and the COMET-Farm whole farm and ranch carbon and greenhouse gas accounting system.

IPCC Tier 1 and 2 approaches are commonly embedded in 'simple' carbon balance tools (e.g.,Milne *et al.* 2010; Bernoux *et al.* 2011). A similar approach has also been used in the Soils Revealed[31] platform, where land use change and IPCC look-up tables were used to predict SOC stock change between 2000 and 2018 at global extent and where multiple land management scenarios were run to predict SOC stock change between 2023 and 2038.

If sufficient paired observations of input and output variables are available, statistical regression models can be calibrated and used to predict output variables from input variables. Historically, multiple linear regression models were used for this purpose, but in recent years machine learning algorithms have taken over and are frequently used to map output variables from explanatory input variables (Perlman *et al.* 2014; Huang *et al.* 2019; Bregaglio *et al.* 2022; Camargo *et al.* 2022; Jones *et al.* 2023). They have gained prominence across various fields, particularly in the era of 'big datasets', artificial intelligence, and machine learning, where they can offer valuable insights and predictions based on the available data (e.g., Heuvelink *et al.* 2020; Acharya *et al.* 2022). The input variables are typically derived using remote sensing (i.e., Earth observation, building block M1) and from other spatial layers (building block M5). Machine learning models are much more flexible than linear regression models and usually outperform them when model predictions are compared with

[31] https://soilsrevealed.org/

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independent observations, but they also require larger training datasets. They are easy to use and can deal with a considerable number of explanatory variables, but they should not be used without solid domain knowledge. Alternatively, empirical models should not be used to extrapolate beyond the range of the training data; extrapolation in 'feature' space must be avoided (Meyer and Pebesma 2021).

One interesting feature of machine learning algorithms is that many of these algorithms allow quantification of prediction uncertainty (e.g., Meinshausen 2006; Cannon 2011). Thus, prediction intervals can fairly easily be derived, which is essential for uncertainty assessments (see Section 2.5).

Machine learning models are frequently used to map key MRV output variables, such as SOC stock, in space, but they can also be used to map these variables in space and time (e.g., Stockmann *et al.* 2015; Heuvelink *et al.* 2021). However, prediction uncertainties are typically large and often much larger than the estimated SOC stock change over time. The same is true for process-based models, although such models are better suited for extrapolation. However, prediction uncertainties of process-based models are usually not quantified because this requires stochastic modelling and uncertainty propagation analyses (see Section 2.5).

2.2.3.4 Hybrid models

This section addresses building block M8 of Figure 4.

There is no consensus yet on what a 'Hybrid model' is, but it typically refers to an approach that combines multiple data sources and modelling techniques. It is defined by Schauberger *et al.* (2020) as an approach that utilises a combination of crop modelling and remote sensing.

In a recent workshop organised by DG CLIMA on Carbon Farming[32], hybrid MRV approaches for SOC were defined as combining remote sensing and process based modelling and verifying the results (C stock changes and intermediate variables such as biomass or CO_2 fluxes) by using long term soil observatories or experiments (e.g., Rothamsted) and flux towers. In the general context of MRV, hybrid models integrate at least two of the following building blocks: field measurements, remote sensing data, ecosystem or SOC models and machine learning, or advanced statistical techniques. More precisely, the approach is to combine a) field measurements which provide the more precise data, e.g., total soil carbon content and aboveground biomass, b) remote sensing, which provides data with a lower accuracy (e.g., vegetation biomass), but with a better spatio-temporal coverage, or is complementary to in-situ measured data (e.g., FAPAR), and c) ecosystem or soil carbon models. This provides a physical link between the environment, and the interactions between the different components of the hybrid system. Many combinations of such approaches to estimate carbon stock change at different scales are described in the literature (Smith *et al.* 2020). In the next section, we present two possible hybrid modelling approaches. The first considers field data, remote sensing and machine learning. The second, considers field data, remote sensing and ecosystem models.

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32 https://climate.ec.europa.eu/news-your-voice/events/expert-group-carbon-removals-carbon-farming-workshop-2023-06-21_en

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Field data – remote sensing – machine learning

In these approaches, the machine learning model can help identify relationships and patterns between vegetation or soil attributes measured by remote sensing and carbon stocks measured *in situ*, enhancing the accuracy of carbon accounting estimates at larger scale. It can benefit from the use of other sources of data, either collected *in situ* or derived from other sources, such as soil maps, topographic attributes, climate variables, or any variables that can contribute to the prediction accuracy of the models. Machine learning models, such as Random Forest, Support Vector Machines or Artificial Neural Networks are well suited in this context: selection thereof will depend on the type of data, scale of the analysis, training dataset size, and expected output (Odebiri *et al.* 2022). Once calibrated and validated on independent data, the model can be applied at larger scale to assess the carbon stocks at broader scale. Note that this approach aims at estimating SOC stocks or SOC stock changes to a greater depth, and not only superficial SOC content, through the use of remote sensing and advanced statistics (Vaudour *et al.* 2022).

Field data – remote sensing – ecosystem models

Remote sensing derived input parameters (e.g., crop growth stages, *day of onset leaves*) and biophysical variables (e.g., LAI, FAPAR) have been reported to improve the prediction of ecosystem models through improving model initialisation and crop parameterisation, and reducing uncertainties associated with biases in climate variables (Ovando *et al.* 2018). Ecosystem models generally use remote sensing-based datasets either as: a) a forcing variable to replace intermediate state variables (e.g., LAI) simulated by models or b) a simulation-rectifier to update model simulated state variables or adjust model parameters to reduce the gap between model predictions and observations (Jin *et al.* 2018).

It is possible to develop spatially explicit models that capture the heterogeneity and variability of ecosystems at different scales. One approach consists in using field measurements or remote sensing data as inputs or to initialise (e.g. crop emergence date, Bandaru *et al.* 2022) the ecosystem models to take into account local/regional heterogeneities in soil properties and plant development (Pique *et al.* 2020b; Pique *et al.* 2020a). Remote sensing data can also help define boundary conditions and vegetation dynamics, land use change, and management practices; all this information is critical to run the model.

Data assimilation techniques are in the continuation of the previous point, in the sense that they can further improve ecosystem modelling by merging ecosystem model outputs with remote sensing and field data. These techniques optimise the model's parameters and/or state variables by integrating one or various data sources (e.g., from remote sensing). Data assimilation can improve the model's accuracy and ensure consistency between modelled outputs and observed data. Commonly used data assimilation algorithms are Bayesian approaches or ensemble Kalman filters (Jin *et al.* 2018). Recently, in-situ (flux tower data) and remote sensing assimilation methods were used in combination with existing crop (e.g., STICS) and grassland models by the Field Observatory Network in Finland (Nevalainen *et al.* 2022) for SOC MRV purposes. Alternatively, for southwest France, a modelling approach dedicated to upscaling at farm/landscape level of the cropland C stocks and fluxes was developed by assimilating high resolution optical remote sensing data in the SAFYE-CO2 model (Pique *et al.* 2020b; Pique *et al.* 2020a). Yet the later approach has so far only been

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parametrised/validated for a few crops species, and only very recently have SOC pools been simulated through the coupling of SAFYE-CO_2 with the AMG (Clivot *et al.* 2019) soil model.

Machine learning models can be combined with physical models to be utilised in the context of vegetation ecosystems carbon accounting (Camps-Valls *et al.* 2021; Wijmer *et al.* 2023). This allows for the incorporation of both data-driven machine learning techniques, such as the one presented earlier, and physical understanding of ecosystem processes. This can be done through data and machine learning choice of features that best matches the knowledge ecosystem functioning. This knowledge is synthetised in the physical model and can be extracted from sensitivity and/or uncertainty propagation. A second option is to combine field data with ecosystem model output in the calibration of the machine learning approach. This gives more physical constraints and relationships within the calibrated machine learning model. It can also complement field data for conditions not measured, and therefore gives results that are more reliable in extrapolation. Finally, such hybrid models present some level of interpretability, which is particularly valuable for understanding the underlying mechanisms.

The combination of field measurements, remote sensing and ecosystem carbon model is used for upscaling purposes, as illustrated above, with the objective of carbon accounting at region, country or global scale. However, it can also be used for downscaling: in that case, large scale data or model output (e.g., with DGVM (Dynamic Global Vegetation Model)) is combined with remote sensing data to refine ecosystem or data-driven model outputs at smaller spatial scales, thus capturing local variations in carbon dynamics (Kinderman *et al.* 2016; Ciais *et al.* 2022).

2.2.3.5 Current operational tools and carbon farming schemes for MRV

Decision support tools, as shown in column two of Table 1, provide information on the quantification of SOC changes, GHG emissions or both. They mainly use Tier 1 and Tier 2 IPCC approaches[33] but can also include a Tier 3 module as was the case with the CBP (Milne *et al.* 2010), COMET-FARM[34] (based on the DayCent soil model (Del Grosso *et al.* 2002) or SIMEOS-AMG[35] (based on the AMG soil model (Clivot *et al.* 2019)). 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 method (IPCC 2019c). Those operational tools (in particular Tier 3 type) depend on several of the building blocks described above (e.g., spatial data for climate or activity data as input, in-situ soil data for validation).

Milne *et al.* (2012), provided a characterisation of tools for landscape-scale GHG accounting in terms of 'basic information', tool description, application at the landscape scale, relevance to smallholders and developing countries farmers, application of the tool and future plans. Examples covered include down-loadable,

[33] Note: The "IPCC 2019 refinement to the 2006 guidelines" introduced a Tier 2 Steady-State Method for Soil Carbon, based on DayCent.

[34] https://comet-farm.com/
[35] http://www.agro-transfert-rt.org/ressources/simeos-amg-2/

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programs such as EX-ACT, Cool Farm Tool, and ALU, as well as tools that can be used online (e.g., USAID AFOLU Calculator, CBP Simple Assessment).

Lesschen *et al.* (2020) developed an elaborate 'rating' system in a study for the Netherlands. It considers criteria and describes characteristics for selected (12) models and tools, to identify their suitability for possible application by farmers in the Netherlands: CANDY, CCB, Century, Cool Farm Tool, Daycent, DNDC, EPIC, NDICEA, ORCHIDEE, 'OS balans MNI', 'OS productschap', and RothC. 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 characteristics such as whether models are maintained, the number of C-pools, temporal scale as well as temporal resolution, spatial resolution, soil depth and number of layers, consideration of water balance and nitrogen interactions. Further details are provided in a report (in Dutch). On the basis of their inventory, Lesschen *et al.* (2020) selected four potentially suitable C-models (i.e., Century, RothC, CCB and NDICEA). 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. (see here). After the qualitative comparison, the four models were compared quantitively using datasets for two long-term experiments in the Netherlands. Ultimately, 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. Riggers et al (2019) showed that a multi-model analysis reduced the uncertainty in simulated SOC stocks in a study for German croplands. All of this will have implications for the verifiability of modelled SOC stock changes at an accepted confidence level (e.g., 90%). It should be noted, however, that carbon markets do not look for change in soil C stocks but a change in Net Abatement from the model prediction with 90% on the prediction.

Future modelling efforts should carefully account for the scale-dependence of their mathematical formulations, especially when applied to a wide range of scales (Manzoni and Porporato 2009), as well as the necessary critical validation against field measured data (Le Noë et al. 2023). The Australian Government method, for example, is based on design-based statistical principles: if the estimates are uncertain higher discounts are applied with as consequence that projects take steps to minimise the sampling variation.

Similar to Lesschen *et al.* (2020), Annys *et al.* (2022) explored which carbon farming schemes have potential for application in the northern region of Belgium (Flanders). For this they adopted a qualitative research approach: conducting in-depth interviews with stakeholders from various professional backgrounds, organizing workshops with policy stakeholders, and extensively reviewing carbon farming schemes used in Belgium (e.g., Claire, Soil Capital), neighbouring countries in Europe (e.g., Label Bas Carbone (FR), Stichting Nationale Koolstofmarkt (NL), and Woodland Carbon Code (UK)) as well as internationally (e.g., Verified Carbon Standard, Gold Standard). Ultimately, similar to other studies (e.g., Lesschen *et al.* 2020; Black *et al.* 2022; Oldfield *et al.* 2022), Annys *et al.* (2022) concluded that "a single perfect MRV system does not exist"; there will always be a need to adapt systems to regional conditions. These are important considerations when proposing n integrative and multi ecosystem MRV framework for SOC stock changes (See Section 4).

Currently, none of the tools mentioned above allow for accounting of spatial variability in soil properties and vegetation development in the quantification of SOC stock changes through for instance remote sensing data assimilation; this is a source of large uncertainty in the outputs of those tools. Alternatively, as indicated by

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Senani Karunaratne (*pers comm.*), if higher uncertainty is created due to inherent spatial variability then higher discounts will apply thus reducing the number of credits that can be issued for credible SOC stock change. Hence, the landholder will cluster/stratify their Carbon Estimation Area (CEA) in such a way that they can reduce the within cluster variability and reduce maximum between cluster variation (Australian protocol).

Recently (January 2022), the 'International Initiative for Development of Article 6 Methodology Tools' (II-AMT) was launched with the aim of developing methodological tools that guide the revision of existing methodologies when applied to activities implemented in the context of Article 6 of the Paris Agreement. Similarly, in November 2022, the European Commission adopted a proposal[36] for a EU-wide voluntary framework to reliable certify high-quality carbon removals.

[36] https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7156

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2.2.3.6 Towards operational hybrid approaches for different contexts of MRV applications

Below, we briefly present examples of how different building blocks (e.g., field measurements, activity data, ecosystem models, long-term experimental data for model validation) including remote sensing data have been or are currently being assembled into an 'Operational Processing Chain' (OPC) or workflow, for different applications (e.g., C offset programmes, CAP, and NDCs) and scales (from plot to national level). As we are focussing on hybrid approaches in this section, we did not consider here operational tools like COMET-FARM or SIMOS-AMG (see previous section) that are adapted to farm scale applications, but that do not take benefit from remote sensing for larger scale applications. OPCs as defined here may be considered to correspond with what Paustian *et al.* (2019) defined as 'scalable quantification platform' (see Figure 3). Five examples are provided below, four from Europe and one from the USA.

In the USA, Geo-CropSim (Bandaru *et al.* 2022) use high (30m) resolution optical remote sensing data to initialise the emergence date in the EPIC model and as input in the PROSAIL (Jacquemoud *et al.* 2009) radiative transfer model that produces LAI time series used to adjust a stress function that affects the crop development simulated by EPIC. Geo-CropSim has not been developed specifically for SOC MRV purposes but more as a decision support tool in agriculture. Yet the processes simulated by EPIC may allow Geo-CropSim to be used has a tool for monitoring cropland C budget components including SOC stock changes at high resolution and over large territories (e.g., one or several states in the USA).

In Europe, we are aware of the following OPCs or prototypes of OPCs:

- The Retina project[37], coordinated by the James Hutton Institute in collaboration with the UKCEH and the University of Aberdeen aim at developing a digital system for MRV implemented at the farm level, used to quantify soil carbon change and GHG emissions combined with novel approaches in predictive modelling and stakeholder engagement. It will develop a dynamic digital system that connects multi-scale sensors (e.g., weather stations, flux towers, drones, satellite data) using AI (Artificial Intelligence) to novel cloud-based soil carbon and GHG modelling approaches for various land uses. A mobile app will allow users to provide activity data that will be used within the Predictive Ecosystem Analyser framework to produce forecasts of GHG emissions and carbon sequestration. Landowners will be provided with decision tools to not only interpret the effects of current land management practices on future emissions and carbon sequestration, but also to explore alternative interventions that can help mitigate the effects of climate change.
- The Field Observatory Network[38] (Nevalainen *et al.* 2022) is developed by the Finish Meteorological Institute. The methodology aims at monitoring and forecasting agricultural carbon sequestration by combining offline (soil sampling) and near-real-time (flux tower) field measurements, weather data, high resolution optical remote sensing data, the model–data integration cyberinfrastructure software

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[37] https://ui.adsabs.harvard.edu/abs/2022EGUGA..2412764C/abstract
[38] https://www.fieldobservatory.org/

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PEcAn cropland and grassland ecosystem models (e.g., STICS, YASSO07, BRASSGRA-N), a user interface for input of activity data/visualisation of the model's output and computing networks. FiON's first phase consists of two intensive research sites and twenty voluntary pilot farms testing carbon farming practices in Finland. The Field Observatory is designed as an online service for near-real-time model–data synthesis, forecasting, and decision support for the farmers who are able to monitor the effects of carbon farming practices on ecosystems SOC stocks and GHG emissions as well as provide an MRV tool for decision support. model–data integration cyberinfrastructure software PEcAn is installed and compiled.

- AgriCarbon-EO[39] (Wijmer et al. 2023) developed by CESBIO[40] /INRAE is a pre-operational processing chain that simulates daily biomass and CO2 fluxes (photosynthesis, plant and soil respiration) and on a yearly basis yield and C-budgets of cropland as well as their uncertainties at 10 m resolution but at regional/national scale. AgriCarbon-EO has been developed to meet the specifications for MRV of soil C established by the international CIRCASA initiative on agricultural soils[41] (see also Smith et al., 2020). It can be applied for several context of application (voluntary C market, insetting, NDC, CAP). The processes performed by the chain includes 1) the preparation of input data, i.e. crop (e.g., IACS data) and soil properties maps (e.g., SoilGrids (Poggio et al. 2021)), climatic data (SAFRAN or ER5) and high resolution optical remote sensing data (Sentinel-2, Landsat-8), 2) the inversion of the PROSAIL radiative transfer model (Jacquemoud et al. 2009) for the computation of the biophysical variables (e.g., LAI) needed as input to the agronomic model, 3) the assimilation of the LAI data into the SAFYE-CO2 agronomic model for calibration of the phenological parameters (e.g. day of emergence) and the light use efficiency, and finally 4) the cartographic representation of the results. Note that recently the outputs of the SAFYE-CO2 model (i.e., the crop residues) were used as inputs for the AMG soil model in order to simulate more realistic/accurate spatial variability in SOC stock changes. Also, the data assimilation in AgriCarbon-EO is based on a novel Bayesian approach (BASALT) that combines Normalised Importance Sampling (NIS) and Look-Up Table (LUT) generation. This approach propagates the uncertainties across the processing chain from the reflectance's to the output variables. The chain can be connected via APIs to farm management information systems (FMIS) to automatically collect activity data (e.g., export or not of straws, organic amendments) to finalise the C budget calculations. No activity data are needed to simulate biomass, yield or the plant's CO2 fluxes, and the outputs are validated against a range of in-situ data (flux towers, biomass and soils collected with protocols dedicated to spatialised modelling approaches developed by the Regional Space Observatory[42]).

39 https://www.cesbio.cnrs.fr/agricarboneo/agricarbon-eo/

40 https://www.cesbio.cnrs.fr/

41 https://www.circasa-project.eu/content/download/4158/40011/version/1/file/CIRCASA_D3.1%20SRA.pdf

42 https://www.cesbio.cnrs.fr/la-recherche/activites/observatoires/l-observatoire-spatial-regional-osr/

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- The NIVA's[43] Tier 1 to 3 approaches and tools[44] developed for the User Case 1B 'Agri-Environmental Indicators' (see also Bockstaller *et al.* (2021), *in French*), was developed to produce carbon budget indicators for the Common Agricultural Policy following the carbon budget component approach described in Ceschia *et al.* (2010). The three TIERs rely on the use of IACS data and high-resolution remote sensing data (Sentinel's constellation) similar to the ones used to verify the farmer's declarations (crop mapping). The objective was to develop tools with various levels of complexity, but all allowing a systematic production of indicators at the pixel/plot level over entire regions/countries and on a yearly basis (to be compliant with the CAP subsidies calendar). The Tier 1 method is based on an empirical relationship between the duration of active vegetation observed by remote sensing and the net annual CO_2 fluxes between the crops and the atmosphere established by Ceschia *et al.* (2010) for a range of crops in Europe by using flux tower measurements. The Tier 1 output is therefore the net annual CO_2 flux of a given parcel (or pixel of a parcel) for an entire cropping year which represents the sum of the annual photosynthesis and of the plant/soil respiration. The Tier 2 method combines the Tier 1 results with activity data provided by the farmers relative to organic amendments and yield to estimate the net annual change in SOC stocks (i.e., the annual C budget). The Tier 3 approach is based on the use of the SAFYE-CO2/AgriCarbon-EO tools. The Tier 3 methods provide all the components of the net annual carbon budget, including SOC stock changes at the plot or pixel level.

2.3 Reporting

This section addresses building blocks R1 and R2 of Figure 4.

2.3.1 Reporting SOC stock change in national GHG inventories

For reporting SOC stock changes at the national level, Parties to the Paris Agreement must follow the IPCC Guidelines defined in '2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories Volume 1 General Guidance and Reporting, Chapter 8' (IPCC 2019c). However, countries are free to deviate from these methodologies for certain emissions items, as long as they are able to propose more relevant parameters and justify their use. Annual update of the reporting is required. Template tables for reporting are defined in Annex 8.2.A Reporting tables of '2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories Volume 1 General Guidance and Reporting'. Specifically, Table 3.2 of the

[43] https://www.niva4cap.eu/

[44] https://gitlab.com/nivaeu/uc1b_indicators_tool

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abovementioned reference addresses SOC stock changes (IPCC 2019a). Note that Tier 1 to 3 approaches can be used for the reporting by the Parties (see Section 3.1 for more details).

The national GHG inventories systematically present emissions year by year (since 1990 for the Annex 1 countries of the Kyoto Protocol), up to the current year minus two years. In the event of a methodological improvement, the entire time series is recalculated to ensure methodological consistency with historical data.

For full reporting, and verification, a full ecosystem C stock assessment is preferable and even essential for ecosystems with perennial/woody vegetation (IPCC 1996; Ravindranath and Ostwald 2008; Chan *et al.* 2023).However, as recently indicated by Pietracci *et al.* (2023), forest carbon crediting programmes are still small in scale and controversy remains, particularly for project-based credits used for offsetting, as to whether these actually benefit the climate (see exchange between The Guardian (2023) and Verra (2013).) Haya *et al.* (2023) prepared a comprehensive review of carbon quantification by improved forest management offset protocols, and recommended specific improvements that would likely result in more accurate estimates of programme impact. According to these authors, more conservative baselines can substantially reduce, but not resolve, over-crediting risk from multiple factors. Similarly, Boyd *et al.* (2023) recently made a proposal to redesign carbon-removal offset to 'help the planet', while West *et al.* (2023) pointed at the need to make carbon offsets from forest conservation work for climate change mitigation.

2.3.2 Reporting SOC stock change for C offset standards

Carbon offset standards refer to "recognised standards, protocols or/and methodologies to guide GHG quantification, monitoring and reporting" (see Glossary). A standard is defined as a set of specifications that lists specific practices (i.e., environmental, social, technical) that must be followed by those who want their products to be certified. The aim of a standard is to enable a remote exchange of information between producers and consumers on the intrinsic qualities of products placed on the market (Fouilleux and Loconto 2017). Here, for each carbon offset standard, the aim is to create a new intangible product called 'carbon credits' that could be traded (Perez Corréa *et al.* 2011) and therefore generate economic value. They could either concern agriculture or forestry activities, and must at least target the management of SOC.

Generally, reporting of SOC stock change is done *ex-ante* (*i.e.,* based on forecasts before the implementation of the practices impacting SOC stocks) and *ex-post* (*i.e.,* after the implementation of the practices impacting SOC stocks). SOC stock changes are calculated by comparing a project scenario, in which practices impacting SOC stocks are implemented, to a baseline scenario (usually referred as a business-as-usual scenario).

VCM soil carbon projects do not account for above-ground biomass unless it is an input/output; the credits are issued on the basis of net soil-derived abatement, except for BCarbon. Methodologies approved by the forest carbon standards consider other carbon pools than SOC (e.g., above-ground biomass for forestry project) and the different sources of GHG emissions generated by the implementation of the project. A full ecosystem carbon stock assessment is preferred, especially if it includes perennial/woody vegetation. Because carbon biomass is a major carbon pool in forestry projects, some specifications related to it are given in the following sections.

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Baseline

Baselines at the start of a project are the foundation for all MRV activities. There are usually three generic approaches to setting project specific baselines (Oldfield *et al.* 2021), i.e. fixed, fixed average and dynamic, but some projects may rely instead on regional baseline. Concerning specific baselines, fixed and fixed average baselines are set at the project start prior to new management practices; fixed baseline is determined for each field while fixed average baselines are determined from a sub-sample of fields. Dynamic baselines are re-evaluated as part of MRV and revised, if necessary, to reflect changed circumstances in the project or project region. Regional baselines may concern initial SOC stocks or carbon farming practices. The principle is that instead of considering a reference status of a given farm in time as the baseline, the baseline will be defined by considering the mean status of the farms in a region surrounding the farm that is willing to start a carbon (C) farming project. The advantage of this approach is that if a farm is already quite advanced in terms of implementation of C farming practices compared to the other farms in the region, considering a regional baseline will allow that farm to receive carbon credits which is an encouragement to maintain the current SOC stocks. Also, in the case of the French 'Label Bas Carbone' methodology for cropland, regional statistics of cover crop biomass can be used as input for the soil model to estimate the subsequent SOC stock changes instead of doing farm specific biomass sampling (but a discount is applied then on the C credits). Remote sensing-based estimates may also be used to quantify cover crop biomass without discount.

Yet most standards specify that historic data are required, varying from 3, 4, 5 to 10 years prior to project start or for at least one full rotational cycle. In setting baselines, data from scientific literature and IPCC emission factors can also be used. Calibration to project's local conditions and modelling for baselines are required (Oldfield *et al.* 2021).

For carbon biomass, similarly the existing C stocks in the above-ground biomass, at least, are assessed in the baseline. Most commonly, this C pool is measured using allometric equations (i.e., a mathematical relationship between several variables, usually the diameter at breast height, the height of the tree and the total dry weight of the tree), and therefore measuring at least the diameter at breast height of the existing trees prior to the project. Below-ground biomass is usually calculated using a root to shoot ratio applied to the above-ground biomass. Commonly, the baseline is considered as fixed over the project duration, but dynamic one can also be applied, depending on the dynamics of the type of vegetation in the baseline. More complex methods have been developed, especially for REDD$^+$ projects, using remote sensing, and LiDAR in particular, to assess the above-ground C stocks (Jucker *et al.* 2017).

Monitoring report

Most standards require reporting on a regular basis (e.g., 1 to 5 years, a full cropping cycle or every 5 years in forestry projects; monitoring frequency for SOC stock is generally on a +4 years basis and generally annually for GHGs). Farm and field management records as well as quantification of soil carbon stocks and/or soil GHGs are required (Oldfield *et al.* 2021). Data reporting templates are usually provided to aid in the collection of data. As a rule, a monitoring report must give information on the sampling design, the rationale of data collection, the methods used to gather data or their sources, the standard operating procedures, the quality assurance and quality control procedures (see section on uncertainty assessment).

Uncertainty in reporting

Quantification of uncertainty from measurement and modelling is reflected in quantification of C credits, based on monitoring reports. Buffers, insurance, clawbacks, and discounting are usually applied by C standards to address the issue of uncertainty.

It should be noted here that Garsia *et al.* (2023) found a general lack of clear reporting, numerous flaws in model performance evaluation, and a poor overall coverage of land use types across countries and pedoclimatic conditions. They concluded that, to date, SOC simulation (alone) does not represent an adequate tool for globally ensuring effectiveness of SOC sequestration effort and ensuring reliable carbon crediting.

2.4 Verification

This section addresses building blocks V1 to V4 of Figure 4.

2.4.1 Verification of SOC stock changes in GHG national inventories

In the context of national emission inventories, 'verification' means e.g., quality checks, independent reviews or the comparison against other data or other inventories. Verification is mandatory. The compilation of the inventory is an ongoing process that draws on the work of the IPCC, reviews organised by the Parties of the UNFCCC and the UNFCCD, and the continuous improvement work carried out by governments. GHG national inventories are peer-reviewed before approval by the UNFCCC. Guidelines for reviewers are given for instance in 'Guide for peer review of national GHG inventories' (UNFCC 2017). A special mention to SOC is given for cropland and grassland where the 'soil carbon pool is more important than other land uses.'

As an illustration of this verification process, in France, the annual GHG inventory is the result of a gradual and highly supervised process throughout the year, based on data feedback from the various sectors of activity:

- validation of the final result for year *n* by the Emission Inventory Consultation and Information Group at the end of year *n*+1;
- Transmission of a provisional version of the inventory to the European Commission in January of year *n*+2, followed by a final version in March of year *n*+2;
- transmission of the final version to the UNFCCC in April *n*+2.

2.4.2 Verification of SOC stock and SOC management changes for C offset standards

For C offset standards, verification is usually carried out by a third party (i.e., an external verifier) that will check the compliance with the rules and procedures of the C standards. Verification may concern directly the carbon stock changes in the soil (and/or in the vegetation for forest projects), e.g., the verification of the SOC stock estimated through a modelling approach with in-situ sampling, or the verification of the implementation of practices that should have led to SOC stock increases (e.g., verification through registries of the application of organic amendments or of a change in crop rotations). A verifier will assess the model predictions and to what degree the modelled stocks reflect measured stocks, but most are verifying the Net Abatement not the stock per se.

Certified verifiers (e.g., validation/verification body (VVB) for VERRA) are selected by project developers who target to get C credits. The first criterion of selection is the accreditation of the verifier to perform such verification. Usually, C validation/verification bodies have websites that list accredited verifiers for given methodologies. One should be aware that such accreditation is given for a defined period and therefore can be suspended or lost. The second criterion of selection is usually related to the cost of the verification as quotations for verification might vary from one verifier to another. One last criterion to be considered by project developers can also be related to the track record of the verifier. In other words, some verifiers have higher rates of success in the approval of the verification step than others.

Verification for C offset standards can be carried out without fixed periodicity. Usually, the project developer will contract with an external verifier when he or she expects to get a certain amount of C credits and generate incomes higher than the cost of verification (e.g., between 20 and 50 k€ for forest projects according to Bernard *et al.* (2010)).

Practically speaking, the verification process consists first in a desk review carried out by the external verifier. This desk review is based on the project documentation, the reporting of the project and the implementation of the standard guidelines for verification. Following the desk review, the external verifier will address a draft report to the project developer highlighting the potential deviations from the applied methodology. Usually, a field visit is carried out by the external verifier with the project developer. The field visit, along with the additional documentation potentially given by the project developer, will help addressing the potential minor and major deviations. Ultimately, a final verification report is produced by the external verifier in which the emission of C credits will be allowed or not and the exact amount of C credits to be emitted specified.

However, at least, regarding forestry projects, recent articles in The Guardian[45] and Science[46] have revealed that the verification procedures were not sufficiently applied or too lax which jeopardises the credibility of carbon offsetting projects in general (for forestry and agriculture). In this context, those articles concluded that remote sensing is an interesting tool as it may provide an objective, cheap, reliable way of verifying the implementation (or not) of a C offsetting project (if trees were planted or not, if carbon farming practices were implemented or not), but also if the project was maintained long enough to be eligible to carbon credits, if it was successful or not (e.g., did the trees die a few years after they were planted?, or how did they develop?, or did cover crop grow as expected?). For instance, LiDAR techniques or the forthcoming BIOMASS[47] satellite mission from ESA could be used to monitor forest biomass and quantify the success of the afforestation projects. Concerning cropland, Sentinel-1 and -2 data can be used for instance to verify if crop rotations have changed according to the C farming project, or if cover crops where grown to store carbon (Fendrich *et al.* 2023) and, in combination or not with models, how much C was stored in the ground thanks to cover crops (Al Bitar *et al.* 2022).

2.5 Uncertainty assessment

Uncertainty quantification plays a pivotal role in MRVs due to their focus on natural systems, which can never be perfectly known. Owing to factors such as spatial variability, complexity of physical, chemical and

[45] https://www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe
[46] https://www.science.org/content/article/farmers-paid-millions-trap-carbon-soils-will-it-actually-help-planet
[47] https://www.esa.int/Applications/Observing_the_Earth/FutureEO/Biomass

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biological processes, and numerous other error sources, estimations of system states frequently harbour significant uncertainties. Often, these uncertainties can be so substantial that they impede the demonstration of the impact of specific land management practices. To illustrate, uncertainties in estimated SOC stocks for a given field or region might be that large to render reported changes in carbon stocks — between project commencement and conclusion or between baseline and regenerative practice implementation — statistically insignificant. This can result in erroneous conclusions and speculative assertions, potentially leading to unwarranted claims of practice effectiveness (referred to as 'green washing'). Recent articles in prominent outlets like The Guardian[48] and Science[49] have highlighted this concern, caused significant commotion and prompted temporary modifications or withdrawals of certain MRVs. Thus, within MRVs, acknowledging and quantifying uncertainty stands as a crucial obligation. Any claims put forth by projects must invariably be substantiated by statistically rigorous evidence.

The aim of this section is to provide a generic description and short review of uncertainty assessment in the Earth and environmental sciences, whenever possible illustrated with examples from MRV practices. It should be noted that uncertainty aspects of specific MRV components have also already been addressed in previous sections.

2.5.1 Statistical modelling of uncertainty

Uncertainty finds its most accurate portrayal through probability distributions. For example, due to laboratory measurement error, our knowledge about the true carbon content of a soil sample is limited. The measured value stands as our best estimate, yet divergence from the true value is both likely and anticipated. This prompts the depiction of the true carbon content via a probability distribution, the width of which (such as characterised by the variance, standard deviation or interquartile range) represents the measurement error's impact. Determining the measurement error variance can be achieved through replication (van Leeuwen *et al.* 2022). Similarly, uncertainties stemming from sampling protocols (e.g., representativity of the soil samples in a field), mapping algorithms, modelling processes, or the use of proxies for the true variable of interest (as in cases where proximal soil sensing provides indirect measurements of soil properties) can all be encapsulated within probability distributions. The challenge, however, lies in the quantification of these uncertainties—assigning numerical values to the parameters of these distributions. Geostatistics routinely quantifies mapping uncertainties (e.g., kriging variance)(Webster and Oliver 2007), and this approach is gaining traction within machine learning algorithms (like Quantile Regression Forest, (Meinshausen 2006) and Poggio *et al.* 2021). Uncertainties associated with mechanistic models are more difficult to assess, relying predominantly on calibration data or independent validation data (Brown and Heuvelink 2005; Pique *et al.* 2020a; Smith *et al.* 2020; Wijmer *et al.* 2023), while uncertainty induced by proximal soil sensing is often explicitly quantified by the regression models calibrated against training data (Viscarra Rossel *et al.* 2016; Breure *et al.* 2022).

Probability distributions of uncertain environmental variables can be overly complex. It would be naïve to assume that all that is needed is a mean and a variance of a probability distribution, because the uncertainty

[48] https://www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe
[49] https://www.science.org/content/article/farmers-paid-millions-trap-carbon-soils-will-it-actually-help-planet

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about some variables is not realistically characterised by a parametric distribution (such as the normal, lognormal or uniform distribution), while cross-correlation, spatial and temporal autocorrelation must also be accounted for (Heuvelink *et al.* 2005). Moreover, there are many sources of uncertainty, which all need a specific approach, as explained in the next subsection.

2.5.2 Sources of uncertainty

Many MRVs make use of process-based models during the reporting phase. In such case, there are three main sources of uncertainty that must be considered (e.g., Heuvelink 1998b) :

1. Uncertainty in the model inputs
2. Uncertainty in the model parameters
3. Uncertainty in the model structure

Here, the difference between model inputs and parameters is that the former refers to environmental variables that can in principle be measured and exist outside the context of a model. Examples are soil moisture, temperature and nitrate concentration of the soil. Model parameters only exist within the context of a model and cannot be directly measured. A typical example of that is a regression coefficient.

Uncertainty in model inputs often result from measurement error. Van Leeuwen *et al.* (2022), for example, stressed the importance of considering measurement error in wet chemistry data, which is particularly important when soil data are derived from various sources. The same applies for dry combustion data derived using various methods (Grahmann *et al.* 2022). Sampling and sample preparation errors were found to be of the same order of magnitude as errors caused in the chemical analyses themselves (Wagner *et al.* 2001) (Fernández-Ugalde *et al.* 2020; Bettingole *et al.* 2023). Similar issues arise for soil physical properties (Holmes *et al.* 2011). When looking at changes in SOC stocks it is also important to consider whether these were computed on a fixed depth or an equivalent soil mass basis (Ellert and Bettany 2002) (Wendt and Hauser 2013). The equivalent soil mass method, for example, is recommended in the GSOC MRV protocol (FAO-GSP 2020) while the IPCC (2019c) guidelines still consider a fixed depth. Further, Stanley *et al.* (2023) indicated that the accuracy of SOC measurements is limited by inherent spatial heterogeneity, variability of laboratory assays, unmet statistical assumptions, and the relatively small magnitude of SOC changes over time, which hampers measuring SOC change.

When models use inputs that are not directly measured but are derived from secondary sources, such as maps (e.g., biophysical variables derived from remote sensing) or expert judgement, additional uncertainty will arise. These could be spatial interpolation errors (Webster and Oliver 2007) or regression errors (Burt *et al.* 2009, Section 12.3). Expert judgement uncertainty can be assessed through expert elicitation procedures(O'Hagan *et al.* 2006), although this is cumbersome and not entirely free of subjectivity. Complex models represent processes better than simpler models (e.g., Tier 3 approaches are preferred over Tier 1 approaches), but complex models require more inputs. If these inputs are poorly known and have large uncertainties, then replacing a simple by a complex model might actually deteriorate results (Heuvelink 1998b).

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Expert judgement could also be used to quantify model parameter and model structural uncertainty, but this is challenging and can be unreliable. A better approach is to derive these uncertainties from statistical approaches that compare model outputs with observations, such as in Bayesian calibration (Kennedy and O'Hagan 2001) and data assimilation (Xu *et al.* 2016; Wijmer *et al.* 2023). Model structural uncertainty is usually represented by an additive or multiplicative noise term (Davoudabadi *et al.* 2021, Wang et al. 2016). There are also approaches that characterise model structural uncertainty by a multiple modelling approach (Refsgaard *et al.* 2006; Liao *et al.* 2022). Quantifying model uncertainty and model validation are still challenging and in practice often lacking (Garsia *et al.* 2023).

Multiple sources of uncertainty can impact the quality of the model's output. However, not all of these sources require inclusion in an uncertainty analysis. Focusing on the sources with the most significant impact, as determined by the uncertainty propagation techniques elaborated upon later, suffices. While discerning the primary sources of uncertainty beforehand is challenging, employing a Quickscan' (Janssen *et al.* 2005; Nol *et al.* 2010) might aid in this determination process.

Quantification of uncertainty is a challenging and complex task. A related challenge is how to comprehensibly communicate this uncertainty to different stakeholders so that they can correctly interpret the results.

2.5.3 Uncertainty propagation

Models and analyses included in MRV guidelines and protocols involve the processing of information. They compute desired outputs (e.g., SOC stock, GHG emission) from inputs (e.g., climate, soil properties, land management) and in this process uncertainties in the inputs and model parameters and structure will propagate to the output. Uncertainty propagation can be traced in various ways, but the most commonly applied methods are the Taylor series method (Taylor 1982; Heuvelink 1998a; Grüneberg *et al.* 2014; Magnussen *et al.* 2014) and Monte Carlo simulation (Lewis and Orav 1989; Nol *et al.* 2010; Fortin 2021). The advantage of the first method is that it is fast and yields an interpretable mathematical equation, while the advantages of the second method are that it is easily implemented, generally applicable and that its approximation errors can be made negligibly small, provided sufficient computing resources are available. The Monte Carlo method is remarkably straightforward and easily applied once the uncertainty of the model inputs, parameters and structure have been fully characterised by probability distributions. Many MRVs listed in Chapter 3 make use of this technique. Examples of uncertainty propagation analyses in MRV context are given elsewhere (Jonas *et al.* 2019; Yanai *et al.* 2020; Wijmer *et al.* 2023).

The end result of an uncertainty propagation analysis is a probability distribution of the model output. Note that in case of Monte Carlo uncertainty propagation this will take an empirical form (i.e., a random sample from the distribution), while the Taylor series method only yields the mean and variance of the distribution, implying that additional assumptions about the shape of the distribution (e.g., normal, lognormal) are needed to fully characterise model output uncertainty. Communication of uncertainty to end users is perhaps best done by presenting the lower and upper limits of a prediction interval (e.g., the 0.05 and 0.95 quantiles of the distribution). For instance, a project might compute and present the lower and upper limits of a 90% prediction interval of the SOC stock difference between the baseline and regenerative practice. Note that if this interval

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includes zero (i.e., if the lower limit is negative and the upper limit positive) this implies that the estimated difference is not statistically significant from zero at the 90% confidence level.

2.5.4 Upscaling uncertainties

Most variables of interest of MRVs, such as GHG emission and SOC, vary in space and time. Often, the interest is not in the value of these variables at points but in the average or total for an area (e.g., a field, region, entire country or the globe) and/or time period (e.g., a day, month, year or decade). Upscaling the predictions of these variables is easy if predictions are available for the whole area or time period, but quantifying the associated uncertainties is much more difficult. It can only be done if the spatial and temporal correlations of the prediction errors are known and accounted for, using autocorrelation functions and/or semi-variograms (Wadoux and Heuvelink 2023). In spite of its importance, this problem seems largely ignored by the scientific community (e.g.,Plaza *et al.* 2018; Harris *et al.* 2021).

Spatial and temporal aggregation lead to a decrease of uncertainty. This is because errors partly cancel out: at some locations inside an area the predictions are bigger than the true value, while at other locations in that same area the predictions will be smaller than the true value. Averaging over the area will thus reduce the overall prediction error. The uncertainty decrease is largest if errors have a low spatial or temporal correlation.

Time series modelling (Box *et al.* 2008) and geostatistics (Webster and Oliver 2007) provide methodologies to quantify the spatio-temporal correlations of prediction errors. Szatmári *et al.* (2021) used a geostatistical approach (block kriging) to derive the uncertainty of the soil organic carbon stock change over time for Hungary at multiple spatial scales. The study confirmed that uncertainty decreases as the area over which is aggregated increases. At point scale, none of the estimated soil organic carbon changes between 1992 and 2010 were statistically significant, while at the county and country scale they were.

Upscaling to large spatial areas, such as the entire study area, can also be done using a design-based statistical approach (De Gruijter *et al.* 2006). This has the advantage that no model assumptions are needed, but a requirement is that the measurement locations are a probability sample from the area of interest, and that the sample size is sufficiently large for each upscaling area. Some relevant applications of this approach are Singh *et al. (2013)* and (Karunaratne *et al.* {2014). See also Section 2.5.5 below, where design-based statistical inference is discussed in some more detail from a statistical validation perspective.

2.5.5 Statistical validation

The preceding sections tackled the quantification of uncertainty in the outputs of models predicting crucial MRV variables. This is achieved through the application of probability theory and uncertainty propagation analyses. These methods are powerful as they not only assess model output uncertainty but also quantify the contributions of individual uncertainty sources. However, their drawback lies in being 'model-based', entailing the incorporation of various assumptions like stationarity, isotropy, and normality (Brus *et al.* , 1997; De Gruijter *et al.*, 2006). Furthermore, as previously mentioned, estimating the parameters of probability distributions is often challenging, a difficulty that persists even after adopting simplifying assumptions (Heuvelink 2002; Kros *et al*. 2012).

Contrary to model-based approaches, the 'design-based' approach has the important advantage that it is entirely model-free (De Gruijter *et al*. 2006). It is based on statistical sampling theory and requires random sampling from the population of interest. The simplest example of that is simple random sampling, while more elaborate approaches are stratified random sampling, cluster random sampling, systematic random sampling and model-assisted sampling (De Gruijter *et al*. 2006; Brus 2022). The statistical inference depends on the sampling design, but in all cases unbiased estimates of the population characteristics are derived from the sample, while the accuracy of the estimates is also quantified. For instance, if the population of interest is defined as all locations in the project area then one could estimate the average SOC stock of the population without bias using the mean of a simple random sample extracted from the population. The estimate's uncertainty would be assessed using the standard error of the mean. When conducted both at the start and end of a project, the SOC stock change over time for the population as a whole could be estimated with zero systematic error and a random error that can be quantified from the sample sizes and sampling variances (Brus 2022). Notably, the advantageous aspect of the design-based approach is its independence from models, yet it necessitates probabilistic sampling selection, accurate statistical inference employment, and measurement precision devoid of systematic errors. Furthermore, practical implementation might entail considerable sample sizes to attain a desired accuracy level (e.g., for attaining adequately narrow confidence intervals ensuring statistically significant estimated SOC stock changes), thereby imposing a substantial resource burden on the project.

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3. Inventory and classification of current MRVs

3.1 General considerations

Different MRV systems may be needed depending on their projected applications. Key elements of national MRV frameworks under the UN Framework Convention on Climate Change (UNFCC, United Nations 2014) are '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.* (2020) reviewed MRV methods already in use in countries participating in the Global Research Alliance on Greenhouse Gases (GRA); all countries that are party to the UNFCCC are required to provide national inventories of emissions and removals of GHG due to human activities. Because different countries have different capacities to produce inventories, the IPCC guidelines lay out tiers of methods for each emissions source, with higher tiers being more complex and/or resource intensive than lower tiers. Smith *et al.* (2020) reported that countries listed as non-annex I face major challenges with either non-existent data (15 countries do not have country-specific information they can use to develop their inventory and eight countries do not consider for SOC changes in croplands because do not have the technical capacity to monitor these sources) or often lack of relevant data. As a result, most GRA countries, formerly classified as non-annex 1 countries, use a Tier 1 approach to report SOC changes associated with areas defined as Cropland land use, while industrialised (Annex I) countries such as Australia, Canada and Denmark use a Tier 3 approach, respectively based on FullCAM, Century and C-Tool. Further, specificities on methodologies and models used in selected GRA countries are provided in the review article.

More recently, Oldfield *et al.* (2022) prepared an overview of soil carbon estimation and sampling methods, listing main issues and approaches to be considered in an MRV-framework. Their study considered 12 published MRV 'protocols' for SOC credits generated on cropland and rangeland (eight from the USA, two from Australia, one from Canada, and the MRV protocol developed by FAO)[50]. They assessed over forty characteristics for each protocol. Not unexpectedly, these protocols take different approaches to quantifying SOC and net GHG removals often building upon national conventions. Some use soil sampling only, some combine sampling with process-based modelling, and others use only modelling and remote sensing (see also Figure 2 and 4). As indicated, differences in the way protocols and carbon markets estimate SOC and net

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[50] The protocols considered by Oldfield et al (2021) include CAR Soil Enrichment Protocol (CAR SEP); Verra Methodology for Improved Agricultural Land (VM0042*); Verra Soil Carbon Quantification Methodology (VM0021); Verra Adoption of Sustainable Land Management (VM0017); Gold Standard Soil Organic Carbon Framework Methodology (GS-SOC); Australian Carbon Credits (Carbon Farming Initiative - Measurement of Soil Carbon Sequestration in Agricultural Systems) Methodology Determination (AUS-SM); Australian Carbon Credits (Carbon Farming Initiative-Estimating Sequestration of Carbon Using Default Values) Methodology Determination (AUS-DV); Food and Agriculture Organization GSOC MRV Protocol (FAO GSOC); Alberta Quantification Protocol for Conservation Cropping (Alberta CC); Regen Network Methodology for GHG and Co-Benefits in Grazing Systems and Carbon Soil Carbon Credit Systems.
* VM0042 is a hybrid sampling-modelling approach that can be applied internationally; VM0017 is a model-only approach that is targeted more specifically for small-holder agriculture.

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GHG reductions, as well as the way they account for issues such as permanence and additionality of carbon sequestered, may create the risk of creating credits that are not equal or even comparable (Demenois *et al.* 2021; Black *et al.* 2022). Furthermore, it should be noted that some of the protocols reviewed by Oldfield *et al.* (2022) have since been retracted by the certifying agencies as some of the claims for carbon offsets made could not be substantiated[51].

According to Arcusa and Sprenkle-Hyppolite (2022), based on an analysis of the carbon dioxide removal (CDR) certification and standards ecosystem for the year 2021–2022, there are at least 30 standard developing organisations proposing at least 125 standard methodologies for carbon removal from 23 different CDR activities and selling, 27 different versions of certification instruments in voluntary and compliance markets. In practice, this diversity makes it cumbersome to determine whether net climate benefits have been achieved or not. This demonstrates the importance of developing a unified multi-ecosystem methodological framework for MRV of SOC and ecosystems C stock, which is one of the main objectives of ORCaSa.

Black *et al.* (2022) presented an innovative global comparative analysis of farmland soil carbon '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, commercialisation and operations for 12 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. Black *et al.* (2022) 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. Practical guidelines for this are provided here.

For France, for example, Yogo *et al.* (2021) proposed three possible options for C balance evaluation and monitoring with different methodologies (with specific recommendations concerning croplands), tools and data that can be mobilised, 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 20 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 models (empirical, soil-plant, soil dynamics, and agro-meteorological), IPCC Tier 1 or Tier 2 emission factors and the use of satellite data.

Similarly, different MRV approaches and protocols are used in the forest sector (e.g., Oliver *et al.* 2004; Lacarce *et al.* 2009; ICP Forests 2021b; Mäkipää *et al.* 2023). Differences in statistical sampling design, for example, as well as field sampling techniques and subsequent laboratory analyses, will impact on predictive quality of different soil monitoring networks (van Wesemael *et al.* 2010; Louis *et al.* 2014; Batjes and van Wesemael

[51] https://www.theguardian.com/environment/2023/jan/18/revealed-forest-carbon-offsets-biggest-provider-worthless-verra-aoe

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2015) making inter-comparison of results derived from various monitoring systems problematic (Saby *et al.* 2008; Bispo *et al.* 2017).

Further, according to Olsson (2023), unmeasurable uncertainties, such as political issues and economic rebound effects, 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 affect land use and crop management decisions (Lehmann *et al.* 2013; Sperow 2018; D'Arcangelo *et al.* 2022) hence achievable carbon sequestration.

3.2 Earmarked guidelines and approved methodologies

Many different guidelines and methodologies relating to MRV exist (Oldfield *et al.* 2021; Arcusa and Sprenkle-Hyppolite 2022; Black *et al.* 2022), and the terms used are not always clear-cut (see Glossary), with a diverse range of associated certification schemes. In this context, reference has been made to a "jungle of certifications schemes" (Demenois *et al.* 2021).

For this review we considered the guidelines and approved methodologies earmarked by the writing team (Table 2), following up on an OrCaSa international stakeholder webinar (5 July 2023). To be considered in the review, the 'resources' had to: a) be freely available and open access online, and b) provide sufficient guidance on procedures methods for measurement (monitoring), reporting and verification (MRV) to allow for a characterisation in Section 3.4, and c) not be 'pending/prospective' methodologies that have not yet been approved under a specific certification programme. For ease of reference, each of these 'resources' was given a concise abbreviation that has been used throughout the report.

Some formerly 'approved methodologies,' such as 'VM0017 Adoption of Sustainable Agricultural Land Management, v1.0', have recently been withdrawn and these are not considered in this review. Similarly, 'VM0021 Soil carbon quantification methodology, v.1.0' has become inactive as of March 2022. See also the worrisome discussion by Popkin (2023).

'Footprint calculators', such as provided by Cool Farm Alliance, FAA or Normative, and 'SOC/GHG scenario tools', such as COMET-FARM, CBP, and SIMEOS-AMG, are not considered here as these on-line tools are "essentially aimed at assisting landowners, project managers and other stakeholders in evaluating the GHG impacts of their management decisions." Similarly, marketplaces aimed at matching local climate efforts with companies that want to reliably offset their CO2 emissions, such as CLAIRE in Belgium or LRQA (UK) that follows ISO 14064 validation protocols, are not considered here. However, we realise that such calculators may be become the primary tool for reporting Scope 3 emission reductions and that it is possible (in the short term at least) that they will be used for C removals (including soil C stock) depending on the outcome from the ongoing GHG[52] protocol review.

[52] https://ghgprotocol.org/

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Overall, it is unfeasible –and beyond the scope and time constraints of this review– to identify and characterise all possible guidelines/protocols and approved methodologies. A brief description for each 'resource' considered in Table 2 is provided below in Section 3.2. Typically, each approved methodology is based on one, or several, standards (or protocols). These are often documented in a central registry which lists whether proposed methodologies are in (scientific) peer review or open for public comment. Also, importantly, registries list inactive (or repealed) methodologies, and their version. A nice overview is presented on the website of the American Carbon Registry (ACR)[53], which only registers project-based carbon offset tonnes that are real, additional, permanent and independently verified.

Table 2. List of reviewed MRV guidelines and approved methodologies.

Typology	Abbreviation	Name
- **Guidelines**		
	BC-SCM	Carbon Soil Carbon Credit Systems 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
	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
	QPCS	Quantification Protocol for Conservation Cropping, v 1.0 https://open.alberta.ca/publications/9780778596288
	WBG-SOC	Soil Organic Carbon (SOC) MRV Sourcebook for Agricultural Landscapes http://hdl.handle.net/10986/35923
	US-SEP	U.S. Soil Enrichment Protocol

[53] https://americancarbonregistry.org/how-it-works/registry-reports

Typology	Abbreviation	Name
		https://www.climateactionreserve.org/how/protocols/ncs/soil-enrichment/
	VCS	Verra Verified Carbon Standard (2023). (There are several approved AFOLU methodologies, see Section 3.2.2 for details). https://verra.org/wp-content/uploads/2022/12/VCS-Standard-v4.4-FINAL.pdf
- Approved methodologies		
	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
	DE-MOOR	MoorFutures https://www.moorfutures.de/downloads/
	FR-LBC	Label Bas Carbone (There are six approved methodologies for SOC, see Section 3.2.2 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/
	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

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Typology	Abbreviation	Name
	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://library.regen.network/v/methodology-library/methodology-for-ghg-and-co-benefits-in-grazing-systems
	SOC-FM	Soil Organic Carbon Framework Methodology v 1.0 https://globalgoals.goldstandard.org/402-luf-agr-fm-soil-organic-carbon-framework-methodolgy/
	UK-PC	IUCN-UK Peatland Code https://www.iucn-uk-peatlandprogramme.org/peatland-code-0
	UK-WCC	UK Woodland Carbon Code https://woodlandcarboncode.org.uk/standard-and-guidance
	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/

The guidelines and methodologies listed in Table 2 above are briefly described below based on information provided on the corresponding websites[54]. Subsequently, in Section 3.5, they are assessed according to the list of characteristics, with associated criteria/options, as defined in Section 3.4.

[54] Please note that the short descriptions were largely "abstracted" from the corresponding websites or reports, as documented in the review.

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3.2.1 Guidelines

BC-SCM: Carbon Soil Carbon Credit Systems

https://static1.squarespace.com/static/611691387b74c566a67f385d/t/63483a986a24ac421c4f4414/1665677979013/2022-10-13-BCarbon-Soil-Carbon-Protocol-V2.pdf

These guidelines define the specifications for measuring the accumulation of soil organic carbon in soil over a true-up period with adequate accuracy to support certification of soil carbon sequestration credits by BCarbon (British Columbia, Canada). Parties using this protocol will need to demonstrate compliance with these procedures. The protocol defines a 6-step process, addressing site selection and stratification, quantification of the accrued carbon mass, and interim credit estimates. Equivalent methods not included in this standard may be applied subject to approval by BCarbon. The protocol defines methods for quantifying the increase in soil organic carbon over time on a property with the necessary statistical reliability to support the issuance and sale of carbon credits.

The protocol is directed to soil organic carbon measurements only and does not encompass the evaluation of above-ground carbon accrual (e.g., trees, shrubs, or other biomass) associated with land management practices. Quantitative analysis of the potential net increase in net greenhouse gas (GHG) emissions associated with a change in land management practices is not required.

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

The Climate Action Reserve (Reserve) Soil Enrichment Protocol (SEP) provides guidance to account for, report, and verify GHG emission reductions associated with projects which reduce emissions and enhance soil carbon sequestration on agricultural lands through the adoption of sustainable agricultural land management activities.

The protocol is designed to ensure the complete, consistent, transparent, accurate, and conservative quantification and verification of GHG emission reductions associated with a soil enrichment project. It focusses on offset projects in the North American voluntary carbon market and operates a transparent, publicly accessible registry for carbon credits generated under its standards.

GSOC-MRV: FAO GSOC MRV Protocol

https://www.fao.org/documents/card/en/c/cb0509en

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This protocol provides a conceptual framework and standard methodologies for the monitoring, reporting and verification of changes in SOC stocks and GHG emissions/removals from agricultural projects that adopt sustainable soil management practices (SSM) at farm level. It is intended to be applied in different agricultural lands, including annual and perennial crops (food, fibre, forage and bioenergy crops), paddy rice, grazing lands with livestock including pastures, grasslands, rangelands, shrublands, silvopasture and agroforestry. Although developed for projects carried out at farm level, potential users include investors, research institutions, government agencies, consultants, agricultural companies, NGOs, individual farmers or farmer associations, supply chain and other users who are interested in measuring and estimating SOC stocks and changes and GHG emissions in response to management practices. Further details are provided in the Appendix, which serves to illustrate a whole MRV workflow.

IPCC: IPCC guidelines for national greenhouse gas inventories

https://www.ipcc.ch/site/assets/uploads/2019/12/19R_V0_01_Overview.pdf

The overall aim of the guidelines is to provide an updated and sound scientific basis for supporting the preparation and continuous improvement of national GHG inventories. The 2019 Refinement (IPCC 2019c) supplements and/or elaborates on the 2006 IPCC Guidelines where gaps or out-of-date science have been identified. However, the 2019 refinement does not replace the 2006 IPCC Guidelines and should be used in conjunction with it (IPCC 2006). Additional information on the IPCC 2006 guidelines is provided in Ravindranath and Ostwald (2008).

QPCS: Quantification Protocol for Conservation Cropping, version 1.0

https://open.alberta.ca/publications/9780778596288

This protocol (Alberta, CA) specifically quantifies greenhouse gas emissions reductions from the following three activities: new carbon stored annually in agricultural soil; lower nitrous oxide emissions from soils under no till management; and associated emission reductions from reduced fossil fuel use from fewer passes per farm field. The quantification protocol is written for project developers and farm operators implementing conservation cropping offset projects in the Dry Prairie and Parkland ecozones. The protocol ended in December 2021 and, apparently, there is no replacement yet[55]. Hence, the protocol has not been evaluated here.

[55] https://www.alberta.ca/agricultural-carbon-offsets-all-protocols-update.aspx#jumplinks-1

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WBG-SOC: Soil Organic Carbon (SOC) MRV Sourcebook for Agricultural Landscapes

http://hdl.handle.net/10986/35923

This sourcebook is designed to provide a conceptual foundation for soil organic carbon measurement and monitoring in croplands and grazing lands or rangelands. It provides methods and simple step-by-step guidance to produce reliable soil carbon measurements across a variety of settings and contexts, with comparisons on what frameworks, approaches, or methods to choose relative to the goal of the assessment, costs, feasibility, and uncertainty. Although greenhouse gas emissions (methane, CH_4, or nitrous oxide, N_2O) associated to agricultural land management can be significant and must be assessed to calculate total net GHG reductions of a project, this sourcebook focuses on soil carbon and specifically changes in soil carbon in agricultural lands that are a direct consequence of land management.

Considering the range of topics addressed, this protocol has not been considered for rating.

US-SEP: U.S. Soil Enrichment Protocol

https://www.climateactionreserve.org/how/protocols/ncs/soil-enrichment

The U.S. Soil Enrichment Protocol (SEP) provides guidance on how to quantify, monitor, report, and verify agricultural practices that enhance carbon storage in soils. The primary GHG benefit targeted is the accrual of additional carbon in agricultural soils, with hopes to incentivise GHG emission reductions from other sources, such as N_2O from fertiliser use. Soil enrichment activities encompass an enormous variety of practices, with tremendous potential for development of new practices. This approach to farming is intended to restore the health of the soil over time, through continuous and adaptive practice change, rebuilding losses due to conventional agricultural practices. This protocol focuses on outcomes in terms of net GHG flux.

VCS: VCS Standard

https://verra.org/wp-content/uploads/2022/12/VCS-Standard-v4.4-FINAL.pdf

The Verified Carbon Standard (VCS) Program is probably the world's most widely used GHG crediting program. Individual projects and jurisdictional programmes can be registered under the VCS Program. Eligible AFOLU projects include: Afforestation, Reforestation and Revegetation (ARR, under development), Agricultural Land Management (ALM), Improved Forest Management (IFM), Reduced Emissions from Deforestation and Degradation (REDD), Avoided Conversion of Grasslands and Shrublands (ACoGS), Wetlands Restoration and Conservation (WRC). There is also an 'Improved agricultural land management methodology' (IALM, under development). The IALM methodology will provide a more comprehensive and flexible approach to the quantification of GHG benefits compared to other published ALM methodologies. Most other methodologies focus on a single GHG source or sink such as SOC, nitrous oxide (N_2O) from fertiliser use or enteric methane (CH_4), or a single ALM activity such as grassland management. In contrast, the IALM methodology will allow for quantifying SOC stock change and N_2O and CH_4 fluxes associated with a range of ALM activities such as improved water, residue and livestock management, as well as reduced tillage and fertiliser use. It also

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includes a novel combined measure and model quantification approach that uses SOC measurements to set the baseline for modelled estimates of SOC stock changes.

3.2.2 Approved methodologies

AU-CFIDV: Carbon Farming Initiative[56] — 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

This Australian Government backed methodology determination (method) provides the rules for crediting carbon stored in soil resulting from altered management practice as part of the Australian Emissions Reduction Fund (ERF). Reductions achieved by sequestering soil carbon under pasture, crops or mixed farming systems can receive carbon credits under the ERF. The default-value based soil carbon projects involve specific project management activities on eligible land and use default abatement values (Legislation text: F2018C00126).

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

This Australian Government backed methodology determination (method) credits increases in soil carbon stocks as a result of one or more new or materially different management activities in grazing, bare fallow or cropping land (including perennial woody horticulture) that store carbon in that land. Soil carbon stocks must be estimated using specified soil sampling methods or using the specified hybrid approach that combines soil carbon model estimates with soil sampling. Samples must be measured for soil carbon content using specified laboratory techniques or calibrated in-field sensors (Legislation text: F2021L01696).

DE-MOOR: MoorFutures

https://www.moorfutures.de/konzept/downloads/

MoorFutures aims to reduce CO_2 emissions through climate protection projects in Germany, with particular attention for rewetting of peat soils, through 'biological climate protection.' It involves project planning, water law approval procedures, compensation payments for land users, structural implementation steps, and the monitoring of the climate impact. MoorFutures projects are intensively managed over a period of 50 years. After the purchase of a certificate, the acquired MoorFutures are 'shut down' in a register. The Methodology and Standards are available online (*in German*).

[56] https://www.legislation.gov.au/Search/carbon%20credits

FR-LBC: Label Bas Carbone

https://carbongap.org/wp-content/uploads/2023/03/carbongap-LCLpolicybrief-March2023.pdf

https://label-bas-carbone.ecologie.gouv.fr/quest-ce-que-le-label-bas-carbone

The low-carbon label (LCL, 'Label Bas Carbone') is a French official certification scheme for greenhouse gas reduction or sequestration projects carried out on French territory. It provides clear rules and transparency to the voluntary carbon market in France by introducing a framework for monitoring, reporting and verification of greenhouse gas emissions reductions or removals and soil organic C storage in an effort to encourage such projects. The label is based on methodologies which are approved by the French Ecological Transition Ministry. To apply for the LCL, projects must go beyond the requirements of national environmental regulations. The certified emissions reductions or removals purchased as part of a labelled project are tracked on an official registry to prevent double counting: the register guarantees that the same reductions have not been sold or used several times. But the labelled emissions reductions/soil C storage do count for the national climate mitigation effort.

Currently, six 'land use' related methodologies, which include SOC, have been approved for LCL:

a) Afforestation: https://label-bas-carbone.ecologie.gouv.fr/la-methode-boisement
b) Forest rehabilitation: https://label-bas-carbone.ecologie.gouv.fr/la-methode-reconstitution-de-peuplements-forestiers-degrades
c) Hedgerow rehabilitation: https://label-bas-carbone.ecologie.gouv.fr/la-methode-haies
d) Planting of orchards: https://label-bas-carbone.ecologie.gouv.fr/la-methode-plantation-de-vergers
e) Cattle breeding/Field crops :https://label-bas-carbone.ecologie.gouv.fr/la-methode-carbonagri
f) 'Field crops' : https://label-bas-carbone.ecologie.gouv.fr/la-methode-grandes-cultures.

The 'field crops' methodology will be evaluated in Section 3.4, as an example.

Gold Standard: Soil Organic Carbon Framework Methodology

https://globalgoals.goldstandard.org/standards/402_V1.0_LUF_AGR_FM_Soil-Organic-Carbon-Framework-Methodolgy.pdf ; https://globalgoals.goldstandard.org/

The methodology presents requirements to quantify changes in GHG emissions and SOC stocks through the adoption of improved agricultural practices. Activities can achieve avoidance of emissions as well as sequestration of carbon in the soil, both which result in increased SOC content. This SOC methodology is applicable for a broad range of activities, from small scale, low tech land use to industrialised, large scale land management, using a variety of SOC improvement approaches. As scientific knowledge of SOC impact or activities covered in this methodology continues to evolve, the methodology is not limited to a specific activity but provides flexibility to apply the most current and best-fit systems.

The SOC methodology provides three approaches for the quantification of SOC improvements for baseline and project scenario. This accommodates the reality that not all relevant measurements and parameters may

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be available to all projects and SOC activities (Figure 5): 1) Take on-site measurements to directly document baseline and project SOC stock levels, 2) Use peer-reviewed publications to quantify baseline and project SOC stock levels, and 3) Apply default factors to quantify SOC changes, relating to the general methodology described in the IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2019) using tier 2 level approach whenever possible. These in-built options make an unambiguous assessment in Table 4 difficult, hence a 'low' rating for 'confidence in ratings'.

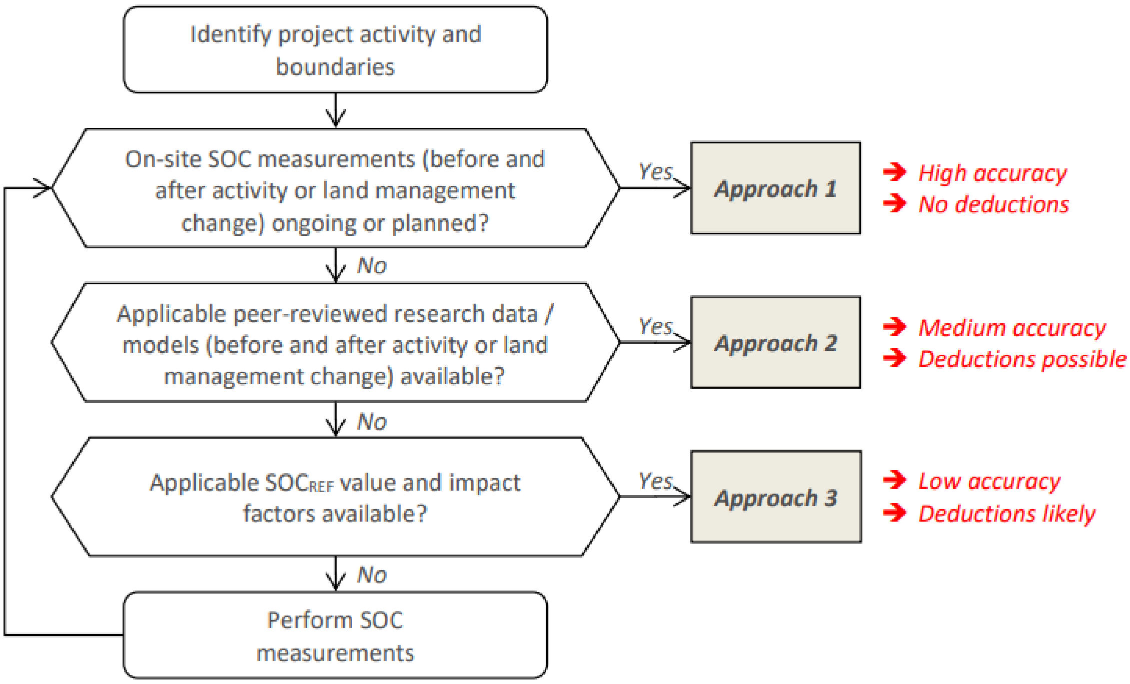

Figure 5. Example of decision tree for identification of appropriate calculation approach based on data availability (Gold Standard, 2020).

NL-SNK: Stichting Nationale Koolstofmarkt

https://nationaleco2markt.nl/

template: https://nationaleco2markt.nl/wp-content/uploads/2019/11/Stramien-methode-document.pdf

The National Carbon Market Foundation (SNK) guarantees the quality of the carbon certificates, so that the market can be confident that the emission reduction or carbon sequestration stated on the certificate has actually been achieved. SNK has established a set of methods for calculating emission reductions for different project types (the 'Rulebook', e.g. for 'CO2-sequestration for grassland on mineral soil' or for agriculture on mineral soils). Project parties use these methods when drawing up a project plan that is validated by SNK. Projects with a validated project plan can start and reduce emissions. The achieved emission reduction is verified by independent experts. SNK issues certificates to the project parties for verified reductions. SNK is an independent entity, i.e., the method documents and rules are only established by the board of SNK, with independent board members, without formal involvement in and influence from third parties, the national government or public and private parties.

Nori: Nori Croplands Methodology, v 1.3

https://nori.com/resources/croplands-methodology

This Nori methodology outlines how increases in SOC stocks resulting from the adoption of regenerative soil treatment and cropping practices are estimated and how those estimates convert into NRT issuance for projects that originate in US croplands. The purpose of the Nori-platform is to host the sale of Nori Carbon Removal Tonnes (NRTs), where one NRT is a digital asset that represents one tonne of CO_2 removed from the atmosphere where the recovered carbon (C) is retained in a terrestrial reservoir for at least 10 years.

Plan Vivo: Plan Vivo standard methodology

https://www.planvivo.org/standard-documents

The Carbon Benefits of Plan Vivo projects must be calculated using an approved methodology. Methodologies must describe all procedures, data and parameters needed to estimate and monitor carbon benefits and can refer to approved Modules and Tools. Approved Methodologies, Modules and Tools are published on the Plan Vivo webpage and are available for use by all Plan Vivo projects that meet the specified applicability conditions. Relevant methodologies approved by other recognised GHG Programs can also be used in Plan Vivo projects, and Plan Vivo Methodologies can also refer to Modules and Tools approved by other recognised GHG Programs. These Methodology Requirements describe the criteria against which all Methodologies, Modules and Tools are assessed. They are aligned with ISO 14064:2:2019, and The Greenhouse Gas Protocol; and are designed to ensure that Carbon Benefits are real, additional, measurable and verifiable. For the assessment in Table 4, we have analysed Plan Vivo's approved approach 'Small-holder Agriculture Mitigation Benefit Assessment' (SHAMBA), for which the documentation proved rather scanty.

Regen: Regen Network Methodology for GHG and Co-Benefits in Grazing Systems

https://library.regen.network/v/methodology-library/methodology-for-ghg-and-co-benefits-in-grazing-systems

The Methodology for GHG and Co-Benefits in Grazing Systems provides a holistic assessment of ecological state indicators for grasslands under regenerative grazing practices. Managed grazing, which involves carefully controlling livestock density and intensity of grazing, has been shown to provide a wide range of ecosystem benefits such as enhanced carbon sequestration, improved soil health, and increased water infiltration. These methodology combines remote sensing data with in-field measurements to provide high quality estimates of soil organic carbon stock and measures additional ecological co-benefits such as animal welfare, ecosystem health, and soil health. Figure 6 gives an example of an 'acceptable' sampling timeline for Regen protocols. Each crediting period is shown in a different colour. The first sampling round is the baseline sampling, which sets 'time zero' for the 10-year crediting term of a project. The last sampling round must

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happen at the end of the 10-year term. Between the baseline sampling date and the last sampling date, at least two (2) other sampling rounds must be carried out (could be more). Number of years between consecutive sampling rounds is flexible, as long as no longer than four years pass between consecutive sampling rounds. (Credit: Regen, p. 8)

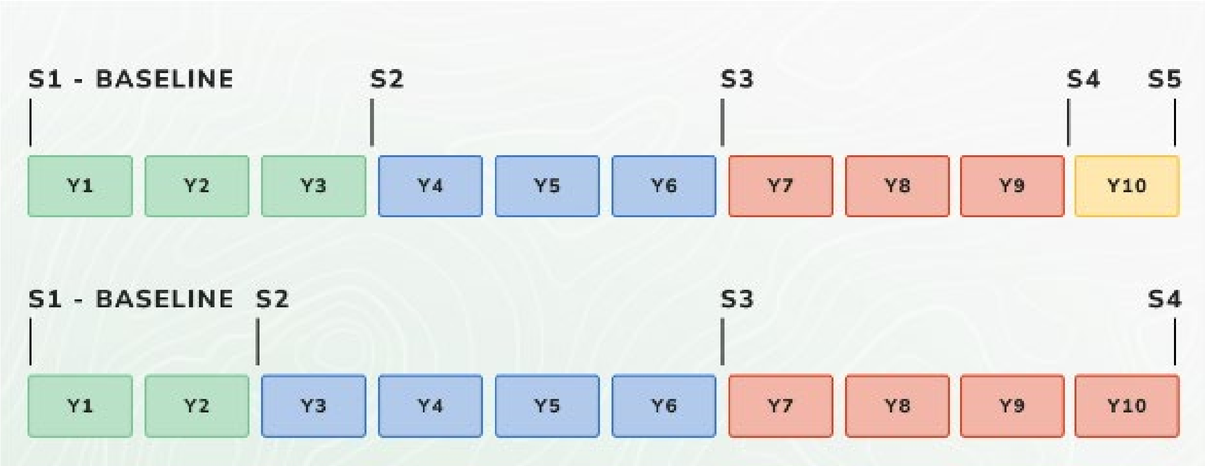

Figure 6. Example of an acceptable sampling timeline for Regen protocols.

UK-PC: Peatland code

https://www.iucn-uk-peatlandprogramme.org/sites/default/files/2023-03/Peatland%20Code%20V2%20-%20FINAL%20-%20WEB_2.pdf

The Peatland Code is an example of natural capital financing. The Peatland Code is a voluntary standard for UK peatland projects wishing to market the climate benefit of restoration. Eligible activities shall be those relating to restoration of either blanket bog or raised bog with a defined associated baseline condition category. Baseline condition category and peat depth shall be determined using the Peatland Code Field Protocol. Restoration shall be achieved as a result of both restoration and management activities. Restoration activities shall revegetate and/or rewet the peatland (excluding removal of plantation forest) and shall result in a change to a condition category with a lower associated emission factor. Management activities shall maintain or enhance the condition category change. An approved validation/verification body will assess whether the combination of restoration interventions and ongoing management of the site is sufficient to maintain the peatland in an enhanced condition. Restoration and management activities shall not conflict with existing land management agreements.

UK-WCC: Woodland Carbon Code

https://woodlandcarboncode.org.uk/standard-and-guidance

The Woodland Carbon Code (WCC) sets out robust requirements for voluntary carbon sequestration projects that incorporate core principles of good carbon management as part of sustainable forest management.

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Landowners and their successors in title must commit to a permanent change of land use to woodland (UK-WCC 2022). Projects shall describe the original condition of the project site including details of the vegetation cover, soil type and their carbon content. The 'Soil Carbon and the Woodland Carbon' code sets out the methodology for organo-mineral and mineral soils. The WCC carbon calculator includes assumptions about the likely soil disturbance and soil GHG emissions. Alternatively, projects can make a soil carbon assessment prior to tree planting with repeat assessments as the project progresses. Soil carbon accumulation can currently only be claimed for projects on a mineral soil where the previous land use was arable or rotational grass, and the woodland will be managed as minimum intervention.

US-ACR: American Carbon Registry

https://americancarbonregistry.org/carbon-accounting/standards-methodologies

Founded in 1996 by Environmental Resources Trust (ERT) as the first private voluntary offset program in the world, ACR has over two decades of experience in the development of rigorous, science-based carbon offset standards and methodologies as well as operational experience in carbon offset project registration, verification oversight and offset issuance. ACR operates in both global voluntary and regulated carbon markets. It Includes four approved methodologies that relate to SOC:

a) Afforestation and Reforestation of Degraded Lands: This methodology is applicable to projects in non-REDD+ countries that are conducting afforestation and reforestation (A/R) on lands that are expected to remain degraded or continue to degrade in the absence of the project. For further details see here and approved version.

b) Avoided Conversion of Grasslands and Shrublands to Crop Production: The methodology was updated to make it simpler to use, reduce project development costs without sacrificing accuracy in accounting, better align with conservation programs, and reflect the latest trends in conversion. An Errata and Clarification document for v2.0 has also been posted and must applied in conjunction with the methodology. For further details see here and approved version.

c) Restoration of California Deltaic and Coastal Wetlands: This carbon offset methodology aims to quantify GHG emission reductions from the restoration of California deltaic and coastal wetlands. The methodology builds upon ACR's approved methodology, Restoration of Degraded Deltaic Wetlands of the Mississippi Delta, by integrating California data and region-specific restoration techniques to create a rigorous framework for quantifying baseline and project emissions that are unique to wetlands in California. For further details see here and approved version.

d) Restoration of Pocosin Wetlands: The ACR methodology for Restoration of Pocosin Wetlands establishes standardised procedures to monitor and account the greenhouse gas benefits associated with restoring drained pocosin habitat. Pocosins are unique freshwater wetlands, often shrub-dominated, on organic soils in the Atlantic coastal plain of the south-eastern United States (Virginia to northern Florida) that are seasonally saturated primarily through precipitation, and easily degraded. For further details see here an approved version.

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VM006: 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/

This methodology quantifies the GHG emission reductions and removals generated in mosaic and landscape scale REDD+ projects by allowing such project activities to be combined with improved forest management, afforestation, reforestation and re-vegetation activities, as well as clean cookstoves initiatives. This allows for a more holistic landscape approach to REDD+ activities that integrates efforts to protect forests with programs to improve the livelihoods of rural communities.

The methodology is applicable to forest that would be deforested in the absence of the project activity and considers a soil component.

VM0042: Verra VM0042 Methodology for Improved Agricultural Land Management v 2.0 (IALM methodology; updated June 2023)

https://verra.org/methodologies/vm0042-methodology-for-improved-agricultural-land-management-v2-0/

This methodology quantifies the GHG emission reductions and SOC removals resulting from the adoption of improved agricultural land management (ALM) practices. Such practices include, but are not limited to, reduced tillage and improvements in fertiliser application, biomass residue and water management, cash and cover crop planting and harvesting practices, and grazing practices.

According to Verra, the revision strengthens the methodology's GHG quantification and makes it more widely applicable and user-friendly. It also includes improvements to VMD0053 *'Model Calibration, Validation, and Uncertainty Guidance for the Methodology for Improved Agricultural Land Management, v2.0.'*

The methodology provides three approaches to quantifying emission reductions and removals resulting from the adoption of improved ALM practices. Quantification Approach 1 (QA1): Measure and Model – a biogeochemical, process-based model is used to estimate GHG fluxes related to SOC stock changes, soil methanogenesis and use of nitrogen fertilisers and nitrogen-fixing species. Edaphic characteristics and actual agricultural practices implemented, measured initial SOC stocks and climatic conditions in sample fields are used as model inputs. Periodic measurements of SOC stocks are required every five years at minimum; QA2: Measure and Re-Measure – direct measurement is used to quantify changes in SOC stocks. This approach is relevant where models are unavailable or have not yet been validated or parameterised for a particular region, crop or practice, or where project proponents prefer to use a direct measurement approach for SOC stock change, and QA3, which directly measures SOC stock changes in the baseline scenario in linked baseline control sites. Here, again, it was not really possible to apply the proposed rating scheme unequivocally.

3.3 Classification characteristics

Based on the sources reviewed in Section 3.1, subsequent discussions with the writing team, and an international consultation during an ORCaSa stakeholder webinar (5/07/2023), main characteristics that should be considered when evaluating/comparing different MRV guidelines have been defined (Table 3). The list considers characteristics such as purpose of the MRV, ecosystem(s) covered, Tier level, geographic scale and geographic scope, scope of monitoring as well as aspects such as 'additionality' and 'permanence.' These relate to different components and building blocks of an MRV system, as visualised in Figure 4.

For each characteristic, either one or several answers are possible. For example, for the classification characteristic 'Ecosystem(s) covered,' one could answer 'croplands' as well as 'grasslands.' Alternatively, for the characteristic 'Leakage requirement' only one answer is possible. Often, however, during the assessments it proved cumbersome to unmistakably assign a class for a given characteristic considering the overall diversity/complexity (or number of options allowed) of the considered MRV methodologies/guidelines. In such instances, pragmatically, 'best estimates' are provided considering the available 'multi-faceted' information. This level of 'uncertainty' is reflected in the rating for the overall 'Confidence in ratings,' which was assessed as: High, Medium and Low.

Results of the assessments themselves were stored in a 'lengthy' Excel file with 29 columns and 20 rows (see footnote g, Table 4). In some cases, specific methodologies are considered (e.g., for NL-SNK or FR-LBC) and these are specified in the footnote to Table 4.

In Section 3.4, we will use a classification algorithm to assess dissimilarities between the MRVs using the Gower metric (Gower 1971), where each MRV protocol is positioned in two-dimensional space.

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

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Classification characteristics	Answer 1	Answer 2	Answer 3	Answer 4	Answer 5	Answer 6	Answer 7
Purpose of MRV	Compliance market (National inventories, CAP)	Corporate Supply Chain (insetting)	Voluntary carbon market				
Ecosystem(s) covered	Croplands	Grasslands	Forest lands	Woodland/ Shrubland	Wetlands/ peatlands	Urban land	Multiple
Geographic scale	Farm	Region	National	Continental	Global		
Geographic scope	Specific country or countries	Specific continent(s)	Whole world				
Aggregation (bundling) of farms	Allowed	Not allowed					
Tier level	1	2	3	All			
Scope of monitoring	SOC stock change	GHG accounting	All				
GHGs targeted	CO2	CH4	N2O	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	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	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					

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Permanence requirement	No	Yes					
Reversal requirement	No	Yes					
Data retention/ sharing policy	No	Yes					

3.4 Characterisation of reviewed MRV systems and methodologies

In previous sections of this chapter, we listed current MRV guidelines and approved methodologies (Table 2) and defined MRV's methodologies characteristics (Table 3). In this section we score each MRV listed in Table 2 on the characteristics defined in Table 3. This requires detailed descriptions and background documents of each MRV. For this we consulted the documentation of all MRVs considered through the weblinks included in Section 3.2. The level of detail of the information varies per MRV and sometimes educated guesses were needed to fill Table 4. It should be noted that Table 4 (i.e., the corresponding data set as compiled for this review) is only a first attempt to list key characteristics of major MRVs. It should be improved in future when MRVs develop and mature and their documentation becomes more detailed.

Table 4. Scoring of MRV guidelines and approved methodologies considered in Table 3 (excerpt of first columns only see g).

Abbreviation	Purpose of MRV	Ecosystem(s) covered	Geographic scale	Geographic scope
AU-CFIDV	Compliance market (National inventories, CAP)	Multiple	Region	Specific continent(s)
AU-CFMM	Compliance market (National inventories, CAP)	Multiple	Region	Specific continent(s)
BC-SCM	Voluntary carbon market	Urban land	National	Specific country or countries
CARSSE	Compliance market (National inventories, CAP)	Multiple	Region	Specific country or countries
DE-MOOR	Voluntary carbon market	Wetlands/peatlands	Region	Specific country or countries
FR-LBC	Voluntary carbon market	Croplands	National	Specific country or countries
Gold Standard	Voluntary carbon market	Croplands	Farm	Whole world
GSOC-MRV	Voluntary carbon market	Multiple	Region	Whole world

Footnotes:

a) **NL-SNK**, considers several methodologies. This assessment is for 'Methode voor vaststelling van CO_2-vastlegging in de bodem', https://nationaleco2markt.nl/wp-content/uploads/2023/06/Methodedocument-koolstofcertificatenakkerbouw-vastgesteld-020623.pdf

b) **DE-MOOR**, considers this methodology.

c) **FR-LBC,** considers several methodologies for forest, grasslands, vineyard, etc. However, this assessment concerns only the croplands, i.e. the 'Grandes Cultures', see here.

d) **Plan Vivo,** ratings relate to 'Small-holder Agriculture Mitigation Benefit Assessment' SHAMBA).

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e) **US-ACR**, 'Restoration of California Deltaic and Coastal Wetlands, see here.

f) **VCS,** ratings relate to 'Avoided Planned Conversion of Grasslands and Shrublands to Crop Production', see here.

g) ***Full ratings*** are given in a separate Excel dataset.

Key characteristics of each MRV methodology (see here) can be used to acquire key information about individual MRVs and compare them. However, while this gives information about key aspects, a comparison of MRVs is cumbersome because of the large number of characteristics involved. Therefore, it would be helpful to reduce the multi-dimensional space in which the MRVs are scored to only two dimensions. As a result, each MRV would take up a position in a two-dimensional plane, where MRVs that have similar characteristics are near and where MRVs that have vastly different characteristics are far apart. This dimension reduction can be achieved with a statistical technique known as multidimensional scaling (Borg and Groenen 2005; Cox and Cox 2020). Here we applied multidimensional scaling using the 'cmdscale' function of the 'cluster' package of the R software for statistical computing (Team 2021).

Multidimensional scaling requires a dissimilarity matrix as input. This is a square matrix that has as many rows and columns as there are MRVs, and whose value at row *i* and column *j* stores the dissimilarity between the *i*-th and *j*-th MRV. The dissimilarity between two MRVs is derived from the characteristics of the two MRVs. Since the characteristics of MRVs listed in Table 4 are measured on a nominal scale, common Euclidean distances cannot be computed. We therefore used the Gower metric instead (Gower 1971). This simply assigns distance 0 if the two MRVs have the same value for the characteristic, and distance 1 if they are not the same. This is done for all characteristics and the average of all distances defines the dissimilarity between the two MRVs. 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.

The results of the multidimensional scaling are shown in Figure 7. The figure shows that the MRVs are fairly uniformly distributed in the two-dimensional space and that there are no clear clusters or extremes, although some patterns can be observed. For instance, Gold Standard and GSOC-MRV are quite close, indicating that they share key characteristics. Indeed, both MRVs aim at the voluntary carbon market, are developed for the whole world, encompass all Tier levels, include quality assurance, are result-based and agree on most of the requirements (Table 4). Other clusters of similar MRVs are: NL-SNK, US-SEP and BC-SCM (all three are developed for a specific country or countries, make use of process-based models, are result-based and have a data retention/sharing policy); VM0006, Nori and Plan Vivo (which all focus on SOC stock change, have a specific country or countries as geographic scope, use historic land management as a baseline setting and do not require ground truth SOC observations). VM0042 is the most isolated MRV. This could be because unlike other MRVs it scores 'low' or 'No' on most requirements. This explanation is supported by the fact that CARSSE, which is opposite VM0042 in the two-dimensional plane, scores 'Yes' for almost all requirements. It is also interesting that VM0042 is not very close to VM0006, although they are in the same quadrant of the plane. This can be explained by the fact that VM0006 is for 'forest lands' whereas VM0042 is for 'croplands'. Regen is another MRV that is at the outside of the two-dimensional plane and quite isolated from other MRVs.

This could be because it is only focussed on grasslands, requires a high frequency of ground truth SOC observations for reporting and uses hybrid models. None or only a few other MRVs have the same values for these characteristics.

It should be noted that five out of the 27 key characteristics are related to an MRV '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 'Target depth interval,' 'Geographic scale' and 'Tier level' than to characteristics such as 'Reporting periods' and 'Frequency or reporting'. Assigning weights involves subjective choices but so does the *a priori* decision about which characteristics are included in the analysis. Hence, it could be worthwhile to organise stakeholder workshops to jointly define and refine key characteristics of MRV methodologies and associated weights and evaluate the sensitivity of the multidimensional scaling results to choices made.

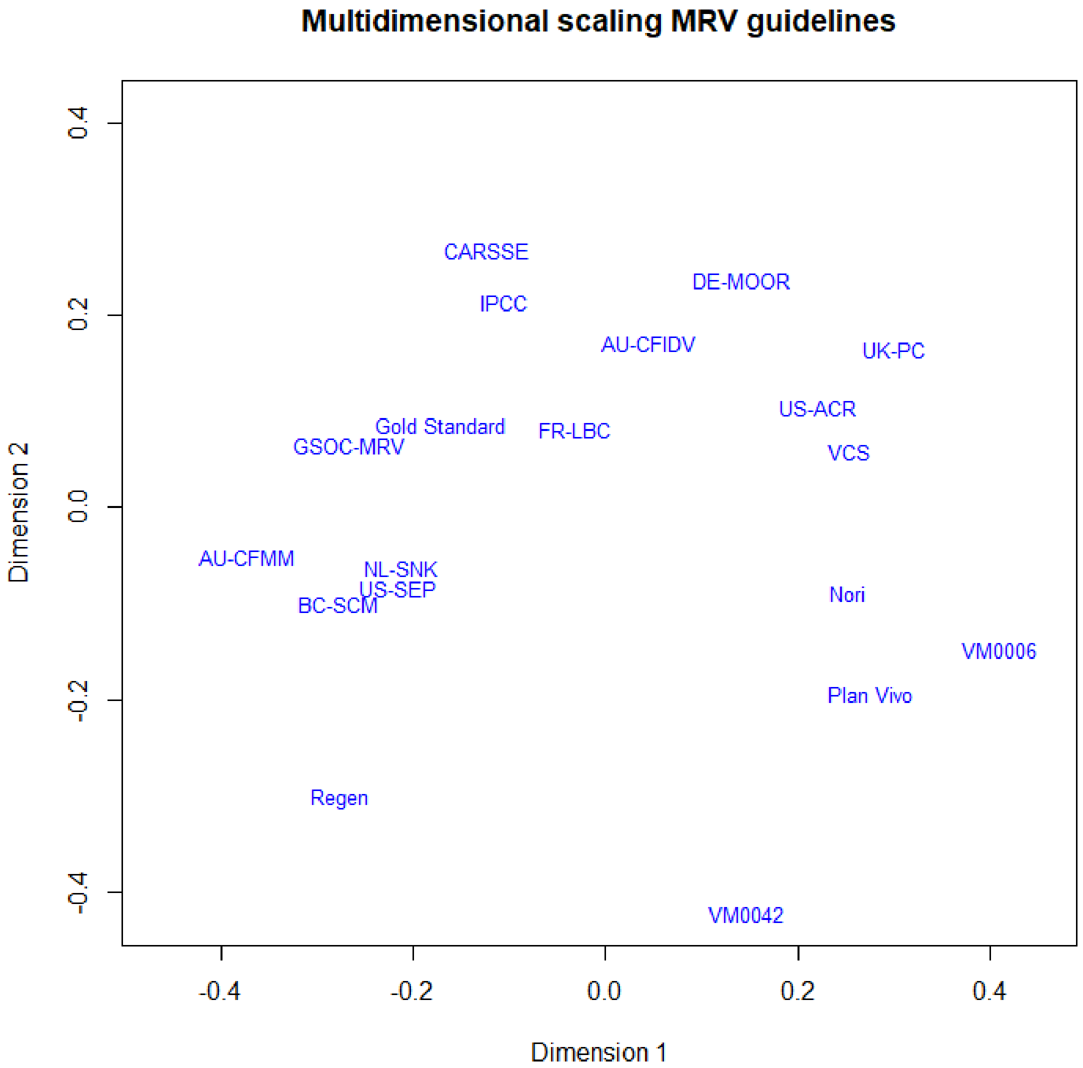

Figure 7. Position of considered MRVs in a two-dimensional space after application of multidimensional scaling to MRV

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characteristics as scored in Table 4.

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4. Towards an integrative and multi ecosystem MRV framework for SOC stock changes

4.1 Motivations toward a more unified but adaptative MRV framework for SOC stocks assessments

As illustrated by the previous sections, regarding soil carbon MRV, there is a wide variety of application contexts (NDCs, CAP, voluntary C market, insetting), ecosystems (e.g., forest, grasslands …), frameworks, guidelines, methodologies for monitoring and verification and even more tools. Currently, none of the guidelines, frameworks or tools allow to address all ecosystems or context of MRV. For instance, MRV frameworks for voluntary C market generally require following projects (e.g., carbon farming) continuously for a duration of 5 to 10 years. Alternatively, in Australia, a landholder can select 25 years and 100 years at the time of project registration. 25 years should provide good evidence that SOC has changed due to management activities as change in SOC is slow under a given management. However, the 25 year projects will have higher discounts compared to 100 year registered projects. In, in practice, in Australia more projects are registered for 25 years due to economic return times.

In the context of insetting, a company that will sell for instance soft maize may contract a farmer for only one year and one plot meaning that it will need to quantify SOC stock changes and pay the farmer accordingly based on the carbon farming practices the farmer has implemented only for that year and that plot[57].

The following year, the company may contract another farmer to produce soft maize. Therefore, the implication in term of monitoring is that for insetting the framework and methods may require an annual assessment, reporting and verification of the SOC stocks changes. Typically, in this context it is unrealistic to rely on an in-situ soil sampling approach to measure SOC stock changes (which is often mandatory in the context of voluntary carbon market) and a carbon budget component modelling approach may be the only method applicable.

This example shows that even for a given type of ecosystem, currently several frameworks, methodologies or tools mays be used depending on the application context. This generates risks of inconsistency in monitoring the evolution of soil carbon stocks between the schemes and it could lead to awkward situations if the same actions (e.g., a farm engaged in new carbon farming practices) were evaluated or financed through two

[57] Note that GGP Scope 3 reporting can be at project level which means that soil C changes associated with commodity can be reported from an entire region, i.e., regional baseline versus regional change. Hence, what is needed are tools and approaches to support different forms of MRV - and not to assume that it all comes from the monitoring the same fields T_0 to T_x. Hence, the soil sampling needs to reflect the different approaches e.g., be sufficient to model and sufficient to validate change at different scales.

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different sources (e.g., CAP and offsetting program). Some would argue that for reasons of non-additionality the same action should not be financed through several schemes (e.g., CAP and carbon offset program), but the reality is that currently the price of a tonne of CO_2 on the voluntary respectively compliance C market (which differ widely) do not often offset the cost of implementing practices (other sources of financing may be needed) and the issues of non-additionality are not fully resolved. Concerning carbon farming in Europe, the European Commission hasn't clarified yet the rules in terms of additionality and the sources of financing (e.g., public through CAP subsidies, private through the voluntary carbon market, a hybrid approach). Given the urgency in implementing climate actions, and the fact that the CAP is now performance-driven, it would be relevant to base support measures on results rather than on actions. However, all the financial risk would be on the side of the farmer (who may do his best to implement C farming practices, e.g., cover crops, but that may fail to store C because of a bad climatic year). At the opposite, in the case of action-based payment (as in the previous CAP), all the risk is on the side of the policy body (that pays for actions that may not result ineffective SOC stock increases). For those reasons, the NIVA project suggested a hybrid scheme[58] where a farmer would get a part of the payment based on actions to increase SOC stocks in the soil (e.g., annually through CAP subsidies), and bonus payments based on results (an effective increase in SOC stocks) through the voluntary C market (e.g., after 5 years of implementation of the C farming actions). In such a hybrid market scheme, the farmer and policy body would share the risk of non-delivery and ideally, the same tool for monitoring should be used (or at least the same kind of methodological approach) for both the payment based on action and results to ensure consistency in the hybrid scheme (e.g., the TIER 3 approach developed in NIVA based on the AgriCarbon-EO processing chain) although the assessment could occur with different temporalities (yearly but during 5 years for the CAP, after 5 years for the voluntary C market).

The examples presented in the two previous paragraphs illustrate the need for a harmonised but flexible monitoring framework. Other considerations are related to the need for consistency in SOC stock changes quantification 1) between countries that may use different Tiers approach to evaluate their NDCs (need for consistency between countries and between the Tiers), and 2) between scales (e.g., countries, regions, local offsetting project) and contexts of MRV (e.g., NDC's, C farming projects) (for more details, see page 22-23 in the appendix of[59]). Note that Tiered approaches/tools currently used for NDCs (following the IPCC guideline) and for the CAP (e.g., NIVA's project C budget indicator approach) may differ.

Another reason for proposing a more unified framework for MRV of SOC stock changes is that most landscapes are composite (several land covers and land uses). A unified framework would reduce the risk of leakage or double accounting. Also, they are similarities in key processes (e.g., photosynthesis) of the main ecosystems (e.g., forest, crops and grasslands) which can lead to the development of approaches/tools with similar architectures or composite block (and therefore relying, at least partly, on similar guidelines). For instance, some processes like photosynthesis or soil organic matter mineralisation can be simulated with similar tools/codes for different land uses, similar data can be used as inputs (e.g., climatic data, high

[58] https://www.niva4cap.eu/wp-content/uploads/2022/12/NIVA-Policy-Brief-nr.-5-Agro-environmental-indicator-carbon-D1.0.pdf
[59] https://www.circasa-project.eu/content/download/4158/40011/version/1/file/CIRCASA_D3.1%20SRA.pdf

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resolution optical remote sensing data) and the same observation networks (e.g., ICOS flux tower networks) can be used for validation or uncertainty assessments of the models/building blocks at different ecosystems.

Finally, all those elements point toward the need of a more unified but adaptative (e.g., with a Tiered approach, monitoring with various temporalities) framework for MRV of SOC stock changes. Because of that ORCaSa aims at producing a cookbook for a blueprint of an MRV framework for croplands SOC stock changes (Task 4.2) and at building an integrative and multi-ecosystem MRV framework for SOC stock changes (Task 4.3).

4.2 Need for a new modular and integrative multi-ecosystem MRV methodology for SOC stock changes

The analysis of the current needs in MRV for different and sometimes new contexts (CAP, offsetting, insetting) but also of the current MRV frameworks, guidelines and building blocks highlights that the main challenges (e.g., large scale, high resolution, repeated & short term assessment for the CAP) concern the monitoring component of the MRV.

4.2.1 Monitoring

Through the frameworks and guidelines survey, we observed that these can be split into: 1) soil MRV that combine soil C stocks with soil derived GHGs and 2) full ecosystem C assessment that include above ground biomass. Some MRVs are too focused on the soil itself, overlooking the fact that organic carbon inputs mainly come from the vegetation. For instance, in the French LBC methodology for arable land, no clear guidelines or protocol are given for estimating crop or cover crop biomass and its fraction that returns to the soil. As a consequence, large uncertainties in the SOC stock changes estimates can result from rough biomass estimates (e.g., the use of regional statistics of cover crop biomass is suggested with discount in the LBC method) or inappropriate methods/protocols for estimating it. Also, methods for quantifying SOC stock changes generally fail to consider the spatial variability in biomass production and restitution to the soil that can be cause by pest, topography, microclimates etc. which is surprising as intra-field heterogeneity is a well-established issue in agricultural applications (e.g., Blackmore *et al.* 2003; Weiss *et al.* 2020). Wijmer *et al.* (2023) showed that assimilating averaged LAI at a plot level instead of high-resolution LAI products (10m) could cause a significant underestimation of the winter wheat biomass estimates (i.e., impact of input spatial support depends on the scale of the MRV application.) Overall, very few guidelines, methodologies or tools rely on biomass quantification by remote sensing (or by hybrid modelling approaches assimilating remote sensing data) to map its spatial variability in an attempt to 'feed' the soil models with more accurate estimates of crop residues. Reasons are probably manyfold: lack of awareness of remote sensing potential by the soil modeler's community, lack or inappropriate remote sensing data (e.g., need for L band satellites to quantify biomass for highly productive forest) or ready to use biophysical products derived from remote sensing (e.g.,

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high resolution multitemporal LAI products) and also, most ecosystem and soil models were not designed initially for spatialised applications but for local (plot, farm) applications. For such models, assimilation of remote sensing data can correct the model's trajectory (e.g., Ferrant *et al.* 2014) but as shown by Casa *et al.* (2012) for cropland or by Le Maire *et al.* (2005 ; 2011) for forest, upscaling processed based model initially developed for local applications model by assimilating remote sensing data is challenging because those models need many input data (on soil, management etc.) and require many parameters to be set. Based on those considerations, current C stocks estimates may benefit from remote sensing assimilation but a dedicated new generation of models (e.g., SAFYE-CO2; Pique *et al.* 2020ab) tailored to upscaling the C budget components may have to be developed.

Monitoring may involve several building blocks described here above in Section 2.2 and illustrated by Figures 2 and 3. Yet, concerning cropland, the frameworks proposed by Paustian *et al.* (2019) and Smith *et al.* (2020) did not clearly describe how to make the different building blocks interact and what the 'scalable quantification platform' mentioned by Paustian *et al.* (2019) should be. For those reasons, in ORCaSa we aim at proposing a 'cookbook for a blueprint of an MRV framework for croplands SOC stock changes,' adapted to different context of MRV (CAP, NDCs, voluntary C market, insetting) and levels of availability/accuracy of farmer's activity data. Those cookbook and prototype built on the different building blocks listed above should consider the recommendations listed by the CIRCASA international consortium on soil carbon sequestration in Agriculture Soussana *et al.* (2020). The main recommendations are listed here below:

- A Tiered approach with for Tier 3, verifying systematically SOC change estimates from soil surveys and long-term fields sites, as well as eddy flux covariance.
- A high spatial resolution (ca. 10 m to include small fields and small owners) based on remote sensing.
- A high accuracy target even if a low initial accuracy is expected, but investment needs to attain high accuracy will be estimated each year.
- A three pillar structure: i) SOC pillar (involving soil science community, soil maps and digital soil mapping and remote sensing of surface soil), ii) Vegetation pillar (remote sensing of vegetation, phenology and biomass of cropland/grassland), and iii) Activity pillar (agricultural activities based on statistics or on self-reporting).
- A modular structure, each pillar derives products that are coupled with other pillars products to derive gridded ΔSOC estimates with their associated uncertainties, specifying the activity that caused the changes.
- Ensembles of calibrated models rather than single models should be used when possible, and synergies with other model consortia (e.g., climate change modellers) should be explored.
- A strong data infrastructure providing seamless access by multiple users and using the FAIR principles. It would include options for self-reporting especially for activities currently not reported (e.g., organic fertilisers, and crop residues).
- A gradual implementation, combining proxies at global scale in the first year (e.g., changes in annual duration of vegetation cover in arable systems could be used as a proxy of OC input to soil) and advanced implementation in pilot areas.
- Provision of resources for ground truthing and for calibration data (e.g., calibration of NPP at eddy flux covariance sites, direct measurements of crop residues etc.).

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OrCaSa also has the ambition of producing a first prototype of scalable quantification platform building on the AgriCarbon-EO operational processing chain for Tier 3 and an evolution of the NIVA's algorithms for Tiers 1 and 2 thereby meeting CIRCASA's recommendations. Yet uncertainty remains on the use of remote sensing for mapping soil surface as it is not clear yet how this information could be used in the monitoring process. Still, for Tier 3, we aim at using a hybrid modelling approach that should contain the following elements:

- A pre-processing module for 'Data ingestion' allowing the updating of existing data sets through automated downloading of e.g., satellite images, weather forcing, activity data and land use maps. Optical Bottom Of Atmosphere (BOA) reflectance of high-resolution optical satellites would be downloaded, uncompressed and relevant spectral bands would be stacked. The weather data would be stored in time series with the associated correspondence matrix to the high-resolution grid defined by the user (to match with remote sensing data). This would be done for the zone defined by the input land cover.
- Then biophysical variables (e.g., LAI) would be retrieved from the satellite reflectance images by inverting a radiative transfer model (e.g., PROSAIL). LAI estimates would be associated to an uncertainty estimate (e.g., following the BASALT approach described in Wijmer *et al.* 2023).
- Then some of the vegetation's model parameters would be inverted by assimilating LAI time series using again a Bayesian approach allowing to assess uncertainty on the output variables. Other parameters would be defined based on the land use maps (e.g., different parameters depending on the crop type). In the next step, the quantity of crop residues estimated through the modelled outputs (simulated plant biomass) and the activity data (e.g., are straw exported or not) and data on organic amendments would be used as input in a soil model simulating the dynamics of the SOC pools and the CO_2 emissions. Depending on the context of MRV, information on soil properties and SOC (content, stability etc.) to run the soil model/module may be obtained through soil products (e.g., SoilGrids) or in-situ data.
- Finally, a post-processing module would allow the construction of the output products based on the posterior crop model parameter distribution and the soil model. Geo-referenced maps of the variables of interest in each model (i.e., radiative transfer, vegetation and soil model) would be constructed as well as cumulative variables (e.g., net annual CO_2 fluxes over one cropping year).

Note that several radiative transfer models, vegetation or soil models could be used in parallel in each modelling step for ensemble approaches and without anticipating too much on the future results of the project, the overall architecture of the processing chain described above could be adapted to other ecosystems like forest and grasslands.

Yet, each ecosystem has its specificities, and some building blocks may have to be specific or implemented in a specific way. For instance, activities or software collecting activity data would differ for different ecosystems and models that would assimilate aboveground biomass estimated form remote sensing would rely on sensors of different wavelength: e.g., LiDAR or L band for forest (Yu and Saatchi 2016), C band (e.g. Sentinel-1) for cropland/grassland (Revill *et al.* 2013; Fieuzal *et al.* 2017; Baup *et al.* 2019). Because of other ecosystems like coastal one or even peatland it probably very challenging or impossible to develop a unique framework. For instance, monitoring SOC stock changes at peatland requires the use of SOC models adapted to organic soils (Premrov *et al.* 2021) and the assessment of the water table depth that is the main driver of

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SOC stock changes (Wilson 2016)[60]. Water table depth can be measured in situ but large scale monitoring of SOC at peatland may require the coupling of soil model adapted to organic soils coupled with hydrological modules.

4.2.2 Reporting and verification

On both those components of the MRV, the CIRCASA initiative made recommendations for cropland that could be adopted or adapted to the other ecosystems.

For reporting, CIRCASA suggested that it should primarily be through gridded data extraction (e.g., of the modelled outputs) for any spatially defined entity (e.g., a field, a farm, a small region, the sourcing area of an industry, or a given crop type, a country etc.) and any time period (e.g., a year for CAP or insetting programs to several years or decades for NDCs or offsetting projects). All SOC stock changes estimates should be provided with the same unit (e.g., g C m^{-2} or CO_{2eq} per time period selected) and an uncertainty estimate would be provided (if possible as RMSE) systematically. Uncertainties would be calculated by reference with verification methods, noting however that reference methods are also uncertain. For modelling approaches, we also recommend assessing the sources of uncertainties (e.g., input data) and to apply methods allowing uncertainty propagation as described in section 2.5.

Note that reporting could benefit from new technologies. For instance, collection of activity data for reporting could be do through new mobile phone technologies, online portal (Fritz *et al.* 2019) or connection to Farm Management Information Systems (FMIS) (Fountas *et al.* 2015) with APIs. Yet our own recent experience shows that activity data in FMIS may lack of reliability/consistency and may require to be checked by a third party (e.g., an agricultural council).

Concerning the baseline, we recommend an adaptative framework and some guidelines/tools that could allow both the accounting of regional and temporal baselines. The operational processing chain described above, would allow both as it could 1) produce information on several years prior, for instance, of a carbon farming program but also all along its life and 2) because this approach based on remote sensing and hybrid modelling allows to simulate plots/farms that have adopted or not C farming practices in the same region.

For verification, we recommend an approach that would be based on soil re-sampling (surveys, grids, demonstration farms, etc.) and remote sensing.

As suggested by CIRCASA, verification should target a high accuracy estimate of vegetation and SOC stock changes over the full soil profile, with sampling and analytical methods limiting biases in final vs. initial C stock estimates. For instance, using the same sampling protocol and tools, using geo-referenced sampling points, using the same analytical procedure done in a single lab.

The number of replicates of soil and vegetation samples in each site (e.g., field, farm, forested parcel) would be sufficiently high to provide a good accuracy (e.g., see CarboEurope or ICOS soil and vegetation sampling

[60] See also: https://www.ucd.ie/auger/t4media/AUGER_ FinalReport_ June 2021.pdf

protocol at eddy flux sites). Yet, in order to optimise the cost/accuracy ratio of verification, statistical studies would be required to design optimal initial and final soil sampling campaigns. In this perspective, pluriannual high resolution maps of biomass and SOC stock changes produced by hybrid modelling approaches assimilating remote sensing (e.g., AgriCarbon-EO) could be very useful as they would provide insights of the spatio-temporal dynamics of C stock changes. This information could be used to identify areas that preferentially store/lose C (e.g., because of soil conditions that are more or less favourable to plant development), allowing 1) a wider range of change in SOC stocks to be measured (than with a random sampling protocol) which is very useful for model's validation/verification, and 2) a sampling scheme more representative of the mean C stock dynamic of the plot/farm. Such an approach could allow a substantial reduction in the number of soil samples to be collected in order to detect SOC stock changes and with a more representative/accurate estimate.

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5. Conclusions

This review has shown that internationally, there is a wide range of application contexts (e.g., NDCs, CAP, voluntary C market, insetting), ecosystems (e.g., croplands, grasslands, forests, wetlands), frameworks, methodologies and guidelines for monitoring, reporting and verification for SOC (and GHG) changes. Similarly, a wide diversity of tools to assess possible effects of land use/management interventions on SOC stocks and GHG emissions are applied in different parts of the world, by a diverse range of stakeholders.

Considering this diversity, and the overarching societal/political demand for a consistent widely applicable and scalable MRV system, a novel framework for a generic MRV methodology was developed. The framework itself expands on earlier influential work (i.e., CIRCASA and CSU, with international partners) further detailing the individual 'building blocks' of each MRV component (i.e., monitoring, reporting and verification). Individual 'building blocks,' as comprehensively inventoried and discussed here, in-turn may be combined, or (re)used at different stages of the MRV cycle. We also emphasised the importance of uncertainty assessment throughout the entire MRV chain.

Current MRVs 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, and so on. A selection of current MRV guidelines and approved methodologies, as applied to various ecosystems in defined geographies, were characterised according to defined 'main characteristics', based on a pre-defined number of classes/options for each characteristic. Subsequent multi-dimensional scaling showed that the considered MRVs 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 indicated: in the future, it could be worthwhile to organise stakeholder workshops to jointly refine and possibly extend the list of key characteristics of approved MRV methodologies, while also assigning weights to each characteristic to evaluate the sensitivity of the results of the multidimensional scaling procedure to various choices.

The present review and analyses (Task 4.1 of the ORCaSa project) provide an outlook on the directions Task 4.2 ('Cookbook for a blueprint of an MRV framework for croplands SOC stock changes') and Task 4.3 ('Building an integrative and multi-ecosystem MRV framework for SOC stock changes') of the ORCaSa project might take. Importantly, such a cookbook should consider decision trees for identification of appropriate calculation approaches (i.e., Tier 1, 2 or 3 type) based on data availability and local conditions. Many hybrid and process-based models, for example, require a high level of specialised knowledge to understand and assess their overall performance and quality. They will need to be accommodated in user-friendly SOC tools.

In addition to the above conclusions, some general observations can be made:

- Adapting or developing new approaches to an MRV methodology applicable in a new country or region is not a simple task. Such procedures must consider local economic, environmental and social factors, including farming systems, soil and climatic conditions, regulations, social norms and values.

- There is a need to decouple SOC sequestration, a longer-term goal mainly aimed at climate change mitigation (and carbon offset markets), from storing (or using) SOC in soil to ensure soil health and food security. This corresponds with the well-known 'carbon-dilemma', i.e., placing more value on soil carbon stocks than the value of soil for other ecosystem goods and services, which could have adverse side-effects such as land grabbing.
- Importantly, farmers should be duly represented/organised in (new) sub-national scale MRV systems, which operate at the landscape scale, so as to facilitate their access to voluntary carbon markets and help improve their livelihoods. Carbon pricing itself will be an important economic incentive, in particular for those farmers that have a short-term objective (i.e., timescales for long-term gains in soil C are a challenge for farmers with shorter term horizons).
- A hybrid monitoring approach that combines in-situ measurements with process-based or hybrid-models is likely a better solution than relying on such models alone.
- Additional soil sampling will be needed to improve the accuracy and scalability of the models themselves by benchmarking them with independent and high-quality measurements from soil sampling.
- There is a need for a global soil resources centre to bring together old (i.e., existing) and newly collated soil data in a uniform, harmonised way for the benefit of the international community. Mechanisms should be developed through which data held by private organisations as well as commercial companies can be accessed freely through a federated, global soil information system, using open standards, with the source data themselves remaining with the respective data providers.
- Research has indicated the need for soil monitoring (to at least a meter depth) to accurately capture the total net SOC changes under differing managements systems, as well as equivalent mass based calculation of SOC stock changes.
- There is an emerging discussion regarding the linkage of SOC and landscape carbon stocks with biodiversity in the policy and market domain. This would mean the MRV products in the future should be linked across the biodiversity and carbon, and also consider the provisioning of other ecosystem goods and services, in particular water quantity and quality.
- Although there is a need for a generic global MRV framework, applicable at various scale levels, for SOC change to support improvements in soil carbon management respectively sequestration, currently there may be an imbalance in monitoring and verification developments with a shift towards commercialisation and a lot of theoretical development (models and frameworks) but insufficient field experimentation providing data to support these. "New" studies on farming that reflect the future of farming, e.g., sustainable systems, should be accounted for.
- The demand for carbon offsets will be exacerbated by countries and private companies that want to win the "race to carbon neutrality", while "circumventing" the need to reduce fossil-fuel emissions themselves. Safeguards against "greenwashing" through uncertainty quantification and solid verification by independent suitably experienced and qualified third parties will be essential.

However, verifiers may not have the right expertise, and many will not have the modelling experience, pointing at a need for training capacity.

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APPENDIX - Example of a support MRV protocol

Prior to defining a list of characteristics that should be considered when evaluating/comparing different MRV initiatives and related methodologies we will discuss an example, to illustrate a possible workflow. For this, we will use the GSOC-MRV framework (FAO-GSP 2020). The framework was elaborated and subsequently reviewed by a wide range of international experts; as such, arguably it may be seen as a global standard for the development/application of an MRV system at various scale levels. It consists of a series of step-by-step stages and sub-protocols needed in order to assess SOC changes and GHG emissions/removals by the adoption of sustainable soil management (SSM) practices.

The GSOC-MRV framework comprises six successive stages:

- Stage 1: Applicability conditions, is intended to verify that the project and activities meet the necessary requirements for this methodology to be applicable (considers: scale, eligible and restricted lands, land uses and management practices).
- Stage 2: Define spatial and temporal boundaries for the project.
- Stage 3: Define baseline (business-as-usual) and projected intervention scenarios and practices. Includes defining indicate historic and projected relevant activity data for the different areas to be assessed (e.g., areas, crops, yields, tillage practices, fertiliser use, organic amendment use, livestock density).
- Stage 4: Preliminary assessment of the additionality of the projected practices (i.e., assess how much carbon would be sequestered in soils and how much GHG emissions will be reduced, compared to a situation in which the proposed technologies or changes would not have existed).
- Stage 5: Monitoring is implemented to monitor effects of implemented practices (can include field sampling as well as modelling).
- Stage 6: Reporting and verification. In the FAO protocol, following up on the pre-implementation report, bi-annual reports are made describing performed activities, soil sampling results and modelling estimates. Verification of results/ projections should be done by an independent party; as such, it seems desirable to define “verification” as a separate stage (e.g., stage 7).

As shown in Figure 8, the successive steps can be subdivided into a ‘pre-SSM implementation phase (includes stages 1 to 3), ‘SSM-implementation’ phase (includes stages 4 and 5), and ‘Reporting a verification’ phase (stage 6 resp. 7). Appropriate methodologies and protocols that may be used during the successive stages of monitoring are succinctly described in the GSOC-MRV report. The framework also includes suggestions and guidelines concerning the various responsibilities of parties when implementing the MRV framework.

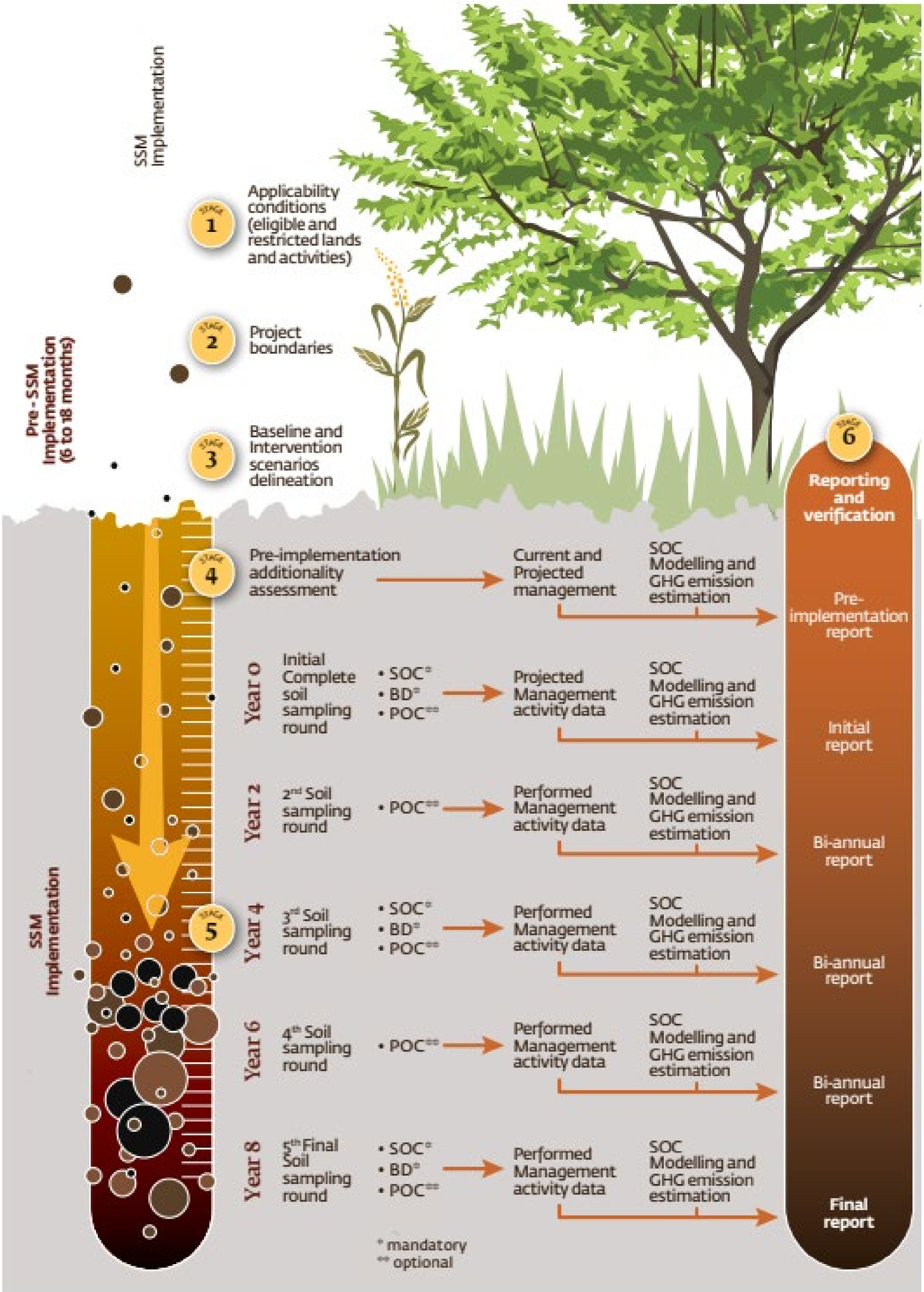

Figure 8 Example of support MRV protocol (Credit: FAO-GSP 2020).

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GLOSSARY

Source: This list of terms has been derived from various sources[61].

Additionality: A demonstration that carbon sequestration and/or reductions in GHG emission associated with the adoption of new land management practices would be greater than the 'business as usual' scenario and would not happen without incentives from the carbon markets. (This is one of four factors to consider when acquiring carbon offsets, i.e., a core provision for environmental integrity in carbon markets.)

Abatement: Refers to reducing the amount of GHG emissions released to the atmosphere (from soil) and/or increased amounts of (soil) carbon sequestered in the environment via the removal of GHGs already in the atmosphere.

Article 6: The cooperation mechanisms enshrined in Article 6 of the Paris Agreement offer Parties the opportunity to cooperate with one another when implementing their nationally determined contributions (NDCs).

Baseline: A baseline scenario assumes the continuation of pre-project conditions, including agricultural management practices. This forms the reference point for determining the outcomes from a soil carbon project with the use of MRV. For soil carbon projects, baselines may be dynamic or fixed. The former will be updated throughout a project while the latter will reflect conditions prior to the start of a project.

Baseline scenario: The most likely scenario in the absence of the crediting mechanism, including all assumptions on drivers for relevant emission reductions.

Building blocks (of MRV framework): One of the separate parts that combine to make the MRV. For example, databases (e.g., soil, management, plant models, soil SOC/GHG models, remote sensing). Building blocks can be assembled in an operational processing chain to be applied in one or several contexts of applications (e.g., CAP, Carbon market, NDC). Note that the same building blocks can be used in one or several components of an MRV (e.g., M or R, see Figure 4 in report itself). [Source: ORCASA]**Cap and trade:** A regulatory procedure that puts a 'cap' on the amount of greenhouse gas emissions that companies are permitted to emit. Firms that come in under their limitations have the option to 'trade' (sell) their excess emission permits to other companies that have exceeded their limit.

[61] This glossary is provided for 'general information.' It is not necessarily authoritative on all terms listed. For example, recent EU-Projects such as MARVIC are specifically focussing on developing a standard "glossary of definitions for the EU MRV Framework for carbon farming." The main sources consulted here are: https://irc-orcasa.eu/ (in consultation with the EU MARVIC's evolving 'Glossary of definitions'); https://carboncredits.com/carbon-credits-glossary/ ; https://ahdb.org.uk/knowledge-library/carbon-a-glossary-of-terms; and, https://apps.ipcc.ch/glossary/.

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Carbon brokers: An individual or company that work with buyers and sellers of carbon credits to facilitate carbon trading. This can be driven by buyers looking to source offsets, or matching creators of carbon credits with a market. Brokers are not themselves regulated, so buyers and sellers should exercise due diligence before engaging with a broker.

Carbon credit: The unit that is certified by a carbon credit programme or standard for trade in carbon markets, representing one metric tonne of carbon dioxide equivalent. Verifiable soil carbon credits will be determined through the relevant quantification approach and MRV methods.

Carbon dioxide equivalent: A metric, often written as CO_{2eq}, used to compare GHGs on the basis of their global warming potential, by converting amounts of other gases, usually nitrous oxide and methane, to the equivalent global warming potential of carbon dioxide. Note that the shorter life span of methane means that the calculation should be done on a 20-year rather than 100-year basis for this gas.

Carbon farming (CF): The management of carbon and GHG fluxes, with the purpose of mitigating climate change. This involves the management of both land and livestock, all carbon pools in soils, vegetation and harvested products, plus fluxes of CO_2 and CH_4, as well as N_2O. The outcome of CF can be: 1) carbon removals, 2) avoided emissions, 3) reduced emissions, or a combination of them. [Source: ORCASA]

Carbon farming scheme (CF scheme): Governance system regulating a set of CF projects and the monetisation of their outcomes. A CF scheme consists of guiding principles, rules and methodologies for monitoring, reporting and verification (MRV). Synonyms : carbon (payment) programme, carbon standard. [Source: ORCASA].

Carbon farming programme, Guiding principles :

1) *Additionality*: implies that the generated emission reductions and/or carbon removals would not have occurred under the 'business-as-usual' scenario (i.e., without the carbon finance or incentive)

2) *Permanence*: indicates the sustained climate mitigation effect in the long-term

3) *Double counting*: appears when a climate benefit (a quantity of CO_{2eq}) is reported twice (or more) either by two different actors into the same sector, or by one (or more) actors in another sector

4) Carbon *leakage*: the (unintended) spatial shift of GHG emissions and/or the shift in GHG emissions within or outside the spatial scope of the CF project due to trade-offs (e.g., due to emissions in other carbon pools or emission types) caused by the implementation of CF practices ; and,

5) Management of *uncertainties and risks* (U&R) — Procedures and buffers adopted to cope with U&R to guarantee that climate benefits have not been overestimated due to uncertainty in the monitoring method (calculation U&R) or by unexpected or accidental human or natural disturbances (project U&R). [Source: ORCASA].

Carbon farming, rules for: Basic agreements for establishing and implementing CF projects, such as the guiding principles and the processes from project plan to certification.

Carbon inset(ting): A broad term to describe emission reductions or removals achieved within the supply chain of an entity that are used to compensate for entity emissions; a carbon credit secured through investment within the supply chain of an entity. Aimed at offsetting a company's emissions or environmental and social impacts, within the supply chain.

Carbon finance: Finance that intends to reduce the impact of greenhouse gas emissions. The term can refer to the concept or methodology of channelling finance towards emissions reducing activities, or the flow of finance or investments themselves.

Carbon market: A market in which units — allowances or credits — are traded between entities. When units are used for voluntary purposes or where carbon credits are certified solely by voluntary programs or standards, the market is often referred to as a 'voluntary' carbon market (VCM). Where units are used to satisfy legal compliance obligations, this is often referred to as a 'compliance' market.

Carbon neutrality: Worldwide equilibrium between anthropogenic emissions and anthropogenic absorption. As such, an organisation, product, or service cannot be carbon neutral by itself but can contribute to achieving global carbon neutrality. The objective of carbon neutrality is twofold: to reduce the total amount of emissions and increase absorption capacity.

Carbon offset(ting): The use of carbon credits, or other units, to compensate for a country's or company's emissions covered by a compliance or voluntary target. Often used when the carbon credit is generated outside of a country or company supply chain to compensate for the country's or company's emissions.

Carbon offset standards: Recognised standards, protocols or/and methodologies to guide GHG quantification, monitoring and reporting.

Carbon registry: Independent authority that approves, lists, and tracks a carbon credit's ownership. See for example the American Carbon Registry (ACR), EU Emissions trading Register (EU-ETS) and VERRA.

Carbon sequestration: The removal of carbon dioxide from the atmosphere and storage in another system, such as soil or vegetation. If the carbon dioxide sequestered is more than the carbon dioxide emitted, the store is increasing and is known as a carbon sink.

Carbon sink: A forest, ocean, land, or soil that absorbs more carbon dioxide than it emits.

Carbon stock: The absolute mass of carbon in a (soil) sample of known volume — typically expressed in tonnes per hectare to a specific depth, or preferably and equivalent mass basis (see Wendt and Hauser (2013)).

Carbon trading: A market used to manage greenhouse gas emissions; instead of cutting their own emissions to meet mandatory targets, companies can pay someone else to cut theirs, or to sequester carbon.

Certification (of carbon credits): Voluntary emission reduction (VER) are carbon credits issued by a verified project. Standards such as VCS or the Gold Standard follow a rigorous methodology to certify the projects and their carbon credits. For a project to be certified, it has to be ***real*** (proven to have taken place), ***measurable*** (all emission reductions/removals have to be quantifiable using recognised measurement tools, with uncertainty and leakage taken into account, against a credible emission baseline), ***permanent*** (in the case of a risk of reversibility, adequate safeguards need to be implemented), ***additional*** (see above), ***independently verified*** (by an independent qualified third party) and ***unique*** (no more than one carbon credit can be associated with a single emission reduction or removal as one metric ton of carbon dioxide equivalent (CO_{2eq})). [Source: SBTI].

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Climate contribution: Supporting an emission reduction project in the Voluntary Carbon Market that not only captures or avoids greenhouse gas emissions but also contributes to the United Nations Sustainable Development Goals. Climate contribution is different from carbon offsetting as there is no definite point of arrival: the more contribution and emission reduction, the more benefits for the planet.

Co-benefits: Additional positive externalities of carbon reduction project, which target the United Nations Sustainable Development Goals (UN SDGs).

Code: The GHG accounting rules that determine project eligibility, additionality, and baseline and project emissions for a particular project type. The code also includes the program requirements for monitoring, reporting, verification, and certification. The terms code, protocol, and methodology are often used interchangeably (which can be confusing).

Compliance markets: Also known as *mandatory markets*, are governed by national, regional, or provincial law and compel emission sources to meet legally mandated GHG emissions reduction targets. Because compliance programmes offset credits are generated and traded for regulatory compliance they typically act like, and are priced like, other commodities.

Crediting period: The period over which credits can be generated for a project, typically between 7 and 25 years. For some codes, a crediting period can be renewed at the end of the term.

Double counting: Term describing the situation in which two parties claim the same carbon removals or emission reductions.

Ecosystem services: The diverse range of services that we derive from the natural environment. Four categories of ecosystem service have been identified: Provisioning, Regulating, Cultural, and Supporting.

EU farming initiative: There are four key elements in the EU carbon farming initiative: adopting a common standard for Monitoring, reporting, and verification; a regulatory Framework for certifications on carbon removals; Knowledge transfer to farmers; and, access to Funding options.

Global warming potential (GWP): The global warming potential of a gas refers to the total contribution to global warming over a defined time frame resulting from the emission of one unit of that gas relative to one unit of the reference gas, carbon dioxide, which is assigned a value of one.

Gold Standard Verified Carbon Standard (GS VER): A non-governmental emission reductions project certification scheme. It participates in the Clean Development Mechanism (CDM), the Voluntary Carbon Market, and many climate and development initiatives.

Greenhouse gases (GHG): Gases that trap heat in the atmosphere. Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases are the primary greenhouse gases. See also: Carbon Dioxide Equivalent.

Greenwashing: A behaviour or some activities that make people believe that a company is doing more to protect the environment than it really is (see here for examples).

Guidelines: A practical translation of the MRV framework [Source: ORCASA].

Insetting: See carbon insetting.

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ISO 14064-1:2018: Standard that specifies principles and requirements at the organisation level for the quantification and reporting of greenhouse gas (GHG) emissions and removals. It includes requirements for the design, development, management, reporting and verification of an organisation's GHG inventory. The ISO 14064 series is GHG programme neutral. If a GHG programme is applicable, requirements of that GHG programme are additional to the requirements of the ISO 14064 series.

Leakage: Leakage is used to account for increased GHG emissions or losses in carbon sequestration beyond a project boundary which have occurred as a result of the project. For example, lower productivity or intensification of land use or management elsewhere.

Mandatory market: Synonym for compliance market.

Monitoring (M in Figure 4)**:** Process of quantifying the net climate mitigation impact of a CF project, including all necessary steps from establishing a baseline (or business-as-usual scenario), to comparing this baseline to a project scenario (e.g., through measurements or modelling). [Source: ORCASA and MARVIC].

MRV: Monitoring, Reporting and Verification (MRV) is a key component of all carbon projects. Information from a carbon project is monitored and reported on a regular basis throughout the crediting and permanence periods. A verification stage then validates that a project has performed as predicted and that anticipated carbon outcomes have been realised, based on the reporting.

MRV framework: Set of guiding principles and rules for implementing CF and forest projects, and definition of methodologies for monitoring, reporting and verification (MRV) of carbon farming projects. For instance, it will define:

- the duration of the projects
- the boundaries of the projects: scale (e.g., parcel/farm level) and Land Use considered for projects
- which type of forest project (e.g., afforestation, protection) or CF practices are accounted for (e.g., will it consider biochar, reduction in mineral fertilisers)
- how is the baseline defined: *regional baseline* (e.g., considering the management practices/cropping or forest systems usually implemented in the region surrounding the farm) or *local baseline* (e.g., considering the management/cropping system of the previous 3 years before stating the CF project)
- the monitoring methods that can be used for calculating C storage and avoided/reduced emissions.
- depth of the soil to be considered for assessing SOC stock changes, and,
- discount depending on the accuracy of the monitoring method. [Source: ORCASA]

MRV method: Guidance and requirements for MRV are generally stipulated in an MRV Method or Protocol document approved and issued by a carbon programme organisation. Specific MRV approaches for a soil carbon project will reflect their application of this MRV document to the project's circumstance.

MRV templates: MRV templates are forms that go with specific guidelines and need to be filled in. [Source: ORCASA]

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Nationally Determined Contributions (NDCs): Countries' self-defined national climate pledges under the Paris Agreement, detailing what they will do to help meet the global goal to pursue 1.5°C, adapt to climate impacts and ensure sufficient finance to support these efforts.

Nature-based solutions: These solutions involve working with nature to address societal challenges, providing benefits for both human well-being and biodiversity. Specifically, they are actions that involve the protection, restoration, or management of natural and semi-natural ecosystems; the sustainable management of aquatic systems and working lands, such as croplands or timberlands; or the creation of novel ecosystems in and around cities. They are actions that underpin biodiversity and are designed and implemented with the full engagement and consent of local communities and Indigenous Peoples.

Net negative: Tonnes of GHGs avoided, reduced or removed that exceed the unabated GHG emissions.

Net zero: A means to reach global carbon neutrality. Net zero corresponds to a situation where the amount of an organisation's greenhouse gas emitted is equal to the amount of greenhouse gas captured or removed from the atmosphere (see also Greenwashing).

Offsetting: See Carbon offsetting

Offset certificates: Paper licences provided in exchange for the purchase of carbon credits. Offset certificates should include a serial number unique to the offset, total tonnage bought, the verifier's name and signature, project location, owner's name and address, and a vintage date.

Paris Agreement: An international treaty on climate change that superseded the 1997 Kyoto Protocol. Signed in 2016, the agreement has been ratified by all but six countries in the world. The long-term goal of the Paris Agreement is to keep global warming below 2°C, and preferably limiting the increase to 1.5°C, and the treaty contains various provisions to enforce this target.

Permanence: A necessary condition for carbon projects to demonstrate that carbon credits reflect a long-term removal of GHGs. For soil carbon projects, this generally means the continuance of the positive carbon management practices to ensure that there are no reversals.

Permanent offsets: Offsets that are long-lasting or guaranteed to be replaced in the event of a loss. This is one of four factors to consider when acquiring carbon offsets.

Permanence period: The defined time period that sequestered C must remain sequestered during the period of the offset credits. The permanence period is individually defined by each code and can vary from one code to another.

Project area: The project area is the physical spatial area or areas submitted for certification. It contains the area required to successfully manage the explicit objectives of the project.

Project boundary: The clearly defined physical boundary or edges of the project that delineate the Project Area from non-Project Areas.

Project scenario: The Project Scenario is defined as the scenario that will exist once the Project is implemented and operational.

Protocols: Describe how a methodology should be implemented (e.g., how to measure SOC or biomass in the field, sample soils, or how to simulate the baseline and the stock change). [Source: ORCASA]

Real Offsets: Carbon offsets that have already actually reduced carbon emissions, as opposed to those that are expected to do so in the future.

Registry: Programme registries are the platforms which enable the trading of carbon credits. A registry facilitates the transparent listing of information on registered carbon projects including issued and retired carbon credits units.

Reporting (R in Figure 4): Process of communicating the monitored results/activity data (farmer's data, earth observation (EO), between project developers (farmer, cooperatives…) and the owners of a CF scheme (e.g., Ministry of Environment for the Label Bas Carbone). Reporting typically details project results, or progress and impact, based on a standardised communication process and a standardised set of proofs and data (generated from the monitoring methods). Reporting can include the flow of data towards a registry [Source: ORCASA and MARVIC].

Regulated carbon market: Market where members are legally obligated to reduce their emissions.

Requirements: Elements (rules, procedures, guidelines) that the activity must conform to in order to proceed through Validation/Verification and ultimately Certification.

Retire: To permanently remove carbon offsets from the market in order to prevent them from being resold after they have been used up. Offsets are typically decommissioned by assigning them unique serial numbers and registering them in an official registry.

Reversal: Reversals are a component of permanence and used to account for losses from a project's net sequestered carbon. Reversals can be intentional (e.g., ploughing) or unintentional (e.g., extreme weather).

Rules for carbon farming: Basic agreements for establishing and implementing CF projects, such as the guiding principles and the processes from project plan to certification (see also **Carbon farming, rules for**). [Source: ORCaSa].

Soil inorganic carbon (SIC): The amount of (mineral forms of) carbon in soil held in carbonates.

Soil organic carbon (SOC): The amount of organic carbon stored in organic matter in the soil. It comes from decomposing plant material and is vital for soil health. About 58% of soil organic matter is carbon.

Tier levels: A tier represents a level of methodological complexity (in the 2006 IPCC Guidelines). Usually, three tiers are provided. Tier 1 is the basic method (based on IPCC default values), Tier 2 intermediate (allows for location-specific coefficients) and Tier 3 (uses mechanistic SOC and biogeochemical models) the most demanding in terms of complexity and data requirements. Tiers 2 and 3 are sometimes referred to as higher tier methods and are generally considered to be more accurate on condition that adequate data are available to develop, evaluate and apply a higher tier method (IPCC 2019c).

Validation: An independent process for the evaluation of a carbon project plan to establish that the project should achieve the predicted carbon abatement and meets relevant eligibility and other programme criteria.

Verifiable offsets: Carbon offsets that can be quantified, tracked, and validated are known as verifiable offsets. (This is one of four factors to consider when acquiring carbon offsets.)

Verification (V in Figure 4)**:** Ability of (independent) external parties to check the truthfulness and accuracy of project outcomes (e.g., soil analysis to measure SOC stock changes, remote sensing to verify that a practice

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was implemented (or not)). A proper verification ensures that the project is implemented according to its proposed rules (e.g., was the baseline correctly defined), methodology, and guiding principles. Hence, an authorised third-party auditor must also conduct an impartial review of the carbon offset project design and baseline calculations prior to the start of project activity. [Source: ORCASA and MARVIC].

Verifier: An accredited (reputable, competent) and independent person or persons with responsibility for performing and reporting on the verification process.

Verra: One of the main carbon credit registries for voluntary carbon credits (alongside The **Gold Standard**). Verra is a non-profit and the first organisation to create an internationally recognised methodology to provide quality assurance to voluntary carbon markets.

Voluntary Carbon Market (VCM)**:** A carbon market in which members are not legally compelled to reduce their emissions but do so voluntarily. These markets enable carbon emitters to offset their emissions by acquiring carbon credits generated by third-party initiatives aimed at removing or decreasing GHG emissions from the environment. Companies can engage in the voluntary carbon market on their own or as part of an industry-wide programme.

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