

**Monitoring, reporting and verification of soil
organic carbon stock changes at arable land:**

**Cookbook for assessment in different MRV contexts and
proposition of a harmonised approach**

Deliverable 4.2

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MONITORING, REPORTING AND VERIFICATION OF SOIL ORGANIC CARBON STOCK CHANGES IN ARABLE LAND: COOKBOOK FOR ASSESSMENT IN DIFFERENT MRV CONTEXTS AND PROPOSITION OF A HARMONISED APPROACH

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Table of Content

EXECUTIVE SUMMARY	XVI
Scope of this document	XVI
Target audience	XVII
Methodology and key results	XVII
Research and technical implications	XVIII
Policy implications.....	XX
1 INTRODUCTION	1
2 CONTEXTS OF APPLICATION OF MRV	9
3 COMPONENTS OF THE MRV FOR SOC	13
4 PROPOSITION FOR A HARMONISED METHODOLOGICAL FRAMEWORK FOR MONITORING SOC	15
4.1 State of the art	15
4.2 Proposition for a harmonised methodological framework for MRV of SOC for cropland ..	19
4.2.1 Project information system.....	20
4.2.1.1 Spatial and temporal boundaries	20
4.2.1.2 Eligibility of the land and context of the MRV for SOC	21
4.2.1.3 Eligibility of the CF practices.....	22
4.2.1.4 Setting the baseline.....	23
4.2.1.5 Uploading of local data	28
4.2.1.6 Decision support system	30
4.2.1.7 Choice of the monitoring, reporting and verification methodologies.....	31
4.2.2 Uploading of spatial data	32
4.2.2.1 Soil types and soil properties maps.....	32
4.2.2.2 Weather data.....	33
4.2.2.3 Land use maps	34
4.2.2.4 Earth observation data	35
4.2.3 Radiative transfer model and data assimilation	37
4.2.4 Evaluation and improvement	42
5 METHODS FOR MONITORING SOC	43
5.1 Soil sampling for monitoring SOC.....	44
5.1.1 Sampling design choices.....	45
5.1.2 Hypothesis testing, costs and accuracy.....	46

5.1.3	Sampling protocols.....	48
5.1.4	Soil sample analysis.....	49
5.2	Other data acquisition methods.....	50
5.2.1	Spectroscopy	51
5.2.2	Other soil sensing methods	53
5.3	Modelling SOC stock changes	54
5.3.1	Tier 1	57
5.3.2	Tier 2	59
5.3.3	Process-based modelling (Tier 3).....	61
5.3.3.1	Soil-centred modelling approach	62
5.3.3.1.1	Soil centred modelling approach without EO assimilation.....	63
5.3.3.1.2	<i>Assessing the baselines for the soil centred approach.....</i>	<i>69</i>
5.3.3.1.3	Soil centred modelling approach with EO assimilation	70
5.3.3.1.4	<i>Assessing the baselines for the soil centred approach with EO assimilation</i>	<i>72</i>
5.3.3.2	Ecosystem modelling approach	74
5.3.3.2.1	Ecosystem modelling approach without EO assimilation	74
5.3.3.2.2	Ecosystem modelling approach with EO assimilation	81
5.3.3.3	Summary of the pro and cons of the different Tier 3 modelling approaches.....	91
5.3.4	Data driven models	93
5.3.5	Guidance on the evaluation of uncertainties associated with the quantification approaches.....	97
5.3.5.1	Scope of this section.....	97
5.3.5.2	Differentiating uncertainties in accreditation and quantification steps.....	98
5.3.5.3	Sources of uncertainties.....	99
5.3.5.4	Propagation of uncertainties	101
5.3.5.5	Upscaling uncertainties	102
5.3.5.6	How to reduce uncertainties	102
5.4	Which method to choose depending on the context and data available	104
6	REPORTING	110
6.1	Reporting SOC stock changes for National Inventories.....	110
6.2	Reporting SOC stock changes for the VCM	110
7	VERIFICATION	112
7.1	Verifying SOC stock changes.....	112
7.2	Verifying activities.....	114

8 FUTURE RESEARCH AND CALL FOR ACTIONS TO ACHIEVE THE IMPLEMENTATION OF AN INTERNATIONAL HARMONISED METHODOLOGICAL FRAMEWORK FOR MRV OF SOC FOR CROPLAND.....	117
8.1 Need for methodological improvements of the monitoring component	117
8.1.1 Improvement of the in-situ data acquisition techniques.....	117
8.1.2 Improvement of the Tier 3 models and SQPs for monitoring SOC.....	119
8.1.3 Improving models and SQPs evaluation.....	122
8.1.4 Accounting for the net climatic effect of CF practices and assessing other agri-environmental impacts	123
8.2 Alignment with other international initiatives and call for action to implement an international framework for MRV of SOC for cropland.....	125
9 ACKNOWLEDGEMENTS	129
GLOSSARY.....	130
REFERENCES.....	136
ANNEXE 1: EXAMPLES OF SCALABLE QUANTIFICATION PLATFORMS FOR MRV OF SOC FOR CROPLAND.....	13680
1 OPERATIONAL SQPS	184
1.1 COMET-FARM.....	184
1.1.1 General description	184
1.1.2 DayCent in COMMET-Farm.....	185
1.1.3 System boundaries.....	186
1.1.4 Geographic limitations	186
1.2 Australian National Scale carbon accounting methods	187
1.2.1 General description	187
1.2.2 FullCAM	187
1.2.3 Modified IPCC (2019) Tier2 Steady-state method.....	189
1.3 Carbon Extract.....	190
1.3.1 General description	190
1.3.2 Features	190
1.3.3 Advantages and limitations	191
1.4 Soils Revealed	191
2 PROTOTYPES OF SQPS	192
2.1 AgriCarbon-EO	192
2.1.1 General description	192

2.1.2	Advantages and limitations	195
2.1.3	Future developments	195
2.2	FiON	196
2.2.1	General description	196
2.2.2	Future developments	197
2.3	The Retina project	198
3	REFERENCES ANNEX	199

LIST OF FIGURES

<i>Figure 1. Sustainable Development Goals from United Nations Environment Program (2023).</i>	<i>1</i>
<i>Figure 2. Schematic representation of the carbon budget component approach aiming at quantifying annual ΔSOC stock changes from the C fluxes, vertical fluxes of CO₂, i.e. the net annual CO₂ flux exchanges with the atmosphere (photosynthesis, GPP; plant respiration, Ra; heterotrophic respiration, Rh) and lateral carbon fluxes, i.e. the amount of C exported at harvest (e.g. grain, straw, tuber) and C inputs as organic amendments.</i>	<i>3</i>
<i>Figure 3. Schematic representation of components and information flow for an approach to quantify soil organic 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 (Source: Paustian et al. (2019)). .</i>	<i>4</i>
<i>Figure 4. Building blocks of a soil monitoring, reporting and verification framework. The letters M, R and V indicate to which component(s) each building block could contribute (Source: Smith et al. 2020).</i>	<i>4</i>
<i>Figure 5. Schematic representation of the different contexts of application of MRV.</i>	<i>9</i>
<i>Figure 6. Schematic representation of components, building blocks, and information flow for a generic, scalable MRV system (Batjes et al. 2024).</i>	<i>14</i>
<i>Figure 7. Schematic representation of the FAO GSOC-MRV Protocol (2020).</i>	<i>16</i>
<i>Figure 8. Proposition for a multi-ecosystem methodological framework depicting a modular flowchart for building an operational MRV tool for assessing net SOC stock changes (abbreviations: A.I., artificial intelligence; M.L., machine learning; IR, infrared; FMIS, Farm Management Information system). Source Batjes et al. (2024).</i>	<i>17</i>
<i>Figure 9. Schematic representation of a harmonised methodological framework for MRV of SOC stock for cropland (abbreviations: A.I., artificial intelligence; M.L., machine learning; IR, infrared; FMIS, Farm Management Information system). Adapted from Batjes et al. (2024).</i>	<i>19</i>
<i>Figure 10. The red frame indicates which part of the MRV framework from Figure 9 will be addressed in this section</i>	<i>20</i>
<i>Figure 11. On the left, 10m resolution simulation of net annual CO₂ fluxes over one cropping year near Toulouse (France) with the AgriCarbon-EO V1.0.1 processing chain (assimilating Sentinel-2 EO data) for maize fields where the cover crops preceding the maize have been ignored in the simulation, and on the right the same fields but considering the effect of the cover crops on the net annual CO₂ fluxes computed with AgriCarbon-EO. The</i>	

difference between the two simulations represents the amount of C input to the soil through the cover crop biomass. (adapted from Al Bitar *et al.* IGARSS 2022). 24

Figure 12. On the left, 10m resolution simulation of SOC stock changes over 5 years (2017-2021) near Toulouse (France) with the AgriCarbon-EO V2.0 processing chain for crop rotations including straw cereals, maize, sunflower and cover crops considering standardised management practices with no organic amendment and straw retention (Wijmer, 2024). In AgriCarbon-EO V2.0, the biomass input to the soil simulated with AgriCarbon-EO V1.0 (Wijmer *et al.* 2024) are used as input for the AMG soil model (Clivot *et al.* 2019) to simulate SOC stock changes. On the right, SOC stock trends for each plot simulated on the left and belonging to one of the four categories of crop rotation shown and having between 0 and 3 cover crops during the crop rotation. The mean of each category of crop rotation x frequency of cover crop, shown with a dashed line, correspond to a hybrid dynamic average baseline in the sense that it considers standardised soil properties (LUCAS maps) and standardised management practices for organic amendments and straw management but plot specific management for cover crops and implicitly the other management practices (e.g. fertilisation, sowing date or density) through the EO data assimilation process in the SAFYE-CO2 crop model (Pique *et al.* 2020 a,b,c). Credits: Taeken Wijmer. 25

Figure 14. The red frame indicates which part of the MRV framework will be addressed in this section 32

Figure 15. The red frame indicates which part of the MRV framework will be addressed in this section 37

Figure 16. Schematic representation of different methods for the assimilation of remotely sensed model state variables in crop models: (a) crop model calibration, (b) forcing methods, and (c) updating methods. (from Jin *et al.* 2018, adapted from Delécolle *et al.* 1992). 41

Figure 17. The red frame indicates which part of the MRV framework will be addressed in this section 42

Figure 18. The red frame indicates which part of the MRV framework will be addressed in this section 44

Figure 19. The red frame indicates which part of the MRV framework will be addressed in this section. 50

Figure 20. Schematic Generic decision tree for identification of appropriate tier to estimate SOC stock changes in mineral soils by land use category (Source: Figure 2.4 from IPCC 2006). 56

Figure 21. The red frame indicates which part of the MRV framework will be addressed in this section. 57

Figure 22. Pro and cons of the Tier 1 approach. 59

Figure 23. The red frame indicates which part of the MRV framework will be addressed in this section. 59

Figure 24. Pro and cons of the Tier 2 approach. 60

Figure 25. The red frame indicates which part of the MRV framework will be addressed in this section. 61

Figure 26. The red frame indicates which Tier 3 modelling approach will be addressed in this section. 63

Figure 27. The red frame indicates which Tier 3 modelling approach will be addressed in this section 70

Figure 28. Schematic representation of the soil centred approach for modelling SOC stock changes and of its pro and cons in a MRV context. 73

Figure 29. The red frame indicates which Tier 3 modelling approach will be addressed in this section. 74

Figure 30. Schematic representation of the “Off-the-shelf” strong coupling ecosystem modelling approach without EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context Credits A. Ihasusta..	80
Figure 31. The red frame indicates which Tier 3 modelling approach will be addressed in this section	81
Figure 32. Schematic representation of the “on the shelf” strong coupling ecosystem modelling approach with EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context. Credits A. Ihasusta	85
Figure 33. Schematic representation of the “parsimonious” light coupling ecosystem modelling approach with EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context. Credits A. Ihasusta	90
Figure 34. Decision tree designed to choose the SOC stock changes monitoring approach according to the MRV context of application and to the local context. Credits A. Ihasusta	106
Figure 35. The red frame indicates which part of the MRV framework will be addressed in this section.	110
Figure 36. The red frame indicates which part of the MRV framework will be addressed in this section.	112
Figure 37. The red frame indicates which part of the MRV framework will be addressed in this section.	112
Figure 38. Annual carbon budget map at 10m resolution in 2019 produced by assimilating Sentinel-2 EO data in the AgriCarbon-EO processing chain (Wijmer <i>et al.</i> 2024) at a farm in South West France. Greenish fields that are sequestering carbon in most of their area were cultivated that year with faba bean cover crops and maize while the yellowish/orange fields were cultivated that year with winter wheat and are mostly losing carbon. The blue dots represent potential <i>in-situ</i> locations for an optimal soil sampling scheme who benefits from the high spatio-temporal resolution of the information on SOC stock trends in order to measure representative SOC stock changes at field/farm scale or to verify SOC stock changes with a high cost-accuracy ratio (low number of soil samples reducing the cost for analysis but matching the scale of simulation, good accounting of the distribution of SOC stock changes at field/farm level and representative of their mean SOC stock changes).	114
Figure 39. The red frame indicates which part of the MRV framework will be addressed in this section.	115
Figure 40. Overview of the FullCAM modelling framework used to simulate carbon flow within agricultural production systems in Australia. Note: De: decomposable plant material; Re: resistant plant material.	188
Figure 41. Key model inputs that govern the FullCAM framework simulations for the agricultural production systems	189
Figure 42 : Schematic representation of the AgriCarbon-EO V2.0 pre-operational processing (credits A. Albitar, T. Wijmer, E. Ceschia adapted from Wijmer <i>et al.</i> 2024).	194
Figure 43 : National map of two key components of the winter wheat carbon budget (biomass and CO ₂ fluxes) and of key phenological stages in 2019 at 10m resolution realized with the chain AgriCarbon-EO V1.0.1. Production carried out in 10 hours on the TREX calculator of the CNES in Toulouse. The maps are composed of 0.6 billion pixels (credits: Al Bitar A., Antonenko V., Wijmer T., Arnaud L., Ceschia E.).	194

List of Tables

Table 1: summary of the pro and cons of different Tier 3 modelling approaches for MRV of SOC stock changes.

Credits A. Ihasusta..... 92

Table 2. Comparison of the key approaches used for measurement, monitoring, reporting and verification of the soil organic carbon stock changes across the agricultural systems in Australia 187

Abbreviations and acronyms

Acronym	Description
4D VAR	4D Variational Methods
AEP	Agricultural and Environmental Policies
AGB	Above Ground Biomass
AI	Artificial Intelligence
AFOLU	Agriculture, forestry and land use
ALU	Agriculture and land use
ANN	Artificial Neural Networks
API	Application Programming Interface
BAU	Business As Usual
BGB	Below Ground Biomass
C	Carbon
CAP	Common Agricultural Policy
CBP	Carbon Benefits Project
CEA	Carbon Estimation Area
CF	Carbon farming
CNNs	Convolutional Neural Networks
DG AGRI	Directorate-General for Agriculture and Rural Development
DNDC	DeNitrification-DeComposition
DSM	Digital Soil Mapping
ECMWF	European Centre for Medium-Range Weather Forecasts
EnKF	Ensemble Kalman Filter
EO	Earth Observation
EPIC	Erosion Productivity Impact Calculator
ESA CCI	European Space Agency Climate Change Initiative
ESM	Equivalent Soil Mass

ESU	Element Sample Unit
EU	European Union
EX-ACT	Ex-Ante Carbon-balance Tool
FAO	Food and Agriculture Organization of the United Nations
FLUXNET	network of regional networks of micrometeorological flux tower sites
FMIS	Farm Management Information System
FullCAM	Full Carbon Accounting Model
GAN	Generative Adversarial Network
GHG	Greenhouse Gas
GIS	Geographical Information System
GLAI	Green Leaf Area Index
GPS	Global Positioning System
GPs	Gaussian Processes
GSA	Global Sensitivity Analysis (GSA)
GSAA	GeoSpatial Aid Application
GSOC	Global Soil Organic Carbon
GSP	Global Soil Partnership
IACS	Integrated Administration and Control System
ICOS	Integrated Carbon Observation System
ICRAF	World Agroforestry Centre
IEM	Integral Equation Model
IPCC	Intergovernmental Panel on Climate Change
IR	Infrared
JRC	Joint Research Centre)
LAI	Leaf Area Index
LCA	Life Cycle Assessment
LPIS	Land Parcel Identification System

LSM	Least Squares Method
LTE	Long Term Experiments (e.g. Rothamsted trials)
LULC	Land-Use and Land Cover
LULUCF	Land-Use, Land Use Change and Forestry
MCMC	Markov Chain Monte Carlo
MDD	Minimum Detectable Difference
ML	Machine Learning
MLR	Multi Linear Regressions
MMRV	Measurement, Monitoring, Reporting and Verification
MRV	Monitoring, Reporting and Verification
NDC	Nationally Determined Contribution
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organisation
NIR	National Inventory Report or Near Infra Red
OC	Organic Carbon
PSO	Particle Swarm Optimization Algorithm
PU	Public
RF	Random Forest
RTMs	Radiative Transfer Models
SAR	Synthetic Aperture Radar
SCE-UA	Shuffled Complex Evolution
SDI	Spatial Data Infrastructure
SIC	Soil Inorganic Carbon
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SQP	Scalable Quantification Platform
SR	Super-Resolution
SSM	Sustainable Soil Management

SVM	Support Vector Machine
UNDP	United Nations Development Programme
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
USA	United States of America
USAID	United States Agency for International Development
USDA-NASS	United States Department of Agriculture - National Agricultural Statistics Service
VCM	Voluntary Carbon Market
VCS	Verified Carbon Standard
VFSA	Very Fast Annealing Algorithm
Vis	Vegetation Indices
VOD	Vegetation Optical Depth
VWC	Volumetric Water Content
WCM	Water Cloud Model

Executive Summary

Scope of this document

This ORCaSa deliverable D4.2, which focuses on the Monitoring, Reporting and Verification (MRV) of soil organic carbon (SOC) changes for arable land, is closely linked to deliverable D4.1 "International review of current MRV initiatives for soil carbon stock change assessment and associated methodologies" of ORCaSa Work Package 4, dedicated to MRV. It also paves the way for deliverable D4.4, that aims at analysing current MRV systems, data and methods for other ecosystems (e.g. forests, grasslands) and at addressing interactions between ecosystems (e.g. leakages), with the objective of providing recommendations to build an integrative and multi-ecosystem MRV framework for SOC stock changes.

This document mainly addresses the monitoring and verification of changes in SOC stocks in response to management practices in arable land that remain arable land, and it only concerns annual crops meaning that agroforestry systems and grasslands are not considered here. While it is recognised that some management practices (e.g. adding organic manure or chemical N fertiliser) may affect SOC stocks (Beillouin *et al.* 2023) and also net greenhouse gas (GHG) emissions (e.g. through changes in nitrous-oxide emissions) (Guenet *et al.* 2021) as well as surface properties such as albedo (Carrer *et al.* 2018; Lugato *et al.* 2020; Pique *et al.* 2023) and surface energy fluxes and partitioning (Davin *et al.* 2014; Luyssaert *et al.* 2014), all having impacts on climate, the scope of this Deliverable is restricted to SOC stock changes only. Note that depending on the context of MRV application and carbon farming schemes, the SOC stock changes are sometimes quantified in reference to an initial SOC stock in the soil or to baselines scenario that can be produced in different ways. A Section of this document is dedicated to the different methodologies to set a baseline.

The aims of this document are to: 1) describe the components of MRV frameworks and the different contexts in which they are applied; 2) provide a description and critical analysis of the different methodologies for monitoring and verifying SOC stock changes, including some considerations on their respective limitations, advantages and disadvantages, cost of implementation, building blocks, depending on the contexts in which MRV systems are implemented; 3) guide entities (e.g. verifiers and auditors of carbon credits, researchers, institutes in charge of GHG national inventories, MRV developers operators of MRV tools) on choosing the appropriate methods for monitoring and verifying SOC stock changes depending on the MRV context of application (e.g. NDCs, voluntary C market, agricultural incentives) and their local context; 4) propose a harmonised MRV methodological framework for SOC stock changes in arable lands considering various building blocks (e.g. data, models) and context of application of MRV (NDCs, voluntary C market...) and methodologies for monitoring SOC stock changes (e.g. measure-remeasure of SOC stocks, modelling); and 5) help entities on building, adapting, improving monitoring & verification tools or building blocks of MRV tools if current implementations are not satisfactory for their local context.

Note that this deliverable is written in the context of the development of the methodology for the European Carbon Removals and Carbon Farming regulation¹ (CRCF) and in the perspective of the creation of the MRV service of the

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

Soil Carbon International Research Consortium² (IRC)³ that aims at: 1) scoping an internationally agreed multi-ecosystem MRV framework; 2) assessing and labelling MRV methodologies; and 3) developing and improving MRV tools (building blocks, processing chains) to monitor SOC stock changes.

Target audience

The target audience and intended use of this deliverable are wide: anyone who has an interest in quantifying or verifying SOC stock changes may find this document useful. Indeed, a set of methods and tools for monitoring and verifying SOC stock changes in various MRV contexts are described, analysed and propositions for methodological improvements are made, decision trees are proposed to help end users choose the appropriate monitoring method for assessing SOC stock changes for their objectives and local context, and a harmonised framework for MRV of SOC for arable lands is proposed. Therefore, this document will be of interest to individual farmers, agricultural advisers, land managers, carbon credit certifiers, MRV tool developers, researchers, those undertaking life cycle assessment studies, environmental consultants, conservation organizations, agribusiness professionals, policy makers or regulators at local, regional, national or international scales.

Methodology and key results

This deliverable is the result of a literature review on the different methodologies, tools and building blocks for measuring and verifying SOC stocks and stock changes or for modelling SOC stocks and stock changes for different MRV contexts, including a review of existing MRV tools. The methodological approaches (e.g. Measure-remeasure of SOC stocks, soil centred or ecosystem modelling with or without remote sensing assimilation) were analysed for their pro and cons in the perspective of being applied operationally in different MRV contexts. This analysis resulted in a draft proposition for a harmonised framework for MRV of SOC stock changes and a decision tree aiming at helping end users choosing the most relevant methods and tools for monitoring and verifying SOC stock changes, depending on the context of application of MRV (e.g. NDCs, voluntary C market) and their local context. The harmonised framework and the decision trees were presented and discussed with various stakeholders (180 participants) during two online international workshops, held on April 24th and 25th 2024, co-organised with the MARVIC project, with the objective of reaching a consensus on MRV approaches and being as much as possible compatible with existing MRV frameworks. The outcomes of the workshops allowed to refine the harmonised framework and the decision tree that are presented in this deliverable, together with an analysis of the current monitoring and verification methodological approaches, as well as reviewing some examples of operational MRV tools.

To our knowledge it is the first time that: 1) a harmonised multi-context methodological framework for MRV of SOC stock changes for arable land is proposed, along with a decision tree combining measure-remeasure and multi-Tier modelling approaches with varying levels of complexity and data requirements; and 2) methodologies for monitoring

² <https://irc-orcasa.eu/join-the-soil-carbon-irc/>

³ <https://irc-orcasa.eu/join-the-soil-carbon-irc/>

and verifying SOC stock changes are compared and assessed for their practical application across different MRV contexts.

Research and technical implications

This deliverable highlight that currently there are no fit-for-all-purpose methodological approaches for monitoring and verifying SOC stock changes in arable land. That is why a harmonised international MRV framework is needed. Such a harmonised framework would allow more coherent assessments of SOC stock changes in different MRV contexts and in different regions/countries of the world. As a consequence, we recommend a similar harmonised MRV approach for other ecosystems. ORCaSa Task 4.3 “Building an integrative and multi-ecosystem MRV framework for SOC stock changes” shall contribute to this as well as other ongoing projects on MRV of SOC, such as the MARVIC and MRV4SOC projects, that are currently developing frameworks, cookbooks, guidelines and tools for other agricultural systems (grasslands, agroforestry) and ecosystems (e.g. peatland, forest). On the longer term, the forthcoming MRV service of the Soil Carbon International Research Consortium (ORCaSa is indeed meant to operationalize the Soil Carbon International Research Consortium and set in place different services including services on MRV) shall pursue this effort of harmonisation and improvement of MRV methodologies and tools.

This deliverable also highlights that for the MRV of SOC stock changes, one of the main priorities is to improve the current monitoring methods and tools so that they become more operational, accurate and cost-efficient. Our study highlights that a more general use of remote sensing data to: 1) better quantify biomass restitution to the soil; 2) map soil properties; and 3) observe the adoption and persistence of carbon farming practices could contribute to better meeting these requirements. The monitoring methodologies should also match as much as possible with the IPCC guidelines for assessing SOC stocks, the CIRCASA methodological specifications (see appendix of the CIRCASA Deliverable 3.1 “Strategic Research Agenda on SOC”⁴) and recommendations from Paustian *et al.* (2019) and Smith *et al.* (2020):

- Several Tier(s) approach.
- High spatial resolution (to include small fields and small owners) assessment of relevant practices and of biomass inputs to the soil based on remote sensing.
- Estimation of N₂O emissions and of the balance of other soil-derived GHGs in CO₂ equivalents.
- Apply a modular structure to allow estimates of SOC stock changes (i.e. Δ SOC) with their associated uncertainties to be derived. Where possible, calibrated sets of models should be used rather than single models.
- Provision of resources for ground truth and for model calibration data (e.g. calibration/validation of CO₂ fluxes at flux tower sites, monitoring networks combining soil and biomass measurements, collection of activity data to analyse SOC stock trends).
- Achieving high precision will take several years. A low initial accuracy is expected, and new investments will be needed each year to achieve higher accuracy. Beyond traditional MRV methods, Artificial Intelligence approaches could be tested to optimize the predictive power of the monitoring based on calibration and verification data.

⁴ <https://www.circasa-project.eu/document-library/deliverables/d3.1-strategic-research-agenda-sra-on-soil-carbon>

- A strong data infrastructure (e.g. Copernicus, ICOS, IACS, data spaces, LUCAS) providing seamless access by multiple users and using the FAIR principles⁵, while ensuring the long-term sustainability of satellite and field monitoring programs to support continuous and reliable data collection for the future.
- Include options for self-reporting, especially for activities currently not reported (e.g. organic fertilizers, crop residues).

Although some tools, like the AgriCarbon-EO pre-operational processing chain (see Section 2.1 in Annex 1), meet several of the required specifications and may be applied in different purposes of MRV (e.g. NDCs, voluntary carbon market), none of these fully match the above specifications/recommendations. Substantial international efforts in research and development are therefore urgently needed, especially in the context of the EU CRCF Regulation⁶ that will go in operation in 2026.

Also, given the number of combinations of monitoring methods versus the context of applications, we considered that a decision tree for choosing the most relevant monitoring method was needed. Our proposal may require updates in the future as technologies and knowledge evolve. Regarding the critical verification component, although recommendations could be made concerning the selection of methods, depending on the local context, additional work will be needed to validate/refine the approach. This may result in the proposition of an additional decision tree. This is one of the objectives of the MARVIC project.

Currently, we identified several main limiting factors for implementing MRV tools in an accurate and operational way:

- **For modelling**, especially at plot scale for the voluntary carbon market or for the payment of subsidies: 1) the access to accurate farmer's activity data corresponding to practices impacting SOC stocks changes is key (most importantly organic amendments and management of straw that cannot be quantified by remote sensing). This would require a (more) systematic digitisation of farmer's activity data (e.g. through the CAP in Europe) and checking this information (e.g. by an agricultural advisor); 2) the lack of accurate and available Δ SOC stock measurement data to validate all approaches, 3) the availability of operational and transparent modelling tools applicable at large scale, high resolution, low cost, allowing for an objective consideration of biomass returns to the soil for SOC stock changes, and calibrated/validated for a wide range of pedo-climatic conditions, cropping systems and carbon farming practices. The current development of scalable quantification platforms assimilating remote sensing data (e.g. Remote-C, AgriCarbon-EO, the Retina platform) could solve part of the problem, keeping in mind that a combined remote sensing and modelling based approach cannot always be applied (e.g. in very hilly areas, over small or narrow parcels).
- **For in-situ soil monitoring**, the cost of soil analyses limits the production of soil property maps (e.g. texture, depth, SOC stocks and SOC stability) that are needed as input for soil models, but also for a more systematic implementation at large scale of measure-remeasure or verification campaigns. New technologies such as Gamma ray for SOC stock mapping or RockEval® for assessing SOC stability and the reductions of their cost of implementation may contribute to solve those issues.

⁵ www.go-fair.org/fair-principles

⁶ https://climate.ec.europa.eu/eu-action/carbon-removals-and-carbon-farming_en

Policy implications

The EU Commission's proposed Framework for Carbon Removals Certification² (30 November 2022) aims to subsidize increased carbon removals. Alongside other removal options, this includes a specific focus on promoting 'carbon farming', a category that includes nature-based solutions such as cover crops or agroforestry. 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 Q.U.A.L.I.T.Y 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 as yet, 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).

This deliverable is therefore a direct contribution to the Q.U.A.L.I.T.Y criteria approach of the CRCF Framework since it aims at improving the current methods of monitoring and verification of SOC stock changes in the long term. It also aims to homogenise and standardise methods of quantification and verification implemented in different MRV contexts to: 1) allow more consistency in the quantification of SOC stock changes as suggested by Dupla *et al.* (2024) and requested by the European Commission; but also 2) make the approaches to financing carbon farming practices more compatible, whether they are for based on the voluntary market or the CAP. Also, this work could provide useful information to the EU DG AGRI for choosing the monitoring approaches best suited to their objectives of producing baselines and monitoring SOC stock changes at plot scale and EU level, compatible with offsetting and insetting programs, in order to feed a EU level carbon registry that avoids double accounting (Additionality criteria).

Finally, an internationally harmonised framework as the one proposed here and improvements of current methods/tools for monitoring and verifying SOC stock changes would give more trust in the voluntary carbon market. More standardized carbon credit pricing, linked to robust MRV, could discourage market dynamics where lower-cost credits with weaker verification outcompete higher-quality credits. Ensuring greater transparency in credit pricing and verification could also reduce risks of poorly regulated projects contributing directly or indirectly to land tenure conflicts and land-use pressure, particularly in regions where land rights are less secure (e.g. in Africa, South America, part of Asia). Of course, the harmonised framework proposed here aims at being as much as possible compatible with current international methodologies (e.g. IPCC guidelines) and regional frameworks (e.g. CRCF in Europe). New developments are planned as part of the Soil Carbon IRC to be built up with the international research community.

² https://ec.europa.eu/commission/presscorner/detail/en/ip_22_7156

1 Introduction

In recent decades, there has been a growing recognition of the importance of monitoring changes in SOC stocks for climate change mitigation purposes (IPCC 2022, Sustainable Development Goal (SDG) 13 (i.e. Climate action, see Figure 1 and UNEP 2023)), but also for halting and reversing land degradation (SDG 15), for ensuring human livelihood/health (SDG 1,2,3) and for reversing biodiversity loss (IPBES 2019; SDG 14, 15).



Figure 1. Sustainable Development Goals from United Nations Environment Program (2023).

Soils are the largest terrestrial reservoir of organic carbon representing a stock of around 1,500–2,400 Gt C (~5500–8800 Gt CO₂) in the top meter of soil globally (Batjes 1996; Sanderman *et al.* 2017; Friedlingstein *et al.* 2022). This carbon pool actively exchanges with the atmosphere via the processes of photosynthesis, plant respiration and the respiration of soil micro-organisms that decompose crop residues and soil organic matter. Therefore, small changes in these SOC stocks can greatly affect the amount of C as CO₂ in the atmosphere and the C balance at a global scale (Minasny *et al.* 2017). In this context, it is important to consider 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.* 2023c; Moinet *et al.* 2023; Don *et al.* 2024). Yet great uncertainty remains in the quantification of those processes as well as in estimates of SOC stocks and changes at all scales (from local to global). There are large differences between global SOC stock estimates, caused by the diversity of data sources and methodologies (Henry *et al.* 2009). Part of the uncertainty comes from the diversity of land uses and from our ability to accurately estimate their respective SOC stocks and SOC stock trajectories. Indeed, soil carbon stocks and 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) in ways that are not fully known (Wiesmeier *et al.* 2019; Beillouin *et al.* 2023).

Over the last 8000 years, agriculture has had a significant impact on the atmospheric concentration of CO₂ and CH₄ (Salinger, 2007b) and cultivated soils have lost around 116 Gt C (~510–550 Gt CO₂; Sanderman *et al.* 2017). Yet, it is known that better management practices can restore at least some of this lost carbon (e.g. Gifford, 2000; Lal *et al.* 2018). Therefore, agriculture has been identified as a sector that can contribute to climate mitigation through reduction in GHG emissions, surface albedo management and through additional SOC storage (Porter *et al.* 2017; Lugato *et al.* 2020; Pique *et al.* 2023; Matthews *et al.* 2022). According to Skeea *et al.* (2022), the implementation of carbon farming practices has the potential to remove 0.6 to 9.3 GtCO₂ yr⁻¹ globally from the

atmosphere. In a previous study, Hutchinson *et al.* (2007) concluded that the carbon sequestration potential of croplands should be considered as a modest but non-negligible contribution to climate change mitigation (between 3% and 6% of anthropogenic fossil fuel emissions), but that the quantification of cropland carbon sequestration potential remains very uncertain because for instance of non-permanency, acceptability and cost of the carbon farming practices... and also challenging due to seasonal changes in carbon sequestration, scalability and cost of current monitoring approaches (UNEP, 2023), ability to capture management changes and their effects... As a matter of fact, global estimates of soil C sequestration potential vary considerably from one study to the other and a recent review by Fuss *et al.* (2018) suggests an annual technical potential of 2–5 Gt CO₂.yr⁻¹, while estimates of economic potentials are at the lower end of this range (Smith, 2016; Smith *et al.* 2008). In France, the maximum potential combining eight practices is estimated at 31 MtCO₂e yr⁻¹ in the soil (55.5 MtCO₂e yr⁻¹ in the soil and biomass) (Bamière *et al.* 2023).

Although soils of arable land 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; Crow and Sierra 2022). Alternatively, labile carbon (particulate organic matter and part of mineral associated organic matter) can also play a role in climate change (Witzgall *et al.* 2021). 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 due to physical protection (Bossuyt *et al.* 2002; Six *et al.* 2002) or correspond to small pieces of chars (Baldock *et al.* 2013; Chassé *et al.* 2021). For the fast decomposing POM, 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. Indeed, possible gains in SOC sequestration are considered to be reversible upon changes in climate or land management practices and use (Zomer *et al.* 2017). Note that theoretically, SOC stocks can increase without limit provided the inputs of carbon continue to increase and losses from the soil are minimised but this is debated, and probably not universally true as some studies show clear saturation (Sayer *et al.* 2019) while others don't (Heinemann *et al.* 2024). Also, the concept of SOC stock stabilisation is an essential aspect of long-term carbon storage in soils. There are various mechanisms proposed to account for the stabilisation of carbon entering into the soil, including: 1) adsorption of SOC onto mineral surfaces (Baldock and Skjemstad 2000); 2) encapsulation of carbon within soil aggregates (Six *et al.* 2000); 3) adverse micro-environmental conditions that create unfavourable conditions for the soil biota, minimising decomposition; and 4) chemical composition of the SOC. See <https://www.publish.csiro.au/sr/Fulltext/SR23096> for more details.

The considerations above highlight the need for robust, long term and harmonised methods for monitoring SOC stock changes and the effect of management practices on SOC stock in various pedo-climatic contexts and at various spatial and temporal scales. Indeed, 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).

Monitoring methods for assessing SOC stock changes can mainly be divided in two categories:

- The first approach is based on *in-situ* or remote measurements of SOC stock changes, e.g. based on soil sampling and analysis (measure and re-measure approach) that are described in Sections 5.1 and 5.2 (e.g. van Egmond and van der Woude, 2023; Broeg *et al.* 2024).

- The second approach is the Net Ecosystem Carbon Budget (NECB) approach (Chapin *et al.* 2006; Béziat *et al.* 2009; Smith *et al.* 2010; Ceschia *et al.* 2010) that is an ecosystem approach aiming at quantifying all of the components of the C budget that represent an increase/loss of C in the soil over a given period (usually a cropping year or a crop rotation). The carbon budget is calculated by: 1) either considering the vertical CO₂ fluxes, exchanged with the atmosphere (i.e. plant photosynthesis, GPP; plant respiration, R_a; heterotrophic respiration, R_h) as in the SAFYE-CO₂ (Pique *et al.* 2020 a and b) or WOFOST (e.g. van Diepen *et al.* 1989) models and the lateral carbon fluxes, i.e. the amount of C exported at harvest (e.g. grain, straw, tuber) and the C inputs as organic amendments; or 2) by quantifying directly the biomass production (i.e. the difference between the photosynthesis and the plant respiration), as well as heterotrophic respiration and lateral carbon fluxes (C harvest and C inputs as organic amendments), as done by most agronomical models (e.g. EPIC (Williams *et al.* 1984), CERES (Ritchie *et al.* 1998), STICS (Brisson *et al.* (1998, 2002)). The CO₂ fluxes and the biomass production can be either modelled or measured at experimental sites, e.g. with chambers or flux towers (e.g. European ICOS network, OZflux in Australia, Ameriflux and NEON in USA and FLUXNET at global scale). This approach allows a dynamic assessment of the SOC stock changes (e.g. annual carbon budgets) and of its components. Tier 3 modelling approaches are all based on a carbon budget approach (see Section 5.3).

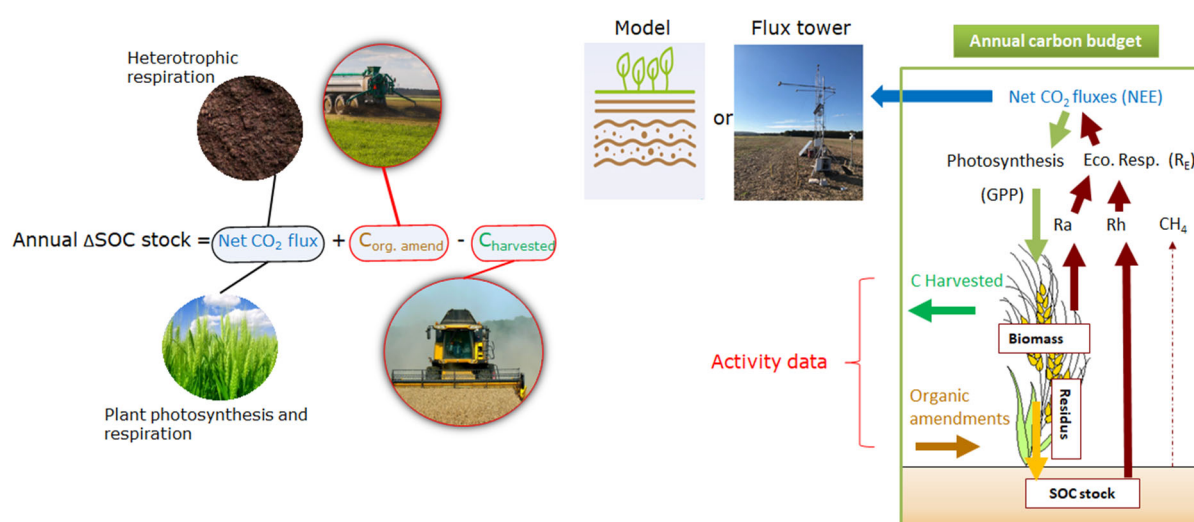


Figure 2. Schematic representation of the carbon budget component approach aiming at quantifying annual Δ SOC stock changes from the C fluxes, vertical fluxes of CO₂, i.e. the net annual CO₂ flux exchanges with the atmosphere (photosynthesis, GPP; plant respiration, R_a; heterotrophic respiration, R_h) and lateral carbon fluxes, i.e. the amount of C exported at harvest (e.g. grain, straw, tuber) and C inputs as organic amendments.

Although much progress in national and sub-national level Monitoring Reporting and Verification (MRV) of SOC stock changes has been achieved over the last two decades (Batjes and van Wesemael 2015; Aitkenhead 2022; Black *et al.* 2022; Kuhnert *et al.* 2022; Oldfield *et al.* 2022; Rumpel *et al.* 2022; Crow and Sierra 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 UNFCCC (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”.

The study by Smith *et al.* (2012) was among the first to describe a framework to monitor SOC stock changes, building on available models, data sets and knowledge, to quantify the impacts of land use and management change on soil carbon. Since then, Paustian *et al.* (2019), see Figure 3, and Smith *et al.* (2020), see Figure 4, have proposed updated frameworks describing the main ingredients or building blocks needed to operate the three components of a MRV system, i.e. Monitoring, Reporting and Verification (see Chapter 3 for a full description) and to some extent they also described part of the recipe to build Scalable Quantification Platforms (see Annex 1 for some examples of SQPs), allowing SOC stock change monitoring in various contexts (e.g. NDCs, voluntary carbon market). According to those studies and the UNEP emission gap report (2023), the most challenging component of the MRV process remains the monitoring (Chapter 5). This is the reason why we will mostly focus on this component in this report, although Chapter 6 addresses the reporting component and Chapter 7 focuses on the verification component.

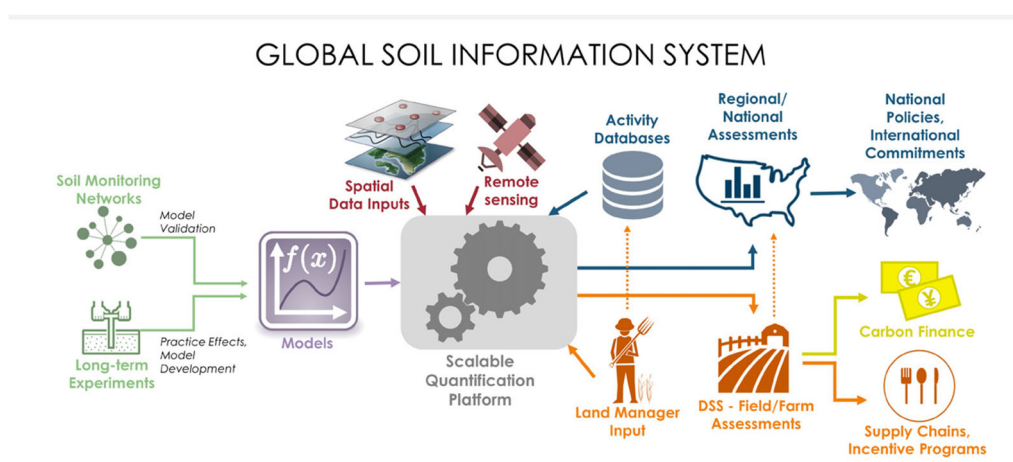


Figure 3. Schematic representation of components and information flow for an approach to quantify soil organic carbon stock changes (and net GHG emissions) from field to national scales, aimed at supporting different implementation policies to remove atmospheric CO₂ and sequester soil carbon (Source: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

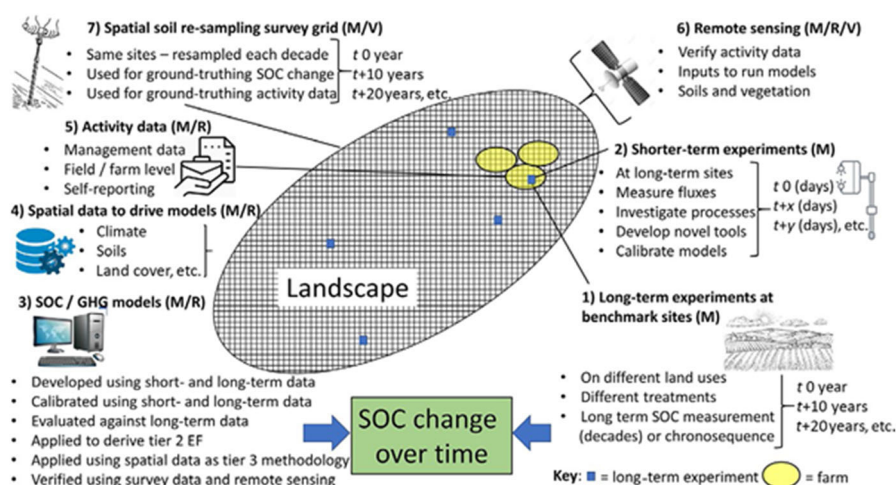


Figure 4. Building blocks of a soil monitoring, reporting and verification framework. The letters M, R and V indicate to which component(s) each building block could contribute (Source: Smith *et al.* (2020)).

As discussed in Chapter 5, different methods for monitoring SOC can be implemented depending on the purpose of a MRV and local context. 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 2019d). The use of such default values, however, is prone to low accuracy and high uncertainty when applied to estimate soil carbon stocks in local/landscape scale projects.

A Tier 2 method (see Section 5.3.2 for more details) is an extension of the Tier 1 method that allows an inventory to incorporate country-specific data (e.g., Sperow 2014; Villarino *et al.* 2014; Peter *et al.* 2016; Cardinael *et al.* 2018). Further, it should be noted that for cropland, the "IPCC 2019 Refinements" offer a different kind of Tier 2 method (IPCC 2019c,d, that consists of a simplified, steady-state method based on process-based models, such as Century (see Section on FullCAM in Annex 1).

Also, through physical (*in-situ*) soil sampling and/or modelling (e.g. data-driven or Tier 3 process-based modelling), 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 (sampled at a nominated depth) shows how land management impacts SOC stocks over time. When paired with sustainable soil management and agricultural practices, the information can be used in financing frameworks to promote carbon sequestration while supporting livelihoods through increased soil health and possibly agricultural yields, as well as addressing climate change. In practice, however, the cost of taking sufficient soil samples to reliably monitor changes in carbon farming projects can be prohibitive, hence the need for using models. Therefore, process-based models accounting for soil properties, climate and the amount of biomass returning to the soil are often used in different MRV contexts (e.g. NDCs, voluntary carbon market) to estimate soil carbon pool dynamics and SOC stock changes. While they were primarily used to support research, they are increasingly being utilized at local to national scales for national inventories (e.g. the RothC soil model as a component of the Full-CAM in Australia's national GHG inventory system (Richard and Evans, 2004; Ogle *et al.* 2005; see also Section 1.2 in Annex 1); the DayCent model for soil C stocks changes and soil emissions of N₂O and CH₄ in the US national GHG inventory and reporting system, US EPA, 2019) or for the voluntary carbon market (e.g. French Low Carbon Label for arable land⁸). They sometimes rely on soil-centred approaches where the focus is on the modelling of SOC pools. In these approaches, the estimates of biomass returning to the soil are usually derived from yield at the regional scale (Del Grosso *et al.* 2005; Yokozawa *et al.* 2010; Lehtonen *et al.* 2016) or from farm- or field-scale yield data (Clivot *et al.* 2019). Coupled plant–soil process-based models simulate the main processes that drive crop growth and biomass allocation (e.g. grain) as well as the quality and quantity of the crop residues that return to the soil in order to assess SOC stock changes. Agronomic models, such as DSSAT-CSM (Porter *et al.* 2010), STICS (Launay *et al.* 2021), DAYCENT (Parton *et al.* 1996), and WOFOST (Supit *et al.* 1994) or land surface models, for example, ORCHIDEE-STICS (Gervois *et al.* 2008), take into account a wide array of environmental conditions to represent crop growth, and some or all the components of the carbon budget (e.g. plant photosynthesis and respiration, soil respiration, amount of C exported at harvest). However, none of those process-based modelling approaches account for the intra-field/farm spatial variability of the soil characteristics and plant growth (de Gruijter *et al.* 2016; Ellili *et al.* 2019). Water and nutrient availability, local topography, pests and diseases, and former land use (e.g. former ditches, roads, field limits) highly influence soil and plant processes (Gregory *et al.* 2009). This can result in high spatio-temporal variability in crop development and soil processes that can be observed, even at the intra-field scale (Stevens *et al.* 2008; de Gruijter *et al.* 2016; Wijmer *et al.* 2024; do Nascimento Bendini *et al.* 2024). Such modelling approaches may therefore present limitations in terms of accuracy and spatial representativeness, hence the need for developing new approaches combining remote sensing data assimilation, crop and soil modelling as pointed out by the Strategic Research Agenda on soil carbon (see

⁸ <https://label-bas-carbone.ecologie.gouv.fr/la-methode-grandes-cultures>

Deliverable 3.1⁹) of the CIRCASA (Coordination of International Research Cooperation on Soil Carbon Sequestration in Agriculture) international research program on soil carbon for arable land. Among other things, CIRCASA recommended:

- Tiered approach,
- Modular & transparent approach with uncertainty assessment on SOC stocks,
- The combined use of several soil models instead of a single model allowing an ensemble approach,
- Assessment of the different components of the C budget (i.e. biomass allocation to different plant organs above and belowground, CO₂ fluxes i.e. photosynthesis and plant/soil respiration, SOC stock changes) in the development/verification process,
- High-resolution monitoring, relying on remote sensing (e.g. Sentinel 2) for objective and more accurate quantification of biomass production and therefore restitution to the soil,
- Relying on strong data infrastructures following the FAIR principles: e.g. Copernicus for remote sensing data, FLUXNET or ICOS flux tower networks, LUCAS soil monitoring network. Note that: 1) currently there is no observation network for biomass and SOC monitoring with a protocol adapted to calibration/validation of EO based approaches/algorithms; and 2) apart from flux tower networks, currently no *in-situ* observation network provides assessment of the different components of the carbon budget together with activity data collection that are critical for model development and validation. Unfortunately, national or international soil monitoring networks (e.g. LUCAS in Europe) usually do not collect activity data or accurate information of land use, meaning that the SOC trends observed at those sites cannot fully be interpreted/understood and therefore their use to develop, train or evaluate models is limited or requires assumptions.

So far none of the tools or Scalable Quantification Platforms (SQPs) currently operationally implemented for SOC monitoring meet the specifications set by CIRCASA. Recent publications question the ability of current models and tools based on Tier 3 approaches to quantify SOC stock changes with sufficient precision (e.g. Popkin 2023; Dupla *et al.* 2024), in particular with a view to the voluntary carbon market. Several reasons can be given for this (the list is not exhaustive):

- Ability of the modelling approaches to truly represent SOC stock changes, for example because: 1) most of the time assessments are done only on the first 30 cm of soil, while SOC stock changes may occur to greater depths; 2) lack of accounting for spatial variability in soil properties (e.g. initial SOC stocks, C pools) and vegetation development (C returning to the soil); 3) lack of representation of certain processes (e.g. priming effect, stoichiometry issues); or 4) consideration by some models of management practices that affect the SOC distribution but not the SOC stock as a lever for storing SOC (e.g. DayCent and RothC consider the effect of no-till on SOC stock changes while AMG doesn't),
- Accuracy and representativeness of SOC measurements (initial stock with equivalent soil mass correction, fraction of the different C pools) needed for model calibration/ validation/ initialisation/ verification that are highly variable in space, while changes over time depend on a multitude of factors, for which detailed information and understanding is not always available,
- Lack of accuracy of other input data (e.g. soil properties, climate, C inputs to the soil) and of the initialisation process for Tier 3 models. For instance, Dupla *et al.* (2024) showed that some carbon credit protocols do not require initial SOC stock measurements (and/or verification processes based on *in-situ* SOC measure and re-measure) to initialise the models, which may not be a source of uncertainty for models like AMG (Clivot *et al.* 2019) but is an uncertainty source for most soil or ecosystem process-based models,

⁹ <https://www.circasa-project.eu/content/download/4158/40011?version=1>

- Moreover, to operate process-based models, farmer's activity data (e.g. organic amendments, straw management) are needed. National or regional statistics can be used for inventory approaches or to test scenarios, but for SOC monitoring in the context of the voluntary carbon market plot or farm scale data are needed. Getting hold of this information based on enquiry is expensive and time-consuming and collecting this information at a large scale is still challenging (Seidel *et al.* 2018). Also, uncertainties on the activity data are rarely accounted for in MRV processes while uncertainty on for example amount of organic amendments (or its estimated C content) or of straw harvested can be high and have a strong impact on the estimated SOC stock changes,
- Depending on the local context, MRV purpose and carbon credit protocols, the method used for calculating the baseline may vary a lot, going from measured to modelled, dynamic or static, plot-specific or standardised (i.e. based on regional statistics on management¹⁰, see Ruyschaert *et al.* 2024). Also, according to Paustian *et al.* (2019), for NDCs, accurate baselines are still missing for many countries and therefore estimates of SOC stock changes within the global carbon cycle are still associated with large uncertainties.

The different contexts of MRVs, of methods for monitoring SOC (e.g. measure or model) or producing baselines, for initialising the models, for feeding them with input data (e.g. soil properties or biomass inputs to the soil relying on *in-situ* measurement or remote sensing) result in very variable and often inconsistent quantifications of SOC stock changes (Goidts *et al.* 2009; Jandl *et al.* 2014).

These considerations highlight the need for harmonised and improved or new monitoring approaches, providing more consistent, accurate, cheap, transparent and scalable monitoring of SOC stock changes across MRV systems, local contexts and purposes (e.g. NDCs, voluntary carbon market). Therefore, building on CIRCASA's recommendations, on previous work from ORCaSa (Batjes *et al.* 2023 and 2024; Wijmer *et al.* 2014), but also on literature review (e.g. Paustian *et al.* 2019; Smith *et al.* 2020; FAO 2019; Guan *et al.* 2023) and on several workshops organized by the ORCaSa project respectively co-organized with the MARVIC project, we propose a harmonised methodological MRV framework for cropland. It describes not only the key ingredients needed to build a SQP for monitoring SOC but also proposes 'recipes' corresponding to several methodological approaches for monitoring (illustrated by several examples of operational SQP, but also some in development) and a decision tree for choosing the best suited monitoring approach, depending on the purpose and context of application. This document also provides recommendations concerning the methods for verification (e.g. of SOC stock changes and practices), recommendations for future developments and ways to fill knowledge gaps.

Following this introduction, the document consists in 7 other Chapters, a glossary of commonly used terms and of an Annex presenting examples of SQPs currently used or under development. The second Chapter describes the different contexts of application of MRV. It is followed by a description of the MRV components for SOC (Chapter 3) and of the proposed harmonised methodological framework for the MRV of SOC stock changes (Chapter 4). Next, the different methodologies for monitoring SOC stock are described in Chapter 5 (e.g. *in-situ* measure-remeasure, Tier modelling approaches) and analysed in a perspective of operational use for different MRV contexts. Chapter 5 also includes a decision tree to assist MRV operators or developers in choosing the right methodology according to the objectives of MRV and local context. Subsequently, Chapter 6 discuss the reporting process and in Chapter 7, we present the verification process and the methods for verifying SOC stock changes as well as the implementation of practices. Chapter 8 addresses the needs for future developments/research for the MRV of SOC

¹⁰ for more information see: https://www.project-marvic.eu/news/marvics_recommendations_for_carbon_removal_certification

stock changes and the calls of actions to achieve the implementation of an international harmonised methodological framework for MRV of SOC for cropland.

2 Contexts of application of MRV



Figure 5. Schematic representation of the different contexts of application of MRV.

Figure 5 illustrates the different contexts of application of MRV addressed in this document:

- **Nationally Determined Contributions (NDCs):** Countries' self-defined national climate pledges under the Paris Agreement, detailing what they will do to limit the global temperature increase below 1.5°C, adapt to climate impacts and ensure sufficient finance to support these efforts. In September 2022, 164 countries (137 Parties including the EU) submitted new or updated NDCs to the UNFCCC (Rose *et al.* 2022). Of these, 36 countries referred to SOC (23 in mitigation contributions, 16 in adaptation contributions). This represents 22 more countries compared to the previous round of NDCs based on an analysis by Wiese *et al.* (2021). Twenty-nine countries included SOC commitments for the first time since the previous round of NDCs. One hundred seven (107) countries also referred in their NDCs to practices associated with increasing SOC sequestration (i.e. cover crops, crop rotation, erosion control, fallow and integrated soil fertility management), but agroforestry, wetlands and grassland management were prioritized in both mitigation and adaptation contributions compared to cropland. As mentioned in Smith *et al.* (2020), SOC monitoring for NDCs may rely on different methods (e.g. Tier 1 to Tier 3 modelling approaches). See Chapter 5 for the description of those methods.
- **Voluntary Carbon market (VCM):** According to the UNDP's High Integrity Carbon Markets Initiative report¹¹ written in December 2023, 'Carbon markets' covers mainly two major categories: 1) a Compliance Market that is the result of a national, regional and/or international policy or regulatory requirement"; and 2) a Voluntary market which refers to the issuance, purchase and sale of carbon credits on a voluntary basis, involving the financing of mitigation actions in companies' value chain (insetting) or outside their value chain (offsetting, or beyond value chain mitigation). Currently, SOC sequestration for cropland is only considered in the context of the voluntary carbon market. The current supply of voluntary carbon credits comes mostly from private entities that develop carbon farming projects, or from governments that develop programs certified by carbon standards that generate emission reductions and/or removals (e.g. the Low Carbon Label in France). In Europe, "**insetting**" programs that are implemented in the context of

¹¹https://climatepromise.undp.org/highintegritycarbonmarkets?_gl=1*1tchodg*_gcl_au*NTExMTAyNDM2LjE3MjY1NjE1NDY.*_ga*MjEwODQ0MTlyLjE3MjE4MzUxNTQ.*_ga_3W7LPK0WP1*MTczMzIzNDQxOC43LjEuMTczMzIzNDQ0Ny4zMS4wLjA

corporate scope 3 reporting rely on GHG emission reductions or on net removals (mostly as C sequestration in the soil) that are achieved within the supply chain of an entity (e.g. agri-food companies). Insetting programs therefore aim at offsetting a company's emissions or environmental and social impacts, by reducing GHG emissions at farm level or by sequestering C in the soil. In carbon "**offsetting**" programs, carbon credits allow to compensate for a country's or company's emissions covered by a compliance or voluntary target. These are 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. Monitoring of SOC stock changes for the Carbon market must align with at least Tier 2 methods, which can capture most sources of emissions and the impact of management actions on similar farms in a relatively accurate way. Tier 3 approaches are likely to be necessary to robustly model soil carbon, which requires higher resolution land-use data. On 6 December 2024, the European Union published the Carbon Removals and Carbon Farming (CRCF) Regulation¹² (EU/2024/3012), creating the first EU-wide voluntary framework for certifying carbon removals, carbon farming and carbon storage in products across Europe. The framework has been developed to facilitate and speed up the deployment of permanent carbon removals, carbon farming (which includes temporary carbon storage activities and soil emission reduction activities) and carbon storage in products activities, as a complement to sustained emission reductions, fight green-washing and harmonise carbon removals market conditions. In order to ensure the quality of carbon removals certified under the framework, removals need to meet several quality criteria (so-called "QU.A.L.ITY" criteria), covering the aspects of quantification, additionality, long-term storage, and sustainability. The European Commission, assisted by Expert Groups, is currently developing methodologies for the certification of carbon removals as part of the broader climate neutrality goal for 2050.¹³

- **Agricultural and Environmental Policies (AEPs):** till recently in the US, government subsidies as direct payments or as cost sharing can incentivize farmers (e.g. the U.S. Department of Agriculture's Environmental Quality Incentives Program, the Conservation Stewardship Program) (Chambers *et al.* 2016). Although these programs were originally designed to meet general resource conservation objectives, the practices they promote are generally compatible with C sequestration and GHG emission reductions (Steele *et al.* 2018). Thus, enhancing the promotion of C sequestration through such programs can be accomplished with relative ease. In Europe, farmers have long been offered incentives to improve their farming practices and safeguard the environment, for example through agri-environment-climate payments and environmental investment support co-financed by Pillar 2 of the CAP (Common Agricultural Policy). Some incentives concern the protection of soil health and functioning, including in some countries maintenance of soil organic matter (SOM) (and hence soil carbon storage) (Borrelli *et al.* 2016). These incentives are commonly action-based payments for compliance with specific farming practices or technologies which have been selected by the managing authority for the assumed environmental benefits. So far, few schemes or projects have offered result-based payments, where the incentive payment is linked to measured outcomes on the farm (e.g. SOC sequestration). The Carbon farming in the CAP strategic plans workshop organised in 2021¹⁴ highlighted the importance of the CAP in contributing to the objectives of the European Green Deal, remarking that climate challenges were already embedded in the new CAP proposal. Concerning SOC sequestration, different EU and national funding mechanisms, including eco-schemes under the new CAP exist, noting that the potential of carbon farming implementation varies greatly among the Member States. Depending on their assets and challenges, each Member States has

¹² https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202403012

¹³ https://climate.ec.europa.eu/eu-action/carbon-removals-and-carbon-farming_en.

¹⁴ https://climate.ec.europa.eu/system/files/2021-07/20210525_workshop_iv_report_en.pdf

to decide on concrete approaches and tools appropriate in their national context. The major challenge comes from the shift from compliance (i.e. action-based) to performance (i.e. result-based) supported by a set of indicators and an upgraded set of environment and climate-related instruments. Up to now, tools were missing to produce such indicators. Therefore, research programs like the H2020 NIVA project aimed at developing carbon sequestration related indicators by making the best use of Integrated Administration and Control System (IACS) combining remote sensing data as already used for the CAP monitoring and modelling. Consequently, the NIVA project proposed a Tiered result-based approach for monitoring cropland SOC stock changes for the CAP¹⁵. According to the Technical Guidance Handbook on Carbon Farming (COWI, Ecologic Institute and IEEP, 2021), result-based incentives offer several advantages, compared to action-based incentives, but also have challenges and limitations as listed below:

Advantages of a result-based scheme for carbon farming:

- ☐ flexibility for the farmer – encouragement of adaptability, innovation and entrepreneurship;
- ☐ clearer link between payment and carbon impacts for buyers – higher credibility/appeal and potential for higher additionality;
- ☐ carbon impacts are an objective, and not a side-effect of sustainable agriculture – potentially higher effectiveness;
- ☐ lower adverse selection of parcels with lower yields by farmers (i.e. with lower opportunity costs);
- ☐ educational role for farmers and wider society.

Challenges and limitations of a result-based scheme for carbon farming:

- ☐ potential higher financial risks/uncertainty for farmers;
- ☐ potential higher transaction costs for developers;
- ☐ challenges related to monitoring, reporting and verification of climate mitigation results (costs, degree of reliability/robustness);
- ☐ challenges of ensuring additionality and of securing permanence of the carbon impacts;
- ☐ the time needed for change in reliable measurements is potentially long, and in some cases the change is appreciable only after the project life span;
- ☐ higher flexibility given to farmers also means that strong advisory support needs to be built into scheme design; however, capacity or resources for this may be lacking.

The Technical Guidance Handbook on Carbon Farming¹⁶ (COWI, Ecologic Institute and IEEP, 2021) aims to support Member State/regional managing authorities in offering EU farmers result-based incentives for carbon farming. It also enables land managers to find the suitable and relevant type of carbon farming scheme for their proposed area of development with a decision-tree approach, including the selection of rewarding mechanisms, for example based on action-based payments, result-based payments and hybrid schemes, the later being also recommended by the H2020 NIVA project. Note that, if the CAP is a substantial instrument that can promote carbon farming practices, it needs to be used in combination with other EU (e.g. CRCF) and national regulatory measures and sources of funding (e.g. French Low Carbon Label) in order to compensate for the low price of carbon credits on the voluntary carbon market (that is often below the cost of implementation of the carbon farming practices) but also to share the risk between the farmer and the buyer of the carbon credits (e.g. in case of adverse weather conditions that do not allow the farmer to store carbon in spite of substantial efforts to do so). Payment models can focus on preserving soil carbon, reducing net emissions from soil, or increasing sequestration of carbon into soils. Four broad types of payment systems applicable to projects sequestering soil carbon in agricultural settings have

¹⁵ <https://hal.inrae.fr/hal-04225931/file/NIVA-Policy-Brief-nr.-5-Agro-environmental-indicator-carbon-D1.0.pdf>.

¹⁶ <https://www.rbpnetwork.eu/media/technical-guidance-handbook-on-carbon-farming.pdf>

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; b) Payment for practice with performance dividend, c) Payment for performance and d) Carbon-market, voluntary or compliance. Note that the economic considerations of carbon market-oriented MRV systems, i.e. underpinning business models, are intricate and beyond the scope of this report (see for example the EJP Soils Road4Schemes¹⁷ project, Cevallos *et al.* (2019) and Nogues *et al.* (2021)).

¹⁷ <https://ejpsoil.eu/soil-research/road4schemes>

3 Components of the MRV for SOC

Building on earlier seminal work from Paustian *et al.* (2019) and Smith *et al.* (2020), on discussions during two international stakeholder workshops organised by the ORCaSa project and initial review, Batjes *et al.* (2024) proposed a new schematic representation of the three components of an MRV framework that shows the interactions of the different building blocks and the flow of information (see Figure 6):

- The monitoring component includes direct (soil) measurements (for measure-remeasure of SOC stocks or for modelling input/initialisation), activity data, spatial data layers, earth observations, experiments (M1 to M5) aimed at developing, calibrating, validating and/or applying models (M6 to M8). The IPCC develops guidance based on best available scientific knowledge to guide countries to calculate their SOC stock changes (and GHG emissions) under international climate agreements (i.e. UNFCCC and Kyoto) (IPCC, 2006). While their monitoring methodologies are designed for national reporting, many aspects are transferable and form the basis of carbon farming methodologies with carbon farming project scale inputs and model parameters. Indeed, carbon farming methodologies should be aligned so that scheme results can be reflected in national GHG accounts. As described in Chapter 6, IPCC guidance includes three different tiers of approaches, increasing in complexity, data, and accuracy. Result-based carbon farming methodologies must align with at least Tier 2 methods, which can capture most sources of emissions and the impact of management actions on similar farms in a relatively accurate way. Tier 3 approaches are likely to be necessary to robustly model soil carbon, which requires higher resolution land-use data. Scheme designers must always consider the trade-off of higher costs and complexity associated with higher tier approaches, and weigh them up against the increased environmental certainty. The gear wheel in the green monitoring box (M) of Figure 5 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). The reporting requirements are linked to the MRV purpose (e.g. national GHG inventories or carbon farming), the stakeholder responsible for the reporting (e.g. a state, a carbon project developer, a farmer) and the nature of the payment systems (i.e. payment for practice, for performance). Generally, the more complex the methodologies are, the more demanding the reporting will become. For example, reporting on the implementation of a practice might be straightforward for a farmer, but this will be far more challenging if a farmer aims for a payment for performance derived from model-based approaches. Note that the reported information (e.g. practices) frequently contains errors and/or inconsistencies (e.g. several seeding dates of cash crops on the same plot in the same year). Therefore, it is essential to consider the heterogeneity of capacities (e.g. reliable access to Internet for online reporting) and expertise of the stakeholder responsible for the reporting.
- Verification, which includes rules and procedures, verification itself, proof of adoption of practice and, data (soil and/or EO) for verification (V1 to V4). Verification of the practices implemented during performance-based projects could benefit from modern technologies. For instance, activity data could be collected through mobile phones (Baumüller 2018; Herrick *et al.* 2016], online portals (Fritz *et al.* 2019) or connection to Farm Management Information Systems (FMIS) (Fountas *et al.* 2015; Melzer *et al.* 2023) with application programming interfaces (APIs) (Arroqui *et al.* 2012). Yet, our own recent experience has shown that activity data in FMIS may lack reliability/consistency and may require to be checked by a third party (e.g. an agricultural council). For verification of SOC stock changes, we recommend an approach based on soil re-sampling (e.g. surveys, grids, demonstration farms) and remote sensing using standardized protocols (See Chapter 7 for more details).

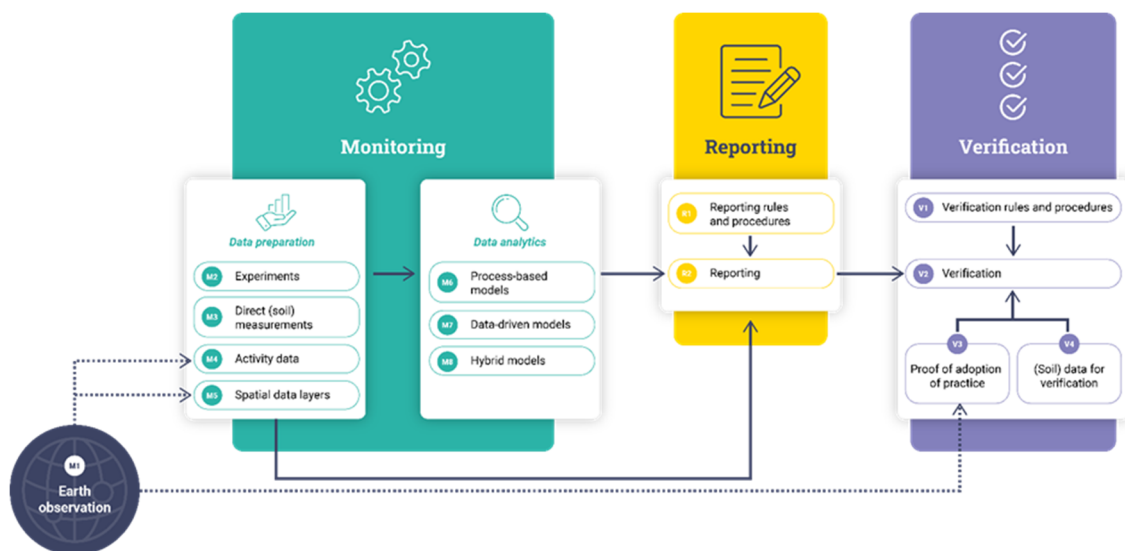


Figure 6. Schematic representation of components, building blocks, and information flow for a generic, scalable MRV system (Batjes *et al.* 2024).

Note that the same building blocks (and their constituting parts) can be used in one or several components of an MRV system. The three components and their building blocks, as well as their practical application, have been discussed in detail in Batjes *et al.* (2023). Importantly, the same building blocks (and their constituting parts) can be used in one or several components of an MRV framework (e.g. soil sampling or EO for monitoring or for verification) as further described in Batjes *et al.* (2023; 2024) and the sections below.

4 Proposition for a harmonised methodological framework for monitoring SOC

4.1 State of the art

As shown in Figures 3 and 4, Paustian *et al.* (2019) and Smith *et al.* (2020) described conceptual MRV frameworks for cropland focussing on NDCs in the latter case and multi-contexts in the former. They described how different “building blocks” (e.g. field datasets models, remote sensing) could contribute to the three components of an MRV framework for SOC changes. Each “building block,” is one of the separate parts that, once combined, allow to build a Scalable Quantification Platform (SQP) as called by Paustian *et al.* (2019). Examples of SQP prototypes are presented in Section 2 of Annex 1. Building blocks are spatial data layers (e.g. maps of soil properties, land management and activity data), models (e.g. process-based soil, vegetation or coupled soil-vegetation models, or data-driven models), or the combination of Earth Observation (EO) data and radiative transfer models that can produce biophysical data from EO to be assimilated in process-based models. The building blocks themselves, many elements of which already exist as loose modules, need to be assembled in SQP to be applied in one or several contexts of applications (e.g. Carbon market, AEP or NDCs) (e.g. Nevalainen *et al.* 2022 see also Section 2.2 of Annex 1; Wijmer *et al.* 2024 see also Section 2.1 of Annex 1).

More recently, Guan *et al.* (2023) proposed a different framework based on the integration of various approaches (e.g. diverse observations, sensor/*in-situ* data, modelling), defined as the “system of-systems” solution. According to these authors, such a “system-of-systems” should simultaneously comprise the following components: (1) scalable collection of ground truth data and cross-scale sensing of crop conditions, management practices, and environment at the local field level; (2) advanced modelling with the necessary processes to support the quantification of carbon outcomes; (3) systematic Model-Data Fusion (MDF), i.e. robust and efficient methods to integrate sensing data and models at each local farmland level; (4) high computation efficiency and artificial intelligence (AI) to scale to millions of individual fields with low cost; and (5) robust and multi-tier validation systems and infrastructures to ensure solution fidelity and true scalability, i.e. the ability of a solution to perform robustly with defined accuracy on all targeted fields.

The FAO GSOC-MRV Protocol (2020), for example, provides both a conceptual framework and proposes standard methodologies and a practical approach focussing on the farm scale for the monitoring, reporting and verification of changes in SOC stocks (combining *in-situ* sampling and soil centred modelling approaches) and GHG emissions/removals from agricultural projects that adopt Carbon Farming (CF) practices at farm level. It is intended to be applied in different agricultural lands, including annual and perennial crops, paddy rice, grazing lands with livestock including pastures, grasslands, rangelands, shrublands, silvo-pasture and agroforestry. The protocol consists of a series of step-by-step stages and sub-protocols in order to assess SOC changes and GHG emissions/removals by the adoption of CF practices (see Figure 7). The first stage (S1: Applicability conditions) is intended to verify that the project and activities meet the necessary requirements for this methodology to be applicable (scale, eligible and restricted lands, land uses and management practices). According to this method, the protocol shall be applicable at the farm scale in defined intervention areas (that may involve one or several fields, plots or paddocks, either within one individual farm or on different farms owned or operated by the same or

different companies that are part of the same project). The project spatial and temporal boundaries are specified during a second stage (S2: Boundaries) and in a third stage (S3: Baseline and intervention scenarios delineation), the baseline and projected intervention management scenarios and practices are defined, indicating historic and projected relevant activity data for the different areas to be assessed (e.g. areas, crops, yields, tillage practices, fertilizer use, organic amendment use, livestock density). In a fourth stage, (S4: Additionality assessment) a preliminary assessment of the additionality of the projected practices shall be performed (that is, 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). In order to do this, process-oriented SOC modelling activities and standardized methodologies to estimate key agricultural GHG emissions are delineated. This shall be performed before implementing time- and resource-demanding monitoring schemes. Once additionality is assessed, the fifth stage (S5: Monitoring) shall be implemented to monitor the implemented practices. In addition, SOC stocks shall be projected using the activity data of the performed practices and the same specified SOC models and GHG emissions methods used in the preliminary assessment. Concurrently, bi-annual reports shall be delivered (S6: Reporting) indicating performed activities, soil sampling results and modelling estimates.

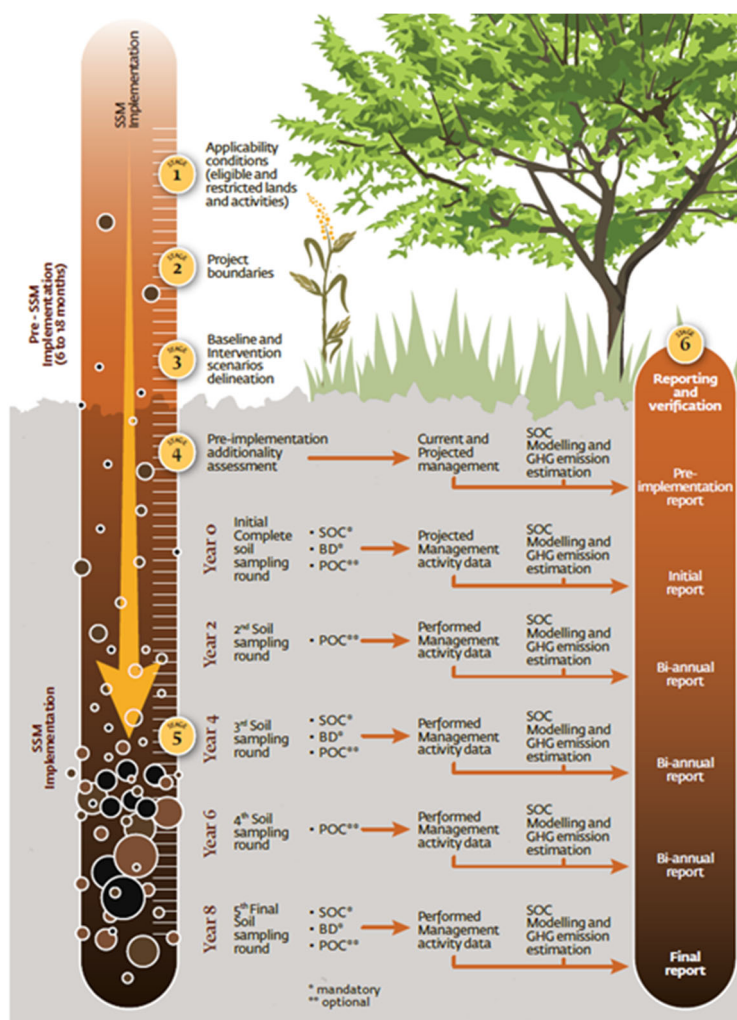


Figure 7. Schematic representation of the FAO GSOC-MRV Protocol (2020).

BD = bulk density, POC = particular organic carbon.

Finally, in an attempt to harmonize the SOC MRV frameworks developed for different ecosystems, two international co-creative workshops were organised by the ORCaSa consortium (April 2024), involving also partners from the MARVIC project, to elaborate on the Monitoring of SOC stock changes workflow (focussing mainly on cropland). The workshops involved 180 stakeholders worldwide, representing a large panel (e.g. private companies, NGOs, researchers). The aims of the workshops were to:

- discuss which methods (e.g. *in-situ* monitoring, modelling approaches) are best suited for monitoring cropland SOC stocks changes depending on the: 1) context of Monitoring Reporting and Verification (e.g. NDCs, inseting, offsetting, AEP); 2) local context (e.g. type of farm, pedo-climatic conditions), and 3) data availability/accuracy (e.g. activity data).
- try to reach a consensus on a harmonised approach for monitoring SOC stock changes in cropland, considering criteria such as cost-accuracy issues, local specificities, and alignment with existing operational national and international MRV frameworks, networks, and carbon farming initiatives. The approach should also ensure accessibility, reflect current and future user needs, and incorporate the latest scientific insights.
- discuss the criteria for building a decision tree that guides the selection of the most suitable monitoring method for each context, ensuring optimal use of data and methods (e.g. process-based models). These decision trees can help non-specialists in choosing and implementing the most appropriate method for SOC stock monitoring in their local context.

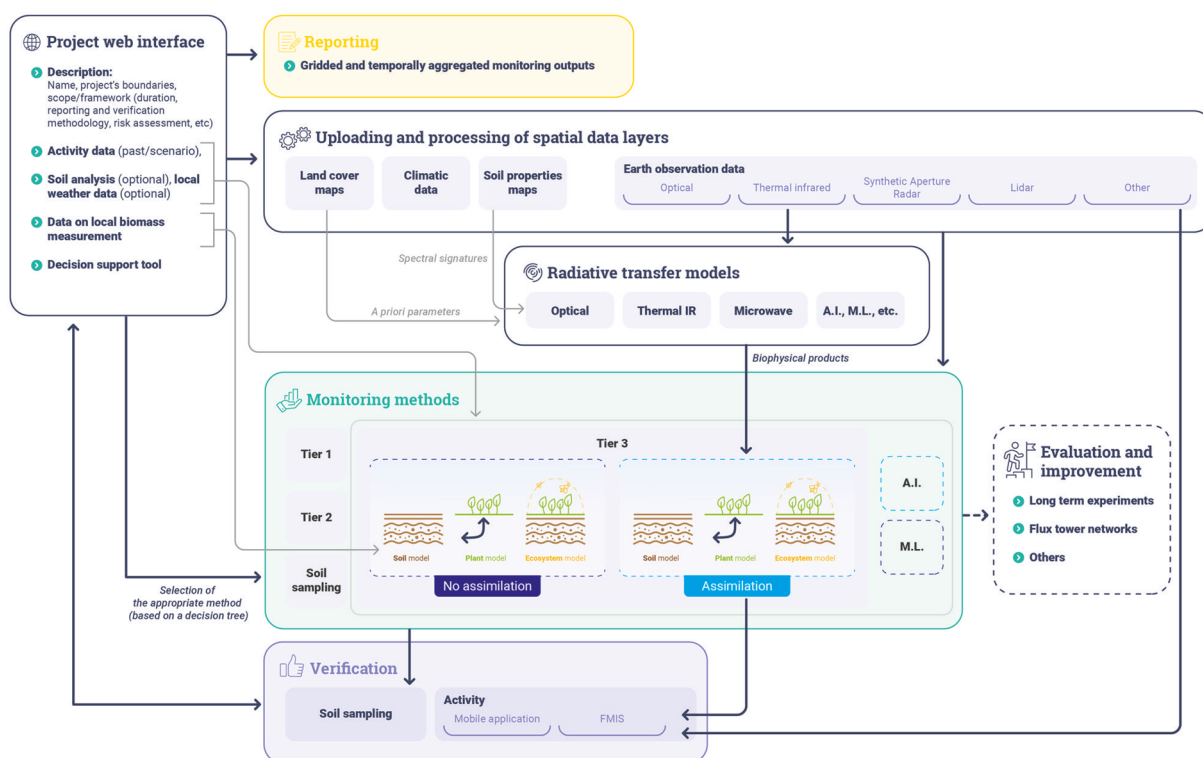


Figure 8. Proposition for a multi-ecosystem methodological framework depicting a modular flowchart for building an operational MRV tool for assessing net SOC stock changes (abbreviations: A.I., artificial intelligence; M.L., machine learning; IR, infrared; FMIS, Farm Management Information system). Source Batjes et al. (2024).

A draft framework for the approach was presented during the workshops, and following the discussions/considering the feedback from the participants and further considerations about the specificities of other ecosystems, we proposed a harmonised multi-ecosystem methodological framework for MRV of SOC that was published in Batjes *et al.* (2024) (see Figure 8). This harmonised framework should allow to: a) define the project's name, boundaries, duration, scope (e.g. NDC, inseting) through for instance a web interface (e.g. as in Nevalainen *et al.* 2022); b) permit the uploading of activity data and other relevant spatial data layers or local data when available (e.g., soil data, climatic data, aboveground biomass data); c) define the relevant method for designing the baseline (e.g. project specific, standardised) and test different scenario's (e.g. new carbon farming practices) to increase SOC stocks and reduce GHG emissions (decision tool); d) select and run an appropriate monitoring methodology based on a decision tree (see Section 5.4), which accounts for data availability, technical expertise, costs, project scope, etc; e) based on radiative transfer models, produce biophysical products derived from EO data (optical, synthetic aperture radar, thermal infrared or a combination of those) that will eventually be assimilated in Tier 3 modelling approaches (e.g. see Sections 5.3.3.1.3 and 5.3.3.2.2); f) define a relevant methodology for reporting (e.g. intervals, risk assessment of non-permanence of SOC storage) depending on the scope of the project; g) define the relevant methodology for verifying (e.g. for result-based or action-based projects) depending on the available technical expertise, costs, project scope, etc. (see Chapter 7); h) provide links to appropriate reporting and verification modules/guidelines; and i) provide guidance on carbon registries.

The different studies mentioned in this section suggest to combine rather similar data (e.g. climatic, soil properties and activity data for model inputs, calibration and validation data, sometimes EO), together with models (e.g. empirical, soil process-based models, coupled soil-crop process-based models) embedded in a spatial data infrastructure (SDI) allowing for handling of databases, intensive computing, decision support systems, verification and distribution of results/reporting. Altogether, this ensemble of building blocks form a SQP.

4.2 Proposition for a harmonised methodological framework for MRV of SOC for cropland

Building on the multi-ecosystem framework from Batjes *et al.* (2024), we propose here a harmonised methodological framework for MRV of SOC tailored to croplands specifications (Figure 9). The framework focuses on MRV approaches for the VCM, but with a methodological approach that could also be applied in the context of NDCs and AEPs (e.g. the CAP in Europe). As proposed in Batjes *et al.* (2024), we suggest that it should allow to perform different procedures and tasks in order to accomplish the three components of the MRV for SOC (see below).

Note that issues relative to leakage and non-permanence of SOC storage are not addressed in this document. For those topics we recommend to refer to the forthcoming ORCASA's Deliverable 4.4, to the Technical Guidance Handbook on Carbon Farming¹⁸ (COWI, Ecologic Institute and IEEP, 2021) or to the FAO (2020) report.

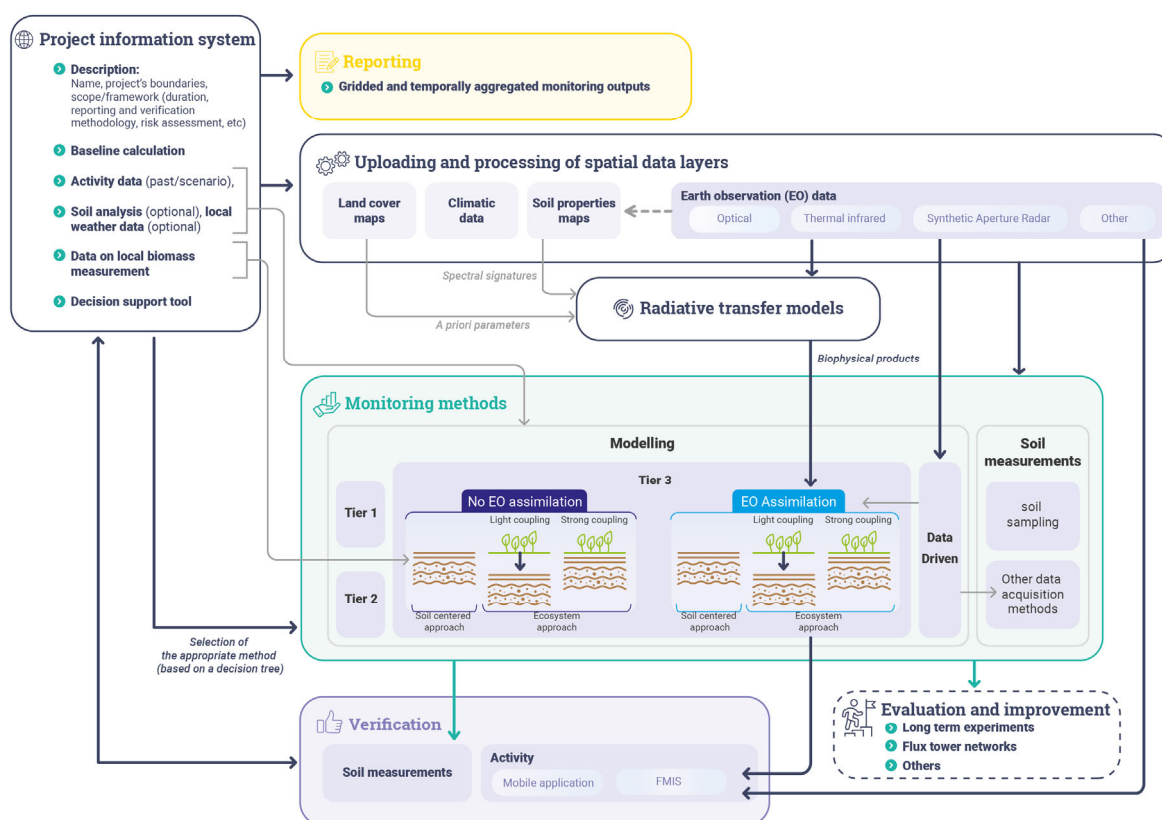


Figure 9. Schematic representation of a harmonised methodological framework for MRV of SOC stock for cropland (abbreviations: A.I., artificial intelligence; M.L., machine learning; IR, infrared; FMIS, Farm Management Information system).

Adapted from Batjes *et al.* (2024).

¹⁸ <https://www.rbpnetwork.eu/media/technical-guidance-handbook-on-carbon-farming.pdf>

4.2.1 Project information system

The project information system mainly concerns insetting and offsetting programs, although it could also be used for Tier 3 methods applied to AEPs and NDCs contexts of MRV.

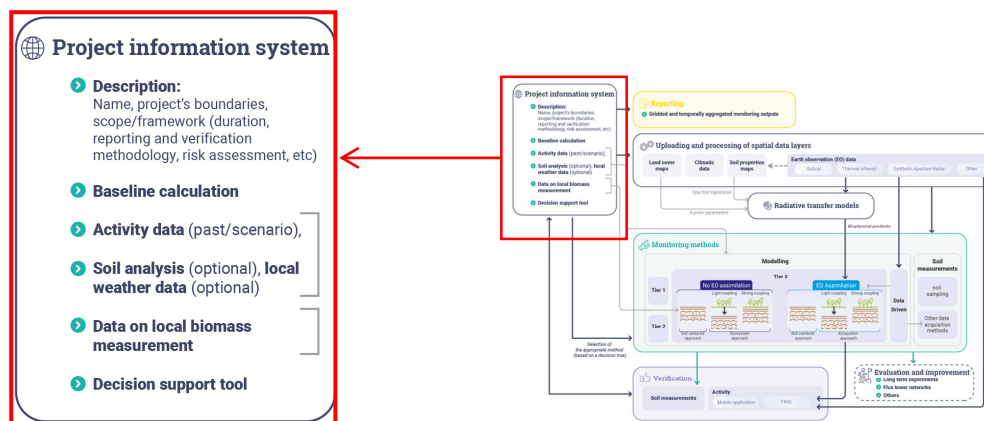


Figure 10. The red frame indicates which part of the MRV framework from Figure 9 will be addressed in this section

4.2.1.1 Spatial and temporal boundaries

The spatial and temporal scale of the MRV framework may vary depending on the context. In the context of NDCs, MRV of SOC stock changes is often operated annually to produce inventories at national or regional/province scale considering either a gridded approach (e.g. in France), survey locations associated with weights (for example, in the U.S.A. each weight represents the amount of area that is expected to have the same land use/management history as the survey point and similar approach as been implemented in Australia for the land sector LULUCF) or it could be applied at parcel scale and then aggregated to national scale. In the context of AEPs (e.g. the CAP in Europe), MRV of SOC may be operated on a cropping year basis at plot scale for all the plots susceptible to benefit from subsidies (Bockstaller *et al.* 2021). Yet, currently none of the EU member states has implemented a result-based SOC monitoring approach for the CAP, mainly due to a lack of adequate operational tools as pointed out by the H2020 NIVA project¹⁹.

In the context of the VCM, the project description interface should allow to identify the owner(s) and/or farmer(s)/companies operating the land(s) that, depending on the MRV context, may belong to a similar CF project that should be identifiable with a unique code/name. Also, each plot, or farm concerned by the CF project, (see Section 4.2.1.1 concerning the spatial boundaries) should be identified with a unique code in order to build a unique spatially explicit carbon registry allowing to avoid/track double accounting of SOC stock changes and of carbon crediting, but also eventually to relate with MRV actions operated in other contexts (e.g. for the CAP) and during previous or following years. This would facilitate the collection of plot/farm activity data over previous years to build activity and C stock changes plot/farm specific baselines, but also to continue to monitor the plot for some years after the end of the CF project in order to verify that efforts were made, at least to maintain the SOC stocks reported at the end of the CF project. In the context of the VCM, this spatially explicit land-parcel registry could provide a foundation for buyers and sellers to safely trade and transfer CF units through a trustworthy market place.

¹⁹ <https://www.niva4cap.eu/>

According to the FAO GSOC-MRV Protocol (2020), the monitoring shall be applicable at the farm scale in defined intervention areas. Each intervention area may involve one or several fields, plots or paddocks, either within one individual farm or on different farms owned or operated by the same or different farmers/companies that are part of the same project. According to this protocol, if one part of the project area is materially different to another, more than one intervention area shall be defined due to the increased likelihood of detecting changes in SOC content in homogeneous intervention areas. Important differences in soil type, land use, land-use history and landform will affect SOC stocks and, thus, trigger delineation of separate intervention areas (IAs).

In France, the Low Carbon Label methodology dedicated to the VCM for arable land, cropping systems (i.e. a combination of crop rotations x soil types x management practices) are considered as the unit of reference and CF projects last 5 years. In EU the Carbon Removals and Carbon Farming Certification Regulation (CRCF) framework considers monitoring at the plot scale and for a period that last several years after the end of the CF projects that should last 5 to 10 years. In EU again, but now in the context of the CAP, monitoring is generally performed on a yearly basis and at the parcel level. Finally, in an insetting context, CF projects may refer to one or several parcels belonging to one or several farms. The carbon premiums are sometimes paid for a given plot of a given farm for a given year and the same or another plot from the same farm or from another farm may be concerned in the following years.

Considering this diversity of spatial and temporal scales of MRV, we recommend an annual (cropping year) and plot scale assessment of SOC stock changes and the building of a unique spatially explicit carbon registry allowing to avoid double accounting of SOC stock changes and of carbon crediting, but also offering the flexibility to combine practice-based (e.g; through agri-environmental measures such as in the CAP) and result-based payment (i.e. through the VCM). See <https://hal.inrae.fr/hal-04225931/file/NIVA-Policy-Brief-nr.-5-Agro-environmental-indicator-carbon-D1.0.pdf> for more details. Considering that plot scale assessment also makes sense as it is the unit of management, it would allow consistent monitoring, reporting and verification across MRV contexts and years.

4.2.1.2 Eligibility of the land and context of the MRV for SOC

Before implementing the MRV framework (Figure 9), the eligibility of the land and the scope of the MRV should be considered. In this document and in our framework, as indicated earlier, we only consider croplands that remain croplands on mineral soils and limit ourselves to annual crops (silvo-arable systems are not considered here). Also defining the context of MRV is important as it will determine the applicable methodologies. In a context of NDCs, according to IPCC (2006), three different modelling approaches (Tier 1 to 3) can be implemented to assess SOC stock changes (see Chapter 6). For instance, in the U.S.A., carbon dioxide emissions and removals due to changes in mineral SOC stocks are estimated using a Tier 3 method for the majority of annual crops (Ogle *et al.* 2010, 2023). However, a Tier 2 IPCC method is used for the remaining crops not parametrised/validated in the Tier 3 method (Ogle *et al.* 2003, 2006). In addition, a Tier 2 method is used for very gravelly, cobbely, or shaley soils (i.e., classified as soils that have greater than 35 percent of soil volume comprised of gravel, cobbles, or shale, regardless of crop). Alternatively, emissions from organic soils are estimated using a Tier 2 IPCC method.

In a VCM context, the FAO GSOC-MRV Protocol (2020) indicates that their method should only be applied to “croplands that show the potential for improvement in their soil organic carbon stock after the adoption of CF practices (compared to business as usual practices) by either gaining or maintaining SOC levels, should be considered”. It concerns a) croplands where SOC levels have reached equilibrium yet it is possible to increase these levels through CF; b) croplands where the SOC level is increasing and can be further increased through CF;

c) croplands where SOC levels are declining and it is possible to stop or mitigate these losses through Sustainable Soil Management (SSM); and d) lands where SOC levels are declining and it is possible to reverse this decrease through CF. The FAO GSOC-MRV Protocol however does not allow to consider the plots/farms of early adopters of CF practices that have already reached equilibrium and where it is not possible to increase levels through CF practices any-further. Therefore, the E.U. CRCF prefers a framework based on a standardised baseline over activity specific baselines. According to the CRCF, these standardised baselines should be highly representative of the standard performance of comparable practices and processes in similar social, economic, environmental, regulatory and technological circumstances, and consider the geographical context, including local pedo-climatic and regulatory conditions (see Section 4.2.1.4 for more details concerning the baseline issue). This approach allows to compare a given farm to similar ones in the same region allowing to reward early adopters of CF practices.

In the context of the VCM and of the agricultural and environmental policies, it is the responsibility of the certification bodies and/or countries to decide what are the rules for considering that plots/farms/projects are eligible. In the case of early adopters whose plots/farm cannot increase their SOC stocks, other rewarding mechanisms may be considered e.g. to promoting SOC stock preservation. Similarly, according to the FAO GSOC-MRV Protocol (2020), in order to avoid potential C losses and damage to biodiversity-rich lands, this methodological framework shouldn't be applied 1) on current or former wetlands and peatlands, 2) on organic soils, Histosols, or soils having a histic or folic horizon and 3) on lands that have been under native forest lands and were converted to grasslands or croplands, at any point during a baseline period (at least ten years), or other baseline periods determined by regulations under national and international legislation.

4.2.1.3 Eligibility of the CF practices

It is beyond the scope of this deliverable to provide recommendations concerning which practice change should be considered under CF. However, according to FAO (2017), the allowed intervention practices shall be based on the Voluntary Guidelines for Sustainable Soil Management (VGSSM). These provide guidance to a wide range of stakeholders. In these guidelines, Sustainable Soil Management (SSM) is defined according to Principle 3 in the revised World Soil Charter as follows: "Soil management is sustainable if the supporting, provisioning, regulating, and cultural services provided by soil are maintained or enhanced without significantly impairing either the soil functions that enable those services or biodiversity."

More recently, the FAO and ITPS (2021) manual on "Recarbonizing global soils: A technical manual of recommended sustainable soil management" described Sustainable Soil Management (SSM) practices applicable at different scales and in different contexts. These are illustrated by case studies with quantitative data, shown to have a positive effect on SOC stocks in practical field applications. Volume 3, dedicated to 'Cropland, Grassland, Integrated systems, and farming approaches', describes a total of 49 practices that have a direct impact on SOC sequestration and maintenance in cropland, grassland, integrated systems and farming approaches. Among these, 29 practices concern specifically cropland: soil cover with biomass (cover cropping, organic mulch), crop diversification (crop rotations, intercropping with multiple crops or strip cropping), tillage (no-till, conservation, reduced and superficial tillage, strip/precision/zone tillage, non-inversion tillage), nutrient management including organic matter additions (manure additions, digestate application, compost application, sewage sludge additions) and chemical and mineral fertilization (macro, secondary and micronutrients, fertigation), integrated soil fertility management, biochar, addition of living organisms (biofertilizers application, earthworm inoculation, dung burial by

beetles), chemical amendments (liming acidic soils, application of gypsum on sodic soils), erosion control techniques (terraces, check dams, shelterbelts, hedges and buffer strips, avoiding improper earth movements before planting tree crops), adequate irrigation practices, limited soil disturbance (i.e. controlled traffic farming).

Note that, depending on the regional or local context, some CF practices may be more relevant than others to sequester organic carbon in the soil. For instance, adoption of no-till management on croplands has become a controversial approach for storing carbon in soil due to conflicting findings (Powlson *et al.* 2011; Virto *et al.* 2012). Based on a literature review, for example, Ogle *et al.* (2019) found that SOC storage can be higher under no-till management in some soil types and climatic conditions even with redistribution of SOC. However, uncertainties tend to be large, which may make this approach less attractive as a possible contribution to mitigate the climate system compared to other options. For this reason, the French Low Carbon Label decided not to consider no-till as a CF management practice. On the contrary, farmers are incentivized by the Department of Agriculture's Environmental Quality Incentives Program to practice no-till. Further, in EU, the CRCF considers implementing soil protection measures like catch crops, cover crops, conservation tillage, and hedgerows but not organic amendments which involve a displacement of organic carbon rather than a net C gain/sequestration.

4.2.1.4 Setting the baseline

The project information system should allow to define the method and select the algorithms for defining the baseline approach suitable for the MRV local context. Indeed, depending on the MRV context (offsetting, insetting, AEP) and the monitoring methodology (e.g. soil measure and re-measure, Tier 3 modelling) that is partly defined by the input data availability/accuracy, different approaches for defining the baseline can be or are currently considered (see Chapter 6 for more details concerning the suitable baseline approaches depending on the monitoring method).

In the context of the NDCs, according to OECD report (2018) on "Accounting for baseline targets in NDCs: Issues and options for guidance", baseline scenarios can be defined as a future projected reference level of emissions against which a goal can be established or progress can be measured (Clapp and Prag, 2012). Baseline scenarios can be provided for information only ("information baselines"), to demonstrate emissions that would have occurred in the absence of certain mitigation policies (WRI, 2014). Information baselines can be relevant to any mitigation target type. Baselines can also be used as a reference to set a target ("target baselines"). A large proportion of Parties – around 41% or 80 out of 197 Parties – have expressed (I) NDC targets in relation to baseline scenarios. Baseline targets express a Party's mitigation response relative to a counterfactual baseline scenario, under which certain emission reductions and associated policies (that could have a direct or indirect effect on emissions) do not take place. Baselines could be static (as in the Australian CF method) or dynamic. In this context of MRV, static baselines are fixed in advance of the time period they cover and can provide some certainty to those making policy or investment decisions over the chosen time period. Dynamic baselines can include recalculations based on updated activity data or changes in other drivers (e.g. technology costs) that take place within the chosen time period. See https://www.oecd.org/content/dam/oecd/en/publications/reports/2018/04/accounting-for-baseline-targets-in-ndcs_6c225b5e/9ae65cc1-en.pdf for more details.

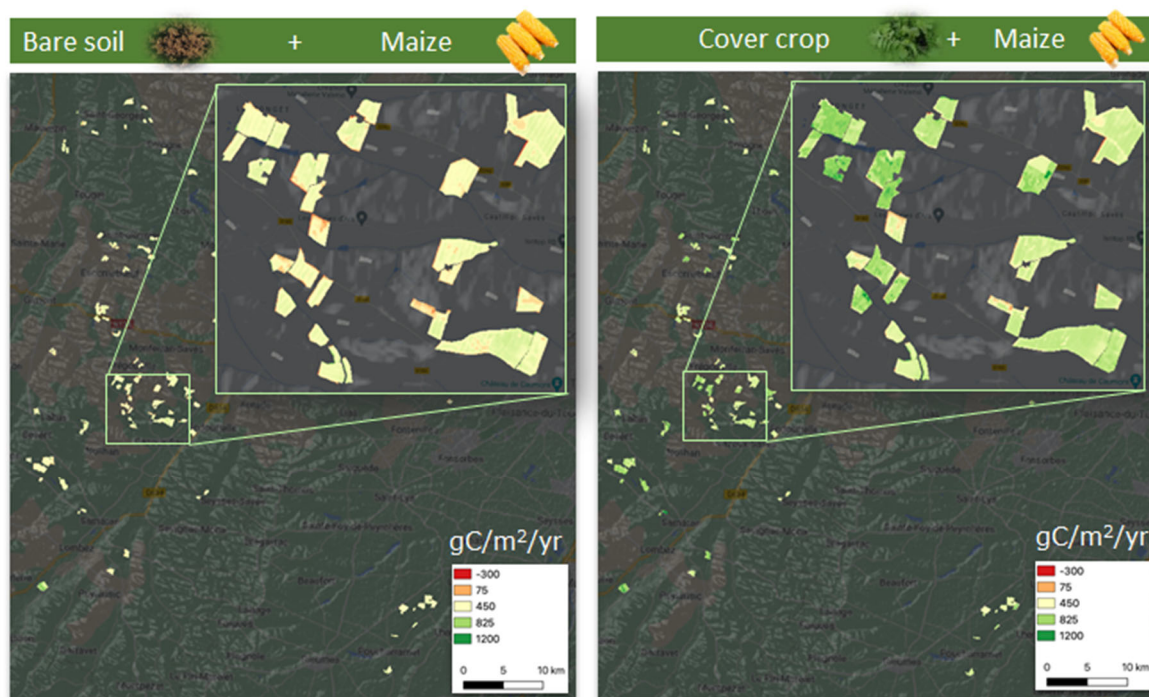


Figure 11. On the left, 10m resolution simulation of net annual CO₂ fluxes over one cropping year near Toulouse (France) with the AgriCarbon-EO V1.0.1 processing chain (assimilating Sentinel-2 EO data) for maize fields where the cover crops preceding the maize have been ignored in the simulation, and on the right the same fields but considering the effect of the cover crops on the net annual CO₂ fluxes computed with AgriCarbon-EO. The difference between the two simulations represents the amount of C input to the soil through the cover crop biomass. (adapted from Al Bitar *et al.* IGARSS 2022).

Baselines at the start of a project are the foundation for all MRV activities in the VCM context. The baseline allows to quantify the evolution of SOC stocks under business as usual (BAU) management practices. In insetting CF projects, if a contract is signed on an annual basis only (e.g. for producing potato for a given cropping year) between the agri-food company and the farmer, the premium paid by the company for the carbon sequestered through one (or several) specific CF practice (e.g. cover crops) will be paid on an annual basis considering, as a baseline, how much C would have been stored or lost that same year without implementing this (or those) CF. Figure 11 shows an example of simulations with the AgriCarbon-EO processing chain (Wijmer *et al.* 2024) of the net annual CO₂ flux (in gC-CO₂.m⁻².s⁻¹) of maize fields in South West France belonging to the network of popcorn producers of the Nataïs company that pays a bonus to the farmers according to how much C they stored in the soil by growing cover crops: on the right, considering the cover crop development observed by remote sensing before the maize, and on the left ignoring the presence of cover crops, i.e. considering bare soil during the fallow period. The difference between the two simulations correspond to the additional C input to the soil with cover crops biomass that is used to calculate SOC stock changes with the AMG soil model (Clivot *et al.* 2019).

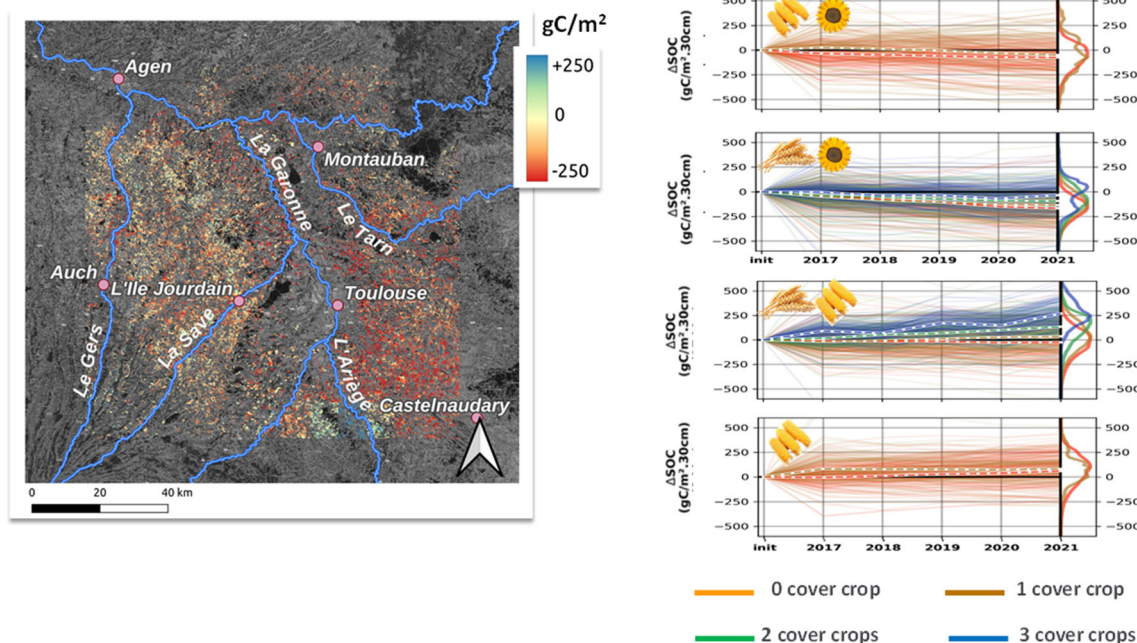


Figure 12. On the left, 10m resolution simulation of SOC stock changes over 5 years (2017-2021) near Toulouse (France) with the AgriCarbon-EO V2.0 processing chain for crop rotations including straw cereals, maize, sunflower and cover crops considering standardised management practices with no organic amendment and straw retention (Wijmer, 2024). In AgriCarbon-EO V2.0, the biomass input to the soil simulated with AgriCarbon-EO V1.0 (Wijmer *et al.* 2024) are used as input for the AMG soil model (Clivot *et al.* 2019) to simulate SOC stock changes. On the right, SOC stock trends for each plot simulated on the left and belonging to one of the four categories of crop rotation shown and having between 0 and 3 cover crops during the crop rotation. The mean of each category of crop rotation x frequency of cover crop, shown with a dashed line, correspond to a hybrid dynamic average baseline in the sense that it considers standardised soil properties (LUCAS maps) and standardised management practices for organic amendments and straw management but plot specific management for cover crops and implicitly the other management practices (e.g. fertilisation, sowing date or density) through the EO data assimilation process in the SAFYE-CO2 crop model (Pique *et al.* 2020 a,b,c). Credits: Taeken Wijmer.

In the context of offsetting (but could apply also to pluri-annual insetting projects), different baseline approaches are currently implemented. Most of the time three generic approaches to setting project specific baselines for offsetting CF projects are considered (Oldfield *et al.* 2021), i.e. static (or ex-ante), static average and dynamic (or ex-post), but some projects may rely instead on dynamic average or standardised baseline (also called 'regional' or 'generic' baselines) or on hybrid baselines as shown in Figure 12. Concerning specific baselines, static and static average baselines are set at the project start prior to new management practices; static baseline is determined for each parcel while static 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. Standardised baselines may concern initial SOC stocks, carbon farming practices or both. The principle is that instead of considering a reference status of a given farm/parcel in time as the baseline, the baseline will be defined by considering the mean status of the farms in a region surrounding the farm/parcel 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. 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.

In the Improved Agricultural Land Management (IALM) Methodology by Verra, whose monitoring approach combines *in-situ* soil sampling and modelling, the baseline approach is static and built on a scenario that is determined by applying a historic look-back period to produce an annual schedule of activities that is repeated over the first project monitoring period²⁰. The historic look-back period identifies actual management activities on each land parcel included in the project scenario; it must be a minimum of 3 years and include at least one complete crop rotation, where applicable. The French Low Carbon Label methodology for cropland has a rather similar approach but it considers cropping systems (i.e. a combination of crop rotations x soil types x management practices) and soil sampling are not mandatory to define the initial SOC stocks. Also, 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 (e.g. Do Nascimento Bendini *et al.* 2024).

In the context of the EU's CRCF, the MARVIC project (Lanckriet *et al.*, 2024) has analysed different options to calculate baselines and has proposed new ones compared to the ones mentioned above (see Figure 13). As shown in Figure 13 (Ruysschaert *et al.*, 2024), the baselines are sorted by 'scale category', i.e., standardised baselines vs specific baselines, 'calculation method category', i.e. measure-remeasure and Tier 3 modelling and 'time category', i.e., static or dynamic.

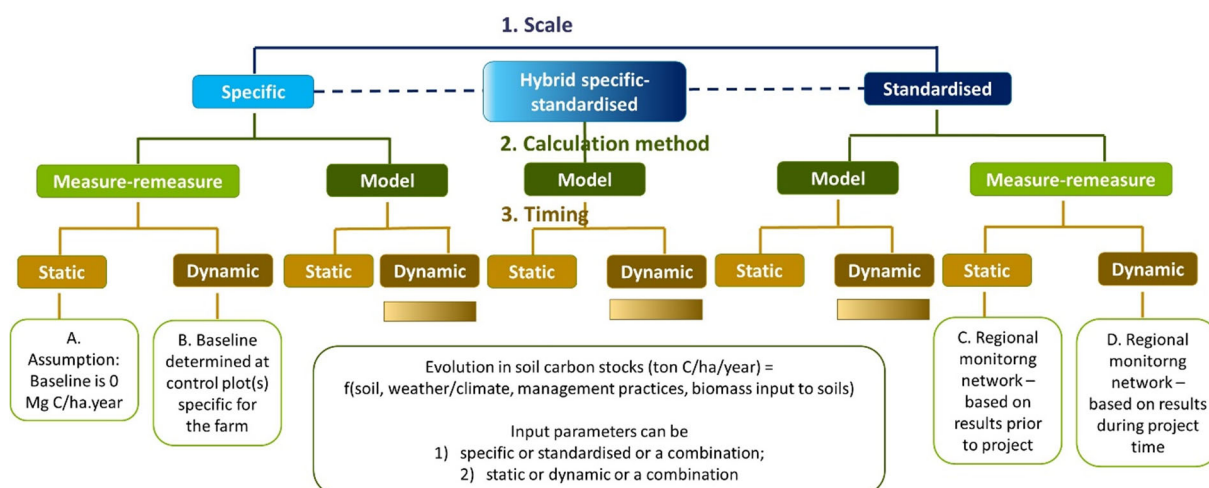


Figure 13. Different options for calculating baselines for carbon farming (derived from Lanckriet *et al.* 2024; MARVIC D1.2). The coloured bars under 'dynamic' indicate that with modelling some input parameters could be 'dynamic', others 'static' (Figure taken from Ruysschaert *et al.*, 2024)

According to the MARVIC project, for monitoring approaches based on Tier 3 modelling, the operator could choose to have a mix of specific (e.g. soil properties) and standardised (e.g. activity data) input parameters. What baseline option should be chosen depends on different criteria, such as: what farmers prefer to incentivise, the choices made regarding the definition of additionality, the modelling approach (e.g., soil centred, ecosystem approach with or without EO assimilation).

²⁰ <https://verra.org/methodologies-main/improved-agricultural-land-management-ialm-methodology-frequently-asked-questions-faqs/>

As the CRCF prefers a standardised baseline, the MARVIC project's main recommendations for standardised baselines (Ruysschaert et al. 2024) were:

- (1) **To use a hybrid specific-standardised approach with a model using 'specific' soil data (e.g., clay content, initial SOC) and 'standardised' management**. This approach allows to account for soil characteristics (e.g., clay and initial SOC content) that influence the carbon removal result of the CF practices. First movers, for example, might have higher SOC stocks than the average in the region, and might as a result sequester less carbon for similar CF practices than their neighbours as maintaining high SOC stocks requires already high SOC inputs which might cause frustration and a feeling of injustice. As maintaining high carbon stocks (regardless of the reason of these high stocks) usually requires better management than average, calculating baselines with soil-specific information guarantees that management that is resulting in maintaining high carbon stocks can be incentivised. The approach of calculating baselines with 'specific' soil data may requires accurate soil data, which could result from initial soil sampling at parcel level or improved soil maps otherwise it will represent a high cost. This may be a disadvantage but this information is often required anyway for quantifying project lines in CF schemes for the voluntary C market.
- (2) **To use for the quantification of the baseline the same quantification method as for the project line (same model, same method to estimate biomass input, same way of dealing with extreme weather events).**

Furthermore, the MARVIC project listed some pros and cons of some other baseline approaches (Ruysschaert et al., 2024):

- Specific baseline measure-remeasure (static): this approach assumes that the baseline is 0 t C/ha/year, but in reality, soils are not in a steady state. They are usually emitting or sequestering carbon under a business as usual scenario;
- Specific baseline measure-remeasure (dynamic): the advantage is that the non-steady state character of the baseline can be captured and that actual (weather) conditions are the same as under the project. It requires control plots where business as usual practices are maintained (time consuming and costly);
- Standardised baseline measure-remeasure: this requires a soil carbon monitoring network for which emission factors per land use type/soil type are calculated. This approach has the same disadvantages as the described above, i.e., that it does not account for differences between average soil conditions and the specific soil conditions of a project.
- Specific baselines (modelled or with control plots) have the advantage that technical additionality is assured. This approach also ensures that farmers with less sustainable management practices in the past can be incentivised; in contrast, when standard management is used to produce the baseline, the barrier might be too large as they first have to bridge the gap to this standard management.

Concerning the Hybrid standardised soil data-specific management/activity approach with SOC model, it allows to account for plot specific CF practices considering average soil characteristics in the region (e.g. from SoilGrids) for both the reference et project line simulations. First movers, for example, would be advantaged by this approach as the model would considered lower initial SOC stocks than in reality and therefore would estimate higher SOC stock increases with the CF practices implemented on that plot. One of the main disadvantages of this approach is the cost for collecting plot level detailed activity data.

Yet, regardless of the cost, soil specific-activity (management) specific dynamic approach for defining the baseline would provide the most accurate estimate of the SOC stock trends if no CF practice had been implemented and therefore for assessing SOC stock changes following the implementation of CF practices.

4.2.1.5 Uploading of local data

4.2.1.5.1 Activity data

The project information system should allow either manual uploading by the farmers or by agricultural councils of plot/farm scale activity data or through automated process, e.g. relying on APIs (Application Programming Interface) and Farm Management Information Systems (FMIS). Note that this step is critical because it will condition to a large extent the accuracy of the SOC monitoring. Based on our own experience, we strongly recommend to implement verification procedures ensuring the consistency and quality of the activity data (e.g. verification by a third party, e.g. an agricultural council) and to use standardised nomenclatures or vocabularies (e.g. building on the ICOS nomenclatures or using the International Consortium for Agricultural Systems Applications standards) and standard international units.

According to Ceschia *et al.* (2010) the activity that impact the GHG budget and SOC stock changes of cropland and that therefore require the most effort concerning their accuracy are:

- harvest i.e. date and how much carbon has been exported from the plot as grain, straw/stubble, tubers... Straw management (*i.e.* are straw exported, buried or burned) is a key driver of whether a plot acts as a C sink or a C source according to Ceschia *et al.* (2010) and Kutsch *et al.* (2010). Yield is often used by Tier 3 soil centred modelling approaches to estimate crop residues (straw, roots) and then C inputs to the soil by using allometric relationships (e.g. via harvest index) (see Section 5.3.3.1.).
- Organic amendments are also a key driver of the SOC stock changes. This is probably one of the highest sources of uncertainty when calculating the SOC stock changes on the plots where they are applied because depending on their form (e.g. solid, liquid), their percentage of humidity, their dry mass carbon content, their carbon composition (quality of the material) and if they have been homogeneously applied in the field (which is often not the case), the amount of C input to the parcel may vary greatly (including at intra-field level) for a given type of organic amendment.
- Crop species (and often date of sowing and harvesting) will be a key driver of how much carbon returns to the soil.
- Cash crop or cover crops implementation and if they are buried or (partially) harvested for forage, energy production etc. as it conditions the annual C exports from the plot.

Depending on the modelling approaches, the need for activity data may vary greatly. For instance, in most soil centred modelling approaches, the previously mentioned activity data as well as tillage and irrigation are usually the main or only activity data needed. However, most ecosystem modelling approaches that are not relying on EO assimilation need more activity data (than the soil centred approach or than the ecosystem modelling approaches dedicated to upscaling assimilating EO data) such as mineral fertilisation, sowing date, sowing density, variety... Note that activity data have uncertainties that are, to our current knowledge, never quantified nor accounted for in assessing the uncertainty on SOC stock changes. It is however obvious that in operational MRV context (e.g. for the voluntary carbon market), the quality and the accuracy of the activity data will be lower compared to contexts in which Tier 3 models are usually developed, calibrated and validated (*i.e.* often at experimental field trials in very

controlled conditions). Therefore, we recommend to assess whenever it is possible to assess the uncertainty on activity data and to account for them in the calculation of the SOC stock changes and of their uncertainties.

4.2.1.5.2 Local weather data

Although climate products (e.g. ERA5 Land, see Muñoz-Sabater *et al.* 2021) are available worldwide and for free for some applications, their spatial resolution and their method of production is a source of uncertainty for the modelling process. Therefore, it may be useful to use data from local weather stations (on farm) or local weather networks to reduce the uncertainty in Tier3 modelling approaches that use climatic data as input. Again, depending on the modelling approach, more or less climatic data will be needed. Ecosystem modelling approaches being usually the most demanding as they generally require not only temperature and precipitation data but also information of incoming solar radiation (e.g. amount, ratio of direct to diffuse radiation) in order to calculate photosynthesis and/or biomass production.

Therefore, the Project information system should allow to upload local climatic data or to automatically download them, e.g; from a server. For more considerations on local weather data see Section 4.2.1.5.

4.2.1.5.3 Local soil data

The collection of local soil data concerns the VCM (insetting or offsetting) context or the AEPs context. Recent and reliable soil point or area data are needed (often collected by new or recent sampling) for monitoring approaches based on measure-remeasure or for Tier 3 modelling (for baseline purpose, model initialization or verification). Existing recent soil data that can be suitable for model initialization, or a regional or local baseline may be available when land managers take regular soil samples for AEPs (e.g. CAP) or precision farming purposes. However, these data will need to be evaluated to assess the suitability of the data for MRV purposes and in many cases additional sampling may be needed. Data for local baselines, for model initialization, or monitoring for each MRV context should in all cases be measured along standard depth intervals (depending on the MRV or certification system, IPCC guidelines indicate 30 cm, FAO 30 cm), either by volume or mass sampling but per MRV system consistently with one of the two, using a standard sampling protocol and measuring at a constant moment in the crop rotation (e.g. just after harvest of a certain crop), with one lab method per soil property. When transfer functions are used the resulting additional uncertainty should be accounted for, have a statistically good coverage of the feature space of the project or MRV area (often described by (variation in) soil type, land use, land management, and geographic space), have an associated uncertainty and unbiased mean result. Strategies for soil sampling are detailed in Chapter 5.1.

Local or additional soil samples are in some cases imported directly from the lab to the FMIS, but in many cases they are supplied in Excel or PDF format, requiring manual transfer and upload to the project information system. Depending on the source and format, their FAIRness may differ. This requires a good description of the data in metadata, an access license or indicated data policy, the use of standard terminology for the soil property, (lab) method, unit of measure, date, etc., preferably using controlled vocabularies with unique identifiers, such as available in AGROVOC, GEMET or other online thesauri. When MRV soil monitoring data are also used for reporting, these aspects may have been addressed already, making their inclusion in a project information system easier.

For sub-national and local scale assessments of SOC stock change, spatially detailed soil maps (or GIS layers), based on environmental covariates and soil data reported/measured at a fine scale, can be available (e.g.,

Grunwald *et al.* 2011; Piikki *et al.* 2017; Venter *et al.* 2021; Dandabathula *et al.* 2022). It is important that these capture the fine-scale soil variability induced by the history of agricultural practices, microclimate, and microtopography, that is needed for sub-national level modelling exercises in the context of the voluntary C market, especially in areas with complex/heterogeneous soil conditions and at local scale. More details and examples and relevance of global soil property maps are described in Section **Erreur ! Signet non défini.**

4.2.1.5.4 Local biomass data

The project information system should allow to upload data on *in-situ* biomass measurements performed at the plot/farm/project level. Indeed, *in-situ* measurements of biomass (usually aboveground) may be very valuable or even mandatory in the context of the MRV for the VCM: first, as input data for the soil centred modelling approach (see Section 5.3.3.1) that only simulate the soil processes and required information on C inputs to the soil as biomass, second for verification purposes and third for developing/validating EO based approaches for monitoring crop or cover crop biomass (e.g. Tucker, 1980; Chen *et al.* 2010; Kross *et al.* 2015; Marshall *et al.* 2015; Hosseini *et al.* 2019). This is particularly critical for cover crops, as for common crops, the total biomass can be estimated from the yield data provided by the farmers and by applying allometric relationships to estimate aboveground and belowground biomass, as in Bolinder *et al.* (2007). For cover crops, this kind of approach cannot be applied and therefore only *in-situ* measurements, regional statistics or EO based approach can provide cover crop biomass estimates and their equivalent C inputs to the soil. As an example, the French Low Carbon Label methodology for cropland, requires either *in-situ* measurements of cover crop biomass, or mean regional estimates of the cover crop biomass (resulting in a discount on the C credits) or EO based estimates of cover crop biomass (e.g. Zheng *et al.* 2004; do Nascimento Bendini *et al.* 2024).

One of the main challenges when sampling crop or cover crop biomass in the field is to collect samples that yield unbiased and accurate estimates of the field's average or of the intra-field spatial variability. For this, stratified random sampling methods based on high resolution remote sensing data can be used as in Lv *et al.* (2021). Note that for more accurate estimates of C inputs through biomass, dry above ground biomass should be considered instead of fresh biomass, as the water content of the vegetation varies in space and time.

Also, if *in-situ* crop or cover crop biomass samplings are used at some point to develop, calibrate or validate an EO based approach (e.g. data driven as in Section 5.3.4 or based on EO assimilation in vegetation or ecosystem models) we strongly recommend to apply Elementary Sampling Unit protocols as in Pique *et al.* (2020 a,b,c), do Nascimento Bendini *et al.* (2024) and Wijmer *et al.* (2024). Indeed, the ESU protocol provides an *in-situ* georeferenced dry aboveground mean biomass estimate (based on the sampling of 5 placets of 1-2 m²) that is representative of the dry aboveground biomass encompassed in a satellite pixel.

4.2.1.6 Decision support system

Decision support tools provide information on the quantification of SOC changes, GHG emissions, or both, under BAU scenario or alternative ones involving CF practices. That is why they are often integrated in MRV tools or SQP

for MRV (e.g. Nevalainen *et al.* 2022). They often use Tier 1 and Tier 2 IPCC approaches²¹ but can also include a Tier 3 modelling approach allowing also to monitor SOC stock changes, as was the case with the CBP (Milne *et al.* 2010), COMET-FARM²² (based on the DayCent soil model (Del Grosso *et al.* 2002) or SIMEOS-AMG²³ (based on the AMG soil model (Clivot *et al.* 2019)). Tier 3 type approaches, the most demanding ones, are run using spatially explicit inputs (e.g. soil properties maps) and farm/region-specific model parameters. Tier 3 is considered to be the most accurate method (IPCC 2019c). Those decision support tools (in particular Tier 3 type) depend on several of the building blocks described in Figures 6 and 9 (e.g., spatial data for climate or activity data as input, *in-situ* soil data for validation).

Decision support tools are typically used to test several CF scenarios (e.g. grow cover crops during the fallow period, change of crop rotation or straw management) that help the farmer choosing the CF practices he will implement considering their potential for storing C, for reducing GHG emissions, technical, workload and financial considerations. Farmers are often assisted by an agricultural advisor during this process.

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 farmers in developing countries, application of the tool and future plans. Examples include down-loadable, 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).

Currently, none of the decision support tools mentioned above allows 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 these tools. Alternatively, as indicated by 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 (Australian protocol).

4.2.1.7 Choice of the monitoring, reporting and verification methodologies

We will not describe here the monitoring, reporting and verification components, as they are respectively described in Chapters 6, 7 and 8.

If some platforms were to include the possibility of implementing several monitoring methods, we would recommend that the Project's interface hosts a tool to choose the most appropriate method based on the MRV objective (e.g. insetting or offsetting CF project) and local context, which would be based on the decision tree presented in Section 4.3.

²¹ Note: The "IPCC 2019 refinement to the 2006 guidelines" introduced a Tier 2 Steady-State Method for Soil Carbon, based on DayCent.

²² <https://comet-farm.com/>

²³ <http://www.agro-transfert-rt.org/ressources/simeos-amg-2/>

Similarly, concerning the choice of the verification approach, the Project's interface could propose, depending on the MRV purpose and local context a decision tool to help identify which is the best methodology for verification of the practice adoption or of the SOC stock changes. See Sections 7.1 and 7.2 for more details.

4.2.2 Uploading of spatial data

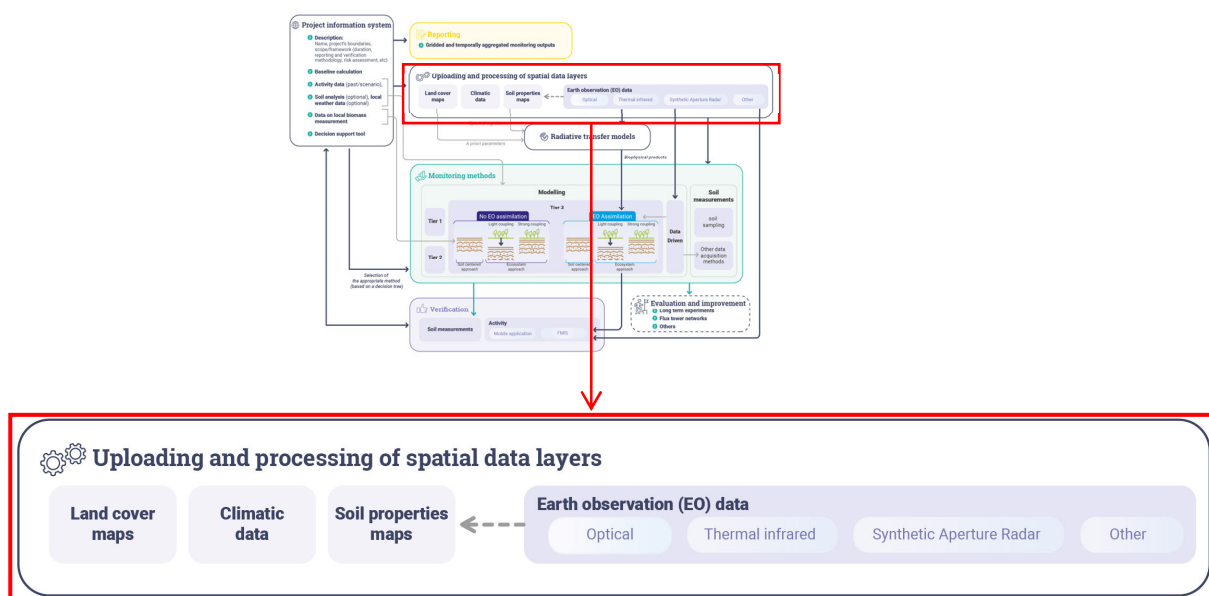


Figure 13. The red frame indicates which part of the MRV framework will be addressed in this section

4.2.2.1 Soil types and soil properties maps

Many global and national soil maps are available through organization or national API's or web-services, findable in repositories and can therefore easily be used in project information systems. When choosing a map to use in a certain context, it is important to consider how well predictive mapping can represent soil geography (or soil landscapes), at a given scale level (Rossiter *et al.* 2021; Han *et al.* 2022). Overall, there are two types of soil property maps that can be divided into two broad categories; those derived from traditional soil survey and those created using Digital Soil Mapping (DSM; see 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; Batjes *et al.* 2024). For Tier 1 approaches, several global soil property maps, like soil organic carbon content and stock, soil texture, are available. Examples are SoilGrids (Poggio *et al.* 2021), GlobalSoilMap (Arrouays *et al.* 2020), 'S-World' (Stoorvogel *et al.* 2017), LUCAS (Ballabio *et al.* 2016; Ballabio *et al.* 2019) and FAO-GSP's Global Soil Organic Carbon (GSOC) map (FAO and ITPS, 2018). SoilGrids provides soil data at six standard depths and at 250 m spatial resolution at global level. Maps are made using DSM techniques, which predict soil properties from their relationship between the environmental covariates (e.g. terrain, climate, parent material and vegetation) using statistical/machine learning models. GSOC map is a country-driven map product that stitches together national maps which are derived using the same DSM procedures, but then with models trained on national data. Both have relatively coarse resolutions and limited prediction accuracy, and although adequate at global, continental and to some extent national level, they are inevitably not able to capture small scale

variation in SOC content at e.g. provincial or local level (Poggio *et al.* 2021), which is needed for soil monitoring for MRV in other tiers. The maps do not capture the fine-scale soil variability induced by the history of agricultural practices, microclimate, and microtopography, that is needed for sub-national level modelling exercises in the context of the voluntary C market, especially in areas with complex/heterogeneous soil conditions and at local scales. In the absence of regular global SOC monitoring, the maps can be used as a baseline, but not for monitoring, unless a LULUCF approach is used in NDC context. In LULU, SOC changes are related to land use (changes), which means that satellite observable land use changes can be an indication of SOC change²⁴.

As Tier 2 soil input data, many countries in Europe, the Pacific, and the Americas have DSM derived SOC (stock) maps for NDC purposes (Viscarra Rossel *et al.* 2014; Viscarra Rossel *et al.* 2019; Orgiazzi *et al.* 2018; Ballabio *et al.* 2019). Depending on the existence of a soil monitoring system and/or a soil survey tradition, the amount and age of SOC data used as input may vary. Due to a lack of data, some maps are made by compiling all SOC measurement data of the last 50 years or more recent data to derive DSM-based SOC maps (Helfenstein 2024, Cornu *et al.* 2023), aiming to strike a balance between fewer but more recent soil point data versus more but older data. This makes them suitable as a regional baseline but unsuitable for Tier 3 approaches. An alternative is to apply space-time mapping. An additional source of uncertainty may be the use of different lab methods to determine the SOC concentration and the use of different measurement methods or pedotransfer functions to derive bulk density data needed to convert SOC concentration data to SOC stock data. When countries have national soil monitoring programs in place, the resulting soil data have a clear time-stamp, are collected according to a sampling design that is optimized to cover the relevant feature space, notably the main land uses and soil types in a country, and samples are analysed using one lab method only. These maps can be used for regional baselines or Tier 2 balance models, but are usually not accurate enough for Tier 3 approaches, model initialization, or local VCM projects. There is also emerging opportunity however to use dynamic DSM fuse with the process-based models (e.g. Ugbemuna Ugbaje *et al.* 2024).

The work done at ISRIC by David A. Rossiter²⁵ compiled attempts to catalogue all freely available primary soils information usable in a geographic information system, either as points, lines, polygons or grids ('rasters'). Many point data, however, are not freely accessible in a digital format (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; Batjes *et al.* 2024).

4.2.2.2 Weather data

SOC stock changes Tier 3 modelling relies on accurate and comprehensive weather data to simulate the dynamic processes influencing carbon sequestration and decomposition in soils. Existing weather datasets, including air and soil temperature, precipitation, solar radiation, and air humidity, are often critical inputs for soil and ecosystem

²⁴ <https://unfccc.int/process/transparency-and-reporting/reporting-and-review-under-the-convention/greenhouse-gas-inventories/submissions-of-annual-greenhouse-gas-inventories-for-2017/submissions-of-annual-ghg-inventories-2006>

²⁵ <https://www.isric.org/explore/soil-geographic-databases/>

models as they directly affect plant growth, microbial activity, and organic matter decomposition rates. Long-term historical weather datasets, such as ERA5 and ERA5-Land from the European Centre for Medium-Range Weather Forecasts (ECMWF), provide deca-kilometric resolution and globally consistent data that are widely used in environmental modelling (Hersbach *et al.* 2020; Muñoz-Sabater *et al.* 2021). ERA5-Land, in particular, offers enhanced spatial resolution (9 km) for land surface variables, making it highly suitable for regional-scale SOC studies (Muñoz-Sabater *et al.* 2021). Other sources, such as national weather data or the Global Soil Wetness Project (GSWP3) and the Climate Research Unit (CRU) datasets, also provide valuable long-term climate data for SOC modelling (Kim *et al.* 2020; Harris *et al.* 2020).

Long-term weather data are essential not only for forcing ecosystem and soil models but also for initializing SOC (e.g. RothC), which require climate conditions to accurately simulate carbon dynamics over time. For instance, RothC uses monthly climate data, including rainfall, temperature, and evaporation, to drive its simulations of organic matter turnover (Coleman & Jenkinson, 1996). Similarly, ecosystem models such as CENTURY and DayCent rely on daily or sub-daily weather data to simulate plant growth, litter decomposition, and soil carbon cycling (Parton *et al.* 1987; Del Grosso *et al.* 2002).

However, challenges linked to spatial heterogeneity and uncertainties in precipitation patterns can limit the accuracy of SOC predictions when using data at 9 km resolution. It is difficult to counter this limitation by using local weather stations alone because of the size of the dataset, the high cost to cover all the regions and the data gaps in the datasets (Webb *et al.* 2020). Two solutions are available:

- Integrating high-quality, site-specific weather data with either advanced modelling or super-resolution approaches to enhance the resolution of the weather data as recommended by IPCC.
- Assimilating high-resolution remote sensing data at the field to intra-field scale into ecosystem models will ensure proper constraining of the spatial patterns to reflect the weather variations at local scale (Wijmer *et al.* 2024).

The use of such approaches for enhanced weather data integrating process-based models or machine learning algorithms can enhance the reliability of SOC estimates (Smith *et al.* 2020; Padarian *et al.* 2019).

4.2.2.3 Land use maps

Land cover and land use maps are essential input data for monitoring SOC, in particular for large scale assessments as in the context of NDCs, CAP or CF projects covering several farms. Several land cover products exist, often based on remote sensing land cover classification approaches but they do not necessarily meet the requirements for SOC monitoring. For instance, at global scale, the ESA CCI land cover map²⁶ provides information at a spatial resolution of 300m relative to rain-fed, irrigated or mosaic vegetation/cropland classes but the spatial resolution often exceeds the size of the fields and the reduced number of classes is limiting for most models or modelling approaches (e.g. for soil centred, ecosystem approaches) that usually require more detailed information on crop species/ types. Even Land Surface Models like the ORCHIDEE (de Noblet-Ducoudré *et al.* 2004; Gervois *et al.* 2004) or ORCHIDEE-CROP (Wu *et al.* 2016) models require land cover maps distinguishing winter (usually C3 metabolism) and spring/summer crops (usually considered as C4 metabolism). Overall, an annual production of high-resolution maps with detailed crop classes is still missing at global scale but such maps are annually produced

²⁶ <https://www.esa-landcover-cci.org/>

at regional/national scale. In the USA, the Cropland Data Layer (USDA-NASS) provides a 30m resolution crop map with approx. 42 classes²⁷. In France, the OSO annual map produces annually a 20 m resolution map with 8 cropping classes²⁸. Other products exist at larger scale as demonstration products such as the E.U. crop map that has been produced by the JRC²⁹.

In Europe, accurate crop maps and crop rotation maps can be obtained from IACS³⁰ (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 implementation is likely to improve model performance and reduce the uncertainty in model predictions when a model is employed at landscape to pan-EU scale. This would not only reduce the uncertainty in model estimates, but could also facilitate MRV processes supporting carbon sequestration initiatives.

Besides land cover, agricultural management plays a key role in determining the magnitude and direction of SOC stocks changes. Information of cropland management and cropland management changes can be obtained over large areas from satellite imagery or products derived from these images. See next Section for more details.

4.2.2.4 Earth observation data

In the context of MRV, satellite imagery, can be used both to produce maps on management that can be used as input data for modelling SOC or for the verification of management implementation, continuity and/or permanence. Data from different satellite missions (e.g. Landsat or Sentinel constellations) from various spectral domains (e.g. optical, thermal infrared, Synthetic Aperture Radar, SAR) have been combined with other geo-referenced socio-demographic, economic and public administration data, for example, to monitor crops, management, CO₂ fluxes or SOC stock changes (e.g. Bégué *et al.* 2018; Fendrich *et al.* 2023; Pique *et al.* 2020a; Wijmer *et al.* 2024).

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 km².) These studies mainly considered SOC content in the uppermost layer of mineral soil and often included limited calibration against field measurements. 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 using similar approaches focus on possible changes in topsoil organic carbon content only, which does not allow to quantify SOC stocks or stock changes. Recently, Broeg *et al.* (2024) used repeated SOC samples from 1986 to 2022 and a time series of multispectral bare soil observations from Landsat and Sentinel-2 to model high-resolution cropland SOC trends. They concluded

²⁷ https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php

²⁸ <https://www.theia-land.fr/product/carte-doccupation-des-sols-de-la-france-metropolitaine/>

²⁹ https://joint-research-centre.ec.europa.eu/jrc-news-and-updates/eu-crop-map-2021-10-18_en

³⁰ https://agriculture.ec.europa.eu/common-agricultural-policy/financing-cap/assurance-and-audit/managing-payments_en

that they were able to detect SOC stock trends but that the prediction of short-term SOC changes based on EO data remains challenging and is currently not possible.

Vegetation Indices (VIs), such as the normalised difference vegetation index (NDVI), obtained from remote sensing have been widely used for quantitative and qualitative evaluations of vegetation cover, vigour, and growth dynamics, among other applications. Xue *et al.* (2017) reviewed more than 100 VIs, discussing their specific applicability and representativeness according to the vegetation of interest, environment, and implementation precision. Those VIs have sometimes been used to estimate crop biomass (Zheng *et al.* 2004; Kross *et al.* 2015) or cover crops biomass (Duncanson *et al.* 2021; Goffart *et al.* 2021; Holzhauser *et al.* 2022; Jennewein *et al.* 2022; do Nascimento Bendini *et al.* 2024). Several current and upcoming missions (e.g., Sentinel-2, Sentinel-1, NISAR³¹) should provide improved data for biomass mapping compared to those obtained with earlier sensors and from approaches based on VIs, as some of them were designed with a primary science goal of mapping biomass. Being of a publicly available nature, these mission datasets are anticipated to form the basis for other new biomass products through data fusion, machine learning (e.g. do Nascimento Bendini *et al.* 2024) and alternative algorithms (Duncanson *et al.* 2021).

Also, maps of plant's biophysical properties derived from remote sensing are often used as input for crop models (e.g., through calibration, forcing or updating, see Section 4.2.3 for more details) as discussed in Padarian *et al.* 2022). Plant's biophysical properties encompass LAI, chlorophyll content, the fraction of photosynthetically active radiation absorbed by the vegetation (FAPAR), the fraction of ground covered by green vegetation (fCOVER)... (e.g. Baret *et al.* 2007; Fang *et al.* 2019). The assimilation of those biophysical products in crop models allow to simulate aboveground biomass and/or yield (e.g. Claverie *et al.* 2012; Battude *et al.* 2016; Jin *et al.* 2018), evapotranspiration (Battude *et al.* 2017), CO₂ fluxes (Sus *et al.* 2013; Pique *et al.* 2020a; Pique *et al.* 2020b) or carbon budgets (Wijmer *et al.* 2024).

Remote sensing is also often used to monitor activity on cropland either for the Verification process or to provide input data for Tier 3 type models (i.e., soil/plant/coupled models) in the Monitoring process. 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. Recent examples of use of EO derived data in applications relating to land management, regenerative agriculture and SOC monitoring are given elsewhere (e.g., Biney *et al.* 2021; Fayad *et al.* 2021; Zhang *et al.* 2021; Gasmi *et al.* 2022). In a review, Bégué *et al.* (2018) grouped the information on management that can be derived from EO into three categories: crop succession (crop rotation and fallowing), cropping pattern (single tree crop planting pattern, sequential cropping, and intercropping/agroforestry), and cropping techniques (irrigation, soil tillage, harvest and post-harvest practices, crop varieties, and agro-ecological infrastructures). They observed that the majority of the studies were exploratory investigations, tested on a local scale with a high dependence on ground data, and used only one type of remote sensing sensor (e.g. see work from Dodin *et al.* (2021) on the mapping of green waste compost and organic amendment from Sentinel-2 data). Furthermore, to be correctly implemented, most of the methods relied heavily on local knowledge on management practices, environment, and biological material. They concluded that the new spatial technologies, and particularly the Sentinel constellation, are expected to improve the monitoring of cropping practices in the challenging context of food security and better management of agro-environmental issues.

In recent years, studies took benefit of those new satellite constellations to produce cover crop maps at national (Nowak *et al.* 2022) and even EU scale (Fendrich *et al.* 2023). Those studies are particularly valuable as cover crops are one of the main levers for sequestering C in agricultural soils (e.g. Poeplau & Don, 2015; Lugato *et al.* 2020)

³¹ <https://nisar.jpl.nasa.gov/>

and as current IACS data in EU do not contain information on cover crops for most member states. Therefore, even the maps presented in Nowak *et al.* (2021) and Fendrich *et al.* (2023) are not produced and distributed annually yet. They demonstrate that including accurate spatial and temporal information of land use from EO data into SOC modelling frameworks could reduce overall uncertainty on SOC stocks assessments. In the coming years, cover crop maps should become available through the OSO products in France (V. Thierion, personal communication).

4.2.3 Radiative transfer model and data assimilation

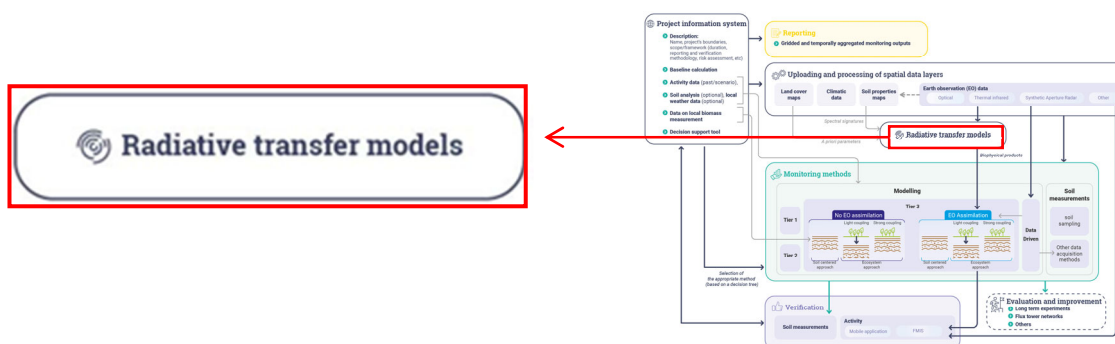


Figure 14. The red frame indicates which part of the MRV framework will be addressed in this section

Remote sensing provides frequent, large-scale observations of vegetation and soil conditions. Still, the direct interpretation of satellite and drone imagery is often limited by atmospheric effects, sensor noise, complex interactions and indirect biophysical relationships between electromagnetic signals and vegetation (Rees, 2013). The most relevant example of an indirect biophysical relationship is the use of vegetation indices (e.g., NDVI) to infer crop properties but do not provide direct estimates of variables like LAI, chlorophyll content, or crop phenology (Carlson *et al.* 1997, Camps-Valls *et al.* 2021). To overcome these limitations, radiative transfer models (RTMs) are used to simulate how electromagnetic radiation interacts with soil, crops, and the atmosphere via scattered, absorbed, and transmitted through different media, enabling retrieval of biophysical parameters (Jacquemoud & Ustin, 2019; Weiss *et al.* 2020). The result is relevant parameters related to vegetation growth, land management and soil properties relevant for SOC monitoring or verification. Concerning SOC, remote sensing techniques primarily estimate SOC at the soil surface only, as deeper soil carbon content is not directly observable from optical or radar sensors (Gomez *et al.* 2008). As a result, vegetation monitoring becomes crucial for assessing overall carbon sequestration since plant growth, biomass accumulation, and residue management influence soil carbon inputs. The integration of RTM-based estimates of biogeophysical parameters into plant, ecosystem or soil models improves carbon budget assessments and supports carbon farming initiatives. The application of RTMs in agricultural remote sensing has advanced significantly in recent years, enabling the retrieval of crucial agricultural parameters (Weiss *et al.* 2020). The ability to estimate biogeophysical parameters (e.g., LAI, biomass, soil moisture, SOC content) and agricultural practices (e.g., irrigation status, fertilization, tillage) using RTMs has greatly improved precision agriculture and crop monitoring (Verhoef & Bach, 2007; Jacquemoud *et al.* 2009).

RTM models are used to simulate spectral responses (reflectances) that are then inverted to estimate biogeophysical parameters. RTMs apply to both satellite-based and drone-based remote sensing data, improving their interpretability and enabling accurate agricultural monitoring. Several RTMs have been developed to represent

vegetation and soil characteristics. 1D canopy models assume a horizontally homogeneous canopy (e.g., PROSAIL, PROSPECT-D) (Jacquemoud *et al.* 2009, Féret *et al.* 2017). They are the most widely used and the most adapted for practical applications. On the other hand, 3D canopy models, while representing heterogeneous crop structures and explicit directional effects (e.g., DART; Gastellu-Etchegorry *et al.* 2017) have greatly advanced in recent years but they remain less adapted for large-scale applications, mainly because of the need for detailed vegetation (e.g. 3D architecture) and soil description. Coupled canopy-atmosphere RTMs that integrate vegetation, soil, and atmospheric interactions (e.g., Modtran and PROSAIL) are less often used for satellite remote sensing data that are often provided at the top of the canopy reflectances or backscatter. They are more commonly used for drone data to take into account atmospheric effects. Currently, in the vast majority of the applications make use of empirical and machine learning based approaches, more so when SAR and microwave data is used.

The main aim of the use of RTMs in agricultural applications is to retrieve biogeophysical parameters from remote sensing data. Key biophysical parameters include:

- **Leaf Area Index (LAI) and Green Leaf Area Index (GLAI)** are crucial indicators of crop development. They are retrieved using canopy RTMs such as PROSAIL by matching simulated and observed spectral reflectance (Jacquemoud *et al.* 2009). Statistical empirical models are also used to retrieve LAI based on SAR data.

- **Biomass and vegetation water content** are mainly retrieved from inverting active or passive microwave RTMs, because of the penetration depth of microwave signals. Water Cloud Model (WCM) is the most widely used empirical RTM that relates radar backscatter (e.g., Sentinel-1 SAR) to vegetation structure, water content and soil conditions. Other models like Tau-Omega Models account for vegetation attenuation and scattering to estimate Volumetric Water Content (VWC) and Vegetation Optical Depth (VOD) from passive microwave data using L-band or from C-band wavelength (Kerr *et al.* 2012). The VOD from passive microwave is not adapted for crop applications as the microwave sensors (e.g. SMOS, SMAP) have low spatial resolutions.

- **Chlorophyll and Nitrogen Content** Leaf-level models (e.g., PROSPECT, PROSPECT-D) simulate leaf spectral properties to retrieve chlorophyll and nitrogen contents, which are essential for assessing plant stress and nutrition (Féret *et al.* 2017).

- **Surface Soil Moisture and Soil Surface Roughness:** surface soil moisture and surface roughness (related to soil work) are key factors affecting carbon decomposition processes. Radar backscatter models like Integral Equation Model (IEM) (Fung *et al.* 1992; Oh *et al.* 2004; Dubois *et al.* 1995) and the Water Cloud Model can track these variables as they are sensitive to soil moisture, surface roughness, and vegetation structure. Surface soil moisture is best retrieved from passive microwave at long wave length (Al Bitar *et al.* 2017), but in this case the spatial resolution is very low. Zribi *et al.* (2019) applied the WCM in semi-arid regions to retrieve soil moisture from L-Band SAR data. Fusion algorithms using SAR and microwave data are used to retrieve high resolution soil moisture taking advantage of the two technologies (Tomer *et al.* 2016). El hajj *et al.* (2017) suggested the use of optical and radar data for surface soil moisture. However, root zone (>5cm depth) soil moisture is a more adequate information for soil carbon models. Root zone soil moisture is not directly observed by existing satellite sensors. It can be retrieved either by statistical models (Souissi *et al.* 2022) or via assimilation into land surface models (Lievens *et al.* 2015; Pique *et al.* 2020b).

- **Surface soil organic carbon (SOC)** can be estimated using hyperspectral and multispectral reflectance data (Gomez *et al.* 2008, Nocita *et al.* 2013) as SOC influences soil reflectance in visible (400–700 nm) and shortwave infrared (1000–2500 nm) bands due to organic matter absorption. Concrete applications of retrieval of surface SOC from remote sensing are based on empirical statistical methods, Random forest (RF), multi linear regressions

(MLR), Support Vector Machine (SVM), Artificial Neural Networks (ANN) (Vaudour *et al.* 2022). These estimates apply only to the surface layer, while deeper SOC must be inferred from models integrating land-use history and carbon inputs from vegetation (e.g. Peng *et al.* 2021). See Section 5.2 for more details.

As mentioned in previous sections, EO based indices or retrieved biophysical parameters from RTMs inversion can also be used to monitor agricultural practices. Tillage and ploughing are retrieved using indices from multispectral or hyperspectral data (Zhang *et al.* 2024), but by combining RTMs outputs into the algorithm the detection precision can be increased. Time series analysis of optical remote sensing (e.g. Sentinel-2) are widely used to detect key crop phenological stages, such as emergence, flowering and harvest by analysing dynamics in vegetation indices (Bégué *et al.* 2018). Time series from SAR satellites such as Sentinel-1 can also track crop development, even under cloudy conditions (Veloso *et al.* 2017). However, purely observational methods may be affected by noise, missing data, or irregular acquisition times. To improve accuracy, data assimilation can be used by integrating these satellite-derived observations from RTMs into crop models (e.g., WOFOST, APSIM, SAFYE-CO2). This approach corrects model predictions, providing a more reliable estimation of phenological stages.

Despite challenges related to RTM complexity and uncertainty, advances in machine learning, sensor fusion, and high-performance computing are improving their applicability. **Advances and recommendations with respect to RTM Applications** are:

- **Leverage Machine Learning and Deep Learning for Retrievals:** Develop hybrid approaches that combine the physical robustness of RTMs with the data-driven capabilities of ML/DL for parameter estimation and uncertainty reduction.
- **Adopt Multi-Sensor Fusion Strategies:** Combine data from optical, thermal, and radar sensors to enhance RTM-based retrievals.
- **Address Uncertainty in Parameter Estimation:** Incorporate uncertainty quantification methods into RTM workflows to improve the reliability of retrievals. Use probabilistic approaches or ensemble modelling to account for uncertainties in input parameters and model structure.
- **Enhance Field Validation Efforts:** Develop strategies to overcome the scarcity of field data, such as targeted field campaigns or collaborations with local stakeholders.
- **Tackle Remote Sensing Saturation Issues:** For deeper soil estimates or other parameters prone to sensor saturation, employ indirect modelling approaches. Combine RTMs with ancillary data (e.g., climate, topography) to improve retrievals in saturated regions.

Data assimilation in soil or crop modelling involves integrating observational data into process-based models to enhance the accuracy of simulations and predictions while considering uncertainties from the observation and the model predictions (see Figure 16). This approach leverages remote sensing based biogeophysical variables to provide timely and spatially extensive data on soil or crop conditions, which, when assimilated into models, improve estimations of variables such as biomass, yield, and soil moisture. Direct insertion method which consist in forcing the remote sensing variable shouldn't be considered as an assimilation method even though it was the first natural and intuitive way used in meteorology. Assimilation schemes may include the output of RTM retrievals, which is more commonly used in crop modelling assimilation (Trepas *et al.* 2020) or include the RTM model as an observation operator inside the assimilation method (Lievens *et al.* 2016). Various data assimilation approaches have been employed to merge remote sensing data with crop models, each presenting unique strengths and

challenges, they can be classified into four families keeping in mind that hybrid methods that blur this classification exist also:

Sequential methods: Sequential methods update model states and parameters iteratively as new observational data becomes available. These methods are particularly useful for real-time applications like determination of irrigation needs. They are also adapted for the assimilation highly dynamic variables like soil moisture. Ensemble Kalman Filter (EnKF) is a popular sequential method that uses an ensemble of model trajectories to estimate error covariances and update model states (Evensen, 2003). It is computationally efficient and well-suited for non-linear systems, such as crop models. EnKF has been extensively used to assimilate remote sensing data (into crop models to improve yield predictions (de Wit & van Diepen, 2007; Huang *et al.* 2019, Trepos *et al.* 2020). However, it requires careful tuning of error covariances and may struggle with high-dimensional systems. Particle filters are another class of sequential methods that use a set of weighted particles to represent the posterior distribution of model states. While more flexible than EnKF, they suffer from the "curse of dimensionality" and are computationally expensive for high-dimensional systems.

Variational methods: 4D variational methods (4DVAR) optimize model states and parameters by minimizing a cost function that measures the discrepancy between model predictions and observations over a time window (Le Dimet & Talagrand, 1986). While they have been applied to crop models (Dente *et al.* 2008), they remain less suited for such exercises as they require the elaboration of an adjoint model with Gaussian approximation which is rarely applicable for crop modelling.

Calibration methods: Consist in modifying dynamic (that differ over crop cycles) model parameters based on the observations by minimizing a cost function that quantifies the sum of squared differences between model predictions and observations or some other cost function. For instance, the Leaf Area Index (LAI) derived from remote sensing is usually assimilated in crop models to optimize crop parameters as LAI is simulated in many crop models. Several algorithms can be used to optimize the parameters, with varying complexity, such as the simplex search algorithm (e.g. Claverie *et al.* 2009; Guérif and Duke, 1998, 2000), GlobalSearch (Pique *et al.* 2020a; Battude *et al.* 2016), Least Squares Method (LSM) (Zhao *et al.* 2013), Powell's conjugate direction method (PCDM) (Fang *et al.* 2011; Fang *et al.* 2008), Shuffled Complex Evolution (SCE-UA) (Jin *et al.* 2010; Ma *et al.* 2013; Huang *et al.* 2015), Very Fast Annealing Algorithm (VFSA) (Dong *et al.* 2013), and Particle Swarm Optimization Algorithm (PSO) (Jin *et al.* 2015a; Liu *et al.* 2015; Wang *et al.* 2014).

Probabilistic methods: Probabilistic methods like Markov Chain Monte Carlo (MCMC) and Bayesian Inference provide a framework for estimating uncertainties in model parameters and states (Dumont *et al.* 2014). They have been adapted for data assimilation in crop modelling considering the need to determine model parameter adaptation over long time windows (e.g. crop cycles) (Wijmer *et al.* 2024). They also have a solid framework to provide uncertainty estimates of the model predictions like the use of likelihood. MCMC methods are sampling techniques used to estimate posterior distributions of model parameters and states. They are computationally intensive but provide robust uncertainty estimates (Wallach *et al.* 2016). Adaptive MCMC algorithms have improved their efficiency for crop modelling applications. Bayesian inference methods update model parameters and states using observational data and prior knowledge. They are highly flexible enabling non-iterative assimilation like the use of Normalised Importance Sampling (Wijmer *et al.* 2024). They have been used to assimilate field measurements (e.g., biomass, yield) and remote sensing data into crop models (Jones *et al.* 2017).

Advances and recommendations with respect to Data assimilation

While computational resources are important, the choice of the assimilation method should first depend on the assimilation objective. In the case of Carbon removal, where crop cycles should be considered over long-time windows and where the system may be highly non-linear (presence of pests, extreme events), variational methods present a challenge. In addition, the use of sequential methods like EnKF and Particular filters while presenting an advantage in terms of real time applications (e.g. irrigation needs, water stress), their ensembles may diverge over long periods of time and will require high computational cost for local application at field scale. Iterative optimisation approaches present the advantage of simplicity but don't provide a theoretical basis to provide uncertainties. Also, they are not adapted for large scale application at high resolution because of the large computing time. Iterative probabilistic approaches (e.g. MCMC) provide a solid statistical basis, but they are computationally demanding. Non-iterative probabilistic approaches emerge as a very promising framework for crop modelling data assimilation systems, because they provide long time scale prediction capacity with associated uncertainty estimates. Their main drawback, which they share with the other assimilation methods is the problem dimensionality. For this reason, it is recommended to use parsimonious modelling approaches that require the least amount of model parameters, while relying on data observation to constrain the modelling predictions.

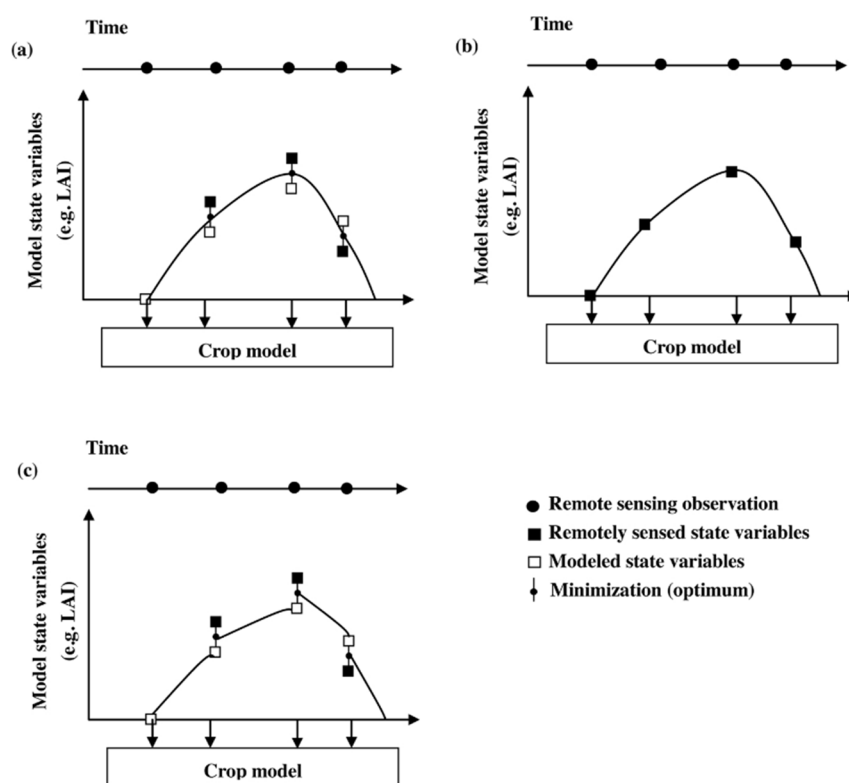


Figure 15. Schematic representation of different methods for the assimilation of remotely sensed model state variables in crop models: (a) crop model calibration, (b) forcing methods, and (c) updating methods. (from Jin et al 2018, adapted from Delécolle et al. 1992).

4.2.4 Evaluation and improvement

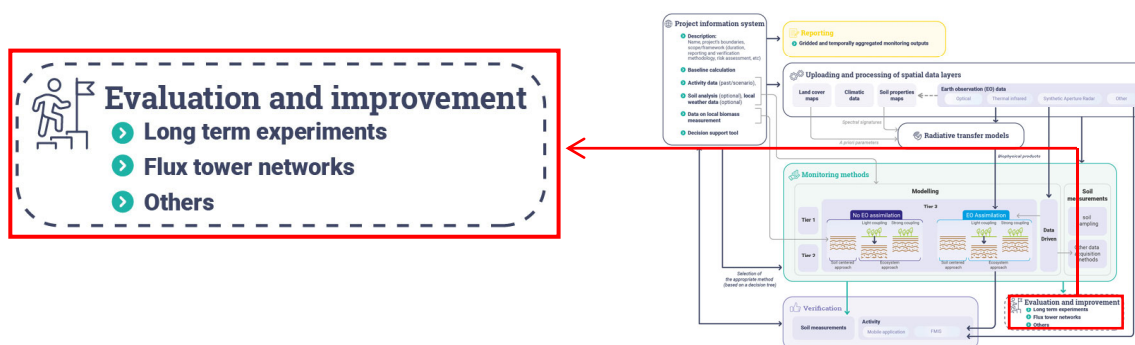


Figure 16. The red frame indicates which part of the MRV framework will be addressed in this section

Monitoring methodologies for SOC stock changes are constantly being evaluated and improved and it concerns both the *in-situ* approaches for measuring SOC stocks and their dynamics (see Sections 5.1, 5.2 and 8.1.1) and the modelling ones. Evaluation may rely on long term experiments (LTEs) such as the Rothamsted trials, on SOC monitoring networks (e.g. LUCAS in Europe; see Orgiazzi *et al.* 2018) or on flux tower networks (e.g. Fluxnet). However, if those experimental or instrumented setups are very useful, for evaluating some of the building block (e.g. soil models, ecosystem models) of SQPs, too few study schemes allow for a more comprehensive assessment of the components of the carbon cycle and of the resulting SOC stock changes in operational monitoring conditions such as regional observatories (e.g. Regional Space Observatory³², FiON³³). For modelling approaches, improvements may come for instance from a better understanding of the processes that control the carbon cycle in agroecosystems and the stabilisation of SOC in soil or may be related to methodological factors. The latter may include, for example, the development of new methods for quantifying different carbon pools in soil for better initialisation of the models, the use of new observation networks (such as flux tower networks that are very seldom used to evaluate soil models simulating SOC stock changes), access to new data streams, e.g. EO data and derived products allowing to follow with more accuracy the evolution of biomass returned to the ground (e.g. Wijmer *et al.* 2024; do Nascimento Bendini *et al.* 2024), methods combining data driven and process based modelling (see Section 5.3.4).

Several ways to better evaluate and improve the monitoring of C are mentioned in Chapter 5 and will be discussed more in depth in Chapter 8.

³² <https://osr.cesbio.cnrs.fr/en/homepage-english/>

³³ <https://www.fieldobservatory.org/index.php/about/>

5 Methods for monitoring SOC

Depending on the MRV purpose (e.g. offsetting, insetting, AEPs, NDCs) and baseline approach, the size of the area (e.g., farm/plot level, landscape level, subnational, national and international) and the number of elements (e.g. plots, farms) to be monitored, the availability/accuracy of the input data (e.g., climate, remote sensing, soil properties or activity data), the monitoring frequency and cost/accuracy considerations, different monitoring approaches and associated tools, can be used.

Currently, few modelling methods and tools for monitoring 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 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 increase the differences between cluster variation (Australian protocol).

Landscape-scale, farm-scale or even intra-field scale assessment of SOC stock changes present a number of practical challenges. In situ data for monitoring, verification or for model input/initialisation are needed from heterogeneous areas (e.g. soil properties or biomass development/inputs to the soil), often for multiple points in time, and the collection and laboratory analyses of these samples can be expensive and time consuming (Arias-Navarro *et al.* 2017). Concerning soil and vegetation sampling, if time and costs can be reduced by taking composite samples, this approach does not allow to assess the spatial variability in soil properties and SOC stock changes if applied at field scale (which can be a problem for instance for the verification process). Relying then on remote sensing or proximal sensing techniques (e.g. MIR/NIR spectroscopy) can be useful (Cécillon *et al.* 2009; Kuhnert *et al.* 2022; Poeplau 2022; Shepherd *et al.* 2022; Viscarra Rossel *et al.* 2022; McBride 2022; do Nascimento-Bendini *et al.* 2024). Overall, field measurements, even when considering the associated uncertainties (Bünemann *et al.* 2018; van Leeuwen *et al.* 2024), are often considered the best option to quantify SOC content and SOC changes but their current cost is prohibitive for detailed large-scale plot or farm level monitoring. Yet they are also needed for model development and calibration as well as verification. The combined use of field measurements, modelling and remote sensing for MRV purposes is often complementary and a smart combination of those approaches is definitely promising (van Wesemael *et al.* 2023; McKenzie *et al.* 2002; Wijmer *et al.* 2024).

Depending on the MRV purpose, modelling may be the only alternative to measure-remeasure (e.g. for short-term assessment of SOC stock changes in the context of insetting or for the CAP). As discussed below and highlighted in Batjes *et al.* (2024) the implementation of Tier 3 approaches may not always be relevant/possible (e.g. if no process-based model is available/calibrated/validated for the project's local context). Also, different Tier 3 approaches may be implemented (e.g. soil centred, ecosystem modelling with or without EO assimilation) and several combinations of Tier 3 approaches could be used (e.g. ensemble modelling approaches, a single vegetation model may provide biomass input data to one or several soil models). It is important to note that when process-based models simulate only the soil compartment they require external information on biomass inputs to the soil, while coupled soil-vegetation models directly estimate biomass inputs. Recently, methods based on EO and ML (e.g. do Nascimento-Bendini *et al.* 2024) or EO assimilated in process-based models (e.g. see review by Dlamani *et al.* 2023 and Wijmer *et al.* 2024) have been developed to estimate crop and cover crop biomass allowing quantification of the biomass that returns to the soil. However, EO based approaches may not always be possible

(e.g. very small plots, optical EO data in very cloudy areas) or relevant (e.g. in terrains with complex topography where the accuracy of biophysical products may cause high uncertainty on the final estimates). Note that several biophysical products (e.g. LAI, superficial soil water content) could be assimilated in a given process-based model and that several radiative transfer models could be used to produce a given biophysical variable in an ensemble approach. Finally, data driven approaches will grow and improve in the coming years (Heuvelink *et al.* 2020; Olawade *et al.* 2024; Ugbemuna Ugbaje *et al.* 2024), either based on large scale dataset or models' output (e.g. surrogate models) as described in Section 5.3.4. Each methodology should be regularly evaluated and if possible improved based on *in-situ* data collected at long term experimental sites (e.g. Rothamsted LTE's, flux tower sites).

In the following sections of this chapter, several methodological approaches for monitoring SOC (e.g. *in-situ* measurements, modelling approach) are described and analysed, each having its pros and cons and being more or less adapted to one or several MRV contexts (see FAO 2019; Paustian *et al.* 2019; Smith *et al.* 2020; Dupla *et al.* 2024).

5.1 Soil sampling for monitoring SOC

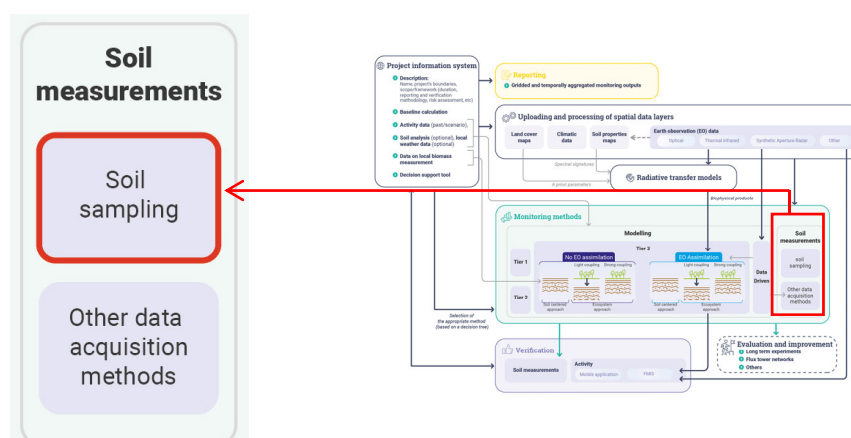


Figure 17. The red frame indicates which part of the MRV framework will be addressed in this section

Soil sampling can be needed or desirable for different aspects of MRV, predominantly for monitoring based on measure-remeasure, but also for verification, for SOC baseline calculation, model initialization, model parametrization and model validation. Additionally, there may be more than one aim for performing soil sampling, either within an MRV context or beyond, for example for other land management decisions such as precision agriculture or reporting on soil health. The aim(s) of the sampling will determine the sampling design, the choice of field protocols, analysis methods and resulting data management. As described in Batjes *et al.* (2024), for all MRV contexts and land uses a plethora of information, protocols and systems is available for soil sampling in general and for MRV in particular. The aim of this section is not to list and repeat these, but to indicate the main choices and options that should be considered when planning soil sampling for monitoring SOC.

Note that the most cost-efficient option in many cases is to use existing soil information, even when not standardized yet, as long as it meets the requirements described in the subsequent sub-sections. When existing data are a partial match to the space, time, design and accuracy constraints posed by the objective (e.g. measure-remeasure, modelling), it may be cost-effective to extend the existing set with new sampling. Only when there are no existing

data or there is no overlap in space, time, design, accessibility of the data, a fully new sampling campaign should be designed.

5.1.1 Sampling design choices

The first choice to make when designing a new sampling campaign or monitoring system is the aim(s) of sampling since this will determine the type of result that is required (such as a spatial average or spatial patterns), the target area and period, and the required accuracy (de Gruijter *et al.* 2006; Brus, 2022). The two main types of sampling design are probability (design-based) and purposive (model-based) sampling. Probability sampling designs randomly select sampling units with a (pseudo) random number generator. It has the advantages that it provides unbiased estimates of population parameters of (soil) properties of interest and the associated uncertainty, and that it does not rely on models and hence model assumptions that could be questioned. Examples of probability sampling designs are simple random sampling, stratified simple random sampling, systematic random sampling, cluster random sampling and two-stage random sampling. Purposive sampling designs typically optimize sampling locations in geographic or feature space in such a way that it gives the most accurate map (or more general, calibrated prediction model) possible given the sample size. Examples of purposive sampling are spatial coverage sampling, feature space coverage sampling, such as responsive surface sampling and conditioned Latin hypercube sampling. The choice of purposive sampling for mapping depends on the (digital soil) mapping method that will be applied. Sampling for monitoring requires a straightforward or simple design to allow adaptations or fine-tuning in time. This means a limited use of sample structures such as strata, and equal probability designs such as simple random and stratified sampling with proportional allocation (Overton and Stehman, 1996; van Egmond, van der Woude, 2022; Teuling *et al.* 2021).

For measure-remeasure (for instance in NDC and VCM MRV contexts of application) an unbiased estimate of (the difference in) mean value of a soil property in a given spatial unit (field, farm, project, country) is required, together with an associated uncertainty measure. These requirements lead to a choice for probability sampling designs. The number of soil samples to be allocated depends on the accuracy needed (which in turn might depend on the expected change in mean SOC and the measurement uncertainty) and the spatial variability in the target area.

For sampling for monitoring it is not needed to return to the same sampling locations in every monitoring round, although this is optimal when estimating changes of the mean. For NDC context returning to the same locations is not a problem and advisable, although some update of the sample locations may be required for each survey due to land use changes in time. For VCM purposes it is advisable to vary the sampling locations per survey to reduce the risk of fraud. This can be facilitated while ensuring unbiased estimates of the mean or change in the mean, for example by using a synchronous, supplemented panel or rotational design (Teuling *et al.* 2021).

For initialisation of soil models or other process-models, the spatial unit for which information about soil properties and other inputs is needed, is the smallest spatial unit of the model. The accuracy of a property per spatial unit that is required depends on the contribution of the uncertainty of the soil property to the uncertainty of the model outcome, as can be calculated using uncertainty propagation techniques (Heuvelink, 2018). It should be noted that this yields a model outcome uncertainty at the level of the spatial unit of the model. Uncertainty will cancel out and hence reduce when model outputs are aggregated to a larger area, such as when the average model output for the area as a whole is needed (Wadoux and Heuvelink, 2023).

For model parametrization, also called calibration, depending on the type of model (see Bishop *et al.* 2015), there is no need for probability sampling, and the link with other MRV measurements, such as biomass and climate, may be more relevant, leading to a purposive sampling design. Concerning the validation of digital soil maps, see also Bishop *et al.* (2015), Karunaratne *et al.* (2014), Brus *et al.* (2011).

Soil sensing measurements need to be calibrated with reference soil samples using a calibration model to allow translation to soil property values. For this purpose, purposive sampling is convenient due to the need to capture the feature space of the sensing signal. Examples of suitable sampling designs are response surface sampling which optimizes the fit of a regression function in (principal component) covariate space or conditioned Latin hypercube sampling which optimizes the frequency distribution of the samples to that of the covariates (Minasny *et al.* 2006).

Probability sampling results can also be used for mapping purposes, because mapping algorithms have no strict requirements on how the locations of the training data were selected. However, while data collected with purposive sampling can be used to estimate the spatial mean, such estimate may well be biased and the associated estimation accuracy cannot be quantified (Domburg *et al.* 1994; Karunaratne *et al.* 2014). Therefore, when multiple applications of the data resulting from soil sampling are foreseen, it is often a safe choice to choose for some form of probability sampling. However, in practice it is not always done given the associated difficulties, such as having to visit backup points if a location is not accessible.

It is easier to include existing soil point data in purposive sampling designs than in probability sampling designs, although Brus (2022) suggested a possible method for this, by considering the existing points to be a separate stratum. All of the above-mentioned methods are described in Brus (2022) with accompanying R scripts to apply in practice.

5.1.2 Hypothesis testing, costs and accuracy

For measure-remeasure for NDC purposes, the main aim is to evaluate the *difference* in of the mean value over a given time period in the target area for SOC stock. SOC stock can be derived from SOC content and bulk density for a specified depth (e.g. 0-30 cm or 0-100 cm). Note that estimating the difference in SOC stocks does not have the same requirements as measuring the absolute SOC stock multiple times as accurately as possible. If there is no change in tillage and land management practices and measurements are conducted at a similar moment in the crop rotation, the bulk density can be considered constant. Which would mean that in these conditions, and if the aim is a difference in SOC stock, it would be enough to (re)measure SOC concentration only.

For measure-remeasure for VCM applications, the main hypothesis that should be tested is the risk of unjustly paying or unjustly not paying a land manager for SOC stock changes. This is a classic hypothesis test (Neyman-Pearson) with the aim to take a decision, in this case the probability of over- or underestimation the change of SOC stock over a certain time period. To perform this test, decisions should be taken about three factors: what is the minimum relevant difference ΔSOC (e.g. the agreed upon increase in SOC, note that this is not equal to the minimum detectable difference), the error rate α which indicates the agreed upon risk of wrongfully rejecting the null-hypothesis, and error rate β which indicates the agreed upon risk of wrongfully not rejecting the null-hypothesis. The error rates α and β should be chosen based on for example a cost-benefit analysis or a risk analysis, they do not necessarily have to be 0.05 as is often used in literature. Given the nature of the null-hypothesis in VCM context, the error rates could be seen as a quantification of the consumer's and the producer's risk. Both involved parties

(certificate supplier and land manager) should agree on the levels of α and β , possibly resulting in $\alpha=\beta$. Once a choice on α has been made, β can be calculated if the following information is available: 1) a distribution of the test statistic; 2) a minimum relevant effect/difference ΔSOC ; 3) prior information on the population variance of the target variable; 4) sample size. Based on this information the sample size can be calculated given α , β and ΔSOC , or β can be calculated given α and ΔSOC , etc. The population variance is a measure of the variation in the target variable which is in this case the change in SOC stock. When the population variance is larger, a bigger sample size is needed to reach the same α , β and ΔSOC and vice versa. (pers. communication (Jan. 2025) Martin Knotters, not yet published work done in the context of the EU MARVIC project³⁴)

The choice for minimum relevant difference in VCM context and the accuracy of the resulting data in other contexts and for other purposes, depends on a chosen trade-off between the costs needed for sampling and a likely resulting accuracy with as minimum the lower limit of detection. In other words, the costs should not be higher than the expected added value of the increase in the value of information: the gain of supplementation and improvement of information (Morgan *et al.* 1990), for example compared to running a model. The costs consist of a fixed cost for calculating the sampling design, a cost for taking a physical soil sample (dependent on the costs, including travel costs, of a sampler divided by the number of samples per day) and a cost per sample for lab analysis including shipment of samples to the lab. Typically costs per sample are smaller in smaller areas with many samples. Lab and shipment costs differ per country and per soil property. The accuracy of a sampling result depends on the number of samples, the variation of the target variable (soil property or change in soil property) in the target area including small scale variation depending on the sampling protocol (Lark *et al.* 2014) and the lab analysis uncertainty (that may depend on the choice of the laboratory analysis method, i.e. direct measurement or estimation via proximal sensing). Cost-accuracy curves depict the relation between cost versus sample size and on a different axis, the accuracy versus sample size and can be a useful tool in deciding the balance or trade-off between costs and accuracy. Due to their dependency on various local or regional factors the curves should be derived or estimated at local or regional level (Schmidinger, 2024; Condon, 2019).

The lower limit of detection of a soil property (SOC stock, SOC concentration, bulk density, coarse fragments, texture) depends on the lab method used and the number of samples taken (due to averaging effect of errors if normally distributed and not biased). In the case of ΔSOC , so the difference in SOC stock or concentration, also the minimum expected potential difference in SOC due to land management, changes in carbon inputs to the soil, and prevailing soil processes and their activity rate due to e.g. climate and the time between the zero and repeat measurement matter. Indications of expectable SOC changes in time and space in literature can be found in Smith (2004).

A way to reduce (lab and shipment) costs and reduce short distance soil variation effects, is to take composite samples instead of point samples. Note that in general, short distance soil variation will be less on cropland than in other land uses such as forests, agroforestry or urban areas. If an uncertainty estimate is required, multiple (composite) samples are needed in a spatial reporting unit (at minima three samples). For example, one composite sample per field if the reporting unit is a farm or group of farms. Short distance soil variation effects can also be mitigated by choosing a sampling support larger than the expected short distance of meaningful variation. An example of this is the LUCAS sampling protocol (Orgiazzi *et al.* 2018, Toth *et al.* 2013), where a composite of 5 sub-samples are taken in a circle with 2 m radius.

³⁴ <https://www.project-marvic.eu/>

In Section 5.1.1 the role of soil measurements and soil sampling are described for the different contexts of application of MRV. For NDC context, the preferred choice is sampling of SOC stocks, costs are not a decision criterium. For CAP sampling is not mentioned but e.g. composite sampling may also be done if the reporting period covers several years (e.g. 5 year instead of an annual reporting) and may be available against little to no extra cost for VCM or CAP purposes. For the VCM, Δ SOC measurements are needed and if available, using these measurements is the preferred choice. If not, a cost / accuracy choice is suggested between measure-remeasure or processed based modelling.

5.1.3 Sampling protocols

Many continental (LUCAS, Fernandez-Ugalde *et al.* 2022; Orgiazzi *et al.* 2022) or national agricultural, forest or general soil monitoring systems that are also used for NDC purposes have their own, defined sampling protocols. The protocol is applied on each location allotted by the sampling design (see section 5.1.1). These protocols specify the spatial support of sample (e.g. x number of subsamples in a grid-cell, 5 samples in a 2m radius), if layers (fixed depth intervals) or horizons are sampled, required soil description and description of surroundings, inclusion of land management data, etc. The monitoring systems have been designed for different purposes (e.g. determining status and trends in soil quality, soil health, soil organic carbon storage, soil pollution), which has led to heterogeneity in sampling design, sampling protocols, sampling depths and applied lab methods (Bispo *et al.* (2021), Froger *et al.* (2024), Meuer *et al.* (2024)). In a survey at several EU countries, the majority indicated they are not willing to change their monitoring system due to existing time series, but are open to extend if needed. Predominantly the differences in sampling support and sampling depth can be challenging for MRV in NDC context. Both will need transformation to align with continental or IPCC sampling depths of 0-30 cm. An effort to derive transfer functions to account for sampling protocol differences between 17 European countries and LUCAS is ongoing, results are expected in 2025 (Fantappie *et al.* 2024).

When the national soil monitoring system is not suitable or not used for NDC reporting and for other MRV contexts, other existing SOC sampling protocols can be used. Main differences to consider are the depth of soil sampling (e.g. 0-20 cm, 0-30 cm, 0-100 cm), sampling according to depth or equivalent soil mass basis, the spatial support per sample (this point has already been discussed in Section 5.1.2). Though not always part of a sampling protocol, when the aim is to measure Δ SOC it is relevant to consider the time in the year and in the crop rotation when sampling. For example, Heesmans *et al.* (2023) showed fluctuation in SOC content related to crop rotation, even when the net trend in SOC sequestration was positive. Bakema *et al.* (2023) showed consistent trends in bulk density throughout the cropping season, due to land management on cropland.

VCM schemes often have their own prescribed sampling protocols or follow IPCC, ICP Forests, LUCAS, FAO-GSP or other main soil sampling protocols for SOC. General guidance on preparing a soil sampling campaign is provided in van Egmond and van der Woude (2023).

5.1.4 Soil sample analysis

With the samples taken, they need to be analysed either in the field or in a laboratory using a reliable, reproducible method with quantified accuracy. In field methods are described in Section 5.2. They are often faster and cheaper than lab analyses, but often have a (slightly or much) lower accuracy as well. Important in the choice of lab method is that it measures the targeted soil property (e.g. SOC concentration, Total Carbon, Soil Inorganic Carbon, other carbon fractions, coarse fragments, soil texture according to the texture classes that the MRV system uses, bulk density, etc.), is available in a certified lab which takes part in proficiency testing or ring testing, follows ISO³⁵ or GLOSOLAN³⁶ lab standard operating procedures, and is consistent in time in case of monitoring and with other soil datasets if these are foreseen to be used in the MRV system. When the aim is to gather information about SOC stock changes the uncertainty and the lower limit of detection of a lab method should be lower than the expected difference in SOC, or Δ SOC. If different lab methods are used either in space or time, this will affect the resulting uncertainty due to either not comparable results or an increased uncertainty due to the application of transfer functions.

Between several lab methods for the same soil property a transfer function can be derived or is available, for some this is not needed because the differences in lab methods is small and does not affect the result, and for some it is not possible to derive a transfer function since they measure different fractions or aspects of the same soil property. (Bittelli *et al.* 2022; Breure *et al.* 2022). A transfer function can be derived by measuring the sample set of samples for two different lab methods for the same soil property. The resulting data can be related using regression, with or without additional explanatory variables such as land use, soil type, pedo-climatic zone, etc. When applying a transfer function, it is important to verify that the transfer function is derived for the same or a comparable domain of interest to which it is aimed to be applied, characterized by for example land use, pedo-climatic zone, etc.

When it is expensive or not possible to measure a soil property or to take a soil sample to measure the soil property, it is in some cases possible to derive an estimate for the soil property using measurements or estimates of other soil properties. A well-known example is the estimation of bulk density based on soil texture and organic matter estimates. These derivations are referred to as pedotransfer functions or soil inference systems (Wosten *et al.* 2001, McBratney *et al.* 2002). Just like with transfer function for different lab methods for the same soil property, when applying a pedotransfer function, it is important to verify that the pedotransfer function is derived for the same or a comparable domain of interest to which it is aimed to be applied, characterized by for example land use, pedo-climatic zone, etc.

³⁵ <https://www.iso.org/ics/13.080.05/x/>

³⁶ <https://www.fao.org/global-soil-partnership/glosolan-old/soil-analysis/standard-operating-procedures/en/>

5.2 Other data acquisition methods

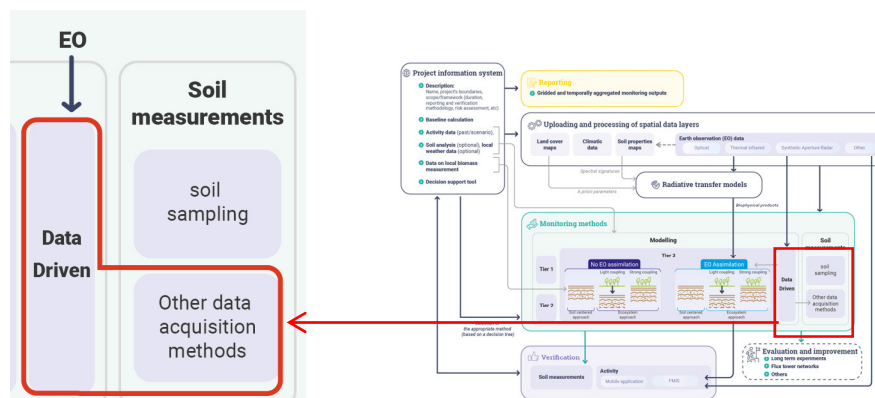


Figure 18. The red frame indicates which part of the MRV framework will be addressed in this section.

Conventional soil sampling and lab analysis methods are accurate but can be costly for larger quantities and without composite sampling approaches, thereby potentially prohibiting the measure-remeasure approach for MRV. An alternative to this approach can be the additional use of soil sensing methods for estimating SOC content, either in the lab, in the field, or from a remote platform such as a satellite (Smith *et al.* 2020). Either by providing a pattern of SOC content variability and thereby more efficient soil sampling location allocation, or by enabling many more measurements, which can negate the difference in accuracy through reducing the sampling error of the mean of the targeted soil property. 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). Although conventional soil sampling/measurements will still be needed for calibration of any sensing method, the number of these samples can be decreased considerably while maintaining overall accuracy and increasing the number of observations of a soil property spatially.

Several soil sensing measurement principles exist, with the potential to estimate a number of superficial soil properties that are relevant for MRV applications (e.g. SOC content). The applicability of each measurement principle and their associated instruments depends on their ability to estimate the desired soil property based on the physics or chemical principles of the method, the platform on which it can be mounted (handheld, on-the-go, UAV, airplane, satellite) and therefore the scale to which it can effectively be applied (global/continental, national, regional, local), the accuracy of the measurement and its calibration needs, the associated costs per day or area and the availability of suppliers the techniques. Decision support tools and literature reviews are in development and available to assist in the selection of techniques for different purposes (Stenberg *et al.* 2024; Lozano Fondon *et al.* 2024b; van Egmond *et al.* 2024), and the main techniques including their applicability for MRV purposes is outlined here.

When performing and using soil sensing measurements it is important to capture and pay attention to the instrumentation, the methods and setting used. A good practice is to store all relevant data about the data (metadata) in a data model that can accommodate this, such as the OGC standard 'Observations, Measurements and Samples' (OGC, 2023³⁷) and its application in common soil data models such as implementations of ISO28258

³⁷ <http://www.opengis.net/doc/as/om/3.0>

standard³⁸, INSPIRE Soil standard, GloSIS conceptual soil data exchange model³⁹. This facilitates transparency and reusability of the data (used) and is an important step towards making the data FAIR. FAIR stands for findable, accessible, interoperable and reusable. Data storage and exchange is not part of this cookbook, but more information is available in van Egmond and van der Woude (2023) and other many other publications.

5.2.1 Spectroscopy

Spectroscopy of the visible, near- and mid-infrared part of the electromagnetic spectrum (VNIR, NIR, MIR) is able to estimate soil organic carbon content, soil total carbon content, soil organic carbon fractions, soil texture and a number of other soil properties due to the presence of strong absorbance peaks for specific chemical bonds related to these properties (Viscarra Rossel *et al.* 2006; Gholizadeh *et al.* 2013; Soriano-Disla *et al.* 2014; Shepherd *et al.* 2022). Some derived soil properties can, depending on the calibration, also be estimated due to their correlation with properties that have clear absorption features, such as pH. The method can be applied in the lab and in the field, with a (range of) handheld and on-the-go sensors, on an UAV, airplane or satellite, making it a very versatile and much applied methodology. Not only for soil but also for vegetation and biomass measurements. The accuracy of the measurements in the lab can be close to the accuracy of conventional measurements if performed and calibrated well. In the field, the measurements with VNIR or MIR spectroscopy from platforms are often not accurate enough at present for SOC change detection or mapping small differences in space or time. However, the spatial patterns and larger differences in SOC and other soil properties can be mapped using spectroscopy and used for mapping, for allocation of sampling points etc. In the 2021 Australian Soil C method, the use of vis-NIR and MIR spectroscopic datasets is allowed for estimating SOC concentration. It is probably the only method that currently supports this and several companies involved in monitoring SOC for CF projects in Australia heavily rely on IR spectroscopy. Note that applications of spectroscopy for vegetation, biomass, land use, and some land management practices can be mapped reasonably well depending on the property and objective (e.g. see Sections 4.2.2.4), and as such spectroscopy is a valuable tool for MRV in general.

When choosing a platform and instrument, several characteristics or main distinctions should be considered. Mid infrared is usually more accurate than near infrared due to the presence of more and primary absorption features for soil properties in the mid infrared. For both wavelengths ranges high-end lab equipment is available, and MIR field equipment is increasing over the last few years, however, most field equipment is still using the NIR range of the spectrum, as are remote applications.

Sensors can be hyperspectral (measuring the full spectral range with high number of narrow spectral bands) or multispectral (measuring a few broader bands allocated at specific parts of the spectral range, often optimised for measuring plant-related biophysical properties, some now also on soil-related bands), where multi-spectral options are often cheaper and more widely available, while hyperspectral instruments are more expensive and/or heavy and less available. For example, the Sentinel-2 satellites are multispectral but have a high coverage in space and time, while several hyperspectral satellites like ENMAP, PRISM, CHIME and commercial satellites can cover much less of the earth's surface and at a lower frequency of revisit. Hyperspectral instruments usually provide better

³⁸ <https://github.com/ISRICWorldSoil/iso-28258>

³⁹ <https://glosis-lid.github.io/glosis/>

accuracies in soil property estimation due to the higher information content of the full spectrum and the better coverage of soil specific absorption features.

In recent years, attempts were made to quantify SOC stocks or SOC stock trends by combining EO data and data driven approaches (e.g. Broeg *et al.* 2024) but as optical satellite only measure the reflectance of the surface, they only provide information about the soil surface properties (or integrated over a few cm for SAR satellites like Sentinel-1). In agricultural soils with tillage this information will be valid for the entire tilled layer due to the expected homogenisation, on no-till soils this will not be the case and this will need mathematical correction and sometimes some (strong) hypothesis on the SOC profile shape. Broeg *et al.* (2024) used repeated SOC samples from 1986 to 2022 and a time series of multispectral bare soil observations from Landsat and Sentinel-2 to model high-resolution cropland SOC trends. They concluded that they were able to detect SOC stock trends but that the prediction of short-term SOC changes based on EO data remains challenging and is currently not possible. An alternative is to take a sample over the prescribed measurement depth, homogenise this in field or in the lab and then take a measurement.

Lab spectroscopy is typically more accurate than any field or remote application due to the more controlled circumstances in the lab and the disturbing effect on the measured signal by the presence of moisture, roughness of the soil surface, differences in texture, large amounts of salinity and atmospheric influences in case of remote applications (airplane, satellite). In recent years, considerable progress has been made on understanding and handling the disturbing effect of soil moisture on field and remote VNIR measurements for soil property analysis. On the one hand by improved field protocols (Stenberg *et al.* 2024, Ben Dor 2024) and on the other hand in mathematical correction methods like EPO and compositional analysis (Knadel *et al.* 2022; Metzger *et al.* 2024). For soil texture effects research shows that correlations and therefore corrections are local or regional at best, making it more difficult to derive generic correction formulas (Wetterlind *et al.* 2025; Khosravi *et al.* 2024).

For calibration of infrared spectroscopy measurements to soil property values soil spectral calibration libraries are needed. These libraries consist of both conventional and spectral measurements of the same samples. Based on this library a spectral model can be derived mathematically that can estimate the soil property value from a newly measured spectrum based on the known relation between that soil property and the spectra in the library. A library is suitable to use for a given soil property and region if the soil properties that need to be predicted are included, if the conventional (wet chemistry) lab methods used to build the library are the same or transposable to the ones needed for the research or project at hand, if the spectrometer used to measure the new spectra is the same or very similar (no calibration transfer needed) to the one used to build the library, and if the newly measured spectra for which the soil properties need to be predicted are in the same feature space (soil property, geography range, possibly geology) as the library covers. There is a wide range of mathematical/chemometric models (based on statistics or machine learning approaches commonly known as chemometrics) available to derive the spectral models. More descriptions, explanations and examples of R scripts are available in among others Wadoux *et al.* (2021), commercial software is available at vendors of instruments and others as well. They typically require less coding but are not free. Typically, local models outperform global models (Wetterlind and Stenberg 2010), but global models can be applied in regions where local libraries are not available (yet) as a first estimate. An in-between modelling option are locally weighed regression models or similar, that select a spectrally most similar subset of a larger spectral library and derive the model on that subset. The combined use of various spectral libraries is possible if spectral measurement protocols (Standard Operating Procedures) are followed by all, initiatives for this are

undertaken by IEEE P4005⁴⁰ and the GLOSOLAN Spectroscopy WG⁴¹, and if standardised wet chemistry methods are used, e.g. following ISO and/or GLOSOLAN standards/SOPs, or if highly accurate transfer functions exist methods. Estimation services are platforms that use (a set of) soil spectral calibration libraries and either a number of standardised spectral models or custom-made models per spectrum to provide a user with a soil property value for their uploaded spectrum. Thus, saving the customer the need to derive spectral models themselves. The initiative to build a global soil spectral calibration library and estimation service (Shepherd *et al.* 2022), and initiatives to build regional calibration libraries and estimation services (Dematte 2022, Viscarra Rossel *et al.* 2016, Soils4Africa project⁴²), the creation of large calibration datasets (USDA-KSSL (Seybold *et al.* 2019), LUCAS⁴³) and commercial services for spectral estimation of soil properties (CIFOR-ICRAF⁴⁴, Eurofins⁴⁵, others) are promising to increase the routine application of soil spectroscopy for more affordable soil property measurements. It should be noted that these services perform best when new samples for measurement are prepared using the same protocol as the library the service is based on, and the library is applicable to the context of the sample, as described above.

Preconditions for successful applications of estimation services or spectral modelling is that an uncertainty is provided with the estimated soil property value. That should include the lab uncertainty of the wet chemistry or conventional soil measurements as well as the uncertainty of the spectral measurements themselves but it rarely does. This combined uncertainty should be compared with the conventional wet chemistry lab uncertainty to evaluate the results (van Leeuwen *et al.* 2022). It should also be noted that for in-field spectroscopy dedicated spectral libraries are often used to estimate the soil property values due to the different spectral signature or per wavelength sensitivity and covered range of the field instrumentation compared to lab instruments. There are several methods and approaches in development to address this challenge (Castaldi *et al.* 2014, Gholizadeh *et al.* 2021; Piccini *et al.* 2024, Partida *et al.* 2025).

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). Batjes *et al.* (2024)

5.2.2 Other soil sensing methods

Apart from spectroscopy there is a range of other in-field sensing methods that can be useful in the measurement of soil properties for MRV purposes. Several are common sensors in precision agriculture and the results can therefore potentially be used for different on-farm applications. Examples are passive gamma-ray spectrometry for spatial quantification and patterns of soil texture and large spatial soil organic matter differences, and spatially static soil moisture differences in time, active gamma-ray spectrometry for soil bulk density sensing, electro-magnetic induction (EMI) for soil texture, bulk density and salinity measurements combined (Doolittle and Brevik, 2014), and in some cases penetration resistance as a proxy for differences in density or potential for root growth. An overview of (on-the-go) proximal soil sensing methods and their reported accuracy and costs in literature is provided in Lozano Fondon *et al.* (2024b), Smith *et al.* (2020). Decision support tools and literature reviews are in development and available to assist in the selection of techniques for different purposes (van Egmond *et al.* 2024). A short

⁴⁰ <https://sagroups.ieee.org/4005/>

⁴¹ <https://www.fao.org/global-soil-partnership/glosolan-old/soil-analysis/dry-chemistry-spectroscopy/en/>

⁴² <https://www.soils4africa-h2020.eu/>

⁴³ <https://esdac.jrc.ec.europa.eu/projects/lucas>

⁴⁴ <https://www.cifor-icraf.org/research/theme/soil-and-land-health/soil-plant-spectral-diagnostics-laboratory/>

⁴⁵ <https://www.eurofins-agro.com/en/soil-health-solutions>

overview of some of these techniques and active gamma radiation for bulk density measurements is provided in this chapter.

Passive gamma-ray spectrometry is mostly applied on-the-go and its measurement principle is the quantitative measurement of the energy spectrum that is the result of radio-active decay of mostly natural radio-nuclides in matter, including soil. The radio-nuclides ^{40}K , ^{238}U , ^{232}Th are part of soil minerals in quantities and ratios that depend on the parent material of the soil, or its provenance. And the differences in abundance of minerals in the different soil texture fractions makes it a good and quantitative predictor of soil texture fractions when calibrated using a calibration dataset or library that reflects the same feature space as the new measurement, just like in infrared spectroscopy as described in Section 51. Due to the attenuation of the gamma radiation by matter, the signal typically originates from the 0-30 cm topsoil depth range with an exponential decline of the signal with increasing depth, with 5 % of the signal originating from soil deeper 30 cm below the surface. (van der Klooster *et al.* 2011; Reinhardt and Herrmann, 2018)

Active gamma-ray spectrometry is currently mostly applied on cores extracted from the soil (Lobsey and Viscarra Rossel 2016c) or on a 3 cm wide probe that is inserted into the soil up to 1 m depth (Pepers *et al.* 2024). The measurement principle is based the use of a (very weak and not harmful to people) radioactive source and detector. The source emits a specific frequency of gamma-radiation that travels through a known volume of soil and in doing so is scattered and absorbed by the soil and water particles present in that volume. The amount of scattering and absorption is determined by the amount of matter present and the decrease of the signal between source and detector is therefore a measure for the amount of matter per volume, which is the bulk density of the soil in grams.cm^{-3} including the moisture content at the time of measurement. The measurement is fast, in field and can be conducted along the soil profile in 5 cm increments with an accuracy that is slightly lower than the accuracy that can be obtained by the conventional method of using Kopecky rings for bulk density measurements. Correction for soil moisture content is needed to convert to dry bulk density measurements, just like is done for Kopecky rings by drying the soil in the lab. This can be done using a soil moisture sensor or VNIR measurements. At present the applicability of this sensor is only validated in sedimentary soils in the Netherlands without stones. Future research is needed to evaluate the performance of the sensor in other geographies and soils where the concentration of coarse fragments influences the soil bulk density. (Pepers *et al.* 2024)

Other techniques that are upcoming and reported in literature are the combined use of a penetration resistance probe with a VNIR sensor or camera for point measurements (Gyawali *et al.* 2025), a combination of VNIR and active gamma-ray measurements on extracted cores, the use of Sentinel (-1 and -2) imagery for high density smart soil sampling and others. The cost/accuracy ratio and their applicability in MRV contexts differs per instrument, calibration, manufacturer, operator and context and should therefore be evaluated before application.

5.3 Modelling SOC stock changes

In this Section modelling approaches for the different context of MRV will be considered. For NDCs, the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006), in particular volume 4, defined different approaches, or Tiers, for carrying out GHG inventories. Each Tier represents a level of increasing methodological complexity:

- Tier 1 is the basic method (see section 5.3.1). Emissions are estimated using average emission/SOC stock change factors for large eco-regions of the world, using globally available data and default equations.

- Tier 2 is of intermediate complexity (see section 5.3.2). It is similar to Tier 1 but considers country specific emission/stock change factors yet uses the same equations as for Tier 1.
- Tier 3 is the most demanding approach in terms of complexity and data requirements. Overall, Tier 3 methods are supposed to be more accurate than Tier 1 and Tier 2 type approaches. They are based on (sub)national inventories and various types of modelling with (some) direct measurements for verification (see Batjes *et al.* (2024), and Section 7). Further details on possible approaches are provided in Section 5.3.3.

Note that data driven approaches (e.g. Machine learning, surrogate models) are addressed in 5.3.4.

In preparing national greenhouse gas inventories, "Good practice" is a key concept for inventory compilers to follow (IPCC 2003, 2006). It defines a set of procedures aimed at ensuring that greenhouse gas inventories are accurate in the sense that they are carried out systematically, i.e. do not over- nor underestimate the changes, and that uncertainties are quantified and kept as small as practicable. For example, "it is good practice for countries to use a Tier 2 method, if possible, even if they are only able to better specify certain components of the Tier 1 method (Bellassen *et al.* 2023). Currently, many countries, also in western Europe, still use Tier 1 for their national GHG reporting (Smith *et al.* 2020). However, the "2023 revised LULUCF regulation"⁴⁶ requires that from 2026 onwards reporting be done using a Tier 2 approach, and then later Tier 3 methods, for a subset of land including among others, forests and peatlands that undergo restoration or protection for nature directives (Bellassen *et al.* 2023). The later requirement is particularly challenging for soil carbon for which Tier 1 is still used by many EU Member States for several land categories as indicated above.

In practice, it is possible that compilers will use different tiers to prepare SOC stock change estimates for mineral soils, organic soils, biochar amendments and soil inorganic C, depending on the availability of resources (see FAO-GSP 2020) and the MRV context (e.g. NDCs, voluntary C market). Figure 20 shows a generic decision tree for selection of an appropriate tier to estimate SOC stock changes in mineral soils by land use category.

⁴⁶ <https://eur-lex.europa.eu/eli/reg/2023/839/oj>

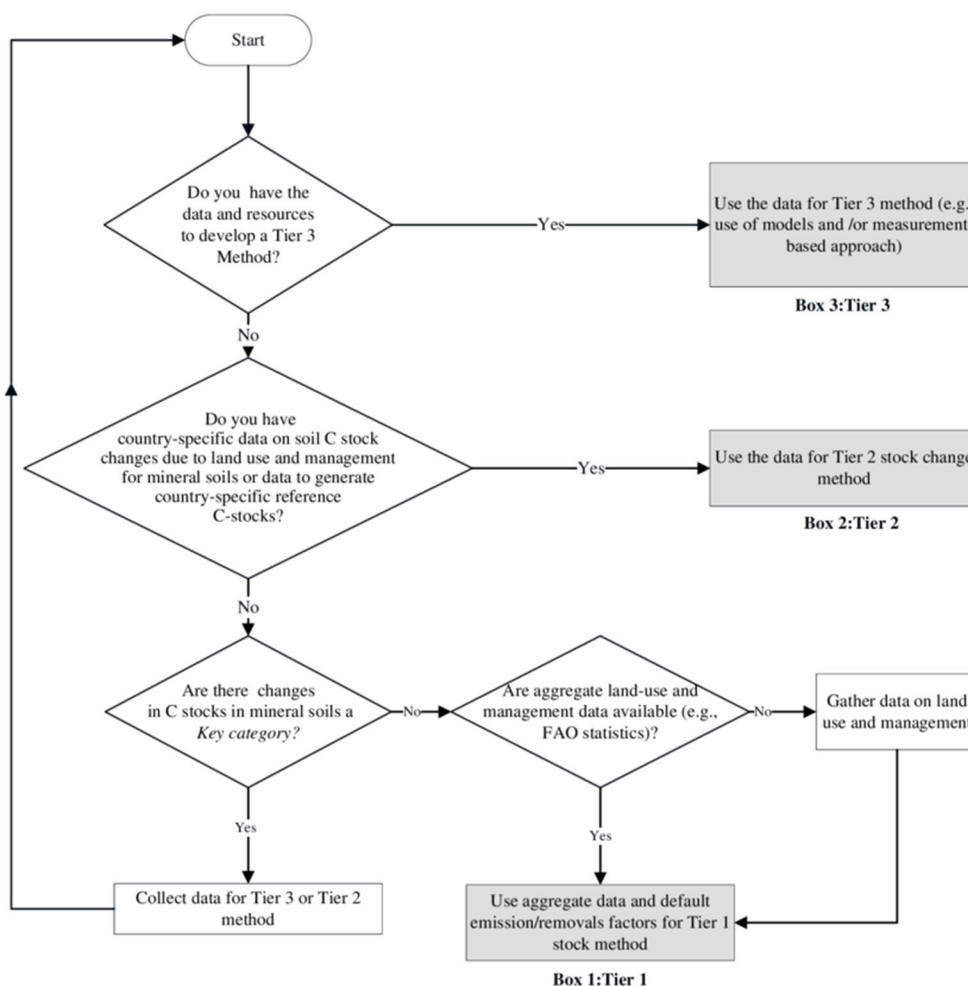


Figure 19. Schematic Generic decision tree for identification of appropriate tier to estimate SOC stock changes in mineral soils by land use category (Source: Figure 2.4 from IPCC 2006).

It should be noted that, so far, for Tier 1 and 2 no methods are provided for estimating the change in soil inorganic C stocks due to limited scientific data for derivation of stock change factors. As a result, the net flux for inorganic C stocks is assumed to be zero. Alternatively, for Tier 3 methods could be developed to estimate changes in the stock of inorganic carbon in mineral or organic soils, see GSOC MRV Protocol (FAO-GSP 2020) for examples.

However, depending on the context of application and the availability/accuracy of input data, the appropriate or feasible Tier level should be chosen (Batjes *et al.* 2024). In the following sections, the different methodological approaches for monitoring SOC stock changes will be presented and analysed in terms of adequacy to different contexts of application for MRV. A decision tree to choose the monitoring methodology adapted to each context of application of MRV for cropland considering data availability and cost/accuracy ratio is presented in Section 5.4.

5.3.1 Tier 1

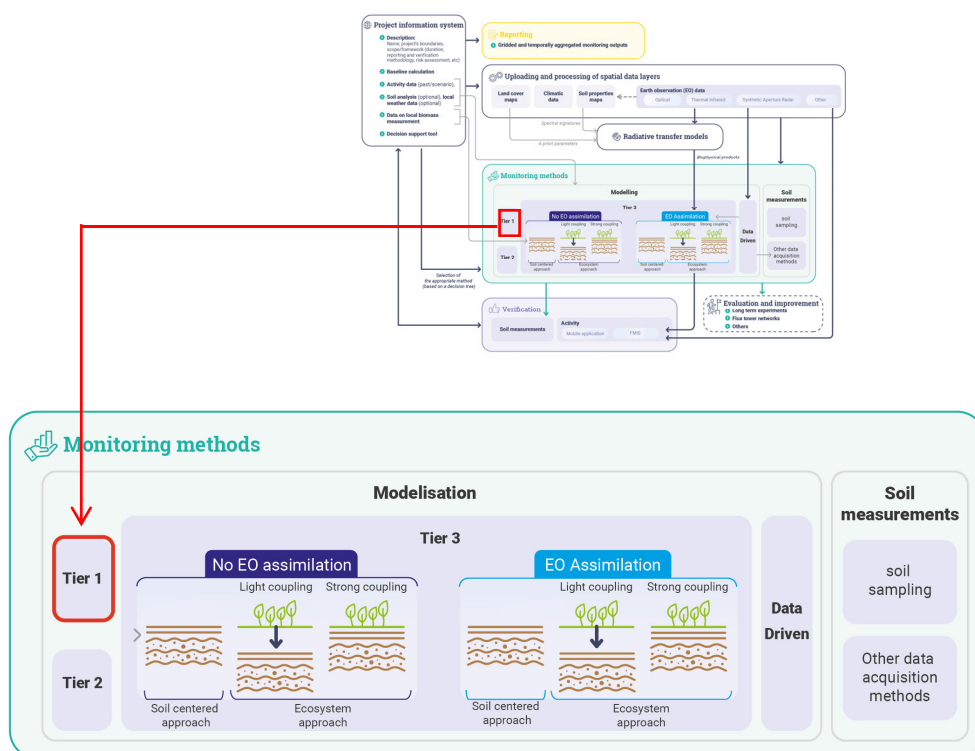


Figure 20. The red frame indicates which part of the MRV framework will be addressed in this section.

The general formula for assessing SOC stock change using Tier 1, corresponding with equation 2.1 in IPCC (2006), is:

$$\Delta C_{AFOLU} = \Delta C_{FL} + \Delta C_{CL} + \Delta C_{GL} + \Delta C_{WL} + \Delta C_{SL} + \Delta C_{OL}$$

where AFOLU is Agriculture, Forestry and Other Land Use, FL is Forest Land, CL is Cropland, GL is Grassland, WL is Wetlands, SL is Settlements, and OL is Other Land.

For a specific land-use (LU) category the equation becomes (see Equation 2.3 in IPCC (2006)):

$$\Delta C_{LU} = \Delta C_{AB} + \Delta C_{BB} + \Delta C_{DW} + \Delta C_{LI} + \Delta C_{SO} + \Delta C_{HWP}$$

where AB is above-ground biomass, BB is below-ground biomass, DW is deadwood, LI is litter, SO is soils, and HWP is harvested wood products. Only the relevant categories for a given land use change are considered (Ravindranath and Ostwald 2008).

Two calculation methods are proposed by IPCC to estimate SOC stock changes:

- The gain loss method (see Equation 2.4 in IPCC (2006)):

$$\Delta C = \Delta C_G + \Delta C_L$$

where ΔC is the annual carbon stock change in the pool, ΔC_G is the annual gain of carbon, and ΔC_L is the annual loss of carbon (all terms expressed in tonnes C yr⁻¹).

- The stock difference method (see equation 2.5 in IPCC (2006)):

$$\Delta C = (C_{t2} - C_{t1}) / (t_2 - t_1)$$

where ΔC is the annual carbon stock change in the pool (tonnes C yr⁻¹), C_{t1} is the carbon stock in the pool at time 1 (tonnes C), C_{t2} is the carbon stock in the pool at time 2 (tonnes C).

For soil carbon, different pools have to be considered in line with equation 2.24 in IPCC (2006):

$$\Delta C_{\text{Soil}} = \Delta C_{\text{Mineral}} - L_{\text{Organic}} + \Delta C_{\text{Inorganic}}$$

where ΔC_{Soil} is annual change in carbon stocks in soils (tonnes C yr⁻¹), $\Delta C_{\text{Mineral}}$ is annual change in carbon stocks in mineral soils (tonnes C yr⁻¹), L_{Organic} is annual loss of carbon from drained organic soils (tonnes C ha⁻¹), $\Delta C_{\text{Inorganic}}$ is annual change in inorganic carbon stocks in soils (tonnes C yr⁻¹), which is ^{assumed} to be zero unless a Tier 3 approach is used.

Further, for Tier 1, soil organic C stocks for mineral soils are computed to a default depth of 30 cm because default reference soil organic C stocks and stock change factors are based on a 30 cm depth (Batjes 2011; IPCC 2019a). The SOC stock present under the reference condition for the Tier 1 method is defined with respect to that observed in non-degraded, unimproved lands under natural vegetation (also called SOC_{REF}).

For mineral soils, the stock change factor is based on changes in soil C stocks ($\Delta C_{\text{Mineral}}$) over a finite period of 20 years assuming a linear increase to a new equilibrium over that period, which is a simplification.

The change in SOC stocks can be computed as follows (equation 2.25 in IPCC (2006)):

$$\Delta C_{\text{Mineral}} = (SOC_0 - SOC_{(0-T)}) / D$$

where $\Delta C_{\text{Mineral}}$ is annual change in organic C stocks in soils (tonnes C yr⁻¹), SOC_0 is mineral soil organic C stock (SOC_{Mineral}) in the last year of an inventory time period (tonnes), $SOC_{(0-T)}$ is mineral soil organic C stock (SOC_{Mineral}) at the beginning of the inventory time period (tonnes), T is number of years over a single inventory time period (yr), D is the time dependence of mineral soil organic C stock change factors which is the default time period for transition between equilibrium SOC values (yr).

SOC_{Mineral} in turn is derived using equation 2.25 in IPCC (2006):

EQUATION 2.25

ANNUAL CHANGE IN ORGANIC CARBON STOCKS IN MINERAL SOILS

$$\Delta C_{\text{Mineral}} = \frac{(SOC_0 - SOC_{(0-T)})}{D}$$

$$SOC = \sum_{c,s,i} (SOC_{\text{REF},c,s,i} \cdot F_{\text{LU},c,s,i} \cdot F_{\text{MG},c,s,i} \cdot F_{\text{I},c,s,i} \cdot A_{c,s,i})$$

(Note: T is used in place of D in this equation if T is ≥ 20 years, see note below)

D is commonly considered to be 20 years, but it depends on assumptions made in computing the factors F_{LU} , F_{MG} and F_{I} . If T exceeds D , the value for T is used to obtain an annual rate of change over the inventory time period ($0-T$ years). Further, c represents the climate zones, s the soil types, and i the set of management systems that are present in a country. SOC_{REF} is the reference carbon stock (tonnes C ha⁻¹), F_{LU} a stock change factor for land-use systems or sub-system for a particular land-use (dimensionless). [Note: F_{ND} is substituted for F in forest soil C calculation to estimate the influence of natural disturbance regimes], F_{MG} is stock change factor for management regime (dimensionless), F_{I} is stock change factor for input of organic matter (dimensionless), A is land area of the stratum being estimated (ha). All land in the stratum should have common biophysical conditions (i.e., climate and soil type) and management history over the inventory time period to be treated together for analytical purposes (IPCC 2006).

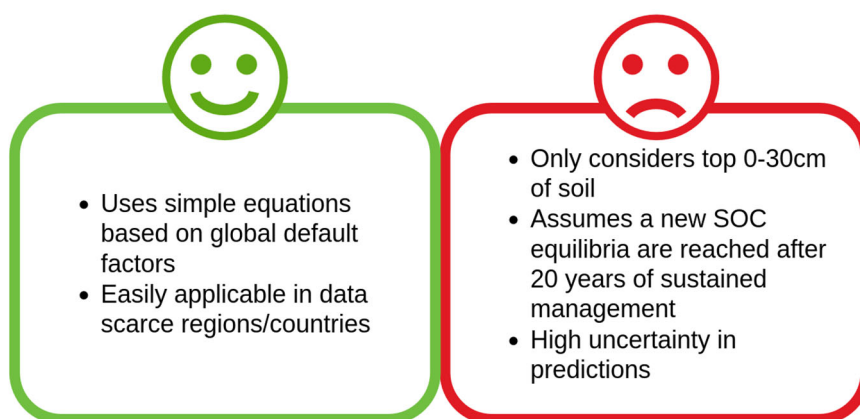


Figure 21. Pro and cons of the Tier 1 approach.

5.3.2 Tier 2

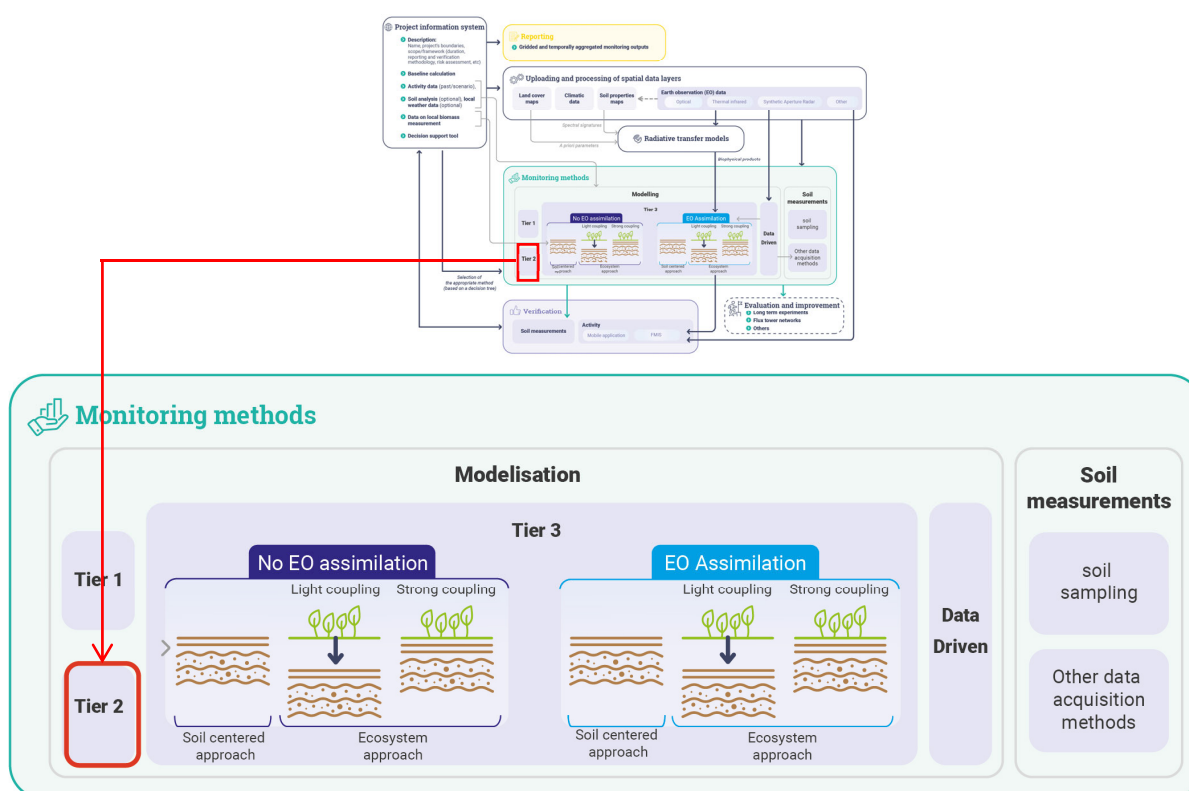


Figure 22. The red frame indicates which part of the MRV framework will be addressed in this section.

As indicated earlier, a Tier 2 method is an extension of the Tier 1 method. It allows an inventory to incorporate country-specific data (e.g., Sperow 2014; Villarino *et al.* 2014; Peter *et al.* 2016; Cardinael *et al.* 2018); as such, it

is considered good practice for countries to use a Tier 2 method when possible (Ravindranath and Ostwald 2008), even if they are only able to better specify certain components of the Tier 1 method (IPCC 2019b).

Regarding Tier 2, Bellassen *et al.* (2023) suggest a step by step method to estimate reference carbon stock (SOC_{REF}) and carbon stock modifying factors (e.g. F_{LU}) using national datasets on soil carbon or international databases such as the LUCAS topsoil survey (Fernandez-Ugalde *et al.* 2022). They also propose a list of F_{MG} emission factors for agricultural practices based on a literature review for the temperate zone.

Further, it should be noted that for cropland, the "IPCC 2019 Refinements" offer a different kind of Tier 2 method (IPCC 2019c,d), that consists of a simplified process-based, steady-state method based on e.g. DayCent (Mathers *et al.* 2023). Alternatively, Villarino *et al.* (2014; 2018), proposed an adapted Tier 2 approach in which the RothC model (Coleman *et al.* 1997) was used to determine SOC change and region-specific SOC_{REF} factors for the Argentinean Pampa region. Similarly, CSIRO, Australia, implemented a steady-state Tier 2 methodology with a spatially-explicit modelling component based on FULLCAM (Fitch *et al.* 2022) (see Section 1.2.3 in Annex 1). Karstens *et al.* (2022) used the CENTURY model (Parton *et al.* 1987) for their Tier 2 level calculations as applied to global croplands. Alternatively, Mishra *et al.* (2012) used regression kriging (RK), a geo-statistical approach, to estimate reference carbon stocks in their IPCC Tier 2 approach. Sensitivity analyses by Bessou *et al.* (2020) pointed at the critical influence of methodological approach and data choices on final results, pointing at the need for defining the uncertainty of the predictions.

The above T2 level studies (e.g., McNeill *et al.* 2014; Thiagarajan *et al.* 2022; Vazquez Amabile *et al.* 2025) show that conceptual limitations of the T1 default method can be overcome by using Tier 2 approaches methods, in which some simple "steady-state" modelling component or geo-statistical model have been incorporated. Further, some Tier 2 approaches consider SOC stock changes in 0-100 cm depth, rather than the default 0-30 cm IPCC default.

Overall, Tier 2 level predictions are more realistic, and less uncertain, to conduct a (sub) regional SOC inventory than using default IPCC Tier 1 equations and factors. When/where possible, however, Tier 3 assessments are preferred (see Section 5.2.3).

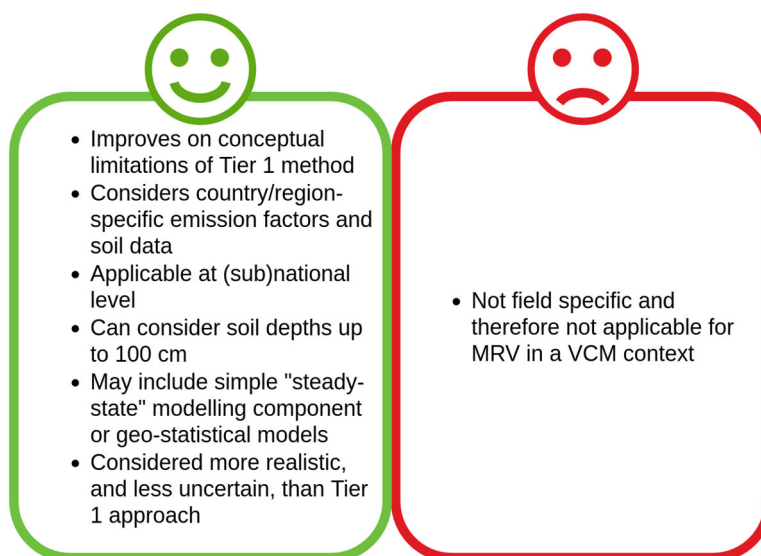


Figure 23. Pro and cons of the Tier 2 approach.

5.3.3 Process-based modelling (Tier 3)

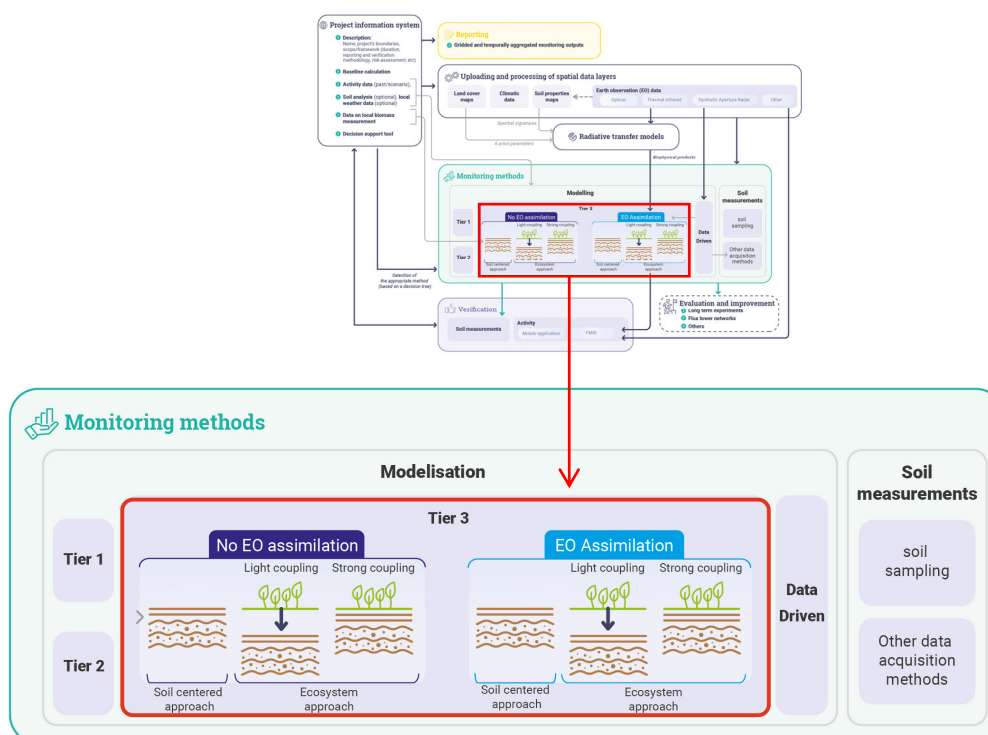


Figure 24. The red frame indicates which part of the MRV framework will be addressed in this section.

Different approaches are used to estimate SOC stock changes based on process-based model simulations. These approaches have their specificities and the choice will mainly depend on the context of application, the spatial extent targeted, the data available and considerations of available expertise and cost accuracy. We decided to describe and classify the modelling approaches based on the system modelled in the approach, i.e. either the soil or the ecosystem, and based on the differences in input data they use (e.g. EO assimilation or not). In this deliverable, we will not analyse or compare the models themselves. Hence, note that some models used in one approach (e.g. soil model) can also be used as a component in another one (e.g. ecosystem model). The following sections will go from the soil centred approach to the ecosystem approach without or with earth observation (EO) data assimilation (see Section 4.2.3. for a reminder of the methods of assimilation of data in models).

We decided to separate the approaches with and without EO data assimilation to highlight their respective strengths and limitations. Approaches without EO data assimilation usually rely on well-established and recognized models with traditional calibration methods, local observation and detailed data on management as input which often limits their spatialized application and realistic assessment of inter or intra field spatial variabilities in plant and soil processes. On the other hand, those models generally provide several agronomical and environmental variables allowing holistic assessment of the effect of management changes on the production and the environment. Modelling approaches with EO data assimilation may allow more realistic accounting of spatial variabilities in soil and plant processes and some models dedicated to upscaling may substantially limit the need for detailed activity data through the assimilation process that allows implicit accounting of some management/pest/extreme climatic

event on soil and vegetation process. However, they require additional skills and expertise compared to “traditional” soil and ecosystem models, they cannot be applied everywhere (e.g. in area with EO scarce observations because of clouds) and they are usually applied to only the most common crops and practices. Moreover, EO products are typically large in terms of numerical data storage and can significantly increase computational time when assimilated into models. This is an important consideration when designing monitoring tools, as the heavy data load can affect processing efficiency. By considering these approaches with and without EO data assimilation distinct, we can better assess when and how to combine EO with modelling for maximum effectiveness regarding the different MRV contexts of application.

5.3.3.1 Soil-centred modelling approach

The soil-centred approach is probably the simplest and easiest method to simulate and monitor SOC stock changes as it only considers one compartment of the system, i.e. the soil. It is based on a soil model that considers the impact of climate, soil type, and carbon inputs (e.g. crop residues, cover crops, organic amendments) on the SOC stock changes. Depending on the complexity of the model it can also consider the impact of management farming practices other than the ones directly impacting the C inputs to the soil (e.g. tillage, mineral fertilisation). Examples of operational tools/SQPs for SOC monitoring using this soil centred approach are described in Annex 1 (e.g. FullCAM, Carbon Extract).

This section will first describe the soil centred approach using soil models without Earth Observation (EO) data assimilation and then we will describe how EO data assimilated could be used in such an approach.

5.3.3.1.1 Soil centred modelling approach without EO assimilation

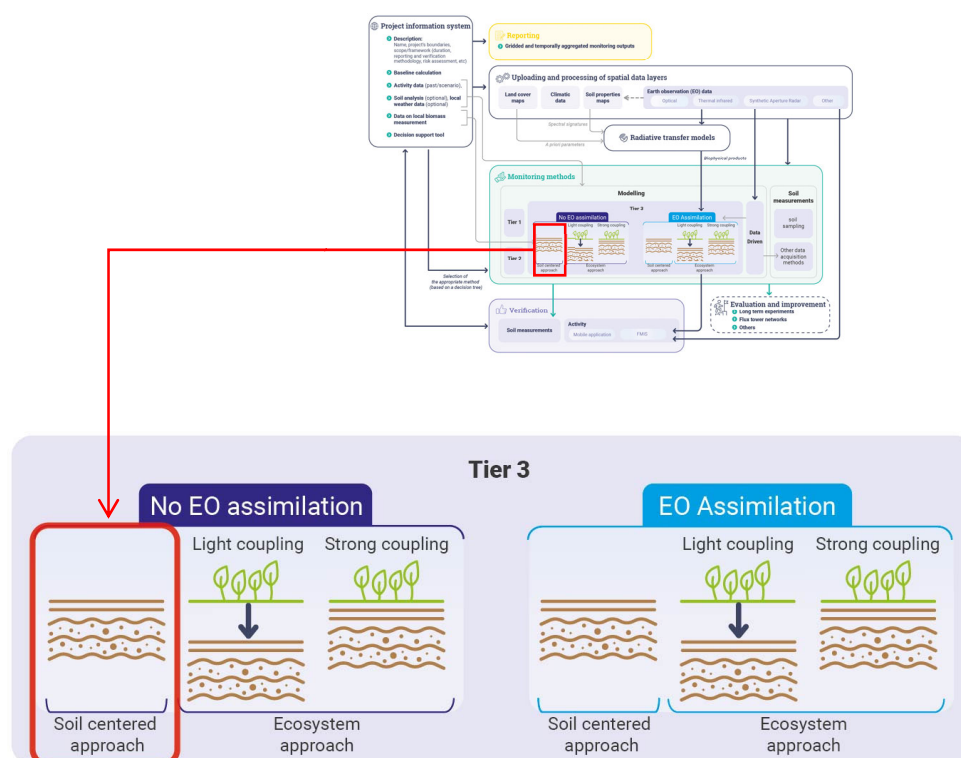


Figure 25. The red frame indicates which Tier 3 modelling approach will be addressed in this section.

The two main families of soil models and their adequacy to MRV contexts

In soil models, two main families can be identified. The first one represents SOC dynamics with a first order decay rate (AMG (Clivot *et al.* 2019), RothC (Coleman & Jenkinson, 1996), ICBM (Andrén & Kätterer, 1997), Century (Parton *et al.* 1988) that can also model the plant compartment, Yasso07 (Tuomi *et al.* 2011; Tuomi *et al.* 2009), etc.), where SOC is divided into several conceptual pools of carbon, classified by their differing turnover times. Each pool is then characterized by its stabilization mechanisms and decomposition rate that is modulated by climatic forcing (temperature and humidity), soil texture and other soil properties (e.g. pH). As the decomposition process modelled are simplified, the time step of these models usually range from monthly to annual, reducing computational time. The conceptual pools are generally not directly measurable, and this family of models needs methods to initialize the distribution of SOC pools. Furthermore, it also means that these models can only be evaluated and validated on the total SOC stock, unless conceptual pools are replaced with measurable SOC fractions (Skjemstad *et al.* 2004). There is actually increasing interest to use those fractions to constrains the models to initialise them or evaluate them, indeed FAO propose to include POC (particulate organic carbon) measurement in their GSOC-MRV Protocol (2020) as shown in Figure 7.

Models with an inert SOC pool are sensitive to the initial fraction of inert SOC (Clivot *et al.* 2019, Puhlmann *et al.* 2006) when estimating absolute SOC, and show better performances when the inert SOC pool size is adjusted to site-specific conditions rather than default parameters (see Clivot *et al.* 2019 concerning AMG and Falloon and Smith, 2002 concerning Century and RothC). The most common way of initialising the soil models is the spin-up method, either analytically or semi-analytically (Xia *et al.* 2012). For linear model such as RothC, analytical solution

at steady state can be used for initialising SOC stock but needs numerical method for the SOC pools distribution. The numerical solution consists of running a model with constant inputs (carbon inputs and defined climatic conditions), until the total SOC stock reaches equilibrium (Thornton *et al.* 2005). Then, the proportion of SOC allocated to each pool at equilibrium is used to initialise the model. The initial SOC stock can be corrected to start simulations with initial value closer to reality, as in the “relaxation” method (Dimassi *et al.* 2018), that correct the value given by the spin up a posteriori with SOC stock measurement, while keeping the pool distribution from the spin up. The two major limitations of this spin up method are 1) the uncertainties of the input used to run the spin up (climatic, land use, carbon inputs) and 2) the most often unrealistic assumption of steady-state (Kanari *et al.* 2022). The assumption that SOC is at equilibrium at the beginning of the simulations is a strong hypothesis (Luo *et al.* 2017; Xia *et al.* 2012), that usually does not reflect the reality, especially in a carbon farming context where farmers implement new CF practices to increase SOC stocks or fields that have undergone a land cover change in the previous decades. Indeed, Herbst *et al.* (2018) conclude that the assumption of carbon turnover equilibrium might not be valid for fields that have been cultivated less than 50 years.

In the case of the AMG soil model, the two carbon pools can be directly initialised with measurement of the total SOC stock and the stable carbon ratio given by the partitioning model PartySOC (Cécillon *et al.* 2021) which uses Rock-Eval^(R) thermal analysis results as input variables of a machine learning model. Initializing active and stable pool sized by PARTYsoc improves simulation accuracy on average in French agrosystems compared to the default initialization (Kanari *et al.* 2022). A recent study applying this approach to AMG by Wang *et al.* (2023) also showed good performances in China. Yet, default values for initialising the size of the stable SOC pool in AMG (65% of stable C for arable land and 40% for grassland) show good performances too for soils with a well-known long-term history with no land cover change (Clivot *et al.* 2019, Saffih-Hdadi and Mary 2008). The accurate measurement of the stable carbon pool is more critical when no information is available about long-term history of the field or if the land use changed few years before the study. In a statistical calibration study involving a multi-model ensemble including AMG, RothC, and ICBM, Bruni *et al.* (2024) found that the ensemble estimate had higher weight on AMG whereas AMG’s optimised calibration was close to its default parametrisation. This was likely due to the fact that AMG was the only one initialised with SOC stock measurements (and a carbon stable ratio corresponding to the field’s long-term history), while the other models were initialised with steady-state spin-up methods.

Several methods have been proposed to align measurable SOC fractions using mid-infrared spectroscopy (MIR) (e.g. Karunaratne *et al.* 2014; Zimmermann *et al.* 2007b) or fractionation methods to isolate fractions with varying turnover rates (Poeplau *et al.* 2018), with conceptual pools for RothC (Zimmermann *et al.* 2007a, Skjemstad *et al.* 2004, Herbst *et al.* 2018) and DAYCENT (Dangal *et al.* 2022). However, the review made by Kanari *et al.* (2022) suggests that even if good correspondence has been made between conceptual pools and SOC fraction measurements (Leifeld *et al.* 2009b; Herbst *et al.* 2018; Zimmermann *et al.* 2007a; Dangal *et al.* 2022), no proper validation has been made and no improvement of the accuracy of the SOC prediction has been shown, without modifying the decomposition rate of SOC kinetic pools (Skjemstad *et al.* 2004; Luo *et al.* 2014). In addition, when using such approaches based on C pool fractions, the initialisation may be closer to reality, but the disadvantage is the need for additional soil data and measurements, which increases the cost of MRV. However, it is still achievable in some contexts, as shown by the FullCam approach applied in Australia for national scale carbon accounting (see Section 1.2 in Appendix 1).

The issue of the initialization of the size of the various SOC kinetic pools concerns all types of modelling approaches using a soil compartment. The estimation of the absolute SOC stock variation in time is quite sensitive to the initial value assigned to the different pools. Nonetheless, with the AMG (Yogo, *et al.* 2021) and ICBM soil models (FAO, 2019. Measuring and modelling soil carbon stocks and stock changes in livestock production systems: Guidelines for assessment (Version 1)) it has been shown that the value of the initial SOC stock and the distribution of carbon pools has no influence on the estimation of the relative SOC stock changes (or Δ SOC stocks) between two management scenarios (e.g. a baseline scenario and one implementing CF practices). Indeed, the difference in total SOC stock simulated by AMG between two treatments with different carbon inputs but starting from the same SOC stock and the same kinetic pools distribution is independent from these initial conditions. This property seems generalizable to models representing SOC dynamics with a first order decay rate (RothC, Yasso, Century without the plant compartment). Concerning other models simulating the effect of carbon input on SOC stock changes such as ecosystem models, the FAO report suggests that the initialisation will also have a negligible effect on the comparison between two scenario practices (Appendix 1 in the FAO 2019 report). Note that in addition to the pool design, the interaction and connection between pools also differs between soil models (parallel pools, serial pools, pools with feedback), which can impact the estimation of the SOC stock changes as explained in Sierra *et al.* (2012).

The second family of soil models has an explicit microbial carbon pool and aims to offer an explicit representation of current understanding of soil organic matter (SOM) dynamic, considering biological, chemical and physical mechanisms. This family of models include MIMICS (Wieder *et al.* 2015), Millennial (Abramoff *et al.* 2022) and MEMS (Cotrufo *et al.* 2013) while MEMS2 (Zhang *et al.* 2024,) also simulates plant growth and CO₂ fluxes from cropland. To represent those complex processes, this family of models often rely on a large number of parameters and equations, along with a smaller time step, usually daily, which increases the computation time of simulations and makes analysis of the propagation of uncertainties more difficult. The SOC fractions modelled by these models are usually derived from the commonly measured SOM pools – particulate and mineral-associated organic matter (POM and MAOM, respectively). The advantage of this approach is that the design of the pools is directly linked to measurable SOC fractions, in contrast to the previous method where RothC's conceptual pools were forced to match measurable SOC fractions. However, while these pools are measurable, additional data are required to initialize the models, which would increase the cost of MRV. One such requirement is microbial biomass data, which is highly uncertain and not available on a large scale. This is a limiting factor in an operational MRV context. While these models are very interesting for research studies, they have not yet been validated on diachronic measurements of SOC evolutions (Le Noë *et al.* 2023) and their practical implementation for MRV initiatives seems too complex and/or expensive (e.g. very complex to address uncertainty propagation).

Methods for estimating carbon inputs from biomass for the soil centred modelling approach

In a soil-centred approach, soil models do not simulate the vegetation growth and C inputs to the soil are prescribed. The complexity of the model and the numbers of parameters are then reduced compared to ecosystem models, meaning that the calibration process can be easier and requires fewer observations as the number of parameters is reduced. However, if those models do not simulate the plant component, it implies that the biomass inputs to the soil have to be estimated before the simulation in order to feed the soil model with the carbon inputs that come from the crop/cover crop residues and from the organic amendments. Depending on the soil models, information about the quality of the carbon inputs (e.g. C/N ratio of the plant material) may also be required.

Some recent studies have shown that the method chosen to estimate the carbon input has significant impact on the uncertainty of the SOC estimation (Keel *et al.* 2017, Riggers *et al.* 2019), even if the choice of the soil model has a bigger impact (Riggers *et al.* 2019).

In a context of application for MRV, the carbon input from crop biomass residues can be computed from the farmer's yield data using allometric coefficient (e.g. from Bolinder *et al.* 2007) as in the French Low Carbon Label method for arable land. In VCM and CAP MRV contexts, field specific biomass inputs to the soil are needed. They can be derived from allometric relationships and the yield that can be obtain through farmers survey (tedious, costly and time consuming for both farmers and the auditor) or through FMIS (see Section 4.2.1.5.1). The main disadvantage of this method is that it does not consider the spatial variability of the vegetation growth. With this approach, in the best case carbon input from crop biomass residues are calculated from mean yield at field level, but very often only an average yield at farm scale is provided by the farmer. In order to account for intra or inter fields spatial variability, yield maps from combined harvester equipped with the adequate sensors could be used (Soto *et al.* 2005). These combined harvesters provide geo-localised measurement of the harvested grain mass along with its associate humidity. However, those data are often quite inaccurate and need correction treatment as proposed by Blackmore and Marshall (1996). The main errors identified are "Unknown crop width entering the header during harvest, Time lag of grain through the threshing mechanism, the inherent 'wandering' error from the GPS, Surging grain through the combine transport system, Grain losses from the combine, Sensor accuracy and calibration". To improve the accuracy of these yield maps the first approach is to improve the accuracy of data collection at source, then to use an "expert filter" (knowledge about the field, combine, crop, GPS etc) and finally to use the "Potential Mapping" method (Blackmore *et al.* 2003; Blackmore and Marshall, 1996).

Note that the overall uncertainty on the yield data provided by the farmers is rarely quantified in MRV approaches based on soil models only, while the sources of uncertainty are diverse (see above). Moreover, the calculation of carbon input from yield data rely on the harvest index (HI), which varies between crop species and varieties, but also for a given crop specie depending on pedo-climatic conditions and management practices (e.g. N fertilisation). For instance, Dai *et al.* (2016) report that for winter wheat the HI varies between 0.33 and 0.61. Therefore, using a constant HI per crop specie can cause large errors on the carbon input estimate that propagate to the SOC stock changes estimates. When there is no yield, several alternative methods can be used to calculate carbon inputs to the soil from crop residues going from the simplest, but leading to large uncertainties, to more accurate ones: regional statistics (e.g. Eurostat or agricultural councils' reports), *in-situ* sampling of biomass (see Section 4.2.1.5.4) or plant models (see Sections 5.3.3.2.1.2 and 5.3.3.2.2.3). Regional statistics can be used to obtain average yield value per crop type or biomass production, however it cannot reflect the specific context of the field induced by the farmer's management practices (e.g. fertilisation, irrigation) and by its environment (e.g. soil properties, topography, micro-climate). Biomass *in-situ* sampling can provide information on total or aboveground biomass and its partitioning (e.g. grains, straws, leaves), which is useful to compute the carbon input derived from biomass residue, however the measurements may not be representative of the average field without a proper sampling strategy (e.g. Stratified sampling based on vegetation indices). Different sorts of models can also be used to estimate biomass production or yield; e.g. plant models like SIMPLE (Zhao *et al.* 2019), SAFY (Duchemin *et al.* 2009) and SAFYE CO2 (Pique *et al.* 2020 a,b), or ecosystem models such as STICS (Brisson *et al.* 1998). Data driven models using remote sensing data can also be a solution to obtain biomass production at large scale (Bolton *et al.* 2013, Chen *et al.* 2023) as explained in Section 5.3.4.

In the case of cover crops whose biomass entirely returns to the soil, there is usually no information provided by the farmers to quantify the biomass produced and returned to the soil (in the context of the French Low Carbon Label methodology for arable land, very few farmers do *in-situ* measurements). This means that the cover crop biomass has to be estimated either from regional statistics or plant models. However, based on our experience, the intra and inter field heterogeneity of the cover crop aboveground biomass is usually large and most of the times larger than that of the main crops. For instance, the French agricultural cooperative Agrod'Oc measured dry aboveground biomass of cover crops (mainly faba beans) ranging from 0.9 to over 9 t.ha⁻¹ (with a mean of 3.98 t.ha⁻¹) in South-West France (between Gers and Landes regions, i.e. on approximately a range of 150 km) (pers. comm). do Nascimento Bendini *et al.* (2024) also showed that the intra and inter field spatial variability in cover crop aboveground biomass is large. Therefore, using regional statistics for cover crop biomass to estimate their total C inputs to the soil could lead to large uncertainties/errors on the SOC stock changes compared to using local biomass samples. A sensitivity analysis made with the AMG soil model (Yogo *et al.* 2021) reveals that the effect of the uncertainties on the biomass of cover crops was one of the most important sources of error on the model outputs (along with the humification coefficient of the organic amendment) when estimating the differential SOC stock between two practices scenario considering bare soil during the fallow period and fallow with cover crops. Fortunately, methods based on high resolution EO data (e.g. Sentinel-2, Landsat-8) to estimate cover crop biomass are developing rapidly and are promising (e.g. do Nascimento Bendini *et al.* 2024). Those methods will be described in the next section concerning the soil centred approach using EO. Finally, note that the resolution and accuracy of biomass estimation will be a major source of uncertainty to consider in the soil centred approach compared to the ecosystem approach, and will determine the spatial support (Heuvelink *et al.* 1998) at which the model is applied (farm level, field level, or intra field level).

Effect of the forcing variables on the model's accuracy

As mentioned previously, forcing variables are also needed to modify the mineralisation rate. Even if the number of forcing variables depends on the model, we observe that climatic variables concern mostly temperature and soil moisture. Precipitation and evaporation are also often used as a proxy for soil moisture. These data can be obtained from local weather stations, from national databases or from global products (see Sections 4.2.1.5.2 and 4.2.2.2). Concerning global products, data from ERA5 Land, produced by ECMWF, is currently considered the reference for agricultural applications. Indeed, with a resolution of 1/10°, this product is among the highest-resolution global weather products, and its free and global distribution facilitates the adoption of this dataset (Muñoz-Sabater *et al.* 2021).

Required soil data typically include texture (notably clay content) and properties such as pH, CaCO₃, C/N, rock fraction and bulk density. The actual need for soil data depends on the accuracy and resolution required. Various digital soil mapping initiatives currently provide maps of soil types and physical and chemical properties at different spatial resolutions. However, the uncertainties associated with these predictions are often too large to model SOC stock changes for CF projects in the contexts of VCM or AEPs that require accurate assessments at plot scale. See Section 4.2.2.1 that describe the different soil products available, respectively on local or global scale.

Lemercier *et al.* (2022) provide a comparative analysis of GSM, SoilGrids, and point measurements, concluding that digital soil mapping products often do not align sufficiently with *in-situ* point measurements to represent local scales. Hence, for key variables, such as carbon content, proportion of carbon pools, bulk density or clay, *in-situ* soil sampling is often necessary to ensure sufficient accuracy. However, there remains a challenge in ensuring the

representativeness of these point measurements, particularly when scaling up to plot or farm-level maps. Also, a comparison of different methods of initializing SOC stock and soil properties by Yogo *et al.* (2021) showed that using low resolution soil products (e.g. SoilGrids, GSM, Lucas) would lead to high uncertainties for soil parameters (SOC, clay, CaCO₃, pH and C/N) (RRMSE = 19-118%, median = 46%) compared to field measurement. Finally, using median values per French county from BDAT (“Base de Données des Analyses de Terre” in French, Saby *et al.* 2014) would reduce the uncertainty (RRMSE=7-26%, median=18%), with a correction to be made in calcareous soil for clay if soil model uses the true clay content as input. They assumed that the uncertainty on soil samples would be lower, around 10% depending on the representativeness of the plot and the sampling method, with an example of coefficient of variation between replicates of the same trial around 4.3% for SOC stock in Clivot *et al.* (2019).

Techniques for producing accurate maps at plot or farm levels are still under development and must address the spatial variability of soil properties to provide reliable insights for SOC modelling, see Section 5.2. for more details.

Methods to evaluate the soil centred approach and their uncertainty

The soil centred approach can only be evaluated/verified with *in-situ* measurements of SOC stock changes (i.e. measure and re-measure), SOC fraction changes or with soil respiration measurements (e.g. using automatic or portable soil respiration chambers) as the other components of the carbon budget are not simulated (e.g. plant biomass, carbon inputs to the soil, net CO₂ fluxes). As mentioned before, conceptual pools models, for which no method of quantifying compartment size has been developed or is in use, can only be evaluated against SOC stock, unless the conceptual pools are re-mapped to match with SOC fraction measurements, as done in Australia for national inventories (NDC's) using RothC soil model as part of the FullCam approach (see Section 1.2 in Appendix 1). Also, explicit microbial pool models can be directly evaluated with SOC fraction measurements or SOC stock. It should be mentioned that there is still an issue with the representativeness of the soil sampling for verification, addressed in Chapter 7. Using independent time series observation of SOC stocks that weren't used to calibrate the model is the best way to evaluate soil models according to Le Noë *et al.* (2023). Indeed, using one observation of SOC stock at a time to compare to the model simulation will only show the ability of the model to predict an isolated point and not the dynamics of the SOC stock changes. A soil model should be chosen first to fit the pedo-climatic and practices studied, regarding the model performances and validation in a similar context. To ease the choice, two studies have been published, reporting the models that have been validated and in which context and underlining the fact that these models have largely yet to be tested and improved: Le Noë *et al.* (2023) and Garsia *et al.* (2023).

The above models themselves do not include an uncertainty assessment; the propagation of uncertainty is studied outside the models, through analytical computation with Taylor series analysis (Martin *et al.* 2021) or with numerical methods such as Monte Carlo (Bruni *et al.* 2021, Ogle *et al.* 2010). Including uncertainty assessment in the model or the approach is crucial for MRV monitoring tools to improve their reliability.

Recent studies consider multi-model ensemble as a way to improve SOC stock changes prediction and reliability (Farina *et al.* 2021, Riggers *et al.* 2019, Bruni *et al.* 2022). It helps reducing the model structure uncertainty, as different soil models may represent processes in different ways or may not be calibrated for the same soil types. Additionally, this can be a pragmatic solution in cases where no single model has been adequately calibrated or has shown good performance in the pedo-climatic and management context of the area to be monitored.

Another potential way to improve this modelling approach and reduce its cost of implementation can be the assimilation of earth observation data from remote sensing. The next subsection will explore these potential improvements.

Cost/accuracy factors and ways to improve it

The costs of implementing this approach may vary greatly depending on the methodology to collect 1) activity data (e.g. type and dose of organic amendment, the crop type, the straw management...), 2) soil carbon input data from biomass (e.g. *in-situ* measurements, EO based products, statistics, farmer's data) and 3) the data to initialize the SOC stock and pools of the model (will depend a lot on the soil model family, the MRV context of application and on the CF scheme, e.g. not mandatory for the French Low Carbon Label). The quality of this information will also drive the accuracy of the SOC stock changes estimation. As explained previously, after choosing the adequate model and initialisation regarding the context, the accuracy of this approach will depend a lot on the accuracy of the biomass estimation and on the method used to convert it into carbon input for the soil model. The use of EO based approach to estimate cover crop biomass (e.g. Goffart *et al.* 2021, Swoish *et al.* 2022; do Nascimento-Bendini *et al.* 2024) would reduce a lot the cost of MRV (only *in-situ* biomass sampling needed to calibrate) and increase their accuracy (as it considers the spatial variability and the environmental stress factors implicitly through remote sensing).

5.3.3.1.2 Assessing the baselines for the soil centred approach

Depending on the context of MRV and the MRV scheme, different baseline approaches may have to be implemented with the soil centred approach (see Section 4.2.1.4).

Standardised baseline: the standardised baseline can be simulated using regional statistics of activity data (e.g. straw management, cover crop burial or harvest, organic amendments), of biomass input to the soil (estimated from regional yield and cover crop biomass), of soil properties or a combination of those. It can be a static baseline, considering the mean practices, soil and climatic conditions before the monitoring period starts (e.g. over a period of 3-5 years) or it can be a dynamic baseline calculated using data collected during the monitoring period (e.g. during the CF project). We recommend the second approach as it allows to account for the effect of (extreme) climatic events that occurred during the project (e.g. drought, flooding, fire) on SOC stock dynamics. In the soil centred approach, dynamic baseline can only be computed if *in-situ* data on biomass production per crop/cover crop type are collected every year and for each pedo-climatic zone.

Specific baseline: specific baseline can be static or dynamic and it is computed using plot specific data on management practices (activity data) and soil properties as well as field specific carbon inputs from biomass (crop residues, cover crops) to the soil.

Hybrid baseline: As mentioned in Section 4.2.1.4, the MARVIC project (Lanckriet *et al.*, 2024; Ruyschaert *et al.*, 2024) proposes a hybrid baseline, combining field specific data for soil properties and standardised management

practices (including biomass input to the soil). The inverse (standardised soil - specific management practices) could also be considered. The soil centred approach is well adapted to hybrid baselines approaches based on specific soil data with standardised management for all the reason listed above.

5.3.3.1.3 Soil centred modelling approach with EO assimilation

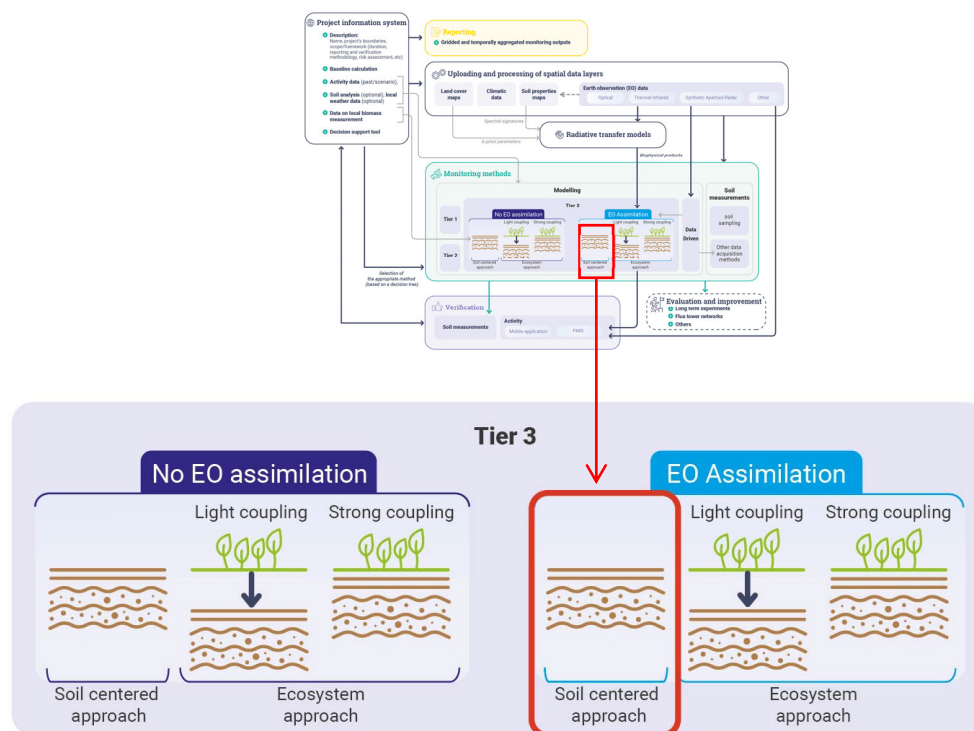


Figure 26. The red frame indicates which Tier 3 modelling approach will be addressed in this section

Earth observation (EO) data or of biophysical products derived from them may facilitate the upscaling of soil centred modelling approaches for SOC stock changes assessment. Recent studies suggest that EO could be used for mapping SOC superficial content (e.g. Vaudour *et al.* 2022), for monitoring soil superficial water content (e.g. Alexakis *et al.* 2017; Bousbih *et al.* 2017; Dupiau *et al.* 2022), or farmers activity (see Section 4.2.1.5.1), even if significant challenges remain. The following section explores how EO data could be used to enhance soil model's accuracy and for upscaling. The models considered are the same as the ones mentioned in the previous section (about soil-centred modelling approach without EO assimilation) because as for now, no soil model dedicated to upscaling with EO assimilation has been developed yet. Indeed, while EO assimilation has been widely used in crop modelling to better represent canopy and vegetation development/spatial variability (Jin *et al.* 2018, Dlamini *et al.* 2023), its application for soil modelling has been limited through fusion of dataset for whole system modelling.

Challenges and benefits of integrating EO data in soil modelling approaches

One of the main limitations of remote sensing for soil monitoring is that it can only monitor the surface or the first centimetres of soil (e.g. for assessing superficial soil water content with active or passive microwave sensors such as Sentinel-1 or SMOS) and not the whole soil profile. This is limiting for soil modelling applications for most contexts of application of MRV systems for SOC that aim at quantifying SOC stock changes over at least the first 30 cm of soil. When the soil is ploughed, it could be assumed that the soil properties (e.g. SOC content) are homogeneous in the top layer. Otherwise, there is generally a carbon gradient within a temperate soil profile (Schneider *et al.* 2021). Moreover, both the signal of optical and SAR sensors are disturbed by the vegetation or by crop residues, which limits the use of EO data for assessing soil properties or SWC to periods of bare soil (Vaudour *et al.* 2022), which is incompatible with certain soil conservation practices that promote no-till and soil cover (with crop residues or cover crops).

However, recent studies show that EO have a great potential in SOC superficial mapping or in assessing SOC stock trends if combined with long term *in-situ* monitoring SOC (Vaudour *et al.* 2022, Urbina-Salazar *et al.* 2023; Richer de Forges *et al.* 2023; Broeg *et al.* 2024). These studies open new perspectives for the initialisation of soil models or for constraining their simulations through assimilation methods considering soil properties and SOC content estimates derived from remote sensing. This could lead to more robust predictions of SOC stock changes, as the model is better constrained to reflect local soil conditions. However, those studies emphasise that these methods are not directly transferable to different locations without further calibration and adaptation (van Wesemael *et al.* 2024). Another challenge is to handle the distribution of SOC in the soil profile from EO observations but also eventually in soil models, keeping in mind that as for now multi-layer soil models (Mary *et al.* 2020, Jenkinson & Coleman 2008) remain complex to use in operational contexts without a solid data infrastructure for calibration and validation.

Another variable to consider in data assimilation for soil models is soil superficial water content derived from remote sensing. For instance, by using Sentinel-1 data (Alexakis *et al.* 2017; Bousbih *et al.* 2017) or by inverting the MARMIT-2 model (Dupiau *et al.* 2022) that predicts soil reflectance as a function of surface soil water content in the solar domain, it is possible to estimate topsoil humidity and use it to force or calibrate soil models. Of course, the same issue as for SOC mapping will arise in relation to the representation of the soil profile. Yet, it is worth to consider in-depth work on this topic as Bruni *et al.* (2022) suggested that better constraining the effect of water-related variables on SOC decomposition would increase the reliability of SOC models, especially under future climate.

EO data also have the potential of mapping some key activity data for soil modelling at high resolution (field or even intra-field) and over large areas (regions to global) in near real time (see Section 4.2.2.4 for more details). It represents a powerful lever to upscale soil models and improve their predictions. For instance, remote sensing allows to map crops and crop rotations, the presence of cover crops (Nowak *et al.* 2021; Fendrich *et al.* 2023), soil work (Hagen *et al.* 2020). Yet it does not allow to map two key management practices for SOC modelling; 1) straw management (i.e. are straw residues left on site or exported and if so, how much and when ?), as remote sensing only provides information on the percentage of residue cover (Wang *et al.* 2023; Daughtry *et al.* 2006), and 2) the type and amount of organic amendments, even if mapping “yes or no application of organic amendment” seems possible according to Dodin *et al.* (2021) and Dodin *et al.* (2024).

Finally, remote sensing can be efficient and useful to monitor vegetation dynamics and estimate aboveground biomass of crops and cover crops at high resolution based on vegetation indices (Zheng *et al.* 2004; Kross *et al.*

2015; Jennewein *et al.* 2022; Holzhauser *et al.* 2022), by combining it with machine learning (Goffart *et al.* 2021 ; Swoish *et al.* 2022 ; do Nascimento Bendini *et al.* 2024) or through EO time series assimilation in crop models (Pique *et al.* 2020a; Pique *et al.* 2020b; Dlamini *et al.* 2023; Wijmer *et al.* 2024). As mentioned previously, having high resolution biomass estimates would allow to consider the intra-field spatial variability and therefore to better estimate the carbon input to soil models. This kind of method is even more crucial for estimating cover crop biomass as very few data are representative of their variability in space and time, and no information such as yield for main crops is available to estimate their biomass based on allometric relationships.

The previous paragraphs of this section highlighted how soil modelling approaches for MRV could benefit from EO data, especially from satellites like Sentinel-1 and Sentinel-2 or Landsat-8, that offer continuous, global-scale, high-frequency and open-source data. Indeed, currently most MRV tools for SOC monitoring heavily rely on *in-situ* data (e.g. activity, soil, biomass), which are often costly and time consuming to collect but also sparse and limited in their temporal and spatial coverage, which makes upscaling and real-time monitoring difficult. Still many challenges remain such as the assessment of soil properties along the soil profiles, the integration of multi-source data (e.g. radar, optical, infrared), and the assessment of the associated uncertainties.

To conclude, assimilating remote sensing in soil models seems promising but on the short term and in an operational perspective, the use of EO is mainly to better assess carbon input to the soil derived from crops and cover crop residues. This information could be used as input for soil models.

5.3.3.1.4 Assessing the baselines for the soil centred approach with EO assimilation

The soil centred approach with EO assimilation can apply the same methods for calculating the baselines as the ones listed in the soil centred approach without EO. However, their assessment could be improved with the help of EO assimilation, in particular for computing specific baselines and dynamic baselines. Indeed, the dynamic monitoring of vegetation development through remote sensing can be used to estimate biomass production at field level which facilitates and enhances the estimates of plot specific baselines, but also the calculation of dynamic baselines since the effects of climatic variability on vegetation are better accounted for.

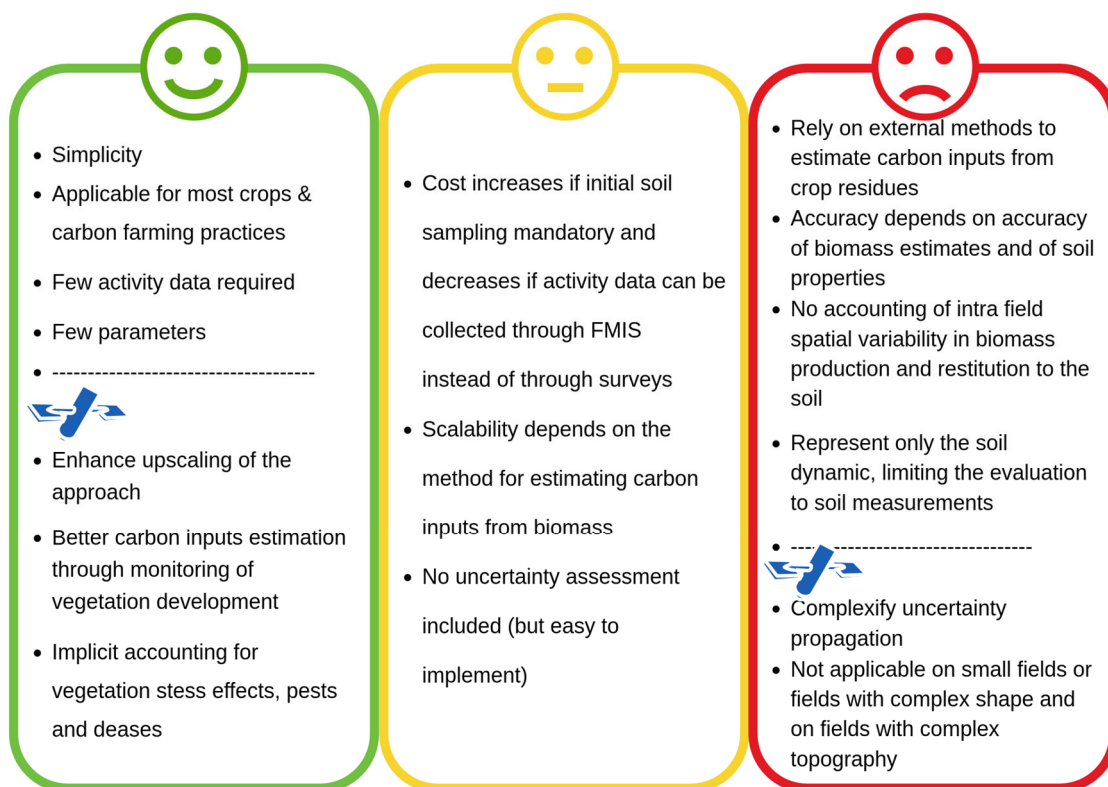
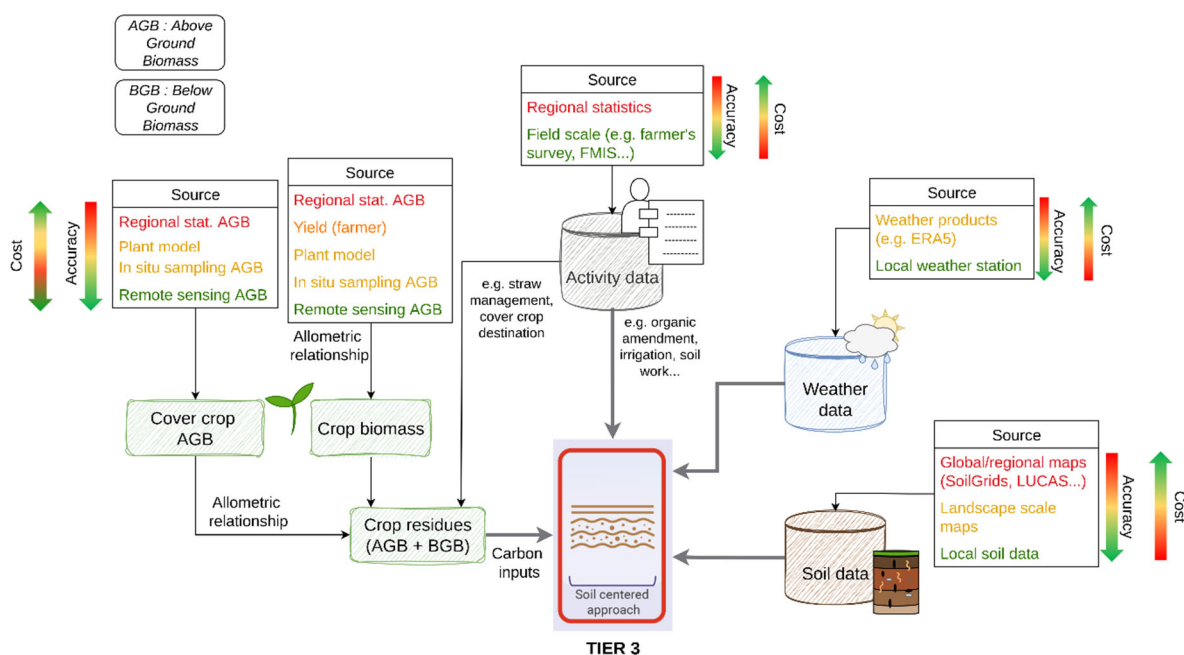


Figure 27. Schematic representation of the soil centred approach for modelling SOC stock changes and of its pro and cons in a MRV context.

5.3.3.2 Ecosystem modelling approach

The ecosystem modelling approach proposes to use more complex, process-oriented models, simulating mechanistically plant and soil processes along with their interactions. An example of operational SQP (COMET-FARM) using this approach is described in Annex 1. Given the operational constraints of MRV applications in the different contexts, two modelling strategies will be considered. One uses already existing ecosystem models (e.g. well-established agronomical models such as EPIC, STICS...) that represent complex interactions inside the ecosystem through a strong coupling between soil and vegetation, referred here below as “off-the-shelf” ecosystem models. However, as they were not developed initially for MRV applications and as they are usually rather demanding in input data and parametrisation/calibration they implementation for SOC monitoring in some operational contexts may be challenging (e.g. for the VCM at commercial farms). Hence a second category of ecosystem models will be analysed, that combine plant and soil models or module (e.g. using plant and soil compartments of current ecosystem models or existing independent crop and soil models) through a light coupling, referred here below as “parsimonious” ecosystem models. This category of models has simplified interactions between soil and plants and they are often less demanding in input data and parametrisation/calibration compared to the first category of models. For this reason, they could be more easily implemented for MRV of SOC in some operational contexts (e.g. at commercial farms in a context of VCM).

In the following sections, the ecosystem modelling approach without EO data assimilation will be analysed first, mainly focusing on “off-the-shelf” ecosystem models with strong coupling, as parsimonious models based on light coupling between the plant and soil need EO assimilation to be accurate and reliable. Then modelling approach with EO data assimilation will be analysed and split in two sub-sections, considering first the “off-the-shelf” ecosystem models assimilating EO data and then the parsimonious ecosystem models assimilating EO data.

5.3.3.2.1 Ecosystem modelling approach without EO assimilation

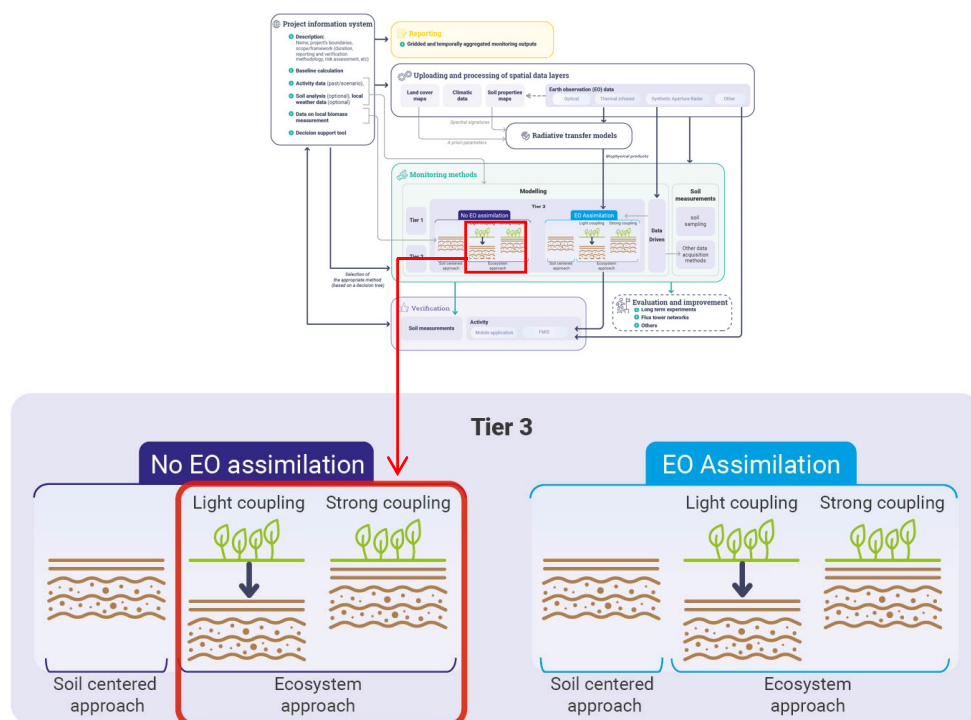


Figure 28. The red frame indicates which Tier 3 modelling approach will be addressed in this section.

5.3.3.2.1.1 “Off-the-shelf” ecosystem modelling approach based on strong coupling between vegetation and soil

Classical cropland ecosystem models (referred as “off-the-shelf” model) simulate the carbon dynamic through a strong coupling between the plant and the soil but they also usually consider processes related to the water cycle and of nutrients. The strong coupling means that the compartments and processes strongly interact with each other and the impact of each dynamic on another is considered through mutual feedback. Additionally, the effects of climate, soil, and management practices are accounted for to represent the dynamics of these different compartments and cycles. The modelling of the soil compartment is sometimes similar to that of the soil models presented in the soil centred approach, with the addition of feedback from the vegetation that can, for instance, influence the water and nutrients availability in the soil.

Here is a non-exhaustive list of cropland ecosystem models: EPIC (Williams *et al.* 1984), CENTURY (Parton, 1996), DAYCENT (Ogle *et al.* 2005; Del Grosso *et al.* 2015; Mathers *et al.* 2023), DNDC (Li, 1996), STICS (originally Brisson *et al.* (1998, 2002)), DAISY (Svendsen *et al.* 1995), DSSAT (Jones *et al.* 2003), SALUS (Basso *et al.* 2006), MEMS 2.14 (Zhang *et al.* 2024). A review of more than 70 models, going from empirical to mechanistic representation of process can be found in DiPaola *et al.* (2015).

Cropland ecosystem models are often developed, calibrated and evaluated at field trials corresponding to deep good soils and where detailed and accurate data on activity, soil and weather were collected (wheat and maize for STICS (Brisson *et al.* 2002), EPIC (Cabelguenne *et al.* 1990), CERES wheat and maize (Iglesias *et al.* 2006), DayCent, DAISY (Bruun *et al.* 2003). It means that the context in which they have been developed and validate may not represent the various and heterogenous conditions encountered at commercial farms. Yet, they have been used in several agronomic or environmental studies (for STICS : irrigation timing for a maize crop, Levrault and Ruget, 2002; optimisation of cover crop management, Justes *et al.* 2001, for DayCent : Stehfest *et al.* 2007; Li *et al.* 2006; Jarecki *et al.* 2008; Smith *et al.* 2008; Hartman *et al.* 2007; Abdalla *et al.* 2011), and they often show robust performances (Smith *et al.* 1997) to predict SOC stock changes in different pedo-climatic conditions and for various practices (generally at agronomic trials). However, Popkin (2023) suggested that in a context of MRV for offsetting at commercial farms such modelling approaches could have high uncertainties. A study by Ogle *et al.* (2010) showed that with the Century model (Parton *et al.* 1987, 1988, 1994) uncertainties were inversely related to spatial scale, with median uncertainties at the regional scale estimated at 118% and 114% during the early and latter part of 1990s, and even higher at the site scale with estimates at 739% and 674% for the time periods, respectively. This relationship appeared to be driven by the amount of the SOC stock change; changes in stocks that exceeded 200 Gg C yr⁻¹ represented a threshold where uncertainties were always lower than 100%. According to them, the uncertainty in estimates derived from process-based models will partly depend on the level of SOC accumulation or loss. In another study, Palosuo *et al.* (2011) compared 9 models (APES (Donatelli *et al.* 2010), CROPSYST (Stockle *et al.* 2003), DAISY (Abrahamsen and Hansen 2000), DSSAT (Jones *et al.* 2003); FASSET (Bernsten *et al.* 2003), HERMES (Kersebaum 2007), STICS (Brisson *et al.* 2009) and WOFOST (Boogaard *et al.* 1998)), applied with limited set of information (for input or calibration) in order to reproduce limited resource conditions of large scale application; they concluded that no model predict accurately the yield and none could be labelled robust without a proper calibration. Last, an inter-comparison exercise by Brilli *et al.* (2017) between nine models (APSIM (Keating *et al.* 2003), CERES-EGC (Gabrielle *et al.* 1995), DayCent (Parton *et al.* 1994), DNDC (Li *et al.* 1992a), DSSAT (IBSNAT, 1993; Tsuji, 1998; Uehara, 1998 and Jones *et al.* 1998), EPIC (Williams, 1995), PaSim (Riedo *et al.* 1998), RothC (Coleman and Jenkinson, 1994) and STICS (Brisson *et al.* 1998)) analysed the strengths and weakness of those models to represent the C and N cycles. They concluded that the main factors leading to

unsatisfactory performances were knowing ill-defined pedo-climatic conditions, management practices and finally the scalability (both in time and space).

In order to reproduce the dynamics of the processes involved in the different cycles and the interactions between the compartments, these models require a lot of parameters (for the vegetation and the soil) and input data, which is often a limiting factor in an operational MRV context as well as a source of multiple uncertainties as discussed hereafter.

Similar to soil models, ecosystem models need weather data as input. However, in addition to the one required by soil model (temperature, precipitation, evaporation), they usually need others like incoming radiation (global, net, diffuse) in order to simulate the photosynthesis process or the biomass production. Using local weather data may reduce modelling uncertainty compared to global meteorological models (Zhao *et al.* 2012) such as ERA 5 data but cannot be applied at large scale. Finally, ecosystem models usually run on a daily time-step (instead of monthly or annual for many soil models) to represent process as the vegetation growth, which means that they are more demanding computationally.

Ecosystem models usually need the same input data on soils (e.g. soil type, soil properties) as soil models for their soil compartment. The challenges related to 1) initializing SOC stocks and their distribution across different pools and 2) accessing accurate soil data at plot scale over large scales remain the same as for the soil centred approaches which are here again a significant source of uncertainty in SOC stock changes assessment and a barrier to upscale the ecosystem modelling approaches, as discussed in the soil-centred approach section.

One big difference with the soil centred approach concerning input data is the need for more information on management such as seeding data (density and depth), date and amount of irrigation, crop type, type and amount of mineral and organic fertilizers along with their date of application. Collecting accurate and consistent data from farmers can be challenging and time consuming, even more at large scale (Seidel *et al.* 2018; Wattenbach *et al.* 2010). Even if activity data from farmers are accessible through a Farm Management Information System (FMIS), activity data need to be verified by an agricultural technician for consistency/accuracy/units and harmonised before using it as input into the models, otherwise it could lead to significant inaccuracies in model outputs, which poses a challenge in operational applications. To our knowledge, none of the current MRV schemes or tools assess the impact on SOC stock changes of the uncertainties on activity data which is a real source of concern.

In addition to high quality input data, the accuracy of the estimations will depend largely on the quality of the parameters calibration to simulate the processes. Calibrating the parameters to new contexts (e.g. pedo-climatic context, crop type, practices) requires expertise and multiple types of observations data such as GHG & water fluxes measurements or biomass measurements, making it costly and time consuming. It also means that this approach is really difficult to upscale and apply over a large region without an easy access to all these data (that should be reliable) and parameters. Also, the large number of parameters and data needed to simulate the different processes and interactions (between plant, soil, water and nutrients) makes uncertainty propagation more complex. Ensuring the reliability of model outputs becomes more difficult, especially in situations where data might be missing or uncertain, and require expertise to make assumptions and handle this uncertainty.

As for soil-centred approach, many ecosystem models do not include uncertainty assessment variables output, which has to be done outside the models. Chapagain *et al.* 2022 did a systematic review of crop/ecosystem model uncertainty assessments and point out the lack of uniform and standard methods to estimate uncertainty. They recommend to focus the effort into standardization of the procedure and include them systematically into modelling studies so that end-users can assess whether the model estimation is reliable and suitable for their specific

applications. The complexity of these models makes an assessment of propagation uncertainty through analytical methods, such as Taylor series, difficult. Hence numerical methods as Monte Carlo analysis are easier but require a large number of samples to ensure reliability, which increase computational time and data storage. Hence this approach may not be suitable to an operational context in regions with limited expertise or resources.

The main advantage of those models (compared to the soil centred approach) is that they simulated the plant growth dynamic as well as the biomass distribution among organs which allows to derive the carbon input to the soil. Also, they already simulate a lot of crop species and farming practices (e.g. harvesting, residue management, fertilization, tillage, irrigation) meaning that they can already be used for MRV systems in different contexts of application with the limitations mentioned above. Depending on the models and on the variables that they simulate, different types of *in-situ* data can be used for calibration or validation: e.g. GHG, water or energy flux measurements (e.g. soil chambers, flux towers), soil water content dynamics measured with soil probes, biomass data, SOC stock changes, nutrients dynamics.

As pointed out by Guan *et al.* (2023), since ecosystem models simulate several plant and soil processes, they allow to evaluate these not only against SOC stock changes but also against other carbon budget components, such as CO₂ fluxes (NEE, GPP, Ra, Rh), biomass production and its allocation (e.g. yield). Also, they can be evaluated for those different processes at different timescales (e.g. day, month, cropping year) depending on the data compared to soil centred approaches that can be mainly evaluated against SOC stock changes on time scales of several years. The monitoring process may therefore be more robust compared to soil centred approach as by having an overview of the carbon budget components of the field at different spatial and temporal scale. In ideal cases where parameters are well calibrated and the required input data are available and accurate, these models are usually applied on plot level. They can simulate plant growth dynamics and soil processes between fields, however they can't represent the intra-plot spatial variability in those processes and growth patterns. According to Luo *et al.* (2019) and Guan *et al.* (2023) not considering the spatial and temporal variability of the photosynthetic capacity can lead to 21% error in the estimates of photosynthesis. In order to better account for intra-field spatial variability, one option is to assimilate of high-resolution vegetation indices or plant biophysical properties (e.g. Leaf Area Index) derived from EO time series. This approach will be discussed further in Section 5.3.3.2.2.

"Off-the-shelf" cropland ecosystem models allow more holistic approaches compared to soil centred ones, since they simulating plant-soil interactions and several biogeochemical cycles, and that's why they are often used for decision-making. They provide a range of agri-environmental variables that allow to have a more comprehensive understanding of the effect of practices on the environment, they can simulate the effects on production and on SOC stock changes of management and climatic scenario which is useful for providing agronomic advices and testing the effect of the implementation of CF practices. However, their operability is limited because they are very data demanding, require complex calibration processes and expertise for proper application. Therefore, they can be used for monitoring SOC changes in VCM contexts at plot or farm scales. However, their cost of implementation (mainly because of the activity data collection and verification) may be very high for field scale assessments of SOC stock changes over large areas as in the context of MRV for AEPs or for large scale offsetting CF projects.

To address this, one strategy is to rely on activity data produced at once over large areas by remote sensing (see Section 4.2.2.4) which would reduce substantially the cost of activity data collection as well as the work burden. Of course, the uncertainty on those EO derived maps of activity data should be assessed and accounted for in the SOC modelling process. Another option is to reduce the complexity of the model or to reduce the accuracy of input data required by making assumptions and hypotheses when using ecosystem models. This can be done for

instance by using regional statistics on farming practices (e.g., using average seed density, sowing, or harvest dates) or making local-specific assumptions about agricultural practices (e.g. organic amendments, residue management, fertilisers application, irrigation, tillage). This approach combined with climatic data obtained from meteorological reanalysis zones and soil datasets has been used in the AgMIP projects («The Agricultural Model Inter-comparison and Improvement Project », Rosenzweig *et al.* 2014; Basso *et al.* 2018; Sandor *et al.* 2020) or for STICS simulations at national scale serving as a foundation for the studies by Pellerin *et al.* (2020) and Launay *et al.* (2021) on the potential of cropland for storing carbon in the soil.

5.3.3.2.1.2 Parsimonious ecosystem modelling approach based on light coupling between vegetation and soil models

An alternative to these “off-the-shelf” cropland ecosystem models with mechanistic processes and strong coupling between the soil and the plant compartments of the ecosystem, is to rely on simplified representation of the processes and interactions between vegetation and soil through a light coupling between these compartments. In this light coupling approach, the biomass of the plant simulated by a vegetation model/module is used as an input to the soil model/module. This simplification reduces the required input data (especially the activity data) and the parameters, making the approach more computationally efficient and easier to apply at larger scales, especially in resource-limited operational contexts. It can be done by combining a parsimonious crop model to predict yield or biomass production (e.g. growth vegetation depending on temperature sum (AqYield model (Constantin *et al.* 2015) only for yield; LINTUL model (Haverkort *et al.* 2015; Farré *et al.* 2000; Habekotté *et al.* 1997; Shibu *et al.* 2010) ; expolinear function (Goudriaan and Monteith, 1990); SIMPLE model, Zhao *et al.* 2019) with the kind of soil model described in the Section 5.3.3.1. on soil centred approach. To keep the number of parameters and input data low, these crop models simplify the processes governing vegetation growth, meaning that they may represent vegetation dynamics less accurately than “off-the-shelf” cropland ecosystem models. Note however that neither the strongly coupled ecosystem approaches nor the light coupled ecosystem approaches do account for all processes or events that occur in real life. For instance, none of them account for pest or disease effects or for extreme climatic events (e.g. hail damages) which is an issue to quantify accurately carbon inputs to the soil by the vegetation.

The real benefit of this light-coupling, ecosystem modelling approach is when it is assimilating EO data to monitor objective and more realistic vegetation development as with the GRAMI (Maas *et al.* 1992) and SAFYE-CO2 (Pique *et al.* 2020 a,b) crop models as described in Section 5.3.3.2.2.3, “Parsimonious ecosystem modelling approach using EO assimilation”.

5.3.3.2.1.3 Assessing the baselines for the ecosystem modelling approaches

One of the main advantages of the ecosystem models is their ability to simulate management and climatic scenario and thus to produce baselines based for instance on the “business as usual” scenario or considering intense CF practices and evaluate their impacts on the SOC stock dynamics.

Standardised baseline: To simulate standardised baselines, as for the soil centred approach, regional statistics on management practices and/or soil properties are needed. However, ecosystem models require more input data than soil centred approaches concerning the weather and the management practices. On the other hand, they do not require input data on yield or biomass as they simulate themselves the production of biomass, for crops and

cover crops. Static baselines can be calculated with data corresponding to the period preceding the CF project while in dynamic baselines can be produced considering the updated weather and activity data during the project.

Specific baseline: Specific baseline require field specific information for the different input data (soil, weather, management). Ecosystem model can simulate the specific baselines, in a static or dynamic way, but the collection of these data is challenging and expensive.

Hybrid baseline: Naturally, ecosystem models can simulate hybrid baseline combining standard and specific input data (e.g. soil specific and standard management practices or the inverse).

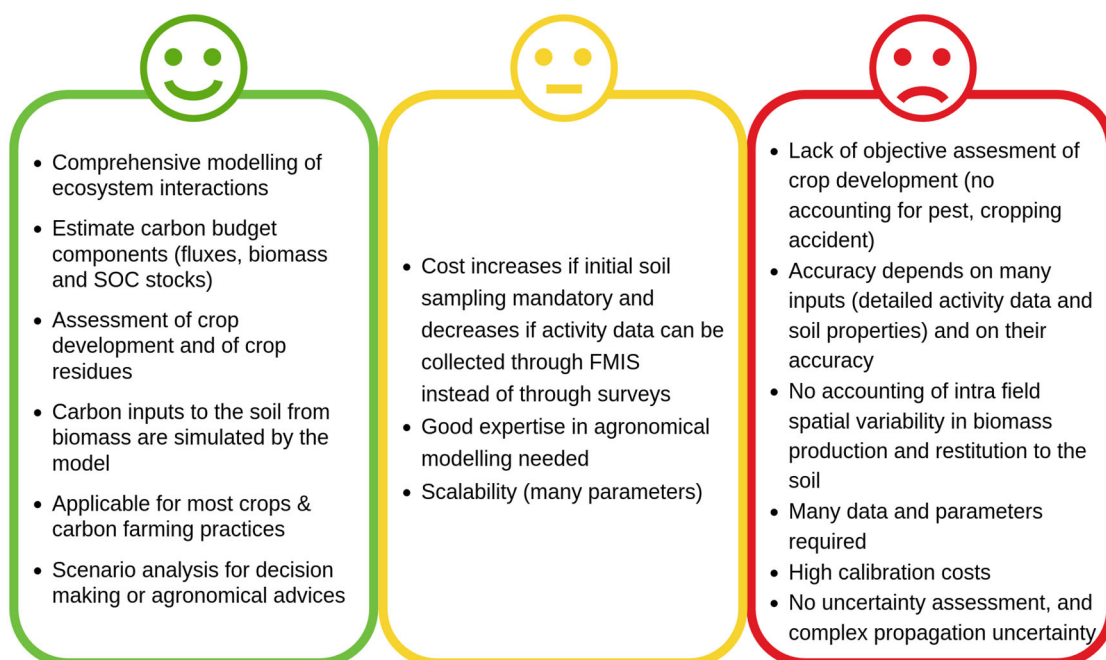
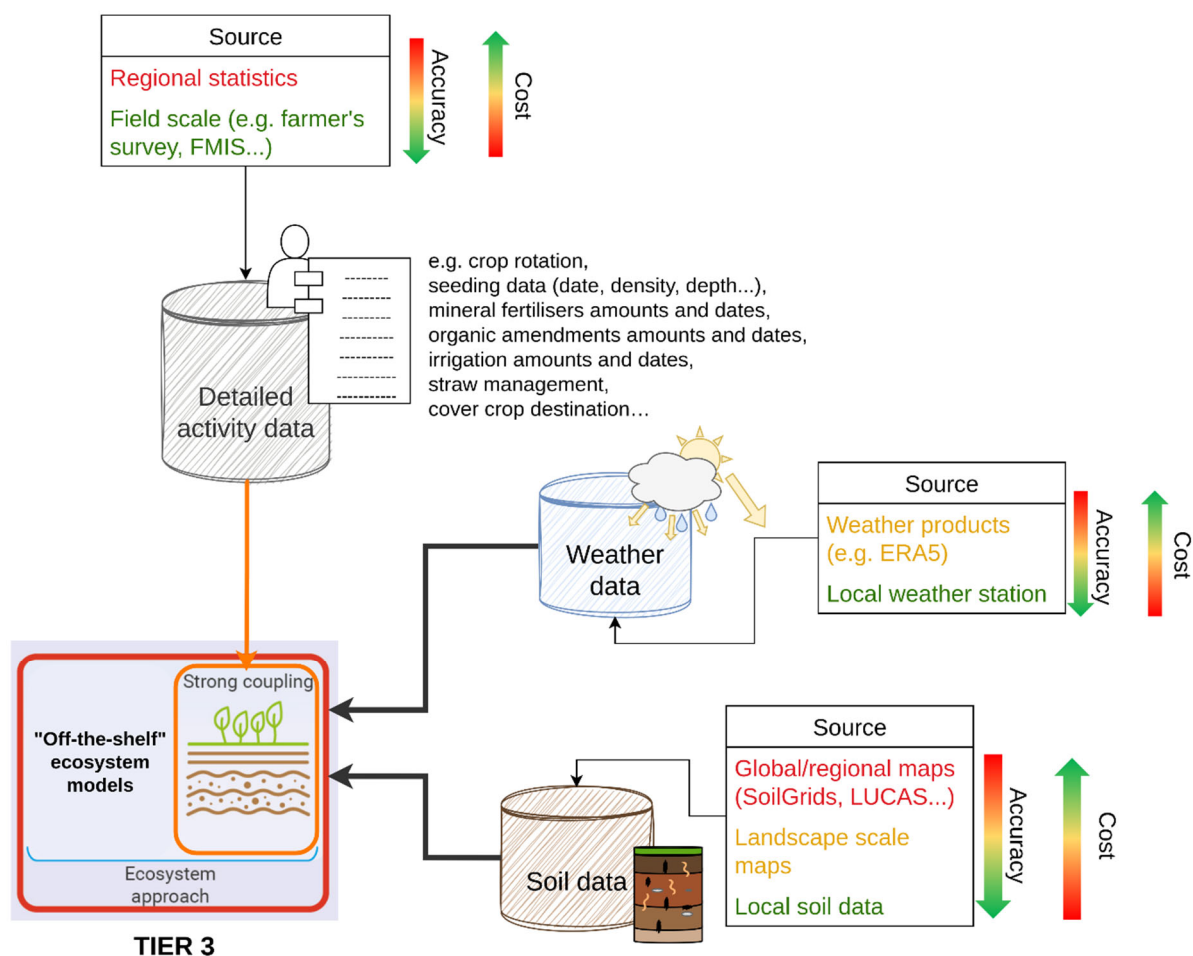


Figure 29. Schematic representation of the "Off-the-shelf" strong coupling ecosystem modelling approach without EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context Credits A. Ihasusta..

5.3.3.2.2 Ecosystem modelling approach with EO assimilation

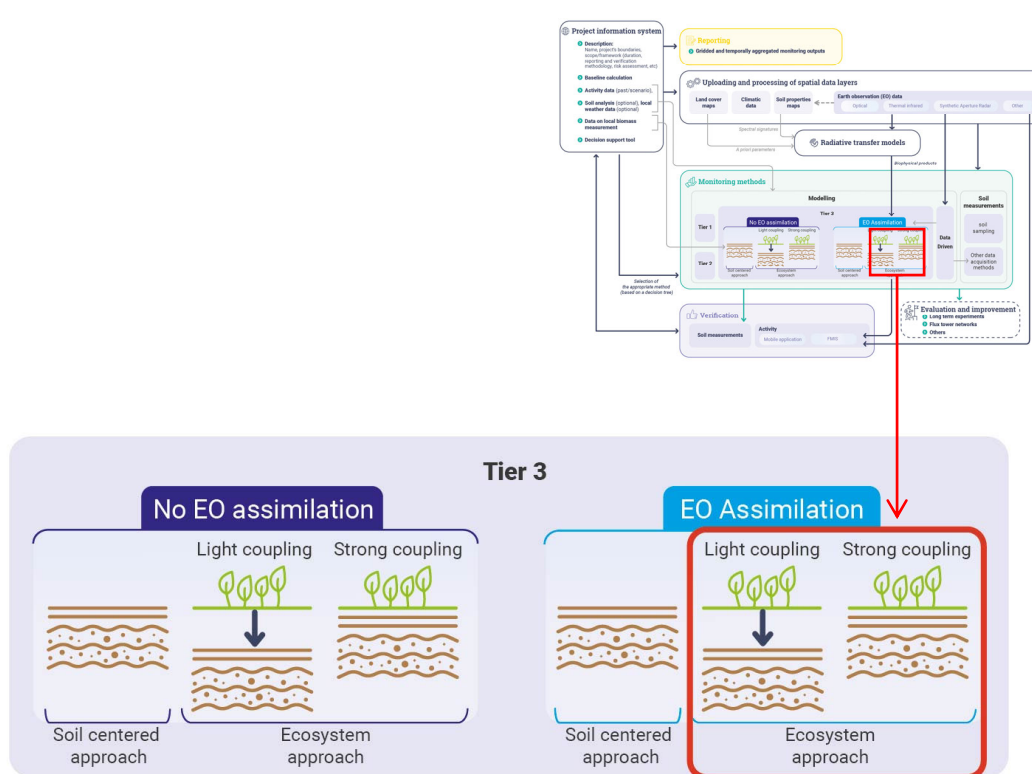


Figure 30. The red frame indicates which Tier 3 modelling approach will be addressed in this section

This section explores ecosystem modelling approaches that integrate Earth Observation (EO) data or biophysical products derived from remote sensing (e.g. Leaf Area Index, LAI) via assimilation methods. To be complementary and non-redundant with the section on soil centred approach with EO assimilation, this section will focus on EO data assimilation for the vegetation compartment in ecosystem models. Recent reviews (Dlamini *et al.* 2023; Jin *et al.* 2018) detail the various state variables concerning vegetation that can be assimilated (e.g. NDVI; LAI; Green Leaf Area Index, GLAI; Fraction of Absorbed Photosynthetically Active Radiation, FAPAR) into models and the assimilation methods associated to improve crop modelling. Nevertheless, other state variables or information (concerning soil properties, superficial soil water content, management practices) can also be assimilated as mentioned before (see Section 5.3.3.1.3 on soil centred approach with EO data assimilation section for a full description).

The assimilation of vegetation index or biophysical properties derived from EO data into the ecosystem model during the crop cycle allows to constrain the model to reproduce the real phenology and development (or not) of the vegetation. The more data are assimilated at crucial stages of the phenology, the more accurate the model will be (see Wijmer *et al.* 2024). Using high resolution EO data and biophysical products allows to consider the spatial and temporal variability of the vegetation development at intra-field scale, which is crucial to estimate spatial heterogeneity of biomass production and their associated carbon inputs to the soil (see Wijmer *et al.* 2024). Depending on the ecosystem model and the assimilation scheme, this approach could also overcome the yield gap between the real yield and the potential yield estimated by most agronomic/cropland ecosystem models, usually overestimated because they do not represent the effect of pest, diseases (Rosenzweig *et al.* 2013) or extreme

climatic events (e.g. hail, floods). The assimilation of EO data related to vegetation development implicitly accounts for such events impacting biomass production, but also for a range of stress effects (e.g. nitrogen or water stress). See Pique *et al.* (2020 a, b) and Wijmer *et al.* (2024) for more details. The continuous assimilation of EO data related to vegetation also supports the detection of spontaneous regrowth, weeds and cover crops, which enable the approach to account for their effects on SOC stocks changes, as done in Pique *et al.* (2020 a,b,c).

Vegetation indices and biophysical products can be obtained via operational services such as Copernicus⁴⁷ or they can be computed using radiative transfer models (see Section 4.2.3). The advantage of using a radiative transfer model inside the modelling framework allows to estimate uncertainties on the biophysical data that are assimilated and to propagate them through the modelling process till the SOC stock change estimates as in Wijmer *et al.* (2024).

However, it should be mentioned that EO data assimilation has its limitations. Even if the launches of recent satellites constellation such as the ones of the Sentinel (e.g. 2 A, B and C) or Landsat allow a high frequency revisit (approx 3-5 days) and a global coverage, optical sensor are limited by clouds, leading to potential gaps in surface observations time series. It highlights the importance of having a well calibrated crop model to be able to predict the vegetation growth during the periods when satellite images are lacking. Moreover, the EO data will not be useful for small or narrow fields that are approximately less than 60 m large (because the contours of the plots need to be eroded to avoid mixed-pixels and shadow effects). As mentioned in Section 4.2.2.4. on Earth Observation data, other satellite data such as the ones from private constellation with higher spatial and temporal resolutions (e.g. Planet) or from Synthetic Aperture Radar (e.g. Sentinel 1 constellation) can be an alternative to the previously mentioned satellite constellation but they have other limitations.

The next two sections describe two key approaches for integrating Earth observation data into ecosystem models. The first one will focus on the assimilation of EO data into classical, "off-the-shelf", ecosystem models presented in the previous sections, which are widely used for simulating plant-soil interactions and carbon fluxes. The second will explore parsimonious ecosystem models specifically designed for upscaling with EO data assimilation, which are more streamlined and computationally efficient.

5.3.3.2.2.1 "Off the shelf" ecosystem modelling approach with EO assimilation and strong coupling between plant and soil

This approach involves combining mechanistic modelling as described in the previous section as classical or "off-the-shelf" ecosystem models (STICS, EPIC, DayCent, CERES, DSSAT, ...), with remote sensing data assimilation, to constrain the vegetation dynamic in the model. Except for EO data, the number of input data needed remains the same, as well as the limitations associated to their accessibility/accuracy, especially for soil data and activity data when this MRV approach is applied at large scale. This approach has been widely used for yield prediction and diagnostics, focusing on plant and water usage, though carbon cycle modelling has recently received more attention (e.g. Luo *et al.* 2023). Nonetheless, we consider that further work is needed to adapt these approaches for use in an operational MRV context on SOC monitoring.

The main current research focuses on integrating new data streams, modifying model formulations for better representation of target variables, and adding new processes to improve accuracy and allow application at various spatial scales (Williams *et al.* 2018; Huang *et al.* 2019; Dlamini *et al.* 2023). When apply ecosystem models at

⁴⁷ see <https://land.copernicus.eu/en/products/vegetation/high-resolution-leaf-area-index>

landscape or regional scales, assimilation and calibration exercises using EO data face a major challenge: scalability. One of the main limitations lies in the computational and logistical demands required to perform simulations with parameter adjustments across thousands or millions of elements (pixels or fields), especially for ecosystem models that contain a large number of parameters. As a result, it has often been necessary to choose between high spatial resolution and the regional coverage of modelling exercises. This aspect is illustrated by several recent studies that use optical remote sensing data assimilation in agronomic models. In the study by Zhuo *et al.* (2022), carbon fluxes are simulated at a resolution of 500 m for several U.S. states using the WOFOST model. While the scope of the diagnosis meets the objectives of their study, this resolution is not fine enough for MRV contexts related to VCM or AEPs that require field scale assessments. Alternatively, Nevalainen *et al.* (2022) proposed a prototype of SQP compatible with MRV ambitions (combining EO assimilation, ecosystem model and field measurements) allowing to evaluate CF practices, but for a limited number of fields (a few dozen only).

Other studies, like Courault *et al.* (2021), focus on a 30x30 km area, running simulations with the STICS model over approximately 3,500 plots and two growing seasons. The study by Upreti *et al.* (2020), on the other hand, integrates Venus satellite data into the Aquacrop model for Bayesian assimilation of Leaf Area Index (LAI) at a 5-meter resolution, highlighting the importance of quantifying uncertainties and the role of very high resolution in capturing intra-plot spatial variability.

In the USA, the Geo-CropSim modelling framework (Bandaru *et al.* 2022) uses high (30m) resolution optical remote sensing data (from the Landsat constellation) to initialise the emergence date of the EPIC crop 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 as 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). Finally, Fowler *et al.* (2024) used the concept of yield stability zones (by using yield maps from combined harvesters) to measure the small-scale variability of soil health on a field relative basis. For this, they measured various metrics of soil health from height commercial farmers' fields in the north central Midwest of the USA in samples replicated across yield stability zones, using a soil test suite commonly used by producers and stakeholders active in agricultural carbon credits markets. They found that the use of yield stability zones allowed to successfully partition field-relative SOC and soil health metrics into statistically distinct regions.

In all those studies, despite differences in spatial and temporal scales, simulations are limited to a few thousand or tens of thousands of elements (note ~3 million fields are cultivated in France). Moreover, ecosystem models like those used by Nevalainen *et al.* (2022) and Courault *et al.* (2021) rely on a large number of input parameters and data (e.g. activity), which are rarely available at large scales. Also, those models because of their structure and parametrisation are likely to be less flexible in representing strong intra-field spatial variability in vegetation development than parsimonious ecosystem models assimilating EO data. Given these limitations, there is a pressing need to propose an approach that can achieve large-scale diagnostics at high resolution, while minimizing the reliance on detailed management data, and incorporating uncertainty indicators for the simulated variables (Martinez-Feria *et al.* 2020; Maestrini *et al.* 2018; Manivasagam *et al.* 2021). Hence, we will focus in Section 5.3.3.2.2.3 on parsimonious modelling approaches dedicated to upscaling.

5.3.3.2.2.2 Assessing the baselines for the "Off the shelf" ecosystem modelling approaches with EO assimilation

The ecosystem modelling approach with EO assimilation using "off-the-shelf" models can use at minimum the same methods for producing baselines as listed in the "ecosystem modelling approach without EO" with additional improvement thanks to EO assimilation. Yet the use of EO data is mostly beneficial to compute specific baseline and dynamic baseline. Indeed, the monitoring of vegetation development in time through remote sensing can be used to estimate biomass production at intra-field level reflecting the effect of the local specificities (e.g. soil properties spatial variability, micro climate) and allowing to be more accurate in the updating required by dynamic baselines, as the effect of climatic conditions on the vegetation development will be better accounted for as well as pest and diseases effects.

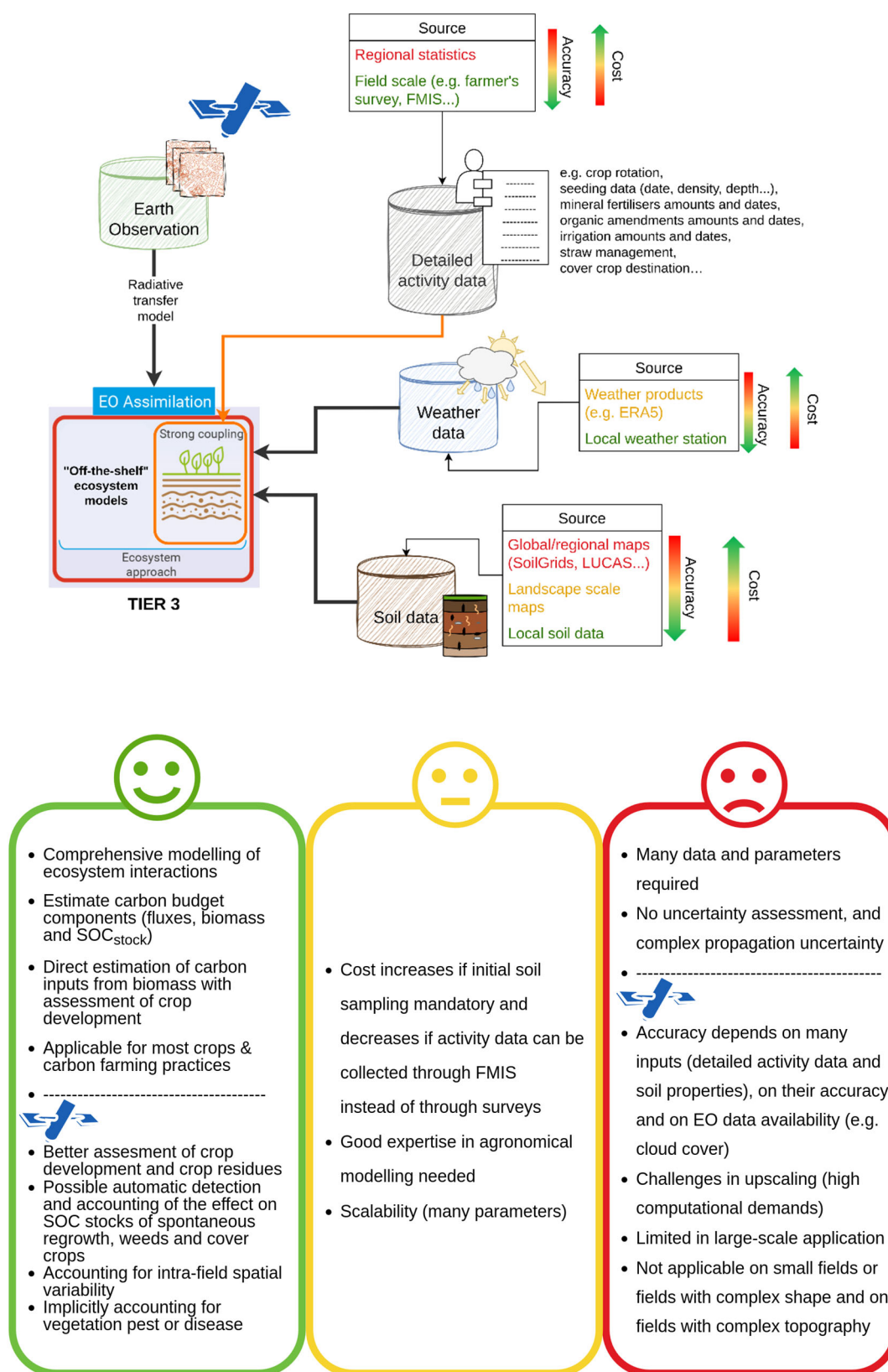


Figure 31. Schematic representation of the "on the shelf" strong coupling ecosystem modelling approach with EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context. Credits A. Ihasusta

5.3.3.2.2.3 Parsimonious ecosystem modelling approach with EO assimilation: light coupling between plant and soil

A promising approach to assess SOC stock changes at large scale and high resolution consists in assimilating EO data in parsimonious models in the objective of balancing the level of complexity of the model and its scalability with operational feasibility. Guan *et al.* (2023) proposed a "System-of-Systems" approach, emphasizing that the challenge of accurately quantifying SOC stock changes in agroecosystems cannot be solved by a single sensor or model alone. Instead, integrating diverse observations, *in-situ* data, and modelling approaches is essential. This methodology aligns well with 1) the recommendations from the CIRCASA international project (see the Annex of Deliverable 3.1⁴⁸), which suggests using a modular structure to derive gridded SOC stock changes estimates along with associated uncertainties, advocating for ensembles of calibrated models rather than relying on a single model and 2) with the current prototypes of SQP (e.g. The Retina Project⁴⁹; Remote-C⁵⁰; AgriCarbon-EO⁵¹; Fion⁵². The FION (Nevalainen *et al.* 2021) and the AgriCarbon-EO pre-operational processing chain (Wijmer *et al.* 2024; Antonenko *et al.* 2024) are presented in Annex 1. The later encompasses the PROSAIL radiative transfer model producing LAI time series (and associated uncertainties) that are assimilated in the SAFYE-CO2 crop model (Pique *et al.* 2020 a, b, c) and more recently Wijmer (2024) coupled the AMG soil model (Clivot *et al.* 2019) to SAFYE-CO2 in the processing chain.

This parsimonious ecosystem modelling approach seeks to combine the simplicity and efficiency of some models of the soil-centred method (mainly from the conceptual carbon pools family with a first order decay) with the capability of crop models to estimate biomass and/or other key ecosystem variables, such as CO₂ fluxes, evapotranspiration or yield. This strategy allows for a more comprehensive understanding of the ecosystem, while avoiding the complexities and feedbacks typically found in traditional "off-the-shelf" ecosystem models.

The key of the success of this approach consists in choosing parsimonious soil and plant models, integrated as modules within a modelling platform to represent the broader ecosystem. Unlike most "off-the-shelf" crop ecosystem models, which involve strong feedbacks and complex interactions between the plant and the soil to simulate several biogeochemical cycles, this approach adopts a "light coupling" meaning mutual feedback is minimized, and the processes are modelled independently. For instance, the plant processes and the soil carbon processes can be treated separately, without feedback loops. The biomass estimated by the plant module allows to estimate the carbon inputs to the soil as biomass required by the soil module. In spite of the absence of interactions between these compartments (e.g. no soil water or N stress function to control plant growth) assimilating EO data allows to simulate accurately and objectively plant development by optimising and calibrating the vegetation's module parameters. Also, it allows to reduce the number of activity data, compared to classical ecosystem models, to simulate vegetation development. The plant model should rely also on other data that are easily available at large scale, such as land use or weather data (see Section 4.2.2), to be applied at large scale. Some examples of parsimonious crop model assimilating LAI time series derived from high resolution EO data are GRAMI (Maas *et al.* 1992) and the SAFY model family (SAFY, Duchemin *et al.* 2008 and Claverie *et al.* 2012; SAFY-WB, Duchemin *et al.* 2015 and Battude *et al.* 2016; SAFY- CO2, Pique *et al.* 2020a; SAFYE-CO2, Pique *et al.* 2020b) that were dedicated to upscaling crop simulations. Despite the rather simple plant processes simulated, model accuracy can still be maintained thanks to the EO assimilation process. The assimilation of high-resolution EO data into the plant

⁴⁸ <https://www.circasa-project.eu/document-library/deliverables/d3.1-strategic-research-agenda-sra-on-soil-carbon>

⁴⁹ <https://meetingorganizer.copernicus.org/EGU22/EGU22-12764.html>

⁵⁰ <https://iris.cnr.it/handle/20.500.14243/518210>

⁵¹ <https://www.cesbio.cnrs.fr/agricarboneo/agricarbon-eo/>

⁵² <https://www.fieldobservatory.org/index.php/home/>

models allows to implicitly account for factors such as climate stress, nutrient stress, pests, diseases, and even farming practices (harvest, cover crop destruction). It also supports the automatic detection of spontaneous regrowth, weeds and cover crops, which enable the approach to account for their effect on SOC stocks changes, as done in Pique *et al.* (2020 a,b,c). Then, in order to represent the soil processes and to calculate SOC stock changes, carbon inputs from the plant model are used as inputs in the soil model along with soil properties and initial SOC stocks.

It is likely that for operational MRV applications, choosing parsimonious soil models/module relying on few input data would offer the best compromise between accuracy and scalability. Therefore, “first order decay rate” soil models with few carbon pools could be a good option (e.g. the AMG model by Clivot *et al.* (2019) has only 2 carbon pools), as they need a small number of parameters and input data than explicit microbial pool soil models. Indeed, in a similar way as increasing the number of parameters would amplify uncertainty propagation, increasing the numbers of pools would amplify it as well. As discussed above in the Section on Soil centred approach (see Section 5.3.3.1.), soil models need environmental data such as climatic data (easily available at large scale) and soil properties that are more difficult to obtain at large scale with a sufficient accuracy for MRV.

By capturing the vegetation dynamics through EO data, the parsimonious ecosystem modelling approach maintains a reasonable level of complexity while reducing the number of required parameters and data inputs (Pique *et al.* 2020 a and b). However, the choice of a parsimonious model alone will not determine the computational time or the feasibility to upscale it at large scale. The choice of the assimilation method is crucial to be able to run simulations over a large number of elements (pixels or fields). The method should be time efficient, include uncertainty traceability through all the simulation steps and be able to represent multiple solutions. This is important because when modelling environmental and ecological systems, different combinations of model parameters can lead to similar performance, meaning that they yield similar outputs or results even though they represent very different underlying processes. This is referred to as the equifinality of processes. In such cases, a single optimal solution may not exist, and therefore it is essential to capture a range of possible solutions. As explained in the section dedicated to assimilation methods, some assimilation algorithms such as the Simplex require a lot of iteration to converge to a solution, which increases the computational time and typically leads to a single solution based on statistical metrics like RMSE.

To solve this issue, in the AgriCarbon-EO processing chain, Wijmer *et al.* (2024) used a combination of Look Up Tables (LUT) and of Bayesian calibration to assimilate EO data in the SAFYE-CO2 crop model, that was primarily limited by the Simplex optimization algorithm to few field simulations exercises (Pique *et al.* 2020a). A LUT can be used to store a set of a priori parameters and corresponding set of simulations. With a sufficient number of samples, it allows to explore a wide range of solutions that can represent the variability of a given area. While this approach may involve heavy computational cost at the beginning of the run (in terms of data storing and computational time), it can save significant time during the simulation phase itself. LUT have the added value of providing parameters and results that are physically interpretable, unlike methods such as neural networks, which often operate as “black boxes”. The performances of an element of the LUT can be evaluated using statistics metrics such as maximum likelihood between the assimilated data and the model prediction associated to this LUT’s element. The Bayesian calibration will allow to handle the outputs as probability distributions rather than fixed values. This allows for the exploration of multiple solutions and incorporates uncertainty into the model predictions. At the end, this kind of method can lead to a ratio $\frac{\text{number of simulations}}{\text{number of element (pixel or field)}}$ close or just below 1, which allows to run simulations over large areas at high resolution.

Currently, the main limitations for the implementation of this kind of approach in a MRV context are that:

- it is calibrated and validated on few crop types (e.g. straw cereals, maize, sunflower, rapeseed, faba bean, white mustard and tomato for AgriCarbon-EO) unlike the traditional “off-the-shelf” ecosystem models, that have been developed, calibrated and validated over the last decades.
- it requires more expertise and access to time series of high-resolution satellite data (e.g. only since 2017 for the Sentinel 2 constellation).
- relying only on optical remote sensing data (Sentinel 2, Landsat 8, Planet...) can be limiting for operational applications when long cloudy periods occur. To address this issue a promising method is to combine optical with radar (SAR, e.g. Sentinel 1) satellite data, that are little sensitive to cloud cover, to fill gaps in vegetation indices time series (e.g. Allies *et al.* 2021; Garioud *et al.* 2021) or to produce biomass proxy to be assimilated in addition or instead of LAI (e.g. Revill *et al.* 2013; Fieuzal *et al.* 2017; Baup *et al.* 2019; Allies *et al.* 2022).
- it requires access to reliable field scale activity data on straw management, cover crop fate and organic amendments (which is currently the strongest limitation) although this is not a discriminatory criterion as it is a common limitation for all modelling approaches at field scale.

Being able to monitor SOC stock changes at high resolution (e.g. with Sentinel-2 data at 10m resolution), allows to account for spatial variability inside the field and leads to better assessment of the biomass production (as demonstrated by Wijmer *et al.* 2024), and therefore of the carbon inputs from biomass to the soil. Wijmer *et al.* (2024) show that assimilating mean-field-level GLAI data instead of assimilating high resolution GLAI data in the SAFYE-CO2 crop model induces a bias of -47 g.m^{-2} and an artificial decrease of relative uncertainty of 39% on the biomass production. In addition, the simulations at high resolution allow to compare the model's outputs with *in-situ* measurements of biomass, yield, SOC stock changes etc, representative of the simulated pixel (i.e. collected on a 10x10m area) which helps ensuring that the model's outputs are representative of the conditions measured in the field and which leads to more accurate validations. This approach solves the issue of representativeness of verification measurement that arises when using soil sampling or *in-situ* biomass measurements to evaluate model prediction done at field or farm scale. Moreover, as this approach also estimates key component of the carbon budget such as fluxes (NEE, GPP, Ra, Rh) and biomass production, the advantages mentioned before in the ecosystem modelling approach without EO remains; 1) the capacity to evaluate the model against independent data sets (fluxes for flux towers, yield from combined harvesters, biomass sampling over a pixel) and 2) the possibility to evaluate/validate the model against measurements (e.g. net CO₂ fluxes, annual carbon budget, biomass, yield as in Pique *et al.* 2020a) and at shorter timescales (day or crop cycle) compared to measure and remeasure of SOC stock changes (~ every 5 years). This approach can overcome the issue of representativeness of soil samples for verification in space and time, by having an overview of the carbon budget components of the field at different spatial and temporal scale (e.g. see Figure 38).

In this parsimonious ecosystem modelling approach with EO assimilation, the goal is to strike a balance between having enough processes modelled to accurately estimate SOC stock changes and the key components of the C budget while keeping the approach simple and scalable for large-area applications, in line with recommendations from Paustian *et al.* (2019) and Smith *et al.* (2020). Depending on the availability of the input data (especially activity data and accurate soil data at large scale), this parsimonious modelling approach with EO assimilation can be

implemented in different MRV contexts of application, going from large scale applications such as the NDC's to field scale applications (or even at pixel scale) for the VCM (both “insetting” and “offsetting”). See for instance the AgriCarbon-EO SQP described in Section 2.1 of Annex 1.

5.3.3.2.2.4 Assessing the baselines for the parsimonious ecosystem modelling approach with EO assimilation

The ecosystem modelling approach with EO assimilation using “parsimonious” models can produce static or dynamic baselines, specific or standardised baselines and also hybrid baselines, but in a slightly different way compared to the other approaches. Indeed, as mentioned in the previous section, the distinctiveness of assimilating EO data in a crop model to monitor vegetation is that the model is constrained to represent the “reality” of crop development while it is not supposed to simulate something that the satellite has not observed. It means that this approach is not tailored to simulate prognostic scenarios (e.g. climatic scenario). Yet, it is possible to simulate several scenarios based on the implementation of different management practices (e.g. for the VCM). For instance, it is possible to simulate SOC stock changes on a field (or on a number of fields) with a crop rotation that includes cover crop in reality (and therefore with a realistic/objective assessment of the cover crop development) as it has been observed by EO, and to compare this first simulation with a second one that would ignore the presence of the cover crop during the fallow period (by forcing LAI values to zero during the fallow period) (see Wijmer *et al.* 2021). Based on the observation of the actual vegetation development in the region, it is also possible to assess the effect of adding cover crops on a plot (or ensemble of plots) that would not have cover crop during the fallow period. The same applies to modifying crop rotations. Also, as for the other modelling approaches, it can be implemented to simulate at field scale (for specific baselines) or at regional scale (for standardised baselines) the effect of a management changes (e.g. considering or not organic amendments, exporting straw or returning them to the soil) based, respectively, either on plot specific activity data or on regional statistics of activity data. The difference with other modelling approaches, here again, is that this approach allows for realistic and objective assessment of spatio temporal variability in biomass production, including the effect of extreme events and management changes, at intra-field scale, reflecting the effect of the plot specificity (soil variability, micro climate, etc). This approach also allows to be more accurate and objective in producing dynamic baselines, as the real effect of climatic events and of many activity data on the vegetation development and biomass restitution to the soil will be considered implicitly through the EO assimilation process. Last, this approach can be used to estimate SOC stock trends per crop rotation considering different cover crop frequencies observed in a region at high resolution, making possible to produce regional statistics for standardized baselines, for field specific baselines or for hybrid baselines as showed in Figure 12.

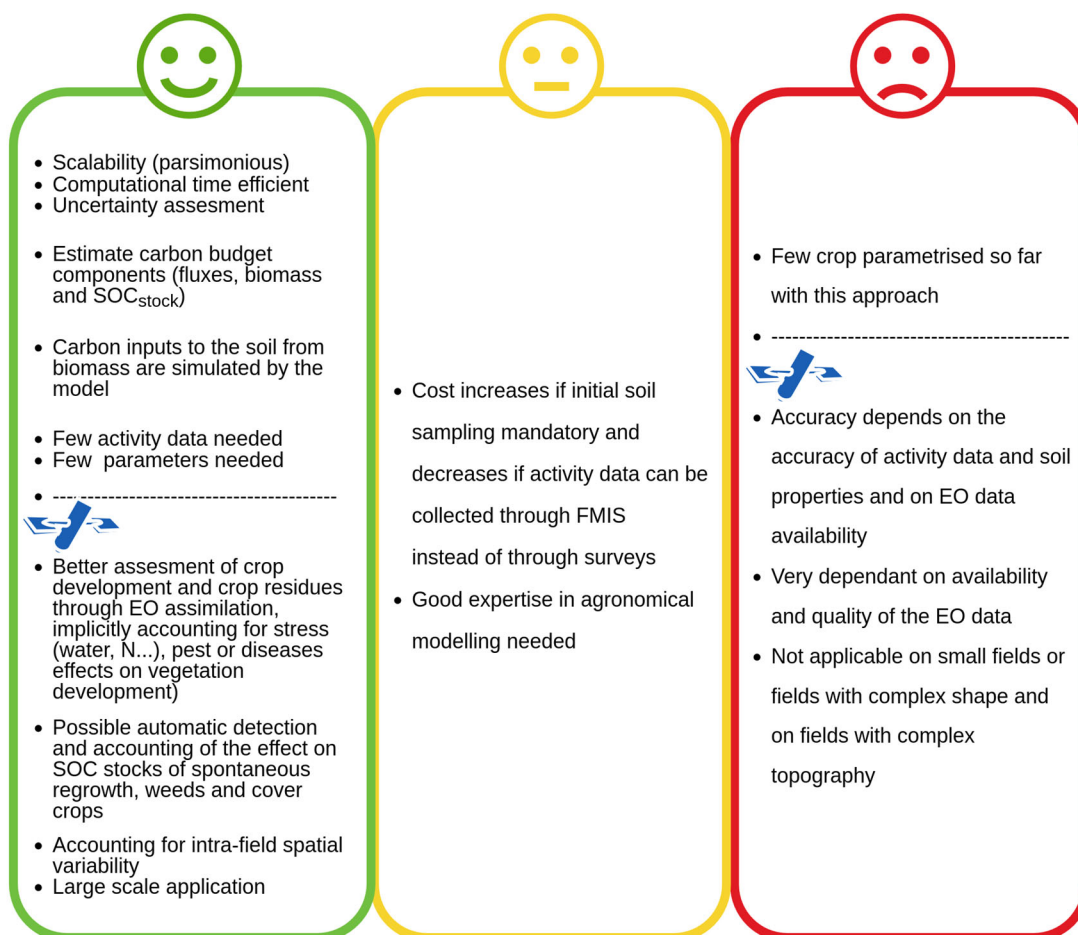
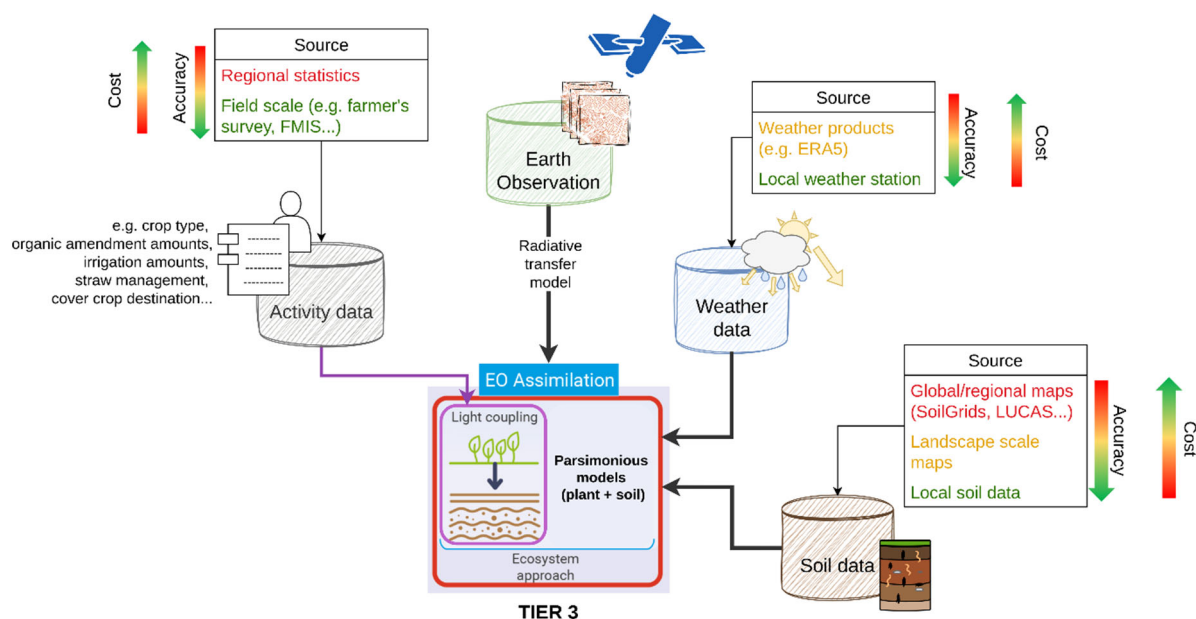


Figure 32. Schematic representation of the “parsimonious” light coupling ecosystem modelling approach with EO assimilation for modelling SOC stock changes and of its pro and cons in a MRV context. Credits A. Ihasusta

5.3.3.3 Summary of the pro and cons of the different Tier 3 modelling approaches

While some MRV studies have focused on assessing and rating models for their suitability in agricultural applications (e.g. Lesschen *et al.* 2020), others have examined the potential of different carbon farming schemes (Annys *et al.* 2022). Lesschen *et al.* (2020) developed a rating system to evaluate models based on criteria such as public availability and licensing, accessibility of input data, model validation, and applicability to cropland and grassland under Dutch climatic conditions, 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. In contrast, Annys *et al.* (2022) explored carbon farming schemes across various European and international contexts, emphasizing the need for region-specific adaptations. 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. That is why Section 5.3.3.1 and 5.3.3.2 explore and analyse different Tier 3 modelling approaches (soil-centred approach, ecosystem approach, and the use of EO data assimilation in the two previous modelling approaches). In this Section (see Table 1), we compare these approaches in order to provide insights into the most effective strategies for quantifying SOC stock changes depending on the MRV context of application and local context (e.g. data availability, scale of monitoring).

Particularly, the parsimonious ecosystem modelling approach with EO assimilation will improve the scalability of the approach first by allowing the application of the approach at once over large areas (reducing the cost of implementation) and by increasing the resolution to intra-field level. The assessment of carbon budget components at intra-field may reduce drastically the cost of verification (see Section 7.1) as the soil sampling scheme can be optimised. Also, it is very likely to be more accurate than the other modelling approaches as it allows objective and more accurate assessment of carbon inputs (from above- and below-ground biomass residues) to the soil compared to most of the other Tier 3 modelling approaches. For those reasons, although it cannot be applied in all situations (e.g. very small plots) the development of this approach will probably be a game changer for SOC stock monitoring in the coming years (see for instance Section 2.1 in Annex 1 for an example of SQP based on this approach). A good alternative would be to combine the soil centred approach with high resolution biomass estimates derived from EO data (see Section 2.2 in Annex 1 for an example of SQP based on this approach).

In general, Tier 3 modelling approaches have a good potential in terms of cost-accuracy and comprehensive evaluation of key carbon budget components. The soil centred approach will be the easiest to implement and the less input data demanding (especially activity data) but it relies on external methods to estimate carbon inputs from biomass and only focus on SOC (see Section 1.3 in Annex 1 for an example of SQP based on this approach). Even if our analysis of these Tier 3 modelling approaches focused on SOC changes only (and not on other GHG emissions), the ecosystem modelling approaches and the use of EO assimilation to monitor vegetation (also in the soil centred approach with EO assimilation) allows to have a more holistic assessment of carbon budget components, considering aboveground and belowground processes of the carbon cycle. Indeed, Guan *et al.* (2023) remind that to determine SOC stock changes, aboveground and belowground processes of carbon cycle should be accounted for, without focusing only on soil carbon pools changes that may lead to limited success (e.g. over-emphasis of soil sampling at the cost of other flux measurements). The use of EO data from remote sensing is a game changer as it allows to include implicitly the effect of different stresses (N, water...) and the effect of pests/diseases/extreme climatic events on the C cycle through vegetation monitoring, without increasing the

number of processes and parameters implemented in the models (see for instance Section 2.1 in Annex 1 for an example of SQP based on this approach).

Table 1: summary of the pro and cons of different Tier 3 modelling approaches for MRV of SOC stock changes. Credits A. Ihasusta

Criteria		Process based modelling without EO assimilation						Process based modelling with EO assimilation					
		Soil centred modelling approach		Ecosystem modelling approach				Soil centred modelling approach		Ecosystem modelling approach			
				Off the shelf ecosystem models		Parsimonious models				Off the shelf ecosystem models		Parsimonious models	
Spatial resolution	Farm level	Yes		Yes		Yes		Yes		Yes		Yes	
	Field level	Yes		Yes		Yes		Yes		Yes		Yes	
	Intra-field level	No		No		No		Yes		Yes		Yes	
General data requirement (inputs)	Remote Sensing	-		-		-		Moderate		High		High	
	Climate	Low		Moderate		Moderate		Low		Moderate		Moderate	
	Soil	Moderate		Moderate		Moderate		Moderate		Moderate		Moderate	
	Crop parameters	-		High		Moderate		Low		High		Moderate	
	Farming practices/Activity data	Low		High		Low		Low		High		Low	
Diversity of crop types represented		High		High		Low to moderate		High		High		Low to moderate	
Diversity of farming practices represented		Moderate to high (depends on soil model)		High		Low to high (depends on models)		Moderate to high (depends on soil module)		High		Moderate to high (depends on soil module)	
Accuracy of carbon inputs to the soil from biomass residues		Low to high (depends on method to estimate biomass)		Moderate to high		Low to moderate		Moderate to high		High		High	
Spatial variability of carbon inputs to the soil from crop residues		Low to high (depends on method to estimate biomass)		Low		Low		High		Moderate		High	
Complexity of the approach	Diversity of inputs required	Low		High		Moderate		Low to moderate		High		Moderate to high	
	Quantity of parameters needed	Low		High		Moderate		Low		High		Moderate	
	Physical and biochemical process represented	Low		High		Moderate		Low to moderate		High		Moderate	
Level of expertise needed		Low		High		Low to moderate		Low to moderate		High		High	
Cost of monitoring	Collecting activity data	Low to moderate		High		Moderate		Low to moderate		High		Low to moderate	
	Collecting soil data	High		High		High		High		High		High	
	Collecting weather data	Low		Low		Low		Low		Low		Low	
	Computation time	Low		Moderate		Low		Low to moderate		High		Moderate	
Upscaling/Scalability	Limitation by computation time	Low		Moderate		Low		Low		High		Low	
	Limitation by collecting activity data	Moderate		High		Moderate		Moderate		High		Moderate	
	Limitation by the number of parameters needed	Moderate		High		Moderate		Moderate		High		Moderate	
	Limition by methods for quantifying carbon inputs from crops residues	High (rely on external methods)		Moderate		Moderate		Low		Low		Low	
Robustness of evaluation	Simulate a set of measurable variables (CO2 fluxes, biomass, crop yield) in addition to SOC stock ?	Low		High		Moderate to high (depends on models)		Low		High		High	
Cost-accuracy of verification	Number of samples required	Low to High		Moderate		Moderate		Low		Low		Low	
	Sample representativeness of simulation unit	Low		Low		Low		High		Moderate		High	
Ability to simulate all different baseline	Standardised	High		High		High		High		High		High	
	Specific	Low to High		High		Moderate		High		High		High	
	Hybrid	High		High		Moderate		High		High		High	
	Static	High		High		High		High		High		High	
	Dynamic	Low to High		High		Low to high		High		High		High	
Uncertainty assesment	Are uncertainty analysis usually implemented for this approach ? (and if not, is it easy to do ?)	No (but easy)		No (complex)		No (moderate)		No (moderate)		No (complex)		Yes (complexity depends, espacially with assimilation scheme)	

Finally, on one hand although they are very valuable tools for many applications and the most commonly used in SQPs (because they are based on well-established models applicable to many pedo-climatic contexts, crop types and practices), “off-the-shelf” ecosystem models may be the least suitable for C monitoring (only) in a VCM context because they require a large number of parameters and input data (which makes them expensive to implement) and because they misrepresent the spatial variabilities of carbon inputs into the soil via biomass when they are not combined with EO assimilation approaches. On the other hand, they provide assessment of other GHGs and of very valuable agro-environmental indicators. Also, they are quite relevant in a context of NDCs as they can use already available (and often free) regional/national statistics on activity data and there is no need to be accurate at field/farm scale in this context of MRV but what matters is to be able to represent annual and regional trends and they have some time already been used for national inventories, meaning that keeping this approach would allow to be consistent with former national reporting. See Section 1.1 and 1.2 in Annex 1 for examples of SQP based on this approach.

In Annex 1, we will illustrate those different methodological approaches for the monitoring of SOC by presenting some example of Squable Quantification Platforms. However, for a more exhaustive inventory of MRV tools and their inter-comparison (considering 48 criteria like geographical scope, etc.) please have a look at the “Inventory of MRV tools and decision-support tool”⁵³ made by Deloitte for the 4 per 1000 initiative with the help of the ORCaSa project.

5.3.4 Data driven models

In the last decade the use of data driven approach based on statistical methods and Machine Learning (ML) methods for prediction of environmental properties has much advanced. They can be used in several components of an MRV framework. When they are applied to spatial prediction of soil properties, they fall under the heading of Digital Soil Mapping (DSM). Such techniques have also been used to map above ground vegetation biomass or plant’s biophysical properties (e.g. LAI). This section briefly explains how data driven approaches are or could be used across the MRV framework for several components.

Landuse maps and cover crop mapping using ML

Machine learning (ML) are a well-suited approach to produce land use and land cover (LULC) maps for crops, cover crops, and grasslands. Transfer learning, a technique where pre-trained models are fine-tuned for specific tasks, has proven effective in crop classification and monitoring, particularly when labelled data is limited (Weiss *et al.* 2016). Inglada *et al.* (2017) demonstrated the utility of transfer learning for crop type mapping using Sentinel-2 imagery, achieving high accuracy by adapting pre-trained convolutional neural networks (CNNs) to specific agricultural contexts. Similarly, Pelletier *et al.* (2019) explored the use of temporal deep learning models for LULC classification, emphasizing the importance of temporal features in distinguishing between crops and natural vegetation. Foundation models, such as those based on transformer architectures, have demonstrated remarkable capabilities in processing large-scale remote sensing data, enabling the identification of crop types, cover crops,

and grassland ecosystems with high precision (Bommasani *et al.* 2021). These models utilize multi-spectral and temporal data to capture phenological patterns, which are critical for distinguishing between agricultural practices and natural vegetation (Clinton *et al.* 2017). ML models have been successfully employed by Nowak *et al.* (2022) at National scale and Fendrich *et al.* (2023) at EU scale for cover crops mapping. Those studies are particularly valuable as cover crops are one of the main levers for sequestering C in agricultural soils (e.g. Poeplau & Don, 2015; Lugato *et al.* 2020) and as current IACS data in EU do not contain information on cover crops for most member states. The integration of transfer learning and foundation models with remote sensing data has improved the scalability and accuracy of LULC mapping. However, challenges such as model generalization across diverse geographic regions and the need for high-quality training datasets remain areas of improvement (Zhu *et al.* 2020).

Enhancing spatial resolution of input datasets using Super-Resolution (SR)

Super-resolution (SR) refers to a set of computational techniques designed to enhance the spatial or temporal resolution of digital imagery or data, producing a higher-resolution output from one or more lower-resolution inputs. In the context of high-resolution remote sensing and weather data, SR methods have been effectively applied to improve crop modelling by providing finer-scale inputs. For instance, deep learning-based SR approaches have been used to downscale high-resolution weather data, such as precipitation and temperature from sources like ERA5 or localized weather station networks, to better capture field-scale variability. A study by Glawion *et al.* (2024) demonstrated the use of a generative adversarial network (GAN) to downscale precipitation data from 24km to 1km spatial resolution. Similarly, SR has been applied to high-resolution remote sensing data, such as Sentinel-2 imagery, to refine inputs like vegetation indices (e.g., NDVI, EVI) and canopy temperature for crop models. For example, Zhang *et al.* (2019) employed a SR CNN to enhance Sentinel-2 thermal bands from 20 m to 10 m resolution, improving the estimation of crop water stress and evapotranspiration in summer corn. These advancements enable crop models to better capture field-scale variability, supporting precision agriculture and optimizing management practices such as irrigation scheduling and fertilizer application.

Soil properties using Digital soil mapping

Digital Soil Mapping (DSM) makes use of mathematical and statistical models to quantify the relationship between a target soil property and its explanatory variables. The explanatory variables are proxies of the so-called soil forming factors, that is climate, organisms, relief, parent material and time (Jenny 1994). The models are calibrated using paired observations of the soil property and explanatory variables. The calibrated model is next used to map the soil property by running it at all (upsampled) locations in the area of interest and predicting the soil property from the explanatory variables. Common explanatory variables are a digital elevation model and the many geomorphometric properties that can be derived from it, and climate variables and vegetation indices derived from remote sensing (McBratney *et al.* 2003).

In the past, much use was made of multiple linear regression to define the relationship between the soil property and its explanatory variables, but machine learning methods are much more flexible and can account for non-linear relations and interactions, provided there are sufficient training data. Examples of machine learning algorithms are Artificial Neural Networks (ANN), Gradient Boosting, Support Vector Machines (SVM) and Random Forest (RF; James *et al.* 2013). The models are complex and cannot be reduced to one or a few equations, but there are ways to 'open the black box' using model interpretation tools (Wadoux and Molnar 2022). These tools reveal the main drivers of soil spatial and temporal variation and can also be used to evaluate how the explanatory variables jointly interact and influence the soil property.

SOC contents and stocks changes using ML

Many recent studies show the potential of machine learning for mapping SOC stock and SOC stock change. Ferreira *et al.* (2023) mapped the SOC stock at 0-30 cm and 0–100 cm depth for a study area in the Amazon forest using three machine learning algorithms, while Agaba *et al.* (2024) used various machine learning algorithms to map the SOC stock in an Alpine valley in Northern Italy. Heuvelink *et al.* (2021) used the random forest algorithm to predict the SOC stock in space and time for Argentina, while Szatmari *et al.* (2021) combined random forest with kriging to predict the SOC stock change and the associated prediction uncertainties at multiple spatial scales between 1992 and 2010 for Hungary. Ugbaje *et al.* (2024) used machine learning to map SOC stock in space and time for Australia and emphasized its potential for carbon accounting, while van der Voort *et al.* (2023) demonstrate its potential for agricultural areas in the USA. Wadoux *et al.* (2023) used Shapley values to identify the drivers of SOC stock prediction in France. Broeg *et al.* (2024) showed that ML approaches for SOC changes mapping across Germany showed weak performances. Machine learning is a powerful tool for predicting SOC stock and changes, but it has limitations. In carbon farming MRV, SOC estimation must capture the impact of agricultural practices at the field level, including intra-field variability. While ML has improved digital soil mapping (DSM) using static (topography) and dynamic (remote sensing, weather) data, most applications operate at large scales, covering multiple fields. Additionally, ML requires large training datasets, but determining the optimal size is challenging. Model accuracy depends on the predictive power of input variables, and ML relies on correlations rather than mechanistic processes, limiting its ability to extrapolate beyond trained conditions, such as in future scenario modelling. To address this problem much attention is recently paid to developing hybrid models, also known as physics-informed machine learning (e.g. Han *et al.* 2023; Zhang *et al.* 2024). For these reasons it is important to consider the ML tools as a complementary or supplementary tool for SOC change estimation.

ML as a surrogate inverse RTM

ML models can serve as surrogate observation operators, linking satellite data to biogeophysical variables like LAI. For instance, instead of relying solely on physically-based Radiative Transfer Models (RTMs), ML models trained on synthetic RTM outputs can approximate the observation process more efficiently, avoiding the problem of data availability. If we consider the case of LAI retrieval with PROSAIL, several ML methods have been applied to this objective, including ANN (Vuolo *et al.* 2016), RF (Campos-Taberner *et al.* 2018), and Gaussian Processes (GPs) (Camps-Valls *et al.* 2016; Svendsen *et al.* 2018). More recently, Zérah *et al.* (2024) applied deep learning constrained by PROSAIL to accurately inverse LAI at high resolution while providing the associated uncertainty. ML approaches demonstrate significant advantages in terms of computational efficiency and scalability, particularly when dealing with large-scale satellite datasets (Verrelst *et al.* 2019). Moreover, ML models can capture complex, non-linear relationships between spectral data and biogeophysical variables, which may be challenging for traditional RTMs to model accurately. Additionally, ML-based surrogate models can be continuously updated and refined as new data becomes available, enhancing their predictive accuracy over time (Reichstein *et al.* 2019). This adaptability is particularly valuable in dynamic environments where vegetation conditions and land surface properties change rapidly (Tramontana *et al.* 2020).

ML for direct prediction of biogeophysical variables

ML has the potential to replace one or several modelling components of the modelling system used in the monitoring component of MRV. In fact, the application of ML to the prediction of biomass, crop yield, and soil moisture, trained on actual field data, has advanced greatly in agricultural and environmental sciences. ML models, particularly those incorporating remote sensing data and in-situ measurements, have demonstrated significant potential in accurately

estimating these key variables. For biomass estimation, do Nascimento Bendini *et al.* (2024) utilised optical Sentinel-2 dense image time series and ML to estimate winter cover crop biomass in France. Their study demonstrated the effectiveness of ML in capturing seasonal biomass dynamics and its potential for large-scale monitoring, even in complex agricultural systems. Similarly, Ali *et al.* (2016) applied random forest algorithms to predict aboveground biomass using multi-source data, showcasing the ability of ML to model complex relationships between vegetation structure and biomass. These studies highlight the growing reliance on ML for biomass estimation, particularly when combined with high-resolution remote sensing data. In the context of soil moisture prediction, Souissi *et al.* (2022) developed a robust ML framework to predict root zone soil moisture by integrating process-related information into an ANN. Their approach combined satellite-derived soil moisture data, ground-based observations, and hydrological modelling across diverse agricultural landscapes. For crop yield prediction, Van Klompenburg *et al.* (2020) reviewed various ML techniques, including neural networks and support vector machines, and found that models trained on field data, weather variables, and soil properties consistently outperformed traditional statistical methods. These advancements underscore the capability of ML to integrate heterogeneous datasets, improve predictive accuracy. But the all studies also highlight the dependence of the ML approach to the size and range of the training datasets.

Hybrid ML and DA approaches

Hybrid machine learning and data assimilation techniques are novel and still in their early development stages. They consist in enhancing crop and SOC modelling by merging data-driven approaches with process-based models as in the AgriCarbon-EO processing chain (see Section 2.1 in Annex 1). In crop modelling, traditional methods often struggle to capture complex interactions between environmental factors, management practices, and crop growth. Machine learning algorithms, such as random forests and neural networks, excel at identifying non-linear patterns in large datasets, complementing the mechanistic insights of crop models. For instance, Zhuang *et al.* (2024) integrated ML with data assimilation and a process-based crop model to improve winter wheat yield forecasting in the North China Plain. Their approach assimilated observational data, such as satellite-derived vegetation indices, into a crop model, while ML corrected residual errors, significantly enhancing prediction accuracy. In SOC modelling, hybrid techniques address the limitations of stand-alone biogeochemical models, such as Century or RothC, which often fail to account for spatial and temporal variability. ML algorithms enhance these models by capturing complex relationships between soil properties, climate, vegetation, and management practices. Data assimilation further refines predictions by integrating field measurements and remote sensing data. For example, Luo *et al.* (2011) emphasized the importance of assimilating observational data into Earth system models to improve SOC projections, while Zhang *et al.* (2020) highlighted ML's ability to handle heterogeneous datasets and improve SOC estimation accuracy.

Challenges and recommendations on data driven approaches:

Key Limitations and Challenges

- **Data Dependency:** ML models need large, high-quality datasets, in the case of observation-based training these are often scarce or expensive to collect, while for surrogate models producing synthetic data is much easier.
- **Model Generalization:** Certain ML models may struggle to perform well in new regions or conditions outside the training data.

- **Transparency Issues:** Questions remain about providing training datasets and making forward models open for reproducibility. It is difficult to accredit a ML model unless training data is provided.
- **Extrapolation Limits:** ML relies on correlations, not mechanistic processes, limiting its use for long term predictions which may be necessary to evaluate the risks of permanence of SOC.

Key Recommendations

- **Improve Data Availability:** Invest in high-quality datasets to enhance model training and validation.
- **Enhance Transparency:** Provide training datasets and open forward models to build trust and reproducibility.
- **Develop Hybrid Models:** Combine ML with process-based models to improve accuracy and interpretability.
- **Provide uncertainties:** Ensure the applied methodology is able to provide predictions with associated uncertainties.

5.3.5 Guidance on the evaluation of uncertainties associated with the quantification approaches

5.3.5.1 Scope of this section

Uncertainty estimates is a critical component when modelling SOC stock changes. Indeed, addressing uncertainties is essential for ensuring the accuracy, transparency, and credibility of SOC measurements, carbon offset inventories, and climate claims. Proper uncertainty management minimizes risks associated with over- or under-estimating carbon stocks, which can impact financial valuations and policy decisions. For example, when higher uncertainty is created due to inherent spatial variability then higher discounts may apply, thus reducing the number of credits that can be issued for credible SOC stock change. Regulatory and certification bodies, include uncertainty estimates validate SOC sequestration projects as a transparent uncertainty reporting enhances stakeholder trust. It also helps identify where efforts should be put in a context of evolving environmental policies and international carbon accounting frameworks. While still a challenge a well-structured uncertainty framework strengthens the integrity of MRV systems and enhances the credibility of carbon farming initiatives

The following guidelines underscore the importance of addressing uncertainties arising from measurement errors, model inputs, parameters, and structural assumptions. The European CRCF mentions that uncertainties should be considered in a conservative manner without explicitly mentioning the implications. One can consider the following points for a conservative estimate:

- using upper-bound uncertainties: applying the higher end of estimated uncertainties.
- applying conservative discounting factors: Reducing reported SOC gains to account for potential errors.
- selecting robust statistical approaches.
- avoiding over-reliance on optimistic assumptions: account for variability in soil and climate fluctuations.

The CIRCASA international research program on soil carbon for arable land identified that the uncertainties on the activity data are rarely accounted for in MRV processes while uncertainties on, for example, amount of organic amendments (or its estimated C content) or of the straw harvested can be high and have a strong impact on the estimated SOC stock changes. It also identified the lack of accuracy of other input data (e.g. soil properties, climate, C inputs to the soil) and of the initialisation process for Tier 3 models. FAO notably for grasslands (FAO, 2019; FAO GSOC-MRV Protocol 2020) recommends the integration of advanced techniques like machine learning, remote sensing, and stakeholder engagement to improve the accuracy and reliability of SOC uncertainty estimates. Additionally, frameworks from Verra and Gold Standard provide practical methodologies for integrating uncertainty estimates into carbon credit programs and agricultural MRV systems. While the Verra protocol emphasis on uncertainties in the calibration, validation and quantification processes, the Gold standard methodologies suggest a qualitative risk assessment of the quantification. Scientific literature, such as Smith et al. (2020) and Luo et al. (2016), further elaborates on these challenges, emphasizing the need for robust statistical and modelling techniques, including Monte Carlo simulations, Bayesian calibration, and sensitivity analysis, to propagate and quantify uncertainties. Publications like Poeplau et al. (2017) highlighted the role of standardized measurement protocols and improved data collection in reducing uncertainties, particularly those related to spatial and temporal variability. There are large differences between global SOC stock estimates, caused by the diversity of data sources and methodologies (Henry *et al.* 2009). Part of the uncertainty comes from the diversity of land uses and from our ability to accurately estimate their respective SOC stocks and SOC stock trajectories. These elements further increase the uncertainties of the SOC quantification.

Since we established that uncertainty dwells with many components and conditions of the MRV system, it is important to define the scope that this section addresses. Here below, we are addressing uncertainty related to the modelling of SOC stock changes only. This section does not address the uncertainties that arise from the risk of permanence, double counting, and additionality even though several concepts presented here may be used for this purpose. For example, risk of permanence due to climate change, evolution of practices can be estimated from the guidance suggested here by constructing a probabilistic framework for realistic future scenarios and applying them to existing modelling tools. This section doesn't address either the uncertainty framework when only soil sampling is used, while it is important to mention the synergistic use of soil sampling and modelling as a mean to reduce uncertainties and increase accuracy is pointed out.

5.3.5.2 Differentiating uncertainties in accreditation and quantification steps

A common source of confusion in addressing uncertainties is the non-distinction between evaluating/accrediting a model and running a SQP (uncertainty propagation). It is essential to separate these two processes, as they serve different purposes.

Accreditation of a modelling framework

Accreditation ensures that a given model is qualified for estimating SOC changes, e.g. in a given pedo-climatic context. In fact, here, we refer to the entire modelling framework, including input datasets, model priors, and reporting protocols. If ensemble modelling is implemented, the tool may involve multiple models. Once accredited, the model can be consistently applicable under the same conditions without requiring revalidation for each application. However, accreditation must assess whether the modelling framework meets the required precision

and robustness for its intended use. This process requires an uncertainty assessment distinct from the one performed while operating a SQP over an area of interest.

A model submitted for accreditation should include a sensitivity analysis to determine how different input parameters influence SOC estimates. This should be a Global Sensitivity Analysis (GSA) in the statistical sense (ensuring comprehensive coverage of uncertainty sources). The EC handbook for extended impact assessment, a working document by the European Commission, 2002, states: "A good sensitivity analysis should conduct analyses over the full range of plausible values of key parameters and their interactions, to assess how impacts change in response to changes in key parameters". GSA is commonly made using Sobol indices, Morris method or Monte Carlo Filtering. The methodology ensures that the limitations of each model are identified.

Quantifying uncertainties for running a SQP (uncertainty propagation)

Once an accredited model is selected and included in a SQP, the MRV framework must provide uncertainty estimates specific to the operational context. Unlike accreditation, which evaluates general model reliability and validity, uncertainty propagation in a SQP is a local statistical analysis that addresses the study perimeter over a given period of time (e.g., climate, soil properties, management practices).

This process involves uncertainty propagation, where inputs (e.g. weather, remote sensing variables, soil properties) and parameters are tailored to pedoclimatic and agricultural practices over the area of interest. Uncertainty sources can be categorized into dynamic and static components. Dynamic inputs, such as remote sensing time series, require continuous uncertainty tracking to account for temporal variability, while static inputs including soil properties have fixed uncertainties that may need periodic updates to maintain accuracy. To propagate uncertainties in input data, model parameters, and structural assumptions, Monte Carlo type methods are commonly used. These techniques run multiple simulations with randomly sampled values from probability distributions, allowing for a robust estimation of uncertainty in SOC assessments. The resulting statistical confidence intervals enhance transparency in reporting and support informed risk assessment.

By clearly distinguishing accreditation from uncertainty propagation in SQP, SOC monitoring can be conducted in a methodologically robust and operationally reliable way.

5.3.5.3 Sources of uncertainties

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).

Generally, model parameters and structure are identified as separate sources of uncertainties while in reality, they are intimately interlinked as the parameter set are defined based on the model structure. These uncertainties are inherently tied to the selection and application of ecosystem or soil models, radiative transfer models, data-driven algorithms, and assimilation schemes (Wijmer *et al.*, 2024). Models always rely on simplifying assumptions—such as steady-state conditions or linear behaviour—that may not fully capture the complexities and non-linear dynamics of real-world systems (Heuvelink, 2018). The structure of a selected model itself can introduce biases or simplifications, which may lead to discrepancies between model predictions and actual observations. To address epistemic uncertainties that include uncertainties associated to the model's structure and its parameters, it is crucial to assess them through the lens of model parameterization, provided that the model has been validated for the specific conditions under study (Luo *et al.*, 2016). This involves identifying and quantifying the uncertainties associated with key model parameters, which can be achieved through sensitivity analysis and probabilistic methods such as Monte Carlo simulations or Bayesian inference (Martin *et al.*, 2021). Based on the sensitivity analysis, it is recommended to focus on a subset of dynamic parameters that have the most significant impact on model outputs. This approach not only simplifies the uncertainty quantification process but also ensures that the most influential sources of uncertainty are adequately addressed. By systematically evaluating and reducing epistemic uncertainties, modelers can improve the reliability and accuracy of their predictions, ultimately enhancing the robustness of MRV systems for SOC monitoring and reporting (IPCC, 2019). Quantifying model uncertainty and model validation are still challenging and in practice often lacking (Garsia *et al.* 2023). A related challenge is how to comprehensibly communicate this uncertainty to different stakeholders so that they can correctly interpret the results.

5.3.5.4 Propagation of uncertainties

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. Examples of uncertainty propagation analyses in MRV context are given elsewhere (Jonas *et al.* 2019; Yanai *et al.* 2020; Wijmer *et al.* 2024).

Probabilistic methods, such as Markov Chain Monte Carlo (MCMC) and Bayesian Inference, offer a rigorous framework for quantifying uncertainties in model parameters and states (Dumont *et al.*, 2014). These methods have been widely adapted for data assimilation in crop modeling, particularly for capturing parameter adaptation over long time windows, such as entire crop cycles (Wijmer *et al.*, 2024). A key advantage of these approaches is their ability to provide uncertainty estimates for model predictions through the use of likelihood functions. MCMC methods rely on sampling techniques to estimate posterior distributions of parameters and states, making them highly effective for uncertainty quantification. Although computationally demanding, they produce robust and statistically sound estimates (Wallach *et al.*, 2016). Meanwhile, emerging non-iterative probabilistic approaches present a promising alternative for crop model data assimilation. These methods offer long-term prediction capabilities while simultaneously providing associated uncertainty estimates, making them well-suited for large-scale and operational applications. The use of Bayesian approaches, such as the Normalised Importance Sampling (NIS) technique, in this context, enable the propagation of uncertainties while ensuring the assimilation of EO data. This approach provides probabilistic estimates of model parameters and outputs, allowing for a more comprehensive quantification of uncertainties.

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 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.

5.3.5.5 Upscaling uncertainties

Most variables of interest of MRVs, such as biomass and SOC, vary in space and time. The heterogeneity in soil properties, climate, and management practices across landscapes and over time introduces significant spatial and temporal variability in SOC assessments. To effectively capture this variability, simulations should be conducted at high resolution, as fine-scale modeling better reflects local conditions and variations. Recent studies, such as that by Wijmer *et al.* (2024), highlight the importance of high-resolution data assimilation in crop models. Their findings showed that using mean-field-level green LAI data, instead of high-resolution data, in the SAFYE-CO2 model led to a bias of -47 g.m^{-2} and an artificial reduction in relative uncertainty by 39% for biomass production estimates. This underscores the need for fine-scale observations to improve SOC input quantifications. Performing simulations at high resolution and then aggregating the results to the field scale helps reduce uncertainty in scaling and offers a more accurate representation of SOC dynamics. 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.

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)

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}).

5.3.5.6 How to reduce uncertainties

Reducing uncertainties in SOC monitoring and verification requires continuous refinement of estimation methods, targeted data collection, and an optimized balance between observations and modeling.

Optimizing the modelling approaches can be achieved by:

- **Parsimony in Modeling:** Simplified “first-order decay rate” soil models, such as AMG (Clivot et al., 2019), offer a reliable balance between complexity and uncertainty. These models, with fewer carbon pools and parameters, mitigate uncertainty amplification compared to explicit microbial pool models.
- **Assimilation of Remote Sensing Data:** Integrating satellite observations (e.g., Sentinel-2 at 10m resolution) helps capture spatial variability within fields, improving biomass production estimates and, consequently, carbon input assessments.
- **Multi-Source Data Fusion:** Combining sampling data with remote sensing and modelling approaches enhances accuracy and robustness.
- **Integration of Advances:** Adopt the latest improvements in sampling strategies, remote sensing, and modeling techniques.

Targeting data collection & high-quality input data :

- **Improving measurement techniques** to reduce the largest sources of uncertainty in input data.
- **Ensure high-quality input data** on soil properties, climate conditions, and management practices.
- **Establish robust baseline methodologies** to improve the accuracy of SOC change assessments.
- **Long-Term Monitoring:** Continuous data collection over multiple years captures temporal variability and strengthens trend analysis.

Continuous improvement & learning from verification

- **Feedback Loops:** Insights from verification processes should be systematically integrated to refine future uncertainty assessments.
- **Stakeholder Feedback:** Incorporate insights from farmers, scientists, and policymakers to refine MRV methodologies.

5.4 Which method to choose depending on the context and data available

The objective of this section is to guide users of monitoring methods, scheme designers or developers of SQPs in choosing the monitoring methodology best adapted to their MRV purpose and local context. As explained earlier, there is no “one-size-fits-all” monitoring approach that is optimal for all carbon farming schemes. Even in a given context of application (VCM, AEPs, NDCs), different monitoring approaches may be selected when applied in different regions, depending on the local context (e.g. the soil types, climate, size and shape of the plots, size of the CF scheme, CF practices, regulatory conditions), the duration of the monitoring period, and the level of accuracy needed.

Also depending on the context of monitoring and of the intended use of carbon removals, the level of monitoring certainty will vary. For instance, if the aim is to sell carbon credits, then the level of monitoring certainty will have to be high to convince buyers that removals/avoided emissions are real and additional. If instead, the objective of the CF scheme is mainly practice-oriented as in the AEPs (e.g. CAP) or aiming to increase farmer knowledge and ability, the monitoring scheme could be less stringent.

Contextual elements, such as data availability and accuracy, or existence SOC monitoring networks, of locally parametrised models, will all shape the selection of the recommended monitoring approach.

In order to facilitate the choice of monitoring method to be implemented or developed depending on the MRV purpose and local context, we built a decision tree presented in Figure 34. Note that data driven approaches do not appear in this figure but they can be used to replace some modelling approaches (e.g. soil centred approach) or some modelling components (e.g. a plant model, a soil model). They can also be used in the EO assimilation approach (e.g. to produce time series of biophysical products such as LAI instead of a radiative transfer model) provided that they conform with additional criteria (e.g. no under or over learning, domain of validity, transposability, transparency).

In order to build the multi-context of application decision tree for monitoring SOC, we started from the generic decision tree for identification of appropriate Tier to estimate SOC stock changes for the NDCs context that is presented in Section 5.3 (Figure 20). Then we started adapting it to the other contexts of SOC monitoring (AEPs, offsetting, insetting). It resulted in a draft of the decision tree (not shown here) that was presented at two international co-creative workshops that were organised jointly by the ORCaSa and MARVIC projects consortia. One of the aims of those workshops was to discuss the criteria to build a decision tree in order to choose the monitoring methods adapted to each context of application and making optimal use of data and methods (e.g. process based models) that could help non-specialist to choose the best method to be implemented depending on their context of Monitoring. Those co-creative workshops allowed to ensure accession of the stakeholders and alignment with existing operational national/international MRV frameworks/networks/carbon farming initiatives, current/future user needs, and the latest (scientific) insights.

The first criterion to determine the most appropriate monitoring method for quantifying SOC stock changes is the context of application (NDCs, AEPs or VCM either for the offsetting or the insetting) as it shapes key elements such as the accuracy and the complexity of the methods that can be considered, the spatial resolution and extent application (field to national scale) or the duration of the monitoring project (one year or more). Hence the decision tree is first divided by the context of application, with distinction for offsetting and insetting inside the VCM as

offsetting projects are minimum five years, while insetting project can last one year or more. In the case of VCM and AEP's, for instance, as we recommend that the monitoring should be done at field level, only measure-remeasure or Tier 3 approaches should be implemented.

Then, according to the duration of the project or of the reporting time, the second question checks whether direct Δ SOC stock measure-remeasure methods are feasible (number of samples to be collected, cost-accuracy acceptable for the project, already existing network) and representative at the field, farm or country scale (depending on the context of application). It is assumed that the cost-accuracy of a Δ SOC stock measure-remeasure for a project that lasts less than five years would be too high as it would probably require several hundreds of samples per field to be able to detect significant SOC stock changes on such a short timescale (Heikkinen *et al.* 2021). If it's possible to do measure-remeasure with acceptable cost-accuracy, then this method is preferred. If measure-remeasure is not possible, then Tier 3 modelling approaches are considered next for every application context (see Section 5.3).

The Tier 3 modelling approach should be adapted to the local pedo-climatic context and management practices considered (domain of validity), i.e the approach should have been evaluated in these conditions and should shown good performances. Note that in order to apply Tier 3 modelling approaches, some key activity data related to carbon lateral fluxes (see Figure 2) are mandatory whatever the Tier 3 modelling approach (i.e. organic amendments, details on harvested organs such as the amount, the date, the part of the plant that is harvested). So, at this stage of the decision process, all Tier 3 approaches are considered, from soil centred approach to ecosystem approach. For NDC's, the approach must be aligned with the IPCC recommendations, and for insetting, the resolution of the approach must be at field level. If none of the Tier 3 approaches are available (calibrated/ validated) for the local context considered, the next steps of the decision tree will differ depending on the context of application. Indeed, for NDC's, a Tier 2 approach (see Section 5.3.2.) can be considered following IPCC guidelines. Of course, it has to be adapted to the local pedo-climatic context and practices. But if no Tier 2 approach is available, and the IPCC consider that in this country the SOC stock changes in cropland are not a Key category, then a Tier 1 approach can be considered. Otherwise, more accurate and reliable methods need to be developed (i.e. measure-remeasure, Tier 2 or Tier 3). Hence, the financial and cost-accuracy questions arise, to determine whether it is preferable 1) to invest in a national SOC stock monitoring network or 2) to collect data for developing a Tier 2 method or for (developing) calibrating and validating a Tier 3 method adapted to this local context. For the AEPs MRV context, according to the established rules, Tier 2 might be considered. As the research program the H2020 NIVA project proposed a tiered approach for the CAP. However, whether the payment is action-based or result-based, the Tier 1 approach seems out of scope. Hence, if no Tier 2 is available, the total cost and cost-accuracy of Δ SOC stock measure-remeasure should be compared to the cost and cost-accuracy of collecting data for developing a Tier 2 method or for (developing) calibrating and validating a Tier 3 method. Those cost and cost-accuracy comparison should lead whether to choose Δ SOC stock measure-remeasure or reconsidering the different modelling approaches (Tier 3 first then Tier 2). For offsetting and insetting contexts, no Tier 2 are considered, so when no Tier 3 approach is available, the comparison between the cost and cost-accuracy of the Δ SOC stock measure-remeasure and of collecting data for (developing) calibrating and validating Tier 3 approaches arises. As mentioned before, offsetting project are minimum five years long, while insetting project can last only one year. In this case, if no Tier 3 approaches is available, the cost of Δ SOC stock measure-remeasure could be higher compared to calibrating and validating an already Tier 3 existing tool to the local context.

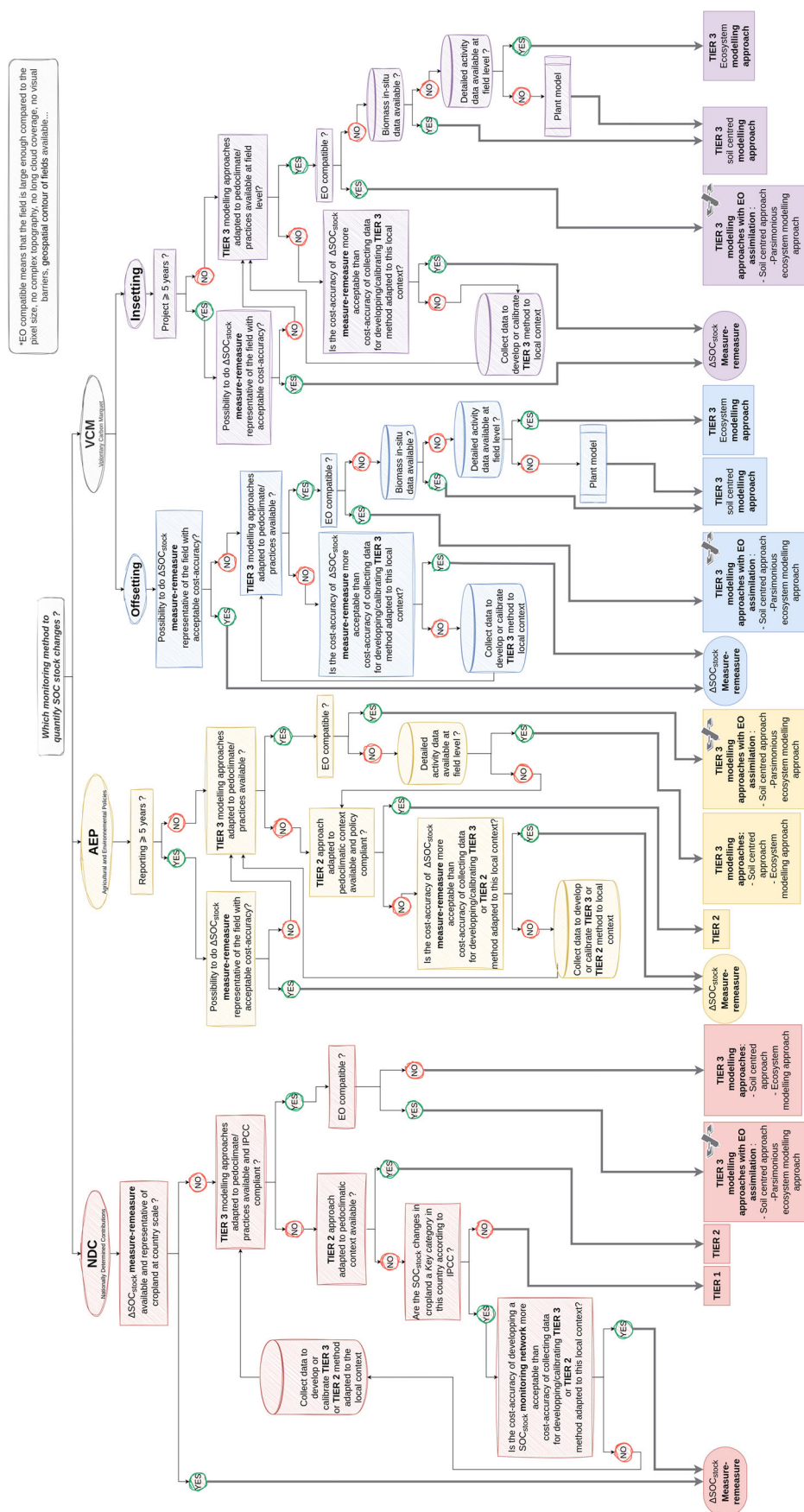


Figure 33. Decision tree designed to choose the SOC stock changes monitoring approach according to the MRV context of application and to the local context. Credits A. Ihasuta

When only Tier 3 approaches remain for the different MRV contexts of application because of their preferable cost and cost-accuracy, the next criteria is the ability to use EO in the local context. The possibility to use EO rely first on the compatibility with the system observed: the monitored field should be large enough compared to the satellite's pixel size, the topography of the field shouldn't be too complex (to avoid error of projection or of surface reflectance correction) and no physical element (e.g. trees, electric pylons or their shadow) should disturb the observations of the field from remote sensing. It also relies on the type of satellite used; e.g. for optical satellites, cloud coverage shouldn't be too long during vegetation development. Lastly, to be able to use EO, the geospatial contour of fields should be available, especially in contexts of application where the monitoring is made at field or farm level (e.g. AEP, offsetting and insetting). If the conditions are EO compatible, then it's preferable to use Tier 3 modelling approaches with EO assimilation such as soil centred approaches using carbon inputs from biomass residues derived from remote sensing product (see Section 5.3.3.1.3) or parsimonious ecosystem modelling approaches that are more prone to EO assimilation (e.g. scalable, time efficient).

If the use of EO data is not possible, Tier 3 approaches can still be considered. For NDC's, the expected accuracy specific of each field is lower, allowing the use of regional statistics as input to Tier 3 approaches, such as biomass production and management practices. It then relaxes the collection of specific activity data. Hence, soil centred approach can be used relying on regional statistics inputs for biomass production and management practices, as well as ecosystem modelling approaches using "off-the-shelf" ecosystem models with simplified assumptions to represent average crop rotations or management practices. For AEPs, we did the assumption that reliable yield and activity data (detailed management practices) are provided by the farmer, reliable (e.g. verified by an agricultural advisor) and accessible at field scale (preferably through FMIS) since they may have been declared formerly in order to be eligible for the subsidies. Under those circumstances, the soil centred approaches could be used as well as ecosystem modelling approaches based on "off-the-shelf" ecosystem models (keeping in mind that simulations without EO assimilation are likely less accurate than with). If this assumption is revealed false (no yield and detailed management practices available at field scale), the question whether or not it is possible to use a Tier 2 approach may arise. If the answer is no (for example because this is not envisaged by the paying agencies), then the question of acquiring new data will arise (for measure-remeasure or for developing new Tier 2 or Tier 3 methods). For the offsetting and insetting contexts, if the use of EO data is not possible then the choice of approaches will depend on the availability of biomass data and detailed activity data. If no *in-situ* biomass data is available but detailed activity data are, then it is preferable to use ecosystem modelling approach using "off-the-shelf" ecosystem models able to represent vegetation growth. However, in the case where biomass *in-situ* data are available, the soil centred approach could be preferred for its ease of implementation. Moreover, if detailed activity are not available, a plant model can be used to estimate biomass production and derive carbon inputs from biomass residues to feed the soil centred approach.

At his stage, it should be mentioned that the availability of soil data was not a discriminating criterion in the decision tree for choosing between different Tier 3 modelling approaches, as they all require these informations to initialize SOC stock and soil properties, which is illustrated in the schematic representation of Tier 3 approaches (Figures 28, 30, 32, 33).

Several other criteria should be considered for choosing the method for monitoring SOC stock changes. They are listed here below. This list is adapted from the Technical Guidance Handbook on Carbon Farming (COWI, Ecologic Institute and IEEP, 2021):

- Transparency, *i.e.* is the method clearly documented and publicly available?

- Scientific robustness. Robustness refers to the ability of monitoring approach to quantify SOC stock changes reliably and accurately (i.e. with low bias and uncertainty). The reliability of the method will depend partly on the reliability of the data (e.g. activity and soil data.). Concerning the activity data, it is recommended that they are verified by an expert (e.g. Agricultural advisor) before being used as input for Tier 3 modelling or data driven approaches. Note the uncertainty of the method cannot always be calculated (e.g. because of a lack of uncertainty estimates on the activity data). Also, no consistent method for measuring scientific robustness could be determined across all methodologies. Last, the monitoring methodology may only be robust under certain conditions (e.g. pedo-climatic conditions, CF practices, duration of the CF project). Therefore, for Tier 3 modelling approaches the domain of validity of the model should be verified before its implementation.
- Transposability: the transposability of the approach will be an important criteria for SQP developers or for operators that need to recalibrate/validate a method to their local context.
- Quality of the scientific assessment: has the methodology gone through scientific peer review? Does it align with or apply best practice or standards (e.g. are IPCC Tier 3 quantification methods used)? How trustworthy and unbiased are the involved scientists? Note that it is not because a method is published in peer review journals that it produces robust and accurate estimates (e.g. it could show rather poor RMSE and R^2 but yet be published as the performance analysis is well performed and honest). Also, a method may perform well at long term experimental (LTEs) trials but poorly at commercial farms i.e. in an operational MRV context because the activity data and the soil properties are known with less accuracy.
- Ease of use, practicality and cost accuracy. Monitoring approaches must be relatively easy and cheap to implement, given local conditions. Often, the simpler and quicker the monitoring approach, the lower the associated cost – for administrators and for farmers (and it doesn't necessarily mean that they have the higher the uncertainty/lower accuracy). The complexity, time and financial costs for farmers are a particular concern, as these act as barriers to their participation in CF projects. Under this criterion it is important to consider whether the monitoring method is simple to explain and whether the actors responsible for implementing it will be able to implement it quickly/easily. Other issues to consider are the availability and accessibility of data: the more data that the person doing the monitoring has to collect "manually" (e.g. through farmer's survey), the more expensive and time-consuming it will be. Accordingly, monitoring approaches should take advantage of data already at hand (for example, already gathered by regional authorities, or related to CAP reporting, or collected by farmers as part of general farm management) or automatically downloadable. Note that a very complex method (ex. a prototype of Scalable Quantification Platform like AgriCarbon-EO, see Annex 1) may be very easy and practical to implement if a well-designed graphical interface is provided. A very good example of that are smartphones that are very complex both in terms of hardware and software but very easy to use. The level of automation of the processes when implementing a method is also a good criterion to define its ease of use and practicality (e.g. automatic download of data through APIs). In practice, the type of monitoring that is practical to implement is highly dependent on the existing skills and knowledge of the operator.
- Scalability: in large scale MRV contexts such as the AEPs (e.g. CAP), the NDCs (when relying on Tier 3 approaches) or some large CF projects, the scalability of the method can be a determining criterion. When considering Tier 3 modelling approaches, both the soil centred and parsimonious ecosystem modelling models with EO assimilation are among the most scalable approaches (see Sections 5.3.3.1. And 5.3.3.2.2.3).

- Trade-off between monitoring accuracy and cost. The quantification of SOC stock changes inherently involves some degree of uncertainty in the direct measure-remeasure or modelling approaches. For measure-remeasure, uncertainty can arise in the upscaling of individual measurements to representative areas (e.g. due to the assumption that the SOC stock measurements in one corner of the field will apply to the whole field). Uncertainty is even more pronounced in some modelling approaches. This occurs particularly for models running on average at field scale which will not be a perfect match for specific individual cases. Uncertainties arise because this average SOC stock assessment will not capture the spatial variability in SOC stock changes, crop development, soil properties, microclimates...Up to a point, scheme designers can reduce uncertainty through more stringent monitoring requirements (e.g. extensive local parametrisation of models, requiring regular on-site visits for measurements, the use of conservative audit tool calculation assumptions, etc.). However, these more stringent monitoring approaches come with a trade-off: increased costs for operators and often less income for the farmers. If farmers bear these monitoring costs as transaction costs (whether they are in the form of time, complexity, or financial costs), these reduce farmer uptake – and therefore the potential overall impact of the scheme. Accordingly, it is important to reduce the cost of monitoring but also to improve their cost-accuracy. As MRV costs are correlated with the need for environmental certainty, a key solution to high monitoring costs is, if possible, to accept some degree of environmental uncertainty. As found in the case studies, different existing schemes balance the trade-off between MRV costs and environmental uncertainty differently. The methodological approach that probably has the best of cost-accuracy ratio is the parsimonious ecosystem modelling approach with EO assimilation as it is developed to be very scalable and therefore applicable at once over large areas (reducing the cost of implementation), it is cheaper to verify when applied at high resolution (see Section 7.1) because the soil sampling scheme can be optimised, and it is very likely to be more accurate than the other modelling approaches as it allows objective and more accurate assessment of carbon inputs to the soil compared to most of the other Tier 3 modelling approaches.
- Assessment of co-benefits and other objectives. Operator of SOC stock monitoring approaches and SQP developers must also consider if the monitoring approach will enable them to monitor other agri-environmental indicators and the level of achievement of other policy goals. In other words, can the monitoring approach help them to understand (and potentially incentivise) co-benefits such as improved water and nutrient use efficiency, other climatic impacts than carbon sequestration (GHG emissions, albedo effects), positive biodiversity impacts, improved farm economic returns, as well as reduced negative externalities (e.g. nutrient leaching, erosion, water quality).

6 Reporting

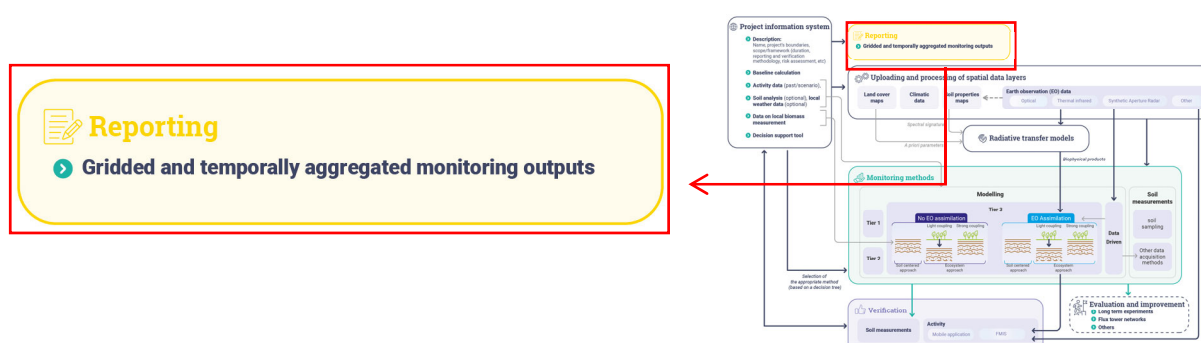


Figure 34. The red frame indicates which part of the MRV framework will be addressed in this section.

The objective of the reporting stage is to make the information accessible to a range of users and facilitate public disclosure and periodic verification of the information provided. The project stakeholders must report the degree to which they have been able to achieve the emissions reductions, by compiling it in inventories and standardized formats, to be then verified by an independent, third-party auditor.

6.1 Reporting SOC stock changes for National 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 above-mentioned reference addresses SOC stock changes (IPCC 2019a). Note that Tier 1 to 3 approaches can be used for the reporting by the Parties.

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.

6.2 Reporting SOC stock changes for the VCM

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

(Pérez 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.

All stages of the MRV require the presentation of reports in certain formats. For the VCM, many of these formats or templates already exist in the world and are available on the Web, such as those proposed by the Certified Carbon Standard (VCSVERRA, 2019) for the VCS Program⁵⁴.

Four types of reports are usually necessary to comply with this MRV context:

- a) Pre-implementation report: this report must include a project description: spatial and temporal boundaries (project duration), records and results of the baseline scenario, records and results of the Intervention Scenario (IS) delineation (e.g. spatial boundaries, description of proposed SSM practices), expected risks of reversals and leakages and proposed activities to reduce risks, soil sampling plan for verification...
- b) Initial report: This report includes implementation status of the projected, activities and deviations, baseline SOC stocks, initial sampling round results. (e.g. initial SOC concentration and bulk density) and methodology (e.g. sampling depth, sample locations, methods for soil analysis), methodology for modelling (modelling approach, version of the model...), modelled SOC stocks for the baseline and IS scenarios and their difference, SOC sequestration rates, projected CO₂ removals; per area unit (ha), for each field and for the whole CF project.
- c) Monitoring report and final report; Those reports should include the following elements, implementation status of the projected activities and deviations, since the beginning of the project; evidence that projected SSM practices are being implemented, relevant invoices, receipts, contractual arrangements and/or sales records, reversals areas, SOC stock changes from the soil measure-remeasure program or from the modelling exercises (IS scenario - baseline scenario) but also report on 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....Most standards require reporting on a regular basis (e.g., 1 to 5 years, i.e. a full cropping cycle; 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, see Oldfield *et al.* 2022). Data reporting templates are usually provided to aid in the collection of data.

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). See Sections 4.2.1.4 and 4.2.1.6 about baselines and decision support tools. Note that VCM soil CF 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.

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 pedo-climatic 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.

⁵⁴ <https://verra.org/project/vcs-program/>

7 Verification

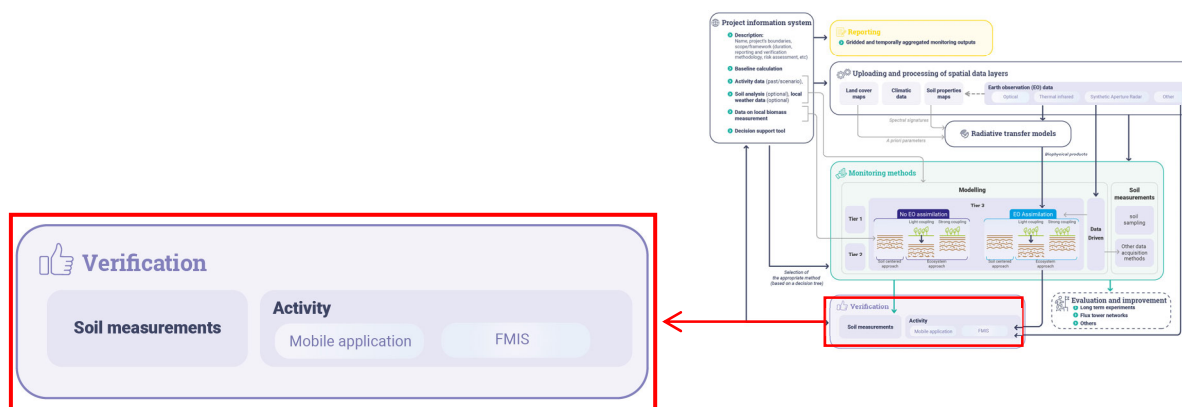


Figure 35. The red frame indicates which part of the MRV framework will be addressed in this section.

Verification refers to the process of independently checking the accuracy and reliability of reported information or the procedures used to generate that information. By providing feedback on measurement/monitoring methods and procedures and improvements in reporting, verification also provides quality assurance and quality control that improves the MRV of SOC.

As previously stated, verification is a process that must be conducted independently of monitoring and reporting processes. Other people and/or companies will be responsible for verification, as with quality assurance and quality control processes described in IPCC Guidelines (IPCC, 2006a).

Verification is achieved by periodically subjecting the reports to external reviewers, in order to establish completeness and reliability. Verification helps to ensure accuracy and conformance with any established procedures, and to provide meaningful feedback for future improvement.

7.1 Verifying SOC stock changes

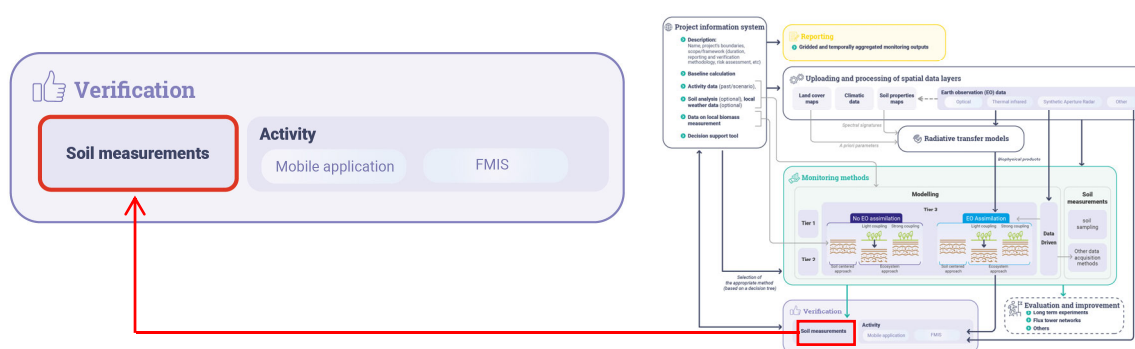


Figure 36. The red frame indicates which part of the MRV framework will be addressed in this section.

Result-based verification of SOC stock changes refers to a case where the verification is based on independent measurements of the SOC stock. For instance, if a monitoring phase of an MRV project indicates that the total SOC stock of an area during a project time period has increased by a certain amount, then this is verified by taking and comparing measurements of the SOC stock at the start and end of the project period. A key problem is that SOC stock measurements are expensive and can only be taken at a limited number of locations from the study area. This implies a sampling error, which can be quantified if probability sampling and associated design-based statistical inference is used. This section briefly summarizes the methodology and provides some examples from the scientific literature. To verify a SOC stock change for a study area during a project period, an obvious approach is to randomly select n locations in the study area and measure the SOC stock at the start and end of the project, by taking soil samples and analysing these in the laboratory. The SOC stock change can then be estimated by taking the mean of the SOC stock changes at the n locations, while the estimation error can be quantified by the standard error, using basic methods from statistical sampling theory. This also allows computing confidence intervals of the SOC stock change for the area, meaning that the statistical significance of the estimated change can be computed.

Efficiency can be improved by replacing simple random sampling by more advanced sampling strategies, such as stratified random sampling, systematic random sampling or model-assisted random sampling (De Gruijter *et al.* 2006; Brus 2022). To eliminate short-distance spatial variability it is advantageous to take composite soil samples, while it is also important to mitigate systematic measurement errors by ensuring that the laboratory analyses are identical at the start and end of the project. Revisiting the same locations is more efficient but to avoid fraudulent practices it might be safer to sample at the second round at locations that are selected independently from the first round (De Gruijter *et al.* 2016). Laboratory costs may also be reduced by replacing wet chemistry soil analyses by proximal soil sensing, but this comes at a cost because such measurements have larger uncertainty.

Bradford *et al.* (2023) quantified the sampling density required to obtain sufficiently accurate SOC stock change estimates. Potash *et al.* (2023) evaluated the efficiency gain obtained by stratified random sampling in eight US Midwest agricultural fields. Singh and Whelan (2020) applied stratified random sampling to estimate soil carbon change across ten farms under different farm management regimes in Australia. Malone *et al.* (2018) tested a method to audit SOC stocks at the farm-scale and found that stratified random sampling was not as efficient as simple random sampling in Australia while results from New Zealand showed the opposite effect. Viscarra Rossel and Brus (2018) explored the added value of incorporating soil sensing in design-based estimation for soil carbon accounting. A new approach will be tested in the ORCaSa project that consist in using the annual SOC stock changes maps estimates produced at high resolution (10m) for several years before the initial sampling and at the end of the CF project over all the fields of a farm (see Figure 38) with the AgriCarbon-EO processing chain (see description in Section 2.1 of Annex 1) in order to optimize the sampling locations. Indeed, this approach provides a spatial and dynamic assessment of the SOC stocks (areas losing and storing SOC) impacted by the crops/cover crops residues inputs to the soil.

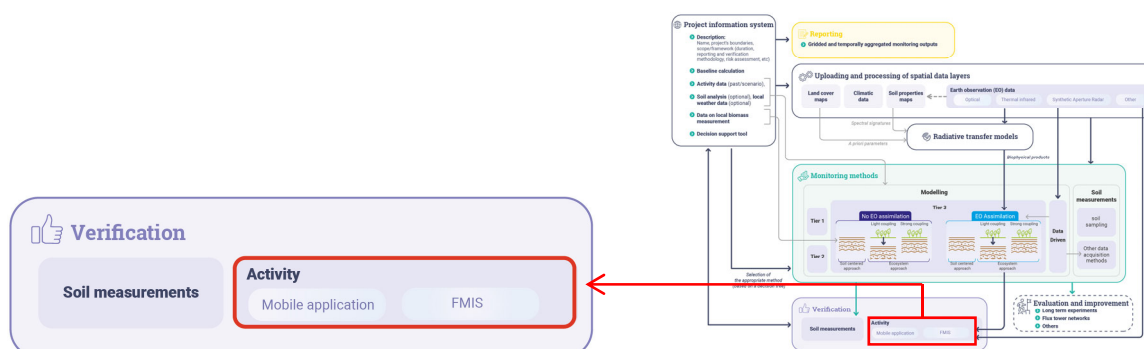
While result-based verification is attractive from a scientific point of view because the 'design-based' statistical inference is completely model-free and hence makes no modelling assumptions, the disadvantages are that it requires probability sampling and that large sample sizes may be needed to ensure that the estimation errors are sufficiently small. But if it is feasible then it can in fact replace the model-based activities conducted during the monitoring phase, since the verification stage produces all information needed, i.e. it provides an estimate of the SOC stock change with quantified uncertainty.

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)⁵⁵.



Figure 37. Annual carbon budget map at 10m resolution in 2019 produced by assimilating Sentinel-2 EO data in the AgriCarbon-EO processing chain (Wijmer *et al.* 2024) at a farm in South West France. Greenish fields that are sequestering carbon in most of their area were cultivated that year with faba bean cover crops and maize while the yellowish/orange fields were cultivated that year with winter wheat and are mostly losing carbon. The blue dots represent potential *in-situ* locations for an optimal soil sampling scheme who benefits from the high spatio-temporal resolution of the information on SOC stock trends in order to measure representative SOC stock changes at field/farm scale or to verify SOC stock changes with a high cost-accuracy ratio (low number of soil samples reducing the cost for analysis but matching the scale of simulation, good accounting of the distribution of SOC stock changes at field/farm level and representative of their mean SOC stock changes).

7.2 Verifying activities



⁵⁵ <https://www.dccew.gov.au/climate-change/emissions-reduction/independent-review-accus>

Figure 38. The red frame indicates which part of the MRV framework will be addressed in this section.

We considered three main approaches for verifying the farmer's activity: the first one relies on farmer's declarations, the second on remote sensing and the third is a combination of modelling and remote sensing.

The first approach is represented by the arrow that goes from the "Project information system" box to the "Activity" box in Figure 39. It relies on the farmer's declaration of activity, e.g. through the Project information system interface itself (e.g. with a web interface as in the Carbon Extract tool, see Section 1.3 of Annex 1), though mobile applications or through FMIS. In the context of the CAP, several mobile applications have been developed to facilitate the farmer's declaration and proof of adoption to farming practices. Those mobile applications seem very relevant in a MRV context. Yet, activity data are dramatically missing for large sections of the world, and if in the Global North more and more farmers use 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, many farmers still note they activities on paper. In many carbon farming schemes, the verification process implies meeting the farmer and collecting individually activity data for each field which is very time consuming and very expensive. Yet, whatever the method for collecting the data for the verification process, the data should be independently audited. Therefore, the more the process is automatized, the cheaper it is but also the higher the risk is to collect erroneous data. Rosenstock and Wilkes (2021) suggest investments in activity data for monitoring should be prioritised as they can also provide benefits to the governments in terms of investment in planning or monitoring national development policies.

The second approach is represented by the arrow that goes from the "Earth Observation data" box to the "Activity" box in Figure 39. Some of farmer 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 Online⁵⁶, even if the spatial resolution can still be a challenge for smallholder farms. However, new private satellite constellations like Planet⁵⁷ or EarthdailyAgro⁵⁸ 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. In a review, Bégué *et al.* (2018) listed the activities that can be derived from EO: crop rotation, fallowing, irrigation, soil tillage, harvest and post-harvest practices. They observed that the majority of the studies were exploratory investigations, tested on a local scale with a high dependence on ground data, and used only one type of remote sensing sensor. More recently, Dodin *et al.* (2021) tested the potential of Sentinel-2 for mapping of green waste compost and organic amendment. Also, Nowak *et al.* (2022) and Fendrich *et al.* (2023) took benefit of respectively Sentinel-2 and Sentinel-1 to produce cover crop maps at national (French) and EU scale. Also, since 2023, remote sensing is used by several E.U. member states to monitor activity on cropland and to verify farmer's declaration for the CAP. In the coming years, a new Copernicus service dedicated to agriculture should provide Pan European data on activity at field scale based on EO⁵⁹. Note however that many practices (e.g., pesticide applications) cannot yet be detected by remote sensing or at least not

⁵⁶ <https://www.collect.earth/>

⁵⁷ <https://www.planet.com/>

⁵⁸ <https://earthdailyagro.com/>

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).

The third approach relies on EO assimilation in crop models (e.g. Pique *et al.* 2020a; Pique *et al.* 2020b; Pique *et al.* 2020c) that allows identifying the presence and the emergence of vegetation (crop, cover crop, spontaneous regrowth, weeds) and of its termination by the farmer (see also Figure 11).

8 Future research and call for actions to achieve the implementation of an international harmonised methodological framework for MRV of SOC for cropland

8.1 Need for methodological improvements of the monitoring component

This Deliverable highlights the need for improvements of the MRV components, in particular monitoring and verification and aims at better scalability and accuracy and reduced cost of monitoring and verification. As areas for improvement of the Verification component have already been discussed in Chapter 7, we will focus on areas for improvement for the monitoring component in the following four subsections.

8.1.1 Improvement of the in-situ data acquisition techniques

As indicated in Chapter 5, for several MRV components the availability of reliable and accurate data is essential yet the costs to collect e.g. soil information is still regularly prohibitive for implementation of a viable MRV system. Techniques and methods for acquiring more reliable, accurate data that can be applied to MRV and other applications at a (much) lower cost per data point are essential, both for the implementation of an MRV system, as for added value of the data for other land management applications, which would alleviate the costs purely for the MRV system. This would allow more extensive and detailed sampling for various MRV aspects, such as measure-remeasure of SOC stocks, but also for initialising or verifying soil models. In combination with remote sensing techniques and information (e.g. through EO assimilation in a parsimonious crop model as in Figure 38), it is possible to improve stratification for soil sampling, which can result in within and more detailed between field maps of variation, initial SOC stocks and other soil information. In addition, improving in situ techniques to include not only topsoil data, as is currently the case, but also subsoil data, down to a depth of 1 m, is beneficial so that the entire carbon stock of mineral soils can be measured, regardless of the depth of the tillage layer and the tillage regime. At present, this is often not done because of the higher sampling costs.

In addition to remote data acquisition techniques, such as satellites for biomass, land use, climate and land management information, improved in situ data acquisition techniques, including improved or more cost-effective laboratory techniques, can contribute to the feasibility of an MRV system. Promising techniques with potential for further innovation include spectroscopy, gamma-ray spectrometry and combinations of these and other detection techniques. The techniques themselves are described in more detail in Section 5.2.

For soil spectroscopy, four potential directions for improvement are evident;

1. **Open, interoperable soil spectral libraries with a global coverage.** Soil spectroscopy as a technique is only cost-effective, reliable and accurate for soil property estimations when good quality calibration libraries have been derived and are available to the user. Although several libraries exist and are open, for large areas in the world no suitable, high quality soil spectral calibration library is available, not for lab application, nor for field application. To increase application of soil spectroscopy and make true on the potential of the technique, this is a crucially needed development. Ideally a federated network of open soil spectral libraries is created, with little to no spectral calibration transfer needed, with high and documented reference data quality, with reliable and adequate transfer functions available for differences in reference methods, openly accessible in a pre-competitive environment or at least accessible, well documented, well stored and structured using e.g. OGC OMS, SOSA, ISO28258, GloSIS conceptual data model or implementations of these, and FAIR. An initiative towards this aim is GSCLES (Shepherd *et al.* 2022), but other modalities are also possible. The above holds true for both lab and field soil spectral calibration libraries. For field application, additionally specific field soil spectral calibration libraries are in development or available. In these libraries the spectral signature of the instrument and in some cases spectra at a range of for soil moisture contents are available.
2. **Improvement and standard application of (standard) field protocols to reduce effects of disturbing factors.** Several field protocols are in development and have been published (IEEE P4005, GLOSOLAN Spec, EJP SOIL Probedfield, Ben Dor *et al.* 2024). Publication and further harmonisation where possible of these protocols will improve comparability of measurements, reduce the effects of disturbing factors such as soil moisture, roughness, presence of (dry) plant residues, etc.). With a widening range of instrumentation for in situ field measurements using infrared spectrometry becoming available, derivation of field protocols per instrument and (spectral) transfer functions and comparative studies will greatly advance the quality and applicability of techniques
3. **Improvement and predominantly standard application of spectral pre-processing to reduce moisture effects.** For in situ field application of soil spectrometry apart from a standard field protocol and possibly specific instrument and field soil spectral calibration libraries, much of the noise in the spectra caused by the presence of water can be removed by smart pre-processing techniques, such as EPO and compositional analysis. Results in literature are promising but this pre-processing may not be applied much in non-scientific applications yet.
4. **Development, testing and application of mid infrared in situ field instrumentation.** Mid infrared is chemometrically better able to estimate soil property concentrations than near infrared, due to the presence of distinct and specific absorption features in the mid infrared range of the electromagnetic spectrum. In the near infrared, the absorption features are often overtones of the absorption features in the mid infrared and less distinct. However, the development of good MIR in situ field instrumentation has proven challenging and only one or a few sensors are in commercial production at present as far as we know. Given the high performance of MIR in the lab (on finely ground soil), good quality in field instrumentation for MIR may be promising if possible to develop and test.

For gamma-ray spectrometry, two improvements are in development:

1. **The use of active gamma-ray spectrometry for soil bulk density measurements, either in situ in a soil auger hole or on an extracted core in the field.** Several proof of concept instruments and local validation studies for mineral soils are available but challenges still exist on stony and organic soils. Validation across geographies and for all soil types is needed, but the technique is promising because of its full profile assessment of bulk density, the potential measurement depth of up to 1 m depth, and its in-field measurement capability,
2. **Concerted efforts for creating an open soil gamma-ray calibration library for passive gamma-ray spectrometry measurements.** Like infrared soil spectroscopy, gamma-ray measurements also need calibration using a calibration dataset or library. The same conditions and principles as described above for soil spectroscopy apply. Current libraries are largely proprietary and not open. Patzhold *et al.* 2024 propose an initiative for an open soil gamma-ray library.

Other improvements that are in development, already applied or possible are combinations of the above techniques, penetrologgers and camera's, either in one instrument or several that can be applied rapidly at the same field location. Current existing combinations are penetrologger and camera, penetrologger and VNIR sensor, active gamma-ray sensor and soil moisture sensor. On extracted cores VNIR and active gamma-ray.

For all current, improving and new techniques and combinations a successful implementation in MRV systems requires sufficient or high accuracy and reasonable to low cost. A lower accuracy can be compensated by small measurement times, since then many less accurate measurements can be performed and averaged or combined in such a way that the error is lowered and the overall accuracy increases.

The availability of these existing and improved in situ data acquisition techniques, their calibration and validation varies a lot globally. There are geographies where all techniques are readily available, calibrated and validated and there are geographies where no or hardly any techniques are readily available, calibrated or validated. To improve the implementation of MRV worldwide, the availability, calibration and validation of these techniques should be improved.

8.1.2 Improvement of the Tier 3 models and SQPs for monitoring SOC

As already mentioned in the Executive summary, none of the current models or SQP meet all the CIRCASA's project requirements in terms of monitoring and each modelling approach has its pro and cons as shown in Table 1 of Section 5.3.3.3.

For instance, the CIRCASA project recommended a **multi-model ensemble approaches** (and multi-Tier approaches) but none of the current SQPs (see Annex 1) propose that. Multi-model ensembles (MME) can be used to improve SOC assessments and avoid over-calibration risks associated with single models. An inter-comparison exercise by Ehrhardt *et al.* (2018) shows the potential of ensembles of crops and pasture models to simulate N₂O fluxes and yields at a range of long-term field sites. Similarly, ensemble simulations for carbon fluxes have been assessed by Sándor *et al.* (2020) and for SOC in Farina *et al.* (2021), Riggers *et al.* (2019) and Bruni *et al.* (2022). The multi-model ensemble approach can be an effective strategy to reduce model structure uncertainty. This approach could be particularly beneficial in contexts where individual models are not adequately calibrated for

specific pedo-climatic and management conditions. However, it still requires a proper evaluation of the multi-model performances against observation data to validate the multi-model in this context and conditions (see next Section). In a near future the AgriCarbon-EO pre-operational processing chain will have several soil models embedded and coupled to the SAFYE-CO₂ vegetation model (see Section 2.1 of Annex 1).

Another potential area of improvement concerning Tier 3 approaches concerns the initialisation of SOC compartments. Indeed, first order kinetic soil models (such as RothC, AMG, Century) need information on SOM structure and stability to initialise carbon pools distribution according to their turnover rate which strongly limits their accuracy on a large scale with limited resource conditions. The spin-up method is the most common approach to initialise models (Dimassi *et al.* 2018), but its assumption of SOC equilibrium is often unrealistic, particularly in carbon farming contexts or fields that have undergone recent land-use changes (Luo *et al.* 2017; Kanari *et al.* 2022). In some models like AMG, a default value can be used to initialise the carbon pool sizes (stable and active) based on the long-term history of the field (cropland or grassland) (Clivot *et al.* 2019; Saffih-Hdadi and Mary 2008), but their accuracy is limited in dynamic environments with recent land-use transitions.

In order to **reduce the uncertainty of SOC estimates due to pool initialisation**, further approaches involve **aligning measurable SOC fractions with the different conceptual pools** of RothC, for instance (Skjemstad *et al.* 2004, Herbst *et al.* 2018; Poeplau *et al.* 2018) or SOC thermal stability analysis from RockEval® method for AMG (Cécillon *et al.* 2021; Wang *et al.* 2023). While increasing the cost of MRV with additional measurements, these methods can increase the accuracy of the SOC stock change prediction and be implemented on soil monitoring network to explore their potential before using more complex models, as suggested in Kanari *et al.* (2022). In a NDC MRV context, the integration of cost-effective measurement techniques to initialise SOC model pools, such as those applied in Australia's FullCam framework (see Section 1.2.2 in Annex 1), may provide scalable solutions for SOC stock changes accounting at regional and national levels of MRV for croplands.

The CIRCASA project also recommended **SOC monitoring at high resolution which often implies assimilating of EO data in parsimonious crop model or the use of biomass estimates derived from remote sensing as inputs for soil centred approaches**. However, the previous sections showed that it is not always possible to rely on EO data (e.g. if the fields are too small). In an operational MRV context (e.g. AEPs, VCM) involving carbon credits or subsidies, the choice of the monitoring method to implement will often be a compromise between accuracy, cost of monitoring but also complexity, and availability of data. Currently, two approaches seem particularly promising. The soil-centred approach that is simple and moderately expensive to implement, allowing consideration of a wide range of crops and practices. For that approach, one of the main sources of uncertainty, the estimation of biomass returned to the ground, could be reduced by using aboveground crop/cover crop biomass estimated by remote sensing for fields compatible with EO (see Section 5.3.3.1.3). It will require the development of methods combining ML and EO (as in do Nascimento *et al.* 2024) or methods based on EO assimilation in parsimonious crop models.

A second approach that seems very promising for monitoring SOC in an operational context, is the parsimonious modelling approach assimilating EO data. However, one of its main limitations is the low diversity of crops currently simulated by models in this category (e.g. SAFYE-CO₂). A significant effort of parametrisation, calibration and validation in different pedo-climatic contexts is therefore necessary in the short term. This action could rely on existing observation networks such as regional (e.g. ICOS, OZflux) or international flux tower networks (FLUXNET) but additional data in the field (e.g. biomass, yield) are necessary for this type of approach as highlighted by, for example, Claverie *et al.* (2012), Pique *et al.* (2020) or Wijmer *et al.* (2024).

Whether for the estimation of biomass produced/returned to the ground for the soil-centred approach or for the parsimonious modelling approach assimilating EO data, one of the main obstacles to the development of these approaches is the lack of *in-situ* dataset of dry aboveground biomass acquired with protocols dedicated to the calibration/validation work of remote sensing-based approaches, namely ESUs (for Elementary Sampling Unit, see Claverie *et al.* 2012) which allows to obtain a dry aboveground biomass measurement representative of a selected satellite pixel. This point will be discussed further in Section 8.1.1.3 here below.

“Off-the-shelf” ecosystem modelling approaches could also benefit from EO data assimilation methods that would allow them to reproduce the intra-fields spatial variability in crop/cover crop development and therefore in biomass restitution to the soil. Another method could consist in correcting a posteriori the model’s output by considering the vegetation development spatial patterns observed in the field by EO.

Yet **whatever the modelling approach concerned by EO data assimilation**, another big constraint is the availability of cloud free optical images allowing to observe the surface. Relying only on optical remote sensing data (Sentinel 2, Landsat 8, Planet...) can be limiting for operational applications when long cloudy periods occur. To address this issue promising approaches are to **combine optical satellite data with radar** (SAR, e.g. Sentinel 1) satellite data, that are little sensitive to cloud cover, to fill gaps in vegetation indices time series (e.g. Allies *et al.* 2021; Garioud *et al.* 2021) or to produce biomass proxy to be assimilated in addition or instead of LAI (e.g. Revill *et al.* 2013; Fieuzal *et al.* 2017; Baup *et al.* 2019; Allies *et al.* 2022).

Among the other ways of improving current monitoring tools for SOC, we also propose to consider:

- Expend the domain of validity of some of the models so that all territories can benefit from a Tier 3 approach,
- Expend the monitoring approach to other agro-ecosystems and to organic soils. This action has already been initiated in the European MARVIC project that also aims at adapting the MRV framework and decision tree presented in this document to agroforestry, grasslands, and arable land on organic soils.
- Systematic conservative uncertainty assessments in SQPs including uncertainty analysis on activity data and their propagation,
- Improvement on EO assimilation techniques and multi-domain assimilation techniques taking benefit from the forthcoming satellite missions (e.g. Trishna⁶⁰, CHIME⁶¹); see Section 4.2.3 for more details,
- Connexion with new data streams like Farm Management Information Systems (FMIS) and developing the procedures and tools (e.g. AI) for verifying the quality and the consistency of activity data in FMIS,
- Developing monitoring tools that can be applied in different contexts of MRV, in order to ensure consistency between the SOC stock change assessments performed in those different contexts and to allow the building of a consistent and unique field level carbon registry. Doing so would allow for instance to create a hybrid scheme where a farmer would get a part of the payment based on actions to increase SOC stocks as well as payments based on results. In such a hybrid scheme, the farmer and policy body share the risk of non-delivery. In a result-based scheme, the farmer bears the full risk, and in an action-based scheme, the policy body does. In a hybrid scheme, the action-based and the result-based approach together form the full payment. So, the land-owner commits to the desired practices, plus there is an incentive to do more and use creativity to store more carbon in the soil.

⁶⁰ <https://cnes.fr/en/projects/trishna>

⁶¹ <https://sentiwiki.copernicus.eu/web/chime>

- Last, with the development of data driven approaches (see Section 5.3.4), it is very likely that both hybrid modelling approaches combining for instance ML and process-based modelling and surrogate models will develop. Although it raises many questions including concerns about transparency, those approaches that are developing rapidly in the climate science community (Bocquet 2023) may allow to reduce substantially the computation time of the SQPs.

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) as discussed in the next section.

Finally, keep in mind that the change in practices associated to increased SOC may also result in indirect changes in SOC in other locations. For example, if the production decreases compared to the reference, the increase in agricultural land may lead to loss of SOC elsewhere. Those issues related to carbon leakage will be addressed in Deliverable 4.4 of the ORCaSa project.

8.1.3 Improving models and SQPs evaluation

As mentioned in Section 4.2.4, in the vast majority of cases, the soil or ecosystem models used for SOC monitoring and sometimes integrated into SQPs have been developed, calibrated and validated based on long term experiments (LTEs) such as the Rothamsted trials and sometimes based on SOC monitoring networks (e.g. LUCAS in Europe; see Orgiazzi *et al.* 2018) or on flux tower networks (e.g. Fluxnet). However, compared to an operational use in a MRV context it may be an issue: indeed their development conditions, calibration and validation are not necessarily representative of the conditions for implementation in commercial farms, due to problems with soils representativeness, practices, varieties, but also because their calibration/validation was carried out on the basis of accurate data of practices, soil properties, biomass returned to the soil while the accuracy of these information will necessarily be degraded in an operational context. As a result, the models that perform best in an experimental context will not necessarily be the same in an operational one.

So, if those experimental trials or instrumented sites are very useful, for developing and evaluating some of the building blocks (e.g. soil models, ecosystem models) of the SQPs, too few models/SQPs evaluation rely on a more comprehensive assessment of the components of the carbon cycle (biomass, CO₂ fluxes...) and of the resulting SOC stock changes and too few assessments have been done in an operational context of monitoring (Nevalainen *et al.* 2022; Popkin 2023; Wijmer *et al.* 2024). In order to do so, regional observatories combining soil and vegetation sampling at commercial farms, flux measurements with eddy covariance flux towers and surveys on field management such as the Regional Space Observatory⁶² and the Field Observatory Network⁶³ are extremely valuable. It is clear that at present, except for fields equipped with flux towers (e.g. ICOS network in Europe), which represent a very limited number of fields in the world for cropland, there is no regional or global observation network collecting data to monitor SOC stocks changes, but also biomass and management data allowing to interpret the evolution of SOC stocks. Even at soil monitoring networks like LUCAS, lack of data on management and biomass inputs to the soil which means that the SOC trends observed at those sites cannot fully be interpreted/understood and therefore their use to develop, train or evaluate models is limited or requires strong assumptions. **This calls**

⁶² <https://osr.cesbio.cnrs.fr/en/homepage-english/>

⁶³ <https://www.fieldobservatory.org/index.php/about/>

for the deployment of an international network to monitor SOC, biomass and management practices at commercial farms allowing to evaluate models/SQPs in an operational context of MRV (See section 8.2).

The areas monitored at those commercial farms could be a square of a few decametres by a few decametres (e.g. 20 x 20 m) compatible with the ESU protocols (Claverie *et al.* 2012) used to calibrate/validate EO based estimates of biomass. Preferably, this network would be built on existing soil monitoring networks like LUCAS or on EO monitoring networks like JECAM⁶⁴.

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.

Finally, note that it is unfortunate that data from sites equipped with flux towers are so seldom used by the community of modellers and developers of SQPs to assess the capacity of models (soil or ecosystems) and of SQPs to reproduce the dynamics of CO₂ fluxes and of SOC. Data from these sites acquired at short intervals (e.g. semi-hourly, daily) could for example allow to evaluate the ability of these models to reproduce the dynamics of the heterotrophic respiration (e.g. by using data during bare soil periods) or even to improve their formalisms (e.g. to simulate the priming effect).

8.1.4 Accounting for the net climatic effect of CF practices and assessing other agri-environmental impacts

Of course, as recalled by the International “4 per 1000” Initiative⁶⁵, storing carbon in the soil is not an end in itself but rather a lever to encourages stakeholders to engage in a transition towards a regenerative, productive, highly resilient agriculture that reduces its environmental impacts, based on appropriate land and soil management, which creates jobs and income and thus leads to sustainable development. Therefore, MRV of SOC should serve the purpose to show that agriculture can provide concrete solutions to the challenge posed by climate change while meeting the challenge of food security through the implementation of agricultural practices adapted to local conditions.

One of the key elements to verify is whether or not the CF practices have a net climate mitigation effect. Indeed, changes in practices associated to increased SOC compared to a reference may result in direct or indirect increase in GHG emissions. That’s why, for applications ranging from carbon offsetting, to low carbon sourcing of agricultural commodities and low carbon policies in agriculture, soil carbon monitoring is required as well as the associated estimation of the GHG budget at field and farm scales. For instance, the European Carbon Removal Certification Framework Regulation (CRCF), which aims to facilitate and promote sustained reductions in greenhouse gas emissions introduces an EU-wide voluntary framework for the certification of carbon removals and soil emission reductions on the voluntary carbon market. Quantifying other GHG emissions, *i.e.* N₂O and CH₄ at field scale was also a strong recommendation of the CIRCASA project. So even if the scope of the ORCaSa project was on SOC only, assessing the full GHG budgets of fields and farms is critical and accounting on GHG emissions in the MRV framework and decision tree that we proposed in this document are key priorities that will be addressed in the

⁶⁴ <http://jecam.org/>

⁶⁵ <https://4p1000.org/?lang=en>

MARVIC European project⁶⁶. Some of the current ecosystem models and SQPs like COMET-Farm (see Section 1.1 of Annex 1) already propose field and farm scale GHG budget estimates. Other tools like Carbon Extract (see Section 1.3 of Annex 1) aim to quantify the GHG emissions of farms (buildings, machines, etc) and to assess the capacity of the fields to store carbon in the soil by simulating the impact of CF practices while evaluating the associated costs (and generated carbon credits), however they do not simulate N₂O and CH₄ emissions of the soil based on process-based modelling.’

Yet **assessing GHG emissions and SOC storage is not enough to evaluate the net climatic effect of CF practices, their mitigation potentials in terms of radiative forcing has to be calculated.** To do so, the different life times and global warming potentials of the GHGs have to be accounted for as well as the **impacts of the CF practices on non-radiative effects (Bright *et al.* 2017) and on the changes in land surface albedo that can have as much impact on the net radiative forcing than the SOC storage effect of those CF practices** (Genesio *et al.* 2012; Kaye and Quemada, 2017; Carrer *et al.* 2018; Lugato *et al.* 2020). In a recent study Pique *et al.* (2023), even alerted on the fact that carbon farming practices may not lead to a net cooling effect because of the drop in surface albedo following the soil darkening (with SOC content increase) if soils are not permanently covered once carbon farming practices have been implemented.

Unfortunately, as highlighted by Chen *et al.* (2024), the current climate models from the IPCC do not simulate the effect of agricultural management changes on surface energy fluxes (e.g. albedo) nor the effect of most CF practices on the SOC stock changes and GHG emissions of the land sector. As a consequence, over the last two decades methods have been developed in an attempt to convert the effect of surface albedo changes in CO₂ equivalent emissions (Bright *et al.* 2016). Although those methods have some limitations, recent studies (Kaye and Quemada, 2017; Carrer *et al.* 2018; Lugato *et al.* 2020) and EU projects like ClieNfarms⁶⁷ or MARVIC are using those methods to better assess the net climatic effect of CF practices.

Another important aspect to quantify the true mitigation potential of CF practices is the **assessment of permanence or of the risk of non-permanence of SOC storage**, e.g. because of climate change (Haas *et al.* 2022). For example, climate change can influence the biomass production of crops and cover crops, and thereby reduce the amount of carbon input to the soil. Changes in soil environmental conditions (e.g., soil moisture and temperature) due to climate change are also known to affect soil C mineralization dynamics and N₂O and CH₄ fluxes from managed soils. For those reasons, the EU MARVIC project will consider changing source or sink strength over time (i.e., potential non-permanence of carbon sinks), accounting for trade-offs by and the different life times of the GHG's and changes in surface albedo since the traditional approach of using GWP falls short when longer time scales are evaluated (Dommain *et al.* 2018).

Unfortunately, carbon farming practices may result in decreased 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.* 2020). 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 is also important to

⁶⁶ <https://www.project-marvic.eu/>

⁶⁷ <https://clienfarms.eu/project/>

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).

More generally, CF practices may impact other important dimensions (production, water quality, biodiversity, cultural heritage, landscape...) that are very relevant to analyse in the comparison of the no-action reference, but this is out of the scope of this document.

8.2 Alignment with other international initiatives and call for action to implement an international framework for MRV of SOC for cropland

As highlighted by ORCaSa's Deliverable 4.1 "International review of current MRV initiatives for soil carbon stock change assessment and associated methodologies"⁶⁸, and by Batjes *et al.* (2024), many different guidelines and methodologies relating to MRV exist (e.g. Oldfield *et al.* 2021; Arcusa and Sprengle-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).

On the basis of this observation, it appeared necessary to propose a harmonised methodological framework and a cookbook on how to implement it, building 1) on the conceptual frameworks from Paustian *et al.* (2019) and Smith *et al.* (2020), 2) on the recommendations from the CIRCASA's project⁶⁹ and on our own experience of mapping soil properties (e.g. SoilGrids), of long-term soil and agricultural observatories⁷⁰ (involving EO, in-situ data of biomass, soil, CO₂ fluxes...) and of developing new modelling frameworks dedicated the monitoring of the carbon budget components in several MRV contexts (e.g. CAP with the H2020 NIVA⁷¹ project, offsetting with the MyEasyBiomass project⁷², insetting with the Naturellement popcorn⁷³ project...). As a result, we proposed a harmonised MRV methodological framework for cropland (see Section 4.2) that embeds a decision tree (see Section 5.4) We also ensured that they are also as compatible as possible with existing MRV methodological frameworks such as those recommended by the IPCC for NDCs (IPCC 2006), the one pre-defined for insetting (SBTi FLAG⁷⁴), the one currently being developed in Europe under the CRCF⁷⁵ for the VCM (e.g., on baselines), those recommended by the FAO, notably for grasslands (FAO, 2019; FAO GSOC-MRV Protocol 2020), the ones currently implemented by certification companies(e.g. Verra, Goldstandard), or the one proposed to extend the SOC's MRV approaches to the CAP (COWI, Ecologic Institute and IEEP, 2021). However, some discrepancies have been noted with the aforementioned frameworks: for example, the COWI, Ecologic Institute and IEEP (2021) report is strongly recommending measure-remeasure methodologies while we consider that in some contexts (e.g. insetting projects shorter than 5 years) modelling approaches should be preferred. Also, while we recommend field scale SOC monitoring, the FAO GSOC-MRV Protocol (2020) recommends considering intervention areas that may involve one

⁶⁸ <https://irc-orcasa.eu/wp-content/uploads/2024/07/ORCaSa-D4.1.pdf>

⁶⁹ <https://www.circasa-project.eu/document-library/deliverables/d3.1-strategic-research-agenda-sra-on-soil-carbon>

⁷⁰ <https://osr.cesbio.cnrs.fr/en/study-area/>

⁷¹ <https://www.niva4cap.eu/>

⁷² <https://www.myeasyfarm.com/en/communique-de-presse-myeasyfarm-myeasybiomass-cesbio/>

⁷³ <https://www.cesbio.cnrs.fr/agricarboneo/naturellement-popcorn/>

⁷⁴ <https://sciencebasedtargets.org/sectors/forest-land-and-agriculture>

⁷⁵ https://climate.ec.europa.eu/eu-action/carbon-removals-and-carbon-farming_en

or several fields, plots or paddocks, either within one individual farm or on different farms owned or operated by the same or different companies that are part of the same CF project. Yet our field based approach is compatible with the one proposed by FAO (2020) as field scale assessments can be aggregated at the scale of intervention areas.

Note that some of the rules and guiding principles considered in most CF schemes and in particular by the CRCF deal with issues that we didn't address in this document: additionality, managing risks such as the risk of overestimation of the mitigation effect due to uncertainty in the monitoring method, risk of non-permanence due to e.g., climate change...and of course other GHG emissions. Those issues are currently being addressed in other EU projects like the MARVIC project that will include assessment of GHG emissions in addition to carbon sequestration and that will adapt our MRV methodological framework to grassland, agroforestry and organic soils.

This project was also part of an ecosystem of MRV and carbon farming projects (e.g. Road4scheme⁷⁶, CarboSeQ⁷⁷ MRV4SOC⁷⁸, MARVIC), of international initiatives (e.g. 4 per 1000⁷⁹, Global Soil Partnership⁸⁰ and Soil Carbon International research Consortium) and of research and development programmes. In Europe, following the European Joint Programme on Soil⁸¹ (EJP Soil) that has just ended in 2024 and that has financed many projects related to SOC and SOC monitoring, the European Union has launched the Mission "A Soil Deal for Europe"⁸² programme in 2021. This new program will fund 10 to 15 projects every year on topics related to soil health, soil carbon and related topics. Many of the research done, techniques, models, data acquisition, data management and earth observation methods developed and improved can contribute to improve components of the MRV framework. Also, one the main goal of the Mission 'A Soil Deal for Europe' is to establish 100 living labs and lighthouses to lead the transition towards healthy soils by 2030 (e.g. LILA4SOILS). Also, in 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.

Because of this diversity of MRV tools/SQPs, schemes, projects, programmes and initiative, the ORCaSa team and the Soil Carbon International Research Consortium ((IRC) launched in November 2023) community call for the following actions:

- 1) **The deployment of an international network to evaluate models/MRV tools/SQPs in an operational context.** Such an international network would allow not only to monitor SOC stock changes but also other carbon budget components (e.g. biomass, yield, CO₂ fluxes) and the management practices in real life conditions, i.e. at commercial farms building on existing networks such as the European LUCAS⁸³ soil monitoring network in Europe and the international flux tower network FLUXNET⁸⁴.
- 2) **A collaborative effort between public research and the private sector to build scalable and practical multi-context MRV tools/SQPs.** Both public and private actors need to be involved in conceptualising and developing transparent, robust and tailored to regional contexts MRV tools/SQPs. Those should also be cost-effective and robust, with public research taking responsibility for model development, calibration, and validation, while the private sector integrates these models into end-user platforms. The end-user

⁷⁶ <https://ejpsol.eu/soil-research/road4schemes>

⁷⁷ <https://ejpsol.eu/soil-research/carboseq>

⁷⁸ <https://mr4soc.eu/>

⁷⁹ <https://4p1000.org/>

⁸⁰ <https://www.fao.org/global-soil-partnership/en/>

⁸¹ <https://ejpsol.eu/>

⁸² https://rea.ec.europa.eu/publications/what-eu-mission-soil-deal-europe_en

⁸³ <https://esdac.jrc.ec.europa.eu/content/lucas-2018-topsoil-data>

⁸⁴ <https://fluxnet.org/>

platform should be user-friendly to make it easy for farmers to use and increase their acceptance, and it should limit the time needed to embed data. This will help ensure wide adoption across various farming systems. The MRV tools/SQPs should be multi-context to ensure consistency between the different SOC stock changes assessment (e.g. for the NDCs and for the VCM) and it should allow plot scale assessment in order to build a unique spatially explicit carbon registry allowing to avoid double counting of SOC stock changes and of carbon crediting, but also offering the flexibility to combine practice-based (e.g. through agri-environmental measures such as in the CAP) and result-based payment (i.e. through the VCM) to ensure enough income for the farmer and to de-risk his transition towards carbon farming practices.

- 3) **MRV tools should link carbon sequestration with agronomic strategies.** Effective soil carbon transition can only be achieved when addressing the entire farm and whole crop rotation. The MRV tool should include a decision support system linking carbon sequestration with agronomic strategies, enabling farmers to manage and track their transition at the farm level. If farmers are expected to adapt to a different cropping system, there needs to be an understanding of the power dynamics in the MRV value chain between farmers and cooperatives and the agri-food industry.
- 4) **MRV tools should be tailored to regional contexts, considering cultural, political, and economic differences.** There are regional differences (cultural, political, economic, etc.) that need to be accounted for when conceiving of a harmonised global MRV framework. That's why the MRV framework has to be flexible enough to be adaptative to regional contexts and MRV tools should be tailored to those regional contexts. This implies understanding the power dynamics in the MRV value chain and ensuring that farmers and local stakeholders are adequately supported. Policymakers should address economic and policy barriers by providing guidance on the quality of methods and ensuring proper implementation.
- 5) **Enhance research and knowledge sharing through international collaboration.** International collaboration is key to advancing soil carbon research and policy. The Soil Carbon International Research Consortium⁸⁵ should continue to facilitate knowledge sharing and cooperation through platforms like Impact4Soil⁸⁶ and regional nodes. Capacity building is also key to ensure MRV tools and data resources are handled properly. An effective MRV framework is not just about selecting the best model or modelling approach, but agreeing on how it is used to ensure the desired results. The Soil Carbon IRC should also promote research alignment and foster collaboration among stakeholders.

To facilitate and coordinate the accomplishment of some of these actions, the Soil Carbon IRC proposes 3 core services and one of them is dedicated to MRV approaches. It shall include the 3 following components:

- 1) **Assessing and labelling MRV methodologies (consultancy service).** The Soil Carbon IRC could be a global assessor (like a label) and provide written scientific and validated guidelines to signal that methods/models/SQPs are scientifically robust. This service would evaluate and label current and new MRV building blocks (e.g. soil model), components (e.g. monitoring tool) or methodologies according to criteria that shall be decided by the IRC expert group. This service could also provide tailor made guidance to end users concerning: 1) monitoring and verification methods/tools that are adapted to their local context (e.g. pedoclimatic conditions, practices), 2) carbon farming scheme (e.g. Low Carbon Label in France), 3) certifiers (e.g. VERRA, Goldstandard), 4) purpose of MRV (e.g. for national inventories, voluntary C market.). The IRC Steering Committee would decide on the constitution of the expert group with the advice

⁸⁵ <https://irc-orcasa.eu/join-the-soil-carbon-irc/>

⁸⁶ <https://www.impact4soil.com/>

of the Scientific and Technical Committee and with the approval of the Ethics Committee in order to avoid any conflict of interest.

- 2) **Update an internationally agreed MRV framework (service for the community + consultancy service):** Building on ORCaSa's Deliverable 4.1 (Batjes et al. 2023) and on this document, the Soil Carbon IRC through a group of experts would regularly update methodological frameworks for each ecosystem. It would also aim at building a multi-ecosystem harmonized framework, in particular for the monitoring and verification components considering all the new technology developments. This service would rely on a group of international experts (nominated by the IRC steering Committee) representing the various ecosystems and stakeholders involved in MRV of Soil Carbon (NGOs, MRV developers, certification bodies, environmental agencies, agri-food companies, farmers and their representatives, researchers...). Those frameworks would be presented and discussed during dedicated events (seminars, workshops...) and the outputs of those events would take the form of guidelines for end users (e.g. FAO, 2019) and/or cookbooks on how to measure and model SOC stock changes and on how to verify them, considering different options according to cost/accuracy, data availability and local context...Another output of those guidelines/cookbooks would be recommendations on how to improve current methodologies that would allow to build a roadmap for research and innovation priorities at international level based and develop joint flagship initiatives thereby maximizing complementarities and avoiding duplication of efforts. While initially focusing on carbon only, this service should progressively expand to address also other GHGs and climatic impacts following land use changes (e.g. albedo effects). The different documents, data, reports, guidelines and cookbook used or produced by the expert group would be available through an online knowledge platform.
- 3) **Assessing and developing multi-ecosystem MRV building blocks and processing chains (Consultancy + Training service + software development):** This service would analyse and assess MRV tools, models and SQPs based on field data (see point above concerning international monitoring network for MRV). It would test, improve current models/methods/tools/building blocks/SQPs or develop new ones. Those developments could benefit for instance from new data streams (e.g. new satellite missions, automatic access to farmer's activity data with APIs) or building blocks (e.g. hybrid approaches combining AI and process-based models) or observation networks/databases. Finally, this component of the MRV service could manage or facilitate the access to some of the codes of the tools/models/SQP and would organise some training sessions.

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Glossary

Source: This list of terms has been derived from deliverable D4.1 (<https://doi.org/10.17027/isric-32Q1-2F50>)⁸⁷ and it has partly been updated based on the MARVIC's glossary (Lorand et al., 2025).

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.

Activity data: Includes information on agricultural practices, that is to say the different methods and techniques used in agriculture to grow plants. This includes dates and doses of seedlings, fertilizers, pesticides, soil tillage dates and depths, dates and rates of irrigation, harvest dates and part of the plant harvested, intercrop management, crop rotations...

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).

Assimilation: Data assimilation refers to a number of techniques aimed at using optimally all available information regarding a system, generally composed of a dynamic model (imperfect), a set of measurements (with noise) and an observation model (imperfect). The objective is to obtain a representation of reality (i.e. outputs of the model) taking into account all the features above.

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 6 in report itself). [Source: ORCASA]

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 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 CO₂ and CH₄, as well as N₂O. 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(ing): 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 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(ing): 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: A carbon registry is the central component of a carbon market trade, positioned between projects that store or offset carbon and buyers that purchase carbon credits. Its where carbon credits are tracked, managed, and traded. You might think of registries as the referees that oversee the carbon market process.

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)).

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].

CO₂ 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.

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.

Greenhouse gases (GHG): Gases that trap heat in the atmosphere. Carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), and fluorinated gases are the primary greenhouse gases. See also: Carbon Dioxide Equivalent.

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

Insetting: See carbon insetting.

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.

Model calibration: The process of comparing model predictions with measurements performed on the system to refine the set of model parameter sets and maximise the model fit compared to measured observations. [source: MARVIC Consortium (Lorand et al., 2025)].

Model Initialization: Process of setting the model state variables to reflect the initial state at the start of the model simulation. Usually conducted during a so-called model “spin-up phase”. [source: MARVIC Consortium (Lorand et al., 2025)]

Model Parametrization: The set of parameter values chosen are deemed suitable for model use in the specific domain of interest. [source: MARVIC Consortium (Lorand et al., 2025)].

Model prediction error: uncertainty in model predictions, as determined from comparison to direct measurements. Measurements used to determine model prediction error must be the same as those used to validate the model.[source: Verra VCS, 2023].

Model Validation: The process of evaluating the degree of model predictions uncertainty relative to measured data. In the case of SOC models, validation consists of in evaluating the level of agreement between model simulation and measured values on one or more SOC pools or of C fluxes. Model validation occurs after or in concurrence to model calibration, on either the same set of data (cross-validation) or on an independent dataset. [source: MARVIC Consortium (Lorand et al., 2025)]

Monitoring (M in Figure 6): 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: *standardised baseline* (e.g., considering the management practices/cropping or forest systems usually implemented in the region surrounding the farm) or *specific baseline* (e.g., considering the local soil properties and 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]

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 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.

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 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]

Radiative forcing: Radiative forcing (or climate forcing) is a concept used to quantify a change to the balance of energy flowing through a planetary atmosphere. Various factors contribute to this change in energy balance, such as concentrations of greenhouse gases and aerosols, and changes in surface albedo and solar irradiance. Source https://en.wikipedia.org/wiki/Radiative_forcing

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 6): 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 Low Carbon Label). 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 6): 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 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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Annexe 1: Examples of Scalable Quantification Platforms for MRV of SOC for cropland

In this Annex, we will illustrate different methodological approaches for the monitoring of SOC by presenting some example of Scalable Quantification Platforms. However for a more exhaustive inventory of MRV tools and their intercomparison (considering 48 criteria like geographical scope, etc.) please have a look at this study made by Deloitte for the 4 per 1000 initiative with the help of the ORCaSa project: <https://4p1000.org/mrv-systems-related-to-soil-health-and-the-4-per-1000-initiative/?lang=en>

1 Operational SQPs

1.1 COMET-FARM

1.1.1 General description

According to the COMET-FarmTM88 manual is a web-based greenhouse gas (GHG) accounting decision-support tool that can be used by farmers, ranchers, conservation planners, and more to run a full greenhouse gas assessment for carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O) from major on-farm emission sources, in addition to CO₂ removal into biomass and carbon sinks within the farm-gate. Implementing the methods outlined in the U.S. Department of Agriculture's (USDA) Methods for Entity-Scale Inventory⁸⁹ (henceforth referred to as the "USDA methods document" or the "Blue Book"), the tool allows users to input land management-related activity data to annual/perennial cropping, grazing, agroforestry, and forestry systems to compare business as usual, baseline management to one or more conservation scenarios.

COMET-Farm was created in parallel with and as a function of the peer-reviewed USDA Methods for Entity-Scale Inventory document. For estimations of soil carbon and GHG impacts for a management activity or conservation practice to be included in the COMET-Tools, clearly defined methods for GHG accounting need to be included in the methods document.

Users can access COMET-Farm via the graphical user interface (GUI) for all accounting activities and/or an application programming interface (API) for only cropland, pasture, range, orchard/vineyard accounting activity

Due to soil and weather data limitations, COMET-Farm can only be used within most regions of the contiguous United States. Regions with too rocky or cobbly soil types are unavailable for accounting in COMET. COMET-Farm is not designed to run analysis on urban agricultural systems.

COMET-Farm itself is entirely independent of the carbon markets and does not advise on credits nor answer questions in regards to carbon credits - COMET-Farm is solely an estimation tool. The methods defined in the

⁸⁸ https://comet-farm.com/COMET-Farm_Manual.pdf

⁸⁹ <https://www.usda.gov/sites/default/files/documents/USDA-Methods-Report-2024.pdf>

USDA methods document, and therefore in COMET-Farm, are not intended as an accounting framework for emission reduction crediting or trading.

As previously mentioned, COMET-Farm was developed in parallel with and as a function of the USDA methods document (aka the “Blue Book”). Each accounting activity in the tool can be associated with a chapter in this document. For estimations of soil carbon and GHG impacts for a management activity or conservation practice to be included in the COMET-Tools, clearly defined methods for GHG accounting need to be included in the methods document.

Concerning cropland, the method relies on the use of the DayCent model to estimate changes in soil-related emissions and direct nitrous oxide emissions resulting from management practices such as planting dates, tillage, and fertilizer application. Emission estimates will only relate to soil-related emissions and direct nitrous oxide emissions within the defined entity or entities.

Soil-related emissions, or those captured in the cropland/pasture/rangeland/orchard/vineyard accounting activity are calculated through the DayCent model, a daily time-step version of the CENTURY biogeochemical model. COMET-Farm switched from the 20cm to 30cm DayCent model in 2022 to align with the national inventory. As the principle soil carbon and direct nitrous oxide estimation model in the tool, DayCent runs simulations about how crops are grown and about how nitrogen and carbon cycle through the soil and the ecosystem. The model also simulates data like how specific crops are harvested, how crop residue decomposes, and how carbon fluctuates between sources and sinks as a result of physical properties of the soil (such as temperature and moisture). COMET-Farm and DayCent pull from the SSURGO soil database and the PRISM weather dataset to drive the model. All the information driving the model comes from a dataset developed from peer-reviewed studies from over 200 sites, going back 170 years, and is maintained by universities and private corporations.

In the cropland accounting activity, the DayCent and COMET-Farm models are going to run on every soil map unit included in a project to provide a weighted average in the report. The more map units included in a project (greater number of fields or greater acreage), the longer it will take for a report to be generated. Because DayCent is only run in the cropland module, all the other reports (animal agriculture, agroforestry, and forestry) should be generated within no more than 30 seconds. See <https://www.usda.gov/sites/default/files/documents/USDA-Methods-Report-Chapter-3.pdf> for more details.

1.1.2 DayCent in COMMET-Farm

Soil-related emissions, or those captured in the cropland/pasture/rangeland/orchard/vineyard accounting activity are calculated through the DayCent model, a daily time-step version of the CENTURY biogeochemical model. COMET-Farm switched from the 20cm to 30cm DayCent model in 2022 to align with the national inventory. As the principle soil carbon and direct nitrous oxide estimation model in the tool, DayCent runs simulations about how crops are grown and about how nitrogen and carbon cycle through the soil and the ecosystem. The model also simulates data like how specific crops are harvested, how crop residue decomposes, and how carbon fluctuates between sources and sinks as a result of physical properties of the soil (such as temperature and moisture).

COMET-Farm and DayCent pull from the SSURGO soil database⁹⁰ and the PRISM weather dataset⁹¹ to drive the model. All the information driving the model comes from a dataset developed from peer-reviewed studies from over 200 sites, going back 170 years, and is maintained by universities and private corporations.

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1.1.3 System boundaries

COMET-Farm is designed to do an entire greenhouse gas inventory within an entity as defined by the user. The boundaries of these entities are important to the interpretation of results because they will include the GHG emissions and carbon sequestration occurring onsite for the management practice of interest. These entities should fall into one of COMET-Farm's four accounting modules: cropland/pasture/rangeland/orchard/vineyard, animal agriculture, agroforestry, and forestry. Entity boundaries include physical boundaries (e.g., actual field boundaries), temporal boundaries (e.g., one year of management for an animal production system), activities boundaries (e.g., land-based activities such as tillage and harvest), and material boundaries (e.g., the assessment of the three main GHG associated with agriculture). The COMET-Farm report will not address any upstream, downstream, or indirect offsite emissions such as from manufacturing or transportation. These emissions can instead be accounted for in COMET-Energy⁹².

The accounting activities in COMET-Farm are entirely separate from one another and do not “talk to” or interact with each other. This means, for example, that even if a grazing event is included in the cropland section of the tool, any enteric emissions from the grazing livestock must be accounted for separately in the animal agriculture module. Greenhouse gas emissions and reductions from each of these accounting activities are also presented as separate reports, even if they are included in the same project.

1.1.4 Geographic limitations

Due to soil and weather data limitations, COMET-Farm can only be used within most regions of the contiguous United States (lower 48). Regions with too rocky or cobbly soil types are unavailable for accounting in COMET-Farm due to the lack of soil data. The tool is not designed to run analysis on urban agricultural systems and will throw an error if non-agricultural lands (housing or water) are included in defined fields or stands.

Assessments of conservation practices in Alaska and Hawaii have limited availability in COMET-Planner⁹³. Regions outside of the United States can be assessed using COMET-Planner Global⁹⁴. See the Other COMET-Tools section⁹⁵ for more information.

⁹⁰ <https://www.nrcs.usda.gov/resources/data-and-reports/soil-survey-geographic-database-ssurgo>

⁹¹ <https://prism.oregonstate.edu/>

⁹² <https://comet-farm.com/quick-energy>

⁹³ <http://comet-planner.com/http://comet-planner.com/>

⁹⁴ <https://comet-planner-global.com/home>

⁹⁵ https://comet-farm.com/COMET-Farm_Manual.pdf#h.644slk8skamp

1.2 Australian National Scale carbon accounting methods

1.2.1 General description

A summary of key approaches used for the Measurement, Monitoring, Reporting and Verification (MMRV) of SOC stocks assessment in Australia is presented in Table 1. These approaches are vital for carbon farming projects and for national-scale accounting. National-scale accounting forms the foundation of Australia's National Inventory Report (NIR), which is annually submitted to the United Nations Framework Convention on Climate Change (UNFCCC). The carbon farming project approach summarised in Table 1 was primarily developed by the Australian Government, with detailed information provided in the Australian Government, (2021). The following sections focus on SOC monitoring and accounting at the national scale, particularly within agricultural systems, such as croplands and pastures production systems, classified under the NIR as cropland remaining cropland and grassland remaining grassland, respectively. Subsequent sections of this note will provide an overview of the two national-scale SOC stock assessments applied to agricultural production systems in Australia. They are based on the Full Carbon Accounting Model (FullCAM) framework (Richards and Evans, 2004) and IPCC Tier 2 steady state model.

Table 2. Comparison of the key approaches used for measurement, monitoring, reporting and verification of the soil organic carbon stock changes across the agricultural systems in Australia

Scale	Model name	IPCC model classification	Depth support	Application
Carbon farming project	Measurement, measure-model (model agnostic)	Direct measurement/Tier 3	0-x cm	Australian Carbon Credit Unit (ACCU) scheme
National	FullCAM	Tier 3	0-30 cm	UNFCCC reporting as part of integrated vegetation, soil, and fire modelling for the LULUCF sector
National (selected sites)	Modified IPCC Tier 2 Steady-State model (2019)	Tier 2	0-30 cm	Validating FullCAM estimates

1.2.2 FullCAM

FullCAM is a hybrid modelling tool that integrates SOC dynamics in agricultural and forest systems. It uses yield and biomass datasets generated from a simple water-balance-based growth model (Unkovich *et al.* 2018) to

simulate crop and pasture growth patterns. Activity data such as crop types, tillage practices, and stubble management are collected at the Statistical Area 2 (SA2) administrative level using surveys and published datasets. The FullCAM framework integrates growth functions, biomass allocation, land management activity datasets, and the decomposition of carbon inputs into soils using calibrated model parameter values. It enables the estimation of carbon flows to the soil from plants to debris pools under various management practices. An overview of the FullCAM modelling framework carbon flow into soils is depicted in Figure 40 Details on the FullCAM modelling framework is found in Australian Government, (2024).

FullCAM incorporates the Rothamsted Carbon Model (RothC) to simulate SOC turnover. In the RothC model, SOC is categorised into five distinct conceptual pools: decomposable plant material (DPM), resistant plant material (RPM), humus (HUM), microbial biomass (BIO), and inert organic matter (IOM) (Coleman *et al.* 1997). The model considers SOC cycling rates influenced by soil clay content, temperature, and moisture.

FullCAM simulations are performed at a 25 m spatial resolution, with input data aggregated from multiple scales/spatial supports. Yield, biomass, and management activity datasets are collected and made available at the SA2 administrative level, while climate inputs are sourced from 1 km gridded monthly raster datasets (Australian Government, 2024). Soil inputs, including clay content and the fractions of particulate organic carbon (POC), humus organic carbon (HOC), and resistant organic carbon (ROC), are available at a 90 m spatial resolution (Viscarra Rossel *et al.* 2014a; Viscarra Rossel *et al.* 2019). The measured SOC fractions are used to initialise RothC model sub-components within the FullCAM framework by matching the conceptual pools of the RothC model, namely RPM, HUM, and IOM, with POC, HOC, and ROC, respectively. This approach contrasts with the traditional method of generating initial SOC pool datasets by running the model to equilibrium to achieve a steady-state condition, as is commonly done in process-based modelling. The model decomposition parameters were calibrated to the Australian conditions using temporal SOC measurable fraction datasets (Chappell and Baldock, 2017).

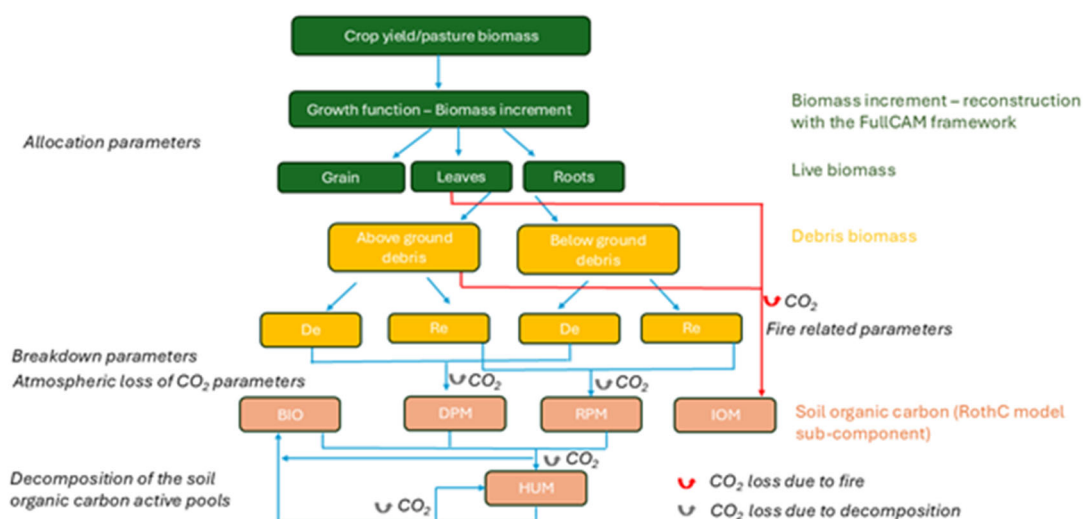


Figure 39. Overview of the FullCAM modelling framework used to simulate carbon flow within agricultural production systems in Australia. Note: De: decomposable plant material; Re: resistant plant material.

Although FullCAM simulations operate at a high spatial resolution (25 m), input data are derived from diverse spatial and temporal scales for agricultural systems, and model outputs are generated at monthly intervals. For example, yield, biomass, and management activity datasets such as crop type, tillage, and stubble management originate from the SA2 administrative scale with varying spatial and temporal resolutions. To address these inconsistencies,

FullCAM proportionally allocates combinations of crop, stubble, and tillage management practices across the SA2 region for a considered period/epoch. While this approach may result in sub-optimal estimates for specific locations, it ensures regionally representative estimates.

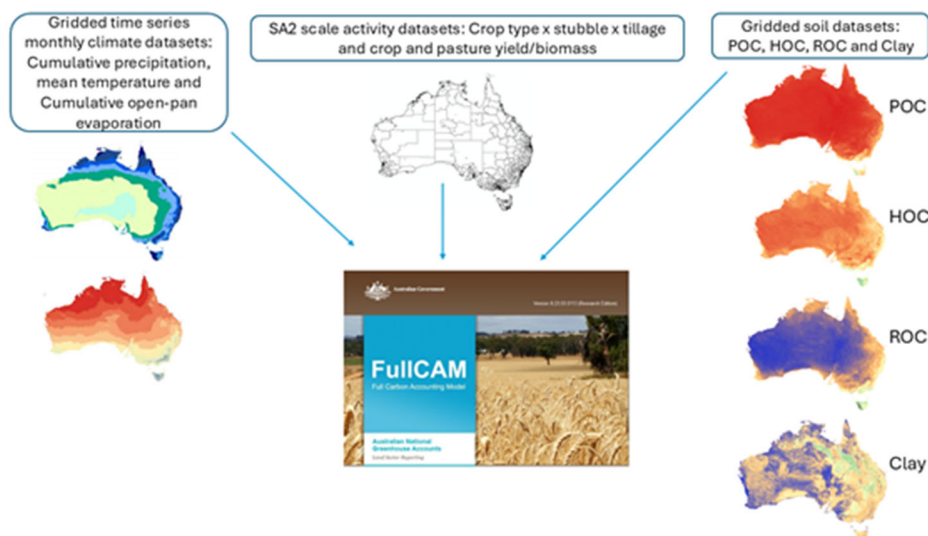


Figure 40. Key model inputs that govern the FullCAM framework simulations for the agricultural production systems

Unlike the default RothC model, which lacks explicit plant growth and debris components sub-models and represents management impacts solely through calculated carbon inputs, FullCAM framework integrates and models plant growth and land management dynamics but lacks feedback interaction between plant-soil modules. This integration enables a comprehensive evaluation of management practices on SOC turnover and dynamics, supporting national-level SOC change estimates. The FullCAM framework offers valuable insights into SOC changes, underpins inventory reporting, and informs sustainable land management practices at both regional and national scales. Figure 41 illustrates the key model inputs that drive the FullCAM modelling framework in the agricultural systems.

1.2.3 Modified IPCC (2019) Tier2 Steady-state method

The 2019 IPCC refinement introduced the Tier 2 steady-state model (T2SSM), an intermediate methodology for estimating SOC stock changes in the 0–30 cm soil layer for croplands. The T2SSM utilises climate, soil, and management data and can be adapted to transition towards Tier 3 modelling when detailed datasets are available. Its design draws on the Century ecosystem model, incorporating management impacts under specific soil and climate conditions, such as tillage practices and carbon inputs.

Initial testing of the T2SSM in Australian agricultural systems highlighted limitations with the default initialisation method. Karunaratne *et al.* (2021) addressed these issues by introducing an alternative approach that uses measurable SOC fractions POC, HOC and ROC to better align the conceptual pools with observable data. In Australia's NIR, T2SSM is currently applied across 1,795 sites distributed across the key agricultural production regions in Australia, and its results are used to assess the accuracy of estimated absolute SOC stocks and annual stock changes generated by the FullCAM framework.

A comparison between T2SSM and FullCAM estimates revealed strong agreement for absolute SOC stock values. However, SOC change estimates showed greater variability with T2SSM compared to FullCAM⁹⁶. Despite this, T2SSM effectively captured much of the inherent variability across the tested sites, similar to the variation in SOC stock changes captured using the Tier 3 FullCAM modelling framework. Currently, the T2SSM analysis is based on globally estimated parameters, and refining these model parameters to local conditions will further enhance the accuracy and applicability of the T2SSM to the Australian agricultural systems.

1.3 Carbon Extract

1.3.1 General description

Carbon extract is a carbon farming MRV digital tool that, in addition to MRV functions, runs simulation of carbon removals and GHG emission reduction at farm level. CarbonExtract is a tool designed to measure and support the reduction of the carbon footprint of farms specializing in arable crops. It has been specifically developed to meet the requirements of the Label bas-carbone (a French voluntary certification framework), to support farmers and their advisors in their transition to more sustainable agricultural practices. Certified compliant with the Arable Crops method, it allows for precise calculation of the main emission sources of farms.

The tool aims to quantify the greenhouse gas emissions of farms and assess their capacity to store carbon in the soil. By simulating the impact of new agricultural practices, it estimates the benefits in terms of emission reductions and increased carbon removal, while evaluating the associated costs and generated carbon credits. CarbonExtract also supports farmers in the commitment and monitoring of Label bas-carbone projects, offering a five-year practice planning and annual tracking of implemented actions.

1.3.2 Features

CarbonExtract offers an interface specifically designed to guide users through all stages of the low-carbon transition. It is structured into four complementary modules:

- Carbon Footprint Assessment: The first module allows for a comprehensive carbon footprint assessment of the farm, measuring greenhouse gas emissions and estimating soil carbon storage. This initial diagnosis serves as a reference to evaluate progress. Two baseline scenario options are available: a specific baseline, based on the average agricultural practices of the farm over the past three years, or a standardized baseline, based on average regional practices for farms without historical data.
- Simulation of New Practices: The second module enables multiple simulations to analyze the impact of new agricultural practices. Users can explore different scenarios, calculate expected emission reductions, estimate benefits in terms of carbon credits, and anticipate the costs associated with each proposed practice.
- Project Engagement: The third module facilitates engagement in a Label bas-carbone project. It offers a structured methodology to develop a five-year action plan, generating a detailed report that meets the

⁹⁶ <https://www.agriculture.gov.au/agriculture-land/farm-food-drought/natural-resources/soils/national-soil-action-plan>

administrative requirements of the certification framework. This module also includes necessary indicators to validate project commitment.

- Project Monitoring and Management: The fourth module ensures the monitoring and management of engaged projects. It allows for annual tracking of the progress of implemented actions, evaluating the evolution of greenhouse gas emissions and carbon storage compared to the initial plan, and adjusting strategies if necessary. The carbon trajectory is thus analysed over the five-year project period.

1.3.3 Advantages and limitations

CarbonExtract stands out for its comprehensive support from initial diagnosis to project monitoring. With its modern and attractive design, this tool allows testing different combinations of practices and identifying the best low-carbon transition scenarios. Using such a tool is essential to project potential carbon credit gains and strengthen the farmer's strategy.

The tool is also interoperable with agricultural traceability systems such as SMAG and Mes Parcelles, reducing data collection time. Furthermore, it is not limited to the carbon footprint alone, as it integrates co-benefit environmental indicators, particularly for biodiversity, water and air quality. CarbonExtract also includes a data aggregation feature for farms, simplifying administrative procedures for collective project leaders.

Comprehensive carbon footprint calculation tools require extensive data. Initial data collection can be time-consuming, although efforts are being made to make this step more efficient. Additionally, the carbon footprint assessment is conducted at the farm level, in accordance with the certification framework requirements. This approach does not yet fully meet the growing expectations of agricultural sectors, which seek tools capable of measuring impacts at both the crop and farm levels. Carbon removal, in particular, remains challenging to translate at this scale and is mainly evaluated at the crop rotation level.

1.4 Soils Revealed

Soils Revealed (soilsrevealed.org) shows time series of global maps of the topsoil organic carbon stock for the 2000-2018 period. The SoilGrids SOC stock map (soilgrids.org) was taken as a baseline for the year 2000, while SOC change between 2000 and 2018 was modelled with annual time steps using a Tier 1 IPCC approach. The platform also shows maps of the historic SOC stock change, that is a map that shows how much SOC was lost or gained as a result of humans' influence on soils in the last 12,000 years. In addition, several future scenarios were tested in which decisions about land management on SOC stock in the next 20 years are shown. These scenarios vary from cropland and grassland restoration to land degradation. The platform allows to toggle between SOC stock maps and SOC stock change maps, and has interactive analysis tools that support interrogating the data for specific areas and time periods.

2 Prototypes of SQPs

2.1 AgriCarbon-EO

2.1.1 General description

AgriCarbon-EO (Wijmer *et al.* 2024; Antonenko *et al.* 2024) is a pre-operational processing chain coded in Python (no graphic interface) developed for cropland at CESBIO since January 2020. AgriCarbon-EO (ACEO) was developed with the objective to simulate the components of the carbon and water budgets (biomass, yield, evaporation, transpiration, soil water content dynamics, photosynthesis, plant/soil respiration) and the SOC stock changes as well as their uncertainties at 10 m resolution over large areas (regions, countries). It has been developed in the objective of being able to apply it in different contexts of MRV: voluntary C market, inseting, NDCs, CAP.

The first building block consisted in developing a new parsimonious ecosystem modelling approach, allowing to reproduce the main processes that drive the cropland C and water budgets, with a level of complexity suitable for spatialised applications. It was achieved by taking benefit from EO assimilation in a parsimonious crop model to overcome as much as possible the need to collect farmer's activity data that cannot be reliably and systematically collected over large territories. The parsimonious SAFY-CO₂ (Pique *et al.* 2020a) and SAFYE-CO₂ (Pique *et al.* 2020b and c) crop models were therefore developed building on the original SAFY (Duchemin *et al.* 2009) model which only allowed estimates of aboveground biomass for crop and yield. In addition, SAFYE-CO₂ simulates evapotranspiration and the CO₂ fluxes over an entire cropping year and the assimilation process allows to detect automatically, and account for cover crop, weeds, spontaneous regrowth effects on the C and water fluxes/budgets (note that weeds & spontaneous regrowth can only be considered via an EO based approach). The model was parametrised and validated for the main crops and cover crops found in South West France (straw cereals, maize, sunflower, faba bean) and for the weeds/spontaneous regrowth developing during the fallow period based on the flux tower measurements and spatialised data of biomass and yield. This approach relying on the assimilation of LAI time series into the crop model dedicated to upscaling makes it possible to consider more accurately and objectively the temporal dynamics and the spatial heterogeneities of vegetation development and its consequences in terms of biomass production, CO₂/water) fluxes and C/water budgets. Through the assimilation process, the modelling approach implicitly accounts for many practices (e.g. sowing density, fertilisation...), stresses (N, water, temperature...) and pest/diseases effects on the crop/cover crop biomass production through the calibration of phenological, C allocation parameters and of the Light Use Efficiency (i.e. the ratio of photosynthesis versus absorbed light). Therefore, it is possible to avoid the collection of detailed farmer's activity data (date and density of sowing, fertilization, irrigation, etc.) since the model is constrained to reproduce the vegetation dynamics observed by remote sensing. It makes this modelling approach more easily spatialized and more objective than "off-the-shelf" agronomic models. Only activity data on straw management (i.e. how much straw is exported and when), organic amendments (i.e. date, dose, type) and irrigation (date, dose) are needed to calculate the SOC stock changes and water budgets with the soil modules.

Yet, this modelling approach was of moderate interest to the international scientific community because it suffered from four main limitations: 1) it was only tested/validated in South West France, 2) the calibration process was slow

as the assimilation scheme was based on a simplex approach, meaning that the model couldn't be applied to more than a couple of 1000 objects (plots on average or pixels), i.e. it was not possible to assess the intra plot spatial variability in crop/cover crop development at regional scales, 3) no uncertainty assessment and propagation in the modelling process was performed, and 4) an empirical function of temperature and soil water content was used to quantify soil respiration with the soil module meaning that the soil C pools dynamics were not simulated, disqualifying the modelling approach for long term assessment of C stock changes and for the carbon market. This choice of using originally an empirical approach was motivated by the lack of high-resolution soil properties products.

To meet the various challenges mentioned above and the limitations of the initial SAFYE-CO₂ approach, the AgriCarbon-EO V1.0.1 pre-operational processing chain (Figure 42) was developed by integrating several bricks, including the PROSAIL (Jacquemoud *et al.* 2009) radiative transfer model and the SAFYE-CO₂ model. This chain relies on several innovations including the parallelisation of the code and the development of the BASALT method of EO data assimilation that allows fast applications of the SAFYE-CO₂ model at high resolution, over large territories, with uncertainty assessment of each variable of interest (Bayesian approach to propagate errors) and all with very reasonable calculation times of the order of 10h for a simulation at French metropolitan scale (see Figure 2). Thus, from crop maps provided as input, ACEO automatically downloads soil property maps (e.g. LUCAS, SoilGrids or local data), climate data and high resolution EO data (e.g. Sentinel-2, Landsat-8) for the area of interest. Then it produces time series of LAI (and their uncertainty) by inverting the PROSAIL radiative transfer model. The LAI dynamics are then assimilated to calibrate for each pixel of the image the phenological and photosynthetic parameters of the SAFYE-CO₂ crop model. This approach provides a consistent sets of variables (Figure 43) and the quantification of the effect of climate, soil properties and practices (e.g. cover crops that are automatically detected, straw management) on biomass, yields, evapotranspiration, CO₂ fluxes and C budgets, as well as their uncertainties, at low cost and at 10 m resolution over large territories. The method was validated for wheat by comparing the outputs of the chain to different datasets: (biomass, yield, CO₂ fluxes) collected at the RSO (<https://osr.cesbio.cnrs.fr/>) and it has successfully been evaluated for wheat and other crops or cover crops (maize, rapeseed, sunflower), tomato and white mustard (Ihasusta *et al.* in prep) and faba bean and phacelia (Wijmer *et al.* in prep) along large pedo-climatic gradients by using data collected at several flux tower sites in Europe or by collaborating with agricultural councils, cooperatives (e.g. Agrod'OC) and private companies (e.g. Nataïs, MyEasyfarm, Airbus). This process of integrating new crops and evaluating the model in various context is a continuous process (e.g. collab. with UNICATT in Italy in the Horizon ClieNfarms project). Recently, the AMG soil model (Clivot *et al.* 2019) was integrated into ACEO V2.0 for simulating changes in soil C stock and C pools. The outputs of SAFYE-CO₂ (biomass, yield) are used as input to the AMG soil model. This approach makes it possible to assess SOC stocks changes on medium/long term meaning that it is now compliant with the certification schemes for the voluntary carbon market and with the EU carbon removal certification framework.

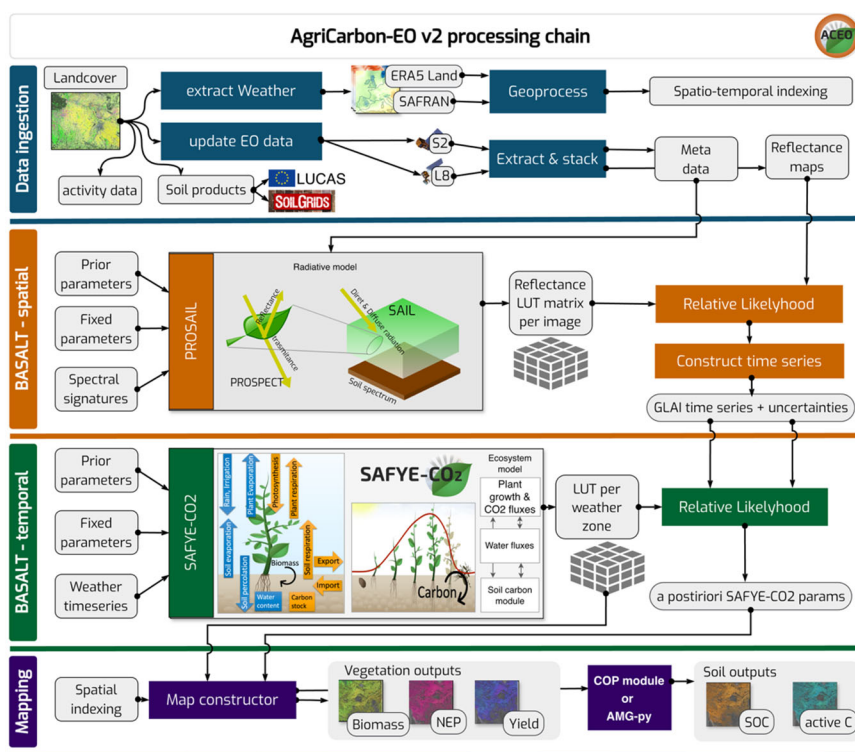


Figure 41 : Schematic representation of the AgriCarbon-EO V2.0 pre-operational processing (credits A. Albitar, T. Wijmer, E. Ceschia adapted from Wijmer et al. 2024).

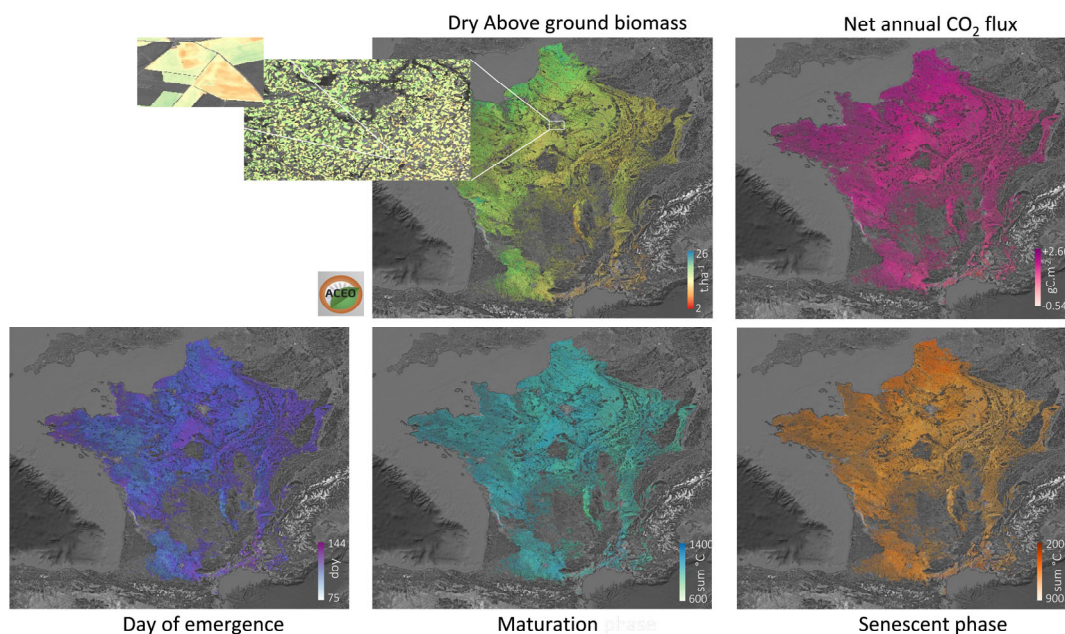


Figure 42 : National map of two key components of the winter wheat carbon budget (biomass and CO₂ fluxes) and of key phenological stages in 2019 at 10m resolution realized with the chain AgriCarbon-EO V1.0.1. Production carried out in 10 hours on the TREX calculator of the CNES in Toulouse. The maps are composed of 0.6 billion pixels (credits Al Bitar A., Antonenko V., Wijmer T., Arnaud L., Ceschia E.).

2.1.2 Advantages and limitations

The assimilation process implicitly accounts for stresses/pest/diseases effects on the crop/cover crop development through the calibration of phenological, C allocation parameters and of the Light Use Efficiency and it avoids the collection of detailed farmer's activity. The only activity data needed to calculate the SOC stock changes and water budgets are straw management (i.e. how much straw is exported and when), organic amendments (i.e. date, dose, type) and irrigation (date, dose). This modelling approach is more easily spatialized and more objective than with conventional agronomic models. It also makes its implementation much cheaper as few activity data need to be collected.

Since the model is constrained to reproduce the vegetation dynamics observed by remote sensing, the biomass spatial variability and intensity of development is well reproduced. Also, the BASALT assimilation scheme allows uncertainty propagation and uncertainty estimates for all simulated variables.

The method can be validated/verified at the scale of simulation (i.e. 10m) for SOC itself but also for intermediary variables (e.g. biomass) by applying the Elementary Sampling Unit (ESU) protocols as described in Pique *et al.* (2020). In short, several components of the C budget (e.g. biomass, grain) as well as soil samples (for SOC stock changes) can be collected following a protocol that allows the measured variable to be representative of the pixel simulated by the model. This approach allows stratified sampling that optimises and reduces the number of samples collected while allowing a better accounting of the spatio-temporal variability of the variables of interest (e.g. areas with high/low SOC stock increases/losses). Doing so less samples need to be collected compared to other modelling approaches providing average SOC stock estimates at field scale and as this method can spot areas which strong SOC stock dynamics, it can detect faster and more accurately SOC stock changes.

ACEO V2.0 can be applied to all current MRV context (NDCs, CAP, VCM).

The main current limitations of ACEO are:

- The limited number of crops/cover crops parametrised/validated so far.
- The limited access to accurate soil properties data and of activity data for large scale applications at field level (the later could be solved if activity data were accessible through FMIS or CAP declarations).
- Long periods of cloud coverage can make the assimilation process inoperative since up to now EO assimilation only relied on optical satellites (e.g. Sentinel-2, Landsat-8). The assimilation of LAI time series gapfilled with SAR satellite data (e.g. Sentinel-1) or of biomass proxy derived from SAR satellites (as in Allies *et al.* 2022) should solve the limitation.
- No ensemble modelling: currently only the AMG soil model is integrated in the ACEO processing chain but soon the integration of other soil models (e.g; RothC, ICBM) should allow ensemble modelling approaches.

2.1.3 Future developments

The future developments of ACEO concern:

- Calibration and validation of more crop and cover crop species (rapeseed, soja, sorghum...) in order to be able to simulate more crop rotations,

- The assimilation of LAI time series gapfilled with SAR satellite data (e.g. Sentinel-1) or of biomass proxy derived from SAR satellites (as in Allies *et al.* 2022) to solve the problem of surface observation during long cloudy periods.
- Coupling of several soil models (e.g. RothC, ICBM) to the SAFYE-CO2 crop model in addition to AMG in order to produce multi-model ensembles.

In the longer term, the addition of the nitrogen cycle in the model to be able to simulate N₂O fluxes.

2.2 FiON

2.2.1 General description

The FiON MRV platform aims to provide a flexible but conceptually and computationally lightweight framework for monitoring changes in SOC stocks from parcel to national scale.

The framework consists of the soil carbon model Yasso20 (Viskari *et al.* 2022) driven by carbon input estimates obtained from Bayesian data fusion that combines SOC measurements, Sentinel-2 derived gross primary productivity estimates and reported harvested biomasses. The system evaluates SOC changes in annual or longer timesteps and connects to the Finnish land parcel identification system, which provides up-to-date crop and geometry information for every agricultural parcel in Finland.

The MRV system is based on a modular structure. The carbon input module evaluates the daily gross primary productivity (GPP) of each field parcel using a Sentinel-2 derived vegetation index, photosynthetically active radiation, and an empirical regression model trained on eddy covariance measurements. The daily gross primary productivity is aggregated to annual level and converted to net primary productivity (NPP) assuming a constant growth yield, and annual carbon inputs are then evaluated from the NPP by subtracting and adding carbon exported (harvest yield) and imported (organic fertilizers) to the field parcel.

The SOC decomposition is evaluated by Yasso20, which is a stand-alone SOC model based on the earlier versions Yasso07 and Yasso15. Similar to other comparable models such as RothC, running Yasso requires externally specified fluxes for biomass inputs such as crop residues. The other input requirements of Yasso20 are minimal; the model requires monthly temperature and annual precipitation as the only meteorological drivers.

The SOC model is initialized by assimilating SOC measurements into a Bayesian data fusion algorithm. In this approach, prior distributions are given for the carbon inputs over the cultivation history of the field parcel (possibly extending over centennial time scale), and for the carbon stock prior to the conversion to cropland, some of which may remain as a legacy carbon pool depending on the field age. These prior distributions are fed to the SOC model (Yasso) and updated using the satellite-derived carbon inputs and observed SOC stocks, resulting in the posterior predictions of the current and past soil carbon stocks and inputs. This approach avoids unrealistic transients arising from initializing the SOC model into an equilibrium, because the equilibrium only needs to be applied at the beginning of cultivation history, typically far in the past. SOC measurements at multiple times can be assimilated to match the observed change SOC content.

Consistent propagation of uncertainties is a central feature of the calculation system. The satellite time series are gap-filled using a Bayesian technique that estimates the uncertainty of the resulting daily time series in response to

the data gaps in the input time series. These uncertainties are combined with parametric uncertainties in the primary productivity model, which have been estimated as a part of the model training. The uncertainties are partitioned into site-specific and site-independent components, which is important, since the site-specific but not site-independent errors start to cancelling out when the predictions are aggregated in space. The final uncertainties are propagated to the data fusion step, which is solved using a computationally efficient Hamiltonian Markov Chain Monte Carlo (MCMC) algorithm.

The Yasso SOC model has, in various versions, been evaluated over a wide range of climatic and ecological conditions (e.g. Thum *et al.* 2011; see also Garsia *et al.* 2023). The method for estimating gross primary productivity (GPP), has been evaluated under Finnish conditions (Vira *et al.* in prep.); the cumulative GPP calculated from the model explained 60-70 % of the variability of a multi-species biomass data set, and the model furthermore explained > 70 % of the interannual and regional variability of cereal yields extracted from a national scale statistical database. Model validation in European scale is ongoing within the MARVIC project.

In summary, the MRV framework can be characterized as a hybrid approach, which combines statistical and process-based models with probabilistic computing. The approach does not involve detailed simulation of vegetation dynamics, which makes it largely agnostic of crop species and management details such as fertilization rates, irrigation, or cover crops. Instead, these effects are implicitly captured by their impact on photosynthesis and harvest yields. While the GPP component is currently trained using flux measurements on Finnish croplands and grasslands, the regression model is straightforward to refine with additional data if needed.

The GPP and SOC model components are computationally lightweight and therefore unlikely to limit the method's scalability. The data fusion algorithm, however, currently limits the number of SOC time series that can be simultaneously processed to tens or hundreds. This limitation could be overcome by switching into an approximate data assimilation method such as Ensemble Kalman Filter. Nevertheless, the current implementation allows aggregated (e.g. farm scale) C balances to be efficiently calculated by evaluating the crop productivity on parcel scale and pooling the SOC measurements and harvest yields. This setup could be attractive when the SOC and/or yield data are available on farm level.

The requirement of externally specified fluxes of exported carbon (harvest yield and straw) can be a drawback if these fluxes are uncertain or not available on the desired spatial resolution. The current evaluation results suggest that cereal yields could be modeled statistically using the satellite-estimated GPP, but such functionality is currently not implemented. However, modelling the plant biomass allocation requires potentially uncertain or cultivar-dependent parameters, and therefore using reported harvest yield data may in some cases be preferable if available.

2.2.2 Future developments

Future developments of the system are focused on extending the evaluation of the GPP to cover more climatic conditions and different crops. For the SOC model, we aim to improve the methodology for estimating the one-meter SOC stocks simulated by YASSO based on the commonly measured topsoil SOC contents. Finally, options to couple YASSO and the data fusion algorithm to online-calibrated crop models are under consideration so as to extend the method to cover hypothetical scenarios assessments in addition to monitoring applications.

2.3 The Retina project

The Retina project⁹⁷, 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.

⁹⁷ <https://meetingorganizer.copernicus.org/EGU22/EGU22-12764.html>

3 References Annex

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