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Earth Observation (EO) for Monitoring, Reporting, and Verification (MRV) of Carbon Farming (CF) - Uncertainty and Benchmarking

Follow up report on the activities of the Focus Group on "Earth Observation for the Monitoring, Reporting, and Verification of Carbon Farming"

Milestone #2#

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Project CREDIBLE: "Building momentum and trust to achieve credible soil carbon farming in the EU".

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Carbon farming: Any practice or process, carried out over an activity period of at least five years, related to the management of a terrestrial or coastal environment and resulting in the capture and temporary storage of atmospheric or biogenic carbon in biogenic carbon pools, or in the reduction of soil emissions (Regulation 2024/3012 Article 2).

Title

Earth Observation (EO) for Monitoring, Reporting, and Verification (MRV) of Carbon Farming (CF[1]) - Uncertainty and Benchmarking

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Focus Group Vision

Earth observation contributes significantly to the EU journey to climate neutrality by 2050. This second draft report is based on ongoing discussions which should support high-level conversations to shape robust carbon farming markets and policies by sharing stakeholders knowledge and experiences, upscaling solutions, and enabling the multiplication of climate actions.[2]

[1] Carbon farming: Any practice or process, carried out over an activity period of at least five years, related to the management of a terrestrial or coastal environment and resulting in the capture and temporary storage of atmospheric or biogenic carbon in biogenic carbon pools, or in the reduction of soil emissions (Regulation 2024/3012 Article 2).

[2] EARSC members participating in the Working Group on Carbon Removals, including: Airbus, Constellr, Disiatek, EarthDaily Agro, e-geos, EOanalytics, Geosat, Geoville, GMV, Latitudo40, OHB, OpenCosmos, Planet, Planetek Italia, Space4Good, and Vortex. Credible Focus Groups (FGs) on Earth Observation (EO) for Monitoring, Reporting, and Verification (MRV) of Carbon Removals, which include: AgroApps, AUTH/MRV4SOC, BeZero, CarbonFarm, CinSoil GmbH, CMCC, Constellr, Copa-Cogeca, CREA, DG CLIMA, EarthDaily, eAgronom, EEA, e-geos, ESA, EURAF, Geosat, Geoville, INRAE, LoamIn, NetCarbon, Planetek Italia, Regen Insight, SAE SL, SouthPole, UCSC/MARVIS, and UFZ. The content is also informed by discussions held during key workshops, such as the ESA–EEA Workshop on EO for Monitoring, Reporting, and Verification of Carbon Removals.

1. Introduction

Climate action and sustainable land management practices must contribute to carbon neutrality by 2050, highlighting the need for robust Monitoring, Reporting, and Verification (MRV) techniques to evaluate the impact of carbon farming practices.[3] Here, we focus on sustainable land management in agriculture, forestry and other land use sectors and their capacity to remove CO2 from the atmosphere and lock it in multiple carbon pools, including soil and above and below-ground biomass. Among these carbon pools, soil remains the largest terrestrial carbon reservoir with a high potential of storing additional carbon after decades of intensive agricultural practices and unsustainable soil management that have caused significant depletion of soil organic carbon and a global decline of soil health. Additionally, the contribution of the carbon sequestered in the biomass of trees in forestry and agroforestry systems is very significant and also brings several environmental co-benefits.

The recently approved Carbon Removal Certification Framework (CRCF) promoted by DG CLIMA (Regulation 2024/3012) supports the European-wide application of permanent carbon removals, carbon farming, and carbon storage in products.[4] A Carbon Farming Delegated Act is under development to define the rules for MRV of three activities: a) agriculture and agroforestry on mineral soils, b) afforestation of degraded and abandoned lands and c) rewetting of peatlands. Earth Observation (EO) technologies are widely acknowledged as playing a central role in providing scalable, cost-effective, and consistent data solutions to MRV across large geographic areas and land use classes.[5] EO offers an array of tools to directly monitor vegetation cover, biomass density and carbon inputs to the soil (e.g. as crop residues), land use change and carbon farming practices, and soil superficial organic matter as a supplement field measurement. However, while these technologies hold promise, their application faces challenges related to standardisation, cost-accuracy tradeoffs and stakeholder trust.

Satellite-derived data plays a pivotal role in supporting MRV systems for carbon farming by offering insights into land use and management practices. Different types of EO data serve specific functions: for instance, LiDAR is particularly valuable for estimating forest and tree biomass, while high-resolution optical data such as Sentinel-2 supports the mapping of vegetation-related biophysical parameters (e.g., LAI, FAPAR), which can be assimilated into plant or ecosystem models to improve

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[3] Throughout this document, carbon removals and carbon farming are intended as defined in the EU Carbon Removals and Carbon Farming Certification (CRCF) Regulation, with a focus on agriculture and forestry (including LULUCF) projects which are participating in various carbon markets that operate at international, regional, or voluntary levels (international carbon markets, regional carbon markets, voluntary carbon markets (VCMs).

[4] This framework recognizes the importance of integrating all land use classes: such as agricultural lands, managed forest, and degraded areas being restored into carbon removal initiatives. Furthermore, it underscores the need to monitor carbon pools beyond soil, including those in vegetation (above-ground and below-ground biomass) and litter and deadwood in forests, as included in the CRCF Regulation (2024/3012) and its draft Delegated Acts

[5] Project CREDIBLE Focus Group 3.3 consultation from the first Carbon Farming Summit (Valencia 2024)

estimates of carbon inputs to the soil. Optical data can also be used for mapping superficial soil organic carbon (SOC) content, although this information has limited utility, as it provides little insight into total SOC stocks and is often too uncertain to initialize SOC stock models reliably. Additionally, SAR (Synthetic Aperture Radar) data is useful for quantifying biomass and for gap filling LAI time series where optical data is obstructed by persistent cloud cover. However, it is important to stress that EO data alone can primarily produce maps of vegetation characteristics, land management practices, or superficial SOC content; to generate meaningful quantitative outputs, such as changes in biomass or SOC stocks essential for MRV purposes, EO must be combined with models (through data assimilation) or machine learning approaches. Furthermore, there are inherent limitations: EO-based MRV can be impractical in cases where fields are too small, cloudiness consistently prevents vegetation monitoring, terrain is too steep and complex, or where visual obstructions like trees or infrastructure (e.g., wind turbines) interfere with observations. Ground-truth measurements are crucial for calibration and validation, but they also carry intrinsic limitations that underscore the need for integrated approaches that combine in-situ, remote sensing, and model-based methods. Understanding the limits of both EO-driven and ground-truth measurements is fundamental to manage expectations from all stakeholders. Policy regulations and guidelines should reflect the current state-of-the-art should support further innovation and technological development. On the contrary, misleading requirements will hinder the evolution of EO-based services.

This paper examines the challenges and opportunities for the use of EO techniques to assist with the MRV of carbon farming. It makes recommendations which focus on the need for reliable and openly-available data on the impacts of land use practices over space and time in order to gain the understanding and trust of the stakeholders.[6] These include farmers and foresters who manage the land, operators who administer the certification schemes, and policy makers who authorise the certification framework itself. Another group of users are the public bodies in each Member State which prepare the national greenhouse gas inventories supplied annually to the UNFCCC. We must develop systems where the impact of carbon farming can be transparently included in national GHG inventories and future predictions. For this to happen, "wall to wall" identification of parcels and their land-use is vital following the LULUCF categorisation of "lands".

The quantification of agroforestry tree and shrub biomass on “grassland” and “cropland” parcels is particularly important and requires the integration of agricultural land use registries (e.g. the CAP LPIS system) and national forest inventories to ensure

[6] Given the vast and dynamic nature of organic matter in soils and biomass, quantifying its changes often requires a minimum of five years to detect meaningful impacts, whether increases or decreases. EO can monitor changes in farming and land management practices, such as the adoption of cover crops, in the short term, serving as an effective tool for both reporting and verifying these transitions.

that no parcel can be classified as both “forest” and “agriculture” in different official databases[7].

Robust MRV requires standardized and transparent approaches, as well as rigorous evaluation and reporting of measurement accuracy, and addressing uncertainties in both direct measurements and model-based estimations. Furthermore, although model benchmarking efforts are underway among various stakeholders, current initiatives such as monitoring networks (e.g. combining SOC stock measurement, collection of activity data and measurement of carbon inputs to allow an understanding of SOC stock trends - as in the ICOS flux tower network) remain insufficient to fully establish trust in the performance of all commercially and publicly available models. We propose implementing benchmarking strategies, including a EU-wide platform to evaluate the performance of different methods and tools across diverse pedoclimatic regions and farming systems. This approach is essential to build trust in carbon removal and carbon farming outcomes at the plot and farm levels as well as across the six “lands” which are recognised for LULUCF and CRCF reporting.

Box 1: LULUCF Land Use Categories[8] (with % EU-27 total area)[9]

FOREST LAND: This category includes all land with woody vegetation consistent with thresholds used to define Forest Land in the national greenhouse gas inventory. It also includes systems with a vegetation structure that currently fall below, but in situ could potentially reach, the threshold values used by a country to define the Forest Land category.[10] (managed 49.3%, unmanaged 0.5%)

CROPLAND: This category includes cropped land, including rice fields, and agroforestry systems where the vegetation structure falls below the thresholds used for the Forest Land category. [11] (28.4%)

GRASSLAND: This category includes rangelands and pasture land that are not considered Cropland. It also includes systems with woody vegetation and other non-grass vegetation such as herbs and bushes that fall below the threshold values used in the Forest Land category. The category also includes all grassland from wild lands to recreational areas as well as agricultural and silvopastoral systems, consistent with national definitions.[12] (managed 16.9%, unmanaged 0.1%)

WETLAND: This category includes areas of peat extraction and land that is covered or saturated by water for all or part of the year (peatlands and other wetland types) and that

[7] Member States have their own definitions of forests, within the thresholds allowed by the UNFCCC Marrakesh Accords, and listed in Annex II of the LULUCF Regulation (2018/841) - see EURAF Policy Briefing #15

[8] Chapter 3 “Consistent Representation of Lands” IPCC 2019 Refinement of the 2026 Guidelines for National GHG Inventories.

[9] Collated from Table 4.1 the Common Reporting Tables CRT of each MS National Inventory Submission for 2024

[10] Defined by Member States in Annex II of the LULUCF Regulation (2019/841) and modified in Regulation 2023/839. See also EURAF Policy Briefing #15 “Defining forests and agroforests in EU Member States”

[11] Defined by Member States in their CAP strategic plans and rules for landscape features and non productive areas. See also EURAF Policy Briefing #21 “Landscape features in the new CAP”.

[12] Defined by Member States in their CAP Strategic Plans. See also EURAF Policy Briefing #29 “Permanent Grassland definitions in EU Member States” and Policy Briefing #22 “Agroforestry definitions in the new CAP”.

does not fall into the Forest Land, Cropland, Grassland or Settlements categories. It includes reservoirs as a managed sub-division and natural rivers and lakes as unmanaged sub-divisions. Further definitions of wetlands sub-divisions are provided in the IPCC Wetland Supplement.[13] (1.9% managed, 3.8% unmanaged)

SETTLEMENT: This category includes all developed land, including transportation infrastructure and human settlements of any size, unless they are already included under other categories. This should be consistent with national definitions.[14] (6.8%)

OTHER LAND: This category includes bare soil, rock, ice, and all land areas that do not fall into any of the other five categories. It allows the total of identified land areas to match the national area, where data are available. (2.2%)

The total area in the EU is around 423 Mha and changes compared to the base year (1990) have been: Settlements (+25%), Croplands (-8%), Forestland (+5%), Grassland (-4%), Wetlands (+1%), Other lands (-5%).[15]

2. Addressing Limitations

Satellite-derived data from public datasets (e.g., the Copernicus programme) or private missions play a pivotal role in supporting carbon farming practices, offering global coverage, frequent revisit times, and robust hyperspectral, optical, radar and LiDAR data. These features are indispensable for a wide range of applications, including monitoring of carbon farming activities, carbon inputs to the soil through biomass and modelling of carbon pools/stocks through the assimilation of EO derived products (e.g. leaf area index, proxies of aboveground biomass) in models. With the ultimate goal of reducing the uncertainty on the modelled or measured changes in carbon stocks (whether in soil or in biomass), it has been shown[16] that EO can play a significant role by integrating different approaches, either for more efficient sampling design or to increase the accuracy of model-based methods through the assimilation of biophysical products (e.g. leaf area index) derived from EO data in the models. The table below highlights what satellite-derived data can and cannot directly achieve, illustrating both its strengths and areas where complementary approaches are necessary.

Table 1: Capabilities and Limitations of Satellite-Derived Data for Carbon Farming MRV

[13] Defined by in the IPCC Wetland Supplement (2014) as interpreted by Member States in their annual GHG Inventories and in rules used to map GAEC-2 LPIS areas- these rules are in flux and will be important for the 3rd CRCF Carbon Farming activity: “rewetting of peatlands”.
[14] Defined by Member States in their annual UNFCCC GHG Inventories. Data also available in urban categories of CORINE land classification (maybe the LMS+ upgrade), the Copernicus Urban Atlas and the Copernicus “land sealing” database
[15] Annual European Union Greenhouse gas inventory 1990-2022, 13.12.24
[16] Wijmer et al. 2024, “AgriCarbon-EO v1.0.1: large-scale and high-resolution simulation of carbon fluxes by assimilation of Sentinel-2 and Landsat-8 reflectances using a Bayesian approach” https://doi.org/10.5194/gmd-17-997-2024

Satellite-derived data currently can	Satellite-derived data cannot[17]
• Detect land use changes (including historical information and real-time changes) and detect areas and duration of bare soil areas. • Estimate topsoil organic carbon and other soil attributes on bare soil composites with ground truth data up to a certain level of accuracy. • Monitor some key carbon farming practices (e.g., crop rotations, cover crops, harvest events and residues, destruction of cover crops, weeds and spontaneous regrowth, grassland mowing). Organic amendments can be detected but not quantified. • Quantify above-ground biomass (directly or through the assimilation of EO products in models) and support SOC model initialization[18]. • Track changes in vegetation health and productivity and predict anomalies. • Supply critical inputs for carbon modeling systems through EO products assimilation (e.g. leaf area index) in ecosystem or plant models that allow more accurate estimates of C inputs o the soil through biomass • Provide intra-plot spatial variability assessment of vegetation development, C inputs through biomass and subsequently of SOC trends[19]. • Provide data for large-scale carbon sequestration projects and repeated measurements over time for trend analysis. • Integrate with land-use records made by farmers in their returns to the Integrated Administration and Control System (IACS)[20] Geospatial Aid Application (GSAA)[21] Land Parcel Information System (LPIS) and Area Monitoring System (AMS)	• Directly measure SOC, conventionally measured at depths of up to 30 cm which is beyond the reach of satellite observations. • Directly indicate SOC stocks and below-ground biomass, nor achieve high accuracy in estimates, without calibration from reference ground data. • Detect some key practices affecting SOC stocks like straw management (i.e. straw exported or buried which is for cropland the main driver of SOC trends[22]) and quantification of the organic amendments, or other practices that have an indirect effect on biomass production and SOC trends (mineral fertilisation, pesticides application…). • Precisely quantify SOC/biomass evolution with small incremental changes (e.g., 0.X%), ensuring the minimum detectable difference allows for reliable measurements.

Soils and vegetation are a critical component of the carbon cycle: soil is the largest terrestrial carbon sink, and vegetation plays a pivotal role in capturing and storing carbon, both through photosynthesis and long-term biomass accumulation, and serves as primary carbon input to soil. Satellite-derived data can detect land use changes, monitor key farming practices, estimate biomass and topsoil SOC (with ground data), and support large-scale carbon trend analysis. It provides critical inputs

[17] Open to future technical developments
[18] E.g. S. Beka et al. https://www.sciencedirect.com/science/article/pii/S004896972207721X?via%3Dihub
[19] e.g. Wijmer et al 2024 : https://gmd.copernicus.org/articles/17/997/2024/
[20] IACS is a key tool used by EU Member States to manage and control payments to farmers under the Common Agricultural Policy (CAP).
[21] Geospatial Aid Application (GSAA) Returns. is an electronic geospatial system that farmers use to submit their subsidy applications under CAP. It includes the mapping of land parcels and crop types with high spatial accuracy.
[22] Ceschia et al (2010) https://doi.org/10.1016/j.agee.2010.09.020

for modeling and links well with farm-level systems like IACS or LPIS. However, it cannot directly measure deep SOC or small changes in carbon stocks. It also struggles with detecting subtle practices like straw management or pesticide use. High-accuracy SOC estimates still depend on ground-truth calibration. Adequate spectral-spatial-temporal resolution imagery provides the detail needed to capture and map fine-scale vegetation structures offering critical insights into land use, land use changes (e.g. deforestation, reforestation, and afforestation efforts, changes in crop rotation), biomass development and subsequent C inputs to the soil. Additionally, LiDAR technology[23] delivers precise 3D data crucial for estimating above-ground biomass, making it particularly valuable for forestry and agroforestry.[24] Together with data assimilation in plant or ecosystem models these technologies form a powerful hybrid approach [25] that strengthens carbon quantification, supports effective monitoring at local and regional scales, and enhances the credibility of carbon removal projects in meeting certification and compliance standards. To complement these geospatial tools, integrating meteorological data adds another layer of insight to carbon monitoring efforts.

Satellite-based meteorological data offers the advantage of covering vast territories, with hourly images available for continuous monitoring (e.g. ERA5-land data). However, one challenge that remains unaddressed is to ensure frequent observation of the surface status which is critical for operationalizing SOC and vegetation monitoring, even during long cloudy periods. This is for instance critical to detect accurately the timing of cover crop destruction and their biomass just before destruction but also to constrain efficiently plant/ecosystem models through EO assimilation in order to quantify carbon inputs to the soil through biomass. For this the combination of optical and SAR data should be encouraged/developed. Another big limitation is rapid access to updated land use maps (e.g., in order to know which crop is on which field) so that models and EO data can be used jointly to simulate the C budget components (biomass, CO2 fluxes, SOC stock changes). Table 2 in the next Section provides an overview on the fragmentation of available land use information from the member states.

Managing uncertainty in EO-derived data is another priority. Differences in land cover mapping accuracy and carbon stock calculations highlight the need for standardized methods to quantify and address uncertainty.[26] Defining acceptable thresholds that vary based on indicators, land use categories, or regional requirements can help build

[23] https://link.springer.com/article/10.1007/s40725-024-00223-7
[24] https://environment.data.gov.uk/dataset/9c41b3c6-2453-44f6-9900-e7821f1a1072
[25] For example, "hybrid approach" in C monitoring can refer to the combined use of EO and modelling or AI+process based modelling with or without EO. See Batjes et al., 2024, “Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment” https://doi.org/10.1080/17583004.2024.2410812
[26] See for example ORCASA Deliverables 4.1 and 4.2 (upcoming): https://irc-orcasa.eu/resource/?category=deliverables

confidence in the results. Enhanced data quality, refined models, and harmonized methodologies are fundamental to minimizing uncertainty and improving the reliability of carbon removal assessments. Also decision trees are needed to choose the adequate methodology given the MRV purpose (e.g., offsetting programs or insetting programs, national inventories) and the local context (e.g. accessibility, availability, accuracy of the soil data, activity data, compatibility with EO based approach or not).

3. Ensuring Data Accuracy, Integration, and Reliability

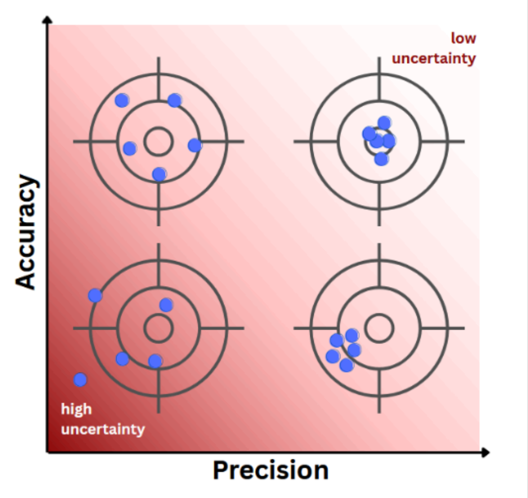

Figure 1: in order to reach low uncertainty, measurements and/or estimates need to be both precise and accurate.

While ground reference observations and field sampling are often regarded as high-quality ground truth, their accuracy and precision (Figure 1) as well as their representativeness are frequently constrained by spatial coverage, temporal frequency, human bias, inadequate sampling designs, sub-optimal sample stratification, measurement techniques, and budget availability[27]. Differences in instruments, calibration, and protocols across sites or projects can lead to systematic biases, reducing the comparability and accuracy of 'ground truth' data.[28] Single-point or sparse sampling cannot always adequately capture spatial heterogeneity, especially in ecosystems like wetlands, forests, or agricultural mosaics, where emissions can vary dramatically over short distances. Temporal discontinuities and infrequent sampling lead to large uncertainties when attempting to upscale from site-level measurements to regional or national estimates. These issues are magnified in diverse farming landscapes, where variability in agricultural practices and natural conditions undermines the robustness of analytics.

Ground-truth data is indispensable for both calibrating and validating algorithms allowing to map C farming practices or the carbon budget components (e.g., biomass, CO2 fluxes, SOC stock changes) simulated by carbon farming MRV systems. In order to address the potentially low representativeness of ground-reference data due to the

[27] Cardael el al (2025) provide a checklist of mandatory and optional measurements which should be made by all agroforestry carbon farming projects. Similar checklists are available for other practices.
[28] BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP, and OIML. Evaluation of measurement data — Guide to the expression of uncertainty in measurement. Joint Committee for Guides in Metrology, JCGM 100:2008. doi:10.59161/JCGM100-2008E.

previously mentioned limitations, careful integration with EO technologies is essential. EO provides continuous, large-scale data that can enhance the precision and reliability of MRV systems. The use of EO data and geospatial modelling can support the collection and use of ground-truth data. For example, de Gruijter et al.[29] show how modeled estimates of soil carbon stocks can be used to optimise further stratified sampling, lowering the number of samples required to achieve a given level of precision. Similarly, spatially adaptive designs, whereby the locations of ground truth data collection is informed by historical data, has been used to support the mapping and estimation of soil properties, species distributions and diseases.[30]

This synergy between ground-based measurements and EO-derived insights ensures more robust and comprehensive assessments of carbon farming practices. The effective use of EO data for carbon monitoring, reporting and verifying hinges on the seamless integration of diverse datasets into modelling frameworks, including satellite imagery, ground truth observations, climate data, and CAP-IACS [31] land management records. This combination of data sources and models is critical to creating reliable and actionable insights for MRV systems. Addressing the inherent complexities of diverse landscapes, climates and agricultural practices across the EU requires tailored solutions that account for the variability in data quality and availability. The EEA has recently released the so-called "State of Play of the Copernicus in-situ" [32] which provides a comprehensive overview of how in-situ data supports Copernicus, from production and validation of data products to the calibration of EO missions. This synergy between ground-based measurements and EO-derived insights is key to robust and comprehensive carbon MRV systems, ensuring that diverse datasets — including satellite imagery, ground observations, climate records, and land management data — are integrated into reliable and scalable models.

In addition to integrating EO data with strategically targeted ground truth measurements, leveraging open-source carbon models calibrated and verified on global datasets can address these challenges. These models, such as those assimilating EO products like leaf area index (e.g. Sentinel-2, Landsat-8) or biomass (i.e. Biomass mission) offer standardised methodologies that are accessible, scalable and globally comparable. For example, combining high-resolution satellite imagery with field data on activity (e.g. organic amendments, cover crops) enables the development and utilization of robust models that accurately reflect local conditions. Continuous refinement of EO methodologies, coupled with machine learning and AI, can further enhance the precision and efficiency of carbon stock assessments. These

[29] de Gruijter, Jaap J., et al. "Farm-scale soil carbon auditing." Pedometrics (2018): 693-720.
[30] Henrys, Peter A., Thomas O. Mondain-Monval, and Susan G. Jarvis. "Adaptive sampling in ecology: Key challenges and future opportunities." Methods in Ecology and Evolution 15.9 (2024): 1483-1496.
[31] Integrated Administration and Crontols system for payments to farmers (EU Commission 2024)
[32] What is the state of play of Copernicus In Situ (Copernicus 2024)

advanced approaches not only optimize data usage but also improve scalability and cost-effectiveness.

3.1 Data Integration and Harmonization

The variability in climates, soil properties, agro-systems, land management and farming practices across the EU presents a significant challenge to the reliability of EO-based carbon analytics. For instance, differing soil conditions influence carbon stock estimates, requiring adaptable and context-sensitive modelling approaches. Achieving consistency across datasets (and modelling frameworks) necessitates standardisation and harmonisation, ensuring that inputs from different systems align to produce coherent results. Land use classification further complicates this process, as inconsistent definitions of categories like "forest," "grassland," or "wetland[33]" across Member States create barriers to accurate mapping. The absence of comprehensive, "wall-to-wall" parcel mapping amplifies these difficulties.

The CAP Integrated Administration and Control System (IACS) provides information on parcel shapefiles (GSAA) and crop/land use (LPIS), but it is not it is not a complete solution: a) because forestry parcels are poorly represented and b) because IACS does not cover all agricultural land.

The latter point is due to Member States applying minimum payment thresholds (ranging between €100 and €500) and/or minimum holding areas (ranging from 0.3 ha to 4 ha) to decide who are "active farmers".[34] In France only 80% of fields are recorded in the GSAA system. Europe has a total of 9.1 million farmers according to cadastral records used for the 2000 Farm Structure Survey,[35] whereas in the same year there were only 6.0 million farmers recorded in IACS statistics.[36] Nevertheless, GSAA and LPIS data are an invaluable resource, and work is underway in a number of Horizon projects to collect and compare this data. These include DigitAF, which is developing an EU-wide *LPIS aggregator*[37], and EuroCrops[38], which maintains a "*Hierarchical Crop and Agriculture Taxonomy*" (HCAT3) to cross-map the crop codes used in around 20 EU Member States. The JRC "*Classification system based on farming practices*"[39] and the EEA "*Handbook on the updated LULUCF Regulation*"[40] are also important steps

[33] The LULUCF definition of "wetlands" encompasses *land that is covered or saturated by water for all or part of the year*. Crucially, LULUCF wetlands exclude land included in the other LULUCF categories - forestland, cropland, grassland, settlements or other. There is therefore a need to reconcile the LULUCF definitions of wetland used by Member States in their GHG Inventories and with definitions of peatland used in CRCF and CAP reporting.
[34] Eligibility for direct payments of the Common Agricultural Policy 2022-27 (EU Commission August 2023)
[35] Farms and farmland in the EU (Eurostat 2025)
[36] Direct payments to agricultural producers - graphs and figures (EU Commission 2024)
[37] DigitAF Project LPIS Integrator https://maps.regenfarmer.com/#11.91/56.07637/12.35133
[38] EuroCrops Project description and GitHub repository of crop types (HCAT3)
[39] https://publications.jrc.ec.europa.eu/repository/handle/JRC133862
[40] Handbook on the Updated LULUCF Regulation - v2 (EEA 2024)

towards harmonisation, or at least to better understanding of differences between Member States.

Table 2: Geospatial Aid Application (GSAA) and Land Parcel Information System (LPIS) information available from Member States through the INSPIRE and DG AGRI Geoportals. Supplemented with searches on a country by country basis.

Country	DGAgri Geoportal		INSPIRE Geoportal		Total All Sources	
	GSAA	LPIS	GSAA	LPIS	GSAA/LPIS	Name
Austria	y	y	y	y	y	LPIS
Belgium-Flanders	y	y	y	y	y	LPIS
Belgium-Wallonia	y	n	y	y	y	SIGEC
Bulgaria	n	(y)	n	n	n	LPIS
Croatia	n	y	n	y	n	LOIS-CROLIS
Cyprus	y	y	n	n	Y	LPIS
Czech Republic	(y)	(y)	y	y	Y	LPIS
Denmark	n	n	(n)	y	y	Markblokke
Estonia	y	y	y	y	Y	LPIS
Finland	y	y	y	n	Y	FLPIS
France	n	n	n	n	y	LPIS
Germany (16 regions)	7	9	(y)	(y)	9	InVeKoS
Greece	n	n	n	n	n	OPEKEPE
Hungary	n	n	n	n	y	MePAR
Ireland	n	y	y	y	y	LPIS
Italy (20 regions)	n	n	n	n	1	SIPA
Latvia	y	n	y	y	Y	LAD
Lithuania	(y)	(y)	n	y	y	LPIS
Luxembourg	n	y	y	y	y	FLIK
Malta	n	n	n	n	n	LPIS
Netherlands	y	y	n	y	y	LPIS
Poland	n	y	n	n	n	ARiMA-LPIS
Portugal	n	y	y	y	y	IFAP-Parcelaria
Romania	n	n	n	(n)	n	APIA-LPIS
Slovakia	y	y	y	y	y	LPIS
Slovenia	y	n	y	y	y	GERK/RABA
Spain	n	n	y	y	y	SIGPAC
Sweden	n	y	y	n	y	jordbruksblock

Recent improvements in availability of GSAA and LPIS data through the DGAGRI Portal or national INSPIRE Portals (Table 2) suggest that, with sufficient pressure from the Commission, stable geospatial parcel boundary and land use data may be available from all Member States and regions by 15th May 2027: marking the 20th anniversary of the INSPIRE Directive entering into force.[41]

However, even GSAA/LPIS data and freely available resources like Copernicus, with its 10-meter resolution and 3-day revisit, may fall short of the requirements of the new "Union Registry" of carbon removals. Access to commercial high-resolution data offers a potential solution, albeit with concerns regarding cost and usability, in particular considering the need for the combination of optical and SAR data for the operational mapping of vegetation, trees and several key carbon farming practices.

[41] The GreenData4All initiative (updated rules on geospatial environmental data and access to environmental information) is welcome for the push it gives towards increased compliance with the INSPIRE Directive, but the proposal to remove agricultural and cadastral parcels from the scope of INSPIRE is concerning since it is the move from pixels to parcels that is vital to link environmental data to the world of farmers.

Further agricultural and forestry open data could be provided by Member States. One example is the “Farm Sustainability Tool for Nutrients”,[42] which obliged MS to provide all farmers with access to a parcel-scale tool providing “*at least: (i) a balance of the main nutrients at field scale; (ii) the legal requirements on nutrients; (iii) soil data, based on available information and analyses; (iv) data from the integrated administration and control system (IACS) relevant for nutrient management”*. It is not clear that any Member State has yet met this requirement.

Actors like the EEA can, through existing initiatives, play a transformative role in raising awareness about these limitations, facilitating structured forums and dialogues among data producers, users, and policymakers, and being a driver for coordinated financing of interoperable and reliable MRV infrastructure. Through initiatives led by their thematic experts, EEA can help promote harmonized methodologies, push for greater transparency and data availability across Member States, and ensure that MRV systems are robust enough to support emerging policies like carbon farming certification and CAP-related reporting obligations. As an example, EEA has produced a series of use cases of several initiatives that enhance stakeholder confidence in carbon farming certification schemes by improving access to soil carbon data, establishing reliable benchmarks, and supporting decision-making in the Agriculture, Forestry, and Other Land Use (AFOLU) sector.

In one use case, the PROSOIL project utilized Copernicus Sentinel-2 satellite data to estimate soil organic carbon (SOC) in croplands across Belgium, Germany, and Luxembourg. The study demonstrated that Sentinel-2's spatial resolution effectively captures SOC variability at both field and regional scales, providing a cost-effective means for farmers and policymakers to monitor and manage soil carbon levels.[43]

In another use case LiDAR has been used to create a database of trees outside forests in England which shows that groups of trees smaller than the UK national threshold of “*forest*” (0.1ha) and individual trees (with crown area more than 5m^2) comprise 30% of the nation´s tree cover.[44] The tool provides a “small woody features” product which identifies blocks of trees outside forests, using the FAO definition of *forest* block size as 0.5ha.[45]. An detailed viewer[46] is available for “all trees in the Netherlands”, which is updated at least four times a year and where the public is invited to make corrections. Finally, Meta and the World Resources Institute have even launched a global map of tree canopy height at 1-meter resolution![47]

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[42] CAP Strategic Plan Regulation 2021/2115 Article 15 paragraph 4g
[43] sentinels.copernicus.eu/web/success-stories/-/copernicus-sentinel-2-data-to-estimate-soil-organic-carbon-in-croplands
[44] https://www.gov.uk/government/news/englands-non-woodland-trees-freely-mapped-for-first-time
[45] eea.europa.eu/en/datahub/datahubitem-view/a3bb6014-54a8-4bd4-871e-e6718e8f2726?activeAccordion=1085961
[46] https://boomregister.nl/overzichtskaart-van-de-bomen-in-nederland/
[47] See “using artificial intelligence to map the Earth's forests (22.4.24) and Tola et al (2024) Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar. Remote Sensing of Environment 300(1) 113888.

3.2 Improving Data Reliability

Strengthening MRV systems requires the limitations of both EO and ground reference data to be addressed. While fully relying on ground samples for accurate MRVs incurs costs that are unsustainable in the long term, in-situ sampling of soil and biomass should always remain a part of the process. Ground truth observations are indispensable for land cover/land management classifiers and for model training, calibration, validation and verification. A viable approach could involve creating a sample-heavy baseline initially, followed by a hybrid monitoring system that combines fewer ground samples with EO data and advanced modeling techniques, ensuring cost-effectiveness without compromising accuracy. However it must be understood that what is considered “ground truth” comes with its own uncertainty. Brinton et al. performed an inter-laboratory challenge, sending identical composite soil samples to four laboratories, and observed a variation in SOC measurements which was comparable to the differences in SOC across fields with different management systems.[48] Another recent study by Even et al. showed high coefficients of variance across samples taken in the same fields with different sampling processing, with a clear trade-off between sample processing time and quantification precision.[49]

In general, there is a lack of standardized protocols for both data collection (in soils and biomass), lack of standardisation and harmonisation of analytical procedures, and common protocols for data exchange and data processing, which poses challenges for consistent and reliable carbon accounting across different regions and applications. Initiatives like FAO Global Soil Partnership (GSP), establishing the Global Soil Laboratory Network (GLOSOLAN),[50] and developing international frameworks such as the SOC MRV Protocol aim to address these gaps by promoting harmonized methodologies and standardized practices globally. Enhanced collaboration and knowledge sharing among stakeholders, including research institutions, industry practitioners, and policymakers, will further contribute to developing robust MRV systems. Investing in capacity building and training is also critical, as it ensures that field operators, analysts, and data users apply consistent standards and procedures. ESA has recently released a *Best Practice Protocol for the validation of Aerosol, Cloud, and Precipitation Profiles.*[51] A similar approach could be employed for critical carbon farming measurements.

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[48] Brinton et al., 2025, An inter-laboratory comparison of soil organic carbon analysis on a farm with four agricultural management systems https://doi.org/10.1002/agj2.70018

[49] Even et al., 2025 https://doi.org/10.5194/soil-11-17-2025

[50] https://www.fao.org/global-soil-partnership/resources/highlights/detail/en/c/1441888/

[51] Amiridis, V., Marinou, E., Hostetler, C., Koopman, R., Cecil, D., Moisseev, D., Tackett, J., Groß, S., Baars, H., Redemann, J., Marenco, F., Baldini, L., Tanelli, S., Fielding, M., Janiskova, M., Tanaka, T., O'Connor, E., Fjaeraa, A. M., Paschou, P., … Kollias, P. (2025). Best Practice Protocol for the validation of Aerosol, Cloud, and Precipitation Profiles (ACPPV) (Version 2). Zenodo. https://doi.org/10.5281/zenodo.15025627

Table 3: Key Challenges and Recommendations for Improving Ground Truth Data

Aspect	Challenge	Examples	Recommendations
Timeliness	Delayed data affects emergency response and short-term decision-making.	- Drought events where in-situ soil moisture data is weeks late. - Forest fire recovery lacking near-real-time biomass loss updates.	- Use EO with short revisit times (e.g. Sentinel-2). - Deploy automated ground sensors to reduce latency.
Data Coverage	Sparse in-situ data in remote or ecologically sensitive areas reduces representativeness.	- Few ground stations in alpine zones or northern peatlands. - EO gaps due to surface interference.	- Fund densification efforts (UAVs, mobile labs, citizen science). - Prioritise white-spot areas in EU data strategies.
Database Updates	Inconsistent definitions of key terms limit data interoperability and comparability.	- No mechanisms to revise reported values with improved techniques.	Create mandatory version-controlled systems in "living databases". - Include mandatory uncertainty fields and traceability protocols.
Vocabulary	Short-term funding leads to unsustainable or fragmented data systems.	-“Depth inconsistencies (e.g., 0–20 cm vs 0–30 cm). - Varying definitions of land cover types like “grassland” across MS.	- Promote Use standard vocabularies (INSPIRE, ISO). - Support ontology tools to align classifications and terms.
Public-Private Data Integration	Lack of guidelines for public-private data sharing	High-resolution imagery is often necessary to detect land management practices like tillage, cover cropping, or crop rotation – but licensing costs and usage restrictions limit broader public access. - sensors deployed by private actors are often not standardized or openly available.	Create and promote standardized templates for data sharing aligned with GDPR and FAIR principles, Including clauses on liability, audit rights, and intended use. Introduce rules for access for sensitive or commercial data (e.g., sensor networks used in voluntary carbon markets) which allow "read-only, non-commercial use" of private data for validation purposes, under data use agreements.
Funding mechanisms	Short-term funding leads to unsustainable or fragmented data systems.	- Sampling campaigns end with project funding. - LPIS and IACS quality varies by Member State due to inconsistent investment.	-Promote co-financing via e.g. EU funds. - Secure permanent funding for core infrastructures (e.g., flux towers, LPIS).

Data Governance and Confidentiality

In the transposition of the INSPIRE Directive into national legislation the openness of soil data and other data that can be related to farmers’ property have been interpreted by some Member States as personal data (GDPR regulation), therefore, falling into an exception to the obligation for sharing.[52] However this interpretation contradicts EU Directive 2019/1024 (the Open Data Directive), and the Implementing Regulation (2023/2018) which specifically lists anonymised IACS agricultural and reference parcel data as being a “high value dataset” under the terms of the Open Data Directive. It is hoped that those countries missing in Table 2 will provide data soon, and some have announced steps towards this.[53] It will be essential to provide information on organic amendments at parcel scale in order to be able to model SOC stock changes (in combination or not with EO data assimilation). Indeed this critical information for assessing SOC changes can only be provided by the farmer.

The *Strategic Dialogue on the Future of Agriculture (DGAGRI 2024)* contained an important commitment: “*Data utilization can offer significant benefits and support the benchmarking system and data exchange in the agrifood systems. It also raises concerns about fairness, quality and privacy. Hence,* robust data governance frameworks *and their proper implementation are essential*”.

Reliable carbon monitoring systems also require robust data governance frameworks. Balancing the need for transparency with data confidentiality is a persistent challenge. For instance, restricted access to critical land parcel datasets, such as LPIS or activity data, limits the broader applicability of EO analytics.[54] Ensuring that such data can be securely shared and utilized without compromising privacy is essential for advancing MRV systems. In light of the most recent developments related to the Data Act (2023) and Data Governance Act (2022) implications in the agricultural sector, it is extremely important that data governance experts become more involved in the discussion on MRV systems for carbon farming, also in view of the developments of the Common European Agriculture Data Space.

Investing in the harmonization of EO data with ground-truth measurements and regulatory standards, while fostering collaboration among EO service providers, policymakers, and carbon market stakeholders, is essential for developing clear standards and robust operational frameworks. Ensuring data interoperability while maintaining compliance with EU standards is another critical issue, vital for building robust monitoring systems. Such interoperability would enhance the precision and reliability of carbon monitoring systems, enabling more effective support for policies like CRCF (Carbon Removal Certification Framework) and LULUCF (Land Use, Land Use Change, and Forestry).

[52] Fantappiè, M., Peruginelli, G., Conti, S., Rennes, S., Le Bas, C., van Egmond, F., Smreczak, B., Wetterlind, J., Chenu, C., Bispo, A., Oorts, K., & Bulens, J. (2021). Report on the national and EU regulations on agricultural soil data sharing and national monitoring activities. Zenodo. https://doi.org/10.5281/zenodo.10014912

[53] agid.gov.it/it/agenzia/stampa-e-comunicazione/notizie/2023/12/22/open-data-online-guida-operativa-sui-dati-elevato

[54] Open access to Land Parcel Identification System (LPIS) and Geospatial Aid Application (GSAA) datasets from Member States improved significantly during 2024 in both the DGAGRI Geoportal and the EU INSPIRE Portal. Hopefully, implementation of the EU GreenData4All initiative will increase national compliance with the INSPIRE Directive further.

3.3 Uncertainty Assessment in Carbon Farming

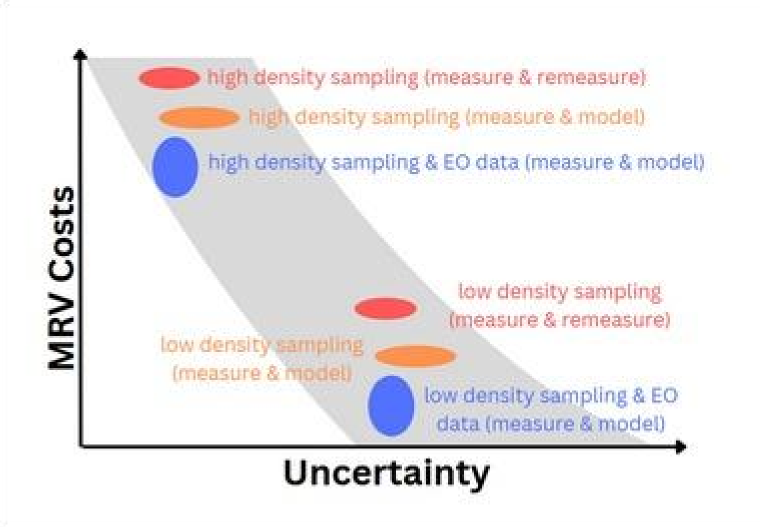


Figure 2: Conceptual diagram showing that modeling with the input of EO data can reduce costs with respect to a measure & remeasure approach, and reduce uncertainty for measure & model approaches. Uncertainties can vary based on sampling methods ("measure" component) and the type and quality of primary data ("model" component, with or without EO). Costs associated with EO data can vary widely depending on the specific EO method (e.g. LiDAR).

In carbon-farming projects, there are two accepted approaches for quantifying additionality: *measure & re-measure* and *measure & model*. *Measure & remeasure* relies on direct, repeated field sampling, with soil cores and/or biomass measurements taken at regular intervals to quantify how much carbon is actually stored or emitted over time. With proper high-density sampling it delivers high confidence data but is labour intensive and costly (Figure 2). *Measure & model* still requires an initial field measurement to set a baseline, but subsequent carbon gains are quantified with calibrated biogeochemical process-based models that blend local weather, soil, and management data, sharply reducing monitoring costs while introducing some uncertainty. Together, the two approaches form a spectrum: measure & remeasure maximizes empirical accuracy (even after the consideration about uncertainties on "ground truth" data discussed in the previous sections), whereas measure & model trades a small precision penalty for scalability and broader project eligibility.

When a model is used to evaluate carbon units, several sources of uncertainties have to be considered, and evaluated together. In general, uncertainty arises from three main sources: model structural uncertainty, input uncertainty, and parameter uncertainty. A sensitivity analysis should be considered a prerequisite to help identify the most influential input parameters affecting simulation outcomes, enabling the selection of only the most relevant variables for Monte Carlo-based uncertainty assessment.[55] The source of uncertainty are the initialization of the model, the model parameters, the model input variability (e.g. meteorological data), the variability of data

[55] Confalonieri, R., Bellocchi, G., Tarantola, S., Acutis, M., Donatelli, M., Genovese, G., 2010. Sensitivity analysis of the rice model WARM in Europe: Exploring the effects of different locations, climates and methods of analysis on model sensitivity to crop parameters. Environmental Modelling & Software 25, 479–488. https://doi.org/10.1016/j.envsoft.2009.10.005).

used for calibration,[56] the protocol followed for model application, the uncertainty of the EO assimilated in the model. If there are sufficient plots with reliable measurements in Baseline and Project scenarios, an analytic approach is possible. Including EO data in the model has shown to contribute to reducing uncertainty, providing an interesting approach to lower the costs associated with carbon farming MRV while maintaining acceptable levels of uncertainty. For example, combining satellite-derived biophysical products (e.g. biomass, leaf area index, superficial SOC) and modelling with smart soil sampling (for soil model initialisation) guided by EO of vegetation and soil spatial variability can improve the precision of the monitoring and verification of SOC and C budget components, would reduce their cost of implementation or increase their accuracy. To support these approaches, in-situ protocols adapted to EO based MRV approaches (e.g; Elementary Sampling Unit protocols) and monitoring networks for calibrating/training/validating/verifying algorithms based on EO for mapping soil and vegetation biophysical properties related to the C budget components (e.g. Leaf area index, biomass, superficial SOC) and carbon farming and forest management practices are needed.

In the literature, models are mostly tested by matching their absolute carbon-stock predictions to field measurements for a single treatment over time. Far fewer studies check the model in the way carbon-crediting schemes actually work, i.e. by comparing the modelled change (project scenario minus baseline). Because many model errors affect both the baseline and the project in the same way, those shared errors mostly cancel when computing the difference, so the uncertainty on the delta carbon-stock estimate is generally smaller than the uncertainty on either absolute prediction. The model uncertainty is then estimated as the variance of prediction of the difference between baseline and the project scenario across all sites in the statistical validation dataset. In the most common case when there is only some specific site that allows for direct measure of the model error in predicting delta, it can be assumed that the variance of the model prediction is the same in the project and baseline and consequently it is possible to use the covariance between model and baseline delta to estimate the uncertainties (see, for details, the Verra protocol VM0042, version 2.1). In absence of sufficient data, Monte Carlo methods can be used. Overall, experience shows that 250 to 1000 model runs are sufficient to estimate uncertainties,[57] but the feasibility will depend on the overall quantification approach. Indeed, a Monte Carlo method will require many simulations to compute uncertainty for all fields, as some large scale projects may model 200,000 fields per monitored period. Therefore the

[56] Gurung, R.B., Ogle, S.M., Breidt, F.J., Williams, S.A., Parton, W.J., 2020 Bayesian calibration of the DayCent ecosystem model to simulate soil organic carbon dynamics and reduce model uncertainty. Geoderma 376, 114529. https://doi.org/10.1016/j.geoderma.2020.114529

[57] Gurung, R.B., Ogle, S.M., Breidt, F.J., Williams, S.A., Parton, W.J., 2020. Bayesian calibration of the DayCent ecosystem model to simulate soil organic carbon dynamics and reduce model uncertainty. Geoderma 376, 114529. https://doi.org/10.1016/j.geoderma.2020.114529 ; Leary, S., Bhaskar, A., Keane, A., 2003. Optimal orthogonal-array-based latin hypercubes. Journal of Applied Statistics 30, 585–598. https://doi.org/10.1080/0266476032000053691

reference for uncertainty calculation must be very well defined by the methodology to enable a valuable comparison of outcomes within a given climate, soil, cropping systems at a comparable MRV cost.

Considering that Europe can be split into four to five climate zones according to the IPCC,[58] or 13 according to Metzger et al.[59] In order to have comparable uncertainty levels across all countries or climate zones a model thus undergoes a calibration and a validation based on peer-reviewed publications. These calculated uncertainty levels will be reassessed at true-up[60] using sampling results. In the past three years, Project MARVIC[61] as well as private companies have all worked on the calibration and validation of various models. To mention a few that operate in Europe: eAgronom and CarbonChange (ARMOSA), Agreena (Roth-C), Regrow (DNDC). The CarbonChange team has calculated the uncertainty for four climate zones for various tillage and cover crop combinations on arable crops across Europe and Ukraine from which the following observations have been drawn:

- Finding studies is not as difficult as retaining a representative volume of good quality studies for the given practices that the CRCF and existing carbon projects aim to *Measure & Model*. For the calibration and validation of the ARMOSA model under Verra VM0042 (VMD0053), only 50 studies provided about 200 acceptable data points.
- Some climate zones had a higher number of datapoints but led to higher uncertainty calculation due to the quality of the data points themselves.
- The overall recommendation to the scientific community is to make up for the gap in long term measurement studies where the uncertainty or quality of data points is, to date, the lowest. The Cool Temperate Moist and Warm Temperate Dry zones present twice as many qualified data points as compared to the Cool Temperate Dry or Warm Temperate Moist zones.
- Providing a central database of publicly available long term results would ease and fasten the calibration and validation of models, thus improving their comparison based on harmonized uncertainty calculations.
- A dynamic uncertainty quantification model is preferable over fixed percentage assumptions.

[58] https://www.ipcc-nggip.iges.or.jp/public/2019rf/corrigenda1.html
[59] Metzger, M.J., Bunce, R.G.H., Jongman, R.H.G., Mücher, C.A. and Watkins, J.W. (2005), A climatic stratification of the environment of Europe. Global Ecology and Biogeography, 14: 549-563. https://doi.org/10.1111/j.1466-822X.2005.00190.x
[60] "True-up" is a periodic reconciliation step in which modelled changes in carbon stocks (whether in soils, trees, or other biomass pools) are compared against newly collected field measurements (e.g. soil cores, timber inventories), and any over- or under-estimations are corrected.
[61] https://www.project-marvic.eu/

4. Benchmarking of MRV Methodologies

Benchmarking is the process of systematically comparing performance, practices, or outcomes against established standards, best practices, or peer groups. It serves as a reference point to measure improvements, identify gaps, and guide decision-making towards achieving optimal performance. In the context of carbon farming, "Baselining” focuses on establishing what constitutes "typical" or expected performance in a specific system under various conditions. These baselines account for regional, environmental, and management differences, such as pedoclimatic conditions and farm systems, ensuring that the performance expectations reflect local realities. It is important to develop baselines tailored to specific ecological contexts and farm operations, so that practices are appropriately evaluated against realistic performance standards. European land managers (from agricultural to forestry operations) are at very different stages of implementing carbon removals and carbon farming practices, meaning that a framework focusing solely on net removals could reward late adopters while inadvertently penalizing early movers. Therefore the choices made for baseline benchmarking must mitigate this risk by recognizing existing efforts and ensuring fairer comparisons across diverse contexts.

Carbon farming is a broad concept that encompasses many practices, such as agroforestry, cover cropping, reduced tillage, and rotational grazing. A MRV model might perform excellently in one type of climate or soil but fail to meet expectations in another. *Model benchmarking* assesses how different carbon removal models perform when exposed to the same set of inputs, for example climate, soil type, and farming practices. This helps identify the strengths and weaknesses of each model under various conditions and supports the development of more robust and generalized frameworks for carbon removal predictions. Model benchmarking is essential to ensure that the models used for MRV are reliable and adaptable across diverse situations. It enables stakeholders to make informed decisions regarding the application of specific models, depending on the land-use type and management practices in question. A comprehensive model benchmarking framework must consider a wide range of farming systems to provide a complete and accurate assessment of carbon removal potentials, building upon the baseline assessment work. Such inclusivity ensures that benchmarks reflect the full scope of carbon farming practices, from traditional agricultural techniques to newer, innovative methods, ensuring that diverse stakeholders can participate and benefit from carbon removal efforts.

For all the above mentioned points, we bring forward the suggestion of establishing a EU benchmarking platform, integrating and harmonizing the ongoing efforts in research and in the private sector. The main objective of such a platform would be to allow any stakeholder to benchmark their MRV application through a standardized methodology and with common, well curated input data, for example from long term monitoring projects. Given the rapid advancements in EO technologies, it is important to ensure continuous updates to MRV methodologies while ensuring their robustness. This would help the carbon market stay aligned with state-of-the-art capabilities in EO, ensuring that monitoring and verification practices remain accurate and effective. The platform could serve as a hub for integrating the latest technological advancements, sharing relevant agricultural dataset, and promoting the adoption of cutting-edge tools for carbon monitoring. The establishment of clear and transparent model benchmarking frameworks (such as the proposed EU benchmarking platform) is essential to address the challenges associated with MRV methodologies for the carbon markets. An accepted model benchmarking framework for MRV is needed to ensure consistency and credibility, and support the assessment of MRV models by independent model experts, which currently introduces a high degree of subjectivity during the audits of carbon farming projects. Such a platform would further enable the development, validation, and dissemination of standardized methodologies, which are crucial for fostering trust and transparency in carbon removal projects.

The EU model benchmarking platform would serve as a critical enabler for aligning MRV methodologies, addressing gaps in standardization, and fostering the integration of EO into the carbon market. This initiative would help unlock the full potential of EO technologies, supporting more transparent, effective, and scalable carbon removal efforts across Europe and beyond. Currently, the lack of standardized frameworks poses significant challenges for both MRV providers and users. Without clear standards, it becomes difficult for these providers to offer solutions that are widely accepted, and for the users to choose a service transparently suitable to their systems. This gap also complicates the process of turning EO data into actionable insights across different scales—whether at the plot, regional, or national level. Challenges such as limited infrastructure for handling big data and the lack of generalized data interpretation frameworks further hinder the effective utilization of EO in carbon removals and carbon farming MRV systems. Several EU funded projects are already working on collecting data on different MRV models performance and harmonizing procedures (see Table 4 for a short list of initiatives). Building a model benchmarking platform would be a way for these efforts to converge into an operational tool available to all relevant stakeholders from the public and private sector.

Table 4:several initiatives at the EU level are contributing to developing baselines for carbon farming practices across different pedo-climatic conditions and assessing robust MRV methodologies. A model benchmarking platform could build on the results from these efforts, maximising their impact.

Baseline assessments	MRV frameworks assessments
EU CAP Network; Climate Farm Demo;	MARVIC; MRV4SOC; ORCaSa; private

Credible FGs 1.5 and 3.4	companies

Beyond the heavy technical requirements, benchmarking is ultimately a political decision. Establishing benchmarking processes requires a careful balance of scientific rigor, economic feasibility, stakeholder trust, and policy objectives. Determining the appropriate standards for reporting and verification is critical for the adoption and credibility of carbon removals and carbon farming practices.

5. Conclusions

Harmonizing data sources and methodologies remains a cornerstone of reliable MRV systems.[62] By leveraging integrated datasets, improving access to high-resolution imagery, and developing models representative of the different pedoclimatic regions,[63] stakeholders can ensure more accurate and actionable insights. Ultimately, these efforts will support the long-term goals of sustainable carbon farming and effective climate mitigation strategies.

To assess the real level of uncertainty in carbon stock quantifications, field reference plots and future trial plots or living labs must monitor carbon dynamics during the activity period. More accurate MRV systems are qualified by lower uncertainty values leading to lower uncertainty deduction from the final number of carbon units, and thus increase trust and transparency in carbon markets. As a result, farmers benefit from fair compensation when carbon sequestration is measured more precisely, and investors gain confidence in carbon farming as a scalable, reliable climate solution.

We strongly recommend that major efforts are put into cross-project harmonization, as currently several EU-funded initiatives are working on different aspects of data and model quality for MRV in carbon farming. For example, two proposals for high-resolution monitoring have recently been selected in the Horizon Soils Mission (2024-SOIL-01-07) "*Development of high spatial-resolution monitoring approaches and geographically-explicit registry for carbon farming*". Amongst other outcomes, these projects are expected to:

- *Increase the confidence of stakeholders (including land managers) in participating in possible carbon farming certification schemes by providing better access to information and data regarding soil carbon (key activity data such as organic amendments or straw management, achievable sequestration and storage, risks of release, etc.).*

[62] See also ORCASA Deliverable 4.2: https://irc-orcasa.eu/resource/?category=deliverables
[63] Batjes, N. H. et al. (2024) 'Towards a modular, multi-ecosystem monitoring, reporting and verification (MRV) framework for soil organic carbon stock change assessment', Carbon Management, 15(1). doi: 10.1080/17583004.2024.2410812.

- *Provide reliable benchmarks or baselines for soil carbon at land management parcel level across the EU, with a view to providing financial rewards to those farmers and forest managers/owners who go beyond the baselines within the proposed framework for Carbon Removal Certification.*
- *Improve decision making in the AFOLU sector at the regional or national level thanks to enhanced quality of national GHG inventories and geographically explicit soil monitoring elements that reflect action at the individual parcel level.*

We emphasize the urgent need for a clear and easy-to-navigate data governance framework for agricultural and land-use information, as many overlapping regulations now affect the sector at different levels. It is unfortunate that several EU Member States are still not making their CAP monitoring data available, despite increasing requirements from recent directives to comply. Specifically for carbon farming, we note that data governance experts haven't been involved enough in helping to align technical innovations with regulations affecting data availability and usability. It is also advisable that organizations such as the European Environment Agency and FAO's Global Soil Partnership, take a leading role and become active with Horizon and national projects such as AgriDataSpace[64], contributing to the development of a Common European Agricultural Data Space (CEADS) that can support technological advancements of MRV systems supported also by EO data.

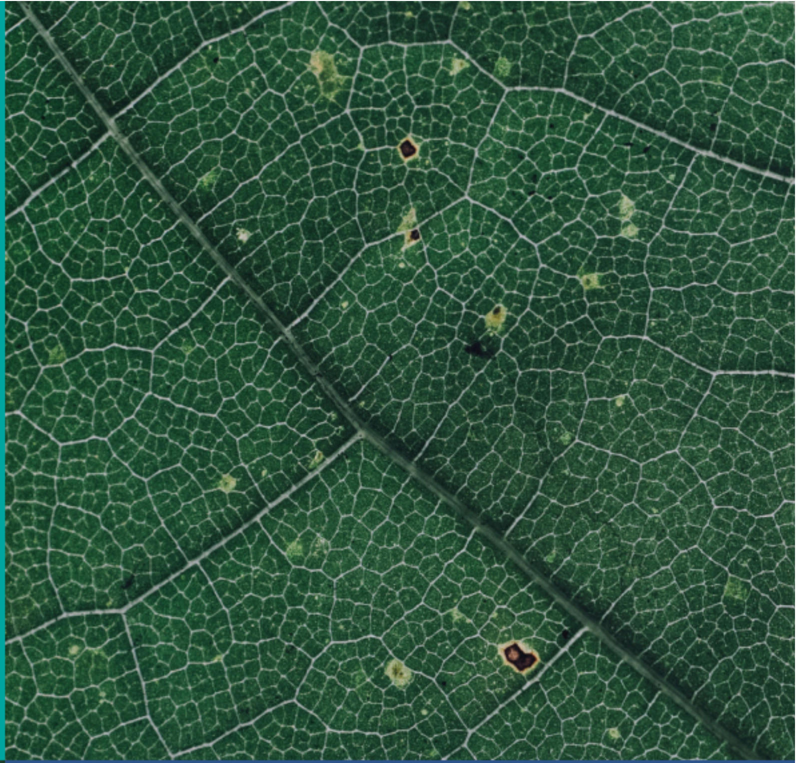
Finally, we advance the idea of a European model benchmarking platform to integrate the ongoing efforts on assessing the validity of different MRV methods and build trust through a transparent model evaluation process.

6. Glossary

Acronym	Meaning
AFOLU	Agriculture, Forestry, and Other Land Use
AMS	Area Monitoring System (CAP)
CAP	Common Agricultural Policy
CEADS	Common European Agricultural Data Space
CF	Carbon Farming
CRCF	Carbon Removal Certification Framework
DG AGRI	Directorate-General for Agriculture and Rural Development (European Commission)
DG CLIMA	Directorate-General for Climate Action (European Commission)
EARSC	European Association of Remote Sensing Companies
EO	Earth Observation

[64] https://agridataspace-csa.eu/

ERA5	ECMWF Reanalysis 5th Generation
ESA	European Space Agency
EU	European Union
EURAF	European Agroforestry Federation
FAIR	Findable, Accessible, Interoperable, and Reusable (data principles)
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation
FG	Focus Group
GHG	Greenhouse Gas
GIS	Geographic Information System
GLOSOLAN	Global Soil Laboratory Network
GSAA	Geospatial Aid Application
HCAT3	Hierarchical Crop and Agriculture Taxonomy (version 3)
IACS	Integrated Administration and Control System
ICOS	Integrated Carbon Observation System
INRAE	French National Research Institute for Agriculture, Food and Environment
INSPIRE	Infrastructure for Spatial Information in Europe
IPCC	Intergovernmental Panel on Climate Change
ISO	International Organization for Standardization
JRC	Joint Research Centre
LAI	Leaf Area Index
LiDAR	Light Detection and Ranging
LPIS	Land Parcel Information System
LULUCF	Land Use, Land Use Change and Forestry
MRV	Monitoring, Reporting, and Verification
NILU	Norwegian Institute for Air Research
SOC	Soil Organic Carbon
UAV	Unmanned Aerial Vehicle
UNFCCC	United Nations Framework Convention on Climate Change



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