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Demands and possibilities for field-scale estimation of agricultural greenhouse gas balances

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ABSTRACT

Soil organic carbon (SOC) changes and greenhouse gas (GHG) emissions from agricultural soils contribute considerably to anthropogenic climate change. This draws attention to the management of agricultural fields and creates the need to assess and understand the resulting SOC changes and GHG balances and their drivers. Currently, GHG reporting systems such as national GHG inventories, carbon footprinting, and reporting practices in voluntary carbon markets largely apply rough estimation methods for these emissions. These methods do not relevantly cover the impacts of management or environmental factors on SOC changes or GHG emissions and their large spatial variability. At the same time, the rapid development of sensor techniques and data analysis methods creates opportunities for creating field-scale monitoring and reporting systems based on various data streams, including remote sensing.

In this paper, we reviewed the existing GHG reporting systems, and how SOC changes and GHG emissions of agricultural soils are currently reported in them. We also reviewed the most important factors affecting field-scale GHG balances and SOC changes, and the current measurement techniques and modeling approaches applied, as well as novel integrated systems combining various data streams. Finally, we identified the key developments towards a credible, operational, and cost-efficient field-scale reporting system. We used Finland, which has already made considerable efforts to report and calculate agricultural emissions, as an example to highlight practical challenges.

1. Introduction

Climate change poses serious challenges to global agricultural production (Anderson et al., 2020; Ortiz-Bobea et al., 2021), while at the same time, agriculture is expected to provide effective means for climate change mitigation (Smith et al., 2007). Currently, agriculture covers about one third of the global land area (FAO, 2023). Greenhouse gas (GHG) emissions from agricultural production and associated land-use changes in 2020 were 10.5 Gt CO_2eq, which with the pre- and post-production emissions (5.6 Gt CO_2eq) represented about 31 % of all global anthropogenic GHG emissions (FAO, 2022). The overall global potential for agricultural climate change mitigation is estimated to be up to 6 Gt CO_2eq yr-1 (Smith, 2012), highlighting the importance of seeking effective mitigation options from the sector.

The mitigation potential of agricultural production systems comes from GHG emission reductions, e.g., via improved livestock management, bioenergy production replacing fossil fuels, and especially from enhanced soil carbon sequestration (SCS) (Smith, 2012). Promising prospects for SCS set bases for the 4 permille soils initiative launched at COP21, which asserted that global anthropogenic carbon dioxide (CO_2)

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emissions could be offset by increasing global soil organic carbon (SOC) stocks by 0.4 % per year (Minasny et al., 2017). For example, enhanced SCS linked to agricultural management practices have been reported with reduced tillage (Ogle et al., 2019), the use of cover crops (Abdalla et al., 2019), the diversification of crop rotations (Francaviglia et al., 2019), agroforestry (Mayer et al., 2022), manure application or crop residue retention (Bolinder et al., 2020), and organic agriculture (Gattinger et al., 2012). However, SCS potential also depends strongly on the local environmental conditions (Wiesmeier et al., 2019) and previous land-management practices (England et al., 2016). This creates huge spatial and temporal variability and uncertainty in SCS potential (Georgiou et al., 2022; Pacini et al., 2023). The same management practice thus does not yield similar SCS rates at different places and times, and actions to realize the SCS potential and reduce GHG emissions must always consider local conditions and be locally verified (Amelung et al., 2020).

Information about the economic, social, and environmental (including SOC and GHG emission) impacts of land management is increasingly required at different scales. Landowners, e.g., farmers and forest owners, need information to optimize their management and to participate in the voluntary carbon market (Mattila et al., 2022). Fast-changing citizen awareness, consumer preferences, and market practices have increased interest in products' sustainability impacts, as well as the sustainability reporting of companies, the development that has also been accelerated by emerging regulation such as the EU's new Corporate Sustainability Reporting Directive (CSRD). At the national level, information about national GHG emissions and their trends is needed to support national and international climate policies, decision making, and the implementation of conventions. Given that the key operational unit within the arable production systems is a field parcel, emission information at the field scale would best serve these information needs.

Increasing pressure for field- or plot-scale and management-specific emission monitoring have led to international calls for platforms, information systems, and standards allowing accurate monitoring and reporting of SOC changes and GHG fluxes from agricultural soils (Bispo et al., 2017; Paustian et al., 2019; Smith et al., 2020, Smith et al., 2012). However, it is still unclear whether they can meet the accuracy and precision required in different applications. The large spatial variation of SOC stocks (Heikkinen et al., 2021), high costs of sampling schemes (Smith et al., 2020), and the still incomplete understanding of processes and factors determining SOC and GHG emission dynamics (e.g., Were et al., 2019) hamper reliable emission and SOC assessments. For example, uncertainties in field-scale (Heikkinen et al., 2021) or regional SOC and GHG emission assessments (Ogle et al., 2010), or those in the GHG emission inventories from the LULUCF sector (McGlynn et al., 2022; Peltoniemi et al., 2006) have been reported to be significant.

This paper focuses on the GHG and SOC reporting of agricultural fields in different GHG reporting systems—that is, national GHG inventories, carbon footprinting, and systems used in voluntary carbon markets. The overall aim is to identify the critical development needs of the current reporting methods to better cover the essential field-scale drivers and complex interactions affecting the accuracy of their emission and SOC estimates. To this end, we 1) review the key GHG reporting systems to describe how and at which level they account for the emissions and the SOC changes, and 2) the most important factors affecting the GHGs and SOC at the field scale; 3) provide an overview of today's measurement techniques and modeling approaches and identify the major data and knowledge gaps; and finally 4) develop a vision for the short- and long-term future reporting taking into account the different requirements of the reporting systems and the practical challenges of data availability and cost-efficiency. We use Finland, which has already made considerable efforts to report and calculate agricultural emissions, as an example to highlight the practical challenges. Our conclusions also contribute to the discussion on the future reporting systems elsewhere in the world.

2. Greenhouse gas reporting systems

2.1. National greenhouse gas inventories

National GHG inventories play a pivotal role in the global effort to combat climate change. They aim to systematically list, quantify, and document GHG emissions and removals within a country's jurisdiction. Governments or agencies conduct the inventories and submit them to international entities, including the European Commission (if a member state) and the United Nations Framework Convention on Climate Change (UNFCCC). They provide a comprehensive assessment of the sources and trends of emissions and establish the baseline, enabling countries to set and follow GHG emission reduction targets in alignment with international agreements such as the Paris Agreement. Furthermore, inventories inform the development of climate policies and strategies, facilitating evidence-based decision making and enabling the modeling of various emission scenarios. In turn, this empowers policymakers to evaluate the consequences of different policy choices on future emissions.

The Intergovernmental Panel on Climate Change (IPCC) provides methodological advice and guidelines for inventory methods and practices, which the parties to UNFCCC have agreed to use in their reporting. IPCC also provides alternatives with different *tiers* that represent a level of methodological complexity: Tier 1 is the simplest default method; Tier 2 is intermediate with country-specific parameters; and Tier 3 is the most complex but also the most accurate method directly applying measurements and modeling. The IPCC recommends the use of validated national Tier 3 methods. The important criteria for the GHG inventory methodologies are transparency, consistency among inventoried years, comparability, completeness, and accuracy.

GHG emissions from agricultural activities fall under three inventory sectors. The agricultural sector encompasses emissions from enteric fermentation, manure management, agricultural soils, the field burning of agricultural residues, liming, urea application, and nitrous oxide (N_2O) emissions from agricultural soils, except the N_2O emissions from the change of land use into cropland and grassland reported in the land use, land-use change, and forestry (LULUCF) sector. The LULUCF sector addresses agriculture's net CO_2 emissions, including net carbon stock changes in the biomass of perennial woody plants (e.g., currants, apple trees) and SOC of croplands and grasslands. In addition, CO_2, methane (CH_4), and N_2O emissions from wildfires on croplands and grasslands are accounted for in LULUCF. The energy sector encompasses emissions from agricultural vehicles and machinery.

In Finland, the agricultural sector accounts for 13 % of national emissions (excluding the LULUCF sector), with soils alone accounting for 6 % (Statistics Finland, 2023). Within the LULUCF sector, the cropland category stands out as the primary emission source, while the grassland category plays a relatively minor role. Several reporting categories are associated with management activities in the fields (Table 1), and many are recognized as key categories, underscoring their significance for emission levels and trends. Organic soils form an emission hot spot, causing 87 % of all net CO_2 emissions in the LULUCF sector, as well as 46 % of all indirect and direct soil N_2O emissions in the agricultural sector (Statistics Finland, 2023). Finland estimates these emissions using Tier 2 emission factors. It applies a Tier 3 method combining regional yield statistics and SOC modeling to estimate mineral soil CO_2 emissions (Palosuo et al., 2016; Statistics Finland, 2023). The Finnish inventory integrates diverse statistical and spatial data, many only available at the national scale (Table 2).

2.2. Carbon footprinting

The environmental life cycle assessment (LCA) is a method for assessing environmental impacts (ISO, 2006), and it is used in the carbon footprinting of products. Carbon footprinting is typically used for environmental communication, monitoring, verification, research, and

Table 1
Emission categories relevant for field-scale reporting and their tiers in the Finnish National Greenhouse Gas Inventory (NGHGI) (Statistics Finland, 2023). Emission categories (3) and (4) belong to the agricultural and LULUCF sectors, respectively.

Reporting categories (CRF[1] numbers)	Emissions reported	Tier applied in the Finnish NGHGI	Identified as key category[2]	The basic calculation scale[3]
Direct N_2O emissions from managed soils (3.D.1)			Yes	
Inorganic N fertilizers	N_2O	Tier 1		National
Organic N fertilizers				
Animal manure applied to soils	N_2O	Tier 1		National
Sewage sludge applied to soils	N_2O	Tier 1		National
Other organic fertilizers applied to soils	N_2O	Tier 1		National
Urine and dung deposited by grazing animals				National
	N_2O	Tier 1		
Crop residues	N_2O	Tier 1		National
Mineralization/immobilization associated with loss/gain of soil organic matter (Cropland remaining cropland)	N_2O	Tier 2		Sub-national
Cultivation of organic soils				
	N_2O	Tier 2		National
Indirect N_2O emissions from managed soils (3.D.2)			Yes	
Atmospheric deposition	N_2O	Tier 2		National
Nitrogen leaching and runoff	N_2O	Tier 2		National
Liming (3.G)	CO_2	Tier 1	Yes	National
Urea application (3.H)	CO_2	Tier 1	No	National
Cropland remaining cropland (4.B.1)			Yes	
Organic soils	CO_2	Tier 2		National
Mineral soils	CO_2	Tier 3		Sub-national
Land converted to cropland (4.B.2)			Yes	
Organic soils	CO_2	Tier 2		National
Mineral soils	CO_2	Tier 1[4],3		Sub-national
Grassland remaining grassland (4.C.1)			Yes	
Organic soils	CO_2	Tier 2		National
Mineral soils	CO_2	–[5]		–
Land converted to grassland (4.C.2)			No	
Organic soils	CO_2	Tier 2		National
Mineral soils	CO_2	Tier 1[4],3		Sub-national

[1] CRF (Common Reporting Format) applied in the UNFCCC CRF Reporter Inventory software.
[2] The key categories in the inventories are those that make the greatest contribution to the overall level of national emissions, those that have had the largest influence on the trend of emissions over time, or those with considerable uncertainty.
[4] Settlements which are converted to croplands or grasslands are calculated with Tier 1.
[3] Sub-national means the division of country into the southern and northern parts, see, e.g., Finland's National Inventory Report 2023, Appendix 6_a.
[5] Grassland on mineral soils consists mostly of abandoned fields. It is assumed no changes in the SOC stocks occur in this category, as no changes were anticipated in the carbon input or quality during the inventory period.

policymaking. The aims of carbon footprinting may be roughly divided into three categories: i) to estimate the global warming potential (GWP; i.e., carbon footprint or climate impact) of a product; ii) to highlight the GHG emission hot spots within the production chain; and iii) to quantify and report GHG emission reductions following improved management.

Different methodologies are applied in LCA, often based on the general LCA framework presented in ISO standards (ISO, 2006; ISO, 2018). In LCA, product life cycle phases are considered from raw material acquisition to production, transportation, use, and disposal/recycling (ISO, 2006), depending on the assessment system boundaries (Fig. 1). Within these boundaries, material and energy inputs to the system are accounted for similarly to the outputs of product(s), co-product(s), emissions, and waste. The assessment accounts for elementary flows—that is, any flows of material or energy to or from the system—without double or partial counting. The typical system boundary of agricultural product carbon footprinting is either cradle-to-farm gate or cradle-to-factory gate.

GWP is an impact category within LCA that illustrates the potential of a product to cause climate warming. GWP consists of fossil, biogenic, land use and land-use change (LULUC)-related GHG emissions (European Commission, 2021). Fossil GHG emissions refer to the release of fossil C and N_2O emissions during the product's life cycle. The biogenic GHG emissions of agricultural products typically contain enteric methane from ruminant metabolism (European Commission, 2021) but not the emissions or sinks of biogenic CO_2. The reason for this is that most agricultural products are short-lived and release the same amount of CO_2 back into the atmosphere at the end of their short life cycles as they captured in the growth process (ISO, 2018). For example, CO_2 sequestrated by cereal plants and allocated to the grains is emitted back into the atmosphere when bread made from the grain is consumed by a human. LULUC-related GHG emissions refer to carbon stock changes in living biomass, soil, and dead organic matter related to land-use changes (e.g., forest conversion to cropland) and land-management changes (e.g., changes in crop rotation or the cultivation of cover crops). The stock changes lead to either net CO_2 emissions (=LULUC emissions) or removals considered as negative emissions (=LULUC removals).

Typical data regarding agricultural plant products need to include the soil and climate conditions of the cultivation site; land-use history; fertilizer, lime, and pesticide types and use rates; application rates and types of manure and other organic amendments; field operation types and numbers; and yield and yield quality. LCA data needs depend on the goal and scope, and therefore the assessment's system boundary (Fig. 1). GHG emissions to air, soil, and water are typically estimated in LCA by emission factors, calculations, or models, depending on goal, scope, and data availability. The most widely used agri-soil-GHG emission factors and calculations are based on the IPCC methodology: N_2O from N-fertilizers and crop residues (IIPCC, 2006a,b; IPCC, 2019a); CO_2 from liming (IPCC, 2006a,b) and LULUC-related GHG emissions (IPCC, 2006b, 2013, 2019b). More site-, crop-, or management-method-specific emission factors and calculations are developed for N-fertilizer N_2O

Table 2
The data used in the national GHG inventory of Finland for estimating agricultural SOC and soil-based nitrous oxide (N_2O) and methane (CH_4) emissions.

Data	Data source[3)]	Spatial scale	Temporal scale	Uncertainty level	Used in emission calculations		
					CO_2	N_2O	CH_4
Cropland and grassland area	Field parcel registry, National Forest Inventory and additional map sources	spatial	annual	low	X	X	X
Soil type (mineral/ organic)	Soil database (Luke)	spatial	constant[1)]	intermediate	X	X	
Crop yield data	Agricultural production statistics (Luke)	regional	annual	low	X	X	–
Inorganic fertilizer input	National database of fertilizer volumes sold (Finnish Food Authority)	national	annual	low	–	X	–
Animal numbers	Agricultural production statistics (Luke, Central organizations for animal husbandry)	regional	annual	low	X	X	X
Animal feeding data	Production surveillance feeding data (dairy cattle), feeding standards and feed composition tables	national	annual[2)]/ constant[1)]	low/ intermediate	X	X	X
Sewage sludge production	Environmental Protection Reporting Service, Waste Statistics	national	annual	low	–	X	–
Sewage sludge use in agriculture	Surveys on the processing and utilization of municipal sewage sludge (Lapinlampi and Raassina, 2002, Vilpanen and Toivikko, 2017)	national	constant[1)]	high	–	X	–
Meat and bone meal and potato cell sap	Manufacturing statistics (Finnish Food Authority)	national	annual	low	–	X	–
Manure management data	Questionnaire studies (Syke, Luke)	national	constant[1)]	intermediate	X	X	X
Weather data	Gridded weather data from FMI	spatial data (10 x 10 km)	monthly	low	X	X	–

1) Information is considered relatively constant, but the database is checked regularly for potential revisions.
2) Feeding data for dairy from 2010 onward come annually.
3) Abbreviations used for research institutes: Natural Resources Institute Finland (Luke), Finnish Environment Institute (Syke), Finnish Meteorological Institute (FMI)

emissions in Finland, for example (Regina et al., 2013).

Currently, the most significant methodological challenges in the carbon footprinting of agricultural products arise from LULUC emissions and removals, which have traditionally been excluded from LCA (Brandão et al., 2013; Goglio et al., 2015), although they have moderate or major effects on the GWPs of agricultural products (Brandão et al., 2011; Joensuu et al., 2021; Karlsson et al., 2017; Knudsen et al., 2019; Röös et al., 2011; Sevenster et al., 2020; Stanley et al., 2018). LULUC emissions or removals are increasingly included in LCA studies and LCA databases such as ecoinvent (Wernet et al., 2016) and Agri-footprint (Blonk et al., 2023). The methods used for LULUC emission and removal estimation remain diverse and unharmonized, varying in their accuracy and coverage (Goglio et al., 2015). For example, GHG emissions from organic soils are often excluded, which can significantly underestimate the GWP of agricultural products, especially in areas with a high share of agricultural organic soils, such as Finland.

An important characteristic of LULUC emission and removal estimation in LCA is the responsibility windows used. It refers to the period during which the LULUC emissions or removals caused by land-use or land-management change are allocated to products. In LCA, Tier 1–2 approaches are often used with a fixed-term responsibility window, which is typically 20 years (BSI, 2011; European Commission, 2021; IDF, 2022). In practice, in plant production, this means that the *total* carbon stock change from a steady-state (i.e., equilibrium) carbon stock to a new steady-state carbon stock caused by a land-use or land-management change is allocated for crops cultivated during a pre-defined period of 20 years. An alternative approach is to consider the emissions or removals until a new steady state is actually reached, which applies to Tier 3 methods (IDF, 2022). The selection of the responsibility window does not affect the total amount of LULUC emissions or removals in LCA, as all past land-use and land-management changes are fully accounted for, and all new land-use and land-management changes create additional new emissions. Only the specific selection of products related to each occasion of land-use or land-management change may differ when different responsibility windows are applied.

2.3. *Reporting practices in voluntary carbon market*

The voluntary carbon market is evolving to meet the need for faster and more effective mitigation of climate change than is possible via mandatory regulations and traditional local actions. Voluntary carbon credits are purchased and used as part of corporate social responsibility (CSR) actions. Companies complement their emission reduction targets with mitigation actions outside their value chains (Trouwloon et al., 2023). Countries can also buy the credits to support the achievement of national climate change mitigation targets. As of 2022, the voluntary carbon market is valued at around $2,000 million (CarbonCredits.com, 2024). After exponential growth until 2021, the market slowed down due to allegations of "greenwashing," which left some companies more hesitant to participate in the market. However, demand for carbon credits is expected to grow due to improved regulatory frameworks and new trust-enhancing initiatives, and because companies with net-zero goals will need to buy credits to cancel out their emissions.

Carbon credits must be trustworthy to ensure the integrity and liability of the voluntary carbon market. Credits are expected to meet the following general principles: The mitigation outcome should be quantified and real, additional, and permanent. The mitigation activity should not cause leakage. A program issuing credits, or any such administrative body, should follow good governance principles, including transparency, tracking, and third-party validation and verification. While the general principles are well established, their interpretation in the context of the Paris Agreement is still evolving (Helppi et al., 2023; Schneider et al., 2020). Moreover, the international and national guidance on the high integrity of carbon credits and their voluntary use are under development (e.g., EU Carbon Removal Certification). Robust and transparent monitoring and reporting systems are central to the credits. The guidelines associated with the voluntary use of carbon credits can also only be used for reporting purposes for those companies that aim to sequester carbon within their value chains and credibly account for them.

Ensuring a real and verified mitigation outcome is one of the key challenges for proper and justifiable SOC sequestration carbon crediting schemes (Jacobs et al., 2020a; Paul et al., 2023). Carbon crediting programs differ in their approaches to measuring, reporting, and

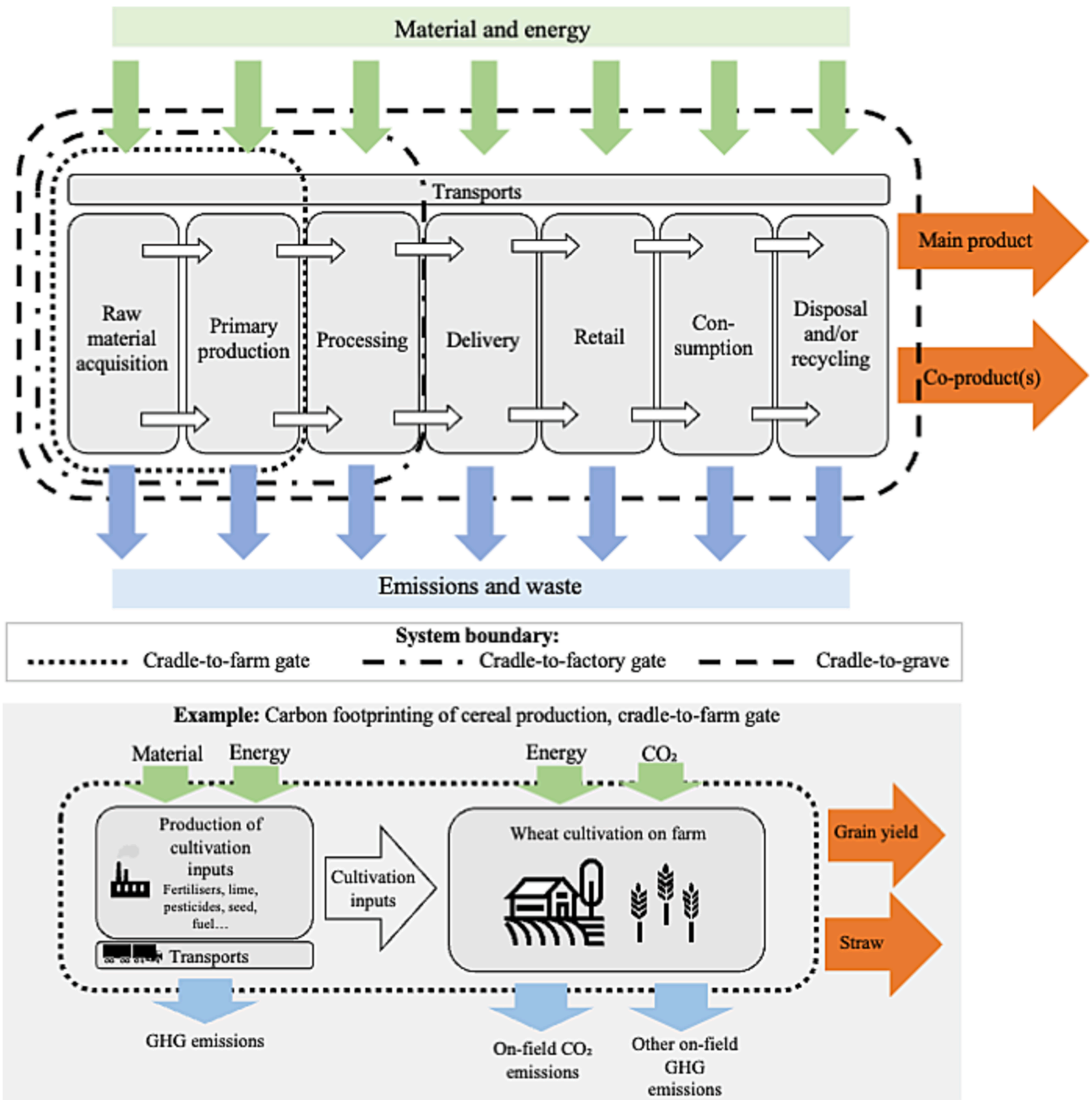

Fig. 1. Product carbon footprinting conducted with life cycle assessment (LCA), including different system boundaries, and an example of cereal carbon footprinting.

verifying the net SOC sequestration in agricultural soils (Oldfield et al., 2022). Carbon credit quantification always requires a baseline or reference case—that is, a counterfactual and preferentially conservative scenario for "business-as-usual" without the mitigation activity. In many cases, field-specific measurements to verify mitigation outcome are unavailable, at least in the context of all activities or smaller projects. The current programs therefore use a combination of measurements and model results, or only the latter, to quantify the amount of sequestered carbon (Black et al., 2022). For example, The Gold Standard Soil Organic Carbon Framework Methodology (The Gold Standard Foundation, 2020) provides three possible approaches. The first and preferred method is onsite measurements of the baseline and projected SOC development. The second is to use peer-reviewed publications to define the baseline and projected SOC development. The third is to apply default factors related to the general IPCC methodology (a type of modeling).

The permanence requirement of GHG emission reductions or removals was first introduced in the Kyoto Protocol and is now a part of nearly all carbon crediting programs (Ruseva et al., 2020). This means that the programs must address permanence risks and compensate for possible reversals of the improvements. Permanence is an issue for all nature-based solutions, including climate-smart agriculture, where SOC accumulation reverses if the improved management is not applied continuously. Nature-based solutions, including those related to SOC, do not fulfill the permanence criterion and are therefore ineligible for the carbon market, where the requirements are strictly followed. However, the new EU carbon removals certification framework makes a clear distinction between permanent and temporary carbon removals and defines separate carbon units for actions creating permanent and temporary storage. This allows carbon farming actions to be included in the EU-certified voluntary carbon market. The proposed certification also allows temporary units to be created from reduced soil carbon emissions, so net carbon sequestration is unnecessary for actions to be eligible for the market. Furthermore, there have been suggestions that account for more flexible approaches that broadly value the environmental and social benefits of mitigation projects and account for the impermanence for investors (Balmford et al., 2023; Ruseva et al., 2020).

The additionality principle means that the mitigation outcome would not have occurred without the transaction of carbon credits. The mitigation outcome is an improved climate impact calculated as the difference between a baseline and an activity. The quantification of the mitigation outcome requires detailed field-scale data on the improved management actions, local environmental conditions, and land-management history. Moreover, good governance principles (e.g., Laine et al., 2023) require transparency and the ability to track the carbon credit to the exact location where carbon is sequestered to avoid double counting.

Mitigation activities may also cause leakage, unintended emissions increase attributable to the mitigation activity outside its boundaries, limiting the climate benefit (Paul and Helming, 2019). An example of leakage is a case where carbon farming practices on certified fields impair practices elsewhere and reduce SOC stocks. The issue of carbon leakage is now part of the EU certification framework, according to which the leakage as a result of indirect land-use changes should be quantified and reported. The response of the field's SOC stock to the carbon addition depends on the initial size of the SOC stock (Sanderman and Baldock, 2010). Continued carbon farming may change the SOC sequestration rate and increase emissions of other GHGs (Lugato et al., 2018). Long-term monitoring is therefore necessary to assess the actual climate benefits of carbon crediting programs.

3. Greenhouse gas balance and associated processes in agricultural fields

GHG and SOC reporting in agriculture must provide simplified but reliable measures of agricultural systems' response to environmental and management changes. A coherent measurement and modeling system must therefore cover multiple factors and processes affecting field-scale carbon and GHG balances. A field parcel is the basic unit of agro-management actions and is usually to some extent homogeneous in terms of its properties and environmental factors. The carbon balance of a field—that is, the change in the carbon stocks in vegetation and soil over a given time—is determined by the difference between the inflows and outflows of carbon (Fig. 2). Photosynthesis is the process providing primary carbon input from the atmosphere, whereas autotrophic and heterotrophic respirations are the biogenic processes that decrease the carbon pools. Carbon can also be lost through erosion or leached out in dissolved form when water percolates through the soil. The field-scale carbon balance is affected by weather and agro-management such as the carbon taken away as a yield in harvests or brought in as manure, sludge, or soil amendments. Agro-management also affects photosynthesis and respiration through species selection, soil preparation, and fertilization, for example. Due to the large size of the SOC pool compared to inputs and outputs, changes in SOC stock occur slowly (Smith, 2004). Historical land use and management therefore have long-term legacy effects on SOC (Heikkinen et al., 2022; Stevens and Van Wesemael, 2008), which complicates the assessment of the status of field-scale SOC balance. Agricultural fields are typically established by clearing forests, or by draining wetlands and peatland forests for agricultural use, the latter being especially common in northern latitudes.

Plant growth processes are central in fields' carbon balances. By far the most important is photosynthesis, which is ultimately driven by light intensity and atmospheric CO_2 concentration, but it is often restricted by abiotic stressors such as a temperature that is too low or too high, low air humidity, or low availability of water. In addition, photosynthesis is also affected by plant species, their competition, and the availability of nutrients, diseases, and herbivores. Plants support vital functions and growth in a process called autotrophic respiration, releasing CO_2 back into the atmosphere. The difference between photosynthesis and autotrophic respiration is known as net primary production (NPP, Fig. 2). While agricultural management aims to improve crop yields, at the same time, it affects the carbon balance and carbon stocks. For example, plants and cultivars grown and fertilization affect growth but also biomass allocation—the shoot-to-root ratio, for example—which in turn, affects the belowground carbon input (root exudates and litter) and quality (Poeplau et al., 2018). These inputs are a central factor in building up the SOC pools as the yield, or any other biomass removed from the site does not contribute to the formation of carbon stocks. In addition, litter input from the rhizosphere is more recalcitrant to decomposition than aboveground litter (Freschet et al., 2013), thus contributing to the stability of the soil organic matter (OM).

The decomposition of OM in soils causing CO_2 and other GHG emissions is driven by microbiological processes. Soil physical and chemical conditions significantly influence microbiological activity. Soil OM serves as an energy source for soil heterotrophic microbes and as a carbon supply to support cell growth, and the availability of OM is therefore positively related to microbial activity (growth and respiration). However, other physical or chemical conditions such as temperature, moisture, or pH may limit the ability of microbes to utilize OM to support their activity (e.g., Malik et al., 2018). Furthermore, the CO_2 released in microbial respiration in different soils is affected by microbial communities, their enzyme production, and substrate preferences (Anthony et al., 2020). The efficiency with which soil microbes use carbon for their growth regulates the CO_2 released in microbial respiration to the atmosphere during the decomposition of OM (Anthony et al., 2020). Respiration is enhanced with increasing temperature but

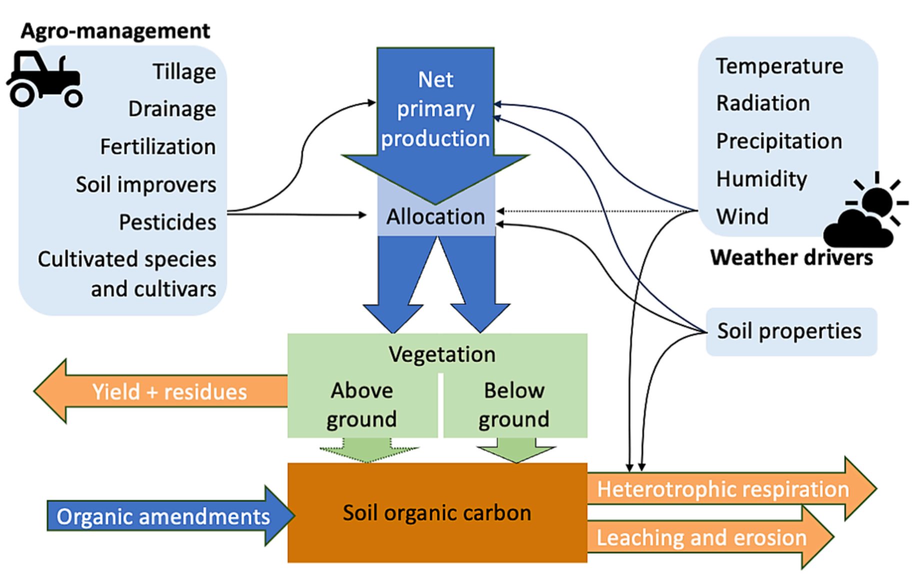

Fig. 2. The carbon balance in vegetation (light green boxes) and soil (brown box) of a single field is determined by the difference between the input (thick blue and green arrows) and outflows (thick orange arrows). The main drivers are marked with thin arrows.

only at sufficient moisture conditions (Lloyd and Taylor, 1994). Drought, as well as excessive moisture and poor aeration, limits microbial activity and therefore OM mineralization (Moyano et al., 2013). In acidic wet soils (pH < 6.2), unfavorable environmental conditions limit microbial activity and decomposition of OM, leading to an accumulation of SOC (Malik et al., 2018).

The OM availability for mineralization is defined by the organic molecule's complexity and physical accessibility in soil. The inherent recalcitrance originating from the complexity of the organic molecules may protect particulate organic matter (POM) from decomposition, whereas mineral-associated organic matter (MAOM) is protected from mineralization through association with mineral particles. The average residence time of MAOM is decades to centuries (O'Brien et al., 2013; Torn et al., 1997), and longer than that of POM. Some studies (Heckman et al., 2022; Rocci et al., 2021) propose that carbon loss resulting from changes in land use predominantly comes from the POM fraction, as it is more susceptible to environmental changes than the MAOM fraction. According to Rocci et al. (2021), changes in POM attributable to the effects of global warming are three times greater than that in MAOM, highlighting the vulnerability of POM-dominated ecosystems.

Nitrous oxide (N_2O) emissions from agricultural soils are significant, and they therefore need to be included in advantageous monitoring systems. In some cases, soil may also act as a sink for atmospheric N_2O (Chapuis-Lardy et al., 2007). The balance is a result of a complex range of soil microbial processes, including nitrification, denitrification, nitrifier denitrification, and nitrate ammonification (Smith, 2017). The key factors affecting the processes and resulting N_2O balance are soil physical properties affecting aeration, water content (Butterbach-Bahl et al., 2013), temperature (Peyrard et al., 2016), and the availability of mineral N (Smith, 2017). N_2O emissions are generally known for their huge spatial and temporal variation. For example, occasional flushes of N_2O emissions are typical after changes in soil conditions favoring OM mineralization that result in enhanced soil-respiration-induced O_2 limitation at the microsite level (Azam et al., 2002). The use of synthetic fertilizers in modern agriculture is the main cause of the increase in atmospheric N_2O (Smith, 2017). Reducing N inputs, applying N inputs only when necessary, and the application of enhanced efficiency fertilizers are therefore proposed as key methods to decrease N_2O emissions (Yangjin et al., 2021).

Methane (CH_4) is produced in the soil in anoxic conditions by methanogens. It is oxidized in aerobic soils by methanotrophs (Tate, 2015), and there is evidence that it can also be oxidized in anaerobic conditions (Ettwig et al., 2010; Gauthier et al., 2015). CH_4 emissions from soils are thus determined by the balance of CH_4 production and its oxidation. Both processes are driven by the oxygen and redox levels of the soil profile that depend on the water table level and soil structure (Boeckx et al., 1997; Le Mer and Roger, 2001). Plants also deliver oxygen into the deeper soil layers through the root systems. CH_4 can escape from the soil through vascular plants or by bubbling in wetland conditions (Tate, 2015). If CH_4 is emitted via diffusion through the soil matrix, it is oxidized, at least partly, on its way into the atmosphere. Changes in land use may affect whether the soil is a CH_4 sink or source (Smith et al., 2000; Tate, 2015). In agricultural environments with good drainage, CH_4 emissions are generally minor compared to CO_2 and N_2O emissions. Globally, however, rice fields under flooded irrigation are an exception because of their high CH_4 emissions (Qian et al., 2023). In northern conditions, peatland fields under paludiculture where soil is kept wet have higher CH_4 emissions than cultivated peatlands with traditional cultivation practices (Kandel et al., 2020; Karki et al., 2014), and reliable monitoring systems should therefore describe CH_4 dynamics for fields with a high water table.

4. Measurements and modeling of SOC and GHGs balances

4.1. In-situ measurements of field-scale carbon and GHG balance

The quantification of GHG fluxes and their responses to changes in environmental drivers across different sites and agro-management practices requires field-scale observations. GHG fluxes between an agricultural field and the atmosphere are usually measured with chambers and the Eddy covariance technique. Additionally, temporal SOC changes and associated CO_2 flux can be detected using repeated samplings (Table 3).

4.1.1. SOC measurements

Topsoil SOC samples are typically collected manually using various types of augers, core samplers, or spades. Machine-operated systems such as a percussion hammer or tractor are required to obtain deep soil samples. Soil samples are commonly combined from several subsamples to account for the spatial variability of SOC within the studied field. The samples' SOC content is measured using wet or dry combustion (Chatterjee et al., 2009). Additional bulk density (BD, g cm^{-3}) measurements are needed to calculate SOC stock.

Soil sampling and the calculation of SOC stock can be carried out

Table 3
Main in-situ measurement techniques for estimating a field's GHG balance and net CO_2 flux.

Eddy covariance	Chambers	Repeated soil sampling
		
Net fluxes of GHGs between a field and atmosphere $> 1{,}000$ m^2 The mean of a field Temporal variation (30 min) Expensive	Net fluxes of GHGs and their components (light response, respiration) < 1 m^2 Spatial variation Temporal variation (days) Laborious	Soil carbon stock and sensitivity of SOC fractions (POM, MAOM) to mineralization < 1 m^2 Spatial and vertical variation Temporal variation (years) Laborious

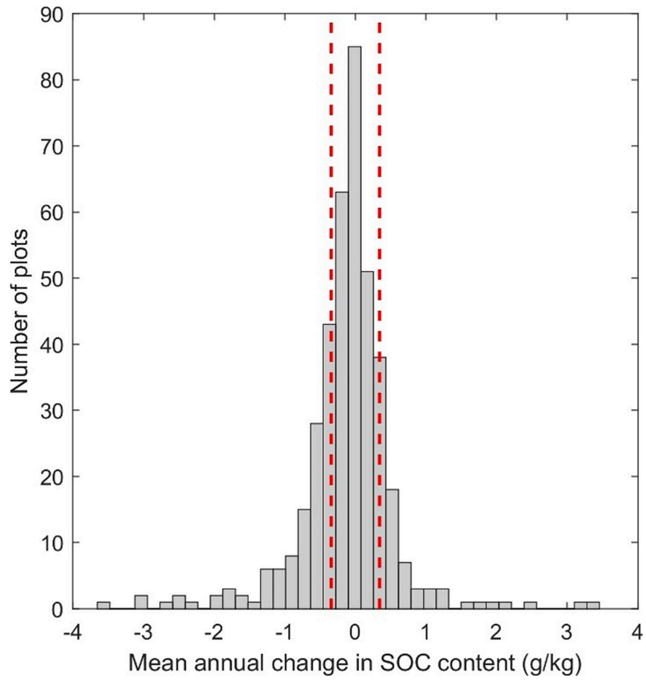

Fig. 3. Mean annual change in SOC content between 2009 and 2018 according to mineral soil samples of the Finnish national soil monitoring network (see Heikkinen et al., 2022). Red vertical lines depict the potential management-induced annual change in SOC. The potential maximum change was assumed to be approximately 500 kg C ha^{-1} yr^{-1} (Freibauer et al., 2004), and it was converted to g/kg by dividing by the average SOC stock (54,000 kg C/ha) and multiplying by the mean SOC content (37 g/kg) in Finnish cultivated soils (Heikkinen et al., 2013).

using either the fixed-depth method (FD) or the equivalent soil mass method (ESM) (Ellert and Bettany, 1995; Wendt and Hauser, 2013). In the FD method, the soil layer is defined based on the depth of the soil layer, whereas in the ESM method, the soil layer is defined based on the mass of mineral soil per unit area. Although it is known that the FD method is sensitive to changes in soil bulk density due to soil management or environmental drivers, it is commonly used, as it is simple and straightforward. The ESM method requires layer-wise sampling with a corer, allowing the calculation of soil mass per unit area within each soil layer.

Measurement-based SOC estimates often have high uncertainty. This is partly the result of the large spatial variability of SOC, which can be significant even within distances of less than one meter (Poeplau et al., 2022). In addition, there are errors related to sampling and analysis (Goidts et al., 2009). Finnish national soil monitoring demonstrates the high uncertainties associated with measured SOC stock change estimates. The rate of change in measured SOC content between 2009 and 2018 was unrealistically high in 40 % of observed cases (Fig. 3). However, countries with a sufficiently high sampling plot density can determine national-scale trends in SOC content with reasonable confidence, making soil sampling-based methods feasible option for a national greenhouse gas inventory (see, e.g., GHG inventory of Sweden, Naturvårdsverket, 2023). In contrast, for LCA and carbon market purposes, soil sampling-based verification methods are likely to be far too laborious and costly (Heikkinen et al., 2021).

SOC content can also be measured in the field using various applications of visible and near-infrared reflectance spectroscopy (VNIR) (e.g., Ge et al., 2020) or laser-induced breakdown spectroscopy (LIBS) (Dwivedi et al., 2023). Their advantages are cost-efficiency, the ability to cover large areas, and the reduced soil disturbance. However, it is important to note that the in-situ measurements nevertheless need to be calibrated and validated against traditional laboratory-based SOC estimation (Gobrecht et al., 2014).

4.1.2. GHG flux measurements

The eddy covariance method is a widely used technique for measuring field-scale CO_2, CH_4, and N_2O fluxes and evapotranspiration at high temporal resolution, typically ½ hourly (Baldocchi, 2014; Anderson et al., 2020). The fluxes between the field and the atmosphere are computed from high-frequency (10 to 20 times per second) measurements of turbulent airflow in vertical wind speed and GHG concentrations using the mass conservation principle applied to a turbulent airflow over a flat, horizontally homogeneous surface. The flux source area depends on the measurement height, crop characteristics, and wind speed and extends hundreds of meters into the upwind direction. This means the eddy covariance method provides direct and near-continuous data on field-scale carbon and GHG balances, but its applicability is limited to sufficiently large fields with mild topography and minor internal variability in soil or crop characteristics and management. The method is thus unsuitable for traditional plot-scale crop variety or fertilization trials, for example. Technical malfunctions and weak wind periods create gaps in the data, which need to be gap-filled (Vekuri et al., 2023) to integrate the flux time series into annual GHG balances. The advantages are automatic data collection and minor maintenance, except for regular calibration, quality control, and data processing. The shortcomings include the need for electricity and high initial costs, as the method needs high-frequency GHG analyzers, a sonic anemometer, sensors for other meteorological variables, a tower, and hardware to collect and store data. Recently, there have been developments toward low-cost eddy covariance systems for more widespread GHG balance monitoring (Cunliffe et al., 2022; Hill et al., 2017) Eddy-covariance data is considered to provide a scientific benchmark on field-scale GHG balance and is commonly used to test and calibrate process-based agroecosystem models (Baldocchi, 2014; Nevalainen et al., 2022). However, the costs and micrometeorological expertise required restrict the use of the method to specific research sites, meaning GHG balances of only a small fraction of possible combinations of agro-management, soil properties, and climate can be covered.

Chamber measurements include a wide range of automatic or manual techniques to estimate the momentary GHG flux rate (Pumpanen et al., 2004). To ensure lightweight and practical operation, a chamber typically covers a small area, rarely exceeding 0.5 m^2. In the common closed chamber method, a chamber is placed on top of the ground with or without vegetation, and the concentration of GHGs is followed inside a chamber airspace during the single closure with portable gas analyzers or by taking vial samples that are further analyzed in the laboratory with gas chromatography (GC). The chamber is commonly attached to a collar that is installed into the soil to prevent leakages. The flux is calculated from the rate of change in GHGs inside the closed chamber. The dark chambers are used to measure respiration and other processes that are independent of light intensity, while the transparent chambers are used to determine the net ecosystem CO_2 exchange and net photosynthesis in ambient conditions. The photosynthetic light response can be obtained by repeating the measurements at different light intensities (e.g., Kulmala et al., 2011). Light-response curves can be further used to determine the gross primary productivity (GPP) for the whole day when the diurnal dynamics in light intensity are available (Trémeau et al., 2023) and for parameterizing and testing agroecosystem models running on an hourly or daily basis.

The advantages of the chamber method are the relatively low investment costs and applicability to small-scale plot experiments. The GHG analyzers suitable for the chamber method are significantly cheaper than those needed in eddy-covariance measurements. The required labor creates a major cost with manual chambers, whereas with automatic chambers, the technical solutions and possible replicates increase costs. One shortcoming arises from the possible disturbance that the chamber and permanently installed soil collar tend to cause in soil temperature, CO_2 concentration, and the ecosystem (Bekin and Agam, 2023; Görres et al., 2016; Pumpanen et al., 2004). For example, the permanently installed collars and chamber deployment could alter the micro-environment around the plants and their roots. Unoptimized ventilation in the chamber is also known to cause systematic errors (Koskinen et al., 2014; Pumpanen et al., 2004). Manual measurements require labor investments, as measurements need to be adequately replicated in space and time due to high spatial and temporal variation in environmental drivers, soil properties, and vegetation, all of which affect the momentary flux rate. However, automatic chambers require higher investment costs even if they are homemade, as well as labor investments in quality control and maintenance.

Low-frequency chamber measurements are sometimes used to estimate annual balances but due to uncertainties and varying calculation protocols, these estimates are difficult to compare with each other—for example, if the measurement interval during the growing season is one to two weeks, the state of the crop has remarkedly altered, and environmental drivers have varied between the measurements. This creates a challenge for estimating long-term balances. In addition, the snow-cover season poses challenges to the use of chambers and easily creates gaps in the data. The snow gradient method is often used to measure GHGs from the snow, but cold temperatures, thin snow layers, or wind may hamper the measurements (Pavelka et al., 2018). In particular, sparse chamber and snow gradient measurements alone, are therefore not optimal for estimating annual balances, but the data allow possibilities to quantify momentary differences between treatments, etc., and serve as testing data for process-based agro-management models that include complex interactions and simultaneously changing environmental controls. Due to spatial heterogeneity within the field, a reliable estimate of field-scale GHG balance requires the fluxes from several chambers to be averaged.

4.1.3. *Crop yield and biomass components*

Biomass development and crop yield are basic indicators of agricultural production. They are increasingly needed to support assessments of field-scale carbon balance and as ground truth data for remote sensing. Harvested yields are measured by weighing the yield, and modern harvesters have sensors to measure the yield in real time in the field. The yield can also be estimated at different phases of the post-harvesting process. Yields are also estimated with traditional means by taking samples from the field and extrapolating the results. Similarly to yields, total aboveground biomass can be measured by sampling, drying, and weighing, as well as directly via modern harvesters. It can also be assessed using crop-specific allometric functions (e.g., Bolinder et al., 2007). Canopy sensors that can measure, for example, light interception or reflectance, which provides information about the leaf area index (LAI), that is, the ratio of plant leaf area to ground area, can also be used to estimate biomass (Dong et al., 2020; Pallottino et al., 2019). The belowground biomass of plants is particularly challenging to measure, as it requires soil sampling, root washing, sieving, and drying for large sample quantities. Allometric functions are commonly used to obtain rough estimates of root biomass, but this approach has also been challenged due to the overall weak correlation between root and shoot biomass (Hu et al., 2018).

4.2. *Satellite and near-ground remote sensing*

Polar orbiting Earth Observation (EO) satellites provide a near-automated data stream for detecting vegetation state (e.g., LAI, aboveground biomass, fraction of absorbed photosynthetically active radiation (fAPAR), leaf nitrogen), management activities, soil moisture, and thermal state for field-scale monitoring on a close to daily basis (Weiss et al., 2020; Xiao et al., 2019). In Northern Europe, the most relevant instruments are the optical-range MultiSpectral Instrument (MSI) onboard Sentinel-2 and the synthetic aperture radar (SAR) onboard Sentinel-1 satellites. Both systems provide a vast range of variables in a spatial resolution of ca. 10 m, depending on product and imaging mode (Drusch et al., 2012; ESA, 2012). Optical sensors measure the reflected sunlight, whereas SAR transmits a microwave signal to the Earth's surface and measures the reflected (backscattered) intensity or correlations between received signals, enabling the collection of "coherence" information (Kellndorfer et al., 2022). The optical-range observations by MSI provide estimates of LAI, and indications of management practices and land-use changes.

In the near future, optical-range satellite systems will include the FLEX mission for global vegetation fluorescence monitoring at a spatial resolution of 300 m (Coppo et al., 2017; Drusch et al., 2017). The observation of sun-induced fluorescence (SIF) is directly related to the photosynthetic activity of vegetation, and its feasibility for predicting GPP has already been demonstrated by applying Sentinel 5P TROPOMI mission data (Guanter et al., 2021). The microwave-range Sentinel-1 SAR observations are related to vegetation and landcover, and the moisture and freeze–thaw status of soil in a more complicated fashion (Steele-Dunne et al., 2017; Veloso et al., 2017; Wang et al., 2019; Xiao et al., 2019). As SAR observations are not hampered by clouds, they can also supplement optical-range observations by filling the cloud-induced gaps in a time series. Recent advances in optical near-ground remote sensing by drones are now expanding the capabilities of detecting within-field variability to guide precision farming activities (Jung et al., 2021; Weiss et al., 2020), as well as bridging the scale mismatch between ground observations and EO products (Guan et al., 2023).

Optical satellite products such as vegetation indices derived from spectral measurements are widely used to estimate field-scale GPP, ecosystem respiration, and crop yields (Joiner et al., 2018; Song et al., 2013; Xiao et al., 2019). A suite of light-use efficiency (LUE) models predicts field-scale GPP as a product of incident solar radiation, crop-specific time-varying maximum light-use efficiency, and fAPAR (Ryu et al., 2019; Song et al., 2013; Xiao et al., 2019). Based solely on EO data streams or a combination of EO and meteorological data, LUE models can produce high-resolution (a few days, dozens of meters) GPP estimates (Song et al., 2013; Xiao et al., 2019). However, significant challenges still remain to describe soil water limitations and/or heat stress conditions (Xiao et al., 2019). Recently, there have been major developments in process-based diagnostic models to utilize the strong relationship between GPP and SIF to produce novel high-resolution estimates of vegetation primary productivity (Xiao et al., 2019). Ecosystem respiration can be modeled based on land-cover and vegetation attributes, GPP, and land-surface temperature (Ai et al., 2018; Rahman et al., 2005; Wiesner et al., 2022), but at coarser spatial resolution and with less confidence in scalability (Xiao et al., 2019) than with productivity estimates. Combining high-resolution time series of EO-based GPP and ecosystem respiration enables the field-scale carbon balance to be estimated.

The soil OM content, SOC, bulk density, and other soil attributes in croplands and grasslands affect soil spectral reflectance in the VNIR-SWIR (400–2,500 nm) range. Using the spectral transfer functions derived in the laboratory with EO-based spectral reflectance, the SOC content can be estimated with promising results, but only for bare soils (see review in Xiao et al., 2019). Both GPP and respiration models are commonly trained and benchmarked against eddy-covariance fluxes and their data-driven generalizations (Jung et al., 2020; Ryu et al., 2019). The representativity and accuracy of the ground truth from direct flux measurements and SOC inventories is therefore a prerequisite for reliable EO-based estimates of field-scale GHG balances. Likewise, accurate field-scale crop-specific in-situ data is necessary to build statistical models to link the available optical and microwave remote sensing and Lidar data to aboveground biomass, yields, and carbon stocks (Xiao et al., 2019).

4.3. *Modeling approaches for field-scale GHG balances*

Models are used to synthesize and generalize available data and the latest scientific understanding. They are also increasingly being used to provide projections and estimates beyond the data coverage. Several modeling approaches are used to assess field-scale C and GHG balances. The IPCC Tier 2 methods with static emission factors or land-use type specific carbon stock values already represent simple data-driven models. There are also many other empirical regression models for predicting field-scale SOC stocks (Funes et al., 2019; Heikkinen et al., 2021), SOC stock changes (McClean et al., 2015), and GHG emissions (Lin et al., 2022) from field properties such as soil and vegetation attributes, management practices, and climate conditions. There are also several regression models of the decomposition of OM based on field or laboratory experiments (Peplau et al., 2023; Xu et al., 2016). In recent years, machine learning has been proposed as an improved statistical-empirical modeling approach capable of inferring the non-linear and temporally variable interactions underlying GHG emissions and SOC dynamics (Saha et al., 2021).

The development of data-driven models requires accurate and comprehensive datasets and is therefore affected by challenges linked to acquiring measured data (Section 4.1). In the context of agricultural applications, data limitations are often encountered due to the wide range of cultivated crops and the myriad of agro-management practices. The applicability of data-driven models is always limited to the domain of data from which they were developed or requires an additional assumption that the statistical relations described in the models remain the same for the application case (e.g., altered management practices or environmental conditions).

Mechanistic process-based models are built on the conceptual ideas and theoretical understanding of the processes and their interactions within the studied system and its environment. These models aim to describe the system as fundamentally as possible and are therefore thought also to be applicable outside their data domain. This is one reason process-based models are widely used for scenario purposes in climate change impact studies, for example (Ewert et al., 2015). In practice, however, all process models have a strong empirical basis via their parameters that are calibrated to certain conditions using empirical data. The models describe the underlying dynamics of complex ecosystem processes with timesteps varying from hours and days to years.

Process-based models used for reporting SOC changes and GHG balances include soil-only models that describe the decomposition of OM and/or nitrogen mineralization, and full plant-soil models, also called agroecosystem models. Examples of the soil-only models and their applications for national GHG inventories for croplands and grasslands include Yasso (Tuomi et al., 2011), used in Finland (Palosuo et al., 2016; Statistics Finland, 2023), RothC (Coleman and Jenkinson, 1996), used in Switzerland (FOEN, 2023), C-TOOL (Taghizadeh-Toosi et al., 2014) used in Denmark (Nielsen et al., 2023), CENTURY (Parton et al., 1987) used in Canada (ECCC, 2022), and ICBM (Andrén and Kätterer, 1997), used in Sweden (Naturvårdsverket, 2023). To predict SOC changes, the models require weather data, estimates of litter and other organic material inputs and their quality, as well as information about soil characteristics such as clay content. Litter estimates are commonly based on crop yield data converted to annual litter inputs using constant harvest indices, root-shoot ratios, root turnover rates, and carbon content (Bolinder et al., 2007; Palosuo et al., 2016).

Agroecosystem models cover different ranges of processes describing the underlying biological, ecophysiological, physical, and chemical processes that govern agricultural systems. The level of detail varies depending on the initial purpose for which the model was developed. Examples of agroecosystem models that have been used to assess field-scale SOC or GHG balances are APSIM (Holzworth et al., 2014), DNDC (Li et al., 1992), and DAYCENT (Parton et al., 1998). For example, the APSIM model has been applied to estimate the SOC change in Australian croplands for the LCA of agricultural products (Sevenster et al., 2020). DAYCENT is used in the US emissions inventory (EPA, 2022). The land surface models (Blyth et al., 2021) used as part of global Earth System Models also contain dynamic vegetation and SOC components and include plant-functional types for agroecosystems (e.g., C3/C4 grasses, and annual and perennial crops). The use of complex agroecosystem and dynamic vegetation models is still mainly limited to research, as they require a detailed understanding of the modeling tools and the studied systems. Their complexity compromises transparency, which is a major challenge for their use in inventory purposes and carbon verification schemes, for example. Another challenge is the limited availability of detailed and reliable data to estimate model parameters and set up, run, calibrate, and evaluate the models. The lack of measured data means that agroecosystem models often remain not thoroughly calibrated and tested for their ability to capture various management impacts or environmental responses.

Model ensembles—that is, using several models in parallel—are increasingly used to assess the uncertainty of model simulations and to achieve robust estimates using multi-model means or medians (Farina et al., 2021; Wallach et al., 2018). For example, Riggers et al. (2019) used an ensemble of soil-only models and litter input estimation methods to quantify past trends in the SOC stocks of Germany, finding the ensemble to perform better than individual models. Sandor et al. (2020) evaluated the use of an agroecosystem model ensemble to predict the C fluxes of various grassland and cropland sites worldwide. The use of model ensembles faces challenges similar to the use of individual models, so it is important to ensure the data used as model inputs, calibration, and evaluation are comprehensive and of high quality. However, model ensembles of several modeling teams bring additional challenges, linked to the understanding of the simulated systems and the data available (Confalonieri et al., 2016).

4.4. Upscaling from field-scale to wider scales

Scaling is a process that changes the spatial and/or temporal resolution of measured or modeled results so that they match the scale required in reporting. Measured or modeled point- or field-scale C or GHG balances are seldom directly applicable to reporting systems, and upscaling for the interest region, product, or production chain is necessary. Typical interest regions in national GHG inventories are countries or counties. For LCA or carbon monitoring for carbon markets, it is essential to obtain robust estimates for a given field or region and for a certain time. Spatially, reporting needs to cover a representative sample of fields with different management practices, soils, topographical conditions, and locations within the interest region. Temporally, the scale should be sufficiently long to achieve robust estimates of the effects of agro-management practices on C and GHG balances. In practice, this requires time series of observed data or model predictions to cover inter-annual weather variability and the effects on long-term SOC and emission dynamics.

Different methods are used for spatial and temporal scaling (Ewert et al., 2006). A simple common method is to extrapolate small-scale results to a higher level. For example, results from one field are considered representative of a wider region, or similar fields in a wider region. An alternative method is to aggregate (typically sum or average) several detailed level results to the next level. Given the typically non-linear responses of C and GHG balances to environmental drivers and management actions and their complex interactions, the most accurate wider-scale results are achieved by aggregating the most detailed scale data possible. This requires stratification of the region under study to the most homogenous possible sub-units considering the combination of field properties (i.e., soil type, field topography) and management practices (e.g., crop rotations, soil tillage, and fertilization) in the region of interest. The availability of GHG observations and ground-truth for combinations of plant, environment, and management is currently the main limiting factor that determines how the agricultural landscape can be classified, and field-scale results upscaled.

In recent decades, there has been a proliferation of open high-resolution geospatial (GIS) data that enables the classification of agricultural land. For example, in Finland, boundaries of all agricultural field parcels (over one million in total) are provided by the Finnish Food Authority, and the topography of field parcels can be obtained from digital elevation models (National Land Survey of Finland, 2020). Soil type and soil texture can be obtained from several sources such as the Finnish Soil Database (Lilja et al., 2017) and national soil maps (Geological Survey of Finland). The European Soil Database contains topsoil textural, hydraulic, and physico-chemical characteristics at different resolutions, from 100 m to 10 km (2024). However, these datasets have yet to be merged into a harmonized database of soil characteristics, required both to upscale field observations and use field-scale agroecosystem models. Nevertheless, significant steps have been taken recently to identify and characterize organic agricultural field parcels in Finland (Räsänen et al., 2018).

Obtaining field-level data on agronomic practices such as the plants grown, sowing and harvest times, fertilizers or other inputs provided, and yields achieved remains a significant challenge for estimating and upscaling the annual field-scale GHG balance. Although in Finland, for example, some information about field management is gathered from farmers who receive agricultural subsidies, such data are not openly available, and they do not cover the entire agricultural land area. Novel EO products (Sect. 4.2) have great potential to address the problems of obtaining LUC and LMC information and improve the spatial upscaling of field observations. For example, Sentinel observations enable the detection of the temporal dynamics of the vegetation state (e.g., LAI, aboveground biomass, leaf nitrogen content), management activities, and soil moisture and thermal state. Such data can improve landscape clustering and upscaling and enable the parameterizing of field-scale agroecosystem models for direct application to real field parcels.

4.5. Integrated systems for field-scale estimation

In the previous chapter we explained that the information relevant for estimating C and GHGs comes in different spatial scales and time-frames. Various measurement and modeling methods are best suited to parts of these scales but do not cover them entirely. We must therefore integrate the techniques for the best C and GHG estimates. We also need various methods for a similar resolution to complement the information they produce, such as modeling gaps in GHG flux data or calibrating satellite data with ground observations.

Components available for the integrated systems include short-term and long-term experiments, C and GHG models, the models' input data, field management data, remote sensing, and data surveys (Smith et al., 2020). Paustian et al. (2019) and Smith et al. (2020) envisioned global SOC monitoring and reporting systems frameworks. The empirical basis of these visions comprised soil monitoring networks, intensively studied benchmark sites with long-term SOC measurements, and shorter-term flux measurements representing different land uses, soil types, and management practices. The systems would use these data to develop and test models, and these models would then interpolate and upscale the observed data. The modeling methods ranged from region-specific IPCC Tier 2 emissions factors representing different management practices and soil combinations linked with spatial information and activity data to Tier 3 models simulating SOC and GHG emissions using spatial climate and soil data. Guan et al. (2023) reviewed the scientific and technical issues in applying the current approaches to estimate field-level C and GHG balances. They identified scalability regarding data and computation requirements as critical challenges. To overcome these difficulties, they formulated an ambitious approach that combined process-based simulations, upscaled in-situ measurements, remote sensing data, and computationally efficient data fusion algorithms and surrogate models.

Rapidly developing automatic measurement techniques, especially EO, and increasing computation capacity are essential for integrated systems development. Examples of systems that incorporate EO data with modeling to estimate the carbon budgets of agricultural fields are the SAFYE-CO2 modeling approach combined with optical remote sensing data (Pique et al., 2020; Wijmer et al., 2024), the Vegetation Photosynthesis Respiration Model (VPRM) integrated with high-resolution Sentinel-2 indices and eddy covariance measurements (Bazzi et al., 2024), and ECOSYS modeling combined with data assimilation (Yang et al., 2023). These systems demonstrate the merging of different data and models for large-scale assessments. However, work still needs to be done for an effective link between the measurements and models. This issue is essential because it limits our ability to use the growing measurement possibilities and improve the C and GHG estimates. Community cyberinfrastructures, systems that integrate measurements, models, and data analysis tools, have been proposed to solve this problem (Fer et al., 2021). In Finland, the agricultural MRV system linked to the Field Observatory Network (FiON) is an example of such an infrastructure (Nevalainen et al., 2022).

5. Development needs

The development of carbon and GHG emission reporting systems (Section 2) requires the balancing of different user requirements, the available resources, and the current capabilities of refining multi-source data to estimate SOC changes and GHG balances in agroecosystems. Below, we will discuss the key criteria for the national GHG inventories, carbon footprinting, and practices used in voluntary carbon markets as specified by IPCC guidelines (IPCC, 2019a, 2019b, 2019c), ISO standards (ISO, 2018, 2018, 2006), or Corporate Sustainability Reporting Directive (CSRD) in the EU, for example. We will highlight the key challenges in fulfilling these criteria in SOC and GHG emissions reporting of agricultural production systems and use the criteria as a basis for defining the realistic goals for robust reporting systems in the short and long terms.

5.1. Criteria of the reporting systems

5.1.1. Credibility

Credibility is a necessary starting point for any reporting system. The accuracy and reliability of the reported results build on the precision and comprehensiveness of the data, emission factors, and modeling approaches applied. Worldwide, a severe lack of data for the myriad of plant × environment × management combinations in agroecosystems remain, which inevitably affects the reliability of the field-scale carbon and emissions estimates. The data gaps hold not only for the SOC and emission data (Paustian, 2013) but also for the key activity data—that is, what is being done in the fields (Beza et al., 2017). Also in Finland, there are thus far only a few long-term GHG flux and SOC datasets from the Finnish arable production systems, leaving many of the factors affecting agricultural emissions unaccounted for. This lack of comprehensive long-term datasets also affects the reliability of modeling, as insufficient data are available for model development, calibration, and testing (Ogle et al., 2010). Satellite remote sensing has become an important source of information on various field-scale variables and agricultural practices (Section 4.2). However, the effective use of satellite data for SOC and GHG emission monitoring requires them to be integrated with the models, and the reliability of such systems is equally affected by the lack of SOC and GHG emissions data. The effective acquisition of high-quality and comprehensive field-scale in-situ SOC and GHG balance data requires major public investment in both the collection and management of data.

Field-scale reporting and monitoring systems are data-hungry, requiring not only SOC or emission data but several other data, from crop and land cover to detailed management information such as crops grown or fertilizer rates applied. The development of the data collection platforms therefore needs to carefully consider the aspect of data ownership in agriculture (Atik, 2022; Wilgenbusch et al., 2022). While detailed field-scale data has the potential to improve decision support and decrease environmental impacts, the ownership rights of farmers over their data have not been thoroughly acknowledged. This involves aspects related to data security and trust that data will not be misinterpreted or misused. In Finland, there have been discussions about the use of field parcel information collected by farmers for public environmental assessments, for example, but data disclosure would require changes in regulations. Similarly, the development of wide-scale reporting systems relies on detailed and well-managed research data. It is increasingly important that the data created are shared openly, and that the value of the existing datasets is acknowledged. This requires the prioritization of sharing and accessibility by researchers, funders, and publishers and long-term investments in data management (Bledsoe et al., 2022).

Securing the comparability of reported results with other countries and cases that have different land-management or soil types is essential for the credible use of the reporting results. This underlines the importance of open and clear documentation, as well as using standardized methods. Very general methods such as global emission factors (e.g., IPCC Tier 1), however, are not equally suitable for different regions and are very limited in the consideration of the various management methods. There is therefore a need for both internationally harmonized and regionally or locally implemented methods. To monitor the development of emissions in time, it is essential that the reporting methods are consistent in time. For example, the evolving nature of satellite technology introduces the possibility of inconsistencies in time series (Xiao et al., 2019). Time series are important in the national GHG inventories for following emission trends, for example. Completeness refers to the extent and detail to which reporting covers all relevant emission sources and activities within the defined system boundaries of reporting. For comparability, the completeness of different assessments is essential to be as similar as possible. At the field scale, this comes back particularly to the question of whether different management activities are relevantly covered. For example, are the crop cultivars with their different properties known and included, or are the assessments done at a more general crop or crop type level—for example, annuals vs. perennials? Completeness in time is also needed, which refers to the consideration of year-to-year variation in SOC stocks and GHG emissions. For example, the consideration of full crop rotations is targeted in LCA to account for crop-to-crop interactions and grass ley renewals.

The transparency of the reporting system refers to clearness, openness, and comprehensibility and is key to good governance and building trust. Transparent reporting systems provide clear and detailed documentation on origin of data and calculation methods and support the interpretation of results. They are supported by openly available codes, scientifically reported methods, and user-friendly interfaces. Clear documentation, including the weaknesses in current data and methods, as well as points for development, is crucial. Verification and assurance processes by skilled third-party auditors, with openly available verification reports, are also important to increase trust in more complex reporting systems. Transparency is easier to achieve with relatively simple calculation systems such as those combining activity data statistics with emission factors. Detailed calculation systems that combine multiple data streams have challenges with transparency, as their structural complexity and the large number of processes, interactions, and dimensions they consider makes them less intuitive and more difficult to interpret than simple systems. However, the ability of process-based simulation models to isolate causal relationships may also provide a means to improve the transparency of GHG reporting. This typically requires sensitivity analyses or other model experiments to be performed that allow an identification of how environmental drivers or model parameters affect the simulated field-scale GHG balances and SOC stock changes, for example.

5.1.2. Feasibility and cost-efficiency

In recent years, the development of sensing technologies has resulted in an enormous accumulation of data from agricultural fields (Kayad et al., 2022). The availability of sensor data from satellites, planes, or drones per se is therefore unlikely to be an economic or technical barrier for field-scale emission and SOC calculations. On the contrary, the acquisition of SOC and GHG emission data from fields is highly laborious and cost-intensive (Section 4.1), and even impossible for SOC stock changes in short time scales (Heikkinen et al., 2021).

Reporting systems that rely on detailed data and fine-resolution calculations also require advanced data management systems (Kharel et al., 2020) and high-level technical capacities such as computing power, data storage, and reliable internet access. In addition, the development, maintenance, and use of these systems require educated and experienced personnel. All this requires long-term institutional commitment and funding. The choice of methods and modeling tools affects costs. The use of remote sensing or other advanced technologies may have higher upfront costs, but they may improve accuracy and be cost-efficient in the long term. Interoperability with other systems such as monitoring systems for agricultural subsidies, which has been based in Finland on satellite images since 2023, for example, could significantly enhance operation and reduce the costs of SOC and emission reporting systems.

5.2. Perspectives for the reliable estimation of SOC changes and GHG emissions at field scale

5.2.1. National greenhouse gas inventories

There are still major challenges in the quality, consistency, and transparency in the reporting of agricultural GHG emissions by national GHG inventories (Dittmer et al., 2023), particularly in developing countries. Data availability and accessibility are the key constraints that limit the capacity of countries to estimate emissions accurately and meaningfully and subsequently to make adequate and effective decisions to reduce emissions. Recommendations as first steps to solve issues related to data availability include the use of novel data products to achieve national-level data on land use and management that could be combined with information about emissions systematically gathered from the scientific literature (Yona et al., 2020). The most detailed Tier 3 method applied in the Finnish GHG inventory for the SOC stock balance of the mineral soils is calculated at the regional level (Table 1; Statistics Finland, 2023). In principle, a switch to field-scale reporting would enhance the national GHG inventories compared to regional calculations by allowing more effective accounting for management practices (e.g., carbon farming) and different soil types that might occur on a small scale but still have a relatively high impact on the total GHG balance. However, this would require that the data on relevant land-management practices and land-use changes were comprehensively available, and that the emissions and SOC stock changes can be reliably estimated. Satellite-based data analysis would also make the calculation procedure more complex and challenging to evaluate.

A key information need to model the SOC change is the carbon input into soils. The majority of SOC input in agricultural soil is attributed to crop residues, with only about 12 % of the total carbon input coming from organic fertilizers, including manure (Jacobs et al., 2020b). Considering field-scale GHG reporting, the substantial contribution of plant residues necessitates the use of satellite-based data to estimate plant biomass production and its allocation to soil. However, it is unclear whether satellite-based estimates are more reliable than the methods based on yield statistics and biomass functions, which are commonly used to convert yield levels into SOC input in the Finnish GHG inventory, for example (Statistics Finland, 2023). In particular, belowground carbon inputs, including root litter and rhizodeposition, are challenging to assess using remote sensing techniques, although they are known to be substantial, particularly in perennial grasses (Kuzyakov and Domanski, 2000). Furthermore, for example, the data for manure application in Finland is unavailable at the field scale, necessitating the estimation of manure-derived carbon in large geographical units, hampering the idea of a field-level calculation system.

In countries like Finland, where emissions from cultivated peat soils are substantial compared to changes in SOC stock in mineral soils, it is most crucial to develop reliable emission estimation methods for cultivated organic soils and the various climate mitigation measures applied in them (e.g., raised water table, paludiculture, rewetting), along with precise estimations of the areas targeted by these measures. This involves the development of emission factors for different mitigation measures by countries or regions (see, e.g., Tiemeyer et al., 2020), as well as improved activity data. The key drivers determining the GHG balances of peat soils and therefore the information needed to estimate them differ from those of mineral soils.

5.2.2. Carbon footprinting

Carbon footprinting of Finnish agricultural products with LCA is often conducted by utilizing global (typically IPCC) or Finland-specific emission factors (e.g., Regina et al., 2013) for on-field GHG emissions. In the current LCA framework, the estimation of GHG emissions on a field scale is neither practical nor necessary. Typically, the number of field parcels included in the production chain of a product is massive, the geographical distribution of the parcels is wide, and source traceability is limited or even impossible. LCA also aims to cover long-term emissions—for example, CO_2, from SOC stock losses—even after decades or centuries, caused by production activities (IDF, 2022). The use of accurate site-specific emission measurements from a limited measurement period would therefore not be representative of the whole production chain and the responsibility window. Considering this, GHG measurements from fields are seldom directly suitable for LCA, as they are very specific in time and space. Yet the currently used, often very general, emission factors and other methods for estimating on-field GHG emissions should be specified to better represent different management practices, as well as soil and climate conditions. To achieve this, spatially and temporally extensive aggregations of measured data or a synthesis of model results may be used to create and improve LCA methods. Long-term and multilocation measurements of GHG emissions and SOC stock changes are especially important for LCA method development. Combinations of several data types (e.g., measurements, satellite data, and modeling) could have the potential to improve the precision of LCA, especially when the aim is to estimate the GHG emission reductions following improved management. Although a large amount of data potentially useful for LCA are already available, their suitability and usability for LCA practitioners use need improving via data aggregation, improved awareness, and better user interfaces.

5.2.3. Reporting practices in voluntary carbon market

Challenges for carbon credits for agriculture revolve around monitoring and the verification of mitigation outcomes at the field scale (Section 2.3). Credible accounting of carbon sequestration or emissions reductions achieved with specific field management is necessary for a functional carbon market. Large spatial heterogeneity in soils limits the precision of estimates (Heikkinen et al., 2021). Management-induced SOC change may not be detectable with sufficient confidence and with the available techniques within the five years typically used in crediting programs. This makes the reliable quantification of SOC change based on field-specific measurement data alone impossible or economically unviable. As a solution, Oldfield et al. (2022) proposed regional accounting and verification to address the shortcomings of smaller projects. A regional unit could be a biophysically defined agroecological zone that has similar soils, climate, and agricultural potential or constraints. Another dimension defining the region is the regulatory circumstances that need to be considered in defining the baseline. Standardization across regions would provide consistency while incorporating parameters specific to each region as required. A regional approach would also align with demonstrating sustainability in typical food supply chains untraceable to the level of a specific farm. Aligned with the regional approach, the Nordic stakeholders code for best practices (Ahonen et al., 2022) proposes joining forces and developing baseline and monitoring methodologies for mitigation activities implemented in the Nordic region. Jacobs et al. (2020a) also suggested integrating SOC certification schemes into harmonized, intensive, and reliable national soil monitoring. However, they questioned the feasibility of such an approach, as the methods for national soil monitoring and GHG reporting need to cover many details at a field scale, resulting in high costs.

Acknowledging the acute need to respond to the extinction crisis, climate mitigation options in sectors relying on land use are increasingly sought from nature-based solutions or solutions that do not endanger biodiversity or hamper rural communities (Griscom et al., 2017; Smith et al., 2022). This underlines the long-term need for even broader assessments of the impacts of mitigating actions that would assure the acceptability of actions and minimize tradeoffs between different social, environmental, and economic impacts.

6. Conclusions

The development of credible and feasible SOC and GHG reporting and monitoring systems for arable production is increasingly being emphasized to support emission management at the national, company, production chain, and farm levels. Field-scale emission estimation, if credibly implemented, allows more precise reporting by activity and operator, which would also improve aggregated results at higher scales. However, major challenges must be solved before credible, feasible, and cost-efficient SOC and GHG balance estimation systems at field scale can be achieved. First, there are still major data gaps related to both field-scale land-management activities and their impacts on SOC stocks and net GHG emissions for different soil types and in varying weather conditions. Due to insufficient empirical data, the emission factors, models, and overall scientific understanding of emissions and their management remain largely incomplete. As tangible steps toward field-scale emission estimation we propose: 1) concentrated efforts to gather comprehensive and long-term empirical data on SOC and GHG emissions dynamics in agricultural fields; 2) systematic programs and investments in data management, storage, and sharing to acknowledge and secure the value of existing data; 3) international efforts for the harmonization of monitoring and verification methods; and 4) the development of standards for the transparent documentation of estimation methods and uncertainties related to the results. In the longer term, the development of methods for more complete assessments of the environmental and social benefits and tradeoffs of mitigation actions will become increasingly important to secure the acceptability and adoption of mitigation actions and to avoid any harmful side-effects they may have.

CRediT authorship contribution statement

Taru Palosuo: Writing – original draft, Supervision, Project administration, Conceptualization. **Jaakko Heikkinen:** Writing – review & editing, Visualization. **Emmi Hilasvuori:** Writing – review & editing. **Liisa Kulmala:** Writing – review & editing, Visualization, Project administration, Funding acquisition. **Samuli Launiainen:** Writing – review & editing. **Anniina Lehtilä:** Writing – review & editing, Visualization. **Ilkka Leinonen:** Writing – review & editing. **Maarit Liimatainen:** Writing – review & editing, Project administration, Funding acquisition. **Miia Salminen:** Writing – review & editing. **Narasinha Shurpali:** Writing – review & editing. **Tarja Silfver:** Writing – review & editing, Visualization. **Helena Soinne:** Writing – review & editing. **Julius Vira:** Writing – review & editing. **Jari Liski:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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