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Research article

What monitoring, reporting & verification (MRV) systems can reduce costs and enhance scalability of carbon farming?

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A B S T R A C T

With the growing emphasis on results-based payments in environmental monitoring of agricultural practices, developing reliable and cost-effective monitoring, reporting, and verification (MRV) systems has become critical. This holds particularly for carbon farming, where existing methods to monitor soil carbon storage are often roughly estimated or prohibitively expensive. This paper examines the factors driving MRV costs for results-based payments in carbon farming. We develop a cost model for three MRV systems: decision support tools, process-based models and direct soil measurement. Using scenario and sensitivity analyses, we estimate substantial cost variations depending on the monitoring approach, project design, and protocol standards, indicating potential burdens to farmers. While process-based models may emerge as the standard in future carbon markets, concerns about economic viability and labour demands persist. Innovations like digitalisation or relying on long-term experimental sites hold promise for reducing costs, but policy support is likely required to ensure the scalability of MRV systems, especially for smaller farms. Our findings are relevant to ongoing policy discussions, such as the European Union's Carbon Removal Certification Framework. From a methodological perspective, our generic cost model can be extrapolated to estimate the MRV costs of carbon farming across various contexts.

1. Introduction

The demand for environmental monitoring of agricultural practices is rapidly growing, driving a shift from action-based to results-based payments for farmers (Deconinck et al., 2023). Monitoring, reporting and verification[1] (MRV) systems are increasingly important to ensure accurate and reliable estimates of environmental impacts. Carbon farming, i.e. applying agricultural practices to increase soil organic carbon (SOC) storage and/or reduce greenhouse gas (GHG) emissions, is no exception to this trend (Smith et al., 2007; Tang et al., 2016). Carbon farmers are typically compensated for additional carbon stored in soils, which can then be sold as credits on the voluntary carbon market (Raina et al., 2024).

Although agriculture is widely recognized for its potential to contribute to carbon sequestration and reduce GHG emissions at a global scale (Bossio et al., 2020; Minasny et al., 2017), the effectiveness of carbon farming practices is highly context-dependent, varying with biophysical, economic, social, and political factors (Smith et al., 2005). Carbon storage potential of the practices remains unknown across different pedoclimatic regions, and some practices may provide little or no benefit (Moinet et al., 2023; Oldfield et al., 2024; Wang et al., 2023). In addition, particularly in short-term carbon farming projects, risks such as reversibility and saturation can undermine the reliability of carbon credits (Craig et al., 2021; Georgiou et al., 2025; Petersson et al., 2025). These challenges underscore the critical need for robust and cost-effective MRV systems to demonstrate both the additionality and permanence of carbon SOC stocks[2] and ensure credible and accurate estimates of carbon credits (Paul et al., 2023).

This need has become increasingly urgent, as carbon farming has expanded rapidly since the 2015 Paris Agreement, supported by national

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[1] In case of carbon farming, monitoring refers to the estimation of SOC stock changes for a project, while reporting involves the procedure of documenting these changes, including quality assurance/quality control of data and report writing for offset projects. Verification ensures that the additional carbon stock is validated before being issued as carbon credits, which includes an audit by a third party under the supervision of an intermediary and a farm visit.

[2] While our study focuses on the economic challenges of quantifying additional SOC stocks, it is important to note that carbon farming strategies vary in scope, targeting soil and/or biomass carbon storage or overall GHG emission reduction (Thorsøe et al., 2025).

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programs such as the Australian Carbon Credit Unit scheme and France's *Label Bas Carbone* (Clean Energy Regulator, 2025; Idele, 2019; Oldfield et al., 2021). Private schemes such as Gold Standard, Verra and Indigo, have proliferated (Dupla et al., 2024). This rapid growth of the voluntary carbon market comes with two major challenges.

First, the lack of standardized and reliable MRV systems across schemes undermines both the environmental integrity of carbon credits and trust in the market (Paul et al., 2023; Raina et al., 2024). In response, the European Union introduced the Carbon Removal Certification Framework (CRCF), a voluntary framework aimed at promoting the environmental integrity and transparency of high-quality carbon credits (European Parliament, Council of the European ParliamentCouncil of the European Union, 2024). A cornerstone of the CRCF is the adoption of the Intergovernmental Panel on Climate Change (IPCC) Tier 3 MRV approaches, which are methods that rely primarily on site-specific or field-based data to quantify SOC stocks, unlike the Tier 1 and 2 approaches that are mostly used in current carbon farming schemes (Batjes et al., 2024; European Parliament, Council of the European ParliamentCouncil of the European Union, 2024).

Second, although Tier 3 approaches offer greater accuracy than Tier 1 or Tier 2 approaches, they often entail higher costs and administrative burdens for farmers (Batjes et al., 2024; Paul et al., 2023; Raina et al., 2024). This is particularly relevant for carbon farming, where direct measurement of SOC is regarded not only as the most accurate MRV system but also as more labour-intensive and costly, especially at large scale (Kuhnert et al., 2022; Paustian et al., 2019). With progress in environmental monitoring, digital technologies offer promising avenues for developing more affordable MRV systems (Meemken et al., 2024). While models might offer cheaper alternatives, they are often accompanied by greater uncertainty (Batjes et al., 2024; Paul et al., 2023). Decision support tools, which are widely used in the market, are user-friendly platforms that estimate carbon or GHG budget based on farm management data. While these tools are relatively affordable, they often rely on national or regional emission factors, resulting in unreliable estimation at field scale (Batjes et al., 2024). Process-based models, on the other hand, predict SOC change with algorithms that integrate the theoretical understanding of carbon dynamics and the impact of management practices (Paustian et al., 2019). However, most models lack local validation, and their accuracy is uncertain when applied to new sites, especially where data availability is limited (Garsia et al., 2023). As the data and modelling requirements are quite intensive, integrated process-based models are still in their infancy in the market but many research efforts are being devoted to developing these models (Batjes et al., 2024; Oldfield et al., 2024; Smith et al., 2020).

With the growing demand for more rigorous and standardized MRV systems, particularly under policy initiatives like the CRCF, it is timely to assess how costs and labour requirements of MRV systems are influenced by their technical and project design. Understanding cost drivers is essential to identifying technical solutions and policy levers that can lower costs and administrative burdens for farmers and project developers. Yet, quantitative evidence on the costs associated with MRV systems of carbon farming is non-existent. MRV costs have been quantified in the context of forest offset projects, but these studies are restricted to national or large-scale initiatives (Cacho et al., 2013; Köhl et al., 2020), with only one study addressing labour costs (Mäkipää et al., 2008). As a result, there is limited understanding of the specific costs and influencing factors for MRV in agriculture in general and for carbon farming specifically. In addition, carbon farming schemes differ in their MRV protocol and project requirements, such as monitoring period and frequency, baseline duration, number of farms into a project or cost of licence (Dupla et al., 2024). Evidence on how these requirements influence costs is also missing. As a result, evidence on the farm economic viability of various MRV systems for carbon farming remains scarce, making it difficult to assess their scalability.

To address these research gaps, this paper aims to 1) quantify the costs and labour of different MRV systems for results-based payments in carbon farming, 2) determine the factors that drive these costs, 3) assess how MRV costs affect farm economic viability, and 4) explore technological and policy pathways to reduce these costs. Based on a hypothetical scheme, we first develop a cost model for three MRV systems of SOC quantification: 1) decision support tools, 2) process-based models, and 3) direct soil measurement. This cost model allows us to quantify total MRV costs, cost structures, and labour for farmers and intermediaries. We then analyse three different scenarios to study how various strategies, including innovations, can reduce costs and labour. Finally, we conduct a sensitivity analysis to assess the influence of external MRV parameters, such as project structure or protocol standards, on MRV costs. The cost model is set up in a generic way, facilitating the applicability of our model to estimate the costs of various MRV systems in different contexts.

2. Methodology

The methodology consists of three steps: 1) determining a hypothetical carbon farming scheme, 2) developing the cost model for the three MRV systems, and 3) conducting a scenario analysis and sensitivity analysis to calculate costs and labour.

2.1. Determining a hypothetical carbon farming scheme

We first need to define a hypothetical results-based payment scheme to calculate costs across different MRV systems. Starting from a hypothetical scheme rather than the evaluation of existing schemes is particularly useful in the context of the voluntary carbon market, where standardization is lacking and MRV parametrizations are countless. We base our approach on two similar recent studies that also use a hypothetical scheme to develop cost models on the monitoring of biodiversity (Markova-Nenova et al., 2023; Schöttker et al., 2023).

We set our hypothetical scheme in the Loam Belt in Wallonia, Belgium. This region represents the largest cropland area in Belgium and is known for its fertile loam soils. However, 90% of cropland has critically low soil carbon content (<20gC/kg) (SPW, 2020). Carbon farming is expanding through private schemes like Soil Capital, with farmers adopting practices such as cover cropping and reduced tillage (Soil Capital, 2023). In our scheme, farmers receive payments for implementing carbon farming practices. The payments are results-based, meaning that the carbon credits are based on SOC stock changes. An intermediary manages the MRV system, sells the carbon on the voluntary market, and provides advisory services to farmers (Raina et al., 2024). Farmers can decide to participate individually or in group. These MRV procedures are common in private schemes (Batjes et al., 2024) and are implemented by market players like Soil Capital (Soil Capital, 2023).

To calculate MRV costs, we model a carbon farming project implemented within the hypothetical scheme, where MRV costs are distributed among participating farms. We take first the following base values for the project parameters, which we will then vary in the sensitivity analysis (see section 2.3.2) to assess their importance in overall costs. We assume a project with 20 farms, each comprising 65 ha of utilized agricultural area entirely dedicated to the project. This farm size is representative of the region (DEMNA/SPWARNE, 2024), and the number of farms reflects the average size of collective projects from France (i.e. *Label Bas Carbone "Grande Culture"*) (Ministère de la transition énergétique, 2024). We assume that the farmers do not have to pay for the software licence to model SOC changes. The monitoring period spans five years, with farmers receiving carbon credits at the end. Monitoring of SOC changes occurs three times during this period, with the baseline measurement in year 0, and two additional SOC quantifications in years 2 and 5. Data on farm activities is collected for each year, if it is included in the MRV system. The baseline is established by collecting historical data from farmers on past management practices, with a retrospective of three years. The values for monitoring period, monitoring frequency and baseline period are based on the main carbon farming standards, such as *Label Bas Carbone* and Gold Standard (Gold Standard, 2020; Idele, 2019).

2.2. Developing the cost model for the three MRV systems

2.2.1. MRV systems

We compare three MRV systems: 1) decision support tools, 2) process-based models, and 3) direct soil measurement. First, decision support tools estimate SOC stock changes using IPCC Tier 1 or 2 emission factors, based on management practices that are entered by farmers (Batjes et al., 2024). Soil sampling is optional as some carbon farming schemes, like Soil Capital, require it initially, while others, such as the method Carbon Agri of *Label Bas Carbone*, do not (Idele, 2019). Second, process-based models integrate carbon dynamics models, such as RothC (Coleman and Jenkinson, 1996), with management practices based on annual activity data collection, climate and environmental covariates derived from remote sensing or experimental sites, and soil samples for training and validation (Paustian et al., 2019; Smith et al., 2020). Third, direct soil measurement typically involves resampling plots over time using a well justified sampling scheme (Brus et al., 1999), with state-of-the art laboratory techniques such as dry combustion for the carbon content and measurement of bulk density and stone content at each sampling point (Dupla et al., 2024).

Table 1 summarizes the different monitoring activities used in the three MRV systems. The first monitoring activity is activity data collection, which is the information about farm management practices provided by the farmer, and is included in decision support tools and process-based models, but not in direct soil measurement. The second monitoring activity is soil sampling, which is the collection of field soil samples, and is included in process-based models and direct soil measurement, and in some scenarios of the decision support tools. The third monitoring activity is modelling, which is the calibration and validation of empirical or process-based models, and is included in the decision support tools and process-based models. The fourth monitoring activity is remote sensing, which is image processing to derive model covariates, and is only included in the process-based models.

2.2.2. Cost model: overview

In this section, we outline the framework of our cost model, with Table 2 presenting the values of all cost parameters that are fixed or used in the base scenario. A justification of these cost parameters is provided in the appendix (Supplementary Material A, Table A-1). The overall MRV cost C_{MRV} for a farm participating in a carbon farming project is presented in equation (Eq. (1)). As costs are incurred over the project lifetime (i.e. monitoring period T^M), we calculate the net present value (NPV) for each year of the project and then aggregate the costs. A constant discount rate i of 3% is used following Schöttker et al. (2023), as this is a value commonly used for projects related to environmental protection and climate change. C_{MRV} comprises all costs, whether they are borne by farmers or by intermediaries. The investment costs linked to the development of the MRV system and project are considered as sunk costs and do not enter the cost model.

Table 1
MRV systems and their monitoring activities used in the cost model.

Monitoring activities	Decision support tools	Process-based models	Direct soil measurement
Activity data collection	Included	Included	Excluded
Soil sampling	Excluded[a]	Included	Included
Modelling	Included	Included	Excluded
Remote Sensing	Excluded	Included	Excluded

[a] Except for uncertainty reduction scenario.

Table 2
Overview of the cost parameters and their values in the base scenario. The parameters encompass general parameters as well as specific costs related to the different monitoring activities used in the process-based model (PBM), direct soil measurement (DSM) and decision support tool (DST).

Parameter	Definition (unit)	Base value[a]	Other values used [b]
General cost parameters			
i	Discount rate (%)	3	/
F^M	Monitoring frequency (#)	3	Sensitivity analysis
T^M	Duration of the monitoring period (year)	5	Sensitivity analysis
w_{fa}	Wage of the farmer (€/hour)	16.87	/
w_{in}	Wage of the intermediary (€/hour)	43.86	/
A_{fr}	Agricultural area utilized per farm (hectare)	65	Sensitivity analysis
n_{fr}	Number of farms participating (#)	20	Sensitivity analysis
Activity data collection			
t_b	Duration of the baseline period (year)	3	Sensitivity analysis
t_{a0}	Time required to enter activity data in the first year (hour)	8	Scenario analysis
t_a	Time required to enter activity data after the first year (hour)	4	Scenario analysis
Soil sampling			
d_{ns}	Sampling interval (ha/sample)	PBM:4; DSM:1.2; DST:0	Scenario analysis
n_{sp}	Number of soil samples collected per farm (#)	PBM:16; DSM:54; DST:0	Scenario analysis
t_{pr}	Time required to plan soil sampling fieldwork for a farm (hour)	1	/
t_{sa}	Time required to locate and to collect a soil sample (hour)	0.125	/
t_{ko}	Time required to collect a core sample with a Kopecki ring (hour)	0	Scenario analysis
c_{ca}	Cost per sample to analyse the carbon content (€/sample)	20.5	/
c_{bd}	Cost per sample to analyse the bulk density (€/sample)	0	Scenario analysis
c_{cl}	Cost per sample to analyse the clay content (€/sample)	0	Scenario analysis
Modelling			
t_{mo0}	Time required to calibrate, process and validate the model at the start of the project (hour)	DST:1; PBM:8	/ /
t_{mo}	Time required to calibrate, process and validate the model after the first year (hour)	1	/
c_{li}	Cost of the licence to use the model per project (€)	0	Sensitivity analysis
Remote sensing			
n_{im}	Number of images used for image processing (#)	5	/
t_{pc}	Time required per image for correction and processing NDVI (hour)	1.52	Scenario analysis
t_{in}	Time required to interpret data after image processing (hour)	1	/
Reporting			
t_{re}	Time required to report information per farm (hour)	4	/
t_{qc}	Time required to transmit information to the standard per project (hour)	16	/
Verification			
n_{au}	Number of farms audited by a third party (#)	2	/
t_{vi}	Time spent per farm by the intermediary during the third-party audit (hour)	4	/
t_{vf}	Time spent by the farmer during the third-party audit (hour)	2	/
c_{th}	Cost per project for a third-party audit (€)	1250	/

[a] Values are indicated for the MRV system that includes these activities as part of its methodology, as explained in Table 1.
[b] This column indicates whether the value varies in the scenario or sensitivity analysis.

$$C_{MRV} = \sum_{t=0}^{T^M} C^m(t)*(1+i)^{-t} \tag{1}$$

The total annual cost $C^m(t)$ is based on three main components: monitoring $C^M(t)$, reporting $C^R(t)$, and verification $C^V(t)$ (Eq. (2)), which will be explained in the next sections.

$$C^m(t) = C^M(t) + C^R(t) + C^V(t) \tag{2}$$

2.2.3. Monitoring

The monitoring cost $C^m_M(t)$ reflects the costs of quantifying SOC stock changes.[3] It depends on which monitoring activities are used: activity data collection $C^M_{AD}(t)$, soil sampling $C^M_{SS}(t)$, modelling $C^M_{MO}(t)$, and remote sensing $C^M_{RS}(t)$, which varies across MRV systems (Eq. (3)). Data from sources such as spatial data layers (e.g., climate data) or long-term experimental sites are considered open-source and thus excluded from this study. The total monitoring cost over a project's lifespan depends on the monitoring frequency F^M and the monitoring period T^M.

$$C^M(t) = C^M_{AD}(t) + C^M_{SS}(t) + C^M_{MO}(t) + C^M_{RS}(t) \tag{3}$$

2.2.3.1. Activity data collection. The cost of activity data collection $C^M_{AD}(t)$ refers to farmers gathering and entering data, while intermediaries support data entry (Eq. (4)). It reflects the opportunity cost of farmers and the labour cost of intermediaries. It varies between the baseline year (t = 0) and subsequent years (t ≥ 1), as farmers become more used to the platform over time but also because more historical data needs to be entered in function of the baseline period (t_b). Based on data provided by Soil Capital, we assume that establishing the baseline ($t_{a0} = 8\ hours$) takes twice as long as in later years ($t_a = 4\ hours$). The hourly wage of farmers ($w_{fa} = 16.87$€/hour) and of intermediaries with a master's degree ($w_{in} =$ €43.86/hour) are based on the regional 5-year average. We assume that activity data collection occurs annually, like most carbon farming schemes.

$$C^M_{AD}(t) = \begin{cases} t_{a0}*(t_b+1)*w_{fa} + t_{a0}*(t_b+1)*w_{in} & t=0 \\ t_a*w_{fa} + t_a*w_{in} & t \geq 1\ year \end{cases} \tag{4}$$

2.2.3.2. Soil sampling. The soil sampling $C^M_{SS}(t)$ cost includes the implementation costs of the soil sampling field mission: planning the field mission C^M_P, sample collection C^M_S, and laboratory analysis C^M_L (Eq. (5)). We consider that the equipment costs (e.g., auger, plastic bags) are negligible and that the farmer combines the soil sampling with other field tasks, so there are no additional transportation costs.

$$C^M_{SS}(t) = C^M_P(t) + C^M_S(t) + C^M_L \tag{5}$$

The planning cost $C^M_P(t)$ includes the opportunity cost, accounting for the time spent preparing the field mission t_{pr} (Eq. (6)). This involves designing the sampling scheme, identifying the plots, and gathering necessary materials for the field visits. We assume that t_{pr} takes 1 h for a field mission based on Schöttker et al. (2023).

$$C^M_P(t) = t_{pr}*\mathrm{w_{fa}} \tag{6}$$

The sampling cost $C^M_S(t)$ is the opportunity cost for the farmer to take the soil samples in the fields (Eq. (7)). We assume that farmers will collect soil samples themselves, resampling the same fields over time, like in the case of Soil Capital. The cost depends on the time required to locate and take a sample t_{sa}, and on the number of samples (n_{sp}). We use the same values as Singh et al. (2013) for t_{sa} (7.5 min). The number of samples is calculated as the ratio of the sampling interval (d_{ns} in hectare/sample) over the farm size (A_{fr}). The sampling interval depends on the MRV system, with 4 ha per sample for process-based models, and 1.2 ha per sample for direct soil measurement. This represents the lower and higher end of a feasible sampling interval for intermediaries in the base scenario, according to Bradford et al. (2023). For a 65-ha farm, this leads to 16 and 54 samples in total. In some scenarios, a direct estimation of the bulk density is required, taking one undisturbed soil core at each sample location using a Kopecki ring. This would involve an additional effort of the farmer (t_{ko}). In the base scenario, bulk density is assumed to be derived from local pedo-transfer functions (Chartin et al., 2017). Therefore, no soil cores are collected in that scenario ($\mathrm{t_{ko}} = 0$ minutes).

$$C^M_S(t) = \mathrm{n_{sp}}*t_{sa}*\ \mathrm{w_{fa}} + \mathrm{n_{sp}}*t_{ko}*\ \mathrm{w_{fa}} \tag{7}$$

Laboratory analysis cost C^M_L involves the cost to determine SOC content (Eq. (8)). The standard agronomic analysis, which includes SOC content c_{ca}, costs €20.5 per sample, according to soil agronomic laboratories in Belgium. For process-based models and direct soil measurement, laboratory analyses such as clay content (c_{cl}) and bulk density (c_{bd}) are needed to calculate SOC stocks. In the base scenario, these costs are free, as they can be derived from local maps and pedo-transfer functions (Chartin et al., 2017).

$$C^M_L = n_{sp}*c_{ca} + n_{sp}*c_{cl} + n_{sp}*c_{bd} \tag{8}$$

2.2.3.3. Modelling. The cost for modelling SOC change $C^M_{MO}(t)$ includes the time required to initiate, process, and validate the models during the first year (t_{mo0}) and the subsequent years (t_{mo}) (Eq. (9)). For complex approaches, such as process-based models, we estimate a time requirement of 8 h per farm in the first year, and 1 h per farm for subsequent years, as the model has already been calibrated and validated. These estimates are based on discussions with soil modelling experts from the consortium of the MRV4SOC project and its advisory board.[4] In contrast, empirical models using IPCC emission factors are simpler, requiring about 1 h per farm, in any given year. This task is carried out by the intermediary. The licence cost c_{li} is assumed to be free in the base scenario but varies in the sensitivity analysis.

$$C^M_{MO}(t) = \begin{cases} t_{mo0}*w_{in} + \dfrac{c_{li}}{n_{fr}} & t=0 \\ t_{mo}*w_{in} + \dfrac{c_{li}}{n_{fr}} & t \geq 1\ year \end{cases} \tag{9}$$

2.2.3.4. Remote sensing. The remote sensing cost $C^M_{RS}(t)$ includes the time required for processing Normal Difference Vegetation Index (NDVI)-time series t_{pc} and interpretation t_{in} (Eq. (10)). We assume that remote sensing is used to derive covariates for the process-based model, particularly NDVI time series, to detect bare soil or the presence of vegetation/cover crops. This approach has been implemented with process-based models in Belgium (e.g. RothC, Spotorno et al., 2024). Other environmental and climatic covariates (e.g., climate, altitude) are derived from regionally available open-access spatial layers (i.e. *Geoportail de Wallonie* - SPW (2025)). The task is performed by the intermediary. Image acquisition is assumed to be open-access and free, so it is omitted from the cost model. The processing cost is shared among farms in the same project (n_{fr}) and depends on the number of images (n_{im}) used, which varies across the scenarios. We assume that 1 h of

[3] In results-based payment schemes, monitoring also assesses farming practices through activity data or remote sensing (Batjes et al., 2024; Raina et al., 2024). However, we omit this from our analysis as this aspect is identical across the four MRV systems.

[4] The MRV4SOC project is an EU-Horizon funded research project, of which the information about the different partners can be found via www.mrv4soc.eu.

interpretation time is required in any scenario.

$$C_{RS}^{M}(t) = \frac{(n_{im} * t_{pc} * w_{in})}{n_{fr}} + t_{in} * w_{in} \tag{10}$$

2.2.4. Reporting

Reporting $C^R(t)$ costs encompass the intermediary's time spent on quality assurance and quality control (t_{qc}) to ensure compliance with certification requirements (Eq. (11)). For carbon farming, this relates to the SOC change quantification report, which establishes the baseline at the project's start and during subsequent SOC quantifications (Batjes et al., 2024). This task typically involves two days per project (t_{qc}) shared among n_{fr} farms in a project. Additionally, we estimate an average reporting time (t_{re}) of 4 h per farm for preparing the SOC quantification report based on Carbon Think (2022).

$$C^R(t) = \left(\frac{t_{qc}}{n_{fr}} + t_{re}\right) * w_{in} \tag{11}$$

2.2.5. Verification

The verification cost $C^V(t)$ involves verification by an independent third party hired by the intermediary (Eq. (12)). The average audit cost c_{th} is €1250 per project, encompassing a desktop review, field visit, and preparation of reports. (Batjes et al., 2024; Resoil, 2024). The intermediary is estimated to spend approximately 4 h per farm gathering information for the audit (t_{vi}), while each audited farmer spends about 2 h in an interview with the auditor (t_{vf}). As not all farms in the project are audited, the verification costs are divided over all farms in a project. The number of farms audited (n_{au}) is specified as $0.5 * \sqrt{n_{fr}}$, as in the case of the *Label Bas Carbone* standard (Idele, 2019).

$$C^V(t) = \frac{n_{au}}{n_{fr}} * (t_{vi} * w_{in} + t_{vf} * w_{fa} + c_{th}) \tag{12}$$

2.3. Scenario analysis & sensitivity analysis to calculate costs and labour

2.3.1. Scenario analysis

We analyse three different scenarios for each MRV system: 1) base scenario, 2) cost reduction, and 3) uncertainty reduction. The base scenario reflects current practices on the voluntary carbon market. Cost reduction explores digitalisation or external data to lower costs, while uncertainty reduction focuses on solutions that could minimise uncertainty. Table 3 presents the specific cost parameters for each MRV system and scenario. Justification of the cost parameters for the cost reduction and uncertainty reduction scenario are provided in appendix (Supplementary Material A, Table A-2 and Table A-3).

For decision support tools, cost reduction is mainly achieved by reducing time spent on activity data collection. Improved digitalisation, aided by auto-filling, data reuse, and better connectivity with farm information systems, could reduce data entry time by half according to intermediaries in Belgium. On the other hand, to reduce uncertainty, more detailed soil sampling is required. For this scenario, we assume a sampling interval of 7.5 ha per sample, which aligns with the typical low-interval sampling practices used by companies in the offset project sector (Bradford et al., 2023). This corresponds to 9 soil samples for a 65 ha-farm.

For process-based models, costs can be reduced by using available processed products, like NDVI time series. Platforms like Belcam (2020) provide such data from Sentinel-2, eliminating processing costs but requiring 1 h for product interpretation by the intermediary. To reduce uncertainty, soil laboratory analysis could be improved by not only assessing the carbon content but bulk density and clay content as well. Soil sampling costs would then rise due to additional fieldwork and laboratory analysis. For bulk density, the farmer collects an undisturbed soil core at each sample location, which takes about 12 min per soil core. Laboratory costs increase by €5 for bulk density and €6 for clay content per sample. These estimates are based on prices from soil agronomic laboratories in Belgium.

Table 3
Cost parameters and values for different MRV systems in different scenarios. Only the parameters that vary from the base scenario are shown; all other parameters remain constant across scenarios.

Parameters	Definition (unit)	Cost reduction	Base	Uncertainty reduction
Decision support tools				
t_{a0}	Time required to enter activity data in the first year (hour)	4	8	8
t_a	Time required to enter activity data after the first year (hour)	2	4	4
d_{ns}	Sampling interval (ha/sample)	0	0	7.5
n_{sp}	Number of soil samples collected per farm (#)	0	0	9
Process-based models				
t_{ko}	Time required to collect a core sample with a Kopecki ring (hour)	0	0	0.2
c_{bd}	Cost per sample to analyse the bulk density (€/sample)	0	0	5
c_{cl}	Cost per sample to analyse the clay content (€/sample)	0	0	6
t_{pc}	Time required per image for correction and processing NDVI (hour)	0	1.52	1.52
Direct soil measurement				
d_{ns}	Sampling interval (ha/sample)	4	1.2	0.1
n_{sp}	Number of soil samples collected per farm (#)	16	54	650

To reduce costs for direct soil measurement, we assume the existence of in-situ data available in the region/landscape of the project, such as long-term experiments like ICOS stations or soil monitoring networks like Requasud. This could allow for a decrease in sampling at the project level, leading to only 16 samples per farm. In contrast, to reduce uncertainty, we set the soil sampling interval at 0.1 ha per sample, which is considered as ground truth for accurate and representative soil sampling (Bradford et al., 2023).

2.3.2. Sensitivity analysis

The sensitivity analysis assesses the changes in MRV costs with changes in parameters of project structure (number of farms, farm size) and protocol standards (baseline period, monitoring period, monitoring frequency, licence cost). Table 4 presents these parameters and their values. Justification of the parameters is provided in appendix (Supplementary Material A, Table A-4).

The number of farms is crucial in designing a carbon farming project, as it can involve either a single farm or a group of farms. Pooling farms into one project might enable economies of scale and affects several parameters, including processing costs, audit frequency, and licence fees. To assess this, we compare the MRV cost per farm when involved in a project with 20 farms versus being alone or part of a 100-farm project. The number of farms is based on project data from the *Label Bas Carbon* registry for the "*Grande Culture*" method. Another important factor is farm size, which largely determines farmers' capacity to invest. In the cost model, farm size only influences the total number of soil samples. We compare farms of 65 ha to farms of 40 ha and 100 ha, which represent the median, 1st quartile and 3rd quartile of farm sizes in the Loam Belt region according to the Farm Accountancy Data Network.

While longer baseline periods enhance model accuracy, they may impose additional administrative burdens on farmers due to the need to retrieve historical information. Typically, baseline periods range from

Table 4
Cost parameters for the sensitivity analysis, showing different values for project parameters and protocol standards. Only parameters differing from the base scenario are displayed, with all other parameters held constant.

Parameters	Definition (unit)	Low value	Medium value	High value
Farm number				
n_{fr}	Number of farms participating (#)	1	20*	100
n_{au}	Number of farms audited by a third party (#)	1	2*	5
Farm size				
A_{fr}	Agricultural area utilized per farm (hectare)	40	65*	100
n_{sp}	Number of soil samples collected per farm (#) for process-based models	10	16*	25
n_{sp}	Number of soil samples collected per farm (#) for direct soil measurement	33	54*	83
Cost of the licence				
c_{li}	Cost of the licence to use the model per project (€)	0*	1000	2700
Monitoring frequency				
F^M	Monitoring frequency (occurrence over 5 years project)	2	3*	5
Monitoring period				
T^M	Duration of the monitoring period (year)	5*	10	15
Baseline period				
t_b	Duration of the baseline period (years)	0	3*	5

Values that are indicated with an asterisk(*) are used in the base scenario.

three to five years, as seen with Verra and Gold Standard (Gold Standard, 2020; Shoch et al., 2023). In some cases, such as Soil Capital, no historical years are required. We compare MRV costs under a 3-year baseline period to no baseline period and to a 5-year baseline period. We also assess the cost implications of different monitoring periods. We compare a 5-year monitoring period, which is the minimum required by the CRCF and is commonly used by standards like *Label Bas Carbone*, Gold Standard, and Verra. However, longer monitoring periods—10 years in general and 15 years for agroforestry—are currently under discussion by the group of experts[5] in charge of developing the official methodologies for the CRCF. Not only the monitoring period influences costs, also its frequency matters. Various standards have different requirements: for example, the “Carbon Agri” method and Gold Standard require three times of monitoring over five years, Soil Capital mandates annual monitoring, and Verra's VM0042 requires only once every five years. We compare a monitoring frequency of three times over five years to two times (i.e. every five years) and five times (i.e. annual monitoring).

Given the significant variability in licence costs for modelling software, we examine their impact on total costs. Licence fees for MRV systems differ across schemes from free (e.g. Decide), over €1000/year (e.g. CAP’2 ER) to €2700/year (e.g. Cool Farm Tool). Licence fees are divided over all the farms participating in a project. For a project with 20 farms, the annual cost per farm would be €0, €50, and €135, respectively.

2.3.3. Labour calculations

From our cost model, we also derive the time that farmers and intermediaries spend on MRV activities per farm (Table 5). The intermediary's total labour is estimated by multiplying the time spent per farm by the number of farms involved in the project, which varies in the sensitivity analysis.

Table 5
Activities allocation for the farmer and the intermediary, highlighting all related time-variables from the cost model.

MRV activities	Farmer parameters	Intermediary parameters
Activity data collection	Gathering and entering information (t_{a0}, t_a)	Verifying information and supporting with entry (t_{a0}, t_a)
Soil sampling	Field mission planning (t_{pr}), locating and collecting a soil sample (t_{sa}); collecting a soil core with a Kopecki ring (hour) (t_{ko})	
Remote sensing		Time for processing (t_{pc}), time to interpret (t_{in})
Modelling		Time to model (t_{mo0}, t_{mo})
Reporting		Time to report (t_{re}), time to ensure quality assurance/ quality check (t_{qc})
Verification	Time for the interview (t_{vf})	Time to assist to the third-party monitoring (t_{vi})

3. Results

3.1. Scenario analysis of MRV costs

Fig. 1 compares total costs per farm across different scenarios for the three MRV systems, showing large differences. In the base scenario, the process-based model is the costliest option (€5718), while the decision support tool is the least costly (€4179). The cost of direct measurement is of the same order of magnitude than decision support tools (€4472). The cost differences become more pronounced in the cost reduction scenario, where the process-based model remains the costliest option (€5671), while direct soil measurement becomes the cheapest (€2062). The disparity is even greater in the uncertainty reduction scenario, with direct soil measurement becoming the costliest option, with a total cost of €42,272, compared to €4797 for decision support tools being the least costly.

The variability in costs is mainly due to monitoring costs, which represent 77.0% of total costs on average for all scenarios. In comparison, reporting and verification costs represent 13.6% and 9.4% respectively. However, the relative share of these components varies according to the MRV systems and the scenarios. For example, in the cost reduction scenario, monitoring costs of direct soil measurement represent 51.5% of the total, reporting costs 28.7% and verification costs 19.8%. Conversely, in the uncertainty reduction scenario, monitoring costs dominate at 97.6%, with reporting and verification contributing only 1.4% and 1.0%, respectively.

Soil sampling and activity data collection are the major cost drivers. In direct soil measurement, soil sampling accounts for 51.5–97.6% of total costs, with sampling interval being the key determinant. In the uncertainty reduction scenario, establishing a “ground truth” requires 650 samples, raising costs by €37,800 compared to the base scenario. However, using a regional soil network reduces costs by €2,410, cutting the number of samples from 54 to 16. In process-based models, soil sampling can represent up to 26.8% of costs. In the uncertainty reduction scenario, additional analyses for clay content and bulk density increases costs by €645. Conversely, assuming open-source NDVI data in the cost reduction scenario results in a minor reduction of €47 compared to the base scenario. The activity data collection represents a significant share of MRV costs, ranging from 57.6% to 73.1% for decision support tools and from 48.0% to 53.9% for process-based models. Enhancing digitalisation of decision support tools can lower costs, as halving the data entry time for intermediaries and farmers in the cost reduction scenario saves €1528.

[5] The Group of Experts on Carbon Removal is a multidisciplinary group of stakeholders that assists the European Commission in implementing the Carbon Removal Certification Framework (CRCF) (https://ec.europa.eu/transparency/expert-groups-register/screen/expert-groups/consult?lang=en&groupID=3861).

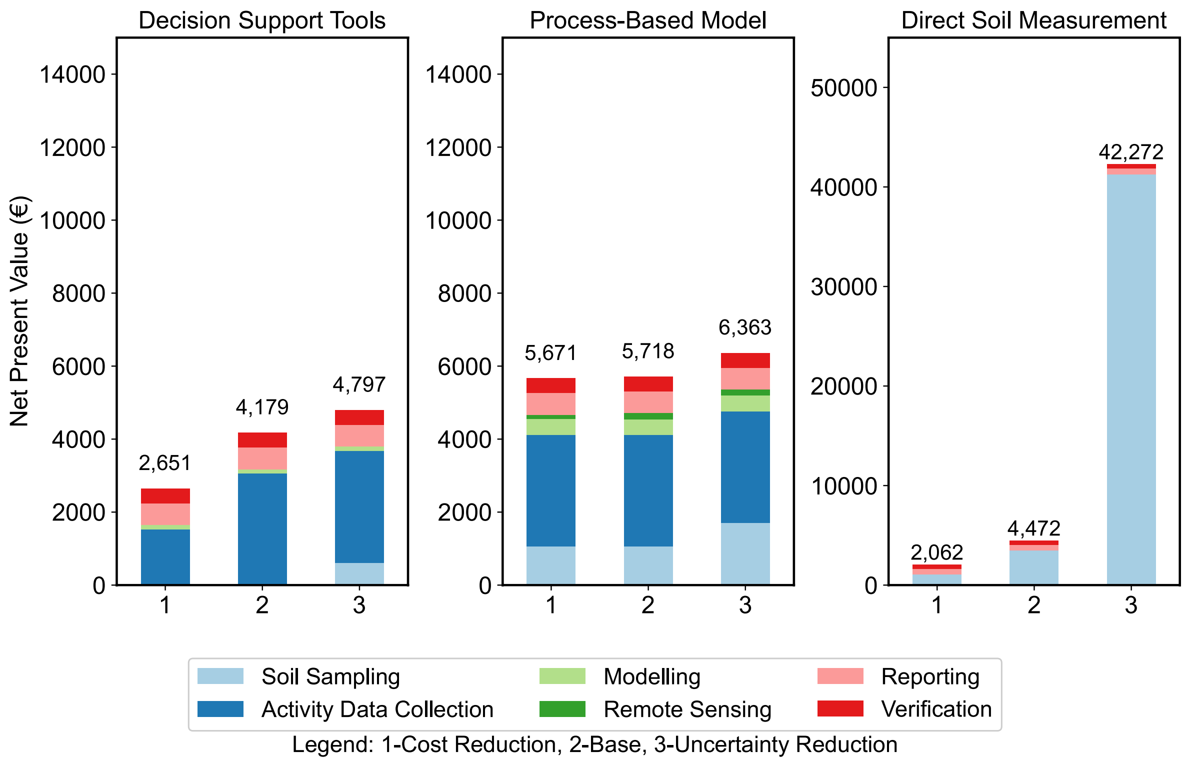

Fig. 1. Net present value of MRV costs per farm across different scenarios for three MRV systems: Decision support tools, Process-based models, and Direct soil measurement. The values are calculated for three scenarios: base, cost reduction and uncertainty reduction, using the values from Tables 2 and 3

3.2. Sensitivity analysis of MRV costs

Fig. 2 presents the sensitivity analysis for the base scenario. Regarding project structure, MRV costs are highly sensitive to the number of participating farms. Single-farm projects incur significantly higher costs by €5554 to €6445 compared to farms in 20-farm projects. For 100-farm projects, per-farm costs drop modestly by up to €321 compared to 20-farm projects. Farm size affects MRV costs primarily by determining the number of required samples, though its impact on total costs is less significant than the number of participating farms. For a 40-ha farm, total costs decrease by up to €1332 (in case of direct soil measurement) compared to a 65-ha farm, while for a 100-ha farm, costs increase by up to 1839€. When the costs are expressed per hectare though, we observe that average costs go down with increasing farm size.

Regarding protocol standards, monitoring frequency has the largest influence on MRV costs. Annual monitoring raises costs by up to €4423 for direct soil measurement and €2323 for process-based models compared to monitoring three times over five years. Reducing frequency from every-two-years to every-five-years over five years lowers costs by €377 (for decision-support tools) to €1503 (for direct soil measurement). On the other hand, the effect of monitoring period is much smaller. Extending the monitoring period from 5 to 10 years with a monitoring event every 5 years increases costs by €1186 to €1584 and by €2209 to € 2951 for a 15-year period. The cost increase is primarily due to the higher number of monitoring events. However, when considering both the monitoring period and frequency, extending the period does not always lead to higher costs. The baseline period affects MRV costs when activity data is required, meaning that direct soil measurement is unaffected. For decision support tools and process based-models, costs rise by €972 over 5 years when the baseline changes from 3 to 5 years and drop by €1458 with no baseline. Licence costs have the least impact on MRV costs. Spread over 20 farms, this translates into €50 to €135 per farm, resulting in an additional cost of €140 to €379 over 5 years.

Figure A-1 and Figure A-2 in appendix (Supplementary Material A), report the sensitivity analysis for the cost reduction and uncertainty reduction scenarios. The cost rankings of the different MRV systems vary between the different scenarios, but the effects of the parameters linked to project structure and protocol standards remain largely consistent.

3.3. Labour comparison

Fig. 3 reports the labour requirements per farm over five years for farmers and intermediaries for the base scenario. The process-based model is the most labour-intensive, requiring 144 h, while direct soil measurement requires 40 h. Farmers' labour ranges from 24 h for direct soil measurement to 62 h for process-based models while the intermediaries require 16 h per farm for direct soil measurement to 82 h per farm for process-based models, meaning a total labour of 315 to 1638 h for one project with 20 farms. Activity data collection is the most labour-intensive activity, as it accounts for up to 99% of total farmer labour and 74% of intermediary labour. Reporting represents 16% of overall costs and 18% to 92% of intermediary labour. Verification requires minimal work, ranging from 1% to 9% for both actors. Figure A-3 and Figure A-4 in Appendix (Supplementary Material A) reports the labour requirements for the other two scenarios. The cost reduction scenario gives similar or slightly lower labour demands, while the uncertainty reduction scenario becomes much more labour-intensive (up to six times more), especially for direct soil measurement.

4. Discussion

4.1. MRV costs and influencing factors

We estimate the magnitude of MRV costs, emphasizing how both the choice of MRV system and the design of protocols or projects can significantly impact overall MRV costs. Our approach focuses on understanding cost variations through scenario and sensitivity analysis, indicating the order of magnitude. We find that process-based models are on average the most expensive, but the costs of direct soil

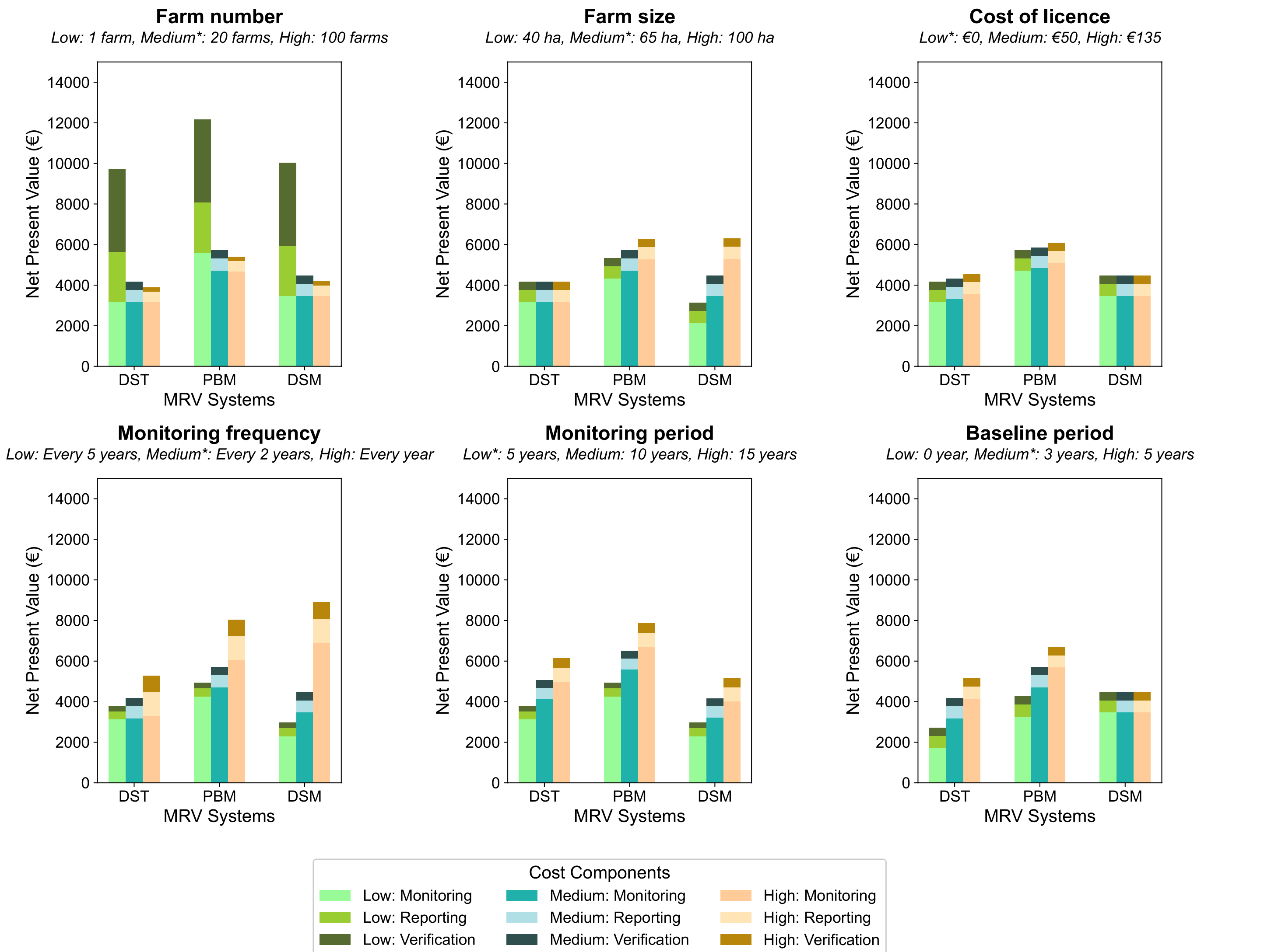

Fig. 2. Sensitivity analysis of the MRV costs in the base scenario. The figure shows the impact of project structure parameters and protocol-related parameters on MRV costs for three MRV systems: Decision Support Tools (DST), Process-Based Model (PBM) and Direct Soil Measurement (DSM). The low, medium and high values are indicated in boxes within the figure, with an asterisk (*) marking the value used in the base scenario.

measurement increase tremendously when a higher soil sampling interval is required. Also monitoring frequency largely drives up the costs, especially when annual monitoring would be required. In contrast, extending the monitoring period to 10 years, as the option currently under discussion for CRCF methodologies, does not substantially raise per-farm costs if the monitoring frequency remains every five years or even biannual. Moreover, frequent monitoring may be unnecessary since significant SOC changes typically become measurable after five years (Paustian et al., 2019).

Direct comparisons of our estimates with other studies are difficult because of contextual differences and limited available evidence. Carbon Think (2022) is the only comparable analysis that aligns with the scale of carbon farming scheme, applicable to the local context of Wallonia. It estimates MRV costs per farm at €4000 over five years for a process-based model under *Label Bas Carbone* certification. Our estimates for process-based models are higher in all scenarios. Differences might stem from our methods using NPV, thereby discounting future costs, and including farmers' opportunity costs, which is required to assess all transaction costs, especially for farmers. Focusing only on direct costs, as in the case of Carbon Think (2022) underestimates the true costs associated with MRV systems.

Monitoring costs are the largest and most variable component of MRV costs. They account for 77% of costs on average, with reporting and verification costs contributing to 13.6% and 9.4%, respectively. In single-farm projects, verification can become the largest cost, especially in the base and cost reduction scenario. Monitoring costs are primarily driven by activity data collection and soil sampling, with encoding time and soil sampling interval as critical constraints. These findings align with Meemken et al. (2024), who highlight the high costs of traditional monitoring methods, such as field-based and survey approaches, as barriers to scalability.

Economies of scale affect MRV costs in two ways: through the number of farms pooled in a project and through the individual farm size. For a single farm, costs can double or triple due to fixed costs (e.g., image processing, reporting, verification) that cannot be shared among other farms. Moreover, licence costs in multi-farm projects are often negligible as they are spread across farms; however, they become significant when borne by a single farm. Yet, costs per farm tend to stabilize when going from 20 to 100 farms. Given that pooling many farms into one project might lead to additional efforts in reconciling farmers' preferences, 20 farms could be considered as a more optimal number than 100 farms. In addition, farm size also reduces MRV costs per

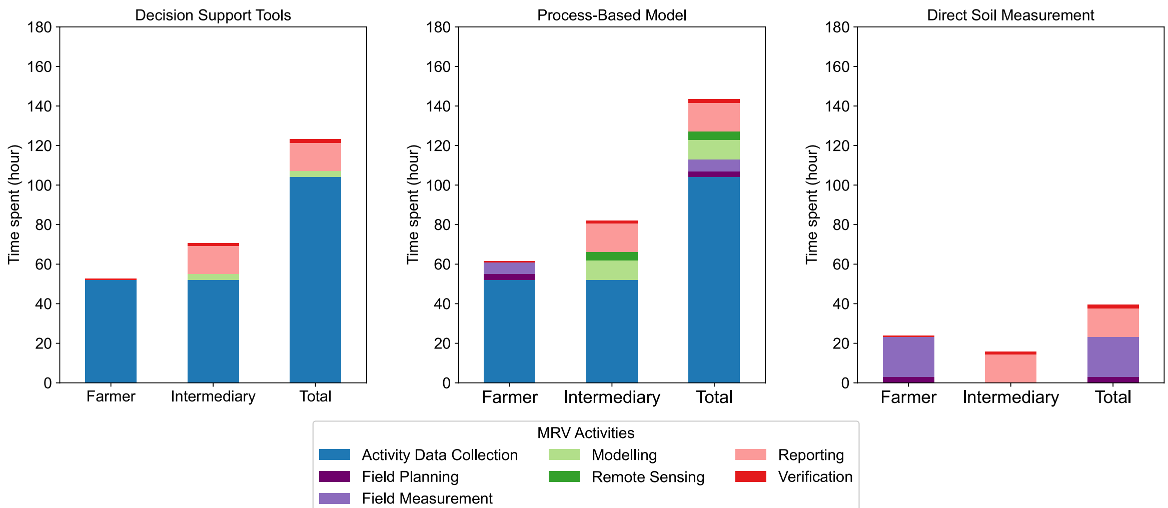

Fig. 3. Time spent (in hours) by the farmer and the intermediary per farm across MRV systems: decision support tool, process-based model and direct soil measurement. The values are derived from the base scenario and account for a 5-year monitoring period.

hectare, as larger farms can spread fixed costs over a greater area, but this effect is not as large as pooling farms together.

4.2. Farmers' perspective: economic viability and labour

To interpret whether MRV systems are economically viable from a farmer's perspective, we make a simple comparison between the MRV costs and potential revenues from carbon credits that farmers may receive.[6] In the most optimistic scenario for SOC storage in a loamy soil, agroforestry offers the highest potential of up to 1.4 tCO_2e per hectare per year (Bamière et al., 2023). Assuming a carbon price of €30/tCO_2e, which is currently paid in the *Label Bas Carbone* scheme, a 65-ha farm in a project with 20 farms could recover the MRV costs of process-based models, but not in all scenarios. Direct soil measurement would only become viable at a carbon price of €100/tCO_2e, illustrating that too low carbon prices limit MRV economic viability at the farm scale. Especially for smaller farms (40-65 ha), prices of €60 to €100/tCO2eq would be needed to compensate for MRV costs, supporting the study by Köhl et al. (2020) and reconfirming the importance of economies of scale. This corroborates that MRV systems are more viable for large farms, which could exclude smaller farms from the voluntary carbon market (Finger, 2023; Meemken et al., 2024). Policies should promote pooling smaller farms to share costs but also to improve sampling accuracy (Bradford et al., 2023; Paustian et al., 2019).

Another burden for farmers related to MRV is the additional time they must spend, especially on activity data collection and soil sampling. We estimate that a farmer would spend three to eight days over a period of five years for direct soil measurement and process-based models, respectively. During monitoring years, this corresponds to one to three full days. Although this represents less than 1% of farmers' total labour, it can still create trade-offs with other tasks, as many farmers already work more than full-time. In addition, administrative work is often perceived as an important burden for farmers (Läpple et al., 2026).

4.3. Market and policy perspective: how to effectively reduce MRV costs?

Process-based models are expected to become the standard MRV system in the EU, as recommended by the CRCF (Batjes et al., 2024; European Parliament, Council of the European ParliamentCouncil of the European Union, 2024). However, we show that they tend to be more expensive than decision support tools and direct soil measurement. Additionally, they can be labour- and knowledge-intensive, raising concerns about how to build farmer capacity and provide adequate training. On the other hand, direct soil measurement remains widely recommended by standards and would be allowed by the CRCF as well (Dupla et al., 2024). Yet, we show that MRV systems entirely based on direct soil measurement would either be prohibitively expensive, if a sampling interval of 0.1 ha per sample is used, or not reliable, if a sampling interval of 1.2 ha per sample is used, as this would not provide accurate estimates for individual fields (Bradford et al., 2023). This is in line with a recent study by Potash et al. (2025), who demonstrate that direct soil measurement is not economically viable for small-scale projects, but may become more viable for larger projects or those with a longer monitoring period.

Our study identifies several cost-reduction strategies for process-based models through leveraging existing infrastructure and digitalisation, in line with the recommendations of the CRCF. The primary strategy, reducing soil sampling costs, can be achieved by lowering the number of soil samples. Integrating data from long-term experiments or soil monitoring networks may reduce costs of soil sampling by up to €2410 per farm over five years for a 20-farm project. If such infrastructure exists, they can offer site-specific regional data at little to no cost. This may facilitate local validation and calibration of the model, thereby reducing the number of samples required per farm, particularly in projects involving multiple farms. In addition, soil sampling costs can be further reduced through subsidizing lab analysis. Reducing labour-intensive activity data collection is another lever for cost reduction. Digital platform improvements could save up to €1528 per farm over five years by minimizing data entry time. The development of co-designed platforms tailored to farmers' needs that ease data sharing while ensuring data protection is also highlighted by Finger (2023) and Meemken et al. (2024). In addition, remote sensing could offer potential cost savings by reducing reliance on activity data and providing wide spatial and temporal coverage (Batjes et al., 2024).

4.4. Limitations and scope for further research

The estimated MRV costs are based on a hypothetical carbon farming scheme in Wallonia (Belgium). Further research is essential to assess MRV costs in different contexts. However, our cost model is designed in a generic way and can be easily adapted to various contexts by adjusting

[6] For simplicity, we do not consider additional investment or maintenance costs or changes in yield levels due to carbon farming practices. We also assume rational economic behaviour and do not account for risk and time preferences.

the parameter values. National and regional factors are major sources of variation, particularly wage levels for farmers and intermediaries, farm size, and farmers' behaviour (e.g., willingness to join collective projects). Laboratory costs may also vary significantly between countries. Whether a scheme or laboratory is public or private is often country-specific and can strongly influence costs, as public programs often benefit from subsidies that reduce costs. Additional differences may arise from specific agricultural factors, standard-specific rules (e.g., model or protocol choice, task allocation between farmers and intermediaries) and MRV system configuration (e.g., data access, model calibration & validation, user experience). These contextual factors may significantly affect both MRV-related costs and labour. The model could also be expanded to include other transaction costs, such as registry, project approval, and training (Cacho et al., 2013), as well as long-term setup and maintenance costs (Köhl et al., 2020). These costs are not included in this study, as the focus is specifically on MRV costs associated with the implementation of the MRV systems at farm scale.

Cost analysis is a crucial first step toward improving the scalability of MRV systems. However, it remains insufficient without accounting for the uncertainty to estimate SOC stock changes, which largely affects the credibility of carbon credits and stakeholders' trust in the certification process. Future research should therefore focus on cost-effectiveness analysis, comparing the trade-off between costs and uncertainties. It could also explore acceptable uncertainty levels among stakeholders, and how more reliable MRV systems could influence the price of carbon credits. Another type of cost-effectiveness analysis could concentrate on carbon farming practices, and how these would relate to the economic viability of MRV systems and minimum carbon prices.

Another type of cost-effectiveness analysis focusing on carbon farming practices should account for regional pedoclimatic and socio-economic factors (Fellmann et al., 2021; Smith et al., 2005). Since some practices provide only limited carbon storage benefits, further research should assess their carbon storage potential under varying conditions, the maximum soil carbon capacity, the risk of leakage, and the vulnerability of soils to carbon loss (Georgiou et al., 2025; Oldfield et al., 2024; Paul et al., 2023). Research should also examine the potential of combined strategies as more cost-effective solutions. For example, integrating woody vegetation through agroforestry or agro-silvopastoralism, may provide greater potential and more permanent carbon storage than practices limited to grassland or cropland (Petersson et al., 2025; Sabia et al., 2025). Another strategy is combining carbon farming practices with measures that target overall GHG mitigation rather than soil carbon alone, for instance by optimizing livestock density while improving livestock efficiency (i.e., increasing product per head), or expanding on-farm feed production instead of purchasing external feed (Oldfield et al., 2024; Röös et al., 2017; Tarruella et al., 2023). However, combined measures do not always yield higher abatement or lower costs and may, in some cases, have the opposite effect, underlining the need for context-specific assessment before adoption (Fellmann et al., 2021). Finally, these dynamics should be explicitly linked to the economic viability of MRV systems and the determination of minimum carbon prices. Such studies should also account for behavioural and other constraints. Farmers' decisions on adopting carbon farming and MRV systems are not only influenced by economic viability, but also by their risk and time preferences, capacity building and tenure security (Kreft et al., 2021; McCann, 2013).

5. Conclusion

In the context of the growing emphasis on results-based payments in agriculture, this study addresses a critical barrier to the scalability of carbon farming: the high and variable costs of MRV systems. Our analysis shows how MRV costs vary significantly depending on the monitoring approaches, their parametrisations, and adherence to protocol standards. As the European CRCF and the voluntary carbon market increasingly favour process-based models, relying on existing infrastructure such as long-term experimental sites, or innovation through digitalisation of platforms offer opportunities to reduce costs. However, the economic viability of MRV systems for small farms remains at risk without strong policy support. Strict uncertainty requirements and low carbon prices could exacerbate these challenges. Measures such as subsidies, collective farming initiatives, and incentives for higher carbon prices are essential but must be tailored to specific contexts and farmer preferences. Our findings offer guidance for developing cost-effective, transparent MRV systems ahead of the CRCF implementation in 2026/2027, aiming to enhance the credibility and scalability of carbon farming while minimizing burdens to farmers. Future research should examine the cost-effectiveness of process-based and direct soil measurement MRV systems in various contexts, ensuring their reliability and feasibility at the farm level.

CRediT authorship contribution statement

Lisa Vanderheyden: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nathan Gayot:** Methodology, Formal analysis, Data curation, Conceptualization. **Goedele Van den Broeck:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT-4 developed by Open AI in order to enhance the readability and check spelling and grammar. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2026.128885.

Data availability

The data and cost models are implemented in several Jupyter Notebooks, which are provided as Supplementary Material B, along with a README file explaining the different files.

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