Received: 16 April 2024 | Revised: 20 June 2024 | Accepted: 3 July 2024

DOI: 10.1111/sum.13092

RESEARCH ARTICLE

Soil Use and Management | BRITISH SOCIETY OF SOIL SCIENCE | WILEY

Are soil carbon credits empty promises? Shortcomings of current soil carbon quantification methodologies and improvement avenues

Xavier Dupla[1] | **Emma Bonvin**[1] | **Cédric Deluz**[2,3] | **Léa Lugassy**[4] | **Eric Verrecchia**[1] | **Philippe C. Baveye**[5] | **Stéphanie Grand**[1] | **Pascal Boivin**[3]

[1]Institute of Earth Surface Dynamics, University of Lausanne, Lausanne, Switzerland

[2]Soil Resources Group, Department of Environmental Systems Science, ETHZ, Zürich, Switzerland

[3]University of Applied Sciences of Western Switzerland, HES-SO HEPIA, Geneva, Switzerland

[4]Pour une Agriculture du Vivant ("For a Living Agriculture") Organization, Paris, France

[5]Saint Loup Research Institute, Saint Loup Lamairé, France

Correspondence
Xavier Dupla, Institute of Earth Surface Dynamics, University of Lausanne, Lausanne, Switzerland.
Email: xavier.dupla@unil.ch

Abstract

As the consequences of climate change are looming large, agricultural soil carbon credits have emerged as an increasingly advocated lever to incentivize the reduction of greenhouse gas emissions and promote carbon storing farming practices. These credits are exchanged on self-regulated voluntary carbon markets, each of them using distinct protocols to assess the changes in soil carbon stocks and convert them into carbon credits. Although serious discrepancies between protocols have already been noted regarding general carbon credit accounting principles, an in-depth evaluation of how changes in soil organic carbon stocks are calculated is still lacking. In this context, the primary objective of our study was to investigate how changes in soil organic carbon stock are estimated by the major carbon credit protocols worldwide. We evaluated the requirements of each protocol regarding the estimation of the initial SOC stock as well as the modelling and/or measurement of changes in stock with time. We found that existing protocols vary greatly in their scientific rigour. We showed in particular that some protocols do not require in situ soil analyses to estimate initial soil carbon stocks but rely on regional values, leading them to potentially overestimate these stocks by up to 2.5 times. Our study also found that the protocols relying on models require different farming practices and different levels of information for each practice to estimate SOC stock changes. The protocols relying, at least partly, on soil sampling also displayed different requirements for the sampling design, sampling tools, SOC analysis methods and SOC stock calculation methods. On this basis, we suggest reforms designed to improve and standardize the quantification of carbon stock changes in soils and to improve the reliability of soil carbon credits.

KEYWORDS

agriculture, carbon farming, carbon sequestration, carbon storage, soil conservation, soil organic carbon

Xavier Dupla and Emma Bonvin contributed equally to this work.

1 | INTRODUCTION

On the verge of the Second World War, Winston Churchill declared: 'The era of procrastination, of half measures, of soothing and baffling expedients, of delays, is coming to a close. In its place, we are now entering an era of consequences'. More than 80 years later, it is tempting to compare the then-looming war with today's global threat: an ever-increasing resource-consumption/waste-production global trend, one of the most serious consequences of which being climate change. Sadly, despite international summits, treaties and conferences, the rise in concentration of greenhouse gases (GHG) in the atmosphere including carbon dioxide (CO_2) – the main anthropic GHG – has not curbed, and the 21st century emerges as the era of climate consequences. So much so that the societal transformations that scientists have called for and that societies have proven reluctant to adopt are not even considered sufficient anymore. On top of needing to transition to fossil fuel-free societies, recourse to atmospheric CO_2 removal technologies is now regarded as inevitable to prevent global warming from going beyond +2°C compared with pre-industrial temperatures (IPCC, 2023).

Part of the solution could lie beneath our feet. Soils contain almost 80% of the carbon of terrestrial ecosystems with soil organic matter (SOM) storing 2416 ± 40 Gt C in the top 0–2 m soil layer (Batjes, 1996), which is three times more carbon than in the atmosphere (IPCC, 2023). The good news is that this sink is far from being saturated. In the last century, conversion of natural to agricultural ecosystems combined with detrimental practices (such as deep and repetitive tillage, lack of organic amendments, overgrazing, monoculture and long bare-fallowing periods) have caused the depletion of the SOM pool by 25%–75% across the globe (Lal, 2011; Sanderman et al., 2017). However, not all practices lead to SOM losses and adoption of favourable farming practices could slow down and even reverse the trend. Practices such as cover-cropping, agroforestry, limiting soil disturbance, preventing overgrazing or complexifying crop rotations and plant diversity are known for their potential to reverse this SOM loss trend (Gonzalez-Sanchez et al., 2019; Morari et al., 2006; Rumpel et al., 2019). These practices are today gathered under a series of fundamentally close umbrella terms: 'climate smart agriculture', 'regenerative farming' or even 'conservation agriculture', which could all act as nature-based negative emission technologies. Provided they do not lead to higher emissions of other GHGs beside CO_2, these practices might be advantageously deployed on a global scale to attempt to mitigate climate change.

One incentive to favour the deployment of these practices is agricultural soil carbon credits (SCCs). SCCs are tradable emission offsets that farmers who adopt carbon offsetting practices can sell to organizations willing to compensate for their CO_2 emissions. These SCC transactions currently only happen on voluntary carbon markets (VCM) regulated by public or private intermediates. In 2022, agricultural SCCs represented a total transaction volume of 5.1 $MtCO_2e$ for an estimated value of USD 50.1 million (Mikolajczyk & Bravo, 2023), with experts expecting the overall voluntary carbon market to reach between \$10 billion and \$40 billion by 2030 (The Voluntary Carbon Market Is Thriving, 2022).

Carbon markets use measurement, reporting and verification (MRV) protocols to calculate the number of SCCs that a project is expected to generate. Among the 10 public MRV protocols that are currently in use, Oldfield et al. (2022) and the non-profit organization CarbonPlan (2024) already exposed serious accounting inconsistencies in terms of *additionality* (SCCs should systematically imply an additional carbon offset in soils compared with non-funded fields), *leakage* (changing practices should not cause unaccounted losses elsewhere) and *permanence* (duration of carbon storage in soils should be guaranteed) between these protocols.

SCCs also differ in the GHGs that are included. SCCs are indeed issued when newly adopted farming practices, compared with past ones, lead to lower overall GHG emissions. Some protocols like B Carbon and Nori only include the evolution of the soil organic carbon (SOC) stock (Figure 1), while others base their calculation on different combinations of SOC, nitrous oxide (N_2O) and methane (CH_4) emissions. Nevertheless, the evolution of SOC stock remains the backbone of all protocols.

On top of the already serious inconsistencies that are mentioned above and that will not be further detailed, a central aspect of existing protocols is how substantially the protocols differ in their soil organic carbon modelling and/or monitoring strategies, thereby potentially questioning the very reliability of the resulting SCCs. To fill this gap in

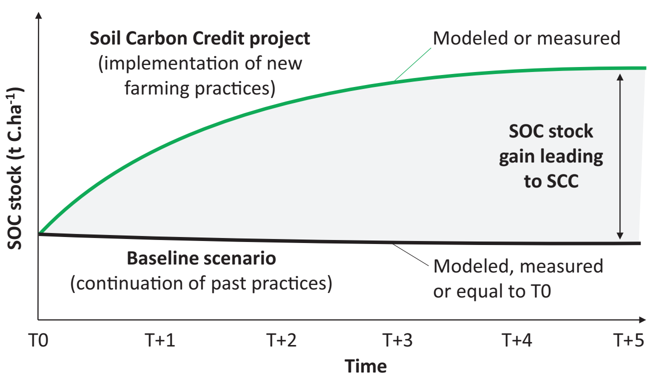

FIGURE 1 Illustration of SCC calculation based on the SOC stock difference between a 5-year SOC storing project (upper green line) and a business-as-usual baseline scenario (bottom black line).

the evaluation of soil carbon protocols, we carried out an in-depth evaluation of the methods they implement. This analysis led us eventually to suggest drastic changes in the perspective from which these protocols, the monitoring of carbon changes in soils, and soil carbon credits are approached, in order to improve the chances that they may contribute efficiently to climate change mitigation.

2 | MATERIALS AND METHODS

Our study aimed to assess the ability of current MRV protocols to reliably monitor SOC stock changes in cultivated fields and grasslands. To do so, we (i) included the protocols already evaluated in terms of general accounting principles by Oldfield et al. (2022), (ii) excluded the protocols that had since been withdrawn (e.g., Alberta Carbon) and (iii) added newly introduced protocols.

The protocols from the following registries were evaluated: Nori (Nori Croplands Methodology v. 1.6); PVivo: Plan Vivo (The Plan Vivo Standard for Community Payments for Ecosystem Services Programs, v. 2.0); CFT: Cool Farm Tool (Technical Method Description v. 2.1.0 – Section 2.11. Carbon Stock Changes). LBC: Label Bas Carbone (Méthode Grandes Cultures v. 1.1); GStd: Gold Standard (Soil Organic Carbon Framework Methodology v1.0); CAR, Climate Action Reserve (U.S. Soil Enrichment Protocol, v. 1.1); Verra (VM42, Verra Methodology for Improved Agricultural Land, v. 2.0); CFI: Carbon Farming Initiative (Estimation of Soil Organic Carbon Sequestration using Measurement and Models. Methodology Determination 2021); BCarb: BCarbon (Protocol for Measurement, Monitoring, and Quantification of the Accrual of Below-Ground Carbon Over Time, v. 2.0); FAO: Food and Agriculture Organization (FAO GSOC MRV Protocol). Although CFT is not a carbon credit organization, its methodology is used by third parties selling SCCs (e.g., Soil Capital), explaining why it was included in this review. A link and additional details for each protocol can be found in Appendix S1.

Our approach consisted in synthesizing how the different protocols approached SOC stock evaluation through time. For each protocol, we looked at how the initial SOC stock was evaluated and how the expected SOC stock increase was monitored. Whenever a model was used (either for the baseline scenario or to predict SOC stock changes), we assessed which minimum information was required in terms of land use, climate, soil parameters (e.g., pH, texture, structure) and farming practices (tillage intensity, crop rotation type and length, cover crop intensity, organic amendments, irrigation and grazing) and to which degree of precision each information was integrated into the model. When soil sampling was included (to measure the initial and/or final SOC stock), we evaluated the sampling design (sampling area, number of composite samples, number of soil cores per composite, sampling pattern) and the recommended SOC analysis procedures (loss on ignition, wet oxidation, dry combustion, spectroscopy).

For both modelling and sampling approaches, a colour code combined with a presence/absence assessment was used in the tables to synthetize the current scientific understanding and facilitate interpretation. Green, the protocol includes explicitly a central aspect of SOC determination and provides enough requirements for it to be reliably taken into account (e.g., providing the annual amount and nature of organic amendments to model SOC stock evolution). Orange, the protocol includes an important aspect of SOC determination but remains vague or too broad on the requirements (e.g., only mentioning if organic amendments were applied or not, without further details, at a given year to model SOC stock evolution). Red, a central aspect for SOC determination is not explicitly required by the protocol (e.g., providing the application of organic amendments is not required to model SOC stock evolution). This colour code should only be seen as facilitating the overall interpretation of SCC protocols and does not substitute for the detailed analysis of each aspect of these protocols carried out in Section 3.

Our study solely focused on SOC stocks and did not cover greenhouse gas (GHG) accounting. Prior to publication, the collected information (displayed in the three tables below) was sent to each organization in charge of a protocol with a 2-month response time for validation or correction. Whenever corrections were needed, these were made until full agreement was reached with the protocol representatives. Out of the investigated organizations, six organizations (BCarb, Verra, Nori, CAR, CFT and LBC) replied and provided us with additional information and explanation whenever necessary. We thank them for their help and voluntary support.

3 | RESULTS AND DISCUSSION

3.1 | A first fundamental difference: Modelling versus measuring SOC changes

SCC protocols are fundamentally different in their methodological approach to SOC changes. The impact of the newly implemented farming practices on SOC stocks is either predicted by models or measured by regular soil sampling campaigns (Table 1). Some protocols such as Nori, CFT or LBC solely rely on *ex ante* modelling. Based on the planned changes in farming practices (and, for some protocols, on a soil analysis to know the initial SOC stock), they predict how SOC will evolve over a given time

TABLE 1 General specifications of all evaluated soil carbon credit protocols.

		Nori	$GStd_{mod}$	PVivo	CFT[a]	LBC	CAR	CFI	Verra	$GStd_{meas}$	BCarb	FAO
SCC general information	Project location	USA	World	Africa	World	France	USA	Australia	World	World	USA, UK	World
	Crediting period (years)	10	5–20	5	na[a]	5	10	25	5	5	5	20
	SOC stock monitoring approach	Modelling	Modelling	Modelling	Modelling	Modelling	Hybrid	Hybrid or Sampling	Hybrid or Sampling	Sampling	Sampling	Sampling
	Other GHGs included to calculate SCCs	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Use of models	Model used for baseline	Yes	Yes	Yes	Yes	Yes	Optional	No	Yes	No	No	No
	SOC baseline is assumed *stable* (= initial SOC stock) or *dynamic* in time	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Dynamic	Stable	Dynamic	Stable	Stable	Stable
	Possible SOC stock evolution	↑	↑	↑/→/↓	na[a]	↑/→/↓	↑/→/↓	↑	↑/→/↓	↑	↑	↑
	Model used to predict SOC stock change	Yes	Yes/ Hybrid	Yes	Yes	Yes	No	Yes	No	No	No[b]	No[b]
SOC stock calculation	Minimum soil depth	20 cm	Not specified	30 cm	30 cm	30 cm	30 cm	30 cm	30 cm	50 cm	30 cm	30 cm
	Recommended soil depth	20 cm	Not specified	30 cm	30 cm	30 cm	100 cm	30 cm	50 cm	50 cm	100 cm	100 cm
	Initial stock is based on in situ measurements	No	No	No	No	Optional	Yes	Yes	Yes	Yes	Yes	Yes

Note: Project location corresponds to the country/region for which the protocol was designed. Crediting period is the period over which SCCs can be credited. SOC stock monitoring approach refers to the way each protocol calculates SOC stock changes either using a model, measurements (sampling) or both (hybrid). The SOC baseline corresponds to the assumed SOC stock level that would have been reached if past practices had been continued. When the baseline SOC stock evolution is modelled (dynamic), SCCs are attributed if the actual SOC stock is above the baseline one. Protocols credit projects that increase their SOC stock with time (↑) although some protocols still generate SCCs if the SOC stock remains stable (→) or even decreases (↓) as long as it remains higher than a declining baseline SOC stock. The colour code indicates whether an aspect is fully satisfactory (green), partially satisfactory (orange) or non-satisfactory (red). It should, however, only be seen as facilitating the overall interpretation and does substitute the detailed analysis conducted in the text of each aspect of these protocols. Nori (*Nori Croplands Methodology v1.6*); PVivo: Plan Vivo (*Plan Vivo Climate Benefit Quantification Methodology*); CFT: Cool Farm Tool (*Technical Method Description v2.1.0 - Section 2.11. Carbon Stock Changes*). LBC: Label Bas Carbone (Méthode Grandes Cultures v1.1); GStd: Gold Standard (*Soil Organic Carbon Framework Methodology v1.0*); CAR, Climate Action Reserve (*Soil Enrichment Protocol v1.1*); Verra (*VM42, Verra Methodology for Improved Agricultural Land v2.0*); CFI: Carbon Farming Initiative (*Estimation of Soil Organic Carbon Sequestration using Measurement and Models. Methodology Determination 2021*); BCarb: BCarbon (*Protocol for Measurement, Monitoring, and Quantification of the Accrual of Below-Ground Carbon Over Time v2.0*); FAO: Food and Agriculture Organization (*FAO GSOC MRV Protocol*).

[a]Although used by several SCC trading companies like Soil Capital, CFT only provides a SOC calculation method and does therefore not require any specific SCC duration nor specific baseline trends.

[b]An optional model-based approach exists to claim for interim credits until the next sampling-based true-up period. However, for both protocols, the publicly available information is insufficient to allow for a detailed assessment of its reliability.

– referred to as a crediting period – and grant the equivalent number of SCCs. Other protocols like CFI or Verra rely on regular soil sampling and analysis to verify that the SOC change has actually happened.

Additionally, SCCs are issued when a project leads to a lower overall GHG budget compared with past practices, but this is not always synonymous with an increase in SOC stock. Whenever the baseline SOC stock (i.e., the SOC stock obtained if past practices had been maintained) is modelled, SCCs are indeed credited provided that the project leads to a higher SOC stock than the baseline. Protocols differ, however, on the baseline trends – positive, neutral, negative – that they accept. If the baseline SOC stock is modelled as remaining stable or increasing with time, the project's SOC stock will need to increase in absolute terms. However, if the baseline SOC stock is modelled as decreasing, some protocols still generate SCCs for projects with an also decreasing SOC stock, as long as the SOC stock loss is lower than the baseline. In other words, SCCs can be attributed to a project that does not store SOC but that slows down an expected SOC stock loss. This is the case for PVivo, LBC, CAR and Verra while Nori and GStd exclude this option. As for the sampling-based protocols that assume the baseline SOC stock to be equivalent to the initial SOC stock (i.e., the SOC stock at the beginning of the SCC period) ($GStd_{meas}$, BCarb, FAO), these can only generate SCCs for projects effectively increasing their SOC stock with time. Depending on which protocol is used, a project will, therefore, either be able to obtain SCCs or not depending on its SOC stock trend, which is non-satisfactory for the coherence of agricultural SCCs worldwide.

3.2 | Current discrepancies and limits of protocols based (partly or entirely) on modelling

Most protocols rely on modelling at least for the baseline scenario and, for some, to estimate SOC stock changes. These protocols display, however, fundamental discrepancies and limits in terms of included parameters (Table 2), which can lead to unreliable SOC change predictions.

3.2.1 | Providing the initial SOC stock is not always required to model SCCs

The first striking element concerns the fact that providing the field's initial SOC level to the model is not systematically required to estimate future SOC changes. While some protocols like CFI, CAR, LBC and Verra ask for this information, CFT, Nori or the model-based approach of GStd ($GStd_{mod}$) rely solely on estimates. More precisely, these protocols use theoretical SOC stocks based on broad soil type, soil use and climate categories. This approach negates however the large SOC stocks variability that exists within each category (Beka et al., 2022). For instance, in a soil inventory conducted at the German scale, Poeplau, Jacobs, et al. (2020) sampled 2234 agricultural fields and concluded that fields with a sandy soil had between 20.9 and 231.8 tC ha^{-1} in the top 0–30 cm for an average stock of 74.2 tC ha^{-1} (see Poeplau, Don et al., 2020 for the full soil inventory database). If any of these fields had enrolled in an SCC program using either CFT or GStdmod, which both use default reference SOC stocks from IPCC (2019), the initial SOC stock would have been assumed to be 35.7 tC ha^{-1}. Their protocols would therefore have overestimated by 71% the C stock of the most depleted fields and underestimated by 549% the amount of the richest ones. One could argue that SCC projects are usually deployed at large-scale over several hundreds – if not thousands – of hectares and that extreme values measured at the field scale would be attenuated when SOC stocks are calculated at larger scales. Using the German soil inventory mentioned above, the average SOC stocks in sandy soils calculated at the state scale (*Land*) led to results ranging from 47.2 tC ha^{-1} in Saxony-Anhalt (44 fields) to 91.0 tC ha^{-1} (174 fields) and even 110.4 tC ha^{-1} (36 fields) in Lower Saxony and Schleswig-Holstein, respectively (Poeplau, Don, et al., 2020). At this scale, CFT and $GStd_{mod}$ would therefore have also underestimated these regional SOC stocks by 32%, 155% and 209% for the three states, respectively. This problem arises for tropical soils as well. In Central Amazonia Brazil for instance, Ceddia et al. (2015) measured SOC stocks in low-activity clay soils ranging from 15.4 to 64.4 tC ha^{-1} while the same protocols would have assumed a unique SOC stock of 38 tC ha^{-1}; an amount being again 2.5 times too high for the poorest soils and 70% too low for the soils with the highest SOC stocks.

This aspect is critical given that the initial SOC stock influences the rate at which a field's SOC stock can increase. Depending on how initially depleted each soil is, its C storage rate will vary over a large range despite similar farming practices. In a global review on the impact of management interventions on SOC stock changes across 103 soils, Georgiou et al. (2022) found that SOC accrual rates ranged from +2 $\text{tC ha}^{-1}\,\text{year}^{-1}$ for the most depleted soil to null for the soils closest to their capacity. This capacity refers to the ability of soil minerals (and mineraloids) to stabilize SOC through organo-mineral interactions (Kaiser & Guggenberger, 2003; Six et al., 2002). Several approaches exist to estimate this capacity either via mechanistic principles (e.g., by considering the soil content relative to the amount of clay-sized particles), which are known to be the most

TABLE 2 Modelling parameters required by soil carbon credit protocols.

		Nori	$GStd_{mod1}$	$GStd_{mod2}$	PVivo	CFT	LBC	CAR	CFI	Verra
Model type	Allowed models	DayCent	Open[a]	IPCC	RothC	IPCC	AMG[b]	Open[a]	IPCC	Open[a]
SOC stock calculation	Minimum soil depth	20 cm	Not specified	Not specified	30 cm	30 cm	30 cm	30 cm	30 cm	30 cm
	Recommended soil depth	20 cm	Not specified	Not specified	30 cm	30 cm	30 cm	100 cm	30 cm	50 cm
	Initial stock is based on in situ measurements	No	No	No	No	No	Optional	Yes	Yes	Yes
Required environmental parameters for modelling SOC changes	Past land use (<5 years)	✓	✓	✓	–	✓	–	✓	✓	✓
	Climate	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Soil pH	–	–	–	–	–	✓	–	–	–
	Soil texture	–	✓	✓	✓	✓	✓	✓	-	✓
	Initial SOC depletion level	–	–	–	–	–	–	–	–	–
Required farming practices for modelling SOC changes	Tillage	✓	✓	✓ (yes/no)	–	✓	–	✓	✓	✓
	Bare fallowing	–	–	–	✓ (yes/no)	–	–	✓ (yes/no)	–	–
	Crop rotation	✓	✓	–	–	–	✓	✓	✓	✓
	Cover crops	✓ (yes/no)	–	✓ (yes/no)	–	✓ (yes/no)	✓	✓	✓	✓
	Grazing	✓	–	✓	–	–	–	✓	✓	✓
	Crop residue removal	✓	–	–	✓ (yes/no)	–	✓	✓	✓	✓
	OM amendments	✓	✓	✓ (yes/no)	✓[c]	✓ (yes/no)	✓	✓	✓	✓[c]
	Irrigation	✓	✓	✓ (yes/no)	–	✓ (yes/no)	✓	✓	✓	✓
Modelling adjustments	Uncertainty assessment	–[d]	✓	✓	✓	–	✓ (fixed abatement)	✓	✓	✓
	Regular resampling	–	–	–	–	–	–	✓ (5 y)	✓ (10 y)	✓ (5 y)
	Weather conditions	✓	✓	–	–	–	✓	✓	✓	✓

Note: Symbols are used when a protocol explicitly requires a parameter (✓) or not (–). Whenever a farming practice was only included based on a binary system (e.g., tillage/no tillage), the term 'yes/no' was added after the checkmark. The colour code indicates whether an aspect was fully satisfactory (green), partially satisfactory (orange) or non-satisfactory (red). It should, however, only be seen as facilitating the overall interpretation and does substitute the detailed analysis conducted in the text of each aspect of these protocols. Nori (*Nori Croplands Methodology v1.6*); PVivo: Plan Vivo (*Plan Vivo Climate Benefit Quantification Methodology*); CFT: Cool Farm Tool (*Technical Method Description v2.1.0 - Section 2.11. Carbon Stock Changes*). LBC: Label Bas Carbone (Méthode Grandes Cultures v1.1); GStd: Gold Standard (*Soil Organic Carbon Framework Methodology v1.0*); CAR, Climate Action Reserve (*Soil Enrichment Protocol v1.1*); Verra (*VM42, Verra Methodology for Improved Agricultural Land v2.0*); CFI: Carbon Farming Initiative (*Estimation of Soil Organic Carbon Sequestration using Measurement and Models. Methodology Determination 2021*). Day-Cent: daily version of the CENTURY ecosystem model (Parton et al., 1998); IPCC, 2019 refinement to the 2006 IPCC guidelines for national greenhouse gas inventories (IPCC, 2019), RothC: RothC-26.3 model for the turnover of carbon in soil (Coleman & Jenkinson, 1996), AMG: Modelling soil carbon dynamics with various cropping sequences on the rolling pampas (Andriulo et al., 1999).

[a]Project owners are free to suggest a SOC simulating model, which, however, needs to meet the calibration and validation requirements to receive approval by the registry.

[b]LBC allows two other models (STIC, Aq Yield) but SCC are currently only credited using AMG.

[c]Exogenous organic matter amendments (i.e., not originated from the farm itself) are either excluded (PVivo) or a SCC penalty is applied (Verra).

[d]Nori selects the most conservative of two models (year-by-year vs. 10-year SOC stock change simulations) but does not include any calculation on the errors propagated throughout the SOC estimation process.

effective at stabilizing SOC (Johannes et al., 2017; Prout et al., 2020; Pulley et al., 2023; Schmidt et al., 2011) or simply by comparing the field's initial SOC stock to local/regional data for similar soil type and use. Most internationally reputed models (RothC, Century, AMG, etc.), on which the CFI, CAR, LBC and Verra protocols rely, implement one of these two approaches to simulate SOC changes over time (Andriulo et al., 1999; Coleman & Jenkinson, 1996; Parton, 1996). This aspect is a pledge of reliability for these protocols. On the contrary, one could argue that the fact that Nori, CFT and $GStd_{mod}$ do not require the actual initial SOC stock prevents these models from accurately assessing the soil's initial C depletion level, which, in turn, fundamentally jeopardizes the estimate of the soil's future C storage rates and of the associated SCCs. Obtaining a representative SOC stock based on field sampling and laboratory measurement is not devoid of challenges, however, as will be discussed in Section 3.3.1.

3.2.2 | Uneven levels of detail regarding the required information on farming practices impacting SOC changes

The protocols do not include the same farming practices in their models and display different levels of detail for each practice. All the protocols include organic matter amendments but the impacts of tillage, crop rotation and cover crops are not systematically considered. LBC and PVivo for instance discount tillage whereas the others take it into account. Similarly, CFT, PVivo and the IPCC-based version of $GStd_{mod}$ do not include crop rotation (i.e., the complexity of the rotation together with the yield of each crop). Finally, cover crops are not explicitly required by $GStd_{mod}$, CFI and PVivo to model SOC changes.

These differences are surprising in the sense that, depending on which protocol farmers will choose, their practices will be differently incorporated in SOC models, leading ultimately to different SCC amounts being calculated. If the benefits of some practices like tillage are disputed in terms of SOC storage (see for instance Dimassi et al., 2014; Powlson et al., 2014), others like cover crops appear less contentious (Seitz et al., 2023). In a meta-analysis of 30 studies covering 139 plots, Poeplau and Don (2015) concluded that cover crops led to annual carbon gains of $0.32 \pm 0.08\,\mathrm{tC\,ha^{-1}}$ in a mean soil depth of 22 cm and during the observed period of up to 54 years. Their exclusion by some protocols are therefore hard to comprehend.

Another source of heterogeneity has to do with the degree of precision with which each practice is characterized to calculate SCCs. Some protocols use binary categories (e.g., tillage/no-till or addition or not of organic amendments) or tertiary categories (e.g., tillage/reduced tillage/no-till), most notably for crop residue management, soil tillage, organic amendments and cover crops, with a score system attributed to each category. On the other hand, other protocols use continuous parameters (e.g., amount of organic matter amendment per hectare per year) and continuous scoring to characterize farming practices.

Minimalist categories can be misleading, however. CFT and the IPCC-based $GStd_{mod}$ require for instance to mention whether manure is added or not without requiring information on the nature of this manure or the amount annually applied, and without including other types of organic amendments such as compost or biochar. For cover crops, CFT and $GStd_{mod}$ use a yes/no category, Verra attributes a factor per cover crop species while LBC considers only their final (measured or estimated) biomass. A simple presence/absence approach does not inform on factors such as (1) cover crop complexity in terms of species number and variety; (2) seeding density; (3) sowing technique (broadcasted, dropped behind the plough, drilled, etc.); (4) the actual success of crop establishment; (5) the inclusion of any fertilizer application; (6) cover crop duration; (7) frequency in the rotation; (8) cover crop final biomass; (9) cover crop destruction technique; and (10) the duration of bare-fallowing periods. All these factors have, however, proven essential to determine whether or not organic amendments and cover crops had any impact on SOC changes over time (Blanco-Canqui, 2022; Dupla et al., 2022).

The same applies to tillage, where pedo-climatic and machinery conditions (axle loading, wheel or track systems, tillage tool), together with the depth, speed and frequency at which the soil is tilled, all determine its impact on soil properties and SOC evolution (Haddaway et al., 2017). Categories like full tillage/reduced tillage as used by CFT and the IPCC-based $GStd_{mod}$ cannot represent this complexity. In both these cases, not mentioning these details or not using a continuous parameter prevents these protocols from accurately estimating SOC gains and their associated SCCs.

3.2.3 | Different approaches to include uncertainties

Most protocols include uncertainty assessment to incorporate the potential errors associated with (1) the initial SOC stock quantification, (2) the modelled SOC evolution and (3), if applicable, the resampling campaigns. Except for Nori, CFT and LBC, all protocols rely on a frequentist error propagation approach to estimate how the summed uncertainties compare with the modelled SOC gain at a given confidence limit. CAR and Verra offer an alternative option based on Monte Carlo simulations for uncertainty simulation. Nori does not apply any uncertainty abatement but runs two SOC stock simulations (year-by-year and over the 10-year period) and selects the most conservative simulation to credit SCCs. CFT mentions the errors associated with each of the factors that are used in their simulation but does not include these errors in their equations while LBC applies a 10% abatement to projects that are not based on in situ measured initial SOC stocks.

Including uncertainty analysis in SOC simulations is essential to evaluate the reliability of the predicted SOC stock changes. In a study evaluating the robustness of the Century model to predict SOC evolution in US croplands, Ogle et al. (2010) found for instance median uncertainties of 119% at the regional level (US major land resource areas) and even 707% at the local site scale (64.75 ha per primary sample units). To conduct such uncertainty evaluation, both frequentist and Bayesian approaches are common in GHG and soil biogeochemical models (Gurung et al., 2020; Ogle et al., 2007; Xiong et al., 2015). Therefore, the approach considered by most protocols appear satisfactory on this aspect, with the exception, however, of Nori, LBC and CFT, which are here insufficiently demanding. The two-simulation approach of Nori and the 10% rebate of LBC assume indeed that the entire uncertainties are included in the most conservative model for Nori and in the 10% abatement for LBC, which cannot be considered accurate across all sites and SCC projects, as exemplified above. Finally, the exclusion of uncertainty calculation from the SOC-stock equations in the CFT protocol prevents this protocol from reliably assessing the significance of the modelled SOC changes.

3.3 | Current discrepancies and limits of protocols based on sampling

In comparison to the challenges listed above, measuring SOC changes through regular soil analyses could appear more reliable at first glance. Currently, six protocols rely at least partly on SOC measurements: BCarb, CAR, the measurement-based protocols of GStd ($GStd_{mes}$), Verra, CFI and the FAO protocol. Sampling strategies and SOC laboratory analyses are, however, not immune to differences and uncertainties that many protocols ignore in part, if not entirely (Table 3). Monitoring SOC stock changes implies indeed to be able to robustly quantify SOC stocks despite the error propagation associated with sampling and laboratory analyses.

3.3.1 | Soil sampling design

Sampling design is perhaps the most significant parameter impacting the robustness of SOC quantification. The field area, the number of composite samples per field, the number of soil cores per composite sample as well as the sampling pattern in the field indeed are all key to take the spatial variability of SOC properly into account.

Regarding first the area of the homogeneous surface to be sampled – often referred to as a stratum – protocols either do not set any upper limit (Verra and CAR) or set relatively large ones (300 ha for $GStd_{meas}$ and 2600 ha for CFI). In cultivated soils, the spatial variability of SOC is known to increase with scale. A large study conducted on 2700 soil profiles in the US grasslands revealed for instance that the CV of the SOC content alone increased with scale expansion, from 39% at the county scale to 54% at the state scale (Conant & Paustian, 2002). Fields are units of homogeneous management leading to inner field SOC spatial variability being, as a trend, smaller than inter-field variability. SOC spatial variability, however, is also known to increase with field size. A meta-analysis on European cultivated soils found that the median coefficient of variation (CV, i.e., the ratio of the standard deviation to the mean) for SOC was 3.5% for plots below 400 m^2, 6.8% for plots between 400 m^2 and 1 ha and 8.0% for plots between 1 and 20 ha (Saby et al., 2008). Even in relatively small-sized fields, there can be sharp contrasts between soil types or history resulting in large SOC variability. A study conducted on sandy soils in South West France found for instance a SOC CV of 24.1% on a 3.4 ha cultivated field because of the field's history (Arrouays et al., 1997). Not setting any limit on the stratum's area or setting limits far beyond the field scale could therefore be detrimental in terms of accuracy. After evaluating the soil monitoring strategies of the 25 European Union member states, the Environmental Assessment of Soil for monitoring (ENVASSO) project concluded that SOC stocks should be monitored at the field scale and even recommended a 1 ha upper limit for the stratum's area (Kibblewhite et al., 2008), together with a sufficiently dense sampling strategy.

In this respect, protocols do not require the number of composite samples to be proportional to the stratum area but require adapting this number to SOC variability. Some protocols require a minimum number of samples per stratum (3 for CAR and CFI, 3 to 5 for Verra and 10 for $GStd_{meas}$). Despite this minimum number, most protocols (FAO, Verra, Bcarb, CAR and $GStd_{meas}$) rather require the actual number to be determined statistically based on SOC variability and on a desired precision level following standard power analysis. To do so, FAO and Verra recommend a preliminary measurement of the SOC variance by extracting 5–10

TABLE 3 Requirements for the different protocols crediting SCCs based on SOC stock soil sampling.

		CAR	CFI	Verra	$GStd_{meas}$	BCarb	FAO
General information	Crediting period	10 years	25 years	5 years	5 years	5 years	20 years
	Sampling frequency	5 years	5 years	5 years	Not specified	5 years	4 years
Soil sampling spatial requirements	Maximum homogeneous surface (ha)	–	2600 ha	–	314 ha	–	–
	Minimum nb of samples/homogeneous surface	3	3	3–5	10	–	–
	Minimum nb of soil cores for a composite sample	–	–	–	–	–	5–15
	Minimum allowed sampling depth	0–30 cm	0–30 cm	0–30 cm	0–50 cm	0–30 cm	0–30 cm
	Recommended sampling depth	0–100 cm	0–30 cm	0–50 cm	0–50 cm	0–100 cm	0–100 cm
	Sampling trajectory for each composite sample	Stratified random	Stratified random	Stratified random	3-point star	–	Stratified random
Recommended SOC stock calculation methods and tools	Sample bulk density is measured on site	✓	✓	✓	✓	✓	✓
	SOC stock calculated using Equivalent Soil Mass method	Optional	✓	✓	–	✓	✓
	Coarse fraction (%) is measured to adjust SOC stocks	–	✓	✓	✓	–	✓
	Allowed tools to measure soil bulk density	Cylinder	Cylinder	–	Soil probe	Several options[a]	Cylinder
	Excluded tools to measure soil bulk density	–	–	–	–	Soil probe	Soil probe
Recommended SOC analysis methods	Loss on ignition	–	–	–	–	–	–
	Wet chemistry (e.g. Walkley-Black)	–	–	–	–	–	✓
	Dry combustion	✓	✓	✓	✓	✓	✓
	Spectroscopy	–	✓ (VIS, IR)	✓ (IR, INS)	✓ (VNIR, FTNIR, FTMIR)	✓ (MIR)	✓ (not specified)
	Proficiency testing is required	✓	✓	✓	–	–	✓

Note: Symbols are used when a protocol explicitly requires a parameter (✓) or not (–). The colour code indicates whether an aspect was fully satisfactory (green), partially satisfactory (orange) or non-satisfactory (red). It should, however, only be seen as facilitating the overall interpretation and does substitute the detailed analysis conducted in the text of each aspect of these protocols. Nori (*Nori Croplands Methodology v1.6*); PVivo: Plan Vivo (*Plan Vivo Climate Benefit Quantification Methodology*); CFT: Cool Farm Tool (*Technical Method Description v2.1.0 - Section 2.11. Carbon Stock Changes*). LBC: Label Bas Carbone (Méthode Grandes Cultures v1.1); GStd: Gold Standard (*Soil Organic Carbon Framework Methodology v1.0*); CAR, Climate Action Reserve (*Soil Enrichment Protocol v1.1*); Verra (*VM42, Verra Methodology for Improved Agricultural Land v2.0*); CFI: Carbon Farming Initiative (*Estimation of Soil Organic Carbon Sequestration using Measurement and Models. Methodology Determination 2021*).

[a]The different accepted sampling methods (clod, Saran-coated clod, variable height, compliant cavity, cylinder, frame excavation, from cylinder sampling to coated clod, excavation method) are detailed in the 2014 USDA *Kellogg Soil Survey Laboratory Methods Manual*.

soil cores in an *area of interest*, without mentioning its size. $GStd_{meas}$, CAR and BCarb also recommend conducting a preliminary sampling program to obtain the SOC standard deviation and CV, respectively, but without further detailing how this presampling should be conducted. To our knowledge, CFI is the only one not recommending this preliminary step. Rather, this protocol penalizes designs that are insufficiently robust by applying a discount for reporting highly variable differences in SOC stocks.

Not all protocols require a set number of soil cores per composite sample nor any statistical formula to calculate it. FAO is the only one explicitly requiring 5–15 soil cores per composite sample. The others do not mention this aspect. Verra has a general recommendation on the use or adaptation of FAO procedures when sampling but does not refer explicitly to this topic. This aspect is problematic given that SOC displays a random and unpredictable short-scale variability. To minimize this phenomenon, known as the nugget effect, multiple core samples are necessary. Deluz et al. (2020) found that a composite sample should include a minimum of 15 samples to detect a 0.1% point change in SOC with an average CV of 10% and micro-heterogeneity standard deviation of 0.14% of SOC. Given that SOC tend to display a CV equal to or greater than 10%, soil samples should not contain less than 15 cores. In more heterogeneous conditions, the required sample size should logically increase to avoid chances of contamination with localized extreme values (Bradford et al., 2023).

$$\text{Stock}_{\text{SOC}}\left[\text{kg SOC m}^{-2}\right]=\frac{\text{Content}_{\text{SOC}}[\%]\times\text{Bulk density}_{\text{soil}}\left[\text{kg m}^{-3}\right]\times\text{Volume}_{\text{soil}}\left[\text{m}^{3}\right]}{\text{Area field}\left[\text{m}^{-2}\right]}\tag{1}$$

As for the sampling trajectory, all protocols recommend a stratified random trajectory, where each stratum is divided into subareas, in which one or several samples are extracted. This trajectory is known for being the most robust (Brus & de Gruijter, 1997), although very demanding in sampling resources and time (Mason, 1992). Another pattern, known as the double-diagonal composite sampling, was demonstrated to offer a balanced compromise between reliability and ease of use, ensuring reasonable representativeness of the plot surface and simplicity in execution, even for farmers themselves (Deluz et al., 2020). It is therefore surprising not to see this pattern at least mentioned in these protocols.

All in all, these differences in sampling requirements between protocols are important but remain difficult to assess in practice, given that the final sampling design of each SCC project is left to the approval of each protocol's internal committee. For a specific SCC project, the details regarding each aspect of the sampling strategy (stratum area, number of soil samples, number of soil cores per sample, sampling pattern) typically remain undisclosed, preventing buyers and external parties from assessing how the errors associated with sampling were minimized. Ultimately, this lack of transparency is detrimental to the reliability of SCCs especially given the voluntary nature of the agricultural SCC market.

3.3.2 | SOC stock sampling tools and calculation methods

The SOC stock is commonly calculated as the stock per unit of volume multiplied by the layer volume for a given field surface (Equation 1). The stock per unit of volume is obtained by multiplying the SOC content by the bulk density (BD). Quantifying stocks therefore implies taking a series of decisions regarding sampling tools, soil depth and calculation methods.

In terms of tools to measure BD, CAR and FAO require a metal cylinder/ring, $GStd_{mes}$ a soil probe, while CFI and Verra do not recommend a specific tool. Not specifying the BD tool is problematic given that each tool has a different precision level. The error associated with BD estimation using soil probes is indeed on average four times higher than with cylinder because of a lower sampled volume and a higher risk of compaction (Walter et al., 2016). Since BD is a factor in determining the stock, the errors and biases associated with BD determination carry on to the layer stock.

On top of this, BD is also susceptible to variations of up to 0.3 t m^{-3} in mineral soils because of changes in soil tillage practices, soil moisture and SOC levels (Fontana et al., 2015; Goutal-Pousse et al., 2016). Depending on when sampling is conducted (e.g., before or after a tillage operation, a drought or a heavy rain, etc.), sampling a soil with a BD of 1.3 at fixed depth can therefore display misleading SOC stock variations of up to 23% (Deluz et al., 2020). To circumvent this bias, several authors have suggested quantifying SOC stocks at equivalent soil mass (ESM) rather than at equivalent soil depth (see for instance Fowler et al., 2023; Rovira et al., 2022; Wendt & Hauser, 2013). ESM quantification is increasingly adopted worldwide and is required by CFI and Verra but remains optional for CAR and is not required for $GStd_{mes}$. This difference between protocols could therefore lead to substantially different SOC stocks and SCCs depending on which approach is selected (as illustrated in Figure 2).

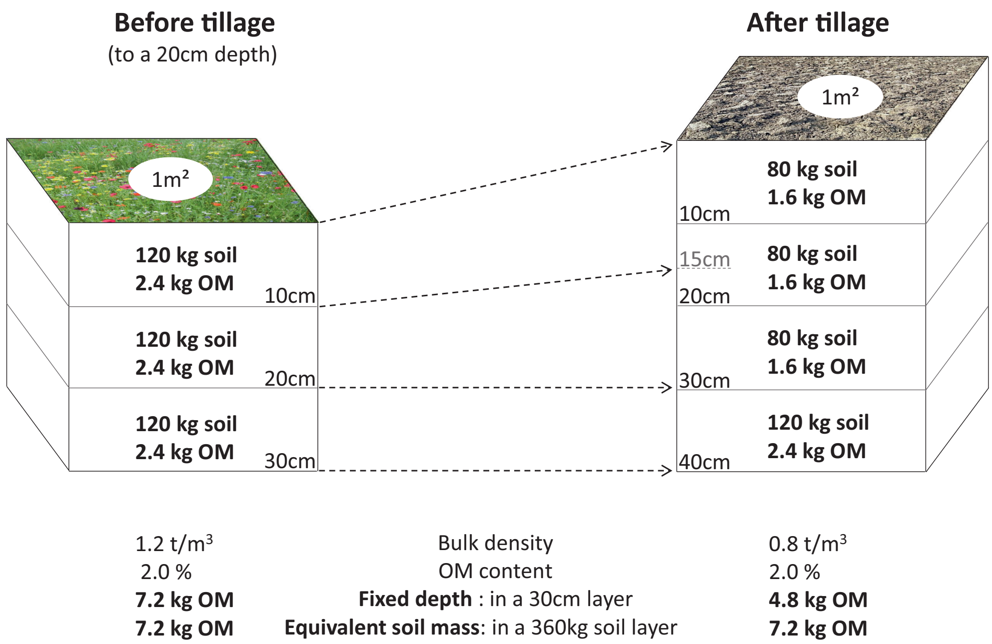

FIGURE 2 Illustration of the importance of sampling at equivalent soil mass (ESM) to avoid flawed SOC stock estimates associated with bulk density changes (here due to recent tillage).

In terms of sampling soil depth, all protocols rely on soil being sampled at least in the top 0–30 cm soil layer, with Verra and $GStd_{mes}$ protocols requiring 50 cm and CAR recommending 1 m whenever possible. On average, the top 0–30 cm soil layer of croplands contains 71% of the SOC incorporated in the last 50 years (Balesdent et al., 2018). The differences in depth between protocols will therefore lead to different SOC accrual kinetics and eventually to different amounts of SCCs for the same farming practices.

One additional limitation concerns the fields in which the soil is tilled at depth greater than 30 cm. In such cases, SCCs associated with the adoption of reduced tillage practices could be problematic. Farming practices are indeed known to modify the spatial distribution of SOC along the soil profile. No-till practices tend for instance to accumulate SOC in the top 0–15 cm layer whereas conventional tillage leads to more homogeneous contents in the ploughed layer (Du et al., 2017). If sampling is not conducted at least in the ploughed layer, then a mere SOC redistribution is susceptible to be wrongly interpreted as SOC gain or loss.

3.3.3 | Varying SOC analysis methods

At the laboratory step, the protocols allow different sets of possible procedures to quantify SOC. Dry combustion – currently considered the most robust method – is always allowed, while loss on ignition (LOI) is systematically excluded, and Walkley-Black titration only recommended by FAO. These different methods provide well correlated but not equivalent results. Differences of up to 20% are observed unless inter-laboratory proficiency testing/ring trials are conducted to apply correction factors (Johns et al., 2015). Spectroscopy methods are also included by GStd, CFI and Verra. Infrared spectroscopy (IR) is allowed by these three protocols, while CFI and Verra also include visible spectroscopy (Vis) and inelastic neutron scattering, respectively. Although encouraging, one could argue that these spectroscopic methods are not mature enough to be approved in SCC programs. Vis and IR spectroscopic methods are indeed not currently standardized and can lead to very variable results depending on the way the samples were prepared (drying time and temperature, milling size, optional use of KBr, etc.) and how the spectroscopic model was calibrated before use (number and quality of local data) (Parikh et al., 2014). Field spectroscopic measurements using portable devices are currently subject to the same limitations and can be also influenced by the amount and nature of the coarse fraction (Reeves et al., 2010).

Additionally, in the SCC context, one could question the ability of spectroscopic methods to accurately quantify SOC changes if the newly introduced conservation practices changed the soil characteristics on which the spectroscopic model was initially trained (e.g., addition of a new type of organic amendment). Regarding inelastic neutron scattering, this non-destructive in situ method has currently only proven reliable to quantify SOC in the top 8–10 cm of soil and can display serious inconsistencies at greater depths if several SOC distribution patterns with depth exist (Yakubova et al., 2016).

The impact of the coarse fraction (>2mm) of soils is unevenly considered by protocols. In agricultural soils, the coarse fraction can range from representing 0% to more than 50% of the soil mass (Weil & Brady, 2017). Its capacity to store SOC remains, however, negligible (Perruchoud et al., 2000). Therefore, Verra, CFI, $GStd_{meas}$ and FAO require this fraction to be weighted separately and subtracted when calculating SOC stocks, while CAR and BCarb do not explicitly require this. Not adjusting SOC stocks based on the importance of the coarse fraction can, however, lead to significant overestimates. In a database containing more than 3000 agricultural soils, Poeplau et al. (2017) showed for instance that disregarding this calculation step would lead to overestimate SOC stocks by 10% on average and by more than 100% for coarse soils specifically.

Finally, even with the most robust methods, significant differences can appear between laboratories based on sample preparation and analytical care. To limit this risk, CAR, Verra, CFI and FAO require laboratories to demonstrate proficiency and quality control. This control is often ensured via external independent programs (e.g., the *American Proficiency Testing Program*) that perform proficiency testing in which participating laboratories receive the same samples to analyse and adjust their practices based on the identified discrepancies. The FAO remains more general and requires the laboratory to participate, at least once a year, in interlaboratory proficiency tests and to take action if the obtained result is questionable or unsatisfactory. Despite the importance of such an approach to ensure the reliability of SOC measurement, $GStd_{mes}$ and BCarb do not explicitly require these external and/or inter-laboratory quality controls.

These differences among protocols could therefore lead to substantially different SOC stocks and stock changes depending on which approach was applied. All these differences have consequences on the quantification of SCCs and ultimately on their reliability.

3.4 | Improvement avenues

3.4.1 | Improving model-based protocols

The MRV protocols relying mainly on models to predict SOC changes display large differences and questionable reliability, which are problematic if SCCs are to be taken seriously. Several models, such as the ones used by CFT and $GStd_{mod}$, rely on simplistic parameters and omit key agricultural variables. At the other end of the spectrum, the protocols from Verra and CFI appear the most robust. Nevertheless, based on the analysis conducted in the previous sections, we suggest the following improvements to increase the robustness of model predictions: (1) initial in situ SOC stock quantification should be compulsory; (2) this quantification should use a robust sampling strategy and SOC analysis methods (see Section 3.4.2 below) by a laboratory demonstrating proficiency and quality control; (3) all models should include the initial level of soil depletion in SOC to avoid serious overestimates (and underestimates); (4) climate parameters and agricultural practices should avoid binary/tertiary categories (e.g., tillage/no-till) and move toward integrative continuous parameters; (5) cover cropping intensity should be systematically required ideally with cover crop biomass measurements or estimates; (6) uncertainty calculation should be systematically included to account for the errors propagated throughout the SOC stock estimation process; and (7) predictions in SOC stock changes should be regularly adjusted with measurements of SOC stocks at least every 10 years.

We argue that models should as much as possible move from qualitative to quantitative result-oriented variables. When dealing with soil tillage for instance, indicators like the Soil Tillage Intensity Rating (STIR) have proven more robust at depicting the impact of soil disturbance than limited categories such as tillage versus no-till (Dupla et al., 2022). The STIR index assigns a score for each farming intervention from seeding to harvesting and offers a quantitative overview of soil disturbance over the period of interest (USDA-ARS-NSL, 2003). Similarly for crops and cover-crops, models should move away from a presence/absence approach and instead target their intensity in the rotation in terms of duration, number of species and care taken to grow the crop (seeding method, fertilizer application, irrigation, etc.) as well as biomass (Blanco-Canqui, 2022).

Regularly adjusting predictions with SOC measurements is especially important as the overall credibility of current models to estimate SOC changes is increasingly being questioned (Le Noë et al., 2023). Indeed, in a recent review, Garsia et al. (2023) found that, out of the 221 existing SOC-simulating models, only 29% had been validated at least once and in very limited geographic areas. The authors also found 'a general lack of clear reporting, numerous flaws in model performance evaluation, and a poor overall coverage of land use types across countries and pedoclimatic conditions' leading them to conclude that 'to date, SOC simulation does not represent an adequate tool for globally ensuring effectiveness of SOC storage effort and ensuring reliable carbon crediting'. Even CFI, CAR and Verra that leave users a free choice of currently existing protocols should therefore not be considered blindly as reliable. The observations from Garsia et al. (2023) on the fragile nature of current SOC simulation models should also serve as a warning that the more exhaustive and complex models we are calling for may first need to be developed, tested and confirmed before actually being included in SCC protocols.

Finally, none of the reviewed protocols, except PVivo, explicitly require excluding exogenous organic amendments. Organic amendments are nevertheless a sensitive category in SCC programs. While their addition is known to significantly increase SOC stocks, their inclusion cannot be straightforward in SCC programs. If organic amendments are exogenous in the sense that they come from another field or farm (e.g., as compost, straw, manure, or slurry), then their addition corresponds to a transfer of carbon rather than a net storage (Petersson et al., 2024). In such circumstances, the observed or modelled SOC increase is not matched by an additional CO_2 drawdown resulting from additional photosynthesis and should therefore be discarded in SCC programs.

3.4.2 | Improving sampling-based protocols

Overall, the MRV protocols relying on SOC measurements provide several indications of soundness. For instance, all protocols require a satisfactory minimum sampling depth (provided that the soil is not ploughed below 30 cm) (Smith et al., 2020). Sampling strategies also appear adequate to minimize variability and errors but remain difficult to fully assess given the discretion left to the applicant and to the undisclosed work of the protocol's internal committee.

Nevertheless, we argue that several aspects should be enforced to ensure SCC credibility: (1) sampling design requirements should be objective and verifiable (homogenous areas should be explicitly limited in size, ideally at the field scale, with a set number of composite samples and a minimum of 15 soil cores per composite sample) and should not be left open to the SCC applicant, to the protocol internal validation team or any potential third parties; (2) soil bulk density measurement should avoid tools associated with exceeding measurement errors (e.g., soil probes); (3) SOC stocks should systematically be calculated at ESM to avoid flawed estimations associated with bulk density changes; (4) the soil's coarse fraction should systematically be measured and excluded from SOC stock calculations; (5) dry combustion should be favoured until other SOC-measurement methods, such as spectroscopy, become mature and standardized; (6) the selected laboratory should demonstrate proficiency and quality control; and finally, (7) SCC programs should not be limited to 5 years but should be extended to 10, or even 20 years. We recognize that most protocols currently rely on uncertainty deductions rather than on prescriptive sampling requirements to ensure that the project developers optimize their sampling strategy. However, as stated above, as long as these aspects remain undisclosed, neither the buyers nor external bodies have the means to assess the actual rigour of this fundamental aspect of SCC quantification.

To be fully reliable, measurement-based SCCs require extending the timescale of SCC programs. In several cases, significant SOC changes are not noticeable within 5 or 10 years. Therefore, rigorous carbon storage programs should be structured as long-term commitments where SCCs would be only granted when SOC changes exceed minimal detectable change thresholds. In the most extreme situations (intense investment in regenerative agriculture on a SOC depleted soil), significant SOC changes can be noticeable after a couple of years, but in most cases, these changes have been measured to take 10–20 years (Dupla et al., 2021). Waiting for 20 years to certify SCCs is however absurd given the climate emergency. The goal of carbon markets is to encourage emitting organizations to include as rapidly as possible the carbon burden in their accounting, hoping that this will trigger a rapid and durable decrease in their carbon footprint. In addition, the operational costs of such a long-term monitoring program may refrain both farmers and brokers from stepping in.

Two avenues of action can be considered here. The first option would be to improve the model requirements and integrate them in the hybrid approach already fostered by CAR, CFI and Verra, where simulated changes would be regularly trued-up by empirical measurements. One way forward could be to produce a unique and standardized method for assessing changes in SOC stocks, along the lines of the ISO standards, already widely used in soil science (Hortensius & Welling, 1996). Such a reform would need, however, to include a reflection on its potential impact in terms of additional socio-economic costs in order to ensure that the gains in reliability do not come at the expense of SCC attractiveness. The other approach would be to broaden the scope of SCC programs so that incentives would move from carbon storage to soil regeneration. Carbon storage is indeed only one function ensured by soils among several other essential ones (e.g., water and nutrient retention and cycling, habitat and food for living organisms, medium for plant growth, etc.). One-eyed soil strategies exclusively focused on SOC storage face the risk of having detrimental consequences on other soil functions and on soil quality as a whole, as explained by Baveye et al. (2020). Deep tillage is an example of this risk of adverse effects. From a SOC storage perspective, occasional deep tillage may offer the potential to safely store SOC in deeper layers with lower mineralization rates. However, this practice disturbs the whole soil structure and ecosystem with potentially dramatic impacts on crop yields, soil erosion, or water regulation, just to cite a few. In broader soil quality schemes, SOC storage and SCCs would be co-benefits ensuring the highest performing farmers are still incentivized to maintain favourable practices, even when their soils reach SOC saturation.

4 | CONCLUSION

On top of moral questions regarding the act of selling non-satisfactory products, the current climate emergency cannot afford empty promises. If agricultural SCCs are to play a leading role in the fight against climate change, then the protocols generating them need to be robust and reliable. Our study indicates that wide disparities currently exist between protocols in terms of their ability to model and/or monitor SOC storage over time. Some protocols, like Verra or CFI, have emerged as largely satisfactory whereas others are currently not precise and restrictive enough in their requirements to lead to reliable SOC stocks estimates. We have therefore suggested improvement avenues aiming at ensuring that initial SOC stocks are accurately quantified and that their change with time is reliably monitored. More generally, SCCs could be integrated into broader soil quality programs in order to ensure (1) that other soil functions and services are equally preserved and possibly even improved and (2) that beneficial farming practices are not halted (or even worse, reversed) once SOC stocks are replenished.

ACKNOWLEDGEMENTS

The authors would like to thank the Canton de Vaud for their financial support as well as the different carbon credit organizations for their time and explanations regarding their protocols. We also thank deeply Arnaud Le Meur, carbon credit consultant, for his careful proofreading and constructive suggestions. Open access funding provided by Universite de Lausanne.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as the article describes the entire theoretical research and provides the data within the manuscript and in the supplementary material.

ORCID

Xavier Dupla https://orcid.org/0000-0002-3181-052X

REFERENCES

Andriulo, A. E., Mary, B., & Guerif, J. (1999). Modelling soil carbon dynamics with various cropping sequences on the rolling pampas. *Agronomie*, *19*(5), 365–377. https://hal.science/hal-00885937

Arrouays, D., Vion, I., Jolivet, C., Guyon, D., Couturier, A., & Wilbert, J. (1997). Variabilité intraparcellaire de quelques propriétés des sols sableux des Landes de Gascogne (France). *Conséquences Sur La Stratégie d'échantillonnage Agronomique Etude et Gestion des Sols*, *4*(1), 5–16.

Balesdent, J., Basile-Doelsch, I., Chadoeuf, J., Cornu, S., Derrien, D., Fekiacova, Z., & Hatté, C. (2018). Atmosphere–soil carbon transfer as a function of soil depth. *Nature*, *559*(7715), 599–602. https://doi.org/10.1038/s41586-018-0328-3

Batjes, N. H. (1996). Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science*, *47*(2), 151–163. https://doi.org/10.1111/j.1365-2389.1996.tb01386.x

Baveye, P. C., Schnee, L. S., Boivin, P., Laba, M., & Radulovich, R. (2020). Soil organic matter research and climate change: Merely re-storing carbon versus restoring soil functions. *Frontiers in Environmental Science*, *8*, 161. https://doi.org/10.3389/fenvs.2020.579904

Beka, S., Burgess, P. J., Corstanje, R., & Stoate, C. (2022). Spatial modelling approach and accounting method affects soil carbon estimates and derived farm-scale carbon payments. *Science of the Total Environment*, *827*, 154164. https://doi.org/10.1016/j.scitotenv.2022.154164

Blanco-Canqui, H. (2022). Cover crops and carbon sequestration: Lessons from U.S. studies. *Soil Science Society of America Journal*, *86*(3), 501–519. https://doi.org/10.1002/saj2.20378

Bradford, M. A., Eash, L., Polussa, A., Jevon, F. V., Kuebbing, S. E., Hammac, W. A., Rosenzweig, S., & Oldfield, E. E. (2023). Testing the feasibility of quantifying change in agricultural soil carbon stocks through empirical sampling. *Geoderma*, *440*, 116719. https://doi.org/10.1016/j.geoderma.2023.116719

Brus, D. J., & de Gruijter, J. J. (1997). Random sampling or geostatistical modelling? Choosing between design-based and model-based sampling strategies for soil (with discussion). *Geoderma*, *80*(1), 1–44. https://doi.org/10.1016/S0016-7061(97)00072-4

CarbonPlan. (2024). *Soil carbon protocols – CarbonPlan*. https://carbonplan.org/research/soil-protocols

Ceddia, M. B., Villela, A. L. O., Pinheiro, É. F. M., & Wendroth, O. (2015). Spatial variability of soil carbon stock in the Urucu river basin, Central Amazon-Brazil. *Science of the Total Environment*, *526*, 58–69. https://doi.org/10.1016/j.scitotenv.2015.03.121

Coleman, K., & Jenkinson, D. S. (1996). RothC-26.3—A model for the turnover of carbon in soil. In D. S. Powlson, P. Smith, & J. U. Smith (Eds.), *Evaluation of soil organic matter models* (pp. 237–246). Springer. https://doi.org/10.1007/978-3-642-61094-3_17

Conant, R. T., & Paustian, K. (2002). Spatial variability of soil organic carbon in grasslands: Implications for detecting change at different scales. *Environmental Pollution*, *116*, S127–S135. https://doi.org/10.1016/S0269-7491(01)00265-2

Deluz, C., Nussbaum, M., Sauzet, O., Gondret, K., & Boivin, P. (2020). Evaluation of the potential for soil organic carbon content monitoring with farmers. *Frontiers in Environmental Science*, *8*, 113. https://doi.org/10.3389/fenvs.2020.00113

Dimassi, B., Mary, B., Wylleman, R., Labreuche, J., Couture, D., Piraux, F., & Cohan, J.-P. (2014). Long-term effect of contrasted tillage and crop management on soil carbon dynamics during 41 years. *Agriculture, Ecosystems & Environment*, *188*(Suppl C), 134–146. https://doi.org/10.1016/j.agee.2014.02.014

Du, Z., Angers, D. A., Ren, T., Zhang, Q., & Li, G. (2017). The effect of no-till on organic C storage in Chinese soils should not be overemphasized: A meta-analysis. *Agriculture, Ecosystems & Environment*, *236*(Suppl C), 1–11. https://doi.org/10.1016/j.agee.2016.11.007

Dupla, X., Gondret, K., Sauzet, O., Verrecchia, E., & Boivin, P. (2021). Changes in topsoil organic carbon content in the Swiss leman region cropland from 1993 to present. Insights from large scale on-farm study. *Geoderma*, *400*, 115125. https://doi.org/10.1016/j.geoderma.2021.115125

Dupla, X., Lemaître, T., Grand, S., Gondret, K., Charles, R., Verrecchia, E., & Boivin, P. (2022). On-farm relationships between agricultural practices and annual changes in organic carbon content at a regional scale. *Frontiers in Environmental Science*, *10*, 1–13. https://doi.org/10.3389/fenvs.2022.834055

Fontana, M., Berner, A., Mäder, P., Lamy, F., & Boivin, P. (2015). Soil organic carbon and soil bio-physicochemical properties as co-influenced by tillage treatment. *Soil Science Society of America Journal*, *79*(5), 1435–1445. https://doi.org/10.2136/sssaj2014.07.0288

Fowler, A. F., Basso, B., Millar, N., & Brinton, W. F. (2023). A simple soil mass correction for a more accurate determination of soil carbon stock changes. *Scientific Reports*, *13*(1), 2242. https://doi.org/10.1038/s41598-023-29289-2

Garsia, A., Moinet, A., Vazquez, C., Creamer, R. E., & Moinet, G. Y. K. (2023). The challenge of selecting an appropriate soil organic carbon simulation model: A comprehensive global review and validation assessment. *Global Change Biology*, *29*(20), 5760–5774. https://doi.org/10.1111/gcb.16896

Georgiou, K., Jackson, R. B., Vindušková, O., Abramoff, R. Z., Ahlström, A., Feng, W., Harden, J. W., Pellegrini, A. F. A., Polley, H. W., Soong, J. L., Riley, W. J., & Torn, M. S. (2022). Global stocks and capacity of mineral-associated soil organic carbon. *Nature Communications*, *13*(1), 3797. https://doi.org/10.1038/s41467-022-31540-9

Gonzalez-Sanchez, E. J., Veroz-Gonzalez, O., Conway, G., Moreno-Garcia, M., Kassam, A., Mkomwa, S., Ordoñez-Fernandez, R., Triviño-Tarradas, P., & Carbonell-Bojollo, R. (2019). Meta-analysis on carbon sequestration through conservation agriculture in Africa. *Soil and Tillage Research*, *190*, 22–30. https://doi.org/10.1016/j.still.2019.02.020

Goutal-Pousse, N., Lamy, F., Ranger, J., & Boivin, P. (2016). Structural damage and recovery determined by the colloidal constituents in two forest soils compacted by heavy traffic. *European Journal of Soil Science*, *67*(2), 160–172. https://doi.org/10.1111/ejss.12323

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

Haddaway, N. R., Hedlund, K., Jackson, L. E., Kätterer, T., Lugato, E., Thomsen, I. K., Jørgensen, H. B., & Isberg, P.-E. (2017). How does tillage intensity affect soil organic carbon? A systematic review. *Environmental Evidence*, *6*(1), 1–48. https://doi.org/10.1186/s13750-017-0108-9

Hortensius, D., & Welling, R. (1996). International standardization of soil quality measurements. *Communications in Soil Science and Plant Analysis*, *27*(3–4), 387–402. https://doi.org/10.1080/00103629609369563

IPCC. (2019). *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories—IPCC*. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/

IPCC. (2023). In Core Writing Team, H. Lee, & J. Romero (Eds.), *Climate change 2023: Synthesis report. Contribution of working groups I, II and III to the sixth assessment report of the Intergovernmental Panel on Climate Change* (p. 184). IPCC.

Johannes, A., Matter, A., Schulin, R., Weisskopf, P., Baveye, P. C., & Boivin, P. (2017). Optimal organic carbon values for soil structure quality of arable soils. Does clay content matter? *Geoderma*, *302*(Supp C), 14–21. https://doi.org/10.1016/j.geoderma.2017.04.021

Johns, T. J., Angove, M. J., & Wilkens, S. (2015). Measuring soil organic carbon: Which technique and where to from here? *Soil Research*, *53*(7), 717–736. https://doi.org/10.1071/SR14339

Kaiser, K., & Guggenberger, G. (2003). Mineral surfaces and soil organic matter. *European Journal of Soil Science*, *54*(2), 219–236. https://doi.org/10.1046/j.1365-2389.2003.00544.x

Kibblewhite, M. G., Jones, R. J., Montanarella, L., Baritz, R., Huber, S., Arrouays, D., Micheli, E., & Stephens, M. (2008). Environmental assessment of soil for monitoring volume VI: Soil monitoring system for Europe. EUR 23490, 72.

Lal, R. (2011). Sequestering carbon in soils of agro-ecosystems. *Food Policy*, *36*, S33–S39. https://doi.org/10.1016/j.foodpol.2010.12.001

Le Noë, J., Manzoni, S., Abramoff, R., Bölscher, T., Bruni, E., Cardinael, R., Ciais, P., Chenu, C., Clivot, H., Derrien, D., Ferchaud, F., Garnier, P., Goll, D., Lashermes, G., Martin, M., Rasse, D., Rees, F., Sainte-Marie, J., Salmon, E., … Guenet, B. (2023). Soil organic carbon models need independent time-series validation for reliable prediction. *Communications Earth & Environment*, *4*(1), 158. https://doi.org/10.1038/s43247-023-00830-5

Mason, B. J. (1992). *Preparation of soil sampling protocols: Sampling techniques and strategies*. Nevada Univ., Environmental Research Center. https://www.osti.gov/biblio/5974467

Mikolajczyk, S., & Bravo, F. (2023). *Voluntary carbon market 2022 overview* (p. 12). Climate Focus.

Morari, F., Lugato, E., Berti, A., & Giardini, L. (2006). Long-term effects of recommended management practices on soil carbon changes and sequestration in north-eastern Italy. *Soil Use and Management*, *22*(1), 71–81. https://doi.org/10.1111/j.1475-2743.2005.00006.x

Ogle, S. M., Breidt, F. J., Easter, M., Williams, S., Killian, K., & Paustian, K. (2010). Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology*, *16*(2), 810–822. https://doi.org/10.1111/j.1365-2486.2009.01951.x

Ogle, S. M., Breidt, F. J., Easter, M., Williams, S., & Paustian, K. (2007). An empirically based approach for estimating uncertainty associated with modelling carbon sequestration in soils. *Ecological Modelling*, *205*(3–4), 453–463. https://doi.org/10.1016/j.ecolmodel.2007.03.007

Oldfield, E. E., Eagle, A. J., Rubin, R. L., Rudek, J., Sanderman, J., & Gordon, D. R. (2022). Crediting agricultural soil carbon sequestration. *Science*, *375*(6586), 1222–1225. https://doi.org/10.1126/science.abl7991

Parikh, S. J., Goyne, K. W., Margenot, A. J., Mukome, F. N., & Calderón, F. J. (2014). Soil chemical insights provided through vibrational spectroscopy. *Advances in Agronomy*, *126*, 1–148. https://doi.org/10.1016/B978-0-12-800132-5.00001-8

Parton, W. J. (1996). The CENTURY model. In D. S. Powlson, P. Smith, & J. U. Smith (Eds.), *Evaluation of soil organic Matter models* (pp. 283–291). Springer. https://doi.org/10.1007/978-3-642-61094-3_23

Parton, W. J., Hartman, M., Ojima, D., & Schimel, D. (1998). DAYCENT and its land surface submodel: Description and testing. *Global and Planetary Change*, *19*(1), 35–48. https://doi.org/10.1016/S0921-8181(98)00040-X

Perruchoud, D., Walthert, L., Zimmermann, S., & Lüscher, P. (2000). Contemporary carbon stocks of mineral forest soils in the Swiss Alps. *Biogeochemistry*, *50*, 111–136. https://doi.org/10.1023/A:1006320129112

Petersson, T., Antoniella, G., Chiriacò, M. V., Perugini, L., & Chiti, T. (2024). The misconception of soil organic carbon sequestration notion: When do we achieve climate benefit? *Soil Use and Management*, *40*(1), e13009. https://doi.org/10.1111/sum.13009

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops – A meta-analysis. *Agriculture, Ecosystems & Environment*, *200*, 33–41. https://doi.org/10.1016/j.agee.2014.10.024

Poeplau, C., Don, A., Flessa, H., Heidkamp, A., Jacobs, A., & Prietz, R. (2020). *Erste Bodenzustandserhebung Landwirtschaft—Kerndatensatz*. OpenAgrar. https://doi.org/10.3220/DATA20200203151139

Poeplau, C., Jacobs, A., Don, A., Vos, C., Schneider, F., Wittnebel, M., Tiemeyer, B., Heidkamp, A., Prietz, R., & Flessa, H. (2020). Stocks of organic carbon in German agricultural soils—Key results of the first comprehensive inventory. *Journal of Plant Nutrition and Soil Science*, *183*(6), 665–681. https://doi.org/10.1002/jpln.202000113

Poeplau, C., Vos, C., & Don, A. (2017). Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content. *The Soil*, *3*(1), 61–66. https://doi.org/10.5194/soil-3-61-2017

Powlson, D. S., Stirling, C. M., Jat, M. L., Gerard, B. G., Palm, C. A., Sanchez, P. A., & Cassman, K. G. (2014). Limited potential of no-till agriculture for climate change mitigation. *Nature Climate Change*, *4*(8), 678. https://doi.org/10.1038/nclimate2292

Prout, J. M., Shepherd, K. D., McGrath, S. P., Kirk, G. J. D., & Haefele, S. M. (2020). What is a good level of soil organic matter? An index based on organic carbon to clay ratio. *European Journal of Soil Science*, *72*, 2493–2503. https://doi.org/10.1111/ejss.13012

Pulley, S., Taylor, H., Prout, J. M., Haefele, S. M., & Collins, A. L. (2023). The soil organic carbon: Clay ratio in North Devon, UK: Implications for marketing soil carbon as an asset class. *Soil Use and Management*, *39*(3), 1068–1081. https://doi.org/10.1111/sum.12920

Reeves, J. B., McCarty, G. W., & Hively, W. D. (2010). Mid- versus near-infrared spectroscopy for on-site analysis of soil. In R. A. Viscarra Rossel, A. B. McBratney, & B. Minasny (Eds.), *Proximal soil sensing* (pp. 133–142). Springer. http://dx.doi.org/10.1007/978-90-481-8859-8_11

Rovira, P., Sauras-Yera, T., & Romanyà, J. (2022). Equivalent-mass versus fixed-depth as criteria for quantifying soil carbon sequestration: How relevant is the difference? *Catena*, *214*, 106283. https://doi.org/10.1016/j.catena.2022.106283

Rumpel, C., Amiraslani, F., Chenu, C., Garcia Cardenas, M., Kaonga, M., Koutika, L.-S., Ladha, J., Madari, B., Shirato, Y., Smith, P., Soudi, B., Soussana, J.-F., Whitehead, D., & Wollenberg, E. (2019). The 4p1000 initiative: Opportunities, limitations and challenges for implementing soil organic carbon sequestration as a sustainable development strategy. *Ambio*, *49*, 350–360. https://doi.org/10.1007/s13280-019-01165-2

Saby, N., Bellamy, P. H., Morvan, X., Arrouays, D., Jones, R. J., Verheijen, F. G., Kibblewhite, M. G., Verdoodt, A. N. N., Üveges, J. B., Freudenschuß, A., & Simota, C. (2008). Will European soil-monitoring networks be able to detect changes in topsoil organic carbon content? *Global Change Biology*, *14*(10), 2432–2442. https://doi.org/10.1111/j.1365-2486.2008.01658.x

Sanderman, J., Hengl, T., & Fiske, G. J. (2017). Soil carbon debt of 12,000 years of human land use. *Proceedings of the National Academy of Sciences*, *114*(36), 9575–9580. https://doi.org/10.1073/pnas.1706103114

Schmidt, M. W., Torn, M. S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I. A., Kleber, M., Kögel-Knabner, I., Lehmann, J., & Manning, D. A. (2011). Persistence of soil organic matter as an ecosystem property. *Nature*, *478*(7367), 49. https://doi.org/10.1038/nature10386

Seitz, D., Fischer, L. M., Dechow, R., Wiesmeier, M., & Don, A. (2023). The potential of cover crops to increase soil organic carbon storage in German croplands. *Plant and Soil*, *488*(1), 157–173. https://doi.org/10.1007/s11104-022-05438-w

Six, J., Conant, R. T., Paul, E. A., & Paustian, K. (2002). Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils. *Plant and Soil*, *241*(2), 155–176. https://doi.org/10.1023/A:1016125726789

Smith, P., Soussana, J.-F., Angers, D., Schipper, L., Chenu, C., Rasse, D. P., Batjes, N. H., van Egmond, F., McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J. E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A., & Klumpp, K. (2020). How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. *Global Change Biology*, *26*(1), 219–241. https://doi.org/10.1111/gcb.14815

The Voluntary Carbon Market Is Thriving. (2022). BCG global. https://www.bcg.com/publications/2023/why-the-voluntary-carbon-market-is-thriving

USDA-ARS-NSL. (2003). *RUSLE1.06c and RUSLE2*. U.S. Department of Agriculture, Agricultural Research Service, National Sediment Laboratory (USDA-ARS-NSL).

Walter, K., Don, A., Tiemeyer, B., & Freibauer, A. (2016). Determining soil bulk density for carbon stock calculations: A systematic method comparison. *Soil Science Society of America Journal*, *80*(3), 579–591. https://doi.org/10.2136/sssaj2015.11.0407

Weil, R., & Brady, N. (2017). *The nature and properties of soils* (15th ed.). Pearson.

Wendt, J. W., & Hauser, S. (2013). An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. *European Journal of Soil Science*, *64*(1), 58–65. https://doi.org/10.1111/ejss.12002

Xiong, X., Grunwald, S., Myers, D. B., Kim, J., Harris, W. G., & Bliznyuk, N. (2015). Assessing uncertainty in soil organic carbon modeling across a highly heterogeneous landscape. *Geoderma*, *251–252*, 105–116. https://doi.org/10.1016/j.geoderma.2015.03.028

Yakubova, G., Kavetskiy, A., Prior, S. A., & Torbert, H. A. (2016). Benchmarking the inelastic neutron scattering soil carbon method. *Vadose Zone Journal*, *15*(2), 1–11. https://doi.org/10.2136/vzj2015.04.0056

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Dupla, X., Bonvin, E., Deluz, C., Lugassy, L., Verrecchia, E., Baveye, P. C., Grand, S., & Boivin, P. (2024). Are soil carbon credits empty promises? Shortcomings of current soil carbon quantification methodologies and improvement avenues. *Soil Use and Management*, *40*, e13092. https://doi.org/10.1111/sum.13092