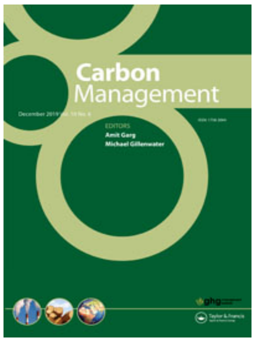

Carbon Management

ISSN: 1758-3004 (Print) 1758-3012 (Online) Journal homepage: https://www.tandfonline.com/loi/tcmt20

Quantifying carbon for agricultural soil management: from the current status toward a global soil information system

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To cite this article: Keith Paustian, Sarah Collier, Jeff Baldock, Rachel Burgess, Jeff Creque, Marcia DeLonge, Jennifer Dungait, Ben Ellert, Stefan Frank, Tom Goddard, Bram Govaerts, Mike Grundy, Mark Henning, R. César Izaurralde, Mikuláš Madaras, Brian McConkey, Elizabeth Porzig, Charles Rice, Ross Searle, Nathaniel Seavy, Rastislav Skalsky, William Mulhern & Molly Jahn (2019) Quantifying carbon for agricultural soil management: from the current status toward a global soil information system, Carbon Management, 10:6, 567-587, DOI: 10.1080/17583004.2019.1633231

To link to this article: https://doi.org/10.1080/17583004.2019.1633231

CARBON MANAGEMENT
2019, VOL. 10, NO. 6, 567–587
https://doi.org/10.1080/17583004.2019.1633231

REVIEW ARTICLE

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Quantifying carbon for agricultural soil management: from the current status toward a global soil information system

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ABSTRACT

The importance of building/maintaining soil carbon, for soil health and CO_2 mitigation, is of increasing interest to a wide audience, including policymakers, NGOs and land managers. Integral to any approaches to promote carbon sequestering practices in managed soils are reliable, accurate and cost-effective means to quantify soil C stock changes and forecast soil C responses to different management, climate and edaphic conditions. While technology to accurately measure soil C concentrations and stocks has been in use for decades, many challenges to routine, cost-effective soil C quantification remain, including large spatial variability, low signal-to-noise and often high cost and standardization issues for direct measurement with destructive sampling. Models, empirical and process-based, may provide a cost-effective and practical means for soil C quantification to support C sequestration policies. Examples are described of how soil science and soil C quantification methods are being used to support domestic climate change policies to promote soil C sequestration on agricultural lands (cropland and grazing land) at national and provincial levels in Australia and Canada. Finally, a quantification system is outlined – consisting of well-integrated data-model frameworks, supported by expanded measurement and monitoring networks, remote sensing and crowd-sourcing of management activity data – that could comprise the core of a new global soil information system.

KEYWORDS

Soil carbon; carbon sequestration; measurement methods; SOC models; soil monitoring; soil health

Take Home messages:

- Increasing soil organic carbon (SOC) stocks would improve the performance of working (managed) soils especially under drought or other stressors, increase agricultural resilience and fertility, and reduce net GHG emissions from soils.
- There are many improved management practices that can be and are currently being applied to cropland and grazing lands to increase SOC.
- Land managers are decision makers who operate in larger contexts that bound their agricultural and financial decisions (e.g. market forces, crop insurance, input subsidies, conservation mandates, etc.).
- Any effort to value improvements in the performance of agricultural soils through enhanced levels of SOC will require feasible, credible and creditable assessment of SOC stocks, which are governed by dynamic and complex soil processes and properties.
- This paper evaluates currently accepted methods of quantifying and forecasting SOC that, when augmented and pulled together, could provide the basis for a new global soil information system.

Introduction

In recent years, soils have garnered increased attention for their crucial roles in food security and delivering key ecosystem services (e.g. primary production, clean water, nutrient cycling), including their capability and potential to help mitigate

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climate change by sequestering carbon – against a backdrop of widespread soil degradation across much of the globe [1–4].

Soils contain one of the largest organic carbon C stocks on the planet, with ca. 1500 Pg C (1 Pg = 10^{15} g = 1 billion metric tonnes) to a depth of 1 m and 2400 Pg C to 2 m depth [5]. This carbon actively exchanges with the atmosphere via the processes of photosynthesis and respiration. As such a large and active C pool, small percentage changes in these stocks can greatly affect the amount of C as CO_2 in the atmosphere and the C balance at a global scale.

At the local scale, there are multiple ramifications when soils gain or lose soil organic carbon (SOC). When SOC stocks are reduced, it is typically coincident with other forms of soil degradation (e.g. topsoil loss, compaction, reduced aggregate structure) [6]. In general, agricultural soils are degraded relative to their pre-agricultural condition and therefore have a capacity for SOC stocks to be rebuilt if managed appropriately [7]. Observations from field experiments suggest that agricultural operations that have been managed to improve SOC levels also improve physical soil quality ('tilth') [8], reduce susceptibility to erosion [9] and outperform more conventionally managed systems with respect to agricultural yields and yield stability, especially under drought stress [10,11].

Soils have a crucial and obvious role to play in the global response to climate change. In the most recent IPCC assessment [12], many of the integrated assessment models for GHG reduction strategies suggest that aggressive fossil fuel reductions must be supplemented with negative emission or C sequestration options to contain warming below 2 °C as laid out in the 2015 Paris climate accords. This finding has been further supported by the recent analysis of Hansen *et al*. [13] on the need for C negative emissions, as well as Rockström *et al*.'s [14] roadmap for decarbonization. It has been suggested that, relative to other negative emission options, soil C sequestration may offer one of the least expensive and most readily implementable near-term options [15]. With widespread adoption of best soil management practices, soils can act as a global carbon sink to help achieve a net removal of CO_2 from the atmosphere [15,16]. Thus, soil C sequestration is a negative-emissions option that must be considered with the double win of improved soil properties (chemical, physical and biological) and associated agro-ecosystem health, resilience and productivity [17].

Early studies on how management might be used to increase soil organic matter (SOM) for the purpose of removing more CO_2 from the atmosphere [18] relied on field experiments [19] and models [20,21] that were originally designed to study SOM as a soil fertility factor. These early field studies and models remain relevant, and, in many ways, still represent core knowledge of SOC dynamics. However, over the past two to three decades, the development of sensitive analytical instruments allowing quantification of SOC at the biomolecular scale, along with new applications of isotopic labelling, have illuminated the myriad factors that control SOC dynamics [22–24]. While many fine-scale details regarding SOM dynamics remain to be elucidated, it is fair to say that, in general, the basic controls on gross SOC stock changes are understood and it is reasonably well known which management practices can be used to increase SOC storage across a wide range of environments. Furthermore, in spite of the complexity of SOC dynamics at the micro scale, scientists are now beginning to understand the relationship between microscale soil processes and macroscale soil structures (e.g. aggregate to peds), that respond to managed changes in SOC such that they can be used as indicators in soil health assessment protocols.

The fact that many agricultural land managers do not currently employ practices that optimize C storage, despite the widely described potential benefits, indicates the need to more explicitly incentivize these practices. Clearly, land managers can be expected to maximize economic returns and thereby focus on yields/commodity production as the conventional income-generating strategy. Increasing SOC may, in some cases, 'pay for itself' through reducing the need for purchased inputs and improving long-term soil health, thus boosting productivity even in times of relative stress, such as drought [25–27]. However, other factors such as lack of knowledge, training or technical capacity may still inhibit implementation of such 'negative-cost' improvements. In many cases, farmers do incur real, increased costs for implementing better C sequestering practices, in terms of higher input costs (e.g. seed and operations costs for sowing cover crops) and/or increased risk of declines in yield. Thus, opportunities for monetary benefits to the farmer are needed to balance the potential added costs and to drive widespread adoption of improved practices.

Currently, there are three main ways in which the value of soil C sequestration can potentially be included in direct financial returns to land managers.

First, government subsidies as direct payments or as cost sharing can incentivize farmers; examples include the U.S. Department of Agriculture's Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) in the US [28]. Although these programs were originally designed to meet general resource conservation objectives, the practices they promote are generally compatible with C sequestration and GHG emission reductions [29], and thus enhancing the promotion of C sequestration through such programs can be accomplished with relative simplicity. Reduced rates for government-supported crop insurance programs offer an additional incentive mechanism [30]. Similarly, the European Union's Common Agricultural Policy (CAP) provides incentives for protecting soil health and function, including maintenance of SOM (and hence soil carbon storage) [31].

Second, agricultural land managers could be directly compensated for CO_2 removal and storage as SOC as a C 'offset', in which the sequestered C could be sold as a commodity to companies engaged in GHG emission reductions, in either a voluntary marketplace or a compliance cap-and-trade system. Some offset projects that include SOC are ongoing, including through dedicated registries (e.g. Verified Carbon Standard, VCS: https://verra.org/project/vcs-program/registry-system/; American Carbon Registry, ACR: https://americancarbonregistry.org/) operating in the voluntary market space. However, low C prices (often $<$ \$5/tonne CO_2) have limited project development to date [32]. Government-sponsored, incentive-based offset projects and trading involving soil C sequestration are ongoing in Australia and Canada, as discussed in detail in case studies below.

Third, companies that produce and market products that are based on agricultural commodities, including food, beverages and fibers, are increasingly interested in developing more sustainable supply chains, including reducing their products' 'carbon footprint'. Diverse practice-based standards, tools and certification schemes, in addition to brand and company pledges, have proliferated to meet this demand. Hence agricultural producers could be incentivized to implement C sequestering practices by earning a premium price for producing agricultural products to achieve sustainable supply chain goals.

Critical to the success of any of these three approaches to incentivize soil C sequestration is the possibility to reliably and cost-effectively quantify SOC stock changes and affirm that they are occurring. However, depending on the accuracy required, the acceptable level of uncertainty, and the allowable costs for measurement and monitoring, the quantification approach will vary. In general, the level of rigor required and the associated cost for quantification will be greatest for offset projects in which SOC has a defined per-tonne value as a fungible commodity, whereas the least stringent requirements likely exist for participants in government programs, where payments are justified based on overall conservation benefits, not just SOC [33]. In general, there is an inverse relationship between the cost and the uncertainty of the measurements, and thus designing the most appropriate quantification approaches will to some degree involve determining the acceptable tradeoff between accuracy/precision and cost.

This paper provides an overview of current methods and approaches for quantifying SOC stock change and the associated removals of CO_2 from the atmosphere. The aim is to illustrate how these methods currently apply to quantifying SOC stock changes at field to national scales, including examples of such methods applied to ongoing programs in Australia and Canada. A concept is then outlined for a comprehensive global soil information system that could support quantification, monitoring and reporting of SOC stock changes for a scaled-up effort to promote widespread adoption of soil management strategies to remove and sequester CO_2 and improve soil health.

Quantification methods

Associating CO_2 removals with soil C stock changes

Biotic carbon stocks exist in a dynamic balance between continual inflow and outflow of carbon. For promoting carbon sequestration, the *net* amount of CO_2 that is removed from the atmosphere and incorporated into the soil is the metric that matters. However, this value is the difference between two large fluxes of CO_2: the uptake of CO_2 by plants and emissions of CO_2 via respiration from plants and the soil biota. Since the net flux of CO_2 on an annual basis is often very small relative to the gross fluxes, net gains or losses of C from the ecosystem are difficult to measure accurately and routinely, requiring sophisticated research instrumentation (see the section below). An alternative approach is to track the *changes* in ecosystem *C stocks* over time. Since the predominant C exchange in terrestrial ecosystems is between the atmosphere and the plant/soil system, an increase in biotic organic C stocks over time is a close proxy for the net uptake of C (as CO_2) from the atmosphere. Conversely, in the absence of erosion or other lateral transport processes, a decrease over time in ecosystem C stocks indicates a net flux of C to the atmosphere. In forests and shrubland, considerable C may be stored in woody biomass that can accumulate and persist over many decades, and so plant biomass C must be considered in any net CO_2 accounting approach. In agricultural systems that lack long-lived woody biomass (e.g. annual cropland and non-wooded grassland), plant biomass stocks are relatively small and mostly ephemeral due to annual harvesting and grazing. Thus, the only large and persistent (from year to year) organic C stock is in the soil. Therefore, SOC stock accounting is what matters for assessing whether agricultural ecosystems are a net source or sink of C. Here, the direct measurement of CO_2 fluxes is only briefly discussed, and most of the discussion is focused on determining SOC stock changes over time.

Direct measurement – CO_2 fluxes

The most direct means to determine whether ecosystems are functioning as a net C sink and therefore acting to reduce atmospheric CO_2 concentrations is by measuring the net CO_2 exchange between the atmosphere and the ecosystem. Recent decades have seen the development, refinement and deployment of flux measurement systems, based on principles of micrometeorology, in all kinds of terrestrial ecosystems [34]. The most widely used technique, eddy covariance (EC), relies on very frequent and highly accurate measurements of CO_2 concentrations and air movements, that can be used to estimate the net gas exchange between the atmosphere and the land surface, as a result of photosynthesis (CO_2 uptake) and ecosystem respiration (CO_2 release). When combined with measurements of harvested and exported biomass, and assuming other C losses (e.g. erosion, leaching) are negligible, EC can provide an integrated estimate of net ecosystem C stock changes and valuable information on its temporal dynamics. These approaches are particularly useful for making ecosystem C balance estimates for grazed grasslands [35,36], in which livestock activities make other on-the-ground sensors difficult to maintain, particularly at the levels of replication needed to account for grazer influence on spatially varying vegetation and soil C stocks. EC techniques are also well suited for estimating net C fluxes from peat soils [37,38], which have varying density and depth of organic layers that make SOC stock changes difficult to measure. However, EC and other micrometeorological methods are (at present at least) restricted to the research environment. The techniques involve sophisticated and expensive instruments and require highly trained technical staff to manage and maintain them and to process and analyze the data. They also require several assumptions including relatively homogeneous study plots and level topography that are not always possible in manipulative field experiments or privately managed working lands. While these types of measurements are very useful for developing and validating ecosystem C models, they are not practical for routine deployment for C offset projects or in extensive farm/ranch-based measurement and monitoring networks. Rather, to meet such needs, soil sampling and measurement of SOC stock change is typically the most feasible field quantification approach.

Direct measurement – soil C stock changes

Take Home messages:

- Calculation of SOC stocks require volumetric soil samples (to estimate bulk density) which are more laborious to collect than soil samples collected for routine nutrient analyses.
- Soil samples must be dried and processed (crushed, sieved, ground) to ensure representative samples are analyzed.
- Ideally, sample preparation is followed by analysis via automated dry combustion in the laboratory. For soils that contain inorganic forms of carbon, acidification may be required to determine organic C concentration.
- Other less expensive and less precise methods of lab analyses may be considered, but often the incremental expense associated with using a modern analyzer is small relative to the costs of collecting and processing the soil samples.
- Spectroscopic methods (lab- and field-based) offer the potential for more rapid, cheaper analyses but at the cost of reduced accuracy and usually require extensive calibration.
- The main challenges to measuring SOC stocks at field-scales are high spatial variability and small changes relative to 'background' SOC stock.
- Efficient, fit-for-purpose sampling designs that employ georeferenced benchmark sites that optimize the balance between sampling intensity and reduced uncertainty can lower the cost and improve accuracy of direct measurements.

Determining the concentration of C in a soil sample is not technologically challenging or especially difficult. However, large aggregated mitigation and soil C valuation projects and policies require more than simply C concentrations determined in the laboratory; they require an estimate of SOC in mass per unit area to a specified depth, and the capability to estimate temporal changes in SOC stock associated with improved management. The main challenges in applying direct measurement methods to accurately and cost-effectively quantify soil C stock changes over time are in designing effective *sampling methods* and reducing the time and effort in *sample processing and analysis*.

Sampling methods

A major challenge in determining SOC stocks and changes at field scales is the high degree of spatial heterogeneity. Even in seemingly 'uniform' fields, SOC content may vary by as much as 5-fold or more [39]. Using conventional approaches with simple randomized and/or stratified sampling schemes, accurate estimation of the 'average' SOC contents across fields of tens of hectares might require tens to hundreds of samples [40]. In addition to lateral variability, organic C usually decreases markedly with soil depth, with the highest concentrations in the top few cm and then usually declining sharply below the topsoil layer. In some cropland soils, SOC content may be fairly homogeneous from 0 to 20 or 30 cm due to mixing by tillage, but in unplowed soils (e.g. pastures, no-till cropland) SOC typically declines more continuously from the surface. Detecting overall changes in SOC requires accounting for this vertical gradient, so measurements are usually taken from multiple depth increments (e.g. 0–10 cm, 10–20 cm and so on), and appropriate analyses to account for inorganic C, especially in sub-surface layers, are required in many regions. Thus, the full depth to which samples should be taken depends on the type of management system being evaluated because different practices (e.g. crop and tillage type) can manifest changes over different soil depth intervals. The 0 to 30 cm soil layer specified by the IPCC [41] for soil C inventories probably captures most short-term land-use and management-induced changes in SOC stocks, although some practices (e.g. cropland conversion to grassland with deep-rooted species) can have impacts deeper in the soil profile [42]. Over decadal time scales, relatively minor changes to subsoil SOC stocks that manifest under many cropping systems can constitute non-trivial quantities of C at the farm scale [43]. Because variability in SOC stocks tends to increase as a function of depth, while the impacts of most management practices on stocks tends to decrease with depth, efficient analyses of SOC changes should evaluate SOC stocks sequentially, from the surface to increasing cumulative depth layers, to the full depth of sampling [44]. This enables statistically significant differences, which may be confined to surface layers, to be revealed without diluting the signal by including non-significant differences at depth.

Finally, the amount of SOC already present in most soils, versus the amount and rate of change that typically occurs from adopting C sequestering practices, represents a typical signal-to-noise problem. Many practices advocated to increase SOC stocks do so at rates of less than 0.5–1 Mg C $ha^{-1} yr^{-1}$, whereas 'background' SOC stocks in many soils, just in the top 20–30 cm, can be in the range of 30–90 Mg C ha^{-1}. Therefore, with potential annual stock changes of 1% or less of the existing stocks, measurement intervals of 5 years or more are generally required to detect statistically significant cumulative SOC stock changes with a moderate sampling density.

Rather than using sampling designs that aim to quantify the total *amount* of SOC in a field, a more efficient and less costly approach is to measure SOC stock *change* over time at precisely located benchmark sites [45–47]. These can be resampled over time, reducing sample requirements by as much as 8-fold compared to simple random or stratified random sampling designs [48].

In addition, because much of the variability of soils occurs at fine spatial scales, *per unit area* sample size requirements decrease greatly as the area of inference increases in size. In other words, while tens of samples might be needed to adequately quantify SOC stocks for a single field, only 2 to 3 times as many samples might suffice to quantify SOC stocks for an aggregate area of several thousand hectares [49]. Accordingly, quantification approaches that require direct field measurement will be more feasible for implementation in C offset projects with many farms and aggregated areas of many thousands of hectares. Schemes that optimize the sampling intensity by taking into account the value of reduced uncertainty (i.e. as monetized in a C offset project), which is related to the number of samples taken, can further reduce costs [50].

Sample processing and analysis

Modern methods to measure SOC concentrations using dry combustion analyzers are the 'gold standard' in soil science. These automated instruments are highly accurate and widely used in soil and environmental research.

With current technology, accurate direct measurement of SOC requires 'destructive sampling' (i.e. soils taken from the field and then sent to a laboratory for processing and analysis). There are two main reasons for this. First, conventional analysis methods to determine C content as a percentage of total soil mass – that is, both dry and wet oxidation methods – require laboratory-scale instruments and facilities that are not practical to bring to the field. Soils have to be carefully processed and standardized (i.e. sieved, homogenized, dried and finely ground) for the analyses. Second, accurate measurement of soil bulk density (i.e. mass per unit soil volume) requires a known volume of soil to be weighed under standard oven-dry moisture conditions, necessitating soil collection from the field. The collection, transportation and processing of soil add considerable time and costs to the operation.

There is active research, ongoing for many years, to reduce the need for destructive sampling and laboratory-based soil processing and combustion-based analysis. Various spectroscopic techniques, such as near- and mid-infrared spectroscopy (NIRS and MIRS, respectively), which measure how soils interact with light radiation of various wavelengths, can yield information on SOC content as well as other chemical and physical properties of the soil [51]. Since the instrumentation consists of a light source and detectors, much faster throughput of samples is possible compared to wet or dry combustion methods. Also, analysis costs are much cheaper and the smaller, less demanding equipment can potentially be deployed in field labs and in developing countries [52]. However, results from spectroscopic methods must be carefully calibrated for different geographic areas and soil types using dry combustion methods as a reference. Various other non-conventional technologies (e.g. laser-induced breakdown spectroscopy, LIBS; diffuse reflectance Fourier transform infrared spectroscopy, DRIFTS; inelastic neutron scattering, INS) have been tested [53] but none has yet emerged as a viable replacement for conventional analysis methods. The most ambitious technological goals are to develop spectroscopic methods that can be used as 'on-the-go sensors', that can be drawn through the soil by tractors or dedicated sampling vehicles to continuously map soil C concentrations [54]. However, such technologies are still at an early stage of development and their utility for quantification in support of soil C offset projects has yet to be determined. Moreoever, these spectroscopic-based estimates of SOC concentrations still require appropriate calibration curves (most likely from conventional destructive sampling) and measures of soil bulk density in order to calculate SOC stocks.

Model-based estimates of soil C stock changes

Models provide a means to predict SOC stock changes, taking into account the integrated effects of different management practices, as well as impacts of varying soil and climate conditions. Mathematical models may be stochastic or deterministic, and some are designed to represent and amalgamate the underlying processes contributing to terrestrial carbon cycling, while others consist of empirical relationships. Models are, of course, an embodiment of theory, experiments and measurement, and particularly for models of soil C dynamics, measurements from long-term field experiments are a primary source of the information upon which these models are based [55].

Take Home messages:

- Both empirical (statistical) and process-based models are widely used to predict/estimate soil C stocks as a function of environmental and management variables.
- Process-based models have potential for a broader range of applicability across gradients of soil, climate and management conditions, but are more complex and difficult to use than empirically based models.
- Model-based quantification systems, if supported by robust, distributed measurement and monitoring networks, have the capability to improve the cost-effectiveness and standardization of estimates of soil C stock change.

Broadly speaking, there are two types of models used to predict SOC stock changes: empirical models, which are based on statistical relationships estimated directly from sets of field experiment observations; and process-based models, in which the model algorithms are based on more general scientific understanding, derived from laboratory- and field-based experiments, as well as a variety of field-based observations of SOC distribution along climatic, vegetation, topographic and geological gradients. Most process-based models aim to achieve a more *general* understanding and predictive capacity, based on the biogeochemical processes that control SOC dynamics and the impacts and interactions of management and environmental factors on those processes. Empirical models are, by definition, restricted to making inferences within the range of conditions represented by the observations used to build the model, whereas process-based models are (in theory at least) more suitable for extrapolation and representation of conditions that might not be well represented in the observational data.

Empirical models

The most well-used and widely known empirical-based model for predicting SOC stock changes is the model developed for the IIPCC national GHG inventory guidelines. The so-called Tier 1 method was developed to provide an easy way for countries (especially developing countries) to estimate national-scale SOC stock changes as a function of changes in land-use and management practices [41,56]. The model uses a broad classification of climate and soil types to derive reference SOC stocks for native ('unmanaged') ecosystems, based on many thousands of measured soil pedons [5]. Then, a set of scaling factors, estimated from statistical estimates of extensive field data sets [57,58], are applied to represent management impacts on stocks (i.e. land-use type, relative C input level, soil management). SOC stock changes are then computed for the stratified (i.e. climate $\times$ soil $\times$ management) land area being considered, as a function of observed land-use and management changes over a given time period. The model for mineral soil C stock change is given by:

$$\Delta SC = \left(SC_0 - SC_{(0-T)}\right)/D \tag{1a}$$

$$SC_i = SC_R * F_{LU} * F_{MG} * F_I * A \tag{1b}$$

where:

ΔSC = annual soil carbon stock change, Mg C yr^{-1};

SC_0 = soil organic carbon stock at time 0, Mg C ha^{-1};

$SC_{(0\text{-}T)}$ = soil organic carbon stock at time t = 20 years, Mg C ha^{-1};

A = land area of each parcel, ha;

SC_R = the reference carbon stock, Mg C ha^{-1};

F_{LU} = stock change factor for land-use type (dimensionless);

F_{MG} = stock change factor for management/disturbance regime (dimensionless);

F_I = stock change factor for carbon input level (dimensionless);

D = Time dependence of stock change factors, which is the default time period for transition between equilibrium SOC values (in years). The default is 20 years but it depends on assumptions made in computing the factors F_{LU}, F_{MG} and F_I. If T exceeds D, the value for T is used to obtain an annual rate of change over the inventory time period (0–T years).

Constraints for the IPCC method include the lack of field experiment data for many climates, soil types and management combinations. The very broad climate, soil and management classes (and consequently the high degree of aggregation of global data sets) from which the model was developed were intended to support national-scale inventory and reporting. For use in more local application such as for C offset projects, additional data from regional and local field studies would be needed to re-estimate model parameters.

Process-based models

Process-based models generally take the form of computer simulation models that employ sets of differential equations to describe the time and space dynamics of SOM. Most of the models that are currently used to support GHG inventory and/or project-scale quantification were originally developed for research purposes, to analyze the behavior of SOM as a function of environmental and edaphic variables (e.g. temperature, moisture, pH, aeration, soil texture) and land-use and management practices (e.g. vegetation type and productivity, crop rotation, tillage, nutrient management, irrigation, residue management). These types of models attempt to integrate these various factors, and knowledge about the intrinsic controls on decomposition and organic matter stabilization, into generalized models of SOC (and often soil nitrogen) dynamics. This comprehensive approach makes process-based models attractive as predictive tools to support SOC quantification at multiple scales.

Examples of widely used process-based models that simulate SOC dynamics are shown in Table 1. The table includes references to specific instances of site- and landscape-level testing as well as model intercomparisons. Some of these models include additional capabilities to simulate changes in non-CO_2 GHG emissions associated with changes in land management (e.g. DayCent, DNDC).

While process-based models are still used primarily to support basic research, they are increasingly being utilized at local to national scales for soil C and soil GHG inventory purposes. For example, the RothC soil C model is used to estimate soil C stock changes as a component of the

Table 1. Some widely used process-based models that include soil carbon, providing examples of their application at different scales and in model inter-comparisons. NA denotes instances where articles were not found for the category of application.

Model	Website	Key reference – model development	Model testing/ application at site scale	Model application at regional scale	Multi-model evaluation	Multi-model application at regional scale
DNDC	http://www.dndc.sr.unh.edu/	Li et al. (1992) [107]	Li et al. (1997) [108]	Grant et al. (2004) [59]	Smith et al. (1997) [109]	Wattenbach et al. (2010) [60]
ROTHC†	http://www.rothamsted.ac.uk/sustainable-soils-and-grassland-systems/rothamsted-carbon-model-rothc	Jenkinson (1990) [61]	Coleman et al. (1997) [110]	Cerri et al. (2007) [111]	Smith et al. (1997) [109]	Falloon and Smith (2002) [62]
APSIM	www.apsim.info	Mccown et al. (1995) [63]	Luo et al. (2011) [112]	O'Leary et al. (2016) [64]	Moore et al. (2014) [65], Basso et al. (2018) [98]	NA
DAYCENT	http://www.nrel.colostate.edu/projects/daycent/	Del Grosso et al. (2001) [66]	Del Grosso et al. (2008) [113]	Nocentini et al. (2015) [67]	Del Grosso et al. (2016) [114], Basso et al. (2018) [98]	Smith et al. (2012) [96]
DSSAT	http://www.dssat.net	Jones et al. (2003) [68]	Gijsman et al. (2002) [69]	De Sanctis (2012) [70]	Yang et al. (2013) [71]	NA
ECOSYS	http://ecosys.ualberta.ca/	Grant (1997) [72]	Grant et al. (2001) [73]	Mekonnen et al. (2016) [74]	Lokupitiya et al. (2016) [75], Basso et al. (2018) [98]	NA
EPIC	http://epicapex.tamu.edu/	Izaurralde et al. (2006) [115]	Apezteguia et al. (2009) [76]	Zhang et al. (2015) [77]	Lokupitiya et al. (2016) [75]	NA
SOCRATES	http://socrates.n2o.net.au/main	Grace et al. (2006a) [78]	Grace et al. (2006b) [79]	NA	Izaurralde et al. (2001) [116]	NA

†For soil C inventory applications, the ROTHC model soil C model can be imbedded within a full ecosystem-scale model framework, such as FullCAM [67] which is used for soil C accounting purposes in Australia.

Full-CAM national GHG inventory system [58], and the DayCent model is used for soil C stocks changes and soil emissions of N_2O and CH_4 in the US national GHG inventory and reporting system [81].

Most model-based decision support systems (DSSs) for soil C estimation employ empirical models, often derived from the IPCC Tier 1 method described above [82], although COMET-Farm, a web-based full GHG accounting DSS, employs both empirical models for some GHG emission sources as well as the dynamic process-based DayCent model for estimates of soil C stock changes and soil N_2O emissions [83]. Combining biogeochemical process models, global positioning system (GPS) sensors and financial calculators can further elaborate decision-support systems for the fine spatial scales employed in precision agriculture [84].

To further develop the capabilities of process-based models for soil C accounting purposes, it will be essential to better integrate models with supporting measurements [55], for example from networks of soil C monitoring sites [85], flux measurement networks and existing long-term field experiments [86]. Continued efforts are needed to extend and evaluate the capabilities of process-based models to predict soil C changes and GHG emissions, to provide full-cost accounting in GHG offset projects and, when possible, to compare performance in model intercomparison experiments [87].

Case studies of soil C quantification for GHG offsets

Soil carbon accounting systems are gaining momentum in several developed countries that are including agricultural GHG offset options as part of their mitigation portfolios. Three examples of soil C accounting systems that have been developed to support agricultural soil C offset projects are those implemented by the national government of Australia and the provincial governments of both Alberta and Saskatchewan (Canada). These three systems are presented as case studies that illustrate the diverse ways in which information from field measurement and monitoring systems can be combined with model-based quantification systems to support programs that promote SOC sequestration and improve function of managed soils. These examples focus on the quantification methods, and other issues associated with offset protocols such as additionality, leakage and permanence are not discussed in detail.

Australia

The Australian government has established the Emissions Reduction Fund (ERF) to encourage the adoption of management strategies that result in either the reduction of GHG emissions or the sequestration of atmospheric CO_2. The ERF is enacted through the Carbon Credits (Carbon Farming Initiative) Act 2011 (CFI). Under the ERF,

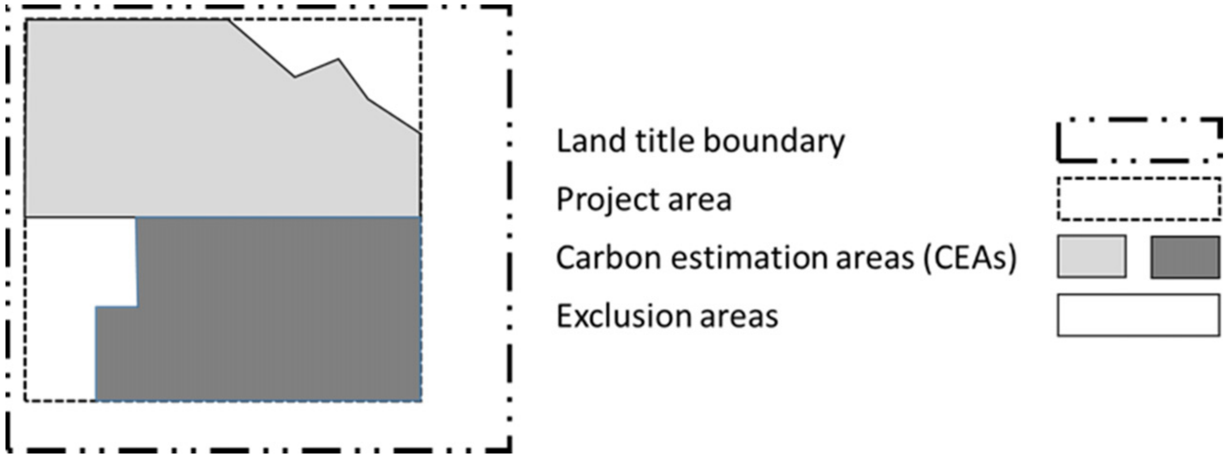

Figure 1. **Schematic representation of the relationship among land title boundary, project area and carbon estimation areas. Source: Author**

Table 2. **Default values for soil carbon sequestration defined for each of the three project types for carbon payments in Australia.**

	Sequestration value (t CO_2-e ha^{-1} year^{-1})		
Project type	Marginal benefit	Some benefit	More benefit
Sustainable intensification	0.11	0.59	1.65
Stubble retention	0.07	0.29	0.73
Conversion to pasture	0.22	0.44	0.84

businesses, farmers and community groups can earn C credits by undertaking projects to reduce emissions or sequester carbon. A range of mitigation activities have been approved for all sectors of the economy; here, the focus is on activities that increase SOC stocks. Projects must comply with the Offsets Integrity Standards, which ensure that any emission reductions, in this case sequestered carbon, are additional, measureable and verifiable, eligible, evidence-based, material and conservative. Once approved and implemented, the methods can be used to generate Australian Carbon Credit Units (ACCUs). One ACCU equates to an emission avoidance or sequestration of 1 tonne of carbon dioxide equivalent (CO_2-e) and can be sold to the Australian government or in a secondary market to generate income.

Initially, two methods for quantifying soil C sequestration were endorsed by the Emissions Reduction Assurance Committee and adopted by the Minister for the Environment and Energy: 'Sequestering carbon in soils in grazing systems' and 'Estimating sequestration of C in soil using default values'. The first method was based on direct measurement of changes in SOC stocks obtained through sampling and analysis over time, whereas the second method was based on the use of default rates of soil C change predicted using the FullCAM process-based model that was designed to be nationally applicable [88,89]. Common to both soil C methods are the definitions of a project, a project area and carbon estimation areas (CEAs) (Figure 1).

'Sequestering C in soils in grazing systems' was the first soil C quantification method developed for use in the ERF. It was designed to quantify the magnitude and certainty of soil C change within CEAs of any size. Under this method, a project proponent measures baseline soil C stocks to a minimum depth of 30 cm, implements new management activities that would not have occurred under a business-as-usual condition and measures future soil C stocks at nominated intervals through time.

The second soil C quantification method, 'Estimating carbon sequestration in soil with default values', offers three project types that can receive ACCUs: sustainable intensification, stubble retention and conversion to pastures. Eligible lands and associated default rates of soil C sequestration associated with each project type were defined using an updated version of the FullCAM model and its associated data tables that were used to prepare Australia's 2015 submission to the UNFCCC [88]. The RothC soil carbon model (Table 1) is a submodel contained within the broader scope of the FullCAM system model.

For the model-based method, there are three defined classes of soil C sequestration rates: marginal benefit, some benefit and more benefit. These rates were determined by a series of simulations and statistical tests to generate a histogram, enabling the three-class regionalization (Table 2; Figure 2). Provided a project meets its reporting obligations and remains eligible, the amount of C sequestered is defined by multiplying the duration of the project by the respective rate of carbon sequestration provided in Table 2. More information on allowable activities and conditions can

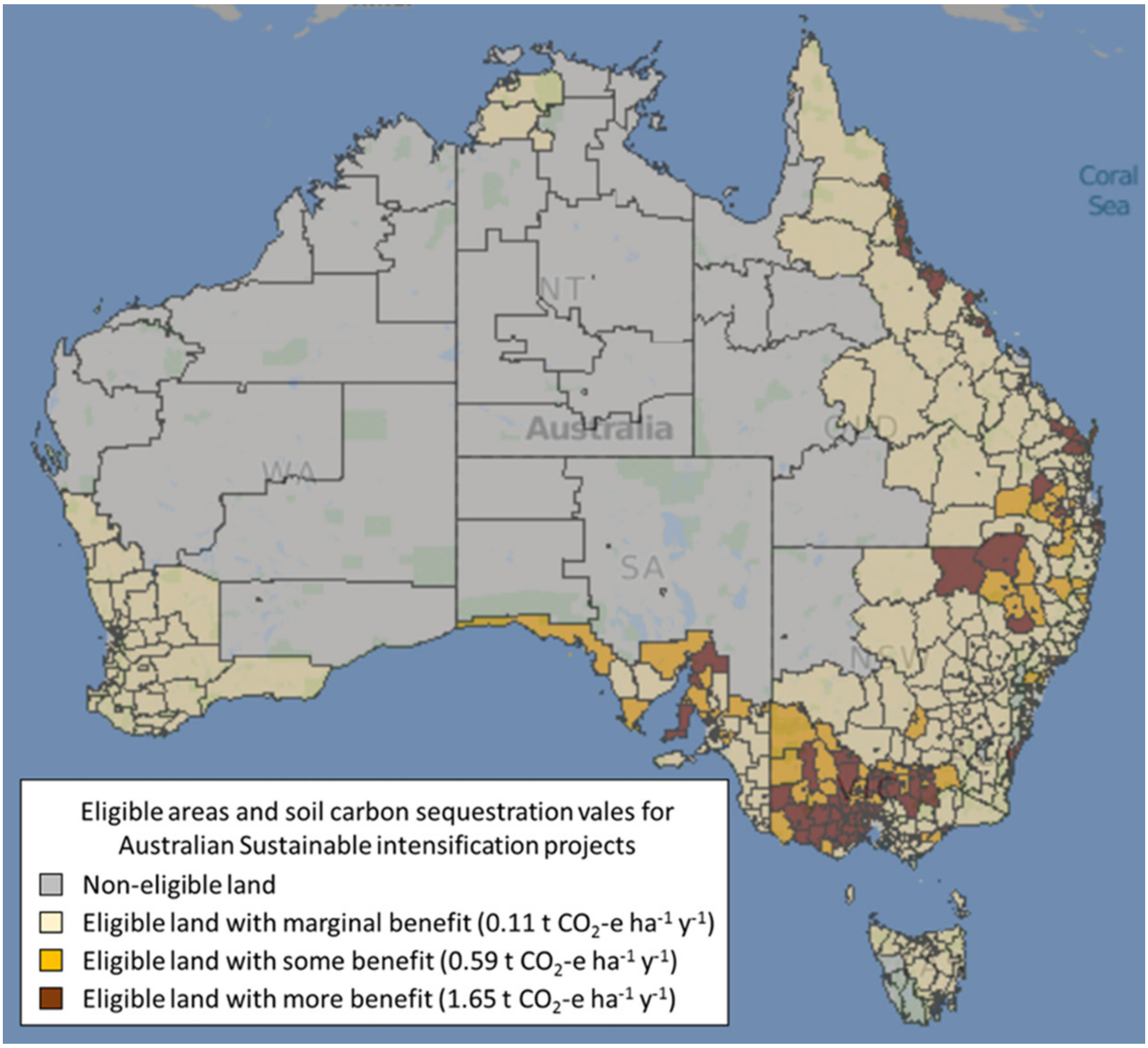

Figure 2. Delineation of eligible and non-eligible lands for sustainable intensification projects, and the areas associated with each of the three levels of soil C sequestration benefit predicted using the soil carbon component of the FullCAM simulation model. Source: Author

be found at www.environment.gov.au/climate-change/emissions-reduction-fund/methods/sequestration-carbon-modelled-abatement-estimates.

For the direct measurement approach, uncertainty associated with measured soil C stock change was addressed in two ways. First, statistical approaches were used to define the level of carbon sequestration associated with a probability of exceedance equal to 60%. This approach applied a discount to measured values, with the size of the discount being linked to the variance of measured soil carbon stock values. Additionally, to help insure against initial over-crediting until such time as a long-term trend is established, credits for any carbon sequestered between the baseline measurement and the first temporal measurement were reduced by 50%. As the number of temporal measurements increased, the potential for spatial and environmental variations to impact the derivation of carbon sequestration values diminished and a regression approach was applied in an attempt to move toward the 'true' temporal trend of soil carbon stock change associated with the applied management practices.

For the emission factor approach, the uncertainty associated with activity data and the model was determined using a Monte Carlo analysis in conjunction with the IPCC 'Approach 1' propagation of error method as described in the IPCC inventory guidelines [41] and reported in the Australian Government Submission to the UNFCCC (http://www.environment.gov.au/climate-change/climate-science-data/greenhouse-gas-measurement/publications/national-inventory-report-2016). For the emissions factors themselves, statistical analysis applied to the derived data enabled a three-class regionalization of the scenarios.

Implementing a soil carbon sequestration project using either of the methods described above may alter emissions of methane (CH_4) and/or

Table 3. **Greenhouse gases required to be included in net abatement calculations for the various potential agricultural management activities that can be implemented in carbon sequestration projects in Australia.**

Carbon pool or emission source	Greenhouse gas	Include/exclude	Justification and process for inclusion
Soil organic carbon	CO_2	Include (contained within the default sequestration values)	This is the primary emission sink associated with soil carbon sequestration projects.
Livestock	N_2O CH_4	Include	Emissions associated with enteric fermentation, dung and urine change with increases or decreases in stocking rates. Impacts of feed quality are excluded. National Greenhouse Gas Inventory emission factors are to be used.
Synthetic fertilizer	CO_2 N_2O	Include	Application of synthetic nitrogen fertilizers result in emissions of N_2O, and in the case of urea also CO_2. National Greenhouse Gas Inventory (NGGI) emission factors are to be used.
Non-synthetic organic-based fertilizers	CO_2 N_2O CH_4	Exclude	Non-synthetic fertilizers are derived from waste streams. No additional emissions are required to be accounted for since emissions from within a Carbon Estimation Area (CEA) to which they have been applied would be no greater than what would have occurred had the materials not been applied.
Agricultural lime	CO_2	Include	Application of agriculture lime has the potential to emit CO_2 as carbonates react with the soil to neutralize acidity. National Greenhouse Gas Inventory emission factors are to be used.
Irrigation energy	CO_2 N_2O CH_4	Include	Irrigating previously non-irrigated areas may involve an increase in emissions due to the consumption of diesel fuel or electricity and must be accounted for. NGGI emission factors are to be used.
Residues – decomposition	N_2O	Include	Retention of residues fromcrops will result in the emission of N_2O when they decompose. NGGI emission factors are to be used.
Residues – burning	CO_2 N_2O CH_4	Exclude CO_2 Include N_2O and CH_4	Any changes in the quantity of residue carbon not going to CO_2 will be reflected in the sequestered carbon within the soil. Net changes in N_2O and CH_4 emissions due to the removal of burning in progressing from the baseline to project conditions need to be accounted for. National Inventory Report emission factors are to be used.

nitrous oxide (N_2O) (Table 3). Changes in CH_4 and N_2O emissions must be taken into account in addition to the amount of C sequestered to derive the total net abatement provided by a project. For each of the management activities eligible under the two methods, the net abatement is calculated by considering each of the gases identified in Table 3. The calculations for emissions incurred as a result of undertaking the carbon sequestration activities are consistent with those applied in the Australian National Greenhouse Accounts.

The 2015–2016 method prioritization process resulted in an agreement that a new soil carbon method should be developed, building on the two existing soil carbon methodologies. The need was identified because there had been limited uptake of the existing soil carbon methods. This outcome was attributed to the narrow range of farming systems that were able to participate and the high costs of direct measurement. The Carbon Credits (Carbon Farming Initiative – Measurement of Soil Carbon Sequestration in Agricultural Systems) Methodology Determination 2018 seeks to overcome these limitations by introducing new components and adapting some components from the two earlier soil carbon methods. This provides proponents with the flexibility to respond to market forces, participate in the Emission Reduction Fund and continue to make land-management decisions enabling them to meet their broader business objectives.

Alberta, Canada

In 2007, the Government of Alberta became the first jurisdiction to enable agriculture offsets with an amendment of the Climate Change and Emissions Management Act (CCEMA) to require industrial facilities with emissions exceeding 100,000 tonnes per year of GHGs (CO_2-e) to report and reduce their emissions to established targets. Under the CCEMA, large industrial emitters are required to reduce their emissions by 12% below their baseline. They could pick any of three options to meet their reduction goal: emission performance credits, technology fund credits or emission offsets.

The Alberta Offset System operates under an extensive set of policies, rules and standards (Offset Quantification Protocols and Guidance Documents). to ensure that offsets are of the highest rigor and quality to meet regulated companies' requirements. The development process for protocols includes expert engagement, defensible scientific methodologies, a rigorous peer-review process, and documented transparency. A range of

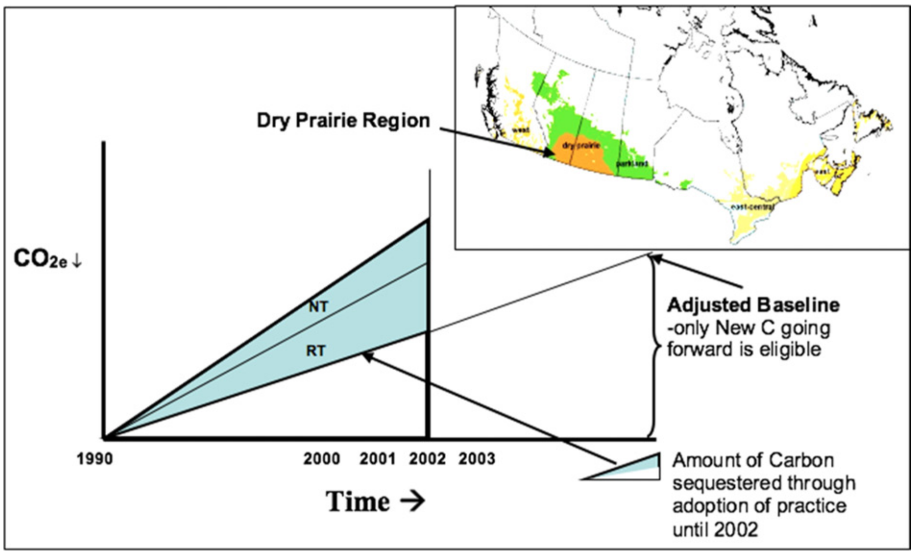

Figure 3. Schematic of the adjusted regional baseline for the Dry Prairie Region – discount based on the adoption rate of reduced till (RT) and no-till (NT) practice for the baseline year (2002). Source: Author

science-based quantification protocols were developed transparently with a technical review to help provide certainty to buyers and sellers and reduce transaction costs. All verified tonnes are serialized and are listed on a registry with oversight by the Canadian Standards Association.

The Alberta market also relies on aggregator companies, which aggregate credits from a number of sources (a group of farmers or land holders) to assemble projects large enough to interest buyers. NGOs and aggregators play a pivotal role in reducing transaction costs so that individual farms can participate in the carbon market and generate revenues. Aggregators ensure all participants adhere to the protocol terms and conditions and arrange for third-party verification of the assembled project. All aggregation and verification costs are borne by the carbon offset project developer.

The Conservation Cropping Protocol (CCP) is a 2012 revision and upgrade of the previous Tillage System Management Protocol. This protocol focuses on sequestration of additional SOC attributable to a change from conventional to no-till annual cropping practices or for reduction in summer fallow. It has been the most sought-after type of agricultural GHG project, and conservation tillage offsets have made up roughly 30% or more of the annual market share, delivering over 1.5 million tonnes of offsets since 2007.

The protocol uses Canada's National Emissions Tier II methodology, which developed soil C sequestration coefficients based on measuring and modeling local crop rotations, soil/landscape types and inter-annual climate variation for geo-specific polygons in the national eco-stratification system. This empirical model approach uses sequestration coefficients to provide a low-range estimate of increased SOC stocks that might be expected from a change from conventional to no-till practices. It presents a simplified way of estimating SOC increases based on a verified change in management practice, without direct measurement by soil sampling and analysis. Alberta's GHG regulations require that all GHGs must be considered (aggregate net CO_2-e mass). Modeling is the most efficient and cost-effective method for accounting for all GHG changes over large, diverse areas. The modeling tools are the same as those for national inventory work and are anchored with verification work using research plot data.

Eligible actions for offsets typically must be new and additional to business as usual. Since reduced tillage and no-tillage practices were already being adopted in western Canada, this proved particularly challenging. The solution was to develop a 'moving baseline' to accommodate early adopters as well as late adopters of the practice. The sequestration coefficient was discounted according to the observed rate of increase in the adoption of no-till and reduced till practices as accounted for by the national agriculture census taken every 5 years. To satisfy additionality, the quantification uses a discounted or 'adjusted baseline' to subtract out carbon accrued before the 2002 start year of the offset eligibility criteria from the more recent adoption rates of zero tillage from a region – deriving regional discounted baselines. In this manner, only the additional or incremental soil C resulting from the continuation of the practice post 2002 can count as an offset credit. Thus, the adjusted baseline is only applied to activities that sequester C on a go-forward basis (Figure 3). Thus, all tillage management projects get a 'haircut' off their carbon tonnes, but early adopters are allowed to participate to maintain the practice, and late adopters get a smaller coefficient for their C storage to satisfy additionality requirements with the adjusted baseline.

The validity of sequestered soil carbon for no-till projects in Alberta is ensured by a government-backed policy approach known as an 'assurance factor', which is applied to every tonne of carbon offset created under the protocol. Each coefficient is discounted by a percentage for the risk of management practice reversal derived for specific regions in Alberta. This fraction of the credit is set aside by the government (e.g. 10% discount on every verified tonne), resulting in 0.1 t CO_2-e collected by the government for each verified tonne. This reserve is held back to protect against soil carbon lost to the atmosphere if conventional tillage practices are resumed in the future; the reserve is operationalized through government policy.

Regardless of how good the scientific basis is, a protocol can fail for a variety of other reasons including escalating transaction and verification costs. Governments focus on science-based systems and often do not consider transaction or implementation costs when designing offset markets. To minimize risks and keep transaction costs from escalating, Alberta Agriculture and Forestry [90] has created and maintained a website to help inform industry stakeholders of rules and guidance materials for the sector. Another burden that sometimes goes unseen is the cost of verification, which does not align with discrete records of financial transactions or recording meters on factory smokestacks. Non-metered biologic systems do not conform easily to existing audit paths and expectations. Similar to designing a project with the end in mind, offset design should keep in mind the verification needs and associated costs in order to maximize revenues to the sources of project tonnes.

What do participating farmers think of all this after a decade? In late 2017 a producer survey was conducted by Team Alberta, a consortium of the wheat, canola, barley and pulse crop commodity organizations. A private survey firm pre-certified respondents with a telephone call to verify they were not a hobby or niche market farm and that they produced annual crops. A follow-up online survey questioned 339 respondents on several topics, one of which was the CCP.

Just over one third of respondents had participated in the CCP, and this proportion increased to almost half of the larger acreage respondents. Nearly three quarters of respondents were either 'satisfied' or 'somewhat satisfied'. The top three improvements suggested were better compensation for their time and effort, simplified program forms and paperwork, and a wider range of available practices.

The compliance cost for mandatory GHG reductions in Alberta was CAD$15/tonne from 2007 to 2015. As of 2018 it became an economy-wide pricing of CAD$30/tonne and is scheduled to move to CAD$50 by 2022 in alignment with new federal legislation, the Pan Canadian Framework on Clean Growth and Climate Change. The higher pricing with no expected increase in transaction costs should make offsets more practical and more attractive to agricultural producers.

A decade of experience plus new policy signals and price changes will enable agriculture to continue in a regulated GHG market and perhaps participate in more pragmatic voluntary offset markets as well as programmatic and sustainability markets for a range of industries and governments. Scientific support and evidence will be needed to fill gaps and provide assurance for future protocols and delivery models.

Saskatchewan, Canada

The Prairie Soil Carbon Balance (PSCB) project was a broad-scale feasibility assessment of direct measurement of changes in soil C stocks in response to a shift from conventional tillage to no-till, direct-seeded cropping systems in Saskatchewan [91]. Although not designed to monetize soil carbon offsets, the PSCB project was partially funded by farm organizations with an interest in securing financial recognition for GHG mitigation. In 1996, a network of 137 benchmark sites was established on commercial farm fields where a shift from conventional to no-till and direct seeding had occurred (in 1996 or 1997; Figure 4). The soil sampling and analysis strategy utilized a benchmark site approach designed for precision periodic resampling as outlined by Ellert, Janzen, and McConkey [92]. At each sampling time, six cores 7 cm in diameter were collected to a depth of 40 cm (sectioned into 10-cm depth increments). In addition to the project establishment year in 1996, soils were collected again in 1999, 2005 and 2011.

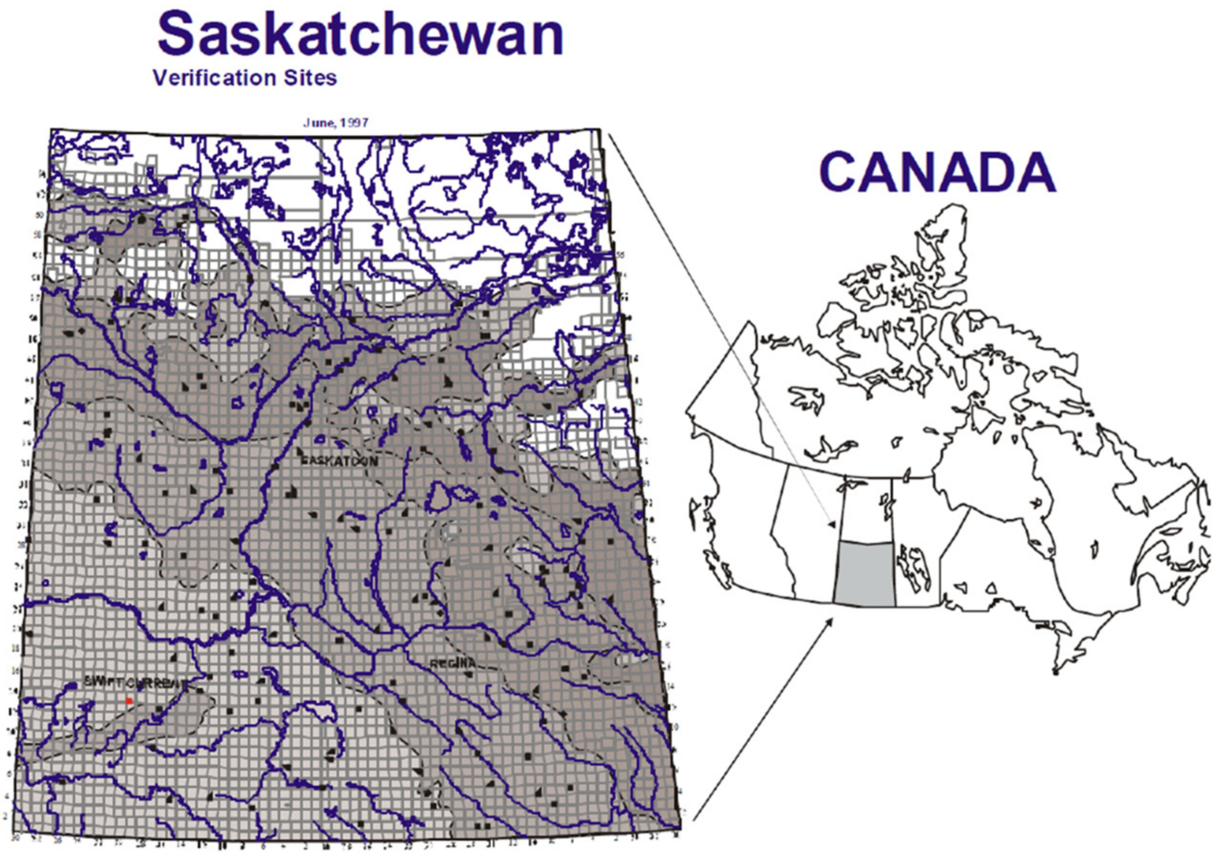

Figure 4. Locations of 137 sites established in 1996 to assess soil organic carbon change in the Prairie Soil Carbon Balance (PSCB) project. The background map depicts the major soil zones of Saskatchewan. Source: Author

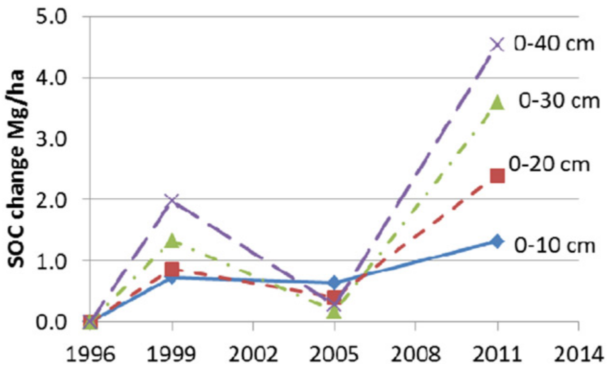

Figure 5. Changes in soil organic carbon (SOC) after adoption of no-till in 1996 (n = 80 sites available in 2011 plotted for all sampling years; 95% confidence interval typically was ± 1.5 for the 30 and 40 cm depths; ± 0.5 in 1996; adapted from [70]).

This 15-year study illustrates some of the logistical challenges of direct sampling of SOC through time. During the study, there were numerous changes in ownership or land management at the study sites and some sites were lost to attrition. In 2005, 121 of the original 137 sites were sampled, and at the last sampling in 2011, only 82 sites had the required management data and manager authorization for inclusion in the project. Additionally, because of the heterogeneity of SOC within fields (30–65 ha), it was prohibitively expensive to collect enough samples to estimate the average stock across the field.

Despite these challenges, this project yielded valuable insights into SOC dynamics. Grouping of the benchmark sites among contrasting fields provided interpretable estimates of temporal changes in SOC stocks associated with adoption of no-till, direct-seeding practices (Figure 5). The temporal changes varied among sampling intervals, and in 2005 soil C stock changes following no-till adoption were not significantly different from zero, possibly because the 2001–2003 drought reduced C inputs to a greater extent than decomposition did. However, by the 2011 sampling, SOC stocks had rebounded, and the gains in soil C attributable to no-till adoption increased with the cumulative depth or soil mass considered (Figure 5). This was contrary to the expectation that a majority of soil C accumulated under no-till would reside in the surface soil layers. Averaged over the 15-year study, no-till practices increased soil C stocks in the 0–30 cm layer by about 0.23 Mg C ha^{-1} yr^{-1}. The PSCB project indicated that increases in soil C stocks in response to the adoption of no-till practices were measurable, but estimates were best made in aggregate for 25 or more microsites distributed across several fields; otherwise, measurement costs for individual fields became prohibitive.

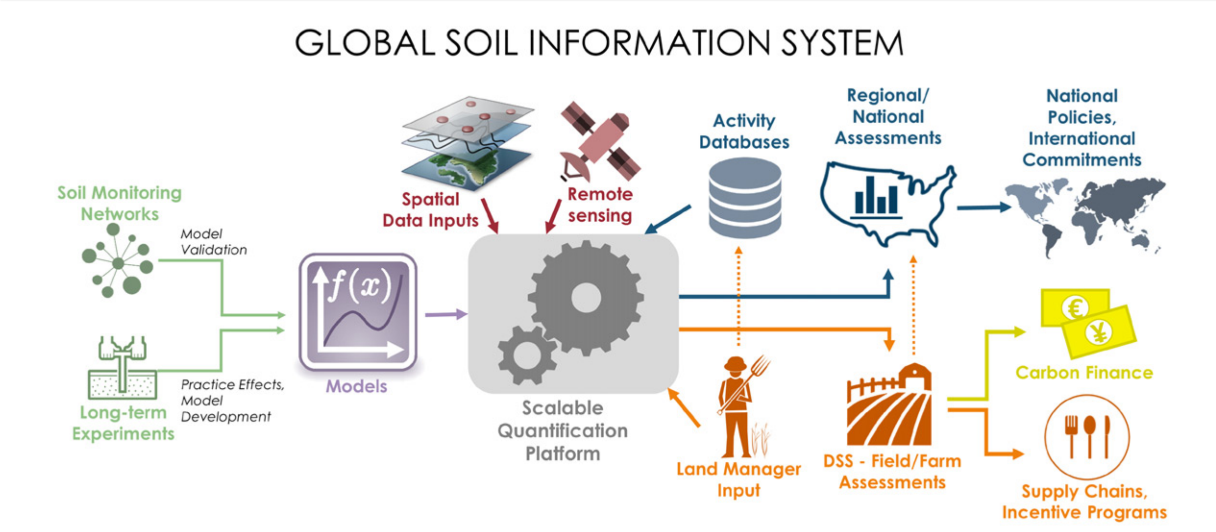

Figure 6. **Overview of the components and information flow for an approach to quantify soil carbon stock changes (and net GHG emissions) from field to national scales, purposed to support different implementation policies to remove atmospheric CO_2 and sequester soil carbon. Modified from [15]. DSS: Decision support system.**

Toward a new global soil information system

There has been substantial progress toward achieving a broader appreciation (e.g. among policymakers, environmental groups and the general public) of the key role of SOC in relation to core ecosystem services from working lands. The science is also advancing, with improved understanding of fundamental mechanisms controlling SOC dynamics as well as in measuring and modeling changes in SOC pools in response to both environmental and management factors. As a result of this progress, entrepreneurial programs and methods are being developed that can help lead the way toward a greater inclusion of soil carbon management in farmers' and ranchers' decision-making going forward.

However, to move toward an aggressive implementation of best land-use and management practices to promote soil health globally and to incentivize CO_2 removal and sequestration in soils at gigatonne-per-year scales [15,17,93], a new soil information system, with global reach and the capacity to evolve as the science advances, is needed (Figure 6).

While much of the data and many of the tools, technologies and collaborations needed already exist [85,94,95], the information is often fragmented and data availability is often limited [96]. More coordination, greater transparency and easier accessibility to the tools and data, among and between field scientists, remote sensing specialists, modelers and land managers, is needed.

Figure 6 depicts a virtual data-model quantification platform that could form the core of a new soil information system. Starting on the left-hand side of the diagram, key data sources to inform and validate SOC estimates are depicted. The utility of data from long-term field experiments to help formulate, parameterize and validate predictive models of soil carbon stock change has long been acknowledged [e.g. 20,97]; expanding the compilation of data from high-quality experiments across the globe, and making the data easily available for modelers and analysts, can accelerate the development and improvement of models [65]. Soil monitoring networks, in which periodic soil measurements are made on actual working lands, have been established in several countries [84] and can play a vital role in reducing model uncertainty [47]. However, such monitoring networks are lacking in most countries, and where the data do exist, they are often not readily available to the research community. Developing data-sharing agreements to combine country-specific SOC monitoring data sets – with appropriate safeguards to protect landowner privacy – could pave the way toward a consolidated global in-field soil monitoring network, the accessibility and utility of which could incentivize other countries to join.

Both research site data and data from distributed soil monitoring networks can feed into dynamic process-based models (such as those listed in Table 1) that predict vegetation and soil carbon dynamics and other ecosystem variables (e.g. water dynamics, GHG fluxes). Such a platform would support and facilitate the use of ensemble modeling approaches. Advantages of an ensemble approach are to provide 'central tendency' estimates from a group of models [98] and to better assess model-associated uncertainty. Ensemble modeling has become standard practice in other fields that depend heavily on model-based predictions, such as weather forecasting and integrated assessment, but has yet to be routinely deployed for soil carbon modeling [95].

Model assemblages are driven by spatially resolved data sets (Figure 6, center) including climatic variables (e.g. temperature, precipitation, solar radiation), edaphic conditions (e.g. soil texture, mineralogy, soil profile depth, topographic features) and land-use and management activity data (e.g. crop rotations, tillage, nutrient management). Provided that the models employed are generalizable over a sufficiently broad range of environmental conditions, the scale of inference for predicted variables (e.g. ΔSOC) is largely determined by the spatial resolution of the data inputs. While high-resolution soil maps and fine-scale gridded weather data sets exist for a number of countries, they are lacking for much of the tropics, which constrains the capacity to perform local-scale (i.e. sub-km^2) analyses. Continuing efforts to improve global soil mapping [99,100], particularly in the tropics, is imperative, as is making existing high-resolution soil maps (e.g. in Europe) more easily available to the research community [101].

The paucity of fine-scale management activity data (i.e. what is actually happening on the landscape) is a major constraint, even in developed countries with well-funded agricultural survey and census capacities. In the latter case, many survey efforts result in highly aggregated management activity data that have limited utility at local scales. The situation is even more challenging in developing countries lacking the resources for extensive land management and rural economic surveys, where there are almost no comprehensive data sets on management activities. However, a major breakthrough to collect detailed and local-scale management activity data is possible by engaging land users themselves in providing local-scale management activity data via a crowd-sourcing model [102]. Initial efforts using the LandPKS system [103] show promise in not only collecting management activity data but also in mobilizing local knowledge about soil characteristics at the field scale, that could provide inputs to model-based assessment.

Finally, remote sensing (RS) offers the potential to provide low cost, fine-scale and globally available data on land cover and crop species as well as information on crop residue coverage, tillage and irrigation practices, which can both supplement ground-based management activity data sources and/or be used as independent verification of land user-reported management activities. Data acquisition and analysis methods, from both satellite and airborne platforms, have been shown to be feasible for many categories of agricultural management activity data [e.g. 104,105]. However, to date many RS methods to assay agricultural practices are still in a research mode and were often applied to limited test areas and without deployment of multiple sensors [58,106]. Hence, there is a need to test promising methods more widely and then build out RS capabilities that can rapidly and routinely provide data on management practices at high spatial resolution, anywhere on the globe.

Taken collectively, dynamic models, supported by experimental and field-based monitoring data, and driven by spatially distributed soil, climate and management data – both ground-based and from remote sensing – can provide robust and low-cost quantification of soil C stock changes (and non-CO_2 GHG fluxes). A scalable system will be needed, capable of analyses at the country level, to support national policies and international agreements, as well as quantification at farm and landscape scales, to support sustainable supply-chain initiatives and/or carbon finance schemes which can directly incentivize farmers to adopt C-sequestering, soil-building and GHG-reducing practices (Figure 6, right).

The two workshops on which this paper was based, as well as recent papers and other meetings convened by government, industry, individual philanthropists and non-profit organizations, reflect a growing consensus among land managers, soil scientists, government, and technology communities of the need to build a new soil information service. Such a service would fully leverage the technological capacity to capture, curate, share and explore more granular and dynamic data and knowledge resources in a learning, deeply interactive, open system. A new soil information service must have a holistic perspective on current and future needs for land and soil resource information (e.g. across multiple scales and across all managed lands) and be nimble, pluralistic and collaborative. Recognizing that such a bold vision lies beyond the capability of any individual entity, including government, this community holds as a core value that long-term success will only be achieved through the coordinated collaboration of a diverse group of motivated stakeholders across the globe.

Acknowledgments

We gratefully acknowledge the leadership and vision of Kat Taylor and a grant from the TomKat Foundation with support from Erin Eisenberg for two workshops held in Bismarck, ND in July 2016 and Pescadero, CA in February 2017 and support to the Jahn Research Group to prepare this manuscript. We thank Liam Hutchison, Taryn Otto, Aaron Kelly, Beth Floyd and Julie Gibes for administrative support and Team Alberta for sharing their 2017 producer survey. MMJ was further supported by the NASA Harvest Consortium (Grant No. 80NSSC17K0625). KP was supported by USDA/NIFA (Grant No. 2011-67003-30205) and USDA/NRCS (Grant No. CESU-68-7482-15-507). We thank the following workshop participants who reviewed the manuscript in draft. Amjad Assi, Todd Barker, Todd Barker, Zenobia Barlow, Sarah Bell, Kevin Boyer, Renata Brillinger, Karen Brown, Sally Calhoun, Chelsea Carey, Adam Chambers, Jena Clark, Ellie Cohen, Carman Cory, Luppo Diepenbroek, Peter Donovan, Erin Eisenberg, Anya Fernald, Michael Fitzgibbon, Annie Fresquez, Jay Fuhrer, Thomas Gardali, Wendell Gilgert, Catha Groot, Mary Ellen Hannibal, Jeff Herrick, Wayne Honeycutt, Kevin Irby, Jena Kuznik, Caroline MacGill, Andrea Malmberg, Alex McBratney, Doug Millar, Wendy Millet, Kelly Mulville, Kellyx Nelson, Erik Norrel, LaKisha Odom, Esther Park, Roger Pulwarty, Ankita Raturi, Calla Rose, Richard Russel, Rebecca Shaw, Ken Spedden, Kurt Squire, Kat Taylor, Brise Tenser, Maggie Thomas, Matt Thunell, Tom Tomich, Corey Vernon, Kevin Watt, Nancy White, John Wick.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This study was funded by a generous gift from the TomKat Foundation with support in kind for two workshops held in 2016 and 2017. MMJ was supported by NASA Applied Sciences Grant No. 80NSSC17K0625 through the NASA Harvest Consortium (www.nasaharvest.org), a multi-disciplinary program that empowers informed agricultural decisions through the use of Earth observations. USDA/NRCS; USDA/NIFA.

References

1. Powlson DS, Gregory PJ, Whalley WR, et al. Soil management in relation to sustainable agriculture and ecosystem services. Food Policy. 2011;36:S72–S87. doi:10.1016/j.foodpol.2010.11.025.
2. Hopkins DW, Gregorich EG. Managing the soil–plant system for the delivery of ecosystem services. In: Gregory PJ, Nortcliff S. Soil conditions and plant growth. 2013;390–416. Blackwell Publishing Ltd.
3. Oldeman LR, Hakkeling RTA, Sombroek WG. 2017. World map of the status of human-induced soil degradation: an explanatory note. International Soil Reference and Information Centre, Wageningen, Netherlands.
4. Smith P, Lutfalla S, Riley WJ, Torn MS, Schmidt MWI, Soussana J-F. The changing faces of soil organic matter research. Eur J Soil Sci. 2018;69:23–30. doi:10.1111/ejss.12500.
5. Batjes NH. Total carbon and nitrogen in the soils of the world. Eur J Soil Sci. 1996;47:151–163. doi:10.1111/j.1365-2389.1996.tb01386.x.
6. Amundson R, Berhe AA, Hopmans JW, Olson C, Sztein AE, Sparks DL. Soil science. Soil and human security in the 21st century. Science. 2015;348:1261071. doi:10.1126/science.1261071.
7. Lal R. Restoring soil quality to mitigate soil degradation. Sustainability. 2015;7:5875–5895. doi:10.3390/su7055875.
8. Watts CW, Dexter AR. Soil friability: theory, measurement and the effects of management and organic carbon content. Eur J Soil Sci. 1998;49:73–84. doi:10.1046/j.1365-2389.1998.00129.x.
9. Beniston JW, Shipitalo MJ, Lal R, et al. Carbon and macronutrient losses during accelerated erosion under different tillage and residue management. Eur J Soil Sci. 2015;66:218–225. doi:10.1111/ejss.12205.
10. Han X, Xu C, Dungait JAJ, et al. Straw incorporation increases crop yield and soil organic carbon sequestration but varies under different natural conditions and farming practices in China: a system analysis. Biogeosciences. 2018;15:1933–1946. doi:10.5194/bg-15-1933-2018.
11. Lal R. Sequestering carbon in soils of agro-ecosystems. Food Policy. 2011;36:S33–S39. doi:10.1016/j.foodpol.2010.12.001.
12. Smith PM, Bustamante H, Ahammad H, et al. Climate Change 2014: Mitigation of climate change. Contribution of working group III to the fifth assessment report of the Intergovernmental Panel on Climate Change. In: Edenhofer O, Pichs-Madruga R, Sokona Y, et al. Forestry and other land use. 2014. IPCC, Geneva, Switzerland
13. Hansen JM, Sato P, Kharecha K, et al. Young people's burden: requirement of negative CO2 emissions. Earth Syst. Dynam. Discuss.4 October 2016:1–40. https://doi.org/10.5194/esd-2016-42.
14. Rockström J, Gaffney O, Rogelj J, et al. A roadmap for rapid decarbonization. Science. 2017;355:1269–1271. doi:10.1126/science.aah3443.
15. NASEM (National Academies of Sciences, Engineering, and Medicine). Negative emissions technologies and reliable sequestration: a research agenda. Washington, DC: The National Academies Press; 2018. doi: https://doi.org/10.17226/25259.
16. Zhao Y, Wang M, Hu S, et al. Economics- and policy-driven organic carbon input enhancement dominates soil organic carbon accumulation in Chinese croplands. Proc Natl Acad Sci USA. 2018;115:4045–4050. doi:10.1073/pnas.1700292114.
17. Paustian K, Lehmann J, Ogle S, et al. Climate-smart soils. Nature. 2016;532:49–57. doi:10.1038/nature17174.
18. Barnwell TO, Jackson RB, Elliott ET, et al. An approach to assessment of management impacts on agricultural soil carbon. Water Air Soil Pollut. 1992;64:423–435. doi:10.1007/BF00477114.

19. Paul EAK, Paustian K, Elliott ET, and Cole CV. Soil organic matter in temperate agroecosystems: Long-term experiments in North America. Am J Altern Agric. 2000;15:43–43. https://doi.org/10.1017/S0889189300008456.
20. Powlson DS. Why evaluate soil organic matter models? In: Powlson, DS, Smith, P, and Smith, J.U., editors. Evaluation of soil organic matter models. Berlin (Germany): Springer; 1996. p. 3–11. https://doi.org/10.1007/978-3-642-61094-3_1.
21. Paustian K. Modelling soil biology and biochemical processes for sustainable agriculture research. In: Pankhurst C, Doube BM, Gupta VVSR, and Grace PR, editors. Management of Soil Biota in sustainable farming systems. Melbourne (VIC): CSIRO Publ.; 1994. p. 182–196.
22. Schmidt MWI, Torn MS, Abiven S, et al. Persistence of soil organic matter as an ecosystem property. Nature. 2011;478:49–56. doi:10.1038/nature10386.
23. Dungait JAJ, Hopkins DW, Gregory AS, et al. Soil organic matter turnover is governed by accessibility not recalcitrance. Glob Change Biol. 2012;18:1781–1796. doi:10.1111/j.1365-2486.2012.02665.x.
24. Lehman RM, Cambardella CA, Stott DE, et al. Understanding and enhancing soil biological health: the solution for reversing soil degradation. Sustainability. 2015;7:988–1027. doi:10.3390/su7010988.
25. Boyer CN, Lambert DM, Larson JA, et al. Investment analysis of cover crop and no-tillage systems on Tennessee cotton. Agron J. 2018;110:331–338. doi:10.2134/agronj2017.08.0431.
26. Poffenbarger H, Artz G, Dahlke G, et al. An economic analysis of integrated crop-livestock systems in Iowa, U.S.A. Agric Syst. 2017;157:51–69. doi:10.1016/j.agsy.2017.07.001.
27. Hunt ND, Hill JD, Liebman M. Reducing freshwater toxicity while maintaining weed control, profits, and productivity: effects of increased crop rotation diversity and reduced herbicide Usage. Environ Sci Technol. 2017;51:1707–1717. doi:10.1021/acs.est.6b04086.
28. Chambers A, Lal R, Paustian K. Soil carbon sequestration potential of US croplands and grasslands: Implementing the 4 per thousand initiative. J. Soil Water Conserv. 2016;71:68A–74A. doi:10.2489/jswc.71.3.68A.
29. Steele R, Hatfield JL. Navigating climate-related challenges on working lands: a special issue by the USDA climate hubs and their partners. Clim Change. 2018;146:1–3. doi:10.1007/s10584-017-2129-3.
30. Bryant L, O'Connor C. Creating incentives to improve soil health through the federal crop insurance program. In Field, DS, Morgan, CLS, McBratney, AB, editors. Global soil security. Springer; Switzerland. 2017. p. 403–409.
31. Borrelli P, Paustian K, Panagos P, Jones A, Schutt B, Lugato E. Effect of good agricultural and environmental conditions on erosion and soil organic carbon balance: a national case study. Land Use Policy. 2016;50:408–421. doi:10.1016/j.landusepol.2015.09.033.
32. Hamrick K, Goldstein A. Raising ambition—State of the voluntary carbon markets 2016. Washington (DC): Forest Trends' Ecosystem Marketplace. http://www.forest-trends.org/documents/files/doc_5242.pdf.
33. Govaerts B, Verhulst N, Castellanos-Navarrete A, et al. Conservation agriculture and soil carbon sequestration: between myth and farmer reality. Crit Rev Plant Sci. 2009;28:97–122. doi:10.1080/07352680902776358.
34. Baldocchi DD. Assessing the eddy covariance technique for evaluating carbon dioxide exchange rates of ecosystems: past, present and future. Glob Change Biol. 2003;9:479–492. doi:10.1046/j.1365-2486.2003.00629.x.
35. Ammann C, Flechard CR, Leifeld J, et al. The carbon budget of newly established temperate grassland depends on management intensity. Agric Ecosyst Environ Greenhouse Gas Balance Grasslands Eur. 2007;121:5–20. doi:10.1016/j.agee.2006.12.002.
36. Matsuura S, Miyata A, Mano M, et al. Seasonal carbon dynamics and the effects of manure application on carbon budget of a managed grassland in a temperate, humid region in Japan. Grassl Sci. 2014. 60: 69-129. doi:10.1111/grs.12042.
37. Hirano T, Segah H, Harada T, et al. Carbon dioxide balance of a tropical peat swamp forest in Kalimantan, Indonesia. Glob Change Biol. 2007;13:412–425. doi:10.1111/j.1365-2486.2006.01301.x.
38. Nieveen JP, Campbell DI, Schipper LA, et al. Carbon exchange of grazed pasture on a drained peat soil. Glob Change Biol. 2005;11:607–618. doi:10.1111/j.1365-2486.2005.00929.x.
39. Robertson GP, Klingensmith KM, Klug MJ, et al. Soil resources, microbial activity, and primary production across an agricultural ecosystem. Ecol Appl. 1997;7:158–170. doi:10.2307/2269414.
40. Garten CT, Wullschleger SD. Soil carbon inventories under a bioenergy crop (switchgrass): measurement limitations. J Environ Qual. 1999;28:1359–1365. doi:10.2134/jeq1999.00472425002800040041x.
41. IPCC. In: Eggleston HS, Buendia L, Miwa K, Ngara T, Tanabe K, editors. 2006 IPCC guidelines for national greenhouse gas inventories. Volume 4: agriculture, forestry and other land use. Intergovernmental Panel on Climate Change. Prepared by the National Greenhouse Gas Inventories Programme. Hayama (Japan): IGES, 2006. http://www.ipcc-nggip.iges.or.jp/public/2006gl/pdf/4_Volume4/.
42. Beniston JW, DuPont ST, Glover JD, et al. Soil organic carbon dynamics 75 years after land-use change in perennial grassland and annual wheat agricultural systems. Biogeochemistry. 2014;120:37–49. doi:10.1007/s10533-014-9980-3.
43. Collier SM, Ruark MD, Naber MR, et al. Apparent stability and subtle change in surface and subsurface soil carbon and nitrogen under a long-term fertilizer gradient. Soil Sci Soc Am J. 2017;81:310–321. doi:10.2136/sssaj2016.09.0299.
44. Kravchenko AN, Robertson GP. Whole-profile soil carbon stocks: the danger of assuming too much from analyses of too little. Soil Sci Soc Am J. 2011;75:235–240. doi:10.2136/sssaj2010.0076.
45. Ellert BH, Janzen HH, Entz T. Assessment of a method to measure temporal change in soil carbon

storage. Soil Sci Soc Am J. 2002;66:1687–1695. doi: 10.2136/sssaj2002.1687.
46. Conant RT, Smith GR, Paustian K. Spatial variability of soil carbon in forested and cultivated sites. J Environ Qual. 2003;32:278–286. doi:10.2134/jeq2003.2780.
47. Spencer S, Ogle SM, Breidt FJ, et al. Designing a national soil carbon monitoring network to support climate change policy: a case example for US agricultural lands. Greenhouse Gas Meas Manage. 2011; 1:167–178. doi:10.1080/20430779.2011.637696.
48. Lark RM. Estimating the regional mean status and change of soil properties: two distinct objectives for soil survey. Eur J Soil Sci. 2009;60:748–756. doi:10.1111/j.1365-2389.2009.01156.x.
49. Conant RT, Paustian K. Spatial variability of soil organic carbon in grasslands: implications for detecting change at different scales. Environ Pollut. 2002; 116:S127–S135. doi:10.1016/S0269-7491(01)00265-2.
50. de Gruijter JJ, McBratney AB, Minasny B, et al. Farm-scale soil carbon auditing. Geoderma. 2016;265: 120–130. doi:10.1016/j.geoderma.2015.11.010.
51. Bellon-Maurel V, McBratney A. Near-Infrared (NIR) and Mid-Infrared (MIR) spectroscopic techniques for assessing the amount of carbon stock in soils—critical review and research perspectives. Soil Biol Biochem. 2011;43:1398–1410. doi:10.1016/j.soilbio.2011.02.019.
52. Shepherd KD, Walsh MG. Review: infrared spectroscopy—enabling an evidence-based diagnostic surveillance approach to agricultural and environmental management in developing countries. J Near Infrared Spectrosc. 2007;15:1–20. doi:10.1255/jnirs.716.
53. Izaurralde RC, Rice CW, Wielopolski L, et al. Evaluation of three field-based methods for quantifying soil carbon. Plos One. 2013;8:e55560. doi:10.1371/journal.pone.0055560.
54. Viscarra Rossel RA, Behrens T, Ben-Dor E, et al. A global spectral library to characterize the world's soil. Earth Sci Rev. 2016;155:198–230. doi:10.1016/j.earscirev.2016.01.012.
55. Campbell EE, Paustian K. Current developments in soil organic matter modeling and the expansion of model applications: a review. Environ Res Lett. 2015; 10:123004. doi:10.1088/1748-9326/10/12/123004.
56. Paustian KO, Andren E, Davidson H, et al. Carbon dioxide from soils. Emissions and uptake of CO2 from soils. In: Revised 1996 IPCC guidelines for national greenhouse gas inventories:. Reference Manual. 1997.(Vol 3). Chapter 5. Land use change and forestry. 5.35-50. https:www.ipcc-nggip.iges.or.jp/public/gl/invs6.html [accessed June 29, 2019}
57. Ogle SM, Conant RT, Paustian K. Deriving grassland management factors for a carbon accounting method developed by the intergovernmental panel on climate change. Environ Manage. 2004;33: 474–484. doi:10.1007/s00267-003-9105-6.
58. Ogle SM, Breidt FJ, Paustian K. Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. Biogeochemistry. 2005;72:87–121. doi:10.1007/s10533-004-0360-2.
59. Grant B, Smith WN, Desjardins R, et al. Estimated N 2 O and CO 2 emissions as influenced by agricultural practices in Canada. Climatic Change. 2004; 65: 315–332. doi:10.1023/B:CLIM.0000038226.60317.35
60. Wattenbach M, Sus O, Vuichard N, et al. The carbon balance of European croplands: A cross-site comparison of simulation models. Agriculture, Ecosystems & Environment. 2010;139:419–453. doi:10.1016/j.agee.2010.08.004
61. Jenkinson DS. The turnover of organic carbon and nitrogen in soil. Phil. Trans. Royal Soc. London B. 1990;329:361–368.
62. Falloon P, Smith P. Simulating SOC changes in long-term experiments with RothC and CENTURY: Model evaluation for a regional scale application. Soil Use and Management. 2002;18:101–111. doi:10.1079/SUM2001108.
63. Mccown RL, Hammer GL, Hargreaves J, et al. APSIM: An agricultural production system simulation model for operational research. Mathematics and Computers in Simulation. 1995;39:225–231. doi:10.1016/0378-4754(95)00063-2
64. O'Leary GJ, Liu DL, Ma Y, et al. Modelling soil organic carbon 1. Performance of APSIM crop and pasture modules against long-term experimental data. Geoderma. 2016;264:227–237. doi:10.1016/j.geoderma.2015.11.004
65. Moore AD, Eckard RJ, Thorburn PJ, et al. Mathematical modeling for improved greenhouse gas balances, agro-ecosystems, and policy development: lessons from the Australian experience. WIREs Clim Change. 2014;5:735–752. doi:10.1002/wcc.304
66. Del Grosso SJ, Parton WJ, Mosier AR, et al. Simulated interaction of carbon dynamics and nitrogen trace gas fluxes using the DAYCENT model. In: M. Schaffer, L. Ma, L.S. Hansen (Eds.) Modeling Carbon and Nitrogen Dynamics for Soil Management. 2001. CRC Press, Boca Raton, Florida, pp 303–332
67. Nocentini A, Di Virgilio N, Monti A. Model simulation of cumulative carbon sequestration by switchgrass (Panicum virgatum L.) in the Mediterranean area using the DAYCENT model. Bioenerget Res. 2015;8: 1512–1522
68. Jones JW, Hoogenboom G, Porter CH, et al. The DSSAT cropping system model. European Journal of Agronomy. 2003;18:235–265. doi:10.1016/S1161-0301(02)00107-7
69. Gijsman AJ, Hoogenboom G, Parton WJ, et al. Modifying DSSAT crop models for low-input agricultural systems using a soil organic matter–residue module from CENTURY. Agronomy J. 2002;94:462. doi:10.2134/agronj2002.4620
70. De Sanctis G, Roggero PP, Seddaiu G, et al. Long-term no tillage increased soil organic carbon content of rainfed cereal systems in a Mediterranean area. European Journal of Agronomy. 2012;40: 18–27. doi:10.1016/j.eja.2012.02.002
71. Yang M, Yang JY, Dou S, et al. Simulating the effect of long-term fertilization on maize yield and soil C/N dynamics in northeastern China using DSSAT and CENTURY-based soil model. Nutr Cycl Agroecosyst. 2013;95:287–303. doi:10.1007/s10705-013-9563-z.

72. Grant RF. Changes in soil organic matter under different tillage and rotation: Mathematical modeling in ecosystems. Soil Sci Soc Am J. 1997;61:1159–1175. doi:10.2136/sssaj1997.03615995006100040023x.
73. Grant RF, Juma NG, Robertson JA, et al. Long term changes in soil C under different fertilizer, manure and rotation: testing the mathematical model ecosys with data from the Breton Plots. Soil Sci. Soc. Am. J. 2001;65:205–214. doi:10.2136/sssaj2001.651205x.
74. Mekonnen ZA, Grant RF, Schwalm C. Sensitivity of modeled NEP to climate forcing and soil at site and regional scales: Implications for upscaling ecosystem models. Ecological Modelling. 2016;320:241–257. doi:10.1016/j.ecolmodel.2015.10.004
75. Lokupitiya E, Denning AS, Schaefer K, et al. Carbon and energy fluxes in cropland ecosystems: A model-data comparison. Biogeochemistry. 2016;129:53–76. doi:10.1007/s10533-016-0219-3
76. Apezteguia HP, Izaurralde RC, Sereno R. Simulation study of soil organic matter dynamics as affected by land use and agricultural practices in semiarid Córdoba, Argentina. Soil Tillage Research. 2009;102: 101–108. doi:10.1016/j.still.2008.07.016
77. Zhang X, Izaurralde RC, Manowitz DH, et al. Regional scale cropland carbon budgets: Evaluating a geospatial agricultural modeling system using inventory data. Environmental Modelling & Software. 2015;63: 199–216. doi:10.1016/j.envsoft.2014.10.005
78. Grace PR, Ladd JN, Robertson GP, et al. SOCRATES—A simple model for predicting long-term changes in soil organic carbon in terrestrial ecosystems. Soil Biology and Biochemistry. 2006;38: 1172–1176. doi:10.1016/j.soilbio.2005.09.013
79. Grace PR, Colunga-Garcia M, Gage SH, et al. The potential impact of agricultural management and climate change on soil organic carbon of the North Central Region of the United States. Ecosystems. 2006;9:816–827. doi:10.1007/s10021-004-0096-9
80. AG-DEE. National inventory report 2015 Volume 2. Department of the Environment and Energy. 2017.
81. US EPA. Inventory of U.S. greenhouse gas emissions and sinks: 1990-2017. Washington (DC): US Environmental Protection Agency; 2019. p. 675. (EPA 430-R-19-001).
82. Whittaker C, McManus MC, Smith P. A comparison of carbon accounting tools for arable crops in the United Kingdom. Environ Modell Softw. 2013;46: 228–239. doi:10.1016/j.envsoft.2013.03.015.
83. Paustian KM, Easter K, Brown A, et al. 2018. Field- and farm-scale assessment of soil greenhouse gas mitigation using COMET-farm. In: Delgado, JA, Sassenrath, Mueller, T. editors. Agronomy monograph: Precision conservation: geospatial techniques for agricultural and natural resources conservation. 59:361-384. Madison (WI): ASA and SSSA.
84. Wolfe ML, Richard TL. 21st century engineering for on-farm food–energy–water systems. Curr Opin Chem Eng. 2017;18:69–76. doi:10.1016/j.coche.2017.10.005.
85. van Wesemael B, Paustian K, Andrén O, et al. How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO2 fluxes in agricultural soils? Plant Soil. 2011;338: 247–259. doi:10.1007/s11104-010-0567-z.
86. Harden JW, Hugelius G, Ahlström A, et al. Networking our science to characterize the state, vulnerabilities, and management opportunities of soil organic matter. Glob Change Biol. 2018;24: e705–e718. doi:10.1111/gcb.13896.
87. Gaillard RK, Jones CD, Ingraham P, et al. Underestimation of N2O emissions in a comparison of the DayCent, DNDC, and EPIC Models. Ecol Appl. 2018;28:694–708. doi:10.1002/eap.1674.
88. Richards G, Evans D. Development of a carbon accounting model (FullCAM v1.0) for the Australian Continent. Austral For. 2004;67:277–283. doi:10.1080/00049158.2004.10674947.
89. Skjemsad JO, Spouncer L. Integrated soils modelling for the national carbon accounting system. Estimating changes in soil carbon resulting from changes in land use. Canberra: Australian Greenhouse Office; 2003. (36. National Carbon Accounting System Technical Report).
90. Alberta Agriculture and Forestry, Government of Alberta. Agricultural carbon offsets. Fact Sheet. n.d. [accessed 2017 Apr 20]. Available from: https://www1.agric.gov.ab.ca/$Department/deptdocs.nsf/all/cl11618
91. McConkey BG, Haugen-Kozyra K, Staley D. Prairie soil carbon balance project summary: soil organic carbon change on direct-seeded farmland in Saskatchewan. University of Saskatchewan. 2013. Available from: http://www.usask.ca/soilsncrops/conference-proceedings/previous_years/Files/cc2000/docs/posters/018_post.PDF
92. Ellert BH, Janzen HH, McConkey BG. Measuring and comparing soil carbon storage. Boca Raton (FL): CRC Press LLC; 2001. p. 131–146.
93. Minasny B, Malone BP, McBratney AB, et al. Soil carbon 4 per mille. Geoderma. 2017;292:59–86. doi:10.1016/j.geoderma.2017.01.002.
94. Lefèvre C, Rekik F, Alcantara V, et al. 2017. Soil organic carbon: the hidden potential. Available from: https://www.cabdirect.org/cabdirect/abstract/20173155458.
95. Soussana J-F, Lutfalla S, Ehrhardt F, et al. Matching policy and science: rationale for the '4 per 1000–soils for food security and climate' initiative. Soil Tillage Res. 2017;188:3–15. doi:10.1016/j.still.2017.12.002.
96. Smith WN, Grant BB, Campbell CA, et al. Crop residue removal effects on soil carbon: measured and inter-model comparisons. Agric Ecosyst Environ. 2012;161:27–38. doi:10.1016/j.agee.2012.07.024.
97. Paul EA, Follett RF, Leavitt SW, et al. Radiocarbon dating for determination of soil organic matter pool sizes and dynamics. Soil Sci Soc Am J. 1997;61:1058–1067. doi:10.2136/sssaj1997.03615995006100040011x.
98. Basso B, Dumont B, Maestrini B, et al. Soil organic carbon and nitrogen feedbacks on crop yields under climate change. Agric Environ Lett. 2018;3: 180026. doi:10.2134/ael2018.05.0026.
99. Grunwald S, Thompson JA, Boettinger JL. Digital soil mapping and modeling at continental scales: finding solutions for global issues. Soil Sci Soc Am J. 2011;75:1201–1213. doi:10.2136/sssaj2011.0025.

100. Hengl T, de Jesus JM, MacMillan RA, et al. SoilGrids1km-global soil information based on automated mapping. PloS One. 2014;9:e105992. doi:10.1371/journal.pone.0105992.
101. Arrouays D, Bellamy PH, Paustian K. Soil inventory and monitoring: Current issues and gaps. Eur J Soil Sci. 2009;60:721–722. doi:10.1111/j.1365-2389.2009.01193.x.
102. Paustian K. Agriculture, farmers and GHG mitigation: a new social network? Carbon Manage. 2012;3:253–257. doi:10.4155/cmt.12.23.
103. Herrick JE, Urama KC, Karl JW, et al. The global Land-Potential Knowledge System (LandPKS): supporting evidence-based, site-specific land use and management through cloud computing, mobile applications, and crowdsourcing. J Soil Water Conserv. 2013;68:5A–12A. doi:10.2489/jswc.68.1.5A.
104. NRC. Verifying greenhouse gas emissions: methods to support international climate agreements. Washington (DC): National Research Council (NRC). National Academies Press; 2010. p. 110.
105. Hively W, Lamb B, Daughtry C, et al. Mapping crop residue and tillage intensity using WorldView-3 satellite shortwave infrared residue indices. Remote Sens. 2018;10:1657. doi:10.3390/rs10101657.
106. Bégué A, Arvor D, Bellon B, et al. Remote sensing and cropping practices: a review. Remote Sens. 2018;10:99. doi:10.3390/rs10010099.
107. Li C, Frolking S, Frolking TA. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. J Geophys Res. 1992;97:9759–9776. doi:10.1029/92JD00509.
108. Li C, Frolking S, Crocker GJ, et al. Simulating trends in soil organic carbon in long-term experiments using the DNDC model. Geoderma. 1997;81:45–60. doi:10.1016/S0016-7061(97)00080-3.
109. Smith P, Smith JU, Powlson DS, et al. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. Geoderma. 1997;81:153–225. doi:10.1016/S0016-7061(97)00087-6.
110. Coleman K, Jenkinson DS, Crocker GJ, et al. Simulating trends in soil organic carbon in long-term experiments using ROTHC-26.3. Geoderma. 1997 ;81:29–44. doi:10.1016/S0016-7061(97)00079-7.
111. Cerri CEP, Easter M, Paustian K, et al. Simulating SOC changes in 11 land use change chronosequences from the Brazilian Amazon with RothC and Century models. Agric Ecosyst Environ. 2007;122: 46–57. doi:10.1016/j.agee.2007.01.007.
112. Luo Z, Wang E, Sun OJ, et al. Modeling long-term soil carbon dynamics and sequestration potential in semi-arid agro-ecosystems. Agric For Meteorol. 2011;151:1529–1544. doi:10.1016/j.agrformet.2011.06.011.
113. Del Grosso SJ, Halvorson AD, Parton WJ. Testing DayCent model simulations of corn yields and nitrous oxide emissions in irrigated tillage systems in Colorado. J Environ Qual. 2008;37:1383–1389. doi:10.2134/jeq2007.0292.
114. Del Grosso SJ, Gollany HT, Reyes-Fox M. Simulating soil organic carbon stock changes in agroecosystems using CQESTR, DayCent, and IPCC Tier 1 methods. In: Del Grosso SJ, Ahuja LR, Parton WJ, editors. Synthesis and modeling of greenhouse gas emissions and carbon storage in agricultural and forest systems to guide mitigation and adaptation. 2016. Adv Agric Syst Model. Vol 6, p. 89–110. ASA, CSSA and SSSA, Madison, WI. doi:10.2134/advagricsystmodel6.2013.0001.5.
115. Izaurralde RC, Williams JR, McGill WB, et al. Simulating soil C dynamics with EPIC: model description and testing against long-term data. Ecol. Modell. 2006;192:362–384. doi:10.1016/j.ecolmodel.2005.07.010.
116. Izaurralde RC, Haugen-Kozyra KH, Jans DC, et al. Soil organic carbon dynamics: measurement, simulation and site to region scale-up. In Lal R, Kimble JM, Follett RF, Stewart BA, editors. Assessment methods for soil carbon. Boca Raton (FL): Lewis Publishers; 2001, p. 553–575.
117. Australian Government Department of the Environment and Energy. http://www.environment.gov.au/.