PROF. PETE SMITH (Orcid ID : 0000-0002-3784-1124)

DR. LOUIS ALBERT SCHIPPER (Orcid ID : 0000-0001-9899-1276)

DR. DANIEL P. RASSE (Orcid ID : 0000-0002-5977-3863)

DR. CRISTINA ARIAS-NAVARRO (Orcid ID : 0000-0002-5125-4962)

DR. DARIO FORNARA (Orcid ID : 0000-0002-5381-0803)

Article type : Research Review

Corresponding author mail id: pete.smith@abdn.ac.uk

How to measure, report and verify soil carbon change to realise the potential of soil carbon sequestration for atmospheric greenhouse gas removal

Pete Smith[1*], Jean-Francois Soussana[2], Denis Angers[3], Louis Schipper[4], Claire Chenu[5], Daniel P. Rasse[6], Niels H. Batjes[7], Fenny van Egmond[7], Stephen McNeill[8], Matthias Kuhnert[1], Cristina Arias-Navarro[2], Jorgen E. Olesen[9], Ngonidzashe Chirinda[10], Dario Fornara[11], Eva Wollenberg[12], Jorge Álvaro-Fuentes[13], Alberto Sanz-Cobena[14], Katja Klumpp[15]

[1] Institute of Biological & Environmental Sciences, University of Aberdeen, 23 St Machar Drive, Aberdeen, AB24 3UU, UK
[2] INRA, 147 rue de l'Université 75338 Paris Cedex 07, France
[3] Agriculture and Agri-Food Canada, 2560 Hochelaga Blvd Quebec, Quebec G1V 2J3, Canada
[4] Environmental Research Institute, University of Waikato, Hamilton, Private Bag 3105, Hamilton 3240, New Zealand
[5] INRA, AgroParisTech. Bât. EGER F- 78850 Thiverval-Grignon, France
[6] Norwegian Institute of Bioeconomy Research (NIBIO), Høgskoleveien 7, 1433 Ås, Norway
[7] ISRIC - World Soil Information, Droevendaalsesteeg 3. 6708PB Wageningen, The Netherlands
[8] Manaaki Whenua - Landcare Research, PO Box 69040, Lincoln, New Zealand
[9] Department of Agroecology, Aarhus University, Blichers Allé 20, Tjele, Denmark
[10] International Center for Tropical Agriculture (CIAT), A.A. 6713, Cali, Colombia

[11] Agri-Food and Biosciences Institute, Belfast, Northern Ireland, Newforge Lane, BT9 5PX, Belfast, UK
[12] CGIAR CCAFS Programme, University of Vermont (UVM), Burlington, VT 05405, USA
[13] Soil and Water Department, Spanish National Research Council (CSIC) PO Box 13034, 50080 Zaragoza, Spain
[14] Research Center for the Management of Environmental and Agricultural Risks (CEIGRAM), Universidad Politécnica de Madrid, Madrid 28040, Spain
[15] INRA, VetAgro-Sup, UCA, Ecosystème Prairial, Clermont Ferrand, France

Key words: soil organic matter, soil organic carbon, measurement, monitoring, reporting, verification, MRV

Summary

There is growing international interest in better managing soils to increase soil organic carbon content to contribute to climate change mitigation, to enhance resilience to climate change and to underpin food security, through initiatives such as international "4p1000" initiative and the FAO's Global assessment of soil organic carbon sequestration potential (GSOCseq) programme. Since soil organic carbon content of soils cannot be easily measured, a key barrier to implementing programmes to increase soil organic carbon at large scale, is the need for credible and reliable measurement/monitoring, reporting and verification (MRV) platforms, both for national reporting and for emissions trading. Without such platforms, investments could be considered risky.

1. In this paper we review methods and challenges of measuring SOC change directly in soils, before examining some recent novel developments that show promise for quantifying SOC. We describe how repeat soil surveys are used to estimate changes in SOC over time, and how long-term experiments and space-for-time-substitution sites can serve as sources of knowledge and can be used to test models, and as potential benchmark sites in global frameworks to estimate SOC change. We briefly consider models that can be used to simulate and project change in SOC and examine the MRV platforms for soil organic carbon change already in use in various countries / regions. In the final section, we bring together the various components described in this review, to describe a new vision for a global framework for MRV of soil organic carbon change, to support national and international initiatives seeking to effect change in the way we manage our soils.

Introduction

Soil organic carbon (SOC) represents a stock of around 1500 – 2400 Gt C (~5500-8800 Gt CO_2) in the top metre of soils globally (Batjes et al., 1996; Sanderman et al., 2017). The lower estimate in the range is approximately three times the stock of carbon (C) in vegetation and twice the stock of C in the atmosphere (Smith, 2012). Small changes in C stocks can therefore have significant impacts on the atmosphere and climate change. Since the onset of agriculture around 8000 years ago (Ruddiman, 2005) soils have lost around 140-150 Gt C (~510-550 Gt CO_2; Sanderman et al., 2017) through cultivation. It is known that best management practices can restore some at least some of this lost carbon (Lal et al., 2018), so it has been suggested that soil C sequestration could be a significant greenhouse gas removal strategy (also called negative emission technology [NET], or carbon dioxide removal [CDR] option; Smith, 2016). Global estimates of soil C sequestration potential vary considerably, but a recent systematic review by Fuss et al. (2018) suggests an annual technical potential of 2-5 Gt CO_2 yr^{-1}. Estimates of economic potentials are at the lower end of this range (Smith et al., 2008; Smith, 2016).

An incomplete understanding on how SOC changes are influenced by climate, land-use, management and edaphic factors (Stockmann et al., 2013), adds complexity to designing appropriate monitoring, reporting and verification (MRV) platforms. For instance, process-level knowledge on how these variables influence changes in C stocks and fluxes remains incomplete (Bispo et al., 2017). Furthermore, the reversibility of C sequestration, when practices that retain C are not maintained, or due to climate variability or climate change, increases uncertainty in the time-frames needed to monitor SOC enhancement activities (Rumpel et al., 2019). In addition, the large background stocks, inherent spatial and temporal variability and slow soil C gains make the detection of short-term changes (e.g. 3-5 years) in SOC stocks and the design of reliable, cost effective and easy to apply MRV platforms challenging (Post et al., 1999).

In 2012, Smith et al. (2012) described a framework, building on available models, datasets and knowledge, to quantify the impacts of land use and management change on soil carbon. That paper concluded by presenting a future vision for a global framework to assess soil carbon change, based on a combination of mathematical models, spatial data to drive the models, short- and long-term data to evaluate the models, and a network of benchmarking sites to verify estimated changes. Here we review the new knowledge since then, and further develop this vision in the light of the need to provide credible and robust MRV capabilities to support the growing International and National initiatives to increase SOC, such as the International "4p1000" initiative (Chabbi et al., 2017; Rumpel et al., 2018; Rumpel et al., 2019).

We focus on methods to *measure* and/or *estimate* SOC change, but these measurement/estimation methods also form the basis of how changes in SOC can be *monitored* and *reported* at plot to national (and even global) scales, and how reported changes could be *verified*. We begin by reviewing the methods and challenges of measuring SOC change directly in soils (section 2), before examining some recent developments that show promise for quantifying SOC stocks (and therefore change) using flux measurements, non-destructive field-based spectroscopic methods and the possibility in future of estimating SOC change through earth observation / remote sensing (section 3). We then review how repeat soil surveys are used to estimate territorial changes in SOC over time (section 4), and how long-term experiments and space-for-time-substitution sites can serve as sources of knowledge and can be used to testing models, and as potential benchmark sites in global platforms to estimate SOC change (section 5). Section 6 summarises recent reviews on models available for simulating and predicting change in SOC, after which section 7 describes MRV platforms for soil organic carbon change already in use in various countries / regions. The finish the review (section 8) by describing a new vision for a global framework for MRV of soil organic carbon change to support national and international initiatives.

2. Direct measurement of SOC stock changes

Accurate estimates of SOC stocks rely strongly on baseline SOC values, which are determined by physical sampling and soil C content measurements. This approach traditionally involves the quantification of (1) fine earth (< 2 mm) and coarse mineral (> 2 mm) fractions of the soil, (2) organic carbon (OC) concentration (%) of the fine earth fraction, and (3) soil bulk density or fine earth mass (FAO, 2019a). In some instances, such as grasslands or forest soils, it may be of interest to quantify and account for the coarse fraction of belowground OC (FAO, 2019a). The challenge remains to accurately estimate the rock content of sampled soils, which can significantly affect soil bulk density (Page-Dumroese et al., 1999; Throop et al., 2012; Poeplau et al., 2017). Changes in management that influence carbon content also affect the bulk density of the soil (Haynes & Naidu, 1998), and thereby the amount of soil that is sampled within a given sampling depth. It is therefore recommended to use an 'equivalent mass basis' approach when comparing SOC stocks across land uses and different management regimes (Ellert & Bettany, 1995; Wendt & Hauser, 2013; Upson et al., 2016).

Direct measurements also rely on appropriate study designs and sampling protocols to deal with high spatial variability of SOC stocks (Minasny et al., 2017). To reduce potential sources of error in SOC stock estimation and minimize the minimum detectable difference (i.e. the smallest difference in SOC stock that can be detected as statistically significant between two sampling periods; FAO, 2019a), a large number of soil samples is often required (Garten & Wullschleger, 1999; Vanguelova et al., 2016;). Sufficient sampling depth is a crucial factor for properly evaluating changes in soil C content (IPCC recommends a minimum depth of 30 cm). Several long-term agronomy experiments suffer from an increase in ploughing depth during more recent decades, as agricultural machinery became more powerful. Insufficient information on historical sampling depth can also add uncertainty to the results.

Several methods for increasing soil C content require deeper sampling for confirming the expected effect. The positive effect of no-till on soil C content measured in the surface soil may not be apparent when measuring to 60 cm depth (Angers and Eriksen-Hamel, 2008; Blanco-Canqui & Lal, 2008). Crops with deep root phenotypes are considered a promising method to increase C sequestration in soils (Paustian et al., 2016), though demonstrating their effect requires deep soil sampling. Deeper soil sampling (100 cm) is recommended (FAO, 2019a), but often requires specific machinery and is costly.

Costs associated with collecting, processing and storing soil samples and C content measurements using, for example, common dry combustion methods (Nelson & Sommers, 1996) can make large-scale direct measurements of soil SOC stocks prohibitively expensive. It was estimated that to detect meaningful changes in soil C stocks across forest ecosystems in Finland (i.e. 3000 plots at the national scale) might cost 4 million Euro for one sampling campaign (e.g. baseline measurement from one year) and then again for the following sampling interval (e.g. 10 years later; Mäkipää et al., 2008). Thus, there is the need to evaluate these costs against the value of soil C sequestered (Smith, 2004b; Mäkipää et al., 2008) and search for trade-offs between costs involved and alternative SOC estimation methods including different modelling approaches.

A combination of direct measurements (at the plot scale) and modelling (at larger spatial scales) can greatly help defining the efficacy of different land management practices in enhancing soil C sequestration and has been used for estimating soil C change in national GHG inventory platforms (e.g. VandenBygaart et al., 2008). It is, therefore, crucial to evaluate the cost-effectiveness of measuring and sequestering C across different land uses and socio-economic conditions (Alexander et al., 2015).

3. Novel methods of measuring SOC change

3.1 Inferring SOC stock changes from flux measurements

An alternative to repeated measurements, is to draw up a full carbon budget. This indirect approach accounts for the initial uptake of carbon through photosynthesis (Gross Primary Production), its subsequent partial losses through respiration (soil, plant and litter) to give net ecosystem exchange (NEE) or net ecosystem production, and further C inputs (organic fertilisation) and outputs (harvest) to and from the system (see Soussana et al., 2010 and Smith et al., 2010). Measurements of the net balance of C fluxes exchanged (i.e. estimating NEE) can be achieved by chamber measurements or by the eddy covariance method (EC, e.g. Baldocchi, 2003). During recent decades, estimates of C sequestration from flux measurements have been reported to be comparatively uncertain due to i) necessary assumptions associated with data processing (e.g. footprint, spectral corrections, i.e. Aubinet et al., 2012), the fact that ii) this method is a point-in-space measurement, and iii) net changes in soil C pools are relatively small compared to C stored in biomass and litter when measured over short time periods (i.e. < 5year).

Despite this, recent developments in instrumentation (analyser performance and setups, e.g. Rebmann et al., 2018), data acquisition and processing (i.e. data loggers, software, QA/QC checks) have greatly improved the reliability of estimates (e.g. Fratini & Mauder 2014). Further, harmonized networks of long-term observation sites, created to provide access to standardised data, and to quantify the effectiveness of carbon sequestration and/or greenhouse gases emission at European (Integrated Carbon Observation System, ICOS, Franz et al., 2018) and global scale (FLUXNET global network, e.g. Baldocchi et al., 2018; Figure 1), have greatly reduced uncertainties in flux and supplementary measurements. Moreover, ongoing analyses on peculiarities of flux measurement likely to increase uncertainties in flux measurements, such as integration of (moving) point sources i.e. grazing animals (Felber et al., 2015, Gourlez de la Motte et al., 2019), ditches (Nugent et al., 2018), and fallow periods, have been studied thoroughly and have allowed routine data analyses to be updated (e.g. Sabbatini et al., 2018).

Concerning the comparison between C sequestration determined *via* the EC technique (i.e. full C balance) and soil C stock changes, some studies have shown poor agreement (Jones et al., 2017), but a number of studies have shown comparable estimates, when applied for time frames >10 year and with soil data including at least both top and medium soil depths (i.e. 0-60cm) (e.g. *grassland*: Leifeld et al., 2011; Skinner & Dell, 2014; Stahl et al., 2017, *cropland*: Emmel et al., 2018, Hofmann et al.2017; *forest*: Ferster et al., 2015). Coupling of eddy-covariance with soil C stock change studies has become a favoured approach to understand both short- and long-term effects of principal drivers (e.g. management, climate) on ecosystem functioning (i.e. Eugster & Merbold, 2015), *in natura* measurement and modelling approaches (e.g. Williams et al., 2009, Beer et al., 2010, Besnard et al., 2018).

3.2 Spectral methods for measuring soil organic carbon stocks

New spectral methods for measuring soil organic carbon concentration and stocks are rapidly becoming available for direct point measurements in-field and in the lab, but also for measurement of patterns at larger scales across landscapes and regions. Each comes with a specific associated accuracy and cost (Bellon-Maurel & McBratney, 2011; England & Viscarra Rossel, 2018). A smart combination of these and more traditional methods can either bring down costs (Nocita et al., 2015), provide more exhaustive spatial patterns of soil organic carbon stocks (Aitkenhead, 2017, Rosero-Vlasova et al., 2018) or provide indications for change in stocks (Li et al., 2018; Zhao et al., 2017).

The methods for measuring soil organic carbon concentration mainly rely on the reflectance of light on soil in the infrared region. The organic bonds and minerals in the soil absorb light at specific wavelengths, resulting is a soil content-specific absorbance or reflectance spectrum. This spectrum is measured with high level of spectral detail (hyperspectral, often in the lab) or limited level of detail in wider bands (multispectral, often from satellites or cheaper field instruments). Using a statistical model based on a spectral library, the soil carbon percentage can be predicted from spectral measurements of the unknown samples. The spectral library is derived from samples on which soil properties have been determined by traditional laboratory methods, such as dry combustion, alongside reflectance measurements. Relevant wavelengths for soil and soil organic carbon are mainly in the mid- (4000-600 cm^{-1}) and the near- or short-wave infrared region (2000-2500 nm). Other key soil properties can also be simultaneously determined if present in the spectral libraries, including fractions of organic carbon and vulnerability of soil carbon to loss (Baldock et al., 2013, 2018), soil texture, pH and others (Stenberg et al., 2010), which can be used inform modelling approaches. Partial Least Squares Regression (PLSR) is a statistical method that is currently most widely-used to predict soil properties from spectra. These machine learning approaches (also e.g. Cubist, Random Forests, Support Vector (regression) Machines and others) are rapidly developing, and new techniques are becoming available, currently referred to as deep learning (Padarian et al., 2018) and Memory Based Learning (Ramirez-Lopez et al., 2013; Dangal et al., 2019). These techniques, such as Locally Weighted PLS Regression, use local calibrations based on spectrally similar subsets of a spectral library. This will likely lead to considerable improvement, reducing the prediction errors. This does not resolve the inherent laboratory measurement uncertainties associated with both reference and spectral data.

Standardisation of reference laboratory methods, spectral measurements and soil data exchange to some extent negates these issues, and they are addressed in several international co-operations, one of which is Pillar 5 of the Global Soil Partnership (GSP, 2017). If standardisation and calibration transfer challenges can be solved, combining spectral libraries can provide a vast data resource for not only local, but also more regional and global SOC analyses (Viscarra Rossel et al., 2016a,b; England & Viscarra Rossel, 2018).

Laboratory costs could be reduced by using Fourier-Transform mid-infrared (MIR) diffuse reflectance spectroscopy for estimation of total carbon, organic carbon, clay content and sand fraction (Wijewardane et al., 2018; Viscarra Rossel et al., 2006). Several commercial laboratories use near-infrared (NIR) for this purpose but once a sufficient spectral library or calibration set is compiled, MIR outperforms NIR (Reeves, 2010; Viscarra Rossel et al., 2006; Vohland et al., 2014). In such studies or applications, bigger libraries are spiked or sub-selected to build local (spectral or geographical) prediction models using machine learning techniques (Janik et al., 2007). Sample preparation is very simple (dry, sieve to <2 mm, fine grind (Soil Survey Staff, 2014) and after a library is built, the measurements are fast and inexpensive, and can assess all of the listed properties at the same time (Nocita et al., 2015).

These spectral libraries can also be used to calibrate field spectrometers, although accuracy will often be lower, mostly due to moisture and surface roughness of the soil. Higher-cost *in situ* systems are available for both NIR and MIR (Dhawale et al., 2015; Hutengs et al., 2018). Alternatives are cheap in-field NIR spectrometers for point measurements (Tang et al., 2019) which tend to have low(er) accuracies due to hardware constraints and which may have bias. On-the-go systems with 2 to 5 wavelengths are on the market as well as penetrometers with VNIR, which also provide a measure for penetration resistance or compacted soil (Poggio et al., 2017; Ackerson et al., 2017; Al-Asadi & Mouazen, 2018; Wetterlind et al., 2015). A final possibility is a core sampler which measures the extracted soil core in field with VNIR and active gamma radiation for (total) bulk density (Lobsey & Viscarra Rossel, 2016).

An important property for calculating soil organic carbon stocks is soil bulk density which is difficult to measure accurately in field (Bellon-Maurel & McBratney, 2011). A method used in a number of setups is gamma attenuation. This can be measured on the extracted soil core (Lobsey & Viscarra Rossel, 2016; England & Viscarra Rossel, 2018) or directly in the soil (Jacobs et al., 2009). With this technique the attenuation by matter of gamma radiation originating from a small radioactive source is measured over a known volume between source and detector. The matter in this case consists of both soil and moisture. The volume is simulated using Monte Carlo simulations. This provides a measure of dry bulk density after correction for moisture content as measured for instance with a TDR (Jacobs et al., 2009) or VNIR (Lobsey & Viscarra Rossel, 2016).

The benefit of these techniques is the possibility to acquire more samples and/or more in-field measurements, allowing a user to address the potential of carbon sequestration of the soil adequately. Some of these techniques are most suitable for describing the spatial distribution of soil carbon, while others are suitable for quantitative estimates or monitoring (in time, allowing the impacts of management on soil carbon to be detected). Choices can be made based on cost and required accuracy of the purpose (value of information or decision analysis).

At larger scales, remote sensing offers added possibilities. This can either be by relating UAV, airplane or satellite data directly to soil properties, or by inferring changes in SOC by vegetation changes, or by using remote imagery as a covariate in digital soil mapping of SOC. Direct interpretation can be performed on hyperspectral imagery in combination with spectral libraries for direct quantification of bare soil patterns (top 1 cm) (Jaber et al., 2011; Gomez et al., 2012), or by using multivariate imagery for mapping bare soil patterns as indication of SOC or soil class differences either using raw or enhanced imagery such as by multi-temporal composites (Rogge et al., 2018; Gallo et al., 2018).

Changes in vegetation patterns visible in remote imagery can be used to detect (changes in) land use and thus infer soil properties and SOC change. Analysis of land use change, net primary productivity and soil organic carbon stocks are instrumental for identifying hotspots of SOC sequestration potential (Caspari et al., 2015; van der Esch et al., 2017).

The third option is to use satellite imagery products as covariates in digital soil mapping, where the relation between soil properties and satellite information is used to predict SOC maps at various depths using point observations and satellite imagery products (McBratney et al., 2003; Minasny & McBratney, 2016; Hengl et al., 2017).

Remote sensing offers a range of possibilities, detail and spatial scales that are not feasible with point measurements alone (Mulder et al., 2011; Ge et al., 2011). That said, a combination of remote and *in situ* or point data will remain necessary to derive high resolution and accurate SOC maps. Apart from the limited penetration depth (top 1 cm while a soil profile would be desirable), this is also due to the fact that in many regions bare soil is never visible, or areas are too often covered in clouds. At the same time, the high temporal frequency and high spatial resolution of remote imagery offers an unprecedented possibility to study and monitor space-time dynamics of SOC change if used in combination with (long term) monitoring stations (Chabrillat et al., 2019).

4. Repeated soil surveys – national / sub-national

Repeat soil sampling programmes have been conducted in a number of countries, such as England and Wales (Bellamy et al., 2005; Kirkby et al., 2005), Denmark (Heidmann et al., 2002; Taghizadeh-Toosi et al., 2014a), Belgium (Sleutel et al., 2003) and New Zealand (Schipper et al., 2014 – see below). These rely on resampling of previously sampled locations after varying periods. Advantages are that repeats sampling schemes measure actual soil carbon contents over large spatial scales and over long periods (Bellamy et al., 2005), but the main disadvantage is that land use change and land management between sampling periods are mostly unknown, making attribution of any observed changes in soil carbon to specific drivers (such as management or climate change) very difficult (Smith et al., 2007). In some cases, records of land use and management have been available allowing the effect of management changes to be assessed for better verification of modelling approaches to quantifying SOC stock changes (Taghizadeh-Toosi et al., 2014a).

Resampling of soil survey sites originally sampled in the 1970-1990s in New Zealand has played an important role in identifying changes in soil carbon stocks in grazed pastures (Schipper et al., 2014). The difficulty with these historical resampling efforts was that sites were not chosen with national survey purposes in mind, so their representativeness was questionable. Additionally, sampling efforts were not carried out uniformly over space and time, so resampling was potentially confounded by the effects of soil type, climate, and other factors. However, these data have been central to development and subsequent implementation of more robust sampling designs of grazed lands. Alongside resampling of sites impacts of management practices on carbon stock have been explored through sampling of adjacent long-term management practices (e.g., Barnett et al., 2014; Mudge et al., 2017).

In the case of Europe, differences exist in the availability of soil surveys among countries. As highlighted in the final report of the ENVASSO project, soil monitoring networks are much denser in northern and eastern European countries compared with countries located in the southern part of the continent (Kibblewhite et al., 2008). For example, countries such as France, Sweden or Poland maintain systematic soil monitoring systems at national level with different density of monitoring sites and sampling frequencies. In the case of France, different soil monitoring system levels exist which operates to either forest and non- forest areas. The Soil Quality Monitoring Network was created 20 years ago for non-forested areas, covering the main land uses in France in a 16 x 16 km grid (King et al., 2005). Similarly, in Sweden, soil monitoring is performed at two geographical levels (national and regional) and with different levels of application: forest land, integrated monitoring (areas with minor impact of forest management), intensive monitoring plots (223 forest plots) and arable land monitoring (Olsson, 2005). Poland has also different soil monitoring systems for forest and cropland soils. For the case of croplands, monitoring soils started in 1994 and since then soils have been sampled every 8 years with different soils properties measured (Bialousz et al., 2005). In Denmark, soils are sampled every 8-10 years to 1-meter depth on a regular 7-km grid covering both agricultural and forest soils (Taghizadeh-Toosi et al., 2014a).

In contrast, EU Mediterranean countries as Italy, Spain or Greece are examples of European regions where systematic national soil monitoring systems are under-developed or non-existent, despite the risks of SOC losses, and soil erosion events resulting from a combination of crop management and regional impacts of climate change (Trnka et al., 2011). For example, in the case of Italy, there is no monitoring system but there is willingness to develop it. In Spain, over the last 20 years, two independent soil national inventories have been performed; one to assess soil erosion and the other to asses soil heavy metal pollution (Ibañez et al., 2005). However, the inventories have not been linked and there is no firm schedule for future resampling yet in place.

5. Long term experiments of SOC change

Since changes in bulk soil carbon occur slowly (Smith, 2004a), long term measurements are required to show the relatively small change against the large background carbon stock. To this ends, long-term field experiments exist in various parts of the world, with some dating from the 19th century. Though many of these experiments were originally set up to examine the effects of management (often fertilization) on crop or grass yield, many have a history of measurements of soil carbon and nitrogen change. Over recent decades, results from these field experiments have been central to testing the accuracy of models of turnover of soil organic carbon. As noted by Smith et al. (2012), the long-term experiments in various parts of the world existed largely in isolation of each other, but in the 1990s, there were attempts to bring the various experiments together into shared networks (Barnett et al., 1995), with two such networks focussing on soil C; the Soil Organic Matter Network (SOMNET) and EuroSOMNET (the more-detailed European component of the larger global network) were two attempts to couple soil organic carbon models with observations from long-term experiments (Smith et al., 1997), with the aims or both testing models and the sharing, comparing and use of data from across the experiments to estimate carbon sequestration potential (Smith et al., 2000). SOMNET later evolved into an on-line, real-time inventory project with a web-site known as LTSEs, Long-Term Soil-Ecosystems Experiments, which now has collected metadata on well over 200 long-term soil experiments Richter et al. (2007), with the metadata currently hosted by the International Soil Carbon Network (iscn.fluxdata.org/partner-networks/long-term-soil-experiments/). Smith et al. (2012) showed the locations and purpose of these long-term experiments. Most (>80%) of the world's long-term field studies address agricultural research questions, and most of the field studies test agricultural questions in the temperate zone. Non-agricultural sites and experiments in the bioclimatic zones other than the temperate region are under-represented (Smith et al., 2012).

Long-term field studies have proved extremely valuable for understanding the long-term dynamics of soil organic carbon and wider issues of soil sustainability (Richter et al., 2007). In terms of monitoring, reporting and verification, the long-term experiments serve as a) a long-term record of change, b) a testbed for soil organic carbon models, c) locations where new practices could be tested and measured and d) sites where shorter term (e.g. flux measurements) could be taken to better understand shorter term processes. Such experiments could therefore form vital components of national and international monitoring, reporting and verification platforms for soil organic carbon change. Existing long-term monitoring sites are extremely valuable but do not exist in every global region, making a compelling case for starting new long-term experimental / monitoring sites in under-represented regions.

6. Models of SOC change

The soil organic matter (SOM) dynamics can be described by different mathematical formulations (Parton et al., 2015), as presented in Table 1, and different model approaches (Manzoni & Porporato, 2009; Campbell & Paustian, 2015). Most common soil organic matter (SOM) models are compartment models, which use between two and five carbon pools (Falloon & Smith, 2000). While the stability and complexity of the organic compounds is not represented explicitly in models, it is represented by varying turnover and residence times of organic carbon in different carbon pools (Stockmann et al., 2013). The residence times are controlled by the decay rate of the carbon in the different pools, which is usually described by first order kinetics (e.g. Paustian, 1994; Falloon & Smith, 2000; Parton et al., 2015). A wide range of different models show this structure, either as independent SOM model or as part of an ecosystem model, dynamic vegetation model or a general circulation model (Ostle et al., 2009; Parton et al., 2015; Campbell & Paustian, 2015). Manzoni & Porporato (2009) identified about 250 different models, but there are still new developments, as there are still unresolved challenges.

Despite the development of different approaches that allow the measurement of different carbon pools in the models (e.g. Skjemstad et al., 2004; Zimmermann et al., 2007; Janik et al., 2007), SOC pools are often still initialised in a spin-up run (Nemo et al., 2017). This is a practical approach if information about the fractionation is not available, but it relies on ideal assumptions of equilibrium (Smith et al., 2002) which impacts the results (Bruun & Jensen, 2002). Further, the residence times of most pools exceed the duration of available measurements, which makes the calibration and validation of the models difficult (Falloon & Smith, 2000; Campbell & Paustian, 2015). Additionally, not all relevant processes (e.g. priming) are represented in the models (Wutzler & Reichstein, 2013; Guenet et al., 2016). Recently, there has been a discussion about the ability of existing models to reflect changes in temperature (Conant et al., 2011; Moyano et al., 2018), which is most relevant to simulate climate change impacts (Conant et al., 2011). In short, it is not clear, if the slower, more stable pools get differently affected by temperature changes (e.g. Conant et al., 2011; Campbell and Paustian, 2015). For these and other purposes there are an increasing number of new model approaches and hypotheses (e.g. Cotrufo et al., 2013; Wieder et al., 2013; Lehmann and Kleber, 2015; Wutzler et al., 2017). Therefore, long-term data sets (section 5) are needed to test the performance of the established and the new models.

Many operational SOC models only simulate turnover and decomposition of the SOC pools and the added organic carbon (Toudert et al., 2018). These models thus rely heavy on proper estimation of carbon inputs in residues and organic amendments (manure, compost etc.) as well as on information on the biological quality of these inputs. Most modelling approaches used for inventory purposes rely on input data from harvest residues or decaying plant parts and external organic amendments. The plant C inputs are mostly derived from measured agricultural yields using simple allometric equations, where the C inputs is related linearly or non-linearly to crop yield (Keel et al., 2017). Comparison of different published approaches of estimating C input, but using the same decomposition model, have demonstrated large uncertainties in simulated changes in SOC (Keel et al., 2017). The selection of allometric functions for estimating C input is therefore a critical step in the choice of model approach. Recent research has also questioned the appropriateness of using simple allometric functions such as fixed shoot:root ratios for estimating C input (e.g. Hu et al., 2018). Rather than assuming a fixed shoot:root ratio, using a fixed amount of belowground C input depending on site and crop may provide the most robust estimate (Taghizadeh-Toosi et al., 2016, Hirte et al., 2018). This has implications for modelling application where changes in crop productivity is a main driver of C inputs.

7. What MRV platforms are currently in use

A number of greenhouse gas emission and soil carbon change quantification schemes have been developed in various parts of the world. For example, the Australian Carbon Farming Initiative/ Emission reduction fund has guidance relating to sampling and measurement of SOC and estimating and reporting SOC stock change for SOC management projects (Australian Government, 2018). In Alberta in Canada, there is a Conservation Cropping Protocol, a tool used to quantify greenhouse gas emissions reductions from conservation cropping (Alberta Government, 2012). For certain production systems (e.g. livestock production), FAO has published guidance on measuring and modelling soil carbon stocks and stock changes (FAO, 2019a). In this section, we examine methods already in use in countries participating in the Global Research Alliance of Agricultural Greenhouse Gases (GRA).

7.1 Operational soil MRV systems in use in GRA countries

We first searched the GRA publications library[1] for operational soil MRV (monitoring, reporting and verification) systems/procedures, giving limited results (e.g., Minamikawa et al., 2018). Subsequently, we searched the Web-of-Science using “((soil AND carbon) OR

[1] https://globalresearchalliance.org/publication-library/

soc) AND ((monitoring OR reporting OR verification) OR mrv)", giving 91 potential sources. Adding the GRA country names (56 as of October 2018) to the initial search reduced this to 14 papers. These studies cover parts of a country (McHenry 2009; Nerger et al., 2017; Steinmann et al., 2016; Wilson et al., 2010), consider selected agro-ecosystems or agricultural practices (Allen et al., 2010; de Gruijter et al., 2016; McHenry 2009; Scott et al., 2002; Wu et al., 2010), outline the basis for a possible national soil monitoring system (Spencer et al., 2011; Visschers et al., 2007), were discontinued due to lack of funding (Goidts et al., 2009; Taghizadeh-Toosi et al., 2014; Yagasaki & Shirato 2014) or, alternatively, concern measurement systems that are in their first (Mäkipää et al., 2002; Nijbroek et al., 2018) or second round (Orgiazzi et al., 2018; Spencer et al., 2011).

Much early work has been done in Australia (McKenzie et al., 2002), and in 2014 the Australian Government approved the first methodology for soil carbon sequestration for use at farm level (de Gruijter et al., 2016); recommended procedures of stratification and sampling, however, may vary between countries (e.g. Australia and New Zealand, see Malone et al., 2018). Overall, a lack of common procedures between (and within) countries affects the suitability of using the SOC stock as absolute indicator for monitoring changes in land quality and soil degradation, for example in relation to the SDG monitoring framework (Sims et al., 2019). Earlier reviews (Batjes & van Wesemael 2015; de Brogniez et al., 2011; Lorenz et al., 2019) also indicated that basic soil data and SOC stock change monitoring systems are not available, or inconsistent (Jandl et al., 2014), for many regions and nations. Within the GRA and the CGIAR CCAFS programme, the initial focus has been on MRV resources for the livestock sector (Wilkes et al., 2017).

There are three main approaches (experimental field-trials, chronosequence studies or paired-land use comparisons, and monitoring networks) to determine relationships between environmental and management factors, and SOC dynamics and GHG emissions (Batjes & van Wesemael 2015; McKenzie et al., 2002; Morvan et al., 2008; Spencer et al., 2011) or changes in soil quality/health (Bai et al., 2018; Leeuwen et al., 2017). An overview of long-term terrestrial soil-experiments (LTEs) is maintained by the International Soil Carbon Network, including those from a European Network of long-term studies for soil organic matter (SOMNET, Powlson et al., 1998). Examples of chronosequence studies include those carried out in Brazil (Cerri et al., 2007; de Moraes Sá et al., 2009), Ethiopia (Lemenih et al., 2005) and China (He et al., 2009), while paired-land use comparisons have been reviewed by various researchers (Bai et al., 2018; Murphy et al., 2003; Oliver et al., 2004).

Following up from the review of European soil monitoring networks (Morvan et al., 2008), the Joint Research Centre of the European Commission launched an initiative to sample the topsoil at 22,000 points of the Land Use/Cover Area Survey (LUCAS project, see Montanarella et al., 2011). The first soil sampling round (2009), based on standard sampling and analytical procedures, followed a stratified sampling design to produce representative soil samples for major landforms and types of land cover of the participating countries. A new LUCAS sampling round is presently underway, providing the basis for a longer-term monitoring system (Orgiazzi et al., 2018). Similarly, for the USA, Spencer et al. (2011) discuss the design of a national soil monitoring network for carbon on agricultural lands, including determination of sample size, allocation, and site-scale plot design. Teng et al., (2014) indicated that for accurate soil monitoring in China, it will be necessary to set up routine monitoring systems at various scales (national, provincial, and local scales), taking into consideration monitoring indicators and quality assurance.

Table 2 serves to illustrate the diversity in soil monitoring networks and sample designs in selected GRA countries. The most common sampling design for networks aimed at monitoring regional/national SOC stocks is either stratified (according to soil/land use/climate) or grid based. Large countries with a low sampling density (<1 site per 100 km^2) generally adopt a stratified design to include all important units (van Wesemael et al., 2011). The (expected) variability within these units should be determined to assess the optimal number of samples for each stratum (Brus & de Gruijter 1997; De Gruijter et al., 2006; Louis et al., 2014). Such an approach will allow a (geo)statistical analysis of SOC stock changes for the soil/land use/climate units under consideration as an alternative or test for process-based models. Continuous soil monitoring for SOC at time intervals of 10 year is often proposed as a compromise between minimum detectability of changes (Garten & Wullschleger 1999), and temporal shifts in trends (Bellamy et al., 2005; Schrumpf et al., 2011; Steinmann et al., 2016). This may be longer than the duration of many land use management projects that involve the measurement of SOC stock changes (Milne et al., 2012).

New Zealand has developed a model-based approach (Tate et al., 2005; McNeill et al., 2014) to track SOC stock changes with time assuming that SOC stock values vary by soil type, climate and land-use, and that the key driver for long-term (decadal) changes in SOC stocks are due to changes in land use, with all other changes due to soil, climate or erosion assumed constant. This country-specific (Tier 2) empirical method was initially described in (Tate et al., 2005) reflecting land-use change issues relevant to New Zealand. As further soil profile data was collected (currently 2050 profiles) the model was increasing improved (McNeill et al., 2014) adding data from specific land use classes (notably indigenous and exotic forest, cropland, horticulture, and wetlands). The approach was also refined to account for spatial autocorrelation to improve the assessment of the overall significance of land use change and reports three validation studies for the model (McNeill et al., 2014). Using low-producing grassland on a high-activity clay IPCC default soil and moist-temperate IPCC default climate class as a reference, the 0-30 cm SOC stock is 133.1 tonnes/ha, the change as a result of land use can be determined, along with the marginal significance. For example, a transition to high-producing grassland results in a change of -0.22 tonnes/ha (not significant), while a transition to perennial cropland results in a change of -19.5 tonnes/ha (significant).

While changes in national or large regional scale carbon stock measurements can be addressed using geo-statistical sampling approaches, aligned targeted approaches (such as sampling of chronosequences and paired land uses) can directly determine land use change factors, while controlling for other spatially dependent variables, i.e. they can determine the carbon gain/loss that will occur with a change in land use or management. When coupled with monitored changes in land area undergoing these changes, estimates of national scale carbon stock changes can be calculated. The change in carbons stocks determined from paired site sampling can also be used to validate interpretations derived from national scale measurements.

7.2 Methods used by GRA countries for estimating SOC changes for the "cropland remaining cropland" category in national inventories

All countries that are party to the United Nations Framework Convention on Climate Change (UNFCCC) are required to provide national inventories of emissions and removals of greenhouse gases due to human activities. The IPCC methodologies are intended to yield national greenhouse gas inventories that are transparent, complete, accurate, consistent over time, and comparable across countries. Because different countries have different capacities to produce inventories, the guidelines lay out tiers of methods for each emissions source, with higher tiers being more complex and/or resource intensive than lower tiers. In the context of agricultural greenhouse gas emissions, inventories remain the main tool connecting policy with mitigation.

Figure 2 shows the categories of methods used by GRA countries for estimating the changes in mineral soil carbon stock for the “Cropland remaining Cropland” category. Countries listed as non-annex I face major challenges with either non-existent data (15 countries do not have country specific information they can use to develop their inventory and 8 countries do not consider for SOC changes in croplands because do not have the technical capacity to monitor these sources) or a lack of relevant data (with the exception of Ghana and Malaysia) GRA non-annex I countries use a Tier 1 approach to report SOC changes associated with areas defined as Cropland land use.

On the other hand, soil C stocks are influenced by multiple factors that affect primary production and decomposition, including changes in land use and management and feedbacks between management activities, climate, and soils. However, only a few countries have taken into account cropland management activities. Table 3 provides an overview of the methods used in GRA countries for estimating carbon stock change and emissions associated with agricultural land-use and management activities on mineral soil.

There are still high levels of uncertainty in the estimates; however, uncertainties are relatively low for Annex I countries due to their well-developed statistical systems and capacity to use higher-tier methods. In contrast, national inventories of many developing countries generally have greater uncertainty and are not sufficiently rigorous to enable monitoring of emissions. For Tier 2 inventory development countries could use the expertise of other GRA members, for instance from those countries that have adopted a Tier 3 method (see Table 4) to estimate soil organic C stock changes in agricultural land.

With increased obligations for reporting on GHG emissions and Nationally Determined Contributions (NDCs) under the Paris agreement, it is important that all countries are able to estimate their GHG emissions to maximise transparency, accuracy, completeness and consistency. Improving inventories requires enhanced national capability to gather relevant activity data to develop country-specific emission factors. There is a need to improve the evidence base and to better connect governments and relevant expertise to subsequently improve the quality of agricultural NDC's and the way their achievements are reflected by national GHG inventories.

8. Proposed global soil MRV platform

The sections above describe the methods available to measure and monitor carbon, models that can be used to simulate and project changes in SOC, different types of experimental platform and data needed to test models and allow them to be run from plot to global scale, and methods / platforms that could be used to verify any simulated change in SOC (summarised in Figure 3). These form the components of a system suitable for MRV of SOC change (Figure 3).

Central to the system are benchmark sites, which could be located at existing or new long-term experiments (Figure 3, item 2; Richter et al., 2007), or could consist of well-characterised chronosequences or paired sampling sites (e.g. He et al., 2009; Oliver et al., 2004). The benchmark sites would preferably be located on representative land cover/ land use types, soil types and with representative management. At these sites, proposed practices to increase SOC could be tested in fully randomised block designs, and SOC change measured over time (measurements every few years), while measuring shorter-term processes (such as greenhouse gas emissions) more frequently (continuously with eddy covariance flux towers or frequently with automated chambers; Figure 3, item 2; Baldocchi, 2003). The same sites could be used to test novel spectral methods for measuring SOC change against traditional direct SOC measurement (England and Viscarra Rossel, 2018). Careful alignment of site selection and experimental design with other goals of land owners, managers and regulators (e.g., quantification of soil quality change or nutrient use efficiency) will promote stronger uptake of an international suite of benchmark sites with additional benefits.

Since it would be prohibitively expensive to set up benchmark sites covering all possible combinations of land use, climate, soil type and management practice, models of SOC change are required to interpolate and infer change across all combinations, and to project changes into the future, across landscapes and under novel combinations (Figure 3, item 3; e.g. Richards et al., 2017). To establish confidence that the chosen model or models are capable of accurately and reliably simulating SOC change, they need to be tested across the full range of parameter space (i.e. multiple soils types, climate zones, land use types and soil management options; Smith et al., 1997; Erhardt et al., 2018). If necessary, the models can be further developed or parameterised using data from the same long -term experiments, of from shorter-term experiments, before being evaluated again against a dataset not used in development or parameterisation (Smith & Smith, 2007).

When the model(s) are deemed to be reliable, they could be applied a) to derive IPCC tier 2 emission or SOC stock change factors, which are specific to the region and conditions represented within the region (e.g. Begum et al., 2018), or b) spatially over the whole landscape (or the entire land area of a country) using spatial databases of soil characteristics, and land cover, management and climate data (Figure 3, item 4), to directly simulate SOC change and GHG emissions, thereby delivering a tier 3 methodology to report emissions (Smith et al., 2012). Data on changes in soil management are necessary for estimating changes in SOC/GHG emissions, and this could also be provided by self-reported or farm-survey-derived activity data (Figure 3, item 5).

If self-reported activity data is used as the primary mechanism for reporting, such activity data could be verified through spot checks / farm visits or could be done using remote sensing (Figure 3, item 7), which can show, e.g. presence of bare fallow, cover crop or residue retention; Rogge et al., 2018; Gallo et al., 2018). In addition to providing a mechanism for verification of activity data, remotely-sensed earth observation products could also provide spatial data to run the SOC / GHG models. For example, earth observation can be used to estimate changes in carbon input to soils, through changes in NPP/GPP (Chen et al., 2019; Neumann & Smith, 2018), land degradation (Sims et al., 2019), and can also be used to determine land cover / land cover change (e.g. Chen et al., 2018).

Well-calibrated models, supported by measurements, can also be used to establish relationships between a management change in a particular situation (combination or soil, climate, land use and management) and a change in SOC / GHG emissions, including estimates of uncertainty (Fitton et al., 2017). This would allow activity data (Figure 3, item 5), self-reported by the farmer / land manager, to be used as the primary source of data for reporting, in place of the need to directly measure SOC of GHG emission change

(Smith, 2004b). More broadly, uncertainties and potential biases in all components of the MRV framework, including all measurements and modelling schemes, need to be addressed. For transparency, there is a need for unified protocols for such uncertainty assessments.

In terms of verification, change in SOC stocks, spatial soil monitoring networks (Figure 3, item 6) could be used to ground-truth SOC changes estimated by the tier 2 method or tier 3 model projections over time. If resampled every few years, the soil monitoring network (on a grid as shown in figure 3 item 7, e.g. Bellamy et al., 2005, or using a stratified sampling protocol; Montanarella et al., 2011) could provide independent estimates of large scale SOC change. Some basic methodological requirements and recommendations can be formulated for 'good SOC-monitoring and MRV practice' to support scientific and policy decisions (Batjes & van Wesemael 2015; Desaules et al., 2010; Morvan et al., 2008; Spencer et al., 2011). These include: (1) the provision of long-term continuity and consistency under changing boundary conditions, such as biophysical site conditions, climate change, methodologies, socio-economic setting and policy context, (2) adoption of a scientifically and politically (e.g., for GRA, UNFCCC, UNNCCD) appropriate spatial and temporal resolution for the measurements, (3) ensuring continuous quality assurance at all stages of the measurement and monitoring process, (4) measurement / observation and documentation of all potential drivers of SOC and GHG change, and (5) soil monitoring network-collated, georeferenced samples archived and the associated (harmonised) data made accessible through distributed databases to enhance the value of the collated data for multiple uses. In addition to this, soil monitoring networks should be included in a broader cross-method validation programme to ultimately permit spatially and temporally validated comparisons both within and between countries. An open-access database, where short- or long-term soil C measurements could be uploaded and shared (e.g. https://dataverse.org/ or an online collaborative platform as used in the CIRCASA project: https://www.circasa-project.eu/), would also be of great benefit for progressing a global MRV system.

As indicated, the implementation of soil monitoring networks poses several scientific, technical and operational challenges. From an operational point of view, to implement an integrated monitoring system it will be crucial to overcome initialization costs and unequal access to monitoring technologies. For developing countries, this will require international cooperation, capacity building and technology transfer (de Brogniez et al., 2011), which could be facilitated within GRA, CCAFS and similar organisations, in synergy with relevant funding mechanisms, or *via* the recently-established “Global assessment of soil organic carbon sequestration potential (GSOCseq)” programme of the UN FAO (FAO, 2019b).

While other components of a soil MRV framework could be added, the components outlined in Figure 3 could certainly fulfil all of the functions necessary for an MRV system. As seen in sections 4 to 7, the existing capacity in terms of existing benchmark sites, soil monitoring programmes and access to models in different countries varies greatly. While some countries are already using tier 2 and 3 monitoring of soil C change, others have barely begun to build capacity. Recently, the UN FAO has established a programme called “Global assessment of soil organic carbon sequestration potential (GSOCseq)” (FAO, 2019b) which aims to build this capacity internationally. Programmes such as this, could pave the way for making this proposed MRV framework a reality.

Acknowledgements

PS, JFS, CC, NB, MK, CA and JO acknowledge support from the CIRCASA project which received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement n° 774378. The input of PS also contributes to the projects: DEVIL (NE/M021327/1), Assess-BECCS (funded by UKERC) and Soils-R-GRREAT (NE/P019455/1). AS-C acknowledges support from the AGRISOST-CM project (S2018/BAA-4330) and MACSUR-JPI initiative, as well as the inspiration and support from the Spanish research networks REMEDIA and NUEVA. JA-F acknowledges support from Ministerio de Economia y Competitividad of Spain (project number AGL2017-84529-C3-1-R). The participation of NC and EW was funded as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), which is carried out with support from the CGIAR Trust Fund and through bilateral funding agreements (https://ccafs.cgiar.org/donors). JEO was funded by the Danish Ministry of Climate, Energy and Utilities as part of the SINKS2 project. LS and SM acknowledge support from the New Zealand Agricultural Greenhouse Gas Research Centre and Global Research Alliance. This paper contributes to the work of the Soil Carbon Sequestration network of the Integrative Research Group of the Global Research Alliance on Agricultural Greenhouse Gases (https://globalresearchalliance.org/). The views expressed in this document cannot be taken to reflect the official opinions of the funding organizations.

References

Ackerson, J.P., Morgan, C.L.S. & Ge, Y. (2017). Penetrometer-mounted VisNIR spectroscopy: Application of EPO-PLS to in situ VisNIR spectra. *Geoderma, 286,* 131-138.

Aitkenhead, M.J. (2017). Mapping peat in Scotland with remote sensing and site characteristics. *European Journal of Soil Science, 68,* 28-38.

Al-Asadi, R.A. & Mouazen, A.M. (2018). A prototype measuring system of soil bulk density with combined frequency domain reflectometry and visible and near infrared spectroscopy. *Computers and Electronics in Agriculture, 151,* 485-491.

Alberta Government (2012). Quantification protocol for conservation cropping (version 1.0). Available at: https://open.alberta.ca/publications/9780778596288.

Alexander, P., Paustian, K., Smith, P. & Moran, D. (2015). The economics of soil C sequestration and agricultural emissions abatement. *Soil, 1,* 331-339.

Allen, D.E., Pringle, M.J., Page, K.L. & Dalal, R.C. (2010). A review of sampling designs for the measurement of soil organic carbon in Australian grazing lands. *The Rangeland Journal, 32,* 227-246.

Andrén, O. & Kätterer, T. (1997). ICBM: The introductory carbon balance model for exploration of soil carbon balance. *Ecological Applications, 7(4),* 1226–1236.

Andrén, O. & Kätterer, T. (2001). Basic principles for soil carbon sequestration and calculating dynamic country-level balances including future scenarios. *Assessment methods for soil carbon*, 495–511.

Angers, D.A. & Eriksen-Hamel, N.S. (2008). Full-inversion tillage and organic C distribution in soil profiles: a meta-analysis. *Soil Science Society of America Journal, 72,* 1370–1374.

Aubinet, M., Vesala T. & Papale D. (2012). Eddy Covariance: A Practical Guide to Measurement and Data Analysis. DOI 10.1007/978-94-007-2351-1. Springer Dordrecht Heidelberg London New York.

Australian Government (2018). *The Supplement to the Carbon Credits (Carbon Farming Initiative—Measurement of Soil Carbon Sequestration in Agricultural Systems) Methodology*

Determination 2018. Available at: http://www.environment.gov.au/system/files/consultations/072b4825-ec0f-49d9-991e-42dfa1fbeae3/files/supplement-soil-carbon-agricultural-systems.pdf

Bai, Z., Caspari, T., Gonzalez, M.R. et al. (2018). Effects of agricultural management practices on soil quality: A review of long-term experiments for Europe and China. *Agriculture, Ecosystems & Environment, 265,* 1-7.

Baldocchi, D. (2003). Assessing the eddy covariance technique for evaluation carbon dioxide exchange rates of ecosystems: past, present and future. *Global Change Biology, 9,* 479- 492.

Baldocchi, D., Housen C. & Reichstein, M. (2018) Inter-annual variability of net and gross ecosystem carbon fluxes: A review. *Agricultural and Forest Meteorology, 249,* 520–533.

Baldock, J.A., Beare, M.H., Curtin, D. & Hawke, B. (2018). Stocks, composition and vulnerability to loss of soil organic carbon predicted using mid-infrared spectroscopy. S*oil Research, 56,* 10.1071/SR17221.

Baldock, J.A., Hawke, B., Sanderman, J. & Macdonald, L.M. (2013). Predicting contents of carbon and its component fractions in Australian soils from diffuse reflectance mid-infrared spectra. *Soil Research, 51,* 577-595.

Barnett V., Payne R. & Steiner R. (1995). *Agricultural sustainability.*, New York., John Wiley & Sons.

Barnett, A.L., Schipper, L.A., Taylor, A., Balks, M.R. & Mudge, P.L. (2014). Soil C and N contents in a paired survey of dairy and dry stock pastures in New Zealand. *Agriculture Ecosystems & Environment, 185,* 34-40.

Batjes, N.H. & Van Wesemael, B. (2015). Measuring and monitoring soil carbon In: *Soil Carbon: Science, Management and Policy for Multiple Benefits*. (eds Banwart SA, Noelmeyer E, Milne E). Wallingford (UK), CABI.

Batjes, N.H. (1996). Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science, 47,* 151-163.

Beer, C., Reichstein, M., Tomelleri, E., et al. (2010) Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate. *Science, 329,* 834-838.

Begum, K., Kuhnert, M., Yeluripati, J., Ogle, S., Parton, W., Pan, G., Cheng, K., Ali, M.A. & Smith, P. 2018. Modelling greenhouse gas emissions and mitigation potentials in fertilized paddy rice fields in Bangladesh. *Geoderma, 341,* 206-215.

Bellamy, P.H., Loveland, P.J., Bradley, R.I., Lark, R.M. & Kirk, G.J.D. (2005). Carbon losses from all soils across England and Wales 1978–2003. *Nature, 437,* 245–248.

Bellon-Maurel, V. & Mcbratney, A. (2011). Near-infrared (NIR) and mid-infrared (MIR) spectroscopic techniques for assessing the amount of carbon stock in soils – Critical review and research perspectives. *Soil Biology and Biochemistry, 43,* 1398-1410.

Besnard, S. et al. (2018) Quantifying the effect of forest age in annual net forest carbon balance. *Environmental Research Letters, 13,* 124018

Bispo, A., Andersen, L., Angers, D. A., Bernoux, M., Brossard, M., Cécillon, L., Comans, R. N. J., Harmsen, J., Jonassen, K., Lamé, F., Lhuillery, C., Maly, S., Martin, E., Mcelnea, A. E., Sakai, H., Watabe, Y. & Eglin, T.K. (2017). Accounting for carbon stocks in soils and measuring GHGs emission fluxes from soils: do we have the necessary standards? *Frontiers in Environmental Science, 5,* 41, https://doi.org/10.3389/fenvs.2017.00041, 2017.2017.00041

Blagodatsky, S. & Richter, O. (1998). Microbial growth in soil and nitrogen turnover: A theoretical model considering the activity state of microorganisms. *Soil Biology and Biochemistry, 30(13),* 1743-1755

Blanco-Canqui, H. & Rattan Lal, R. (2008). No-tillage and soil-profile carbon sequestration: An on-farm assessment. *Soil Science Society of America Journal, 72,* 693-701.

Borgen, S.K., Grønlund, A., Andrén, O., Kätterer, T., Tveito, O. E., Bakken, L.R., & Paustian, K. (2012). CO_2 emissions from cropland in Norway estimated by IPCC default and Tier 2 methods. *Greenhouse Gas Measurement and Management, 2(1),* 5–21.

Brus, D.J., De Gruijter, J.J. (1997). Random sampling for geostatistical modelling? Choosing between design-based and model-based sampling strategies for soil (with discussion). *Geoderma, 80,* 1-44.

Bruun, S., & Jensen, L. S. (2002). Initialisation of the soil organic matter pools of the Daisy model. *Ecological Modelling, 153(3),* 291–295.

Campbell, E.E., & Paustian, K. (2015). Current developments in soil organic matter modeling and the expansion of model applications: A review. *Environmental Research Letters, 10(12).* https://doi.org/10.1088/1748-9326/10/12/123004

Caspari, T., van Lynden, G. & Bai, Z.G. (2015). Land Degradation Neutrality: An Evaluation of Methods. Environmental Research of the Federal Ministry for the Environment, Nature Conservation, Building and Nuclear Safety, Project No. 46658 Report No. (UBA-FB) 002163/E.

Cerri, C.E.P., Easter, M., Paustian, K. et al. (2007). Simulating SOC changes in 11 land use change chronosequences from the Brazilian Amazon with RothC and Century models. *Agriculture, Ecosystems and Environment, 122,* 46-57.

Chabbi, A., Lehmann, J., Ciais, P., Loescher, H.W., Cotrufo, M. F., Don, A., SanClements, M., Schipper, L., Six, J., Smith, P. & Rumpel, C. (2017). The 4‰ initiative: a nexus between agriculture and climate policy to offset CO_2 emissions. Nature Climate Change 7, 307-309.

Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T. & Van Wesemael, B. (2019). Imaging spectroscopy for soil mapping and monitoring. *Surveys in Geophysics, 40,* 361-399.

Chen, C., Park, T., Wang, X.H., Piao, S.L., Xu, B.D., Chaturvedi, R.K., Fuchs, R., Brovkin, V., Ciais, P., Fensholt, R., Tømmervik, H., Bala, G., Zhu, Z., Nemani, R.R. & Myneni, R.B. (2019). China and India lead in greening of the world through land-use management. *Nature Sustainability, 2,* 122-129.

CITEPA (2019). *Rapport OMINEA - 16 ème édition*. Organisation et méthodes des inventaires nationaux des émissions atmosphériques en France.

Coleman, K. & Jenkinson, D.S. (1987). RothC - A model for the turnover of carbon in soil. Model description and users guide, ROTHC manual. Harpenden, Herts, UK.

Coleman, K. et al. (1997). Simulating trends in soil organic carbon in long-term experiments using RothC-26.3. *Geoderma, 81(1),* 29–44.

Conant, R. T., Ryan, M. G., Ågren, G. I., Birge, H. E., Davidson, E. A., Eliasson, P. E., … Bradford, M. A. (2011). Temperature and soil organic matter decomposition rates - synthesis of current knowledge and a way forward. *Global Change Biology, 17(11),* 3392–3404.

Cotrufo, M. F., Wallenstein, M. D., Boot, C. M., Denef, K., & Paul, E. (2013). The Microbial Efficiency-Matrix Stabilization (MEMS) framework integrates plant litter decomposition with soil organic matter stabilization: do labile plant inputs form stable soil organic matter? *Global Change Biology, 19(4),* 988–995.

Dangal, S., Sanderman, J., Wills, S. & Ramirez-Lopez, L. (2019). Accurate and Precise Prediction of Soil Properties from a Large Mid-Infrared Spectral Library. *Soil Systems, 3,* OI: 10.3390/soilsystems3010011.

De Brogniez, D., Mayaux, P. & Montanarella, L. (2011). Monitoring, Reporting and Verification systems for Carbon in Soils and Vegetation in African, Caribbean and Pacific countries. Luxembourg, Publications Office of the European Union.

De Gruijter, J.J., Brus, D.J., Bierkens, M.F.P. & Knottters, M. (eds) (2006). *Sampling for natural resource monitoring*. Heidelberg, Springer.

De Gruijter, J.J., Mcbratney, A.B., Minasny, B., Wheeler, I., Malone, B.P., Stockmann U. (2016). Farm-scale soil carbon auditing. *Geoderma, 265,* 120-130.,

De Moraes Sá.J.C, Cerri, C.C., Lal, R., Dick, W.A., De Cassia Piccolo, M. & Feigl, B.E. (2009). Soil organic carbon and fertility interactions affected by a tillage chronosequence in a Brazilian Oxisol. *Soil and Tillage Research, 104,* 56-64.

Del Grosso, S. & Parton, W.J. (2011). Understanding greenhouse gas emissions from agricultural management. In: *Symposium - A quarterly journal in modern foreign literatures* (Guo, L., Gunasekara, A., and McConnell, L., Eds), Washington, D.C.: American Chemical Society.

Del Grosso, S. et al. (2001). Simulated Interaction of Carbon Dynamics and Nitrogen Trace Gas Fluxes Using the DAYCENT Model. In: *Modeling carbon and nitrogen dynamics for soil management*. (Schaffer, M., Ma, L., Hansen, S., Eds), pp. 301–332, Boca Raton, Florida: CRC Press.

Desaules, A., Ammann, S. & Schwab, P. (2010) Advances in long-term soil-pollution monitoring of Switzerland. *Journal of Plant Nutrition and Soil Science, 173,* 525-535.

Dhawale, N.M., Adamchuk, V.I., Prasher, S.O., Viscarra Rossel, R.A., Ismail, A.A., Kaur, J. (2015). Proximal soil sensing of soil texture and organic matter with a prototype portable mid-infrared spectrometer. *European Journal of Soil Science, 66,* 661-669.

Ehrhardt, F., Soussana, J.F., Bellocchi, G., Grace. P., McAuliffe, R., Recous, S., Sándor, R., Smith, P., Snow, V., Migliorati, M.D.A., Basso, B, Bhatia, A., Brilli, L., Doltra, J., Dorich, C.D., Doro, L., Fitton, N., Giacomini, S.J., Grant, B., Harrison, M.T., Jones, S.K., Kirschbaum, M.U.F. , Klumpp, K., Laville, P., Léonard, J., Liebig, M., Lieffering, M., Martin, R., Massad, R.S., Meier, E., Merbold, L., Moore, A.D., Myrgiotis, V., Newton, P., Pattey, E., Rolinski, S., Sharp, J., Smith, W.N., Wu, L.H. & Zhang, Q. (2018). Assessing uncertainties in crop and pasture ensemble model simulations of productivity and N_2O emissions. *Global Change Biology 24,* e603–e616.

Ellert, B.H. & Bettany, J.R. (1995). Calculation of organic matter and nutrients stored in soils under contrasting management regimes. *Canadian Journal of Soil Science, 75,* 529–538.

Emmel, C. et al. (2018) Integrated management of a Swiss cropland is not sufficient to preserve its soil carbon pool in the long term. *Biogeosciences, 15*, 5377–5393.

England, J.R. & Viscarra Rossel, R.A. (2018). Proximal sensing for soil carbon accounting. *SOIL, 4,* 101-122,

Eugster, W. & Merbold, L. (2015). Eddy covariance for quantifying trace gas fluxes from soils, *SOIL, 1,* 187–205, 2015

Falloon, P.D., & Smith, P. (2000). Modelling refractory soil organic matter. *Biology and Fertility of Soils, 30(5),* 388–398.

FAO (2019a) Measuring and modelling soil carbon stocks and stock changes in livestock production systems – Guidelines for assessment. Version 1 – Advanced copy. Rome. 152pp.

FAO (2019b) Submission by the Food and Agriculture Organization of the United Nations (FAO) to the United Nations Framework Convention on Climate Change (UNFCCC) in relation to the Koronivia joint work on agriculture (4/CP.23) on Topics 2(b) and 2(c). https://www4.unfccc.int/sites/SubmissionsStaging/Documents/201905031649---FAO%20Submission%20on%20KJWA_2(b)_(c).pdf.

Felber, R. et al. (2015). Eddy covariance methane flux measurements over a grazed pasture: effect of cows as moving point sources. *Biogeosciences, 12,* 3925–3940

Ferster, C.J. et al. (2015). Comparison of carbon-stock changes, eddy-covariance carbon fluxes and model estimates in coastal Douglas-fir stands in British Columbia. *Forest Ecosystems, 2***,** 13.

Fitton, N., Datta, A., Cloy, J.M., Rees, R.M., Topp, C.F.E., Bell, M.J., Cardenas, L.M., Williams, J., Smith, K., Thorman, R., Watson, C.J., McGeough, K.L., Kuhnert, M., Hastings, A., Anthony, S., Chadwick, D. & Smith, P. (2017). Modelling spatial and inter-annual variations of nitrous oxide emissions from UK cropland and grasslands using DailyDayCent. *Agriculture, Ecosystems and Environment 250,* 1-11.

FLUXNET (2019). Fluxnet Datasets List. https://daac.ornl.gov/cgi-bin/dataset_lister.pl?p=9.

Franz, D. et al. (2018). Towards long-term standardised carbon and greenhouse gas observations for monitoring Europe´s terrestrial ecosystems: a review. *International Agrophysics, 32,* 439-455.

Fratini, G. & Mauder, M. (2014). Towards a consistent eddy-covariance processing: an intercomparison of EddyPro and TK3. *Atmospheric Measurement Technology, 7,* 2273–2281.

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., de Oliveira Garcia, W., Hartmann, J., Khanna, T., Koch, N., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., del Mar Zamora, M. & Minx, J.C. (2018). Negative emissions - Part 2: Costs, potentials and side effects. *Environmental Research Letters, 13,* 063002. doi: 10.1088/1748-9326/aabf9f.

Gallo, B.C., Demattê, J., Rizzo, R. et al. (2018). Multi-temporal satellite images on topsoil attribute quantification and the relationship with soil classes and geology. *Remote Sensing, 10(10)*, 1571.

Garten, C.T. & Wullschleger, S.D. (1999). Soil carbon inventories under a bioenergy crop (Switchgrass): measurement limitations. *Journal of Environmental Quality, 28,* 1359-1365.

Ge, Y., Thomasson, J.A. & Sui, R. (2011). Remote sensing of soil properties in precision agriculture: A review. *Frontiers of Earth Science, 5(3),* 229–238.

Global Soil Partnership (2017). *Implementation Plan for Pillar Five of the Global Soil Partnership, Harmonization of methods, measurements and indicators for the sustainable* *management and protection of soil resources, Providing mechanisms for the collation, analysis and exchange of consistent and comparable global soil data and information*. http://www.fao.org/global-soil-partnership/pillars-action/5-harmonization/en/

Goidts, E., Wesemael, B.V. & Van Oost, K. (2009). Driving forces of soil organic carbon evolution at the landscape and regional scale using data from a stratified soil monitoring. *Global Change Biology, 15,* 2981-3000.

Gomez, G., Lagacherie, P. & Bacha, S. (2012). Using Vis-NIR hyperspectral data to map topsoil properties over bare soils in the Cap Bon region, Tunisia. In: *Digital Sail Assessments and Beyond*. Eds: Minasny, B., Malone, B.P. & McBratney, A.B., 387-392.

Gourlez de la Motte et al., (2019). Herd position habits can bias net CO_2 ecosystem exchange estimates in free range grazed pastures. *Agricultural and Forest Meteorology, 268*, 156–168.

Guenet, B., Moyano, F. E., Peylin, P., Ciais, P., & Janssens, I. A. (2016). Towards a representation of priming on soil carbon decomposition in the global land biosphere model ORCHIDEE (version 1.9.5.2). *Geoscientific Model Development, 9(2),* 841–855. https://doi.org/10.5194/gmd-9-841-2016

Haynes, R.J. & Naidu, R. (1998). Influence of lime, fertilizer and manure applications on soil organic matter content and soil physical conditions: a review. *Nutrient Cycling in Agroecosystems, 51*, 123-137.

He, N., Wu, L., Wang, Y. & Han, X. (2009) Changes in carbon and nitrogen in soil particle-size fractions along a grassland restoration chronosequence in northern China. *Geoderma, 150,* 302-308.

Heidmann, T., Christensen, B.T. & Olesen, S.E. (2002). Changes in soil C and N content in different cropping systems and soil types. Report 81. In: Greenhouse Gas Inventories for Agriculture in the Nordic Countries (eds Petersen SO, Olesen JE), pp. 77–86. Ministry of Food, Agriculture and Fisheries, Danish Institute of Agricultural Sciences, Foulum, Denmark.

Hengl, T., Mendes De Jesus, J., Heuvelink, G.B. et al. (2017). SoilGrids250m: Global gridded soil information based on machine learning. *PLoS One, 12,* e0169748.

Hirte, J., Leifeld. J., Abiven, S. et al. (2018). Below ground carbon inputs to soil via root biomass and rhizodeposition of field-grown maize and wheat at harvest are independent of net primary productivity. *Agriculture, Ecosystems and Environment, 265,* 556-566.

Hofmann, M. et al. (2017). Detecting small-scale spatial heterogeneity and temporal dynamics of soil organic carbon (SOC) stocks: a comparison between automatic chamber-derived C budgets and repeated soil inventories. *Biogeosciences, 14,* 1003–1019.

Hu, T., Sørensen, P., Wahlström, E.M. et al. (2018). Root biomass in cereals, catch crops and weeds does not depend on aboveground biomass. *Agriculture, Ecosystems and Environment, 251,* 141-148.

Hutengs, C., Ludwig, B., Jung, A., Eisele, A. & Vohland, M. (2018). Comparison of portable and bench-top spectrometers for mid-infrared diffuse reflectance measurements of soils. *Sensors (Basel), 18(4),* pii: E993. doi: 10.3390/s18040993.

Ibáñez, J.J., Sánchez Díaz, J., de Alba, S., López Arias, M. & Bioxadera, J. (2005). Collection of soil information in Spain: A review in 2003. In: *Soil Resources of Europe, second edition*. Eds: R.J.A. Jones, B. Houšková, P. Bullock and L. Montanarella. European Soil Bureau Research Report No.9, EUR 20559 EN, Office for Official Publications of the European Communities, Luxembourg, 357-363.

Jaber, S.M., Lant, C.L. & Al-Qinna, M.I. (2011). Estimating spatial variations in soil organic carbon using satellite hyperspectral data and map algebra. *International Journal of Remote Sensing*, *32*, 5077-5103.

Jacobs, W., Eelkema, M., Limburg, H. & Winterwerp, J.C. (2009). A new radiometric instrument for in situ measurements of physical sediment properties. *Marine and Freshwater Research, 60(7),* doi: 10.1071/MF08056.

Jandl, R., Rodeghiero, M., Martinez, C. et al. (2014). Current status, uncertainty and future needs in soil organic carbon monitoring. *Science of The Total Environment, 468–469,* 376-383.

Janik, L.J., Skjemstad, J.O., Shepherd, K.D. & Spouncer, L.R. (2007). The prediction of soil carbon fractions using mid-infrared-partial least square analysis. *Soil Research, 45(2),* 73-81.

Jenkinson, D.S. & Rayner, J.H. (1977). The turnover of soil organic matter in some of the Rothamsted classical experiments. *Soil Science, 123,* 298-305

Jones, S.K. et al. (2017). The nitrogen, carbon and greenhouse gas budget of a grazed, cut and fertilised temperate grassland. *Biogeosciences, 14,* 2069–2088.

Keel, S.G., Leifeld, J., Mayer, J. et al. (2017). Large uncertainty in soil carbon modelling related to carbon input calculation method. *European Journal of Soil Science 117,* 953-963.

Kibblewhite, M.G., Jones, R.J.A., Montanarella, L., Baritz, R., Huber, S., Arrouays, D., Micheli, E. & Stephens, M. (2008). *Environmental Assessment of Soil for Monitoring Volume VI: Soil Monitoring System for Europe*. EUR 23490 EN/6, Office for the Official Publications of the European Communities Luxembourg, 72pp.

Kirkby, K.J., Smart, S.M., Black, H.I.J., Bunce, R.G.H., Corney, P.M. & Smithers, R.J. (2005). *Long term ecological change in British woodland (1971–2001)*. English Nature Research Report 653.

Lal, R., Smith, P., Jungkunst, H., Mitsch, W., Lehmann, J., Nair, P.K., McBratney, A., Sá, J., Schneider, J., Zinn, Y., Skorupa, A., Zhang, H., Minasny, B., Srinivasrao, C. & Ravindranath, N.H. 2018. The carbon sequestration potential of terrestrial ecosystems. *Journal of Soil and Water Conservation, 73,* 145A-152A.

Leeuwen, J.P.V., Saby, N.P.A., Jones, A. et al. (2017). Gap assessment in current soil monitoring networks across Europe for measuring soil functions. *Environmental Research Letters, 12*, 124007.

Lehmann, J. & Kleber, M. (2015). The contentious nature of soil organic matter. *Nature, 528,* 60–68.

Leifeld, J. et al., (2011). budget to detect soil carbon stock changes afterconversion from cropland to grasslands. *Global Change Biology, 17,* 3366–3375.

Lemenih, M., Karltun, E. & Olsson, M. (2005). Soil organic matter dynamics after deforestation along a farm field chronosequence in southern highlands of Ethiopia. *Agriculture, Ecosystems & Environment, 109,* 9-19.

Li, W., Ciais, P., Guenet, B. et al. (2018). Temporal response of soil organic carbon after grassland-related land-use change. *Global Change Biology, 24,* 4731-4746.

Liping, C., Yujun, S., Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE 13(7),* e0200493. https://doi.org/10.1371/journal.pone.0200493.

Liski, J., Perruchoud, D. & Karjalainen, T. (2002). Increasing carbon stocks in the forest soils of western Europe. *Forest Ecology and Management, 169(1),* 159–175.

Lobsey, C.R. & Viscarra Rossel, R.A. (2016). Sensing of soil bulk density for more accurate carbon accounting. *European Journal of Soil Science*, 67, 504-513.

Lorenz, K., Lal, R. & Ehlers, K. (2019). Soil organic carbon stock as an indicator for monitoring land and soil degradation in relation to United Nations' Sustainable Development Goals. *Land Degradation & Development*, *30(7),* 824-838.

Louis, B.P., Saby, N.P.A., Orton, T.G. et al. (2014). Statistical sampling design impact on predictive quality of harmonization functions between soil monitoring networks. *Geoderma, 213,* 133-143.

Mäkipää, R., Häkkinen, M., Muukkonen, P. & Peltoniemi, M. (2008). The costs of monitoring changes in forest soil carbon stocks. *Boreal Environmental Research 13 (suppl. B),* 120–130.

Mäkipää, R., Liski, J., Guendehou, S., Malimbwi, R. & Kaaya, A. (2002). *Soil carbon monitoring using surveys and modelling - General description and application in the United Republic of Tanzania*. 46pp. FAO Forestry Paper 168, Rome, FAO. http://www.fao.org/forestry/32545-078ade939238335dea8570f134cd68fca.pdf.

Malone, B., Hedley, C., Roudier, P., Minasny, B., Jones, E. & Mcbratney, A.B. (2018). Auditing on-farm soil carbon stocks using downscaled national mapping products: Examples from Australia and New Zealand. *Geoderma Regional*, *13,* 1-14.

Manzoni, S. & Porporato, A. (2009). Soil carbon and nitrogen mineralization: Theory and models across scales. *Soil Biology and Biochemistry, 41(7),* 1355–1379.

Matthews, R. et al. (2014). *Changes to the representation of forest land and associated land-use changes in the 1990-2012 UK Greenhouse Gas Inventory*. Report to Department of Energy and Climate Change, Contract GA0510, Edinburgh.

Mcbratney, A.B., Mendonça Santos, M.L. & Minasny, B. (2003). On digital soil mapping. *Geoderma, 117,* 3-52.

McConkey, B.G., Angers, D.A., Bentham, M., Boehm, M., Brierley, T., Cerkowniak, D., … Worth, D. (2014). *Canadian agricultural greenhouse gas monitoring, accounting and reporting system. Methodology and greenhouse gas estimates for agricultural land in the LULUCF sector*. Agriculture and Agri-Food Canada. Ottawa, Canada.

McHenry, M.P. (2009). Farm soil carbon monitoring developments and land use change: unearthing relationships between paddock carbon stocks, monitoring technology and new market options in Western Australia. *Mitigation and Adaptation Strategies for Global Change, 14,* 497-512.

Mckenzie, N., Henderson, B., Mcdonald, W. (2002). *Monitoring Soil Change: Principles and practices for Australian conditions*. 112 pp. CSIRO Land & Water, CSIRO Mathematical & Information Sciences, National Land and Water Resources Audit. http://www.clw.csiro.au/publications/technical2002/tr18-02.pdf.

McNeill, S.J.E., Golubiewski, N. & Barringer, J. (2014). Development and calibration of a soil carbon inventory model for New Zealand. *Soil Research, 52(8),* 789-804.

Metherell, A. K. et al. (1993). *CENTURY Soil Organic Matter Model Environment. Agroecosystem version 4.0. Technical documentation*. GPSR Tech. Report No. 4, USDA/ARS. FT. Collins, CO. https://www2.nrel.colostate.edu/projects/century/MANUAL/html_manual/man96.html#CONTENTS.

Milne, E., Neufeldt, H., Smalligan, M. et al. (2012). *Methods for the quantification of emissions at the landscape level for developing countries in smallholder contexts*. CCAFS Report 9. 59 pp, Copenhagen (DK), CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). https://hdl.handle.net/10568/24835.

Minamikawa, K., Yamaguchi, T., Tokida, T., Sudo, S. & Yagi, K. (2018). *Handbook of monitoring, reporting, and verification for a greenhouse gas mitigation project with water management in irrigated rice paddies*. 42 pp., Tsukuba (Japan), Institute for Agro-Environmental Sciences, NARO. https://www.naro.affrc.go.jp/publicity_report/publication/files/MRV_guidebook.pdf.

Minasny, B. & Mcbratney, A.B. (2016). Digital soil mapping: A brief history and some lessons. *Geoderma, 264,* 301-311.

Minasny, B., Malone, B.P., McBratney, A.B., Angers, D.A., Arrouays, D., Chambers, A., et al. (2017). Soil carbon 4 per mille. *Geoderma, 292,* 59-86.

Montanarella, L., Tóth, G. & Jones, A. (2011). Soil component in the 2009 LUCAS Survey. In: *Land quality and land use information in the European Union*. (eds Tóth G, Németh T), Luxembourg, Publication Office of the European Union. doi: 10.2788/40725.

Morvan, X., Saby, N.P.A., Arrouays, D. et al. (2008). Soil monitoring in Europe: A review of existing systems and requirements for harmonisation. *Science of The Total Environment, 391,* 1-12.

Moxley, J., Anthony, S., Begum, K., Bhogal, A., Buckingham, S., Christie, P., … Yeluripati, J. (2014). *Capturing Cropland and Grassland Management Impacts on Soil Carbon in the UK LULUCF Inventory*. Contract Report prepared for the Department for Environment, Food and Rural Affairs Project SP1113. http://sciencesearch.defra.gov.uk/Default.aspx?Menu=Menu&Module=More&Location=None&Completed=0&ProjectID=18355

Moyano, F. E., Vasilyeva, N. & Menichetti, L. (2018). Diffusion limitations and Michaelis–Menten kinetics as drivers of combined temperature and moisture effects on carbon fluxes of mineral soils. *Biogeosciences, 15(16),* 5031–5045.

Mudge, P.L., Kelliher, F.M., Knight, T., O'Connell, D., Fraser, S. & Schipper, L.A. (2017). Irrigating grazed pasture decreases soil carbon and nitrogen stocks. *Global Change Biology, 23,* 945–954.

Mulder, V.L., De Bruin, S., Schaepman, M.E. & Mayr, T.R. (2011). The use of remote sensing in soil and terrain mapping — A review. *Geoderma, 162,* 1-19.

Murphy, B., Rawson, A., Ravenscroft, L., Rankin, M., Millard, R. (2003). *Paired site sampling for soil carbon estimation - New South Wales*. 360 pp., Canberra, Australian Greenhouse Office. http://www.fullcam.com/FullCAMServer/Help/reps/TR34%20Paired%20Site%20Sampling%20for%20Soil%20Carbon%20Estimation%20-%20New%20South%20Wales.pdf

Nayak, A.K., Rahman, M.M., Naidu, R., Dhal, B., Swain, C.K., Nayak, A.D., Tripathi, R., Shahid, M., Islam, M.R. & Pathak, H. (2019). Current and emerging methodologies for estimating carbon sequestration in agricultural soils: A review. *Science of the Total Environment, 665,* 890-912.

Nelson, D.W. & Sommers, L.E. (1996). Total carbon, organic carbon, and organic matter. In: Sparks, D.L., et al. (Eds.) Methods of soil analysis. Part 3. Chemical Methods, SSSA Book Series No. 5, SSSA and ASA, Madison, WI. pp. 961-1010.

Nemo, Klumpp, K., Coleman, K., Dondini, M., Goulding, K., Hastings, A., … Smith, P. (2017). Soil organic carbon (SOC) equilibrium and model initialisation methods: an application to the Rothamsted carbon (RothC) model. *Environmental Modeling & Assessment, 22(3),* 215–229.

Nerger, R., Funk, R., Cordsen, E., Fohrer, N. (2017). Application of a modeling approach to designate soil and soil organic carbon loss to wind erosion on long-term monitoring sites (BDF) in Northern Germany. *Aeolian Research, 25,* 135-147.

Nijbroek, R., Piikki, K., Söderström, M., Kempen, B., Turner, K., Hengari, S. & Mutua, J. (2018). Soil organic carbon baselines for land degradation neutrality: map accuracy and cost tradeoffs with respect to complexity in Otjozondjupa, Namibia. *Sustainability, 10,* 1610.

Nocita, M., Stevens, A. & Van Wesemael, B. et al. (2015). Soil spectroscopy: an alternative to wet chemistry for soil monitoring. *Advances in Agronomy, 132,* 139-159.

Nugent, K.A., Strachan, I.B., Strack, M, Roulet, N.T & Rochefort, L. (2018). Multi - year net ecosystem carbon balance of a restored peatland reveals a return to carbon sink. *Global Change Biology, 24,* 5751-5768.

Ogle, S.M., Breidt, F.J., & Paustian, K. (2006). Bias and variance in model results associated with spatial scaling of measurements for parameterization in regional assessments. *Global Change Biology, 12(3),* 516–523.

Ogle, S.M., Breidt, F.J., Eve, M.D., & Paustian, K. (2003). Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997. *Global Change Biology, 9(11),* 1521–1542.

Oliver, G.R., Beets, P.N., Garrett, L.G., Pearce, S.H., Kimberly, M.O., Ford-Robertson, J.B. & Robertson, K.A. (2004). Variation in soil carbon in pine plantations and implications for monitoring soil carbon stocks in relation to land-use change and forest site management in New Zealand. *Forest Ecology and Management, 203,* 283-295.

Olsson, M. (2005). Soil survey in Sweden. In: *Soil Resources of Europe, second edition*. (R.J.A. Jones, B. Houšková, P. Bullock and L. Montanarella, Eds). European Soil Bureau Research Report No.9, EUR 20559 EN, Office for Official Publications of the European Communities, Luxembourg. pp. 357-363.

Orgiazzi, A., Ballabio, C., Panagos, P., Jones, A. & Fernández-Ugalde, O. (2018). LUCAS Soil, the largest expandable soil dataset for Europe: a review. *European Journal of Soil Science, 69,* 140-153.

Ostle, N.J., Smith, P., Fisher, R., Woodward, F.I., Fisher, J.B., Smith, J.U., Galbraith, D., Levy, P., Meir, P., McNamara, N.P. & Bardgett, R.D. (2009). Integrating plant–soil interactions into global carbon cycle models. *Journal of Ecology, 97,* 851–863.

Padarian, J., Minasny, B. & Mcbratney, A.B. (2019). Using deep learning to predict soil properties from regional spectral data. *Geoderma Regional, 16,* e00198.

Page-Dumroese, D.S., Jurgensen, M.F., Brown, R.E. & Mroz, G.D. (1999). Comparison of methods for determining bulk densities of rocky soils. *Soil Science Society American Journal, 63,* 379–383.

Palosuo, T., Heikkinen, J. & Regina, K. (2015). Method for estimating soil carbon stock changes in Finnish mineral cropland and grassland soils. *Carbon Management, 6(5–6),* pp. 207–220.

Parton, W.J. et al. (1987). Analysis of factors controlling soil organic matter levels in Great Plains grasslands 1. *Soil Science Society of America Journal, 51,* 1173–1179.

Parton, W.J. et al. (1994). A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. In: *Quantitative modeling of soil forming processes*. (R.B. Bryant & R.W. Arnold, Eds.), pp. 147-167, SSSA Spec. 677 S. Segoe Rd., Madison, WI 53711, USA: Soil Science Society of America.

Parton, W.J. et al. (1998). DAYCENT and its land surface submodel: description and testing. *Global and Planetary Change, 19,* 35–48.

Parton, W.J., Del Grosso, S.J., Plante, A.F., Adair, E.C. & Luz, S.M. (2015). Modeling the Dynamics of Soil Organic Matter and Nutrient Cycling. In *Soil Microbiology, Ecology and Biochemistry, Fourth Edition.* (Paul, E.A., Ed.), pp. 505-537. Academic Press, London.

Parton, W.J., Stewart, J. W. B. and Cole, C. V (1988). Dynamics of C , N , P and S in grassland soils : a model. *Biogeochemistry, 131,* 109–131.

Paustian, K. (1994). Modeling soil biology and biochemical processes for sustainable agricultural research. In *Soil Biota: Management in Sustainable Farming Systems*. (P.G. Clive Pankhurst, Bernard Doube, VVSR Gupta, Eds.), pp. 135–162, Victoria, Australia: CSIRO.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G.P., & Smith, P. (2016). Climate-smart soils. *Nature, 532,* 49-57.

Perruchoud, D. et al. (1999). Evaluating timescales of carbon turnover in temperate forest soils with radiocarbon data. *Global Biogeochemical Cycles, 13(2),* 555–573.

Poeplau, C., Vos, C., Don, A. (2017). Soil organic carbon stocks are systematically overestimated by misuse of the parameters bulk density and rock fragment content. *Soil, 3,* 61-66.

Poggio, M., Brown, D.J., Bricklemyer, R.S. (2017) Comparison of Vis–NIR on in situ, intact core and dried, sieved soil to estimate clay content at field to regional scales. *European Journal of Soil Science, 68,* 434-448.

Post, W.M., Izaurralde, R.C., Mann, L.K. & Bliss, N. 1999. Monitoring and verifying soil organic carbon sequestration. In *Carbon sequestration in soils: science, monitoring, and beyond* (NJ Rosenberg RC Izaurralde & EL Malone, Eds), pp 41-66, Batelle Press Columbus OH.

Powlson, D.S., Smith, P., Coleman, K., Smith, J.U., Glendining, M.J., Korschens, M. & Franko, U. (1998). A European network of long-term sites for studies on soil organic matter. *Soil & Tillage Research, 47,* 263-274.

Ramirez-Lopez, L., Behrens, T., Schmidt, K., Stevens, A., Demattê Ja., M. & Scholten, T. (2013). The spectrum-based learner: A new local approach for modeling soil vis–NIR spectra of complex datasets. *Geoderma, 195-196,* 268-279.

Rebmann, C., Aubinet, M., Schmid, H.P., Arriga, N., Aurela, M., Burba, G., …Franz, D. (2018). ICOS eddy covariance flux-station site setup: a review. *International Agrophysics, 32,* 471-494.

Reeves, J.B. (2010). Near- versus mid-infrared diffuse reflectance spectroscopy for soil analysis emphasizing carbon and laboratory versus on-site analysis: Where are we and what needs to be done? *Geoderma, 158,* 3-14.

Richards, G.P. (2001). The FullCAM carbon accounting model: development, calibration and implementation for the National Carbon Accounting System (National Carbon Accounting System Technical Report No. 28). Australian Greenhouse Office, Canberra.

Richards, M., Pogson, M., Dondini, M., Jones, E.O., Hastings, A., Henner, D., … Smith, J.U. & Smith, P. (2017). High-resolution spatial modelling of greenhouse gas emissions from land-use change to energy crops in the United Kingdom. *Global Change Biology Bioenergy, 9,* 627–644.

Richter, D. deB. Jr., Hofmockel, M, Callaham, M.A. Jr., Powlson, D.S & Smith, P. (2007). Long-term soil experiments: keys to managing earth's rapidly changing terrestrial ecosystems. *Soil Science Society of America Journal, 71,* 266-279.

Rogge, D., Bauer, A., Zeidler, J., Mueller, A., Esch, T. & Heiden, U. (2018). Building an exposed soil composite processor (SCMaP) for mapping spatial and temporal characteristics of soils with Landsat imagery (1984–2014). *Remote Sensing of Environment, 205,* 1-17.

Rosero-Vlasova, O.A., Vlassova, L., Pérez-Cabello, F., Montorio, R., & Nadal-Romero, E. (2019). Soil organic matter and texture estimation from visible-near infrared-shortwave infrared spectra in areas of land cover changes using correlated component regression. *Land Degradation & Development, 30,* 544-560.

Rovira, P., Romanyà, J., Rubio, A., Roca, N., Alloza, J. A., & Vallejo, V. R. (2007). Estimación del carbono orgánico en los suelos peninsulares españoles. In *El papel de los bosques españoles en la mitigación del cambio climático*. pp. 197–222. Barcelona: Fundación Gas Natural.

Ruddiman, W.F. 2005. *Plows, Plagues and Petroleum: How Humans Took Control of Climate*. 240pp. Princeton: Princeton University Press.

Rumpel, C., Amiraslani, F., Chenu, C., Cardenas, M.G., Kaonga, M., Koutika, L.-S., Ladha, J.K., Madari, B. et al. (2019). The 4p1000 initiative: Opportunities, limitations and challenges for implementing soil organic carbon sequestration as a sustainable development strategy. Ambio (early online). https://doi.org/10.1007/s13280-019-01165-2.

Rumpel, C., Amiraslani, F., Koutika, L.S., Smith, P., Whitehead, D. & Wollenberg, E. (2018). Put more carbon in soils to meet Paris climate pledges. Nature 564, 32-34.

Sabbatini, S. et al., (2018). Eddy covariance raw data processing for CO_2 and energy fluxes calculation at ICOS ecosystem stations. *International Agrophysics, 32,* 495-515.

Sanderman, J., Hengl, T. & Fiske, G.J. (2017). Soil carbon debt of 12,000 years of human land use. *Proceedings of the National Academy of Sciences, 114*, 9575-9580.

Schipper, L.A., Parfitt, R.L., Fraser, S., Littler, R.A., Baisden, W.T. & Ross, C. (2014). Soil order and grazing management effects on changes in soil C and N in New Zealand pastures. *Agriculture Ecosystems & Environment, 184,* 67-75

Schrumpf, M., Schulze, E.D., Kaiser, K. & Schumacher, J. (2011). How accurately can soil organic carbon stocks and stock changes be quantified by soil inventories? *Biogeosciences, 8,* 1193-1212.

Scott, N.A., Tate, K.R., Giltrap, D.J., Smith, C.T., Wilde, R.H., Newsome, P.F.J. & Davis, M.R. (2002). Monitoring land-use change effects on soil carbon in New Zealand: quantifying baseline soil carbon stocks. *Environmental Pollution, 116,* S167-S186.

Shirato, Y., & Taniyama, I. (2003). Testing the suitability of the Rothamsted Carbon model for long-term experiments on Japanese non-volcanic upland soils. *Soil Science and Plant Nutrition, 49(6),* 921–925.

Sims, N.C., England, J.R., Newnham, G.J., Alexander, S., Green, C., Minelli, S. & Held, A. (2019). Developing good practice guidance for estimating land degradation in the context of the United Nations Sustainable Development Goals. *Environmental Science and Policy, 92*, 349–355.

Skinner, R.H. & Dell, C.J. (2014). Comparing C sequestration estimates from eddy covariance and soil cores. *Agriculture, Ecosystems and Environment, 199,* 52–57.

Skjemstad, J.O., Spouncer, L.R., Cowie, B. & Swift, R.S. (2004). Calibration of the Rothamsted organic carbon turnover model (RothC ver. 26.3), using measurable soil organic carbon pools. *Australian Journal of Soil Research, 42,* 79–88.

Sleutel, S., De Neve, S. & Hofman, G. (2003). Estimates of carbon stock changes in Belgian cropland. *Soil Use & Management, 19,* 166–171.

Smith, J. et al. (2010). Estimating changes in national soil carbon stocks using ECOSSE – a new model that includes upland organic soils. Part I. Model description and uncertainty in national scale simulations of Scotland. *Climate Research, 45,* 179-192.

Smith, J.U. & Smith, P. 2007. *Environmental Modelling. An Introduction*. Oxford University Press, Oxford. 180pp.

Smith, J.U., Smith, P., Monaghan, R., & MacDonald, A. J. (2002). When is a measured soil organic matter fraction equivalent to a model pool? *European Journal of Soil Science, 53(3),* 405–416.

Smith, P. (2004a). How long before a change in soil organic carbon can be detected? *Global Change Biology, 10,* 1878-1883.

Smith, P. (2004b). Monitoring and verification of soil carbon changes under Article 3.4 of the Kyoto Protocol. *Soil Use and Management, 20,* 264-270.

Smith, P. (2012). Soils and climate change. *Current Opinion in Environmental Sustainability, 4,* 539–544.

Smith, P. (2016). Soil carbon sequestration and biochar as negative emission technologies. *Global Change Biology, 22,* 1315–1324.

Smith, P., Chapman, S.J., Scott, W.A., Black, H.I.J., Wattenbach, M., Milne, R., Campbell, C.D., Lilly, A, Ostle, N., Levy, P., Lumsdon, D.G., Millard, P., Towers, W., Zaehle, S. & Smith, J.U. (2007). Climate change cannot be entirely responsible for soil carbon loss observed in England and Wales, 1978-2003. *Global Change Biology, 13,* 2605-2609.

Smith, P., Davies, C.A., Ogle, S., Zanchi, G., Bellarby, J., Bird, N., Boddey, R.M., McNamara, N.P., Powlson, D.S., Cowie, A., van Noordwijk, M., Davis, S.C., Richter, D.D., Kryzanowski, L., van Wijk, M.T., Stuart, J., Kirton, A., Eggar, D., Newton-Cross, G., Adhya, T.K. & Braimoh, A.K. (2012). Towards an integrated global framework to assess the impacts of land use and management change on soil carbon: current capability and future vision. *Global Change Biology, 18,* 2089–2101.

Smith, P., Lanigan, G. Kutsch, W.L., Buchmann, N., Eugster, W., Aubinet, M., Ceschia, E., Béziat, P., Yeluripati, J.B., Osborne, B., Moors, E.J., Brut, A., Wattenbach, M., Saunders, M & Jones, M. (2010). Measurements necessary for assessing the net ecosystem carbon budget of croplands. *Agriculture, Ecosystems & Environment, 139,* 302-315.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H.H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, R.J., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., Wattenbach, M. & Smith, J.U. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society, B., 363,* 789-813.

Smith, P., Powlson, D.S., Smith, J.U., Falloon, P.D. & Coleman, K. (2000). Meeting Europe's climate change commitments: Quantitative estimates of the potential for carbon mitigation by agriculture. *Global Change Biology, 6,* 525-539.

Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov O.G., Coleman, K., Franko, U., Frolking, S, Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek, H., Komarov, A., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M. & Whitmore, A.P. (1997). A comparison of the performance of nine soil organic matter models using seven long-term experimental datasets. *Geoderma, 81,* 153-225.

Soil Science Staff (2014). *Kellogg Soil Survey Laboratory Methods Manual*. Soil Survey Investigations Report No. 42, Version 5.0. (R. Burt and Soil Survey Staff, Eds.). U.S. Department of Agriculture, Natural Resources Conservation Service. https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1253871.pdf.

Soussana, J.F., Tallec, T. & Blanfort V. (2010). Mitigating the greenhouse gas balance of ruminant production systems through carbon sequestration in grasslands. *Animal*, *4,* 334–350.

Spencer, S., Ogle, S.M., Breidt, F.J., Goebel, J.J. & Paustian, K. (2011). Designing a national soil carbon monitoring network to support climate change policy: a case example for US agricultural lands. *Greenhouse Gas Measurement and Management, 1,* 167-178.

Stahl, C. et al., (2017). Continuous soil carbon storage of old permanent pastures in Amazonia. *Global Change Biology, 23,* 3382–3392.

Statistics Lithuania. (2018). Agricultural Statistics database. https://www.stat.gov.lt/web/lsd/

Steinmann, T., Welp, G., Wolf, A., Holbeck, B., Große-Rüschkamp, T. & Amelung, W. (2016). Repeated monitoring of organic carbon stocks after eight years reveals carbon losses from intensively managed agricultural soils in Western Germany. *Journal of Plant Nutrition and Soil Science, 179,* 355-366.

Stenberg, B., Viscarra Rossel, R.A., Mouazen, A.M. & Wetterlind, J. (2010). Visible and near infrared spectroscopy in soil science. *Advances in Agronomy, 107,* 163-215.

Stockmann, U., Adams, M. A., Crawford, J. W., Field, D. J., Henakaarchchi, N., Jenkins, M., … Zimmermann, M. (2013). The knowns, known unknowns and unknowns of sequestration of soil organic carbon. *Agriculture, Ecosystems & Environment, 164,* 80–99.

Taghizadeh-Toosi, A. & Olesen, J.E. (2016). Modelling soil organic carbon in Danish agricultural soils suggests low potential for future carbon sequestration. *Agricultural Systems, 145,* 83-89.

Taghizadeh-Toosi, A., Christensen, B.T., Glendining, M. & Olesen, J.E. (2016). Consolidating soil carbon turnover model by improved estimates of belowground carbon input. *Scientific Reports*, *6,* 32568.

Taghizadeh-Toosi, A., Christensen, B.T., Hutchings, N.J. et al. (2014b). C-TOOL: A simple model for simulating whole-profile carbon storage in temperate agricultural soils. *Ecological Modelling, 292,* 11-25.

Taghizadeh-Toosi, A., Olesen, J.E., Kristensen, K. et al. (2014a). Changes in carbon stocks of Danish agricultural mineral soils between 1986 and 2009. *European Journal of Soil Science, 65,* 730-740.

Tate, K.R., Wilde, R.H., Giltrap, D.J., Baisden, W.T., Saggar, S., Trustrum, N.A., Scott, N.A. & Barton, J.R. (2005). Soil organic carbon stocks and flows in New Zealand: System development, measurement and modelling. *Canadian Journal of Soil Science, 85(4),* 481-489

Teng, Y., Wu, J., Lu, S., Wang, Y., Jiao, X. & Song, L. (2014). Soil and soil environmental quality monitoring in China: A review. *Environment International, 69,* 177-199.

Throop, H.L., Archer, S.R., Monger, H.C. & Waltman, S. (2012). When bulk density methods matter: Implications for estimating soil organic carbon pools in rocky soils. *Journal of Arid Environments, 77,* 66–71.

Toudert, A., Braimoh, A., Bernoux, M.M.Y., St-Louis, M., Abdelmagied, M., Bockel, L., Ignaciuk, A., Zhao, Y., 2018. Carbon accounting tools for Sustainable Land Management. The World Bank, Washington DC, 135pp. Available at: http://documents.worldbank.org/curated/en/318251544164909341/Carbon-Accounting-Tools-for-Sustainable-Land-Management.

Trnka, M., Olesen, J.E., Kersebaum, A.C., et al. (2011). Agrolimatic conditions in Europe under climate change. *Global Change Biology, 17,* 2298-2318.

Tuomi, M. et al. (2011). Soil carbon model Yasso07 graphical user interface. *Environmental Modelling and Software, 26,* 1358–1362.

Upson, M.A., Burgess, P.J. & Morison, J.I.L. (2016). Soil carbon changes after establishing woodland and agroforestry trees in a grazed pasture. *Geoderma, 283,* 10–20

Van Der Esch, S., ten Brink, B., Stehfest, E., Bakkenes, M., Sewell, A., Bouwman, A., Meijer. J., Westhoek, H. & Van Den Berg, M. (2017). Exploring future changes in land use and land condition and the impacts on food, water, climate change and biodiversity: Scenarios for the Global Land Outlook. PBL Netherlands Environmental Assessment Agency, The Hague. https://www.pbl.nl/en/publications/exploring-future-changes-in-land-use.

Van Wesemael, B., Paustian, K., Andrén, O. et al. (2011). How can soil monitoring networks be used to improve predictions of organic carbon pool dynamics and CO_2 fluxes in agricultural soils? *Plant and Soil, 338,* 247–259.

VandenBygaart, A.J., McConkey, B.G., Angers, D.A., Smith, W.S., de Gooijer, H., Bentham, M. & Martin, T. (2008). Soil carbon change factors for the Canadian agriculture national greenhouse gas inventory. *Canadian Journal of Soil Science, 88,* 671-680.

Vanguelova, E.I., Bonifacio, E., De Vos, B., Hoosbeek, M.R., Berger, T.W., Vesterdal, L., Armolaitis, K, Celi, L. et al. (2016). Sources of errors and uncertainties in the assessment of forest soil carbon stocks at different scales - review and recommendations. *Environmental Monitoring and Assessment, 188,* 630.

Viscarra Rossel, R.A., Behrens, T., Ben-Dor, E. et al. (2016). A global spectral library to characterize the world's soil. *Earth-Science Reviews, 155,* 198-230.

Viscarra Rossel, R.A., Brus, D.J., Lobsey, C., Shi, Z. & Mclachlan, G. (2016). Baseline estimates of soil organic carbon by proximal sensing: Comparing design-based, model-assisted and model-based inference. *Geoderma, 265,* 152-163.

Viscarra Rossel, R.A., Walvoort, D.J.J., Mcbratney, A.B., Janik, L.J. & Skjemstad, J.O. (2006). Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. *Geoderma, 131,* 59-75.

Visschers, R., Finke, P.A. & De Gruijter, J.J. (2007). A soil sampling program for the Netherlands. *Geoderma, 139,* 60-72.

Vohland, M., Ludwig, M., Thiele-Bruhn, S. & Ludwig, B. (2014). Determination of soil properties with visible to near- and mid-infrared spectroscopy: Effects of spectral variable selection. *Geoderma, 223-225,* 88-96.

Wendt, J.W. & Hauser, S. (2013). An equivalent soil mass procedure for monitoring soil organic carbon in multiple soil layers. *European Journal of Soil Science, 64,* 58-65.

Wetterlind, J., Piikki, K., Stenberg, B. & Söderström, M. (2015) Exploring the predictability of soil texture and organic matter content with a commercial integrated soil profiling tool. *European Journal of Soil Science, 66,* 631-638.

Wieder, W.R., Bonan, G.B., & Allison, S.D. (2013). Global soil carbon projections are improved by modelling microbial processes. *Nature Climate Change, 3(10),* 909–912.

Wijewardane, N.K., Ge, Y., Wills, S. & Libohova, Z. (2018). Predicting physical and chemical properties of US soils with a mid-infrared reflectance spectral library *Soil Science Society of America Journal, 82*, 722–731.

Wilkes, A., Reisinger, A., Wollenberg, E. & Van Dijk, S. (2017). Measurement, reporting and verification of livestock GHG emissions by developing countries in the UNFCCC: current practices and opportunities for improvement. CCAFS Report 17, 114 pp., Wageningen, the Netherlands. https://ccafs.cgiar.org/publications/measurement-reporting-and-verification-livestock-ghg-emissions-developing-countries#.XSmwnOhKjIU

Williams, M. et al. (2009). Improving land surface models with FLUXNET data. *Biogeosciences, 6,* 1341–1359.

Wilson, B.R., Barnes, P., Koen, T.B., Ghosh, S. & King, D. (2010). Measurement and estimation of land-use effects on soil carbon and related properties for soil monitoring: a study on a basalt landscape of northern New South Wales, Australia. *Soil Research, 48,* 421-433.

Wu, Y., Clarke, N., Mulder, J. (2010). Dissolved organic carbon concentrations in throughfall and soil waters at level II monitoring plots in Norway: Short- and long-term variations. *Water, Air, and Soil Pollution, 205,* 273-288.

Wüst-Galley, C., Keel, S.G. & Leifeld, J. (2019). A model-based carbon inventory for National greenhouse gas reporting of mineral agricultural soils (in prep).

Wutzler, T., & Reichstein, M. (2013). Priming and substrate quality interactions in soil organic matter models. *Biogeosciences, 10(3),* 2089–2103.

Wutzler, T., Zaehle, S., Schrumpf, M., Ahrens, B., & Reichstein, M. (2017). Adaptation of microbial resource allocation affects modelled long-term soil organic matter and nutrient cycling. *Soil Biology and Biochemistry, 115,* 322–336.

Yagasaki, Y. & Shirato, Y. (2014). Assessment on the rates and potentials of soil organic carbon sequestration in agricultural lands in Japan using a process-based model and spatially explicit land-use change inventories Part 1: Historical trend and validation based on nation-wide soil monitoring. *Biogeosciences, 11*, 4429-4442.

Zhao, G., Ye, S., Li, G., Yu, X. & Mcclellan, S.A. (2016). Soil organic carbon storage changes in coastal wetlands of the Liaohe Delta, China, based on landscape patterns. *Estuaries and Coasts, 40*, 967-976.

Zimmermann, M., Leifeld, J., Schmidt, M. W. I., Smith, P. & Fuhrer, J. (2007). Measured soil organic matter fractions can be related to pools in the RothC model. *European Journal of Soil Science, 58*, 658–667.

Figure legends

Figure 1 Map of flux towers and available time series worldwide (Source: Fluxnet, 2019)

Figure 2. Tier methods used by GRA countries for estimating the changes in mineral soil carbon stock for the "Cropland remaining Cropland" category. NA indicates that the country has not developed a GHG inventory. NE indicates that the country has not included SOC changes in croplands in the inventory. Countries reporting carbon stock change associated with agricultural land-use and management activities are indicated by (*).

Figure 3. Components of a soil measurement/monitoring, reporting and verification framework, indicating which components contribute to measurement / monitoring (M), reporting (R) or verification (V). See text in section 8 for explanation of linkages between the components.

Tables

Table 1. List of different functions to simulate the decomposition in models following the discussion of Parton et al. (2015). The publications listed refer to the example models. The abbreviations describe the carbon (C) at the start (C_0) and at a certain time (t) step (C_t), the decomposition rate (k), the Michaelis-Menten constant (K_m) and the maximum reaction velocity for the process (V_m), the carbon demand by the microbes (X_0), the Monod constant (K_t) and the maximum growth rate (□$_{max}$). The graphs show C_t in a time series for one set of arbitrary parameters.

Approach	Equation	Graphical relation (C(t))	Example model	Publications
Zero order kinetics	$C_t = C_0 - kt$			
First order kinetics	$C_t = C_0 e^{-kt}$		RothC, ICBM	Jenkinson & Rayner, 1977; Andrén & Kätterer, 1997
Enzyme kinetics	$\frac{dC}{dt} = V_m \frac{C}{K_m + C}$		CLM, SEAM	Wieder et al., 2013; Wutzler et al., 2017
Microbial growth	$-\frac{dC}{dt} = \mu_{max} \left(\frac{C}{K_t + C} \right) (C_0 + X_0 - C)$		NICA	Blagodatsky & Richter, 1998

Table 2. Examples of soil monitoring networks and sample design in selected GRA countries [a]

	Belgium	Brazil	China	Mexico	New Zealand	Sweden
Objective	National SOC monitoring	SOC response to land use/management change	Regional SOC monitoring	National SOC monitoring	National SOC monitoring	National SOC monitoring
Region covered	cropland and grassland in southern Belgium	Rodônia, Mato Grosso, Central Amazonia	Northeast (120 sites), North (241), East (356), South (119), Northwest (148), Southwest (97).	Forest and non-forest land in particular pasture and shrubs	All regions and land uses	Cropland ~3 Mha.
Starting date	National Soil Survey 1950-1970; resampled 2004-2007	~2007	78 % started before 1985 and 87.5% continued until at least 1996	started in 2003; each year 1/5 of the sites will be re-sampled	National soils database from 1938; Land use and carbon analysis system started in 1996[c]	Full scale in 1995, some data from 1988
Site density (km² per site)	18 km²	N/A	N/A	78 km²	202 km²	10 km²
Site selection	Stratified	Stratified	Stratified	Grid	Stratified	Grid
- Soil sampling:						
- Sub-samples	Composite	Composite	Composite	Composite	Single	Composite
- Depth	0-30 cm and 0-100 cm	0-10, 10-20, 20-30, and 30-40 cm	0-20 cm	0-30 cm and 30-60cm	Variable, sampled by soil horizon; in 2009, 1235 samples to 30 cm	0-20 cm and 40-60 cm
- Frequency	Future sampling rounds largely depend on funding (Goidts et al., 2009)	Once (chronosequences and paired sites)	Annual sampling from 2010, see Teng et al. (2014) [b]	Every 5 years	A fit-for-purpose method is being designed to monitor SOC stocks at ~ 5-year intervals over upcoming decades.	1995 and 2005round completed; in principle repeated every 10 years

[a] Adapted from Van Wesemael et al. (2011)

b For accurate soil monitoring in China, it will be necessary to set up routine monitoring systems at various scales (national, provincial, and local scales), taking into consideration monitoring indicators and quality assurance (Teng et al., 2014)

c For recent developments see https://soils.landcareresearch.co.nz/index.php/soils-at-manaaki-whenua/our-projects/soil-organic-carbon

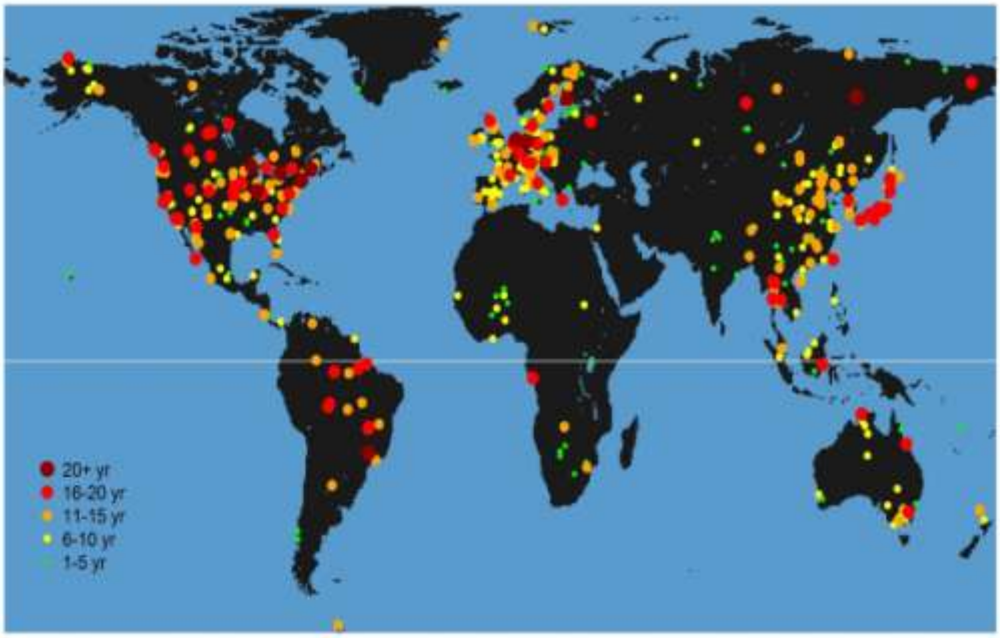
Table 3. Methodology used to estimate changes in soil C stocks for Cropland Remaining Cropland, including agricultural land-use and management activities on mineral soils.

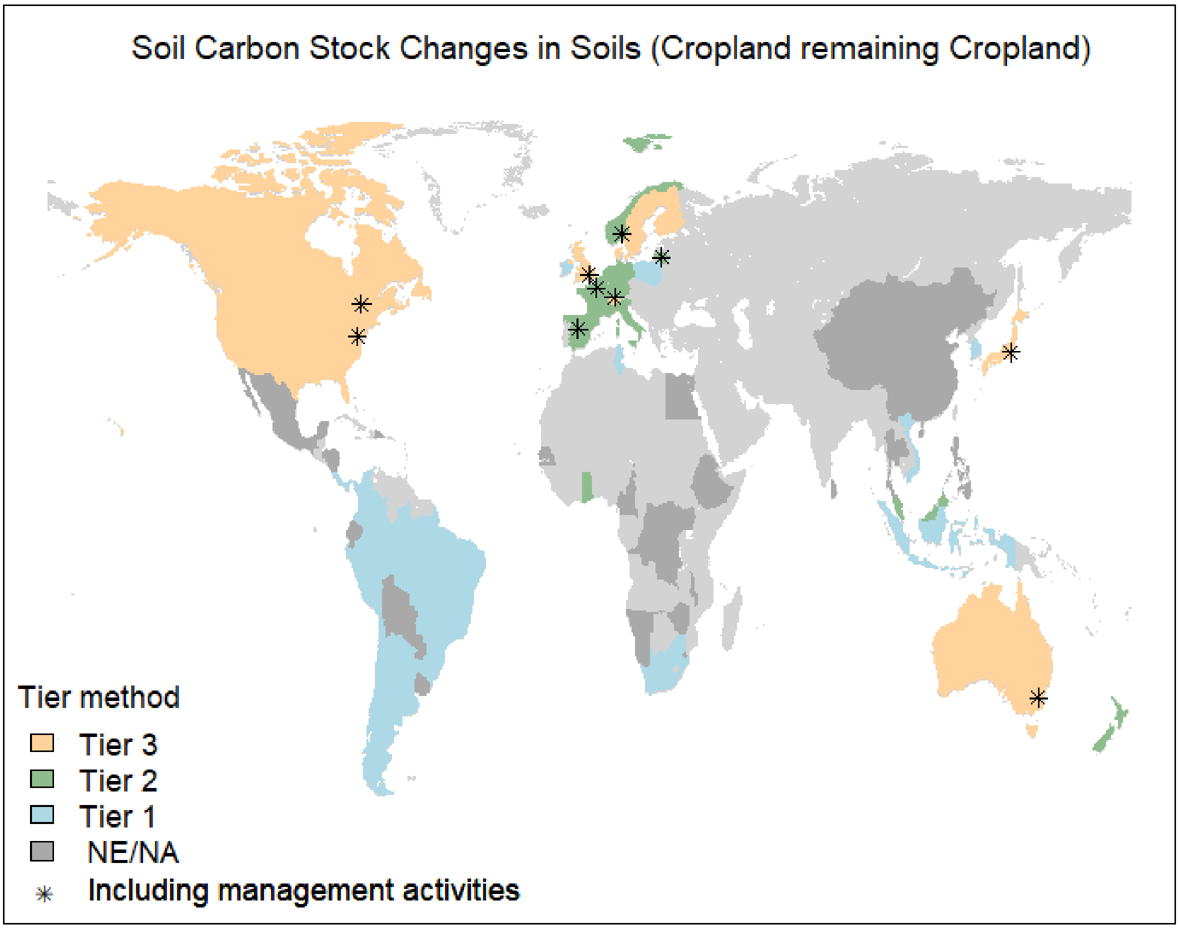
GRA Country		Tier	Land management activities	Reference
Australia	The Full Carbon Accounting Model (FullCAM)	Tier3	Crop type and rotation (including pasture leys) Stubble management, including burning practices Tillage techniques Fertiliser application and irrigation Application of green manures (particularly legume crops) Soil ameliorants (application of manure, compost or biochar) Changes in land use from grassland	(Richards, 2001)
	Crop-specific coefficients sourced from the literature combined with ABS agricultural commodities statistics	Tier2	Changes in the area of perennial woody crops	
Canada	Process model (CENTURY) based on the National Soil Database of the Canadian Soil Information System	Tier3	Change in mixture of crop type (Increase in perennial crops and increase in annual crops) Change in tillage practices Change in area of summer fallow Land use, tillage, type and amount of input Crop residue, farmyard manure, and presence or absence of vegetative cover. Perennial and Organic management systems	McConkey et al. (2014)
Denmark	Average SOC calculated annually per soil type and region based on process-based model (C-TOOL) using data on temperature and estimated C input from crop residues and manure using national databases	Tier3	Crop type and crop yield Cover crops Residue management Manure application	Taghizadeh-Toosi and Olesen (2016)

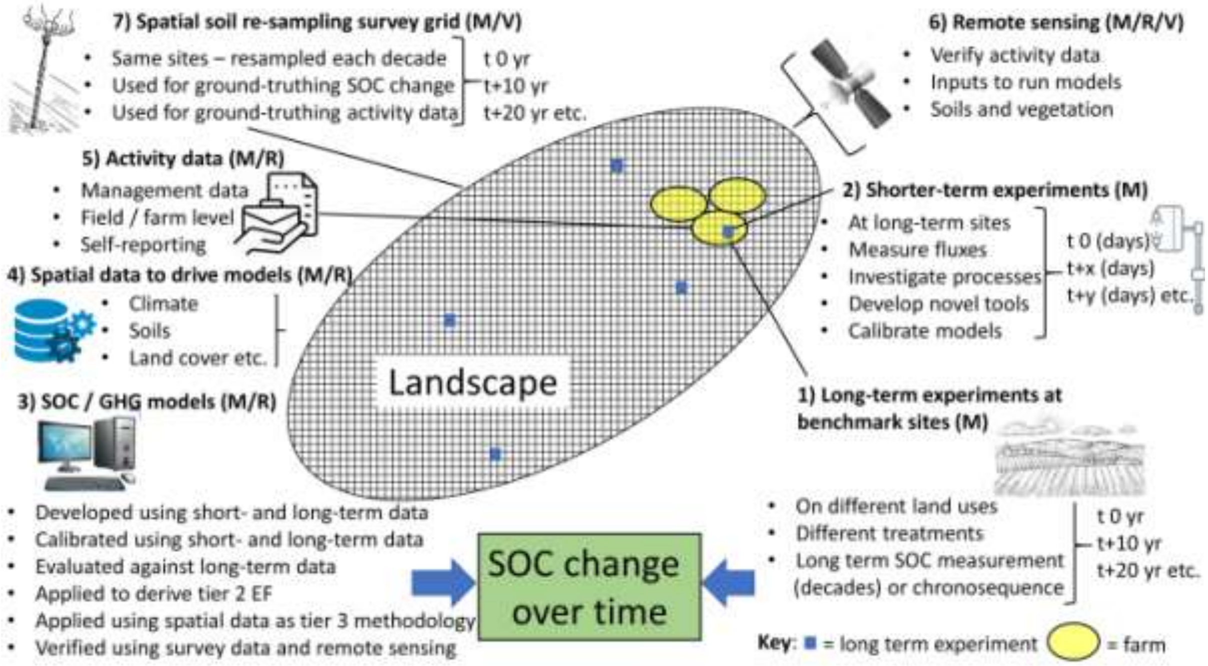
			Grassland management	
France	The IPCC Guidelines and OMINEA database	Tier1	Land use Tillage Type and amount of input	(CITEPA, 2019)
Japan	Average carbon stock changes in each year by land use subcategory (rice fields, upland fields, orchards and pastural land) calculated by the Roth C model by the mineral soil area of each prefecture obtained from statistical material, map data and questionnaire survey.	Tier 2	Carbon input from crop residue Farmyard manure Presence or absence of vegetative cover	(Shirato and Taniyama 2003)
Lithuania	National statistics for woody crops and available data of arable land certified as organic in FAOSTAT and ecological agricultural land statistics.	Tier2	Crop type (Perennial crops, Certified organic crops, Other crops) Amount of input	(Statistics Lithuania, 2018)
Norway	Reference stock and stock change factors estimated by the Introductory Carbon Balance Model (ICBM) in a study where CO2 emissions were estimated for Norwegian cropland	Tier2	Crop rotations Carbon inputs Tillage	(Borgen et al., 2012)
Spain	SOC values calculated by use and province, together with the reference values of the management factors provided by the IPCC Guidelines	Tier1	Land use Crop rotations Amount of input Tillage	(Rovira et al., 2007)
United Kingdom	Review UK relevant literature on the effects of cropland management practices on soil carbon stocks to model UK specific emission factors (methodology developed in Defra project SP1113)	Tier1	Manure Residue inputs Crop type (Perennial, Cropland, Set-aside)	(Moxley et al., 2014a)
		Tier2	Tillage	
United States	Published literature to determine the impact of management practices on SOC storage. Activity data based on the historical land-use/management patterns recorded in the 2012 NRI (USDA-NRCS 2015).	Tier2	Tillage Cropping rotations Intensification Land use change between cultivated and uncultivated conditions	(Ogle et al., 2003, 2006)

Table 4. Models used to estimate carbon dioxide emissions and removals from the cropland remaining cropland soils component (Tier 3 method) in GRA countries.

GRA country	Model		Reference
Australia	The Full Carbon Accounting Model (FullCAM)	Estimates emissions from soil through a process involving all on-site carbon pools (living biomass, dead organic matter and soil) on a pixel by pixel (25m x 25m) level.	(Richards, 2001)
Canada	CENTURY	process model used for estimating CO2 emissions and removals as influenced by management activities, based on the National Soil Database of the Canadian Soil Information System	(Parton et al., 1987, 1988)
Denmark	C-TOOL	3-pool dynamic soil model parameterised and validated against long-term field experiments (100-150 years) conducted in Denmark, UK (Rothamsted) and Sweden and is “State-of-the-art”.	(Taghizadeh-Toosi et al., 2014b)
Finland	Yasso07 soil carbon model	The parameterisation of Yasso07 used in cropland was the one reported in Tuomi et al., (2011b).	(Palosuo et al., 2015)
Japan	Soil Carbon RothC model	In order to apply the model to Japanese agricultural conditions, the model was tested against long-term experimental data sets in Japanese agricultural lands (Shirato &Taniyama 2003)	(Coleman et al., 1997; Coleman & Jenkinson 1999)
Sweden	Soil Carbon model ICBM-region	Calculate annual C balance of the soil based on national agricultural crop yield and manure statistics, and uses allometric functions to estimate the annual C inputs to soil from crop residues	(Andrén & Kätterer, 2001)
Switzerland	Soil Carbon RothC model	The implementation of RothC in the Swiss GHG inventory is described in detail in Wüst-Galley et al. (2019).	(Coleman et al., 1997; Coleman & Jenkinson 1999)
United Kingdom	CARBINE Soil Carbon Accounting model (CARBINE-SCA)	Simplified version of the ECOSSE model (Smith et al., 2011), coupled with a litter decomposition model derived from the ForClim-D model (Perruchoud et al., 1999; Liski et al., 2002).	Matthews et al. (2014).
United States	DAYCENT biogeochemical model	Utilizes the soil C modelling framework developed in the Century model (Parton et al., 1987, 1988, 1994; Metherell et al., 1993), but has been refined to simulate dynamics at a daily time-step.	(Parton et al., 1998; Del Grosso et al., 2001, 2011)


20+ yr
16-20 yr
11-15 yr
6-10 yr
1-5 yr


Soil Carbon Stock Changes in Soils (Cropland remaining Cropland)
Tier method
Tier 3
Tier 2
Tier 1
NE/NA
Including management activities


7) Spatial soil re-sampling survey grid (M/V)
Same sites – resampled each decade
Used for ground-truthing SOC change
Used for ground-truthing activity data
t 0 yr
t+10 yr
t+20 yr etc.
6) Remote sensing (M/R/V)
Verify activity data
Inputs to run models
Soils and vegetation
5) Activity data (M/R)
Management data
Field / farm level
Self-reporting
2) Shorter-term experiments (M)
At long-term sites
Measure fluxes
Investigate processes
Develop novel tools
Calibrate models
t 0 (days)
t+x (days)
t+y (days) etc.
4) Spatial data to drive models (M/R)
Climate
Soils
Land cover etc.
Landscape
3) SOC / GHG models (M/R)
1) Long-term experiments at benchmark sites (M)
Developed using short- and long-term data
Calibrated using short- and long-term data
Evaluated against long-term data
Applied to derive tier 2 EF
Applied using spatial data as tier 3 methodology
Verified using survey data and remote sensing
SOC change over time
On different land uses
Different treatments
Long term SOC measurement (decades) or chronosequence
t 0 yr
t+10 yr
t+20 yr etc.
Key: = long term experiment = farm