Viresco Solutions

End-to-end sustainability

Soil Organic Carbon, Carbon Intensity, and Canadian Canola

June 9, 2022

Prepared for

Canola Council of Canada

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Executive Summary

The western Canadian cropping system that supplies Canada's canola has been transformed over the past several decades to one that is more environmentally sustainable and profitable. The expansion of canola production was a key factor in that process. This transformation is resulting in soil organic carbon (SOC) increases, primarily from the reduction in summerfallow (intentionally leaving land without vegetation for one year) and reduction in tillage, including the large-scale adoption of no-till practices. This increase in SOC represents a removal of carbon dioxide from the atmosphere. Therefore, under the international standard for calculating carbon footprints (ISO 14067), changes to SOC should be included with the footprint.

The approach of quantifying SOC change within sophisticated national greenhouse gas inventories that combine calibration and verification with measured SOC, use of big data methods, and process modelling represent the most accurate practical methods. Canada's official SOC estimates are regularly reviewed for their adherence to internationally accepted good practice guidelines for transparency, accuracy, completeness, consistency, and comparability. Therefore, these SOC estimates using a national inventory approach are suitable and implementable for all jurisdictions. Including these SOC change estimates in Canada's national inventory confirms that SOC reduces the carbon intensity of biofuel produced from Canadian canola by up to 35%. The canola cropping system continues to improve and its carbon footprint is expected to decrease further in the future.

Ongoing research and development are leading to increasingly sophisticated approaches for SOC change quantification. Approving estimates of SOC change for footprints is best based on demonstrated performance of the quantification system that produced those estimates to meet the regulator-set criteria for acceptably low levels of uncertainty and bias. Performance-based approval works across SOC change quantification systems and jurisdictions and allows for innovation and flexibility.

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1. Soil Organic Carbon in Canada

Soil organic carbon (SOC) is carbon in the soil that is derived from plants and animals. Green plants grow by converting carbon dioxide from the atmosphere via photosynthesis into carbon-containing materials. These organic materials are added to soils from the plants themselves or from animals that either eat the plants or eat other plant-eating animals. Once in the soil, a diverse community of soil microorganisms decompose and biochemically transform these organic materials. These organic materials are incredibly diverse, consisting of substances that range from the residual material from prolonged microbial decomposition whose carbon can have been in the soil for thousands of years to that year's additions from plants and animals.

SOC is a large and active part of the global carbon cycle. The world's soils contain nearly four times as much carbon as is contained in total global vegetation and almost twice as much carbon as is in the atmosphere[1]. The amount of SOC in the soil is determined from the balance between addition and decomposition (see Annex A for more information on SOC). Any increase in SOC is a net removal of carbon dioxide from the atmosphere because photosynthesis was the source of the SOC. Conversely, any decrease in SOC is a net emission of carbon dioxide to the atmosphere. The increase in SOC is often described as carbon sequestration or a soil sink. The Intergovernmental Panel on Climate Change (IPCC) identifies increasing soil organic carbon (SOC) as an important climate mitigation strategy with multiple co-benefits and no downsides[2].

Land Management Practices and SOC in Western Canada

The soils of western Canada produce essentially all Canadian canola and have made Canada the global leader in the export of canola seed, oil, and meal. The basis of the productivity of these soils is their SOC. Within a few decades of breaking from native grassland, these soils lost 25 to 40% of their SOC (Figure 1). The practice of summerfallow was prevalent from initial land breaking in the late 19th and early 20th centuries. This accelerated the loss of native SOC and left the soils vulnerable to soil erosion.

[1] IPCC, Climate Change 2021

[2] IPCC, 2019, Special Report on Climate Change … in Terrestrial Ecosystems.

During the 1930s, there was widespread and devasting soil erosion over much of western Canada that was exacerbated by droughts and grasshopper plagues. To reduce soil erosion, by the 1950s the plow had been abandoned in favor of tillage implements, such as the cultivator, which left more residue on the soil surface. However, the use of summerfallow (deliberately leaving the land without vegetation for the whole year) remained prevalent and this kept SOC low. The 1984 report "Soils at Risk: Our Eroding Future" to the Parliament of Canada made it clear to governments and the public that low SOC was an existential threat to the sustainability of western Canadian agriculture.

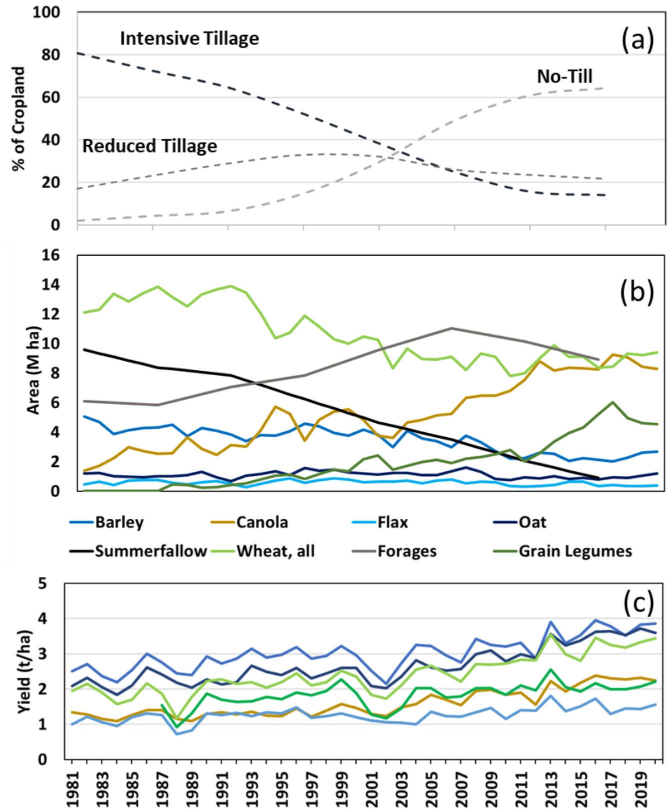

Figure 2. Over the past 40 years, there has been a shift to no-till from intensive tillage (a). The crop mix has changed towards more non-cereal crops of which canola is the most important (b). Crop yields have generally increased (c). (Source Statistics Canada)

In response to the challenge of degraded soils with poor soil health, innovative farmers experimented with no-till and the elimination of summerfallow to rebuild the soils' SOC. Successful innovations in no-till equipment became the basis for an important farm machinery manufacturing industry in western Canada to meet the needs of dryland no-till farming. Governments, the farm supply industry, and agricultural organizations aided the transformation to improved cropping systems by supporting research and development in new products and technologies along with providing technology transfer to growers.

The cropping system was transformed from one in 1981 that was primarily intensive tillage (80%), cereals (91% of cropped land), and frequent fallow (32% of cropland) to a SOC regenerative cropping system in 2016. By this year there were dramatic reductions in intensive tillage and fallow land with majority of cropland in no-till (64%), a large shift to growing non-cereals (54%), and with little fallow (3%) (Figure 2).

The changes to the system were synergistic. Reduction in tillage intensity improved water conservation that made fallow less valuable. As well, the reduction in fallow and tillage gave the ability to capture the agronomic benefits of more diversified crop rotations. Crop sequences that alternate cereal and broadleaf crops became normal because they better managed weeds, diseases, and crop residue in continuously cropped no-till systems than rotations of mostly cereals. Canola, a broadleaf crop, is well suited to the varied rotations, soil landscapes, and climates of western Canada. Over the last decade, canola has accounted for about one-third of the cropped land, vying with wheat for the area while exceeding wheat in monetary value. Grain legumes (pea, lentil, chickpea, and soybean) have also become important broadleaf crops and grew from virtually zero area in 1981 to as much 19% of cropped land in 2016.

Owing to improving soil health, improved cropping systems, and crop genetic advancements, yields of western Canadian crops have dramatically increased over the last 40 years (Figure 2). As a result, the switch of cropped area to non-cereal crops from cereals did not decrease the total production of cereals; in fact, the average total cereal production for 2016-2020 was 15% greater than that for 1981-86 despite an almost one-third smaller harvested area. The production of non-cereals in 2016-2020 was nearly 10-fold that in 1981-86.

Total SOC change

The main drivers of current SOC change in western Canada have been reductions in tillage intensity and an increase in C input to the soil (Figure 3). The C input to the soil is from crop residues and livestock manure applied on the soil. The important SOC increases from C input are mainly caused by: 1) reduction in summerfallow, since no crop residue is added in that year, 2) general increase in crop residue over time from improved agronomic management (Figure 2 c), and 3) increase in canola area (see Figure 2 b) that typically adds more C to soil than other crops. When crop production is severely lowered by regional droughts, there can be a loss of SOC such as occurred during 2002 and 2003 (Figure 3).).

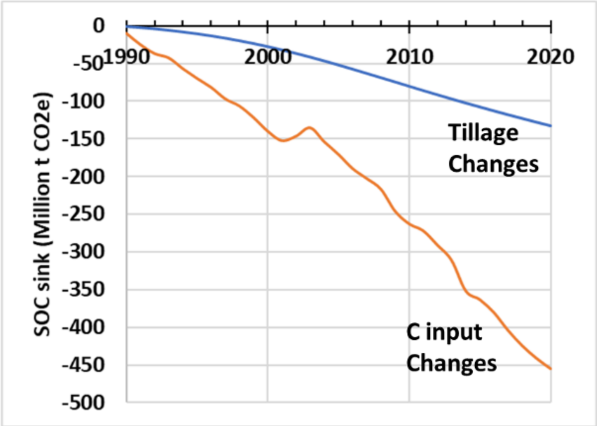

Figure 3. Cumulative SOC changes from 1990 to 2000 (ECCC, 2022)

In 1997, the farmer organization, Saskatchewan Soil Conservation Association, in cooperation with researchers, set up a network of over 100 SOC monitoring sites on commercial farm fields in the Canadian province of Saskatchewan. The SOC was measured on these fields in 1999, 2005, 2011, and 2018[3]. The measured SOC changes were consistent with the SOC changes that were estimated for these fields in Canada's National Inventory Report (Figure 4)(see Annex A for description of Canada's National Inventory for SOC.

Quantification of SOC

Quantifying SOC changes over time and/or over soil landscapes has been the subject of decades of research, investigation, peer-reviewed scientific papers and regulatory discussion. The three basic approaches to estimate SOC change are using only direct measurement of SOC change, a dynamic SOC process model, or an empirical model (i.e., digital SOC mapping). See Annex C for more detail on the quantification of SOC.

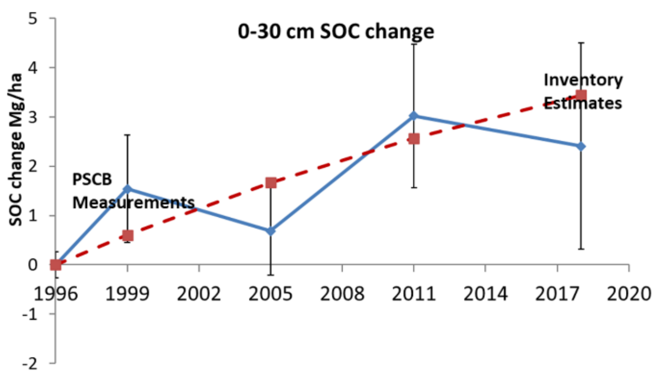

Figure 4. Measured and estimated National-Inventory SOC change for a network of commercial farm fields (error bars are 95% confidence limits for the measured).

Direct SOC measurements are expensive but are fundamental to all three approaches. The two model-based approaches absolutely require having excellent direct measurements of SOC relevant to the area for which SOC is being quantified to calibrate and validate the models. Quantifying SOC by direct measurements means having very small gaps between measurements. Therefore, the SOC over the whole can be estimated from the measurements alone with minimal need for intelligence about relationship between SOC and land properties and land management to fill in those small gaps in time or space. Using process models and digital SOC mapping allows large gaps between measurements and employs human, and increasingly artificial, intelligence about how SOC responds to its circumstances to fill in the gaps between limited directly measured SOC. Process models are the strongest as estimating SOC over time while digital SOC mapping are strongest at estimating SOC over space. There is an emerging

[3]Paustian et al. 2019. Carbon Management 10; Prairie Soil Carbon Balance Project 2020 https://www.ssca.ca/prairie-soil-carbon-balance-pscb

consensus that the intelligent integration of process models, digital land mapping capabilities, and strategically located direct measurements is the optimal approach for quantifying SOC[4].

Ongoing research and development are leading to increasingly sophisticated approaches for SOC change quantification. With increasing use of machine learning and artificial intelligence, simply describing the how the SOC change quantification system makes estimates for a specific application becomes challenging. Approving SOC change estimates simply because of the type of methodology used to make the estimate is no longer reliable. Instead, approval of the estimates is best based on demonstrated performance of the quantification system that produced those estimates to meet the regulator-set criteria for acceptably low levels of uncertainty and bias. Performance-based approval works across SOC change quantification systems and jurisdictions and allows for innovation and flexibility.

2. Life Cycle Assessment and the Carbon Footprint

Life cycle assessment (LCA) is the best method to determine the total environment impact of biofuel production. LCA is the systematic evaluation of the impacts of the production system. The boundaries of the production system are carefully defined, and the impacts of all the activities and materials used in the production are calculated based on standardized approaches. When the only environmental impact of interest is that on the climate through the emission of greenhouse gases, the LCA is usually called the carbon footprint. The units of impact for a carbon footprint are kilograms of the emission of the greenhouse gas, carbon dioxide (CO_2). The emissions of greenhouse gases other than CO_2 are converted to CO_2 equivalent emissions based on the relative radiative forcing (warming) impact of the gas to that of CO_2.

Standard for Carbon Footprints

The principles and methods for LCA are laid out in International Standards Organization (ISO) methods 14040 (2006) and 14044 (2006). Because carbon footprints have become so important to decision making regarding the choice of products and services, these LCA methods were updated and clarified specifically for carbon footprints in ISO method 14047 (2018). The American National Standards Institute (ANSI) establishes standards for the USA and sets ISO 14047 as its standard for carbon footprinting. Similarly, for Canada, the Canadian Standards Association uses ISO 14067. The carbon intensity of a fuel is an LCA of climate impact (carbon footprint) expressed in CO_2 equivalents per kg of fuel from the production and use of the fuel.

[4] Paustian et al., 2019. Carbon Management 10; Smith et al., Global Change Biology 26

SOC Change for Carbon Footprints

For biofuels produced from agricultural feedstocks, the production of the feedstock accounts for a large part of the biofuels' total carbon intensity. In turn, much of those agricultural emissions are from the soil, such as the emission of the potent greenhouse gas, nitrous oxide, emitted from nitrogen added to the soil to increase crop growth. Additionally, increases in soil C stocks represent a removal of CO_2 from the atmosphere, while decreases of soil C stocks represent an emission of CO_2. Under ISO 14047, changes to soil carbon stocks should be reported with the carbon footprint.

For its forthcoming Clean Fuel Standard, the Government of Canada will recognize SOC changes for calculating carbon intensity values for fuels produced from terrestrial biomass. While the need to report SOC changes in carbon footprints is well recognized, there is no established method to estimate those changes in carbon footprints. Although ISO 14067 does not recommend specific emission estimation methods, it does state that greenhouse gas emission estimates from methods that meet IPCC inventory good practice, such as is the values from Canada's national inventory that is used for the carbon footprint of Canadian canola, are fully acceptable.

The SOC is affected by the whole cropping system over time, so it is more accurate to estimate changes over the whole rotation or cropping system[5]. Modeling SOC along with representative multi-decade field measurements to confirm the modeling results is effective in representing SOC changes. (see Annex C for a detailed review of this issue.)

Sophisticated Official National Inventories Provide Best Estimates of SOC

Canada provides its official estimates of SOC change in its National Inventory Report (see Annex B for more details). These are the best estimates for calculating the carbon intensity of Canadian canola-based biofuels for the regions of canola production. This is because they were produced by a feasible, accurate quantification system and these estimates adhere to the internationally accepted good practice guidelines as set out by the Intergovernmental Panel on Climate Change (IPCC)[6] (see Annex C for more detail). Using these estimates enables that the full effect of a cropping system is included.

The method also ensures there was no bias by selecting the land for the estimate – the SOC change is for the whole production area and includes the impacts of practices that are reducing SOC on cropland as well as the practices that are increasing SOC. In addition, this method also addresses the challenge of SOC

[5] Brankatschk and Finkbeiner, 2015, Agricultural Systems 138:66-76; Sevenster et al. 2020, International Journal of Life Cycle Assessment 25:1231-1241
[6] IPCC 2006, 2019 Guidelines

change rates varying with time because the average blends SOC changes for past changes in land management practices as well as current changes in these practices.

Importantly, the Secretariat for the United Nations Framework Convention on Climate Change (UNFCCC) reviews these estimates annually to assess if they follow IPCC Guidelines. Additionally, about every 5 years, the UNFCCC Secretariat selects independent subject experts to do an in-depth review of the SOC change estimates and methods to evaluate if they best meet the criteria of transparency, accuracy, consistency, completeness, and comparability given Canada's circumstances. The inventory methods are fully compliant with ISO 14067.

An important advantage of sophisticated national inventory approaches is that they are not prescriptive regarding quantification methods and encourage continual improvement. Therefore, the principles are implementable and comparable across all jurisdictions.

SOC Change Required

An important reason that changes in SOC stocks should be reported for a carbon footprint under ISO 14067 is that the non-requirement or the failure to report could hide SOC decreases or increases under current production practices. For example, where SOC change on agricultural land is assessed by measurement, these programs have frequently revealed that SOC is declining – an additional GHG emission for products produced on such land. This has been observed in Denmark, Belgium, France, Germany, eastern Canada, and observed in multiple long-term field measurement studies in the US and in Switzerland[7]; exceptions are Hungary and the UK[8] , with no measured overall SOC change. Therefore, the decision not to require reporting SOC change to be included can underestimate the carbon intensity of biofuels from agricultural feedstocks whose production practices are causing SOC decreases.

In Canada, including the positive SOC change associated with cropping system practices has a marked impact on the footprint. For example, for canola, SOC can reduce the C footprint by 10 to 35% for western Canada from what would have been without including the SOC change[9].

Biogenic Carbon

[7] Denmark: Taghizadeh-Toos et al. 2014, European Journal of Soil Science 65:730-740; Belgium: Sleutal et al. 2006, Soil Use and Management 22:188-196; France: Antoni & Arrouays 2007, Institut Français de l'Environnement; Germany: Capriel 2013, European Journal of Soil Science 64: 445-454; eastern Canada: Nyiraneza et al. 2017, Canadian Journal of Soil Science 97:745-756; US: Khan et al. 2007, Journal of Environmental Quality; Switzerland: Keel et al. 2019, Agriculture, Ecosystems & Environment 286: 106654

[8] Hungary: Szatmári, G. 2019, Soil & Tillage Research; UK: Reynolds et al. 2013, Vadose Zone Journal 12

[9] $(S\&T)^2$ Consultants Inc., 2017, Carbon Footprint of Canadian Canola, Canada Grains Council.

Under ISO 14067, it is necessary to report the biogenic carbon in the biofuel in the carbon footprint. Some users may also want to know if the biogenic carbon in the fuel is additional to what would have been taken up by the vegetation in the absence of biofuel demand[10]. The amount of Canadian canola produced in response to biofuel demand is additional in this sense as it is from increasing yields plus some production on land that would have been left unvegetated otherwise (i.e., summerfallow, see section 1).

3. SOC and Future Opportunities

While changes to cropping systems in western Canada continue to contribute to greenhouse gas mitigation, there remain significant opportunities to attain more greenhouse gas emission mitigation from positive changes to SOC (Figure 4). Most notably, increasing canola production holds potential to significantly increase SOC levels in the soil.

Canola has more root biomass than other common crops and has a relatively higher Carbon input. Therefore, continued increases in canola production due to yield improvements could result in increased SOC. As illustrated in Figure 4, studies show that growing more canola could mitigate more than 8 million t CO2e/yr by 2030. For the climate change to be consistent with the Paris Agreement target, Canadian canola yields are expected to increase[11].

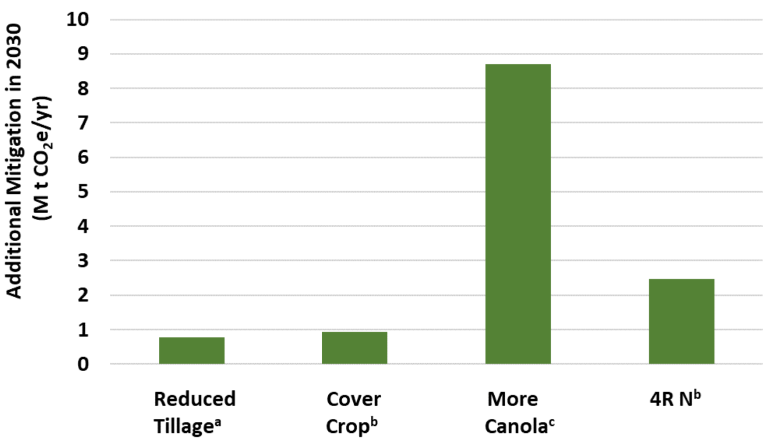

Figure 4. Future mitigation opportunities in western Canada with estimated greenhouse gas reduction in carbon dioxide equivalent (CO_2e) in 2030. ([a]*Drever et al. 2021. Natural Climate Solution for Canada, Sci. Adv 7.*; [b]*Farmers for Climate Solutions, 2021, GHG Analysis and Quantification*; [c]*Fan et al. 2019, Geoderma 336:49-58*).

In addition, future improvements in accounting for climate impacts for unreported mitigation that is already

[10] De Kleine et al. 2017, Biofuels, Bioproducts & Biorefining 11:407-416

[11] *Qian et al. Agronomy Journal 110: 133-146; Qian et al. 2019, Environmental Research Letters 14*

occurring from increasing C input[12] and increased cropland reflectance[13] would increase the reported mitigation.

Conclusions

The western Canadian cropping system that supplies Canada's canola has been transformed to one that achieves a large removal of CO_2 from the atmosphere due to the use of soil-improving practices for its production. The expansion of canola production was essential to that transformation. Under the international standard for calculating carbon footprints (ISO 14067), changes to SOC should be included with the footprint. Canada's official estimates of SOC changes are contained in its National Inventory Report on Greenhouse Gases. Canada's official estimates represent best practices for feasible and accurate quantification of SOC change needed for carbon footprints. Including these SOC change estimates confirms that biofuel produced from Canadian canola has a low carbon intensity. The canola cropping system continues to improve and its carbon footprint is expected to decrease further in the future.

Approving SOC change estimates is best based on demonstrated performance of the quantification system that produced those estimates to meet regulator-set criteria for acceptably low levels of uncertainty and bias. Performance-based approval works across SOC change quantification systems and jurisdictions and allows for innovation and flexibility.

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[12] *Fan et al. 2019, Geoderma 336:49-58*
[13] *Liu et al. 2022. Journal of Environmental Management (in press)*

Annex A. An introduction to SOC and how it is affected by soil management

SOC is vital to good soil health and thereby to productive and efficient crop production. SOC is essential to good soil fertility because with the carbon are important amounts of essential plant macronutrients of nitrogen, phosphorus, and sulfur. SOC also increases the availability and uptake of micronutrients (boron, iron, manganese, etc.) In addition to these fertility benefits, SOC fosters a rich soil microbial community, provides good soil structure, and improves water storage and movement. SOC is the most important single measure of soil health and increasing SOC over time is a telling indicator of sustainable soil management.

The amount of SOC is determined by the sum of C inputs over time minus the sum of C losses over time. The understanding of SOC dynamics from observations is that C decomposition is proportional to the total amount of SOC. If the C input increases so that SOC increases, then the amount of decomposition will increase and vice versa. Once C input and C loss from decomposition are in equilibrium, then the SOC amount is stable (Figure B.1). After a disruption of the input-loss balance, the magnitude of the rate of net SOC increase or decrease will decrease over time as decomposition shifts to the same amount as C input.

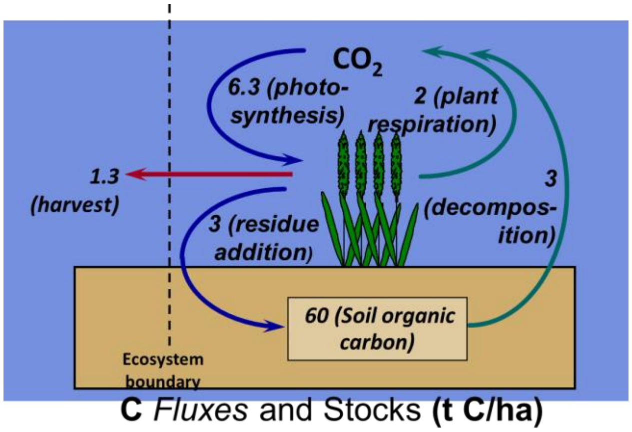

Figure B.1. Soil plant system with balanced C additions and losses having no change in SOC.

Reaching a new stable SOC amount after a change to the C input-SOC decomposition balance typically takes decades. The time to SOC equilibrium depends on the microbial biological activity that in turn depends on soil chemistry, (nutrient availability, pH, salinity), oxygen availability, temperature, and moisture availability. In continually waterlogged soils, the decomposition amount may never reach the level of C additions, such as what happens in peat bogs. Soil erosion complicates the C balance by removing C with eroded soil and adding C with deposited eroded soil elsewhere. The eroded soil may be transported to a totally different environment with different decomposition rates, such as in or underwater bodies. The deposited soil can also bury existing SOC and thereby change the C input-decomposition balance of that buried SOC.

There are two basic ways to build SOC on cropland: 1) increase carbon input to the soil, and 2) decrease losses from decomposition. Increasing carbon input can be accomplished by increasing productivity of the current crops, choosing crop types or cultivars that provide higher carbon input, reducing removal or burning of crop residues, growing cover crops when otherwise there would be no vegetation, and/or adding carbon-containing soil amendments such as compost or livestock manure. Reducing soil disturbance from tillage is an important method to reduce decomposition. Tillage breaks up soil clods and mixes the soil and these actions expose more organic material to decomposition. Thus, decomposition slows when tillage is stopped with the adoption of no-till practices. Compared to intensive tillage, reduced tillage also slows decomposition but to a lesser extent than no-till. Changing the chemistry and/or physical form of organic material additions affects their decomposition. Choosing vegetation that adds relatively more carbon through roots puts that carbon deeper in the soil where decomposition is slower.

Many practices affect both carbon addition and decomposition. Summerfallow or bare fallow, the practice of controlling all vegetation growth during the growing season, both reduces carbon input since there is no vegetation and increases decomposition because it keeps the soil moister and warmer than if vegetation were growing. Perennial crops of hay or pasture grown in rotation with annual crops provide more carbon input in total and through roots than many annual crops while also reducing decomposition since there is usually no tillage during the perennial's growth.

Annex B. Monitoring, Reporting, and Verification of SOC Changes for Canada

Because of the importance of SOC Changes in relation to climate change, every country is required to report its greenhouse gas sources and sinks, including those from SOC change, under the United Nations Framework Convention on Climate Change (UNFCCC). Developed countries, like Canada, do this monitoring, reporting, and verification through an annual National Inventory Report (NIR). A great deal of effort is put into the SOC change estimates so that they achieve the required attributes of transparency, accuracy, consistency, completeness, and comparability. Under the UNFCCC, the NIR is reviewed after each annual submission. Additionally, about every 5 years, the UNFCCC Secretariat selects independent subject experts to do an in-depth review of the SOC change estimates and methods to confirm that they best meet the criteria of transparency, accuracy, consistency, completeness, and comparability given Canada's circumstances.

Canada reports changes to SOC for a soil depth of 0-30 cm in its NIR based on changes in land use and management and changes in C input to the soil. These SOC changes are estimated for each of the 3500 soil landscapes of Canada (SLC) polygons. These polygons are the smallest division of Canada's ecological framework[14] and represent units of similar soils, landforms, and climate. Survey data and earth observation are used to identify the amount and location of land use and management changes.

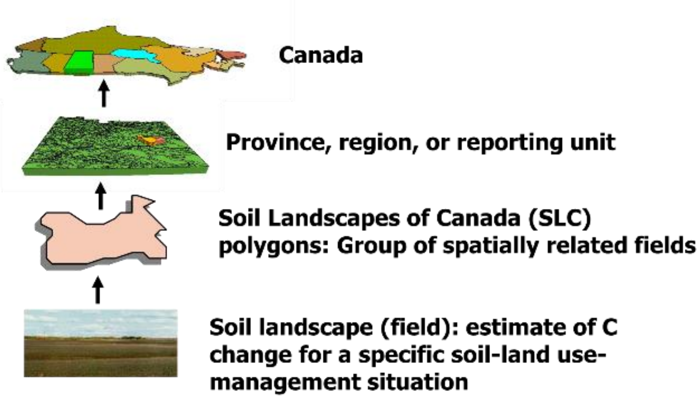

Figure A.1. Bottom-up estimate of SOC change.

The Census of Agriculture conducted every 5 years, the latest was in 2021, enumerates all farms and collects detailed data on a farm basis. More detailed farm surveys augment the Census and, increasingly, remotely sensed data from satellites contributes to quantification. Known relationships between agricultural systems with soils, location, and climate were used to allocate practice changes within and between SLC polygons. Once a land management change, such as a change in tillage system, is identified and allocated to a soil landscape, the SOC change for that area of change is estimated. Owing to the use of surveys, the SLC polygons, with an average of 9300 ha (23,000 acres) of agricultural land each, are the

[14] A National Ecological Framework for Canada, https://sis.agr.gc.ca/cansis/publications/manuals/1996/index.html

smallest practice unit to estimate SOC changes. These changes are then summed from the bottom up to estimate SOC change for the SLC polygon and from there to larger geographical units (Figure A.1).

The SOC change for the specific soil-land use-management change, like tillage system, was estimated relative to no land use or management change base condition. This was done by modeling both the base and SOC with the practice change using the Century soil organic matter model. To estimate the effect of changing C input due to annual changes in areas of different crops and their yields, the Century model-based steady state model[15], developed by IPCC, is used. The SOC change due to C input is relative to the SOC change before 1990. Underpinning these models is an extensive, cross-country, network of past and current long-term agricultural field measurement studies for which SOC has been conducted by Agriculture and Agri-Food Canada research stations and Universities. About two dozen such studies have been conducted for more than 20 years (the oldest is now 110 years old) and about an additional 60 field measurement studies have been conducted for up to 20 years[16]. The Century models were validated with the SOC change data[17] from this research network.

This model validation is fundamental to the verification of the quantification system. A dynamic SOC change factor was then derived from the difference from the base and that was applied to the appropriate soil-land use-management situations (Figure A.2). The factors have reducing rates of SOC change with time since the change of practice (Figure A.3). While much of the total change occurs in the first 20 years after adoption, in the cold climate of western Canada significant SOC change occurs for several additional decades. The factors differ by soil texture and location (climate, initial SOC, and crop production). Figure

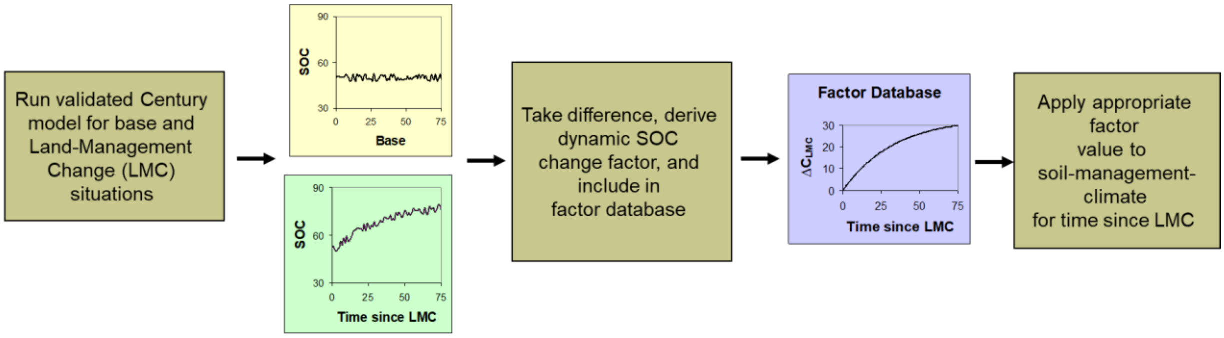

Figure A.2 Basic method for estimating SOC change factors.

[15] IPCC, 2019, 2019 Refinements to the 2006 IPCCC Guidelines: Vol. 4, Ch. 5
[16] For a listing of most of these studies, see Liang et al. 2020, Soil and Tillage Research 198:104529 and VandenBygaart et al. 2003, Canadian Journal of Soil Science
[17] VandenBygaart et al. 2008, Canadian Journal of Soil Science 88:671-680, Thiagarajan et al. 2022, Geoderma Regional: e00534

A.4 shows some typical factor values for western Canada. An important advantage of deriving factors with modelling rather than using empirical data directly from field studies was the ability to have a realistic representation of the temporal dynamics of SOC change.

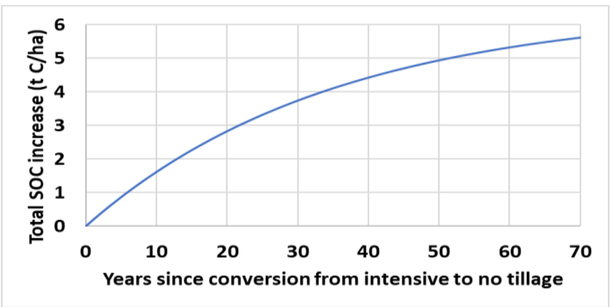

Figure A.3. The NIR factors estimate that the rate of SOC increase decreases with time since adoption as shown for this example for conversion from intensive to no tillage.

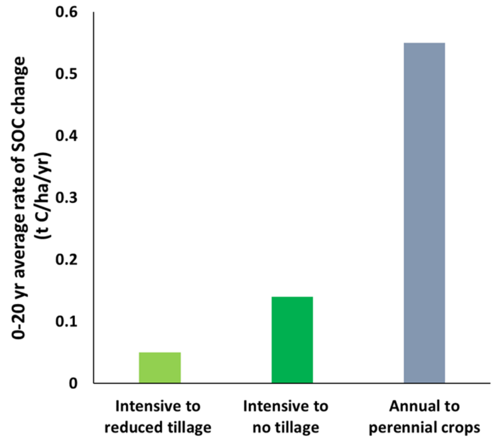

Figure A.4. Typical rates of SOC change for initial 20 years after various land management changes from the NIR factors.

The Canadian NIR estimates for SOC change under no-till assume the discontinuous practice of no-till, i.e., no-till factor assumes some tillage periodically as described in the NIR methodology[18]. The rationale is that the nature of activity data does not indicate practices over time for individual fields and land manager are not necessarily continuous over time as leasing of land is common (40% of farmland was leased in 2016, Statistics Canada). Therefore, assuming some tillage in no-till systems provides a more conservative (lower) estimate of SOC change from no-till. As expected, then, the factor of SOC change with NT adoption is much lower than that measured by the Canadian network of field studies[19] since the latter are strictly continuous no-till.

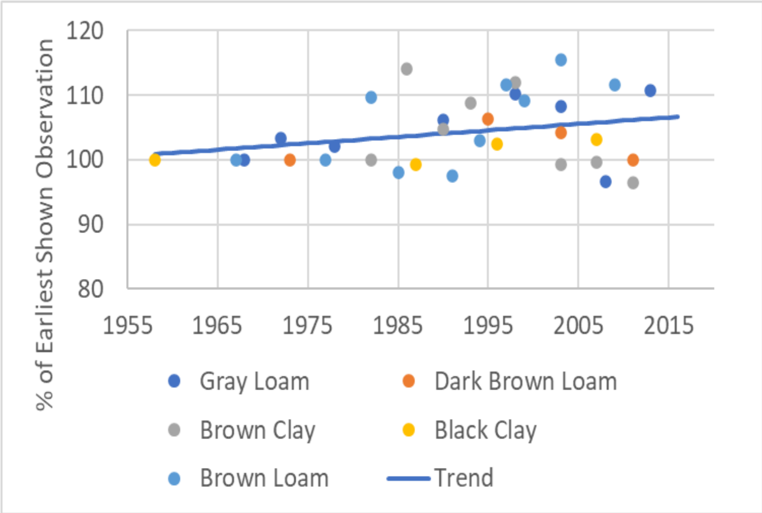

Figure A.5. Continual crop-fallow is not causing recent SOC loss (the soil colors refer to the soil zones, see https://sis.agr.gc.ca for information about soil zones). The weak, non-significant, trend for increasing SOC can be related to more productive crop varieties plus better herbicides that reduced the amount of tillage needed in tilled systems. (References: Campbell et al. 2007, Canadian Journal of Soil Science 87:23-38; Grant et al. 2020, Canadian Journal of Soil Science 107:1-22; Karimi et al. 2018, Canadian Journal of Soil Science 98:580-593; Maillard et al. 2018. Soil and Tillage Research 177:97-104; Lemke et al. Canadian Journal of Soil Science 92:449-461)

The SOC changes are relative to the base situation. Western Canadian soils became significantly degraded by the 1950s, primarily due to the prevalence of fallow in the past. Repeated measurements under the intensely soil degrading management practice of crop-fallow in the Canadian field study network has shown no further SOC decrease from 1950 to the 1970s (Figure A.5). This indicates that SOC in western Canada was at an effective floor by the mid 20th century. This means that SOC increases in the NIR in western Canada will be absolute increases in SOC and represent CO_2 removals from the atmosphere. (Note, in contrast to western Canada, the NIR indicates that the soils in eastern Canada are losing SOC currently, and this has been corroborated with SOC monitoring in the province of Prince Edward Island[20].)

[18] McConkey et al. 2014, Methodology and greenhouse gas estimates for agricultural land in the LULUCF sector for NIR 2014, Environment and Climate Change Canada.
[19] Liang et al., 2020.. *Soil and Tillage Research 198*
[20] Nyiraneza et al. 2017, Canadian Journal of Soil Science 97:745-756

Annex C. Technical Note - Methods for Quantification of SOC

Summary

Achieving the optimal method to quantify either SOC changes over time or SOC changes over soil landscapes in ways that are both accurate and economically feasible has been the subject of substantial investigation and discussion. A large amount of research and development on SOC quantification has focused on the development of cost-effective, but accurate, methods to estimate SOC change. This has concentrated on how to best combine strategic direct measurements, the use of dynamic process models for quantification of SOC, and the use of advanced analytical techniques for geospatial data, such as digital SOC mapping, to estimate SOC with acceptable accuracy over a large, diverse areas.

There is an emerging consensus that quantification approaches that intelligently integrate direct measurement, dynamic SOC process models, and digital geospatial analysis are optimal in terms of feasibility and accuracy. Such integrated systems are now best represented by sophisticated SOC change estimation in many greenhouse gas inventories by national governments including Canada, the United States, and several western European countries. Future developments leading to increasingly sophisticated approaches to SOC change quantification require that the quality of the SOC change estimates be assessed based on the demonstrated ability of the SOC quantification system that produced those estimates to meet criteria for acceptably low levels of uncertainty and bias. Performance-based approval works across all SOC change quantification systems and jurisdictions and allows for innovation and flexibility.

No standards for estimating landscape-scale SOC or SOC change over time, IPCC Guidelines are best available guidance

While there are dozens of international standards that cover the point sampling of soils and the analysis of soils for various properties, there are no international standards that cover the quantification of SOC at the field to larger scales or that cover estimating changes in SOC over time (Bispo *et al.*, 2017). Although not a standard, the IPCC Guidelines for national greenhouse inventories (IPCC, 2006, 2019) are the only widely accepted international guidelines regarding both quantification of SOC change and for quantification over large areas (Bispo *et al.*, 2017). Usefully, the IPCC Guidelines are applicable for all types of models and measurements or combinations of models and measurements.

Direct Measurement of SOC at Specific Locations

Direct measurement with point estimates is the measurement of SOC to a prescribed depth at points or specific locations.

<u>Dry combustion</u>

Dry combustion (DC) is currently considered the de facto standard for determining the SOC concentration in soil. The DC method oxidizes the SOC in a small (<1g) soil sample by heating to a high temperature in pure oxygen. The CO_2 evolved from DC is then measured with an atomic analyzer.

Wet Combustion

Wet combustion measures SOC concentration with chemical oxidants and was widely used in the latter half of 20th century but is not so widely used in the 21st century because wet combustion typically does not measure all SOC. So, it underestimates the amount of SOC (Fernandes *et al.*, 2015).

Soil Inorganic Carbon

Many soils contain significant amounts of inorganic carbon. This carbon needs to be excluded from the soil to provide a measurement of only SOC. The inorganic carbon can be measured separately by measuring the CO_2 released when the soil is treated with a strong acid. In that case, the total carbon for the soil is measured and SOC is the difference between total carbon and soil inorganic carbon. For DC, the inorganic carbon can also be removed with a strong acid without measuring the CO_2 before analysis, in which case then all the carbon evolved during DC is SOC.

Soil Bulk Density

All the direct measurements of SOC require soil bulk density. Bulk density is the mass of dry soil for a given volume. It is necessary to convert SOC concentration to the mass of SOC for a given depth of soil. Bulk density is both variable in space and time. Therefore, soil bulk density needs to be quantified for each soil sampling. Direct measurement of soil bulk density involves measuring the mass of soil in an original volume of a soil sample. The soil must be both carefully sampled and processed to produce good estimates of bulk density. The amount of labor involved makes bulk density expensive to measure.

An empirical model, usually called a pedotransfer model, that is based on soil properties such as texture and SOC, can be used, albeit with introduced uncertainty, where the empirical model has been validated.

Gamma ray attenuation is a proximal sensor that makes an estimate of soil bulk density based on the attenuation of emitted gamma rays between a gamma-ray source and detector that increases as the bulk density of the soil between the source and detector increases. If the gamma ray source is inserted to different depths it is possible to estimate the bulk density with depth. The gamma ray attenuation method is not widely used to measure soil bulk density for SOC quantification.

Coarse Fragments

Coarse fragments of stones or rocks > 2mm in effective diameter do not contain any SOC. The coarse fragments are purposely excluded from SOC concentration measurement. Therefore, if their contribution to soil mass is not accounted, they cause the amount of SOC to be overestimated because the measured

SOC concentration for the fine (clay, silt, and sand) soil particles is applied to the coarse fragment mass. Standard methods for direct measurement of bulk density include removing and quantifying the amount of coarse fragments. However, for other methods to estimate the soil bulk density, the quantity of coarse fragments in the soil needs to be also estimated.

Modeled SOC from outputs from Proximal Sensors

IR Spectrometry

A widely used SOC quantification is a model of the relationship between the SOC concentration and the spectroscopic analysis based on the reflectance of radiation frequencies bands in the near- and mid-infrared (IR) spectrums but can also combine the IR with the visible (Vis) spectrum (Ramirez-Lopez *et al.*, 2019; Angelopoulou *et al.*, 2020). Usefully, empirical models can be developed for IR spectroscopy that can estimate both soil inorganic and organic carbon separately. Relationships can also be developed for many other soil attributes including fractions of soil organic matter. Portable instruments, including handheld units, are available for use.

The empirical model to convert spectral reflectances to estimated SOC is derived from data of SOC from DC to the spectral signatures. Because the model is data driven, it requires much good quality SOC data from DC for the soils for which it will be applied. This data set for developing or training the model is often called the training set. The training set need to cover the application soil domain -- all the types of soils and soil conditions for which it is planned to be used for the planned application (Soriano-Disla et al., 2014).

If applied to soil conditions outside of what is in the calibration data set, then the predictions can be inaccurate and biased. Also, because calibration is data-driven, it is prone to overfitting (Beisbart and Saam, 2019). Overfitting refers to the model being trained to match the training data set so well that it does not perform well for soil outside of the training set even if from the same soil conditions expected to be covered by the training set, such as being from the region and soil types in the calibration data set.

To validate that the model is accurate and produces an unbiased estimate of its uncertainty, it is necessary to have a validation data set of SOC from DC that is independent of the training set. This data set is often called the testing set. If there are problems identified through validation, additional data can be collected for the training set or different procedures applied to model derivation so that the model performs better for data independent of the training set and so, presumably, likewise when applied for SOC measurement anywhere in the soil domain (range of soil types and conditions) to those in the training and testing data sets. The data used for training and testing are often referred to as a soil spectral library.

The soil domain also includes the state of the soil subject to IR spectroscopy. For example, for field use, the data used to derive the empirical model to relate to SOC must include the states of soil moisture and structure that would be encountered in the field. Inaccuracies may occur when an empirical model derived for IR spectroscopy is used of dried and ground soil samples in a laboratory and applied to fresh soils with varying degrees of surface roughness, moisture, and occlusion of soil organic matter. Each individual spectroscopy instrument used for estimation also needs to be separately calibrated to the spectroscopy instruments used to derive the model of relationship between reflectance and SOC.

There are considerable costs to developing high-quality models for IR spectroscopy but once developed and shown to be accurate, the analytical costs to estimate SOC are much lower than by DC. Obviously, the estimates from IR spectroscopy are not as certain as those from DC, but more low-cost measurements can be with IR to compensate for its increased uncertainty.

Laser-Induced Breakdown Spectroscopy

Laser-induced breakdown spectroscopy (LIBS) is a more recent method where a tiny portion (≈ 1 mg) of soil is vaporized by a laser into individual elements. The spectral peaks are analyzed for elements including carbon. A general empirical model is required for calibration to a range of SOC concentrations measured (Senesi and Senesi, 2016). Although the empirical model can work across a wide range of soil textures and mineralogy, the soil structure, chemical forms, and mineralogy can affect C released from the soil, Therefore, soil-specific calibration gives the best accuracy. The method can also discriminate between soil organic and inorganic carbon using multivariate analysis (Martin et al., 2013). Portable LIBS analytical units for use in the field are available.

Inelastic Neutron Scattering

Inelastic neutron scattering (INS, sometimes called neutron-gamma analysis or neutron stimulated gamma spectroscopy) is a new method which uses a radioactive neutron source (Cs-137) and detects gamma rays emitted from interaction with atoms. Without disturbing the soil, INS measures roughly a hemisphere of soil about 2 m in diameter and 25-45 cm deep – so the location measured is not a point and the exact volume and shape of soil measured will depend on the physical and chemical properties of the soil.

INS will be affected by any carbon in that hemisphere including any plant material or soil fauna. Because of the different amounts of soil measured, there is no possibility of a perfect relationship between direct SOC measurement at a location and INS detected gamma rays. Nevertheless, these relationships need to be estimated with an empirical model to account for the effects of soil inorganic carbon, non-soil carbon such as large roots, the depth distribution of soil carbon and the changing soil bulk density. Thus, there are many challenges in knowing what carbon was measured to what depth. Local calibration using direct measured SOC mass improves estimates but other methods to determine SOC appear more accurate than INS (Izaurralde *et al.*, 2013). When mounted on a vehicle and driven over a whole area, INS can provide an estimate of SOC for that whole area to the accuracy for which the INS measurements can be related to the SOC to a set depth. INS is still in the research and development phase for SOC quantification.

Non-Direct Estimation of SOC

Process models

Process models of SOC dynamics represent our understanding of SOC transformations mathematically in a computer program. There are many process models available, three widely used models are DNDC (Li, 1996), Century (Metherell *et al.*, 1993), and RothC (Coleman and Jenkinson, 1996). The exact model used is not as important as the model used having been calibrated and then validated. In fact, the average estimate from an ensemble of different process models is often more accurate than any single model (Riggers *et al.*, 2019; Sándor *et al.*, 2020). The models estimate SOC for a homogenous location with the same soils under the same management and weather that would correspond to the whole field or to homogenous subareas of a field where there is significant variability within the field.

Calibration refers to the modification of the model so that it produces a better match between model estimated and measured estimates. Validation is the testing of the model against data not used in the calibration to assess inaccuracies and estimate model uncertainty. Verification is another form of validation and is the substantiation that the model continues to produce estimates that meet desired performance.

To both calibrate and validate, process models require data that is relevant to the application domain of soil types and conditions, vegetation types, and soil management for the planned application of the model. Process models are designed to capture the primary drivers and flows and transformations of organic carbon that collectively determine the quantity of SOC stocks and their changes over time. Therefore, calibration is the modification of the model parameters that describe the amount and rates of those flows and transformations to produce a good fit between measured and modeled masses of SOC. If calibrated to one site, the model parameters will tend to be overfitted to the conditions of that site. Therefore, there is a need for multiple sites for calibration. Nevertheless, calibration of process models does not require as much data as empirical models because the process in the models constrains the range of estimates for a given input. Because the process model captures the average effects of primary drivers in the application domain, process models typically do not predict the results for anyone calibration site perfectly. Therefore, the validation set that is independent of the calibration data set also needs to include multiple sites to provide meaningful validation across the application domain to provide a meaningful assessment of modeling uncertainty for the application domain.

With proper calibration, process models can achieve fits with measured data in the validation data set within the variability of measured SOC (Smith *et al.*, 2013; Khalil *et al.*, 2020).

The process models treat SOC dynamically so that estimates of SOC amount over time are produced with time intervals from an hour to year depending on the process model. Therefore, process models are perfectly suited to estimate SOC changes over times needed to estimate SOC change for life cycle assessments for agricultural production.

A significant cost to applying process models is to collect or develop the input data on land use and management, as well as the weather over time, that is needed as model input.

Digital SOC mapping with empirical models

Worldwide, most research and development investments in SOC quantification, particularly by the private sector, is focused on digital SOC mapping methods.

Digital SOC mapping is the use of an empirical model that relates available SOC data to various other data that are covariates with SOC (Xiong *et al.*, 2015; Malone *et al.*, 2017; Richardson *et al.*, 2017). The empirical model is derived from measured SOC data for locations. Once developed and validated that it meets desired performance standards, the SOC is then estimated for other locations based on the covariate values. The covariates include static data like soil type data from soil surveys and digital elevation models and dynamic data from remote sensing. Reflectance in wavelengths of the bands used for IR spectroscopy is usually included in remotely sensed data as improves estimates where bare soil is visible to the remote sensor.

Often these empirical models use techniques from artificial intelligence such as machine learning to specify the relationship between SOC and the covariates. Since the covariates are geospatial these latter empirical models produce a map of SOC stocks across the landscape. Validation of SOC mapping is essential since much of the SOC data used to develop the empirical model is not collected randomly. So, it can introduce biases (Biswas and Zhang, 2018). Validation is that the fit of SOC estimated at a point with measured SOC data at that point that was not used in the development of the empirical model meets desired performance.

Conventional digital SOC mapping determines SOC at one time – the time when the measured SOC data used for empirical model development was collected. Although any difference between covariates at two times will produce an apparent difference in SOC between those times, this apparent difference can not be considered valid until verified by measured SOC (Venter et al., 2021; Minasny et al., 2013). There has been limited work on the ability of SOC mapping to detect SOC change since measured data of SOC change are scarce. In the one study where data of SOC change over 7 years was available, digital soil mapping accounted for less than one-half of the variability in SOC change (Ellili et al., 2019). Combining process modelling of SOC change with digital SOC mapping capabilities appears to be the best approach for cost-effectively using digital SOC mapping capabilities to estimate SOC change (Minasny et al. 2013).

Upscaling necessary to produce area SOC estimates

Location-specific SOC masses from direct field measurements or process models needs to be upscaled to produce an estimate for a large area relevant to the production of any agricultural product. The upscaling relates the location specific SOC mass estimates to the area between locations with estimates. This can be done with functions that relate to covariates to SOC that are available everywhere, such as when SOC is strongly related to where it is on the landform. The landform can be continuously described with digital elevation models.

Another method is to stratify the large SOC-heterogeneous area into smaller subareas for which SOC is more homogenous and then apply the appropriate location-specific SOC estimates to those subareas (also called strata) to estimate SOC across a large, stratified area of production. Digital SOC mapping is already an upscaled estimate by design since covariates are geospatially defined. Many of the same data used for digital SOC mapping are used for upscaling location-specific estimates such as soil type maps, field boundaries, digital elevations, and land use. Increasingly, digital soil mapping methods are used to pick optimal sites for location-specific measurements needed for calibration, validation, and/or verification (Cunningham *et al.*, 2017; de Gruijter *et al.*, 2018). For process models, dynamic data such as vegetation type and production for the strata are also useful for upscaling.

An Integrated System is an Effective Way for Quantifying SOC Change

Given the different capabilities and limitations of different methods for quantification of SOC, an approach that integrates these methods is an effective way to take advantage of the capabilities while minimizing the limitation (Smith *et al.*, 2012). The basis of an integrated approach is the use of a process model that estimates SOC and SOC changes. An important advantage of a process model is that it estimates SOC change at relevant time scales needed for assessments, such as carbon foot printing, that support decision making. Another advantage of process modeling is that it can provide assessments for future scenarios that inform private and public policy.

In an integrated system (Paustian *et al.*, 2019; Smith *et al.*, 2020):

- Direct measurements are used to calibrate, validate, and verify the SOC estimates from process models. Adequately calibrated and validated proximal sensors are used to reduce analytical costs for direct measurement.
- More expensive measurements from DC will be used to calibrate other methods for direct measurement such a Vis-IR spectroscopy.
- Digital geospatial analysis, including SOC mapping, informs the strategic placement to get the most value for limited direct measurements.
- Digital geospatial analysis is used to inform the upscaling of output from process models.
- Various remote sensed data is used both for digital soil mapping but also provide some input data for process models.
- Finally, the data collation system required for data on SOC covariates are not only used for digital soil mapping but also for management of input and output data for process modeling.

<u>Canada's National Inventory – An integrated Approach</u>

Currently, SOC change estimation as done in sophisticated greenhouse gas inventories by national governments including Canada, the United States, and many European countries provides the best representation of such integrated systems. These inventories are based on process models but use available SOC measurements for calibration, validation, and verification. Various geospatial covariates are used for upscaling the model estimates. The estimates are relevant for specific agricultural production practices because of the need to identify the direct anthropogenic effect on SOC and greenhouse gas emissions. These systems make intensive use of remotely sensed data both to improve upscaling and provide model input data. Thus, all the elements of the integrated SOC estimation system are included. They are the best examples of economically feasible, accurate systems for SOC quantification.

Approve quantification based on performance.

As the SOC quantification approaches become increasingly more integrated, the concept of what is the exact method behind a quantification system becomes imprecise. In fact, with increasing use of machine learning and artificial intelligence (AI), even describing the how the underlying methods are employed becomes difficult. A single quantification system with AI may use different, possibly previously unimagined, approaches depending on the problem and available data. Therefore, approving SOC change estimates based on the underlying methods in a quantification system is losing relevancy. Approving the estimates based on the demonstrated ability for the quantification system that produced the estimates to meet regulator-set criteria for acceptable performance always remains relevant. Undeniably, any acceptable quantification system needs to provide estimates of SOC change with an acceptably narrow confidence interval and, particularly for any method that involves models of any sort, including approaches that involved proximal sensors, with an acceptably low bias.

Both the confidence interval and the bias can be evaluated by comparing the SOC change estimates with direct measurements that are independent of any direct measurements used in the development or refinement of the quantification system. The comparison against these independent direct measurements can be called validation, verification, and/or testing of the quantification system. The performance of all SOC quantification systems can be assessed from their uncertainty and bias -- including quantification systems based primarily on direct measurements since the upscaling procedures creates uncertainty and potential bias. Therefore, accepting SOC change in carbon footprints should not be dependent on the methods used to estimate the SOC change, but rather, on the uncertainty and bias of the SOC change estimates. Logically, the regulator who decides on the value of the carbon footprints also decides on the acceptance criteria. Consistent criteria for acceptance based on quantification system performance provides a fair way to use carbon footprints derived from different quantification system and jurisdictions while also enabling innovation in SOC quantification and flexibility to address the circumstances of a specific application.

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