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VERSION 1

Measuring and modelling soil carbon stocks and stock changes in livestock production systems

Guidelines for assessment

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Contents

<i>Acknowledgements</i>	<i>v</i>
<i>Abbreviations and acronyms</i>	<i>xi</i>
<i>Glossary</i>	<i>xii</i>
<i>Executive summary</i>	<i>xiv</i>
1. INTRODUCTION	1
1.1 Objectives and intended users	1
1.2 Scope	1
1.2.1 Land use systems	1
1.2.2 Soil carbon	2
1.3 Soil organic matter and soil organic carbon	2
1.4 Livestock systems and soil organic carbon	3
1.5 Land use change, land management and soil organic carbon stocks	7
2. DETERMINATION OF SOIL ORGANIC CARBON STOCKS	8
2.1 Introduction: The need to measure soil organic carbon stocks	8
2.2 Planning the sampling	10
2.2.1 Site heterogeneity and stratification	12
2.2.2 Sampling strategies	13
2.2.3 Compositing	16
2.2.4 Sampling depth	17
2.3 Errors and uncertainties	18
2.4 Soil processing and analysis	21
2.4.1 Drying, grinding, sieving, homogenizing and archiving soil samples	22
2.4.2 Bulk density	23
2.4.3 Coarse fraction of belowground organic carbon	27
2.4.4 Inorganic carbon	28
2.5 Analytical methods for total soil organic carbon determination	29
2.5.1 Dry combustion method	29
2.5.2 Wet digestion/oxidation of organic carbon compounds by dichromate ions ($Cr_2O_7^{2-}$)	30
2.5.3 Loss-on-ignition method	30
2.5.4 Spectroscopic techniques for soil organic carbon determination	31
3. MONITORING SOIL ORGANIC CARBON STOCK CHANGES – REPEATED MEASUREMENTS AGAINST A BASE PERIOD, AND MEASUREMENTS AGAINST A BUSINESS-AS-USUAL BASELINE	34
3.1 Planning and implementing a monitoring strategy for soil organic carbon stock change	34
3.2 Introduction to soil organic carbon stock change assessment by measuring against a baseline	35
3.2.1 Sources of error and bias in soil organic carbon stock change monitoring	36
3.3 Sample size	37
3.3.1 Pre-sampling for soil organic carbon stocks and variability to guide sample size	37
3.3.2 Using minimum detectable difference to determine sample size	38

3.4 Sampling frequency	41
3.5 Calculating soil organic carbon stock change	42
3.5.1 Equivalent soil mass	42
3.5.2 Calculating soil organic carbon stock changes	44
4. DATA MANAGEMENT AND REPORTING. SAMPLE ARCHIVING	50
4.1 Handling data	50
4.1.1 Data gathering	50
4.1.2 Data processing	51
4.1.3 Data storage and retrieval	51
4.1.4 Data quality control	52
4.2 Reporting results	53
5. MONITORING SOIL ORGANIC CARBON CHANGES – NET BALANCE OF ATMOSPHERIC CARBON FLUXES	54
6. MODELLING SOIL ORGANIC CARBON CHANGES	58
6.1 Introduction	58
6.1.1 What is modelling and who is it intended for: decision support and reporting	58
6.2 The different modelling approaches	59
6.2.1 Level 1. Empirical models	59
6.2.2 Level 2. Soil process models	62
6.2.3 Level 3. Ecosystem models	65
6.3 Deciding on the approach	67
6.3.1 Technical capacity and activity data	69
6.4 Implementation	70
6.4.1 Data availability	70
6.4.2 Initialization of the model	73
6.4.3 Validation of results	74
6.5 Uncertainty and sensitivity analysis	76
6.5.1 Sensitivity and uncertainty - Introduction	76
6.5.2 Sensitivity analysis	79
6.5.3 Calibration	80
6.5.4 Uncertainty estimates from calibration and validation	80
6.5.5 Model prediction uncertainty	81
6.5.6 General guidance	81
7. SPATIAL INTERPRETATION AND UPSCALING OF SOC	83
7.1 Introduction	83
7.2 Sampling for spatial interpolation	84
7.3 Interpolating methods for soil organic carbon predictions	86
7.4 Geostatistics	88
7.5 Digital Soil Mapping	92
7.6 Practical application of interpolation techniques	93

8. INTEGRATING CHANGES IN SOIL ORGANIC CARBON INTO LIFE CYCLE ASSESSMENT	95
8.1 Introduction	95
8.2 Implications of including SOC stock changes in LCA	97
8.2.1 <i>System boundaries and cut-off criteria</i>	97
8.2.2 <i>Representativeness and appropriateness of LCI data (SOC data or model)</i>	98
8.2.3 <i>Types, quality and sources of required data and information</i>	98
8.2.4 <i>Comparisons between systems</i>	98
8.2.5 <i>Identifying critical review needs</i>	99
8.2.6 <i>Emerging reporting requirements</i>	99
9. APPENDIX ONE: TECHNICAL INFORMATION ON MODEL INITIALIZATION	101
9.1 Initialisation Challenges and Approaches	101
9.2 Initialisation of soil pool sizes is less important for comparisons between two or more concurrent scenarios	103
9.3 Guidance for Initialisation	104
10. APPENDIX TWO: TECHNICAL DETAILS OF MODEL CALIBRATION AND UNCERTAINTY EVALUATION USING MONTE CARLO APPROACHES	106
11. REFERENCES	107

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AUTHORSHIP AND DEVELOPMENT PROCESS

The Technical Advisory Group, (TAG) on soil carbon stock changes, hereafter called Soil Carbon TAG, is composed of experts from various backgrounds and areas of research and extension services, including soil science, ecology, livestock production systems, animal science, agriculture science, capacity development, and Life Cycle Assessment (LCA). The Soil Carbon TAG was formed by the Livestock Environmental Assessment and Performance (LEAP) Partnership.

These LEAP guidelines can be used in conjunction with other LEAP guidelines depending on goal and scope of the assessment.

These guidelines are a product of the Livestock Environmental Assessment and Performance (LEAP) Partnership. The following groups contributed to their development:

The Soil Carbon TAG conducted the background research and developed the core technical content of the guidelines. The TAG was composed of 37 experts: Pete Millard (co-chair, Manaaki Whenua Landcare Research, New Zealand), Fernando A. Lattanzi (co-chair, Instituto Nacional de Investigación Agropecuaria - INIA, Uruguay), Aaron Simmons (Department of Primary Industries NSW, Australia), Amanullah (Dept Agronomy, The University of Agriculture Peshawar, Pakistan), Beáta Eموke Madari (EMBRAPA, Brazil), Bernard Lukoye Fungo (National Agricultural Research Organisation, Uganda), Beverley Henry (Queensland University of Technology, Australia), Bhanooduth Lalljee (University of Mauritius, Mauritius), Brian McConkey (Agriculture and Agri-Food Canada, Swift Current, Canada), Carolyn Hedley (Manaaki Whenua Landcare Research, New Zealand), Chiara Piccini (Council for Agricultural Research and Economics, Italy), Christopher Poeplau (Thünen Institute of Climate-Smart Agriculture, Germany), Daniel Rasse (Norwegian Institute of Bioeconomy Research - NIBIO, Norway), Dario Arturo Fornara (Agri-Food & Biosciences Institute, UK), Denis Angers (Agriculture and Agri-Food Canada, Canada), Ermias Aynekulu (World Agroforestry Centre, Kenya), Esther Wattel (National Institute for Public Health and the Environment, Netherlands), Francisco Arguedas Acuna (Instituto Nacional de Innovación y Transferencia en Tecnología Agropecuaria - INTA, Costa Rica), Gary John Lanigan (TEAGASC, Ireland), Guillermo Peralta (National Institute of Agricultural Technology, Argentina), Johnny Montenegro Ballesterro (Costa Rican Government, Costa Rica), Jorge Álvaro-Fuentes (Spanish National Research Council, Spain), Katja Klumpp (INRA, France), Martine J. J. Hoogsteen (National Institute for Public Health and the Environment, Netherlands), Mia Lafontaine (Friesland Campina, Netherlands), Miguel A. Taboada (National Institute of Agricultural Technology, Argentina), Miguel Mendonça Brandão (Royal Institute of Technology, Sweden), Otgonsuren Avirmed (Wildlife Conservation Society of Mongolia, Mongolia), Prakaytham Suksatit (National Metal and Materials Technology Centre, Thailand), Roberta Farina (Council for Agricultural Research and Econom-

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Steering committee members

Douglas Brown (World Vision, until December 2016), Angeline Munzara (World Vision, since November 2016, South Africa), Richard de Mooij (European Livestock And Meat Trading Union, EUCBV; International Meat Secretariat, IMS), Matthew Hooper (Embassy of New Zealand, Italy, until 2018), Don Syme (Embassy of New Zealand, Italy, since May 2018), Alessandro Aduso (Ministry for Primary Industries, New Zealand, since 2018), Victoria Hatton (Ministry for Primary Industries, New Zealand, since January 2017), Peter Ettema (Ministry for Primary Industries, New Zealand), Hsin Huang (IMS, France, LEAP Chair 2016), Gaelle Thyriou (Beef + Lamb, IMS, New Zealand), Ben O’ Brien (Beef + Lamb, New Zealand, IMS, from January to December 2017), Jean-Pierre Biber (International Union for Conservation of Nature, IUCN, Switzerland), María Sánchez Mainar (International Dairy Federation, IDF, since January 2018, Belgium), Caroline Emond (IDF, Belgium, since January 2018), Lionel Launois (Ministère de l’Agriculture, France), Pablo Manzano (IUCN, Kenya, LEAP Chair 2017), Nicolas Martin (European Feed Manufacturers’ Federation, FEFAC, Belgium; International Feed Industry Federation, IFIF), Frank Mitloehner (University of California, Davis, IFIF, the United States of America, LEAP Chair 2013), Anne-Marie Neeteson-van Nieuwenhoven (International Poultry Council, IPC, the Netherlands, until May 2018), Peter Bradnock (IPC, since May 2018), Edwina Love (Department of Agriculture, Food and the Marine, Ireland), Frank O’Mara (Teagasc –Agriculture and Food Development Authority, Ireland), Lara Sanfrancesco (IPC, Italy), Nicoló Cinotti (IPC, Italy, since May 2018), Marilia Rangel Campos (IPC, Brazil), Alexandra de Athayde (IFIF, Germany), Julian Madeley (International Egg Commission, IEC, United Kingdom), Dave Harrison (Beef + Lamb, New Zealand, IMS, until De-

cember 2016), Paul McKiernan (Department of Agriculture, Food and the Marine, Ireland, until December 2016, LEAP Co-chair 2015), Representatives of the International Planning Committee for World Food Sovereignty, Jurgen Preugschas (Canadian Pork Council, Canada, IMS), Nico van Belzen (IDF, Belgium, until December 2017), Elsbeth Visser (Ministerie van Economische Zaken en Klimaat, EZK, the Netherlands, from July 2015 to July 2016), Niek Schelling (EZK, the Netherlands, from July 2017 until July 2018), Henk Riphagen (EZK, the Netherlands, from July 2016 until July 2017), Kim van Seeters (Ministry of Agriculture, the Netherlands, since July 2018), Hans-Peter Zerfas (World Vision, until December 2017), Gianina Müller Pozzebon (Permanent representation of Brazil to FAO, Italy, since March 2018), Felipe Heimburguer (Division of Basic Commodities, Ministry of Foreign Affairs, Brazil, since September 2017), Eric Robinson (Alternate Permanent Representative of Canada to FAO, until September 2017), Tim McAllister (Agriculture and Agri-Food Canada), Robin Mbae (State Department of Livestock, Kenya), Julius Mutua (State Department of Livestock, Kenya), Mauricio Chacón Navarro (Ministero de Agricultura y Ganadería, MAG, Costa Rica), Fernando Ruy Gil (Instituto Nacional de Carnes, INAC, Uruguay, LEAP Chair 2018), Walter Oyhantcabal (Ministerio de Ganadería, Agricultura y Pesca, Uruguay), Francois Pythoud (Permanent representative of Switzerland at FAO), Alwin Kopse (Swiss Federal Office for Agriculture, FOAG, Switzerland), Jeanine Volken (FOAG, Switzerland), Martin Braunschweig (Agroscope, Switzerland, until December 2017), Jennifer Fellows (Permanent Representation of Canada to FAO), Emmanuel Coste (Interbev, France, IMS), Beverley Henry (International Wool and Textile Organization, IWTO, Australia, from January 2016 to December 2017), Dalena White (IWTO, Belgium), Paul Swan (IWTO, Australia, since March 2018), Sandra Vijn (World Wildlife Fund, WWF, the United States of America), Pablo Frere (World Alliance of Mobile Indigenous Peoples, WAMIP, Argentina), Henning Steinfeld (FAO - LEAP Vice-Chair), Carolyn Opio (FAO, Italy, LEAP Secretariat Coordinator since Jan 2015), and Camillo De Camillis (LEAP manager, FAO), Damien Kelly (Irish Embassy in Italy, until June 2018), Gary John Lanigan (Teagasc–Agriculture and Food Development Authority, Ireland), Paul McKiernan (Department of Agriculture, Food and the Marine, DAFM, Ireland, until December 2016, LEAP Co-Chair 2015), Roberta Maria Lima Ferreira (Permanent representation of Brazil to FAO, Italy, until October 2017), Renata Negrelly Nogueira (from October 2017 until March 2018), Delanie Kellon (IDF, until December 2017), Aimable Uwizeye (FAO), Felix Téillard (FAO), Juliana Lopes (FAO, until December 2017).

Observers

Margarita Vigneaux Roa (Permanent representation of Chile to FAO), Zoltán Kálmán (Hungarian Embassy in Italy), István Dani (Ministry of Agriculture, Hungary, since December 2017), Officers of the Permanent Representation of Italy to the UN Organizations in Rome, Yaya Adisa Olaitan Olaniran (Embassy of Nigeria in Italy), Officers of the United States of America Embassy in Italy and of USDA, the United States of America, Ian Thompson (Sustainable Agriculture, Fisheries and Forestry Division, Australia), Rosemary Navarrete (Sustainable Agriculture, Fisheries and Forestry Division, Australia), Mark Schipp (Department of Agriculture and Water Resources, Australia), María José Alonso Moya (Ministerio de Agricultura, Alimentación y Medio Ambiente, Spain), Wang Jian (Department of

Livestock Production, Ministry of Agriculture, People's Republic of China), Li Qian (Department of International Cooperation, Ministry of Agriculture, People's Republic of China), Tang Liyue (Permanent Representation of People's Republic of China to the United Nations Agencies for Food and Agriculture in Rome), Nazareno Montani (Permanent Representation of Argentina to FAO), Margarita Vigneaux Roa (Embassy of Chile in Italy), Keith Ramsay (Department of Agriculture, Forestry and Fisheries, South Africa), Madan Mohan Sethi (Embassy of India in Italy), Lucia Castillo-Fernandez (European Commission, Directorate-General for International Cooperation and Development, Belgium), Rick Clayton (Health for Animals, Belgium), Eduardo Galo (Novus International), Coen Blomsma (European Union vegetable oil and protein meal industry association, Fediol, Belgium), Jean-Francois Soussana (INRA, France), Fritz Schneider (Global Agenda For Sustainable Livestock), Eduardo Arce Diaz (Global Agenda for Sustainable Livestock), Harry Clark (Global Research Alliance), Angelantonio D'Amario (EUCBV, Belgium, IMS), Brenna Grant (Canadian Cattlemen's Association, IMS), Philippe Becquet (DSM, Switzerland, IFIF), Maria Giulia De Castro (World Farmers Organization, WFO, Italy), Danila Curcio (International Co-operative Alliance, Italy), Matthias Finkbeiner (International Organization for Standardization, ISO; TU Berlin, Germany), Michele Galatola (European Commission, Directorate-General for Environment, Belgium), James Lomax (UN Environment), Llorenç Milà i Canals (Life Cycle Initiative, UN Environment), Paul Pearson (International Council of Tanners, ICT, United Kingdom), Primiano De Rosa (Unione Nazionale Industria Conciaria, ICT, Italy), Christopher Cox (UN Environment), Gregorio Velasco Gil (FAO), James Lomax (UN Environment), Franck Berthe (World Bank), Patrik Bastiaensen (OIE), An de Schryver (European Commission, Directorate-General for Environment, Belgium), and Brian Lindsay (Global Dairy Agenda for Action), Judit Berényi-Üveges (Ministry of Agriculture, Hungary), Csaba Pesti (Agrieconomy research institute, Hungary), María José Alonso Moya (Ministerio de Agricultura, Alimentación y Medio Ambiente, Spain), Pierre Gerber (World Bank), Rogier Schulte (Wageningen University, the Netherlands, LEAP Co-Chair 2015 on behalf of Ireland), Peter Saling (ISO, since February 2018; BASF), Erwan Saouter (European Food Sustainable Consumption and Production Roundtable), Ana Freile Vasallo (Delegation of the European Union to the Holy See, Order of Malta, UN Organisations in Rome and to the Republic of San Marino, until September 2016).

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MULTI-STEP REVIEW PROCESS

The initial draft guidelines developed by the TAG over 2017 and 2018 went through an external peer review before being revised and submitted for public review. Matthew Brander (ISO, The University of Edinburgh), Jean-Baptiste Dolle (IDELE, France), Wim de Vries (Wageningen University), Marie Trydeman Knudsen (Aarhus University, Denmark), Budiman Minasny (University of Sydney), Bruno José Rodrigues Alves (Embrapa, Brazil) and the Intergovernmental Technical Panel on Soils peer reviewed these guidelines in early 2018.

The LEAP Secretariat reviewed this technical guidance before its submission for both external peer review and public review. The LEAP Steering Committee also

reviewed the guidelines at various stages of their development and provided additional feedback before clearing their release for public review. The FAO Climate, Biodiversity, Land and Water Department (CB), WWF, Agriculture and Agri-Food Canada, Hungary, and Costa Rica provided feedback. The public review started from May, 23rd 2018 and lasted until August, 22nd 2018. The review period was also announced to the public through an article published on the FAO website. The scientific community working on life cycle assessment and the accounting of greenhouse gas (GHG) emissions and removals from livestock was alerted through national networks of the Global Research Alliance, “the 4 per 1000” initiative, and through the Livestock and Climate Change Mitigation in Agriculture Discussion group on the forum of the Mitigation of Climate Change in Agriculture (MICCA) Programme, the Global Alliance for Climate-Smart Agriculture (GACSA), IDF Scenv, and the LCA list held by PRé Consultants. Experts in soil carbon stocks assessment, carbon sequestration were informed through mailing lists, announcements, articles in social networks, and newsletters.

FAO officers were encouraged to participate in the public review through the FAO Livestock Technical Network Newsletter and through invitations to the FAO Climate, Biodiversity, Land and Water Department (CB) and the Secretariat of the Global Soil Partnership and its Intergovernmental Technical Panel on Soils. The LEAP Secretariat also publicized the 2018 LEAP public review through invitations to the Life Cycle Initiative and oral speeches in international scientific conferences and meetings, including those arranged by the Global Agenda for Sustainable Livestock, European Food Sustainable Consumption and Production Roundtable, World Farmers’ Organization, and the European Commission’s Product Environmental Footprint. The following have participated in the public review and contributed to improving the quality of this technical document: Brenna Grant (Canfax Research Services, Canadian Cattlemen’s Association), Amanullah (Dept Agronomy, The University of Agriculture Peshawar, Parkistan), María Sánchez Mainar (IDF), and Hans Blonk (Blonk Consultants). The latter was invited to check consistency with other LEAP guidelines and reference technical guidance documents recommending approaches to account for GHG emissions from direct land use change.

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Abbreviations and acronyms

C	carbon
ESM	equivalent soil mass
GHG	greenhouse gas
IPCC	Intergovernmental Panel on Climate Change
LCA	life cycle assessment
MDD	minimum detectable difference
MRV	monitoring, reporting and verification
OC	organic carbon
SIC	soil inorganic carbon
SOC	soil organic carbon
SOM	soil organic matter
UNFCCC	United Nations Framework Convention on Climate Change

Glossary

Bias: In general terms, deviation of results or inferences from the truth, or processes leading to such deviation. More specifically, the extent to which the statistical method used in a study does not estimate the quantity thought to be estimated or does not test the hypothesis to be tested.

Carbon estimation area (CEA): The area, composed of strata, for which SOC stocks will be estimated.

Confidence interval: A range of values, calculated from the sample observations, that is believed with a particular probability, to contain the true parameter value. A 95% confidence interval, for example, implies that where the estimation process was repeated again and again, 95% of the calculated intervals would be expected to contain the true parameter value. Note that the stated probability level refers to properties of the interval and not to the parameter itself which is not considered a random variable.

Grazing intensity: Grazing intensity can be considered as a combination of the number of animals per unit area, coupled with the duration of their presence. So, the definition you might use for a steppe, with wide areas over which animals can move, might well be different than for an intensively managed farm with high stock numbers per unit area and frequent rotation of animals.

Measurement error: Errors in reading, calculating or recording a numerical value. The difference between observed values of a variable recorded under similar conditions and some fixed true value.

Random sampling: Either a set of n independent and identically distributed random variables, or a sample of n individuals selected from a population in such a way that each sample of the same size is equally likely.

Sample: A set of sampling units, that is, a selected subset of a population, chosen by some process usually with the objective of investigating particular properties of the parent population. In these Guidelines, samples refer to soil cores taken in the field.

Sample size: The number of sampling units to be included in an investigation. Usually chosen so that the study has a particular power of detecting an effect of a particular size.

Composite sample: A sample in which the sampling units are pooled together and homogenised. Thus, a composite sample is taken as a sampling unit in a sample comprising several composite samples.

Sampling: The process of selecting some part of a population to observe, to estimate something of interest about the whole population. To estimate the amount of recoverable oil in a region, for example, a few sample holes might be drilled, or to estimate the abundance of a rare and endangered bird species, the abundance of birds in the population might be estimated on the pattern of detections from a sample of sites in the study region. Some obvious questions are how to obtain the sample and make the observations and, once the sample data are to hand, how best to use them to estimate the characteristic of the whole population.

Sampling design: The procedure by which a sample of units is selected from the population.

Sampling error: The difference between the sample result and the population characteristic being estimated. In practice, the sampling error can rarely be determined because the population characteristic is not usually known. With appropriate sampling procedures, however, it can be kept small and the investigator can determine its probable limits of magnitude.

Sampling frames: The portion of the population from which the sample is selected. They are usually defined by geographic listings, maps, directories, or membership lists.

Soil: The upper layer of earth in which plants grow, typically consisting of a mixture of organic remains, silt, sand, clay, and rock particles.

Soil organic carbon content: The amount of carbon in a soil sample relative to the total mineral content of the sample. Soil organic carbon content is expressed as a (mass) percentage.

Soil organic carbon stocks: The mass of carbon in a sample of known bulk density. Soil organic carbon stocks are generally expressed in tonnes or Mg per hectare for a nominated depth and commonly restricted to the fraction <2mm in size.

Standard error: The standard deviation of the sampling distribution of a statistic. For example, the standard error of the sample mean of n observations is, where σ^2 is the variance of the original observations.

Strata: The areas of a carbon estimation area that results from the stratification process

Stratification: The division of a population into parts known as strata, particularly for the purpose of accounting for variation for a drawn sample.

Stratified random sampling: Random sampling from each strata of a population after stratification.

Stratum: Each subpopulation of strata.

Executive summary

These guidelines aim to give a harmonised, international approach for estimating soil organic carbon (SOC) stock and stock changes in livestock production systems. Despite the attention given to SOC, current knowledge remains limited regarding SOC baselines and changes, the detection of vulnerable hot spots for SOC losses and opportunities for SOC gains under both climate and land management changes. Accurate baselines are still missing for many countries and estimates of carbon fluxes due to changes in SOC stocks in the global carbon cycle are associated with large uncertainties. Global SOC stocks estimates do exist, but there is high variability in reported values among authors, caused by the diversity of data sources and methodologies.

The intended uses of this document are wide, due to the range of objectives and scales for SOC stock change studies, for example:

- Global or regional accounting for GHG emissions and removals from the land sector as a component of climate change accounting
- Monitoring, reporting and verification obligations for the United Nations Framework Convention on Climate Change
- Analysis of the climate change impact of livestock products
- Evaluation of the environmental impacts of grazing land management for animal agriculture
- Assessment of the mitigation potential of agricultural practices at an industry, region or farm scale
- Implementing mitigation options in an emissions trading or other market mechanism where payments for SOC sequestration depend on accurate and verifiable quantification
- Research into soil and biological processes affecting SOC stocks and dynamics

In principle, anyone who has an interest in quantifying soil carbon stocks or stock changes should find these guidelines helpful. A set of methods and approaches are recommended for use by individual farmers or land managers, by those undertaking life cycle assessment of livestock products, policy makers, or regulators at local, regional or national scales. The guidelines are a product of the Livestock Environmental Assessment and Performance (LEAP) Partnership, a multi-stakeholder initiative whose goal is to improve the environmental sustainability of the livestock sector through better methods, metrics and data.

The table below summarises the major recommendations of the technical advisory group for measuring soil C stocks and stock changes and for integrating these changes into lifecycle assessments to evaluate SOC stock changes in reporting environmental performance of livestock production on rangelands and grasslands. It is intended to provide a condensed overview and information on the location of specific guidance within the document. LEAP guidance uses a precise language to indicate which provisions of the guidelines are requirements, which are recommendations and which are permissible or allowable options, that intended users may choose to follow. The term “shall” is used in this guidance to indicate what is required. The term “should” is used to indicate a recommendation, but not a requirement. The term “may” is used to indicate an option that is permissible or allowable.

Topic	Summary recommendation	Section
DETERMINATION OF SOIL ORGANIC CARBON STOCKS		
Minimum measurement requirements	To determine SOC stocks, the user shall quantify within a specific soil sampling depth: (i) SOC content of the fine earth mass (< 2 mm size), (ii) coarse mineral fraction content (> 2 mm size) and, (iii) soil bulk density. Sampling depth shall be at least 30 cm, and should be as deep as possible where soil depth is greater than 30 cm. All samples shall be georeferenced. Appropriate error and uncertainty should be reported.	2.1
Soil sampling strategy	To identify the most appropriate approach for soil sampling, the user shall make key decisions considering: (i) purpose and linked requirements, (ii) stratification and representativeness, (iii) soil depth, and (iv) land management. The sampling strategy should be based on a decision tree, such as the one provided in Figure 2.	2.2
Sampling strategy in relation to the environment	To sample a study area in a representative way, the user shall identify a minimum of three sampling strata (relatively homogeneous units) based on the main environmental factors determining SOC variability, including – depending on the scale– climate, soil type, hydrology, topography, land use and management and land use history, amongst others.	2.2.1.1
Composite sampling	Within each homogeneous unit (stratum) at least 5 soil cores should be collected to form a composite sample. Composite samples should represent the total area of the unit/strata and be collected in the same day.	2.2.2
Report SOC stocks to 30 cm depth	Soil organic carbon stocks should be reported for the 0–30 cm layer to comply with IPCC recommendations, and appropriate error and uncertainty should be reported. Soils less than 30 cm deep should be sampled as deep as possible and stocks extrapolated to 30 cm. Soils more than 30 cm deep should be sampled as deep as possible, and the SOC stock in the 0–30 cm layer shall be reported separately. Sampling to depths greater than 30 cm or subsampling the 0–30 layer may be warranted, however the impact of increased costs and potential increase in uncertainty need to be considered.	2.2.3
Estimation of error	The sampling approach shall be consistent with standard operating procedures to reduce the variability originating from the sampling itself. Sufficient laboratory duplicates and randomising the order of sample analysis should be carried out to allow quantification of combined field and laboratory measurement errors. Whenever sufficient data and resources are available, an uncertainty analysis may be performed following the 2006 IPCC guideline.	2.3
Soil processing	Soil processing for SOC analysis shall follow standard procedures. Consistency control of procedures shall be observed during the project and if the analyses are done in more than one laboratory, or more than one equipment/machine is measuring the same soil property, consistency check shall be carried out between them.	2.4
Sample storage	Fresh soil samples should not be stored at temperatures higher than 4°C or for more than 28 days after collection. Soil samples shall be thoroughly homogenized. SOC content analysis shall be done in the fine earth (<2mm) fraction. For archiving, dried soil samples should be stored in a dark, cool and dry room for potential future use and verification.	2.4.1
Bulk density measurements	Soil bulk density should be determined in the same core in which SOC concentration is measured. For estimating bulk density, direct measurement methods should be used, specifically the undisturbed (intact) core method and the excavation method, because these can provide the most accurate determination of bulk density. The clod method should not be used because for SOC stock measurements the bulk density of soil layers or horizons has to be represented.	2.4.2
SOC and SIC measurements	To measure the SOC correctly, contributions from SIC shall be removed. A small-scale acidification technique using HCl followed by automated dry combustion is recommended. In some soils SIC could represent a significant and dynamic portion of soil carbon (e.g. calcareous, irrigated, and amended soils), and may be quantified by direct determination of total inorganic carbon or by the difference between total soil C and SOC.	2.4.4
Laboratory accreditation	SOC content analysis shall be performed in a laboratory that has well established quality control and assurance systems.	2.5

Topic	Summary recommendation	Section
SOC measurement	The dry combustion method shall be used for measuring SOC content when possible. If not available, wet oxidation may be used, except on weathered soils or when charcoal is present. If dry combustion is not available, loss-on-ignition may be used on organic soils.	2.5.3
Spectroscopic measurements	Spectroscopic techniques -which show promise for estimating the SOC content and which enable the analysis of large numbers of samples- may be used when technical capacities for adequate chemometric calibration are available.	2.5.4
MONITORING SOIL ORGANIC CARBON CHANGES		
Identification of errors	In planning a SOC stock change study, a process of identification of potential sources of error and bias in SOC stock estimation shall be undertaken and steps should be taken to minimise their impact, as described in Chapter 2. Consistent methodologies and practices should be used to minimise the minimum detectable difference (Eq. 9) and the number of samples required to obtain it (Eq. 10).	3.2.1
Design of a sampling strategy	To analyse lateral and vertical spatial variability of SOC stock, a pre-sampling (5 to 10 cores per strata) of the area of interest may be undertaken to get an indication of the SOC stocks mean value and variability in SOC stocks and, therefore, attainable minimum detectable difference for a given sampling effort. This information should be used to guide estimation of the number of samples needed to determine SOC stock change with an acceptable level of uncertainty. Based on estimated SOC stocks and variability from the pre-sampling and the maximum number of analyses that can be afforded, a decision on whether individual or composite sample cores are analysed should be made.	3.1.1
Minimal detectable difference	Minimum detectable difference calculations shall be used to estimate the number of samples needed to detect the expected SOC stock change (or alternatively the number of years required for a given rate of change in SOC to produce a statistically detectable change). The number of samples may differ between sampling campaigns (repeated measurements with baseline at t0) or treatments (paired plots with assumed business-as-usual baseline). This reduces sampling effort when the baseline was estimated with a large sampling size.	3.3.2
Frequency of repeated measures	For repeated measurements to capture SOC stock change related to management activities, sampling shall typically occur 4 to 5 years apart. Sampling strategies shall always consider the estimated minimum detectable difference (Eq. 9) and corresponding number of required samples (Eq. 10). A sampling campaign should take no longer than 60 days within the same season, i.e. all sampling should occur no more than 30 days before/after the median day and month of the baseline sampling round. The record of each sampling round shall include the day (or days), the month (or months), the year (or years), and the median day.	3.4
Equivalent soil mass	To consider possible changes in bulk density over time or due to management, comparisons of SOC stocks shall be made on an equivalent soil mass basis (ESM). Samples from at least three discrete, contiguous and successive soil layers should be available to describe how bulk density and SOC concentrations change from the surface layer downward. Only the lowermost layer in any nominated ESM must be based on assumed rather than directly measured bulk density and SOC concentration. An exception may be made only when estimating SOC stock changes for a relatively small and uniform area without stratification, in which case ESM may be neglected and the lowest mass of all samples may be taken at baseline. When using ESM for repeated SOC measurements or point-in-time comparisons, estimates shall be made for the same point (i.e. spatial and depth) or area over time. For sampling schemes where individual samples are taken, these should be aggregated to ensure they represent the same point or area. The method for calculating ESM shall remain consistent across all sampling times.	3.5.1

Topic	Summary recommendation	Section
Comparisons of land use or management change	To calculate changes in SOC stock, soil samples shall be collected and analysed with a consistent sampling protocol (Chapter 2). Further, a baseline that corresponds to the aim of the study should be chosen using Figure 8. (i) Changes in SOC stocks estimated over time shall be calculated in accordance with recommended methods and use of statistical tools (e.g. regression analysis), and in some cases knowing the ‘natural’ baseline might be necessary. (ii) Changes in SOC stocks estimated from paired-plot comparisons of new land use or management conditions against a business-as-usual baseline shall only be made when the starting point is consistent (i.e. same soil properties, climate, and prior land use and management); the conditions defining the land use or management states shall be thoroughly described. In both cases, estimated relationships should not be extrapolated beyond the period of the last measurement, as changes in SOC cannot be assumed to be constant over time	3.5.2
DATA MANAGEMENT AND REPORTING		
Complementary data	The geographical coordinates of the sampling location and of the boundaries of the represented area shall always be documented. When planning the assessment of SOC stock changes, possible complementary data from the field, such as net primary productivity, soil texture and pedoclimatic data, should be considered and collected as required.	4.1.1
Data storage	Data shall be stored in a suitable format, such as the template (tab- or comma-delimited text, .txt.csv), and include all necessary data for identification (e.g., year, field, replicates, soil layers, etc.), variables for estimates (coarse fragment, roots, residual humidity), sample treatments (CaCO ₃ , sieving, drying, etc.).	4.1.4
Data reporting	Data/results reporting shall include a detailed description of methods including site of stored data and metadata. Reported results should be accompanied by an estimate of error or uncertainty.	4.2
MONITORING CARBON CHANGES – NET BALANCE OF ATMOSPHERIC CARBON FLUXES		
The use of eddy covariance measurements	When using a full-system carbon budget approach as an alternative to repeated physical measurement methods to determine SOC stock changes, it shall firstly be established that adequate funds and equipment and a research team with the required expertise can be dedicated to the project. For eddy covariance measurements to determine SOC stock changes, assessment of site suitability shall be undertaken to determine that the spatial area is sufficiently large (4 to 8 hectares, minimum, depending of wind direction) to fully quantify contributions to fluxes of all material carbon sinks and sources (e.g. harvest, leaching, animal products). Established research groups and networks (e.g. Fluxnet, Ameriflux, NEON, ICOS) with experience in use of eddy covariance methods should be consulted when seeking to set up instrumentation and programs using full carbon budget methods.	5.0
MODELLING SOIL ORGANIC CARBON CHANGES		
Use of models	Models shall be used when the objective is to estimate or extrapolate changes in carbon stocks in or to conditions in which they have not been measured e.g. soil type, climate and management. As a guiding principle, the complexity of the model should be aligned to the context.	6.1.1
Use of level 1 models	Level 1 modelling without modification may provide a first indication to predict the magnitude or direction of carbon stock changes. Level 1 modelling should be used when there is access to data-based factors that have been specifically determined for the system of interest (e.g. IPCC factors that can be adapted based on region-specific experiments). Users should note that Level 1 models can be used for reporting or claims but the simplicity of these models translate into limited accuracy if region specific factors are not used.	6.2.1
Use of level 2 models	Level 2 modelling should be used when regional factors for SOC change and factors affecting the change (e.g. humification coefficients) are not available, but data about plant carbon inputs and environmental parameters affecting carbon losses, that are needed to feed the model, are available.	6.2.2

Topic	Summary recommendation	Section
Use of level 3 models	Level 3 modelling shall be used when the objective is to integrate the feedbacks from multiple soil-plant-atmospheric processes on SOC dynamics. They should be used to investigate multiple impacts between agricultural management, crops and soils and to estimate the impacts of climate change feedbacks between crop productivity and SOC dynamics. They may be used to estimate the trade-offs between SOC change and other environmental indicators.	6.2.3
Choice of model	The choice of modelling approach should consider the purpose and spatial scale of the study, as well as the availability of quality data to run the model. The complexity of the model should be aligned to the context, but the simplest, locally validated model is preferred. Internal calibration of a model (based on region-specific data), where model “factors” are adapted based on experiments, leads to more accurate results, regardless of the level of assessment.	6.3
Modelling requires a significant investment	Significant investment should be made in improving and engaging existing modelling expertise in making decisions for validation, calibration and implementation of selected models. This includes setting up input data to reduce uncertainty for sound scientific practice for the specific application. Users should recognise that without this investment, using a model carries a large risk that project results will not be accepted upon professional review.	6.3.1
Check data availability	Data availability for both model input parameters and to test model outputs shall be investigated before choosing a modelling approach.	6.4.1
Preliminary data	The amount and type of SOC shall be used to initialise the model to produce reliable estimates of SOC amount over the simulation period. Good estimates of the SOC and C input from the vegetation and land use and conditions for many decades prior to the simulation period should be used to improve the ability to accurately predict the initial SOC, by calibrating model parameters where needed.	6.4.2.1
Preliminary check of the model	Before any other evaluation, preliminary model results should be graphed to see if they look approximately similar to the measured values. Once the model output appears to give a good simulation of the measured data, a full evaluation should be performed.	6.4.3
Model validation and calibration	To minimize model uncertainty, the model shall be validated for the conditions (e.g.: country or climatic zone) in which it will be applied when possible. If a model is not validated for the region of interest, the model should be calibrated using local time series of SOC stocks. Thereby, only a limited number of parameters should be modified and only those that do not have many interdependencies with other parameters. Guidance on model calibration and validation and advanced methods of sensitivity and uncertainty analysis can be found in the appendix of this document. Because soil carbon turnover models are most sensitive to initial SOC stocks and carbon inputs, a measured baseline of SOC stock shall be used whenever available, and C inputs should be estimated as accurately as possible..	6.5.1
Sensitivity analysis	A model sensitivity analysis and uncertainty assessment should be conducted to inform decisions about the suitability of the model, and provide valuable information on which model inputs and processes are most important..	6.5.4
SPATIAL INTERPRETATION AND UPSCALING OF SOIL ORGANIC CARBON		
Geostatistical sampling design	There is no universally best sampling design approach. For geostatistical analyses, collecting samples on a regular grid allows directional variograms over several different directions to be calculated easily, mostly along the axes of the grid (for regular grids, where the lag distances and directions are known and the number of pairs per lag interval is a function of grid spacing). A rule of thumb is not to estimate semivariances for lags greater than half the maximum distance of the sampled area. The main disadvantage of regular grids is that resolution is limited by grid spacing. We strongly recommend adding more closely spaced pairs of points at some randomly selected grid nodes, so that the form of the variogram at the most critical short distances and the nugget variance can both be better estimated.	7.2
Suitability of data	When using kriging to perform a geostatistical interpolation, it should be checked that the data used follows a normal distribution and are spatially auto-correlated.	7.4

Topic	Summary recommendation	Section
Digital soil mapping	There is no spatial prediction method which is generally best for any case. The best method for SOC mapping should be selected on a case by case basis.	7.5
Reporting geostatistical analyses	When up-scaling SOC stock change estimates, an overview of the data integration and spatial modelling procedure as well as the related uncertainty should be documented and reported together with the produced maps.	7.5

1. INTRODUCTION

1.1 Objectives and intended users

Estimation of greenhouse gas emissions for livestock production systems worldwide is critical for evaluating climate change mitigation options. Livestock production systems are responsible for a large portion of the global carbon footprint (Ripple *et al.*, 2014). However, they are most often based on grazed rangelands, grasslands and pastures, which offer significant potential for carbon sequestration in the soil to offset greenhouse gas emissions (Conant, 2010). Nevertheless, that potential has been neglected in life cycle assessments of the sector (Nijdam *et al.*, 2012). Here, we offer guidelines for estimating soil organic carbon (SOC) stock changes in livestock production systems. Despite the attention given to SOC, knowledge about SOC baselines and changes and the detection of vulnerable hot spots for SOC losses and gains under climate change and changed land management is still limited. Accurate baselines are still missing for many countries and estimates of SOC within the global carbon cycle are still associated with large uncertainties. Global SOC estimates exist, but there is high variability in reported values among authors, caused by the diversity of data sources and methodologies (Henry *et al.*, 2009).

SOC measurements are highly variable in space, while changes over time depend on a multitude of factors, for which detailed information and understanding is not always available. There is a need to estimate benchmarks and potential changes, which, depending on the purpose will require different levels of data precision. The recommended methods provided in this document aim to align with the intended use and available data. Uncertainty levels thus depend on the method and the intended use.

The intended uses of this document are wide: anyone who has an interest in estimating SOC or stock changes should find these guidelines helpful. A set of methods and approaches are recommended to be used by individual farmers or land managers, or by those undertaking life cycle assessment studies, policy makers or regulators at local, regional or national scales. A decision-tree is presented to help the user identify and align the available data and intended use with a measurement or modelling method. A series of case studies is also presented to illustrate how to use many of the techniques and approaches that are described herein.

1.2 Scope

The focus of these guidelines is on measuring SOC and monitoring change in SOC stocks in response to management practices in grasslands and rangelands. While it is recognised that some management practices e.g. adding manure or chemical N fertiliser may affect net greenhouse gas emissions of livestock production systems through changes in nitrous oxide emissions as well as SOC sequestration, the scope of these Guidelines is restricted to SOC stock changes. Further information on accounting for net change in greenhouse gas emissions may be found in LEAP guidelines for large ruminants, small ruminants and feed.

1.2.1 Land use systems

These guidelines consider soils from all land use systems that directly support livestock production, which include lands with vegetation suitable for grazing or browsing use, predominantly composed of grasses, grass-like plants, forbs, or shrubs. These may be grasslands, savannas, steppes, wetlands, some woodland, some deserts, tundra, and certain forb and shrub communities, or cultivated pastures on converted land. Some of these land cover types may be

extensively managed through fire and the control of livestock stocking, while others by practices such as plant species introduction, fertilization, mowing, and irrigation.

Other systems that support livestock production considered in scope for these guidelines include cropland producing forage that is mowed for hay or silage, or croplands that are producing other feed for livestock.

1.2.2 Soil carbon

The soil C stock consists of two components: SOC and soil inorganic C (SIC). SOC is the carbon component of soil organic matter (SOM), a heterogeneous pool of C comprised of diverse materials including fine fragments of litter, roots and soil fauna, microbial biomass C, products of microbial decay and other biotic processes (i.e. such as particulate organic matter), and simple compounds such as sugar and polysaccharides (Jansson *et al.*, 2010). Soil inorganic C comprises pedogenic carbonates and bicarbonates, which are particularly abundant in alkaline soils. These guidelines consider only SOC in relation to measuring soil C stocks and stock changes, and the standard operational definition of SOC is used – organic carbon present in the fraction of the soil that passes through the 2 mm sieve (Whitehead *et al.*, 2012).

The methods described in these guidelines will focus on estimating SOC stocks and stock changes, considering the fine fraction of the soil (< 2 mm). However, it is acknowledged that coarse fragments of belowground biomass at varying levels of decomposition form an important C pool associated with the soil, which should not be neglected. Therefore, general guidance will also be offered for measuring organic C stock changes considering the coarse (> 2 mm) fraction of belowground biomass by applying, on the same collected cores, procedures that are complementary to the ones used for the fine soil fraction.

1.3 Soil organic matter and soil organic carbon

Soil organic matter (SOM) encompasses all organic components in the soil and is traditionally divided into "dead" and "living" components. The living component includes plant roots and microorganisms and the dead component root and leaf litter, water soluble organic compounds, soil enzymes and the so-called humic substances (Stevenson, 1994). The dead SOM is far bigger than the living and within the it the humic substances are the biggest component. Dead SOM comprises the largest pool of recalcitrant organic carbon in the terrestrial environment. Recent research, including the development of new analytical and molecular techniques (Simpson *et al.*, 2007) has changed our thinking about the composition of SOM. The majority of operationally defined humic material in soils is a very complex mixture of microbial and plant biopolymers and their degradation products, but not a distinct chemical category (Kelleher and Simpson, 2006; Simpson *et al.*, 2007). The various compound classes and individual structures within these classes reflect, to a large extent, the chemical composition within the specific soil microenvironment (Simpson *et al.*, 2007). A wide range of ecosystem properties that drive interactions among different soil components will ultimately define the pool of persistent organic residues in soil (Masoom *et al.*, 2016; Yu *et al.*, 2017).

The use of comprehensive multiphase nuclear magnetic resonance (NMR) to investigate SOM in its natural state has further confirmed that organic matter is a mixture of molecules, which result from the decomposition of biomass. The positioning of these molecules within the soil microstructure depends on molecular characteristics including the presence of bipolar molecules, such as carbohydrates and lipids which occupy the solid-water interface in the soil matrix, while lignin and most microbes are found in more hydrophobic inner places (Masoom *et al.*, 2016).

Lignin usually can be strongly associated with clay minerals and the silt fraction. The accessibility, availability, solubility and reactions of these molecules largely depend, besides molecular characteristics, on their position within the soil matrix, which characterizes physical and chemical protection. Lehmann and Kleber (2016) proposed a “consolidated view” of SOM turnover, the so-called soil continuum model. According to this, SOM is controlled by parallel biotic and abiotic processes, including continuous decomposition of plant and animal debris and oxidation that enables solubilisation, or to the contrary, stabilization through chemical linkage to minerals, depending on the characteristics of the soil ecosystem. The persistence of SOM cannot be primarily attributed to chemical recalcitrance (Marschner *et al.*, 2008; Schmidt *et al.*, 2011; Dungait *et al.*, 2012) and is likely due in part to the capacity of the soil to stabilise C through the availability of charged mineral surfaces (Yu *et al.*, 2017).

SOC is the carbon component of SOM. The theoretical C content of the different organic matter pools varies considerably. Despite the wide range in C concentrations of the different SOM pools, a single multiplication factor may be used to convert SOM to SOC. The most often used factor, known as the Van Bemmelen factor, is 0.58 (Van Bemmelen, 1891). Over time, empirically found values varied from 6 to 74%. However, theoretically, the SOC content of SOM ranges from 40% (simple carbohydrates) to 71% (on the assumption that SOM consists of 80% of humins and 20% lipids with C contents of 70 and 80%, respectively). A detailed literature survey on the SOM to SOC conversion factor by Pribyl (2010) showed a median value 51% based on 481 observations. For this reason, a SOM to SOC multiplication factor of around 0.50 instead of 0.58 would result, in most cases, in a more accurate estimate of soil C content based on SOM measurements. For estimating changes in SOC, the carbon component of the SOM only is measured by quantifying C directly and reported as carbon stocks (Mg SOC ha⁻¹). Therefore, for the purposes of these guidelines, conversion factor from SOM to SOC is unnecessary.

1.4 Livestock systems and soil organic carbon

Grazed livestock production systems are an integral part of the cultural, social and economic identity of many nations worldwide. Key agricultural commodities such as milk and meat come from ruminant (cud-chewing) animals, predominantly cows, goats and sheep (Eisler *et al.*, 2014). Overall, livestock consume about 6 billion Mg of feed material in dry matter annually, including one-third or more of the world’s cereal grain, with 40% of such feed going to ruminants, mainly cattle, while grazed herbage represents 46 to 57% of the ruminants’ intake (FAO, 2002; Opio *et al.*, 2011).

The livestock sector has been charged as responsible for approximately 14.5% of all anthropogenic greenhouse gas emissions worldwide (Gerber *et al.*, 2013) including methane (CH₄), nitrous oxide (N₂O) and carbon dioxide (CO₂) emissions. Thus, livestock production systems are often considered not sustainable and practical solutions have been sought to reduce the carbon footprint of these human-managed systems. Mitigation solutions include reducing emissions from enteric fermentation, better manure management and improved feed quality to optimise weight gains and reduced nutrient losses. Grassland management optimization to increase SOC stocks is a further option. However, the above cited estimations of emissions by the livestock sector do not consider C losses and gains in the soil.

Grasslands are of particular importance for the global carbon cycle due to their extent and relatively high SOC stocks, compared to equivalent croplands in temperate regions. Globally, grasslands and rangelands cover 68% of the total agricultural area (Leifeld *et al.*, 2015) with estimated associated SOC stocks of 245 Gt (Bolin and Sukumar, 2000). Large areas of the world’s grasslands are under intensive environmental pressure due to degradation by overgrazing, resulting in potential changes in SOC stocks (Oldeman, 1994). However, at the landscape scale, differences in SOC stocks result from complex interactions among multiple variables, including climate, land management and inherent soil biophysical attributes, such as soil texture and/or

chemical properties (Dalal and Mayer, 1986; Grace *et al.*, 2006; Badgery *et al.*, 2014; Luo *et al.*, 2016; Pringle *et al.*, 2011). For example, Figure 1 shows the relationship between rainfall and SOC at a landscape scale. Thus, to quantify management effects on SOC stocks, which are usually small as compared to effects of abiotic site conditions, long-term plot experiments are indispensable. Long-term field experiments are also important because the effect of management generally declines through time. This is illustrated with long-term experiments, stretching back to the middle of the nineteenth century (1843), which show that the C sequestration levels off within several decades (Poulton *et al.*, 2018)

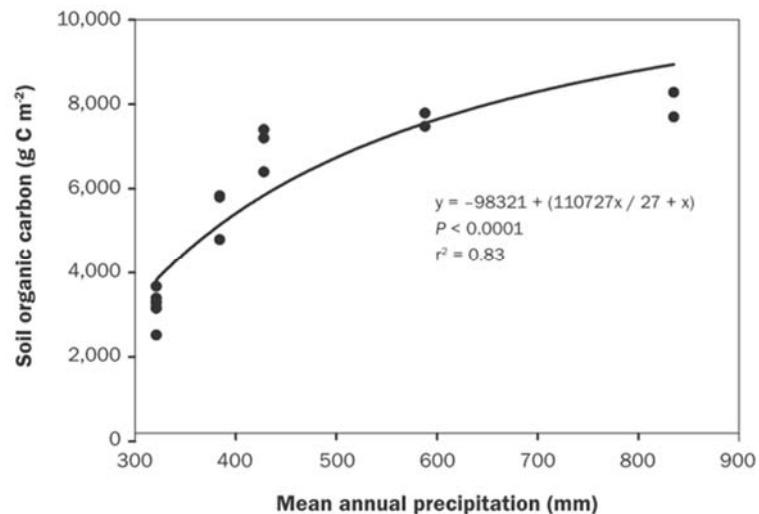


Figure 1. Soil organic carbon pools to 30 cm depth across a mean annual precipitation gradient in the North American Great Plains. (Data from Frank *et al.*, 1995; Schuman *et al.*, 1999; Reeder *et al.*, 2004; Derner and Schuman, 2007.)

Major anthropogenic interventions and their potential effects on SOC dynamics are described below. For most of these interventions, existing studies are few in a global context and results often contradictory. In a comprehensive list of agricultural long-term experiments of the world, only 49 out of >600 experiments were conducted on permanent grasslands (Debreczeni and Körschens, 2003).

Grazing intensity. In the literature, the effects of grazing on SOC stocks range from strongly negative (Golluscio *et al.*, 2009) to strongly positive (Pei *et al.*, 2008). McSherry and Ritchie (2013) conducted a global meta-analysis trying to explain the observed variation in the SOC stock response to grazing. The authors of this meta-analysis found only a total of 17 studies and 47 individual fertilization contrasts (pairs), indicating the limited number of available datasets. They found that 85% of the variation associated with SOC was explained by key variables including soil texture, precipitation, grass type, grazing intensity, study duration and sampling depth. The abiotic and biotic context of the system in which grazing management occurs, is thus important to predict the direction of SOC change with grazing. For example, in the Central Asian dry steppe, a region with low annual precipitation, the risk of overgrazing and subsequent loss of vegetation cover associated with soil erosion and a decrease in biomass production is high (Steffens *et al.*, 2008). Potentially, livestock systems may culminate in major changes in geomorphology (soil erosion and deposition) with massive effects on soil carbon stocks. The elementary protocols to assess SOC change discussed in this guidance are best applied to landscapes with negligible contemporary erosion. McSherry and Ritchie (2013) also found a strong influence of biotic factors,

i.e. grass type and grazing intensity. For C3 grasses, a slightly positive response of SOC was found to light grazing, while moderate to heavy grazing caused a decline in SOC stocks (Reeder and Schuman, 2002). This is in line with a more recent meta-analysis (Zhou *et al.*, 2017), which mainly summarized studies conducted in China. The opposite trend was observed for mixed C3/C4 grasslands and C4-dominated grasslands, in which SOC stocks showed a positive response to increasing grazing intensity (Frank *et al.*, 1995; Derner and Schuman, 2007; López-Mársico *et al.*, 2015). In conclusion, grazing effects on SOC stocks are certainly site specific, but might be best described by an optimum curve with SOC gains in light to moderate grazing intensities (depending on the abundance of C4 species) due to stimulated productivity and root turnover (Zhou *et al.*, 2017) and the risk of SOC losses via overgrazing. According to Oldeman (1994), approximately 7.5% of global grassland soils are degraded by overgrazing.

Fertilization. Livestock systems receive either organic (e.g. farmyard manure, slurry or sewage sludge), or mineral fertilizers, which contain a combination of macronutrients such as nitrogen (N), phosphorus (P) and potassium (K), to stimulate plant growth. Nutrient availability is one of the most critical factors affecting the build-up of SOM, especially the formation of more stable fractions (Kirkby *et al.*, 2013). Nitrogen availability is essential for enhancing the accumulation of SOC (Boddey *et al.*, 2010) and it has been shown that the presence of N₂-fixing legume plants can significantly contribute to improve soil SOC stocks (Tarré *et al.*, 2001; Fornara and Tilman, 2008).

Increased plant biomass following fertilisation tends to result in greater carbon inputs to the soil, with associated positive effects on SOC stocks (Kätterer *et al.*, 2012). Furthermore, organic fertilizer application is an additional source of carbon input, leading to increased SOC stocks. Recently, Fornara *et al.*, (2016) showed that in after 43 years of liquid manure applications at one site, SOC stocks had increased by ~21 Mg ha⁻¹ as compared to unfertilized control soils. In a literature review, Conant *et al.* (2001) found a significantly positive effect of fertilization (both organic and inorganic fertilization combined) on SOC stocks with an annual sequestration rate of 0.3 Mg ha⁻¹y⁻¹. However, fertilization effects on SOC dynamics are certainly more complex than a mere change in carbon inputs. For example, Bélanger *et al.* (1999) found no difference in belowground biomass after long-term NPK fertilization, but a strong negative correlation of SOC stocks and soil pH, with the latter declining upon fertilization. Unchanged belowground biomass despite higher aboveground biomass upon fertilization can be explained by altered plant C allocation with higher investment into aboveground biomass due to light rather than nutrient limitation (Poeplau, 2016). Sochorová *et al.* (2016) found a significant decrease in SOC stocks with CaNP fertilization as compared to Ca or no fertilization, despite much higher aboveground biomass in the CaNP treatments. This was explained by decreased colonization of arbuscular mycorrhiza fungi (AMF) following CaNP fertilization, which play an important role in SOC build up and stabilization.

Spohn *et al.* (2016) found a strong positive effect of NK, NP and NPK fertilization on microbial carbon use efficiency, which is considered a key factor for carbon sequestration (Manzoni *et al.*, 2012). Altered nutrient availability can thus influence SOC cycling in various ways, which are not entirely understood and thus difficult to predict. However, the repeated addition of animal slurries or manure will significantly impact on C and N coupling with potential implications for changes in soil C (and N) stocks. Soils receiving either liquid slurries or manure have the ability to retain some of the C added through these animal wastes. For example, recent findings from a long-term grassland study showed a cattle slurry-C retention efficiency of grassland soils of 15% (Fornara *et al.*, 2016). Similarly, findings from a meta-analysis study show a global manure-C retention coefficient of 12% (Maillard and Angers, 2014). These studies suggest that the long-term addition of organic nutrients to soils within livestock-production systems can increase SOC stocks. However, the actual role of animal manure application in sequestering atmospheric C and mitigating climate change depends on the alternate fate of the manure (Powlson *et al.*, 2011).

Cutting frequency. In areas of intensive livestock production, animals may not spend much time outside the stable and are fed by hay from surrounding meadows. The frequency of cutting events on these meadows might influence SOC stocks due to changed net primary production (NPP) via changed canopy properties and plant species composition (Klimeš and Klimešová, 2002; Wohlfahrt *et al.*, 2008). In addition, root turnover may be affected by cutting frequency (Volder *et al.*, 2007). However, the direct effect of cutting frequency on SOC stocks is not well understood and difficult to separate from the effect of fertilization, since more frequently cut meadows usually receive higher doses of fertilizer. After 19 years of cutting frequency contrasts ranging from 12-weekly to 2-weekly intervals with unchanged fertilization, Kramberger *et al.* (2015) found no difference in SOC stocks. While the direct effect of cutting frequency might not be of significance, the indirect effect via increased NPP might be positive for SOC accumulation, especially when a proportion of the assimilated C is returned to the soil, e.g. via manure or plant residues. For example, Poeplau *et al.* (2016) found significantly higher SOC stocks in frequently mown urban lawns as compared to lawns that were cut only once or twice and explained this by higher aboveground NPP, with biomass not being removed but left as clippings on the lawn.

Reseeding. Reseeding is a popular and common management practice where grasslands are improved with newer and more desirable cultivars e.g. *Lolium perenne* L. (perennial ryegrass) and/or *Trifolium repens* L. (white clover). Re-seeding will increase plant yields and thus the economic income from farmed grasslands. Re-seeding can occur via spreading of seed or through the mechanical preparation of a seedbed followed by sowing of seed into the seedbed. Where mechanical preparation is used, re-seeding will be associated with a great deal of physical soil disruption. Re-seeding has been previously linked to significant changes in soil C and nutrient cycling in grasslands (Bhogal *et al.*, 2000; Soussana and Lemaire, 2014). Other common practices associated with re-seeding such as fertilisation and liming help maintain plant yields (Allard *et al.*, 2007), but their net effects on SOC stocks when combined with re-seeding remain poorly understood. A recent study shows how management-induced effects on key soil physical properties (i.e. bulk density) may have significantly greater implications for C sequestration in permanent grassland soils than high disturbance (but infrequent) re-seeding events (Carolan and Fornara, 2016).

Species selection. Improving grassland also comprises the choice of grass species. In general, species rich grasslands tend to have a higher aboveground NPP (Hooper *et al.*, 2005) and to penetrate larger soil volumes due to more diverse and complementary root traits, both of which have potentially positive effects on SOC stocks. Experimental evidence shows how increased species richness has positive effects on SOC stocks (Fornara and Tilman, 2008; Steinbeiss *et al.*, 2008; Chen *et al.* 2018). Species richness, however, may potentially negatively affect SOC if N availability in soils is reduced through increased complementary uptake by higher diverse plant communities (Niklaus *et al.*, 2001). The introduction of N-fixing leguminous species is generally considered positive for SOC accumulation (Conant *et al.*, 2001; Conrad *et al.*, 2017). Furthermore, the introduction of deep-rooting grass species can have positive effects on SOC storage (Fisher *et al.*, 1994).

A general problem of long-term experiments on SOC responses to grassland management is the isolated and mostly incomplete view on those management options and thus the transferability to real life situations. For example, when the effect of mineral fertilization in mown grasslands on SOC stocks is assessed, this might not resemble the total effect of mineral fertilization. The additional mown plant biomass will find its way back to the soil, where it will further increase SOC stocks, which is not accounted for. More holistic, potentially farm-scale experiments would thus be desirable but are expensive to maintain in the long-term. Ultimately, the effect on SOC of e.g. grazing, fertilization, cutting frequency etc. all depends on how much extra C is given to the soil in the form of roots, crop residues or manure. If the practice increases plant and root growth and

even deposits manure, compared to earlier practice SOC will increase. If the practice removes more C from the system than before, then SOC will decrease (Petersen *et al.*, 2013).

1.5 Land use change, land management and soil organic carbon stocks

Changes in land use and/or land management can significantly affect soil C stocks associated with different livestock-production systems. Humans have modified many natural and semi-natural habitats to support and develop, for example, grassland-based livestock economies. The significant expansion of either extensively grazed rangelands or improved grassland systems has been often accompanied by important changes in ecosystem structure and function including changes in the ability of soils to accumulate organic C. Potentially, livestock systems may culminate in major changes in geomorphology (soil erosion and deposition) with massive effects on soil carbon stocks. The protocols to assess SOC change discussed in these Guidelines are best applied to landscapes with negligible contemporary erosion.

Soil C response to land use change or management will likely depend, at least partially, on previous land uses and will thus show a 'legacy effect' (Foster *et al.*, 2003), which could help explaining changes in soil C stocks (Guo and Gifford, 2002). For example, a generally held view is that C accumulation will be faster when the land use change involves a shift from cultivated (disturbed) soils to permanent grassland soils. It is assumed that, under constant agricultural practices (e.g. 50 to 100 years after a land use/management change) and at 0-30cm depth, grassland soil C will eventually reach a steady state and that as the C content approaches this steady state, rates of C accumulation will decline (Smith, 2014). It is not clear, however, when soil C accumulation might reach a new steady state, mainly because this will depend on the interaction between climatic factors and the combination of multiple management practices (i.e. grazing, nutrient fertilization, liming, re-seeding etc.). For example, results from a recent study in the UK show that permanent grassland soils have not yet reached C steady state after 43 years of intensive management (Fornara *et al.*, 2016). Other studies have shown continuing changes in SOC stocks over the long-term (e.g. Bellamy *et al.*, 2005; Klumpp *et al.*, 2011). Significant knowledge gaps remain in relation to how past and present management might influence soil C (and N) content through changes in soil biogeochemical properties.

Diversification of agricultural landscapes may benefit both ecosystem service delivery (including soil C sequestration) and biological diversity (Isbell *et al.*, 2017). As an example, one possibility for landscape diversification includes the adoption of both grazed grasslands and silvopastoral systems where livestock graze between widely spaced trees (Mosquera-Losada *et al.*, 2009). The combination of grazed grasslands and silvopastoral systems can provide a wide range of ecosystem services including the regulation of nutrient and water in soils, aboveground sequestration of atmospheric CO₂ in woody plants and in soils (Montagnini and Nair, 2009; Torralba *et al.*, 2016). Evidence from meta-analysis studies suggest, however, that tree planting on permanent grassland may only have limited impact or even reduce rather than increase SOC content and stocks (Guo and Gifford, 2002; Laganière *et al.*, 2010). Similar meta-analyses as well as long-term field studies show no evidence of significant soil C accumulation following planting trees in grasslands across different climatic regions (Poeplau *et al.*, 2011; Hoogmoed *et al.*, 2012; Bárcena *et al.*, 2014; Fornara *et al.*, 2017). More experimental studies are needed at the landscape level (or farm level) to be able to quantify the soil C sequestration contribution of different soils within these agricultural landscapes.

2. DETERMINATION OF SOIL ORGANIC CARBON STOCKS

2.1 Introduction: The need to measure soil organic carbon stocks

The actual size of SOC stocks associated with different livestock systems ultimately depends on: (1) the rate of C gain or loss during a specific period and, (2) the maximum amount of C that can be stored by soils until they reach relatively stable SOC levels (Smith, 2014). In general, the conversion of semi-natural or natural ecosystems to human-managed agro-ecosystems determines a decline in SOC stocks (Hüttl *et al.*, 2008; Schlesinger and Bernhardt, 2013). The use of default SOC values (such as those determined by IPCC Guidelines 2006) or of measured SOC values from pristine ecosystems may not be suitable for estimating SOC stock changes across human-managed ecosystems. For example, the conversion of forest to pasture may result, over the long-term in similar or even higher SOC stocks, despite an initial decline of SOC stocks (Cerri *et al.*, 2007).

A baseline of SOC stocks can be estimated by physical sampling and measurement, modelled estimation, or assumed values. A key challenge when measuring SOC stocks is how to deal with the high spatial variability in SOC content and in soil biogeochemical properties associated with different soil and vegetation types, climate, land use and management (Conant *et al.*, 2011). The initial choice of the method to be used will determine how robust the baseline SOC value is, which will then determine the possibility to detect potential changes in SOC stocks. At this early stage the main objective should be the selection of the most rigorous method possible considering the available financial resources and the aim of the assessment, which could vary depending on what spatial scale and land use and management are of particular interest.

Physical sampling is the required approach to quantify baseline SOC stocks when the main objective is to estimate SOC temporal changes. Any soil physical sampling needs to be well planned at the outset to ensure that main objectives will be met. This means considering a series of environmental factors that cause heterogeneity in SOC content and which are discussed in more detail in the sections below. Also, physical sampling methods need to fulfil standard methodology criteria that will ensure confidence in results. For example, it is essential that sampling methods allow parameters such as soil bulk density to be estimated.

The basic approach of physical sampling involves the collection of soil samples within a specific soil depth increment (e.g. 0-30 cm depth) using a soil corer tool of known volume with a diameter between 5 and 10 cm, which will allow determination of soil C content and bulk density (adjusted for coarse mineral fraction content, see section 2.4.2) or soil mass. Vertical soil coring and excavated pits are well accepted practices to soil sampling. The former allows a larger number of samples as it is less time consuming, but the latter can be a good choice to readily reveal soil profile characteristics, reducing uncertainties of vertical soil coring related to soil compression or accounting for coarse mineral fragments like large gravel (Davis *et al.*, 2018).

The internationally accepted operational definition of SOC is the organic carbon present in the fraction of the soil that passes through the 2 mm sieve (Whitehead *et al.*, 2012), which is the fine earth fraction. For inventory purposes, therefore, the measurement of SOC in the fine soil fraction (<2mm) should be adequate. However, beyond occasionally containing mineral coarse fragments (see section 2.4.2), soils include macroscopic organic matter such as root fragments (see section 2.4.3). These are greatly variable spatially and quantitatively in the soil, ephemeral in nature, and can contribute disproportionately to total organic carbon in soils. However, the assessment of the coarse organic matter may provide important ancillary information if done in the same soil cores (see section 2.4.3). If it is retained and quantified as an additional source of information, it shall be separated from SOC quantification. This will entail careful, systematic identification, separation and optionally quantification of organic layers (field inspection of the soil profile) and coarse

organic matter fractions separated from the fine mineral fraction by systematic dry sieving and from the coarse mineral fraction by hand sorting.

In fields where biochar has been applied particles with diameter larger than 2 mm could be present. In such cases, the accounting for the SOC in the coarse fraction may be necessary.

Thus, to determine SOC stocks, the following measurements are essential:

- Quantification of the fine earth (< 2 mm) and coarse mineral fraction (> 2 mm) of the soil
- Quantification of SOC concentration in the fine earth (< 2 mm) soil fraction
- Soil bulk density or fine earth mass

Additionally, the same soil cores can be used to measure the coarse fraction of belowground organic carbon (see section 2.4.3).

After these parameters are measured the SOC stock can be calculated using this formula for each depth increment (*i*):

Equation 1:

$$SOC_i \text{ stock (Mg C ha}^{-1}\text{)} = OC_i \times BD_{fine_i} \times (1 - vG_i) \times t_i \times 0.1$$

where,

SOC_i = soil organic carbon stock (in Mg C ha⁻¹) of the depth increment *i*

OC_i = organic carbon content (mg C g soil⁻¹) of the fine soil fraction (< 2 mm) in the depth increment *i*

BD_{fine_i} = the mass of the fine earth per volume of fine earth of the depth increment *i* (g fine earth cm⁻³ fine earth = dry soil mass [g] – coarse mineral fragment mass [g]) / (soil sample volume [cm³] – coarse mineral fragment volume [cm³])

vG_i = the volumetric coarse fragment content of the depth increment *i*

t_i = thickness (depth, in cm), of the depth increment *i*

0.1 = conversion factor for converting mg C cm⁻² to Mg C ha⁻¹

See section 2.4.2 for further details on the calculation of soil bulk density and alternative formulae for SOC.

To obtain the fine earth dry matter weight, the residual water content after soil drying must be subtracted from the measured weight.

Soil coring is a seemingly simple method to use. However, it requires careful consideration of: (i) factors that cause heterogeneity (*e.g.* soil type, topography, hydrology, management), (ii) the core diameter and the specific depth of sampling and, (iii) the number of cores needed to provide a statistically meaningful sample size. Effective soil sampling can be carried out only when homogeneous sites are identified within the heterogeneous landscape and then a suitable number of soil cores are collected (see section 2.2.1, for the concept of stratification).

It is highly recommended that the same methods and the same calculations are repeated across multiple sites to reduce uncertainty and errors. Further, when assessing SOC stock changes, the equivalent soil mass principle must be considered to enable the identification and correct quantification of changes when a bulk density change occurs (see section 3.5.1). In this respect, it is important to remember that changes in coarse fragment content will increase variability in the estimation of SOC stocks.

RECOMMENDATION 1. To determine SOC stocks, the user shall quantify within a specific soil sampling depth: (i) SOC content of the fine earth mass (< 2 mm size), (ii) coarse mineral fraction content (> 2 mm size) and, (iii) soil bulk density. Sampling depth shall be at least 30 cm, and should be as deep as possible where soil depth is greater than 30 cm. All samples shall be georeferenced. Appropriate error and uncertainty should be reported.

2.2 Planning the sampling

The quantification of SOC stocks for the assessment of SOC stock changes across livestock-based production systems is of great interest to a wide range of end-users, who might, however, have different ambitions and be motivated by different goals. The flowchart below (Figure 2) aims to assist end-users in the process of making informed decisions about the correct way to proceed in the estimation of SOC stocks. It refers the user to further sections within this Chapter for further information and clarification.

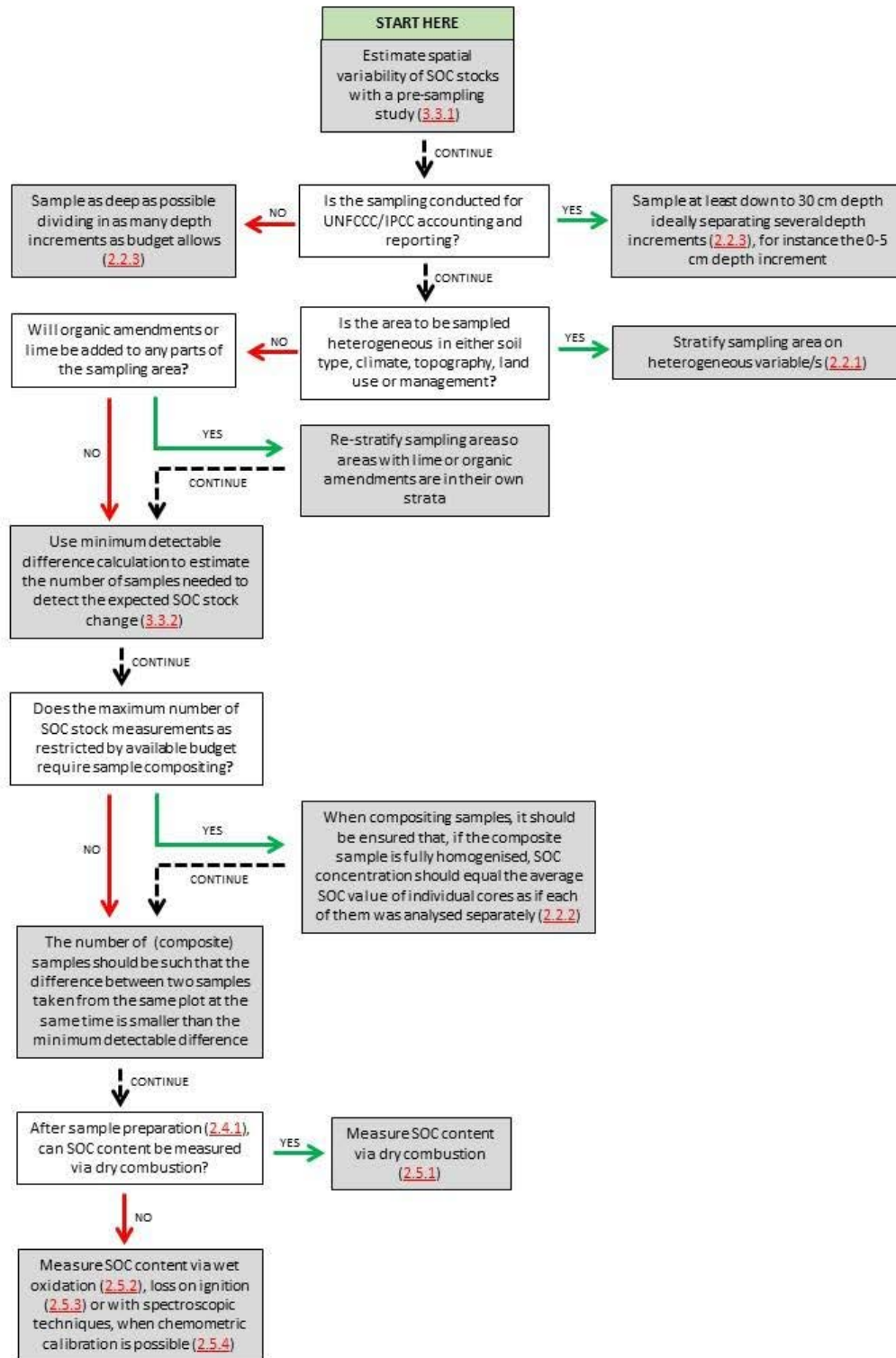


Figure 2. Decision tree to guide the process of SOC stock measurement. Green arrows following a question indicate a positive answer, red arrows a negative one. Black dashed arrows lead to the next question. Underlined numbers in brackets refer to subsequent sections in this Chapter, where further details can be found.

RECOMMENDATION 2. To identify the most appropriate approach for soil sampling, the user shall make key decisions considering: (i) purpose and linked requirements, (ii) stratification and representativeness, (iii) soil depth, and (iv) land management. The sampling strategy should be based on a decision tree, such as the one provided in Figure 2.

2.2.1 Site heterogeneity and stratification

The heterogeneous nature of the soil environment affects SOC dynamics and its variability in space and time. At the fine, process scale, the degree of heterogeneity depends on the soil physical structure, that is the spatial arrangement of solid particles (mineral particles, SOM) and pores in which fluids, decomposers and soluble compounds circulate (Dignac *et al.*, 2017). At larger scales, some determinants have been identified that significantly alter the rate and direction of soil change (in past and present). Thus, at the landscape scale, SOC heterogeneity is driven by soil texture (Figure 3), pH, mineralogy, topology and land-use. At the plot scale, changes in land management (agricultural) practices and in plant species diversity and composition can increase SOC heterogeneity.

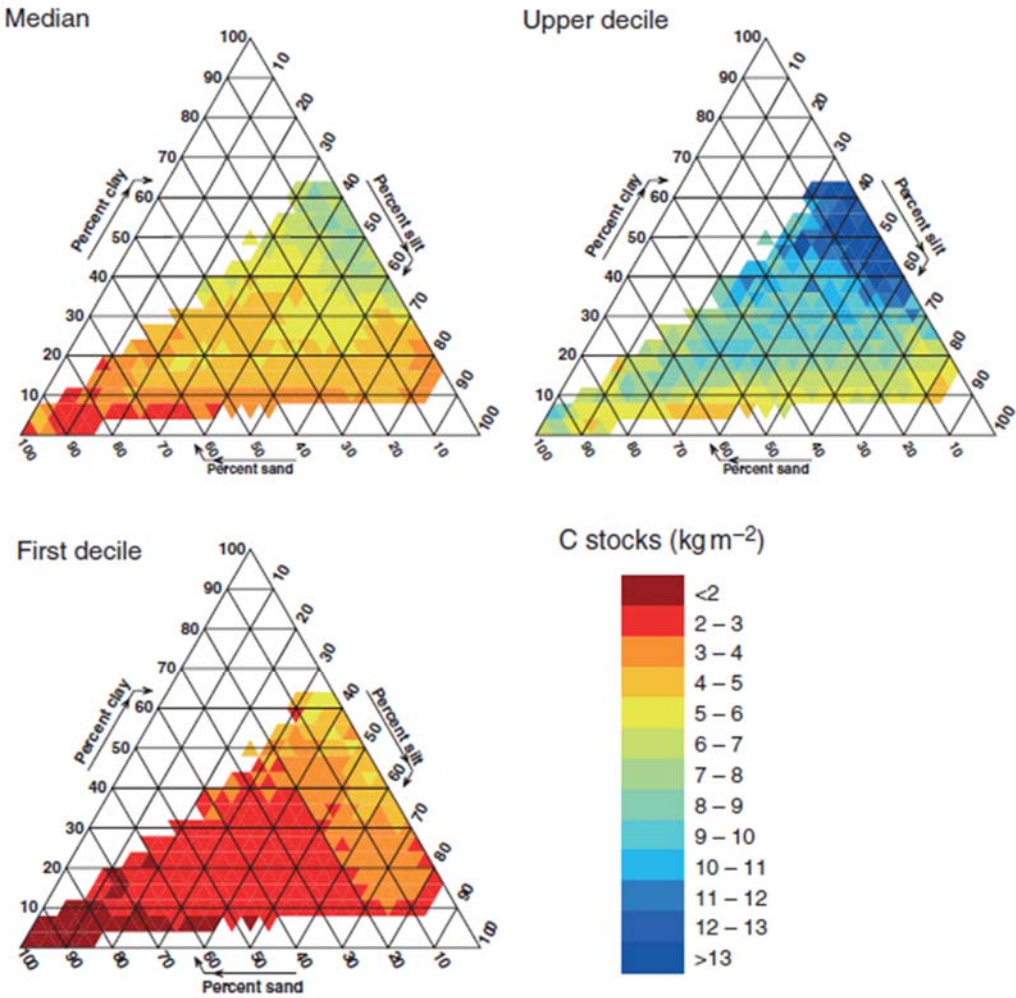


Figure 3. Example of SOC stock variability in Central Europe dependent on soil texture. Median and decile values were calculated for each sub-triangle delineated by 4% classes of particle-size fractions (Arrouays *et al.*, 2006).

Soils used for livestock production, can show a great spatial heterogeneity in their properties, due to the superimposed effects of the activities of animals (grazing, excreta deposition, treading).

There is also a distinct vertical distribution of C in soils, primarily associated with the vertical variability in organic matter input to soils and the uneven decomposition and downward transport of SOC within a soil profile. The vertical distribution of SOC is thus mainly controlled by climate and cultivation (Jobbágy and Jackson, 2000). The amount of carbon located deeper in the profile is negatively correlated with temperature and positively correlated with rainfall. With increasing depth, clay content becomes the main controlling factor (Jobbágy and Jackson, 2000). For Central and Eastern European soils, about 44 % of the total C pool down to 1 m soil depth is located within the top 0.3 m of the soil (Batjes, 2002; Soussana and Lemaire, 2014).

Considering heterogeneity and spatial variability is essential when measuring soil carbon stocks and stock changes (see section 3). In general, variability in soil properties becomes greater with increasing study area and considered soil depth. It is hard to overemphasize how critical is the consideration of spatial variability in SOC stocks in designing sampling schemes. Spatial variability of SOC can rise sevenfold when scaling up from point sample to landscape scales, resulting in high uncertainties in calculations of SOC stocks. This hinders the ability to accurately measure changes in stocks at scales relevant to emissions trading schemes (Hobley and Willgoose, 2010).

2.2.2 Sampling strategies

Different approaches can be distinguished when it comes to monitoring and sampling. Two main sampling approaches are:

- A design-based (classical) statistical approach, in which a randomized sampling procedure is important to avoid bias;
- A model-based (geo-statistical) approach for which randomization is not a prerequisite (Brus and de Gruijter, 1997; Brus, 2014).

A combination of approaches can also be applied (Viscarra Rossel *et al.*, 2016). The strategy depends primarily on the aim of the study, but also on the scale (cost): on a field level a more intensive sampling scheme might be financially feasible, while on a regional or national scale, a combination of sampling and (geo)statistical inter- and extrapolation is more likely to be useful (Conant *et al.*, 2011). As these guidelines target a broad audience, we will here focus on the classical design-based approach as it is considered easier and more commonly applied.

Well-known design-based approaches are non-stratified random sampling and stratified random sampling. In general, grid sampling is applied when no prior information is available in an area, while stratified sampling is used when prior information is available and can be used in stratification. Indeed, there is a continuum between a grid and stratified sampling design (de Gruijter *et al.*, 2016).

The design of a sampling scheme can be determined by the indicator to be monitored and the output and precision required for that indicator. If maps are required, a systematic grid would be appropriate for monitoring (Bellamy *et al.*, 2005), for specific threats in certain areas (e.g. the decline of organic matter), a stratified approach would be more appropriate (Van Camp *et al.*, 2004; European Commission, 2006). Both will be briefly explained below.

Non-stratified sampling: The study area is considered a unit, sampled in a systematic or random manner. For instance, as a systematic approach, a grid or linear sampling pattern can be applied. When working randomly, the sample locations are selected at random from the area, with equal probabilities of selection and independently from each other (Carter and Gregorich, 2007). This is done by taking the geographical coordinates of each sampling location from a random number

generator or from a table of random numbers (Brus and De Gruijter, 1997). This method is not recommended here as results often have a relatively high uncertainty.

Stratified sampling: the study area is first divided into several relatively homogeneous units, called strata, and then random sampling is applied within each stratum. We recommend using this method to determine changes in carbon stocks as it is a promising strategy to reduce uncertainty (Maillard *et al.*, 2017). Stratifying the study area in terms of factors that influence SOC stocks will normally reduce errors associated with project-scale estimates of SOC stocks. Indeed, at landscape/regional scales stratification is crucial to reduce the uncertainties with which SOC stocks and changes can be estimated, as well as to enable meaningful comparison and integration with other inventories. Scaling up of SOC stocks from plot or farm level to landscape level is a critical step, and uncertainties are especially related to whether calculations are based on reliable spatial data.

The homogenous units are expected to have similar SOC stocks. For this reason, stratification is based on factors affecting SOC content and changes in SOC stocks, such as soil type (partly determined by texture), land use, topography (e.g. slope position), hydrology, and (micro)climate. The criteria to select strata depends on the scale, e.g. at a continental level, climate and soil properties tends to explain more variation in SOC than other factors (Jobbágy and Jackson, 2000; Ren *et al.*, 2011). Local historic land use – which may not be well reflected by current land use – often has a dominant influence at smaller scale (Vågen *et al.*, 2006; Setiawan and Yoshino, 2014). Stratifying on too many variables can rapidly become unmanageable in terms of the number of strata produced. The World Reference Base for Soil Resources of the FAO can be helpful in choosing different strata. More information can be found on this website (www.fao.org/soils-portal/soil-survey/soil-classification/en/).

Example of stratification

An example of stratified sampling followed by random sampling approach is given in Table 1. For the Dutch National Soil Quality monitoring program, eight main strata were defined, based on land use and soil type information derived from an annual agricultural census. In this census, all Dutch farmers are obliged by law to share information with the government on the number and type of livestock, the plots they own or lease, land use and management practices (such as the use of fertilizers and manure). Based on the entire population of farmers, Wageningen Economic Research creates strata of the most common combinations of land use and soil type (Table 1; see Wattel-Koekkoek *et al.*, 2012 for the exact definition of each stratum).

Table 1. Area and number of farms for which each stratum is representative in the Dutch National soil quality monitoring program (2006-2010).

Year	Farm type and soil type	Number of farms for which the sampled farms in a stratum is representative (% of total*)	Area for which the locations in a stratum is representative (in 1000 ha) (% of total area land in The Netherlands**)
2006	Dairy cattle (low and high intensity) on sandy soils	10609	13% 405 21%

2007	Cattle breeding and dairy cattle on sandy soils	533	1%	12	1%
2007	Forest/heath on sandy soils	-	-	235	12%
2008	Arable farming on sandy soils	1160	2%	81	4%
2008	Dairy cattle on peat soils	3695	5%	178	9%
2009	Arable farming on sea clay	4545	6%	279	15%
2009	Dairy cattle on river clay	1223	2%	60	3%
2010	Dairy cattle on sea clay	3065	4%	170	9%
Total				1420	74%

Source: Agricultural Census, CBS/Wageningen Economic Research, several years, in year of soil sampling of the given stratum (Wattel-Koekkoek *et al.*, 2012).

* the exact number of farms is determined per year via the agricultural census. The percentages in the table were calculated based on the exact number of farms in the sampling year. The Netherlands on average had approximately 75.000 farms during the sampling period (2006-2010).

**Approximately 1.9 million ha.

Within each stratum, 20 farms were randomly selected and the farmers were asked to participate in the monitoring program. Thus, farm selection is not strictly random, as farmers participate voluntarily - randomly selected farmers cannot be forced to allow field workers on their land. Per stratum, 20 farms (or forests plots) were sampled. Over 300 small soil samples were taken for each farm, considering plot/paddock size when taking the samples. They were thoroughly mixed and homogenized and from this large composite sample, subsamples were taken for analyses (see section 2.2.2, for more information on compositing samples). These subsamples are assumed to be representative for an entire farm, and the median values of the 20 sampled farms were assumed to be representative for the entire stratum.

Sample size (=Number of composite samples, see definitions in the Glossary): To determine the variability in the area needing to be sampled, it is recommended to take 5 to 10 composite samples prior to sampling (pre-sampling, see section 3.3.1). In case of a stratified sampling method we recommend a minimum of three samples per stratum, preferably five or more, depending on budget. The number of samples taken affects the minimum change in C stock that can be detected. For instance, Conant and Paustian (2002) found that SOC changes related to grassland management could only be verified after 5-10 years by collecting 34, 224 and 501 samples at the county, state and national scales, respectively (USDA data). The number of samples in a stratum can be chosen to be proportional to its area but does not have to. Vanguelova *et al.* (2016) recommend using 4 to a maximum of 25 samples per 0.25 ha plot, and at least 5 m between sampling points to eliminate spatial auto correlation. Quantifying SOC changes at national or regional scales require more modest sampling densities (Mäkipää *et al.*, 2008; Conant *et al.*, 2011). More information on the recommended sample size can be found see section 3.3).

Where to sample, and where not to sample? Within a stratum, the sampling locations where soil cores are taken should be determined randomly to avoid bias. However, certain areas shall be excluded in grazed lands, such as patches with animal excreta, animal pathways, driveways to enter/leave fields, very near watering points.

Geo-referencing: GPS coordinates of each sampling location shall be recorded, so that the site can always be revisited. Also, geospatial upscaling requires georeferenced SOC stock values (see also Chapter 7).

Volume of cores: For bulk density, the core diameter should be between 50- and 100-mm. Cores with diameter smaller than 50 mm may hamper, if present, proper representation of coarse roots and coarse mineral fragments in the sample and cores with diameter larger than 100 mm may be difficult to handle. Cores with a 100 cm³ volume (53 mm diameter, 51 mm height) are recommended by ISO 11272:2017 (Soil quality - Determination of dry bulk density). Ideally bulk density will be estimated for the same core used to collect the sample for SOC analysis (Ellert *et al.*, 2008; Walter *et al.*, 2016).

RECOMMENDATION 3. To sample a study area in a representative way, the user shall identify a minimum of three sampling strata (relatively homogeneous units) based on the main environmental factors determining SOC variability, including – depending on the scale – climate, soil type, hydrology, topography, land use and management and land use history, amongst others.

2.2.3 Compositing

Compositing (or bulking) refers to the procedure of pooling together several soil cores (subsamples) into one homogeneous composite (or bulked) sample, which is then analysed for SOC content. If the composite sample is fully homogenised, SOC concentration should equal the average SOC value of individual cores (had each of them been analysed separately). Soil compositing is important for reducing both spatial variability and the overall costs related to the analysis of multiple soil samples.

The processing and analysis of a composite sample is recommended in most cases except when the main goal is to estimate variation of soil properties at small spatial scales (e.g., few meters). As a rule, the number of subsamples should be such that two composite samples taken from the same plot at a given point in time are no more different between each other than the minimum detectable change (Section 3). That is, the change in space shall not be confounded with the change in time. There is some evidence in the literature that this precision may be achieved by including from 4 to 6 soil cores per composite sample (see Vanguelova *et al.*, 2016 for details).

It is recommended that the number of homogeneous sites (i.e. number of strata) and soil composite samples are increased to the maximum that can be afforded to ensure that the:

- Composite samples are representative of the total area,
- Variance between composite samples collected at any individual time is reduced,
- End-user's ability to detect temporal changes in SOC stocks is increased.

RECOMMENDATION 4. Within each homogeneous unit (stratum) at least 5 soil cores should be collected to form a composite sample. Composite samples should represent the total area of the unit/strata and be collected in the same day.

2.2.4 Sampling depth

The depth to which soil is collected to estimate SOC stocks requires careful consideration. If temporal SOC stock changes are to be used for national or global carbon accounting purposes under the IPCC, then stocks shall be reported for at least the 0-30 cm profile (Eggleston, 2006).

Sub-sampling within the 0-30 cm layer is sometimes desirable. But if IPCC recommendations are to be followed, the 0-30 cm sample must be collected and analysed separately. Likewise, proponents are encouraged to sample deeper, however following IPCC recommendations the 0-30 cm sample needs to be analysed separately. Further, when sampling below 30 cm, the 0-30 cm and below-30 cm samples shall be taken from the same core, as short-range spatial variability means that using samples taken from different holes will increase error and, therefore, the ability to detect temporal changes. As a rule, the deeper a sample is taken the greater the chances of a textural change through the profile and more difficulty in homogenising the sample for analysis (see section 2.4.1).

RECOMMENDATION 5. Soil organic carbon stocks should be reported for the 0–30 cm layer to comply with IPCC recommendations, and appropriate error and uncertainty should be reported. Soils less than 30 cm deep should be sampled as deep as possible and stocks extrapolated to 30 cm. Soils more than 30 cm deep should be sampled as deep as possible, and the SOC stock in the 0–30 cm layer shall be reported separately. Sampling to depths greater than 30 cm or subsampling the 0-30 layer may be warranted, however the impact of increased costs and potential increase in uncertainty need to be considered.

Notwithstanding the IPCC recommendations, a large proportion of SOC stocks is found below 30 cm, as just about 40% of SOC is in the topsoil (Soussana and Lemaire, 2014; Orgill *et al.*, 2014). While shorter-term changes in SOC mostly appear in the top of the profile (Conant *et al.*, 2001), longer-term stabilization of SOC can occur in the deeper soil layers. These stores may be important for global C budgets and for C sequestration strategies (Batjes 1996, IGBP 1998 in Jobbágy and Jackson, 2000).

Survey type studies have shown that short term differences in SOC stocks between land uses are more likely to occur in the upper profile (Badgery *et al.*, 2014), while changes in deeper soil layers appear after several years (> 10 years) following a land use/management change (Stahl *et al.*, 2016; Knops and Bradley, 2009). Thus, depending on the objectives of the programme, management and production system applied, and the time scale considered, lower soil depths may be considered for SOC stock change assessment. If because of the desired sampling depth associated cost of analysis cannot be consolidated using standard methods of SOC analysis, alternative faster and cheaper SOC quantification techniques may be considered (see sections 2.5.1 and 2.5.4).

Subsoil C frequently has a high radiocarbon age, which suggests that a high proportion of this C is stable at longer timescales (Paul *et al.*, 1997). SOC stabilization at depth may occur due to its interaction with the mineral phase (e.g. sorption on amorphous Al and Fe oxides in acid (Gu *et al.*, 1994) or complexation with Ca²⁺ (Muneer and Oades, 1989) and organo-mineral interaction with reactive, positively charged minerals in near neutral soils (Grunewald *et al.*, 2006) and occlusion in soil aggregates (Rasmussen *et al.*, 2005).

Organic C input into deeper soil horizons occurs mainly in the form of dissolved organic carbon via preferential flow pathways (Kaiser and Guggenberger, 2000; Michalzik *et al.*, 2001) or through biological disturbance (Wilkinson *et al.*, 2009) and by the root system (Lorenz and Lal, 2005). Introducing deep rooting vegetation into shallow-rooting systems, for example, will affect the

vertical distribution of SOC fractions (Heile *et al.*, 2010) and potentially store C in deeper soil layers. Examples of this are shrub encroachment in grasslands (Jobbágy and Jackson, 2000; Allen *et al.*, 2016), introduction of pasture in annual crop systems or trees in annual crop systems or pastures/grasslands (Oliveira *et al.*, 2017; Cardinael *et al.*, 2017).

SOC in deeper soil horizons, however, may be destabilized by adding more labile C forms, for example through the addition of fertilizing materials (Fontaine *et al.*, 2007; Kuzyakov *et al.*, 2000). Therefore, land use and soil management that affect these processes will likely influence subsoil C pools (Guo and Gifford, 2002; Wright *et al.*, 2007; Follett *et al.*, 2009; Strahm *et al.*, 2009).

2.3 Errors and uncertainties

Because the absolute true mean value of SOC stocks of a certain spatial unit is not possible to determine, it is good practice to report the average (usually as statistical mean or median) value and a measure for uncertainty. Uncertainty is defined as the description of the lack of knowledge of the true value of a variable based on its probability (IPCC, 2006). Uncertainty is often reported as the standard error of the mean, which accounts for the two factors that determine it: the standard deviation (or in a relative manner, the coefficient of variation, also known as relative standard deviation) and the number of samples. In general, increasing sample size will enable a more precise approximation to the average resulting in smaller uncertainties.

One source of variability, and thus uncertainty, is that SOC distribution in a defined spatial unit is heterogeneous, even at field or plot scale. Collecting and analysing several soil samples within one spatial unit (or stratum) will, therefore, always produce unequal values for the respective SOC stocks. Larger scales have usually a larger variability, especially in grasslands. For instance, in a national scale study of Belgium, the main source of SOC stock variability in grasslands was found to be the variability in the thickness of the first horizon (Goidts *et al.*, 2009). Also, in stony soils, the rock fragment tends to largely influence SOC stock variability.

The intrinsic variability cannot be altered and is a given property of a certain spatial unit, but through optimization of sampling schemes the sampling variance can be effectively reduced (Pitard, 1993; De Gruijter *et al.*, 2006). Thus, the sampling strategy is of large influence on the sampling variance and can be evaluated beforehand. Arbitrary sampling or haphazard sampling is not recommended because the inclusion probabilities are unknown (Brus, 2014). The purpose of the SOC stock assessment shall be the driver for determining a sampling strategy (see section 2.2.1). In BOX 1 a case study illustrates this last point.

In addition to such intrinsic or fundamental variability of SOC stocks, further uncertainties arise from sampling and analytical procedures (Pitard, 1993). Such uncertainty of measurements can be reduced when undertaking the SOC stock assessments by adequate sampling protocol and effective quality control. Errors to be considered include those related to sampling depth, complete removal of the organic layer, mix-up of sampling bags, proper mixing of composite samples as well as differences between laboratories in indoor-climate among other conditions (FAO, 2017b).

Analytical errors are those related to the determination of SOC content or bulk density. A specific error is attached to each method and used equipment. The determination of SOC content (see also section 2.5) generally generates larger errors for samples with low SOC contents (Goidts *et al.*, 2009) because most of the available techniques are not calibrated for low values. The use of standards for calibrating equipment is an essential element of good laboratory practices. Bulk density determination by the core method (see section 2.4.2) has different errors depending on the size of the sampling rings and the stone content of the soil, but in general smaller errors than estimation via pedotransfer functions (Walter *et al.*, 2016). The analytical errors can be estimated

by taking sufficient duplicates and can be minimized by randomizing the order of analysis. If block or stratified sampling was used, the randomization of the order of analysis should occur within the block.

There exist different approaches to perform a full uncertainty analysis in which all errors involved in the determination of SOC stocks are considered. Whenever sufficient data and resources are available, uncertainties should be quantified. A detailed guideline with worksheets is available in Chapter 3 “Uncertainties” of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Presented approaches include the calculation of error propagation, Monte Carlo Simulation and combinations of both approaches. Uncertainty quantification is especially relevant when relatively small SOC stock changes are expected and the uncertainty is possibly larger than the detectable change (see section 3.3.2).

To order the potential sources of uncertainty at various scales, and possibilities to reduce them, Table 2 – a summary of sources of errors in SOC evaluation at sample, profile, plot and landscape scales by Vanguelova *et al.* (2016) – should be helpful.

Table 2. Sources of errors in SOC evaluation at sample, profile, plot and landscape scales. The sources likely to produce high errors are **in bold** (Vanguelova *et al.*, 2016).

Sample	Soil composite samples are not homogenised Different analytical procedures for C applied Bulk density is not assessed correctly Coarse fragments volume not assessed Separation of soil horizons and layers not done accurately
Profile	Sampling by horizon versus soil depth depending on research aims Sampling at not full soil depth to account for vertical variability
Plot	Micro-spatial variability not accounted for (not appropriate sampling strategy) Statistical sampling error due to different sampling schemes Different inventory teams are not harmonised Lacking quality of the geo-referenced (or the reported values) Not adequate numbers of sampling points Bulk density and coarse fraction content not analysed Analytical (measurement) errors including sample preparation Missing values, recording and truncation errors Model errors (e.g. from the selection of inadequate pedotransfer rules or functions, inadequate model constants and conversion factors, etc. not site/soil specific calibrated)
Landscape /National	Lack of local and regional representativeness of sampling plots Important strata are underrepresented (e.g. wet mineral soils or peat soils) Lack of tree species/forest cover maps Lack of accurate soil/hydrology maps Landscape insufficient resolution of climatic data

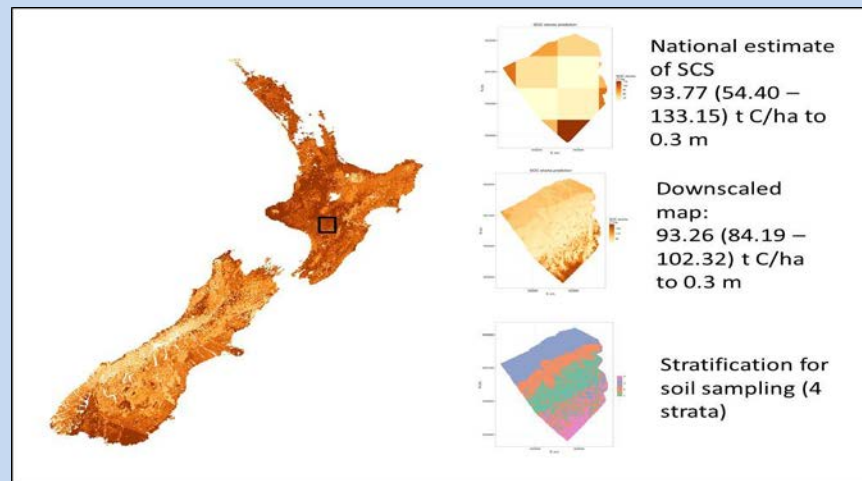
RECOMMENDATION 6. The sampling approach shall be consistent with standard operating procedures to reduce the variability originating from the sampling itself. Sufficient laboratory duplicates and randomising the order of sample analysis should be carried out to allow quantification of combined field and laboratory measurement errors. Whenever sufficient data and resources are available, an uncertainty analysis may be performed following the 2006 IPCC guideline.

BOX 1. Farm scale soil carbon auditing

Overview: A soil carbon auditing protocol has been developed and tested at farm-scale. It is designed to be appropriate for land owners to earn regulated carbon credits if a changed land management, e.g. a changed grazing practice, could be shown to sequester soil carbon.

Approach: Where national scale soil carbon maps are available, it makes sense to use them to guide the development of a finer scale map. Therefore, existing national scale digital soil carbon maps for Australia and New Zealand were downscaled (disaggregated) with local high-resolution environmental data, to derive fine scale soil carbon maps for a target area, maintaining mass balance. The fine scale soil carbon map effectively stratified the area and formed the basis for assigning sampling positions to collect soil samples for: (i) deriving a mean weighted estimate of soil carbon stocks for the target area and, (ii) associated statistical confidence of the measurement. The method used a Value of Information approach, deriving an optimal sample size by balancing data value and data cost (taking into consideration the financial gain expected from a carbon trading scheme). Once the baseline carbon stocks have been established, subsequent soil sampling campaigns become the soil carbon monitoring programme.

Case study: The method was used for a 476-ha New Zealand hill country sheep and beef station, to provide a SOC stock estimate for Time One (figure below). A national soil carbon map, at a nominal resolution of 1-km was disaggregated using: (i) LiDAR survey data and derived terrain attribute layers at 10-m resolution, and (ii) a legacy soil map. The fine scale map was then classified into four strata, to guide the soil sampling campaign. Volumetric soil carbon content was estimated for fifty soil cores to 0.3-m soil depth.



A New Zealand soil carbon map was disaggregated to farm scale, using high resolution local data, and then stratified to guide a soil sampling campaign. The method is designed to monitor any changes in soil carbon stocks through time.

Summary: The method described above stratifies an area for on-going monitoring, to establish whether carbon is being sequestered or lost from the soils. We expect soil carbon auditing to play a role in the future of agriculture to meet: (i) international monitoring commitments of greenhouse gas emissions, and (ii) regulations placed on landowners to sustain the soil resource.

de Gruijter, J.J. et al. 2016. Farm-scale soil carbon auditing. *Geoderma* 265, 120-130.

Malone, B.P. *et al.*, 2012. A general method for downscaling earth resource information.

Computers and Geosciences 41, 119-125.

Malone, B.P. *et al.*, 2018. Feasibility of stratified random sampling of downscaled national soil carbon mapping for auditing on-farm carbon stocks: examples from Australia and New Zealand. *Geoderma Regional* 13, 1-14.

2.4 Soil processing and analysis

Adequate sample processing is of great importance to avoid bias in SOC stock assessment. During the collection and handling of samples for SOC content analysis (see section 2.4.1), losses of organic compounds may occur due to microbial degradation, sample drying, oxidation, volatilization, and selective removal of carbon-bearing components (Schumacher, 2002).

The internationally accepted operational definition of SOC is the organic carbon present in the fraction of the soil that passes through the 2 mm sieve (Whitehead *et al.*, 2012). For inventory purposes, therefore, the measurement of SOC in the fine soil fraction (<2mm) should be adequate. However, beyond occasionally containing coarse mineral fragments (see section 2.4.2), soils include macroscopic organic matter such as root fragments (see section 2.4.3). These are greatly variable spatially and quantitatively in the soil, ephemeral in nature, and can contribute disproportionately to total organic carbon in soils. Assessment of the coarse organic matter may provide important ancillary information. If it is retained and quantified as an additional source of information, it shall be separated from SOC quantification.

It is of great importance that standard procedures are set up and followed over the whole process of field sampling, soil processing and laboratory analysis of SOC stocks (consistency control) to diminish the influence of occasional differences or errors during sample processing. If analyses are carried out by different laboratories a consistency check shall be carried out before processing soil samples. Periodic quality control and quality assurance of analyses and procedures (e.g. based on samples with known value) is highly recommended (Klesta and Bartz, 1996; Mäkipää *et al.*, 2012).

RECOMMENDATION 7. Soil processing for SOC analysis shall follow standard procedures. Consistency control of procedures shall be observed during the project and if the analyses are done in more than one laboratory, or more than one equipment/machine is measuring the same soil property, consistency check shall be carried out between them.

2.4.1 *Drying, grinding, sieving, homogenizing and archiving soil samples*

Soil samples should be collected into airtight plastic bags (LDPE plastic), and most of the air should be removed immediately after sampling (Whitehead *et al.*, 2012).

Soil samples should not be stored wet as this may quantitatively affect SOC. If drying is not possible immediately after sampling, soil samples should be stored at 4°C in the dark to reduce microbial activity (Nelson and Sommers, 1996), preferably for less than 28 days (Schumacher, 2002), as microbial degradation does not completely stop at 4°C and could lead to loss of organic materials. Freezing is not recommended. When large amounts of roots or macrofauna (e.g. earthworms) are present in the sample, it should be processed within a week, so that SOC concentration is not altered by decomposition of those components (Whitehead *et al.*, 2012).

Sample transport, unpacking and transfer to other containers in the laboratory may produce particle sorting via different particle densities, shapes, sizes, and resistance of certain minerals to mixing (Schumacher *et al.*, 1990a). Therefore, care should be taken during the subsampling phase of soil preparation to eliminate this bias.

If SOC and bulk density determination are performed in the same sample, then field-moist samples of known volume should be weighed first, and then spreading it out as a thin layer in a shallow tray and air-dried in a ventilated room, a custom-made solar dryer, or a forced-air oven at 40°C. Large clods should be broken up to accelerate the drying process, avoid soil aggregation and to separate roots from fine soil to avoid contamination at sieving. Samples should then be crumbled and the fraction that passes through a 2 mm sieve separated for SOC analysis. It is essential at this stage to avoid loss or contamination from dust or other potential contaminants.

At *sieving* the > 2 mm size rocks and pebbles (coarse fraction or gravel) should be separated and weighed for correcting the bulk density (see section 2.4.2). Roots and other organic soil constituents that are > 2 mm generally have negligible mass compared to the mineral phase, but the varying level of its fragmentation may be a source of uncertainty in the estimation of C stock changes, for roots that are more fragmented, either naturally or in the processing, will become part of the fine soil fraction. When the assessment of the coarse organic matter carries important ancillary information, the coarse fraction of belowground C may be separated and quantified separately as additional source of information (see also section 2.4.3).

The fine earth fraction shall be thoroughly *homogenized*, which is best achieved by milling the sample. Homogeneity is the degree that the material under investigation is mixed resulting in the random distribution of all particles in the sample. Completely homogenous materials are rare, yet it is essential to aim for as homogenous a sample as possible to minimize error attributable to sample heterogeneity (Schumacher *et al.*, 1990b). Poor sample homogenisation can lead to greater uncertainty in values therefore making temporal changes in SOC stocks more difficult to detect.

An aliquot of around 5 to 10 g should be used to determine the gravimetric water content of the air-dried, homogenised sample. To ensure representative subsampling, a sample splitter is optimal, but also other manual techniques are available. Standard procedures for the determination of soil moisture are available (ISO 11465: 1993 Soil quality - Determination of dry matter and water content on a mass basis - Gravimetric method; ASTM D4959-16). Further preparation and weighing of the soil samples will depend on the type of analyses for SOC determination (see section 2.5). For instance, for the analyses of total N and C by dry combustion a sub-sample of fine earth shall be further ground to a fine powder (<0.15 mm) to improve accuracy as such equipment generally works with small soil aliquots (200 mg or less). Smith and Myung (1990) describe a roller grinder that is inexpensive and easily constructed, eliminating the potential for cross contamination by using individual sample containers.

Archiving soil samples will allow their re-analysis, either to confirm or correct questionable results, or to obtain additional attributes of a specific sample to augment the original results. For long-term field studies, analytical methodologies often improve over time and the archived samples may also be used to validate a new method and relate the results to the old method (Sheppard and Addison, 2008). The samples should be stored in an inert, airtight container (ideally, glass jars or LDPE bags) with proper labels. Preferentially, archived samples should be kept at a maximum temperature of 4 °C, even if samples are dry. If it is not possible, they should be stored in a cool, ventilated and dark space, free from moisture and dust. In addition, proper archive documentation is important and should include sample identification (e.g. barcode), collection details, preparation and storage conditions, links to the researcher, and primary analysis that researcher completed (Sheppard and Addison, 2008). See Chapter 4 for detailed guidance on data handling.

The diagram in Figure 4 represents essential steps of sample processing for SOC analysis.

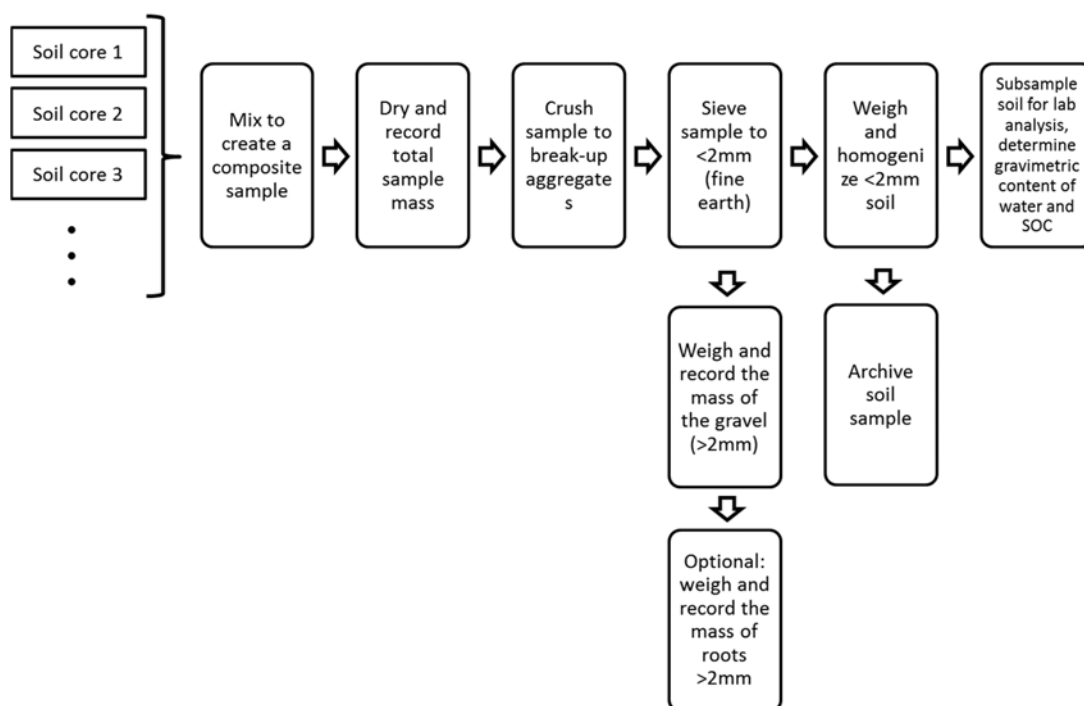


Figure 4. General steps of soil sample preparation for laboratory SOC analysis.

RECOMMENDATION 8. Fresh soil samples should not be stored at temperatures higher than 4°C or for more than 28 days after collection. Soil samples shall be thoroughly homogenized. SOC content analysis shall be done in the fine earth (< 2mm) fraction. For archiving, dried soil samples should be stored in a dark, cool and dry room for potential future use and verification.

2.4.2 Bulk density

Soil bulk density is the mass per unit volume of the soil (FAO, 2006). The soil volume includes solids and pores, which may contain air, water, or both. Bulk density reflects soil structure and depends on the proportion and quality of the mineral and organic soil components. Thus, particle size distribution (texture), mineralogy, soil chemical composition and organic matter content and

quality all influence bulk density, which is finally a result of complex interactions of soil constituents combined with the effect of soil forming processes and soil use and management.

Bulk density is usually expressed in Mg m^{-3} or the numerically equivalent g cm^{-3} (Cresswell and Hamilton, 2002). It is a soil property that typically has high spatial variability and it is particularly sensitive to non-representativeness of the samples (e.g. presence of coarse fragments, cracks, roots, etc.). If possible, analyses should always be in triplicate for one sample (Blake and Hartge, 1986). As bulk density changes with water content, the water status of the soil at sampling must be specified (Blake and Hartge, 1986). Small errors in bulk density can lead to relatively high SOC stock variability.

The soil bulk density used in calculating SOC stocks (and Equivalent Soil Mass, Chapter 4) should be the density of the same core in which SOC concentration is measured. This is because the sampling of soils by coring almost invariably results in some compaction (Ellert *et al.*, 2001). Thus, for example, the true depth of sampling when a 0-30 cm core is extracted almost always exceeds 30 cm and, therefore, the soil density in the core removed exceeds the actual field bulk density. This can lead to serious errors when later calculating soil carbon stock on an equivalent mass basis using bulk density and SOC concentration measured in independently taken samples. Ideally, soil compaction during sampling will be minimized, but information on the soil mass per volume sampled is more crucial than true bulk density (that may be required for detailed characterization of in situ gas and water transmission, but not of SOC stocks).

The most well-known, direct methods to determine soil bulk density are the undisturbed (intact) core method and the excavation method.

The undisturbed (intact) core method: The most common method of measuring soil bulk density is by collecting a known volume of soil using a metal ring pressed into the soil (intact core) and determining the weight after drying (Blake and Hartge, 1986; Grossman and Reinsch, 2002). This method works best for moist soils without coarse fragments. If the soil is too dry, it is possible to wet the soil manually to keep the core intact. To do this, a bottomless drum should be placed on the soil and filled with water, allowing the soil to wet naturally for 24 hours. Then, a flat horizontal surface should be prepared in the soil with a spade at the depth of sampling. A steel ring is pushed or gently hammered into the soil. A block of wood may be used to protect the ring. Avoid pushing the ring in too far or the soil will compact. Excavate around the ring without disturbing or loosening the soil it contains and carefully remove it with the soil intact. Remove any excess soil from the outside of the ring and cut any plants or roots off at the soil surface with scissors. Pour the soil into the plastic bag and seal the bag. Common sources of error when measuring bulk density are: disrupting the soil while sampling, inaccurate trimming, and inaccurate measuring of the volume of the ring.

Excavation method: This method has been found useful for loose soils, especially surface soils, when it is impossible to collect an intact soil sample applying the undisturbed core method, or for soils with abundant coarse fragments. Bulk density is determined by excavating a quantity of soil, drying and weighing it, and determining the volume of the excavation by filling the hole with sand of known volume per unit mass or water (Blake and Hartge, 1986; Grossman and Reinsch, 2002; Aynekulu *et al.*, 2011). A special apparatus called sand-funnel can be used. After levelling the soil surface, a hole should be excavated using the template of the apparatus. The size of the hole will depend on the apparatus, but a larger (approximately 12 cm in diameter) hole will likely result in smaller error in bulk density estimation. The depth of the hole will depend on the depth of the evaluated layer. All the excavated soil should be retained in a container to determine its dry weight as described in the undisturbed core method. The volume of the hole should be determined by filling it up with clean, dry, free-flowing sand (standard sand with uniform particle-size 0.841-0.25 mm is recommended). The level of the sand should be adjusted to the level of the bottom of the template. An error of 1 mm in adjusting the sand level may result in an error of 0.01

in the bulk density. Using a funnel placed on the template to avoid this error is highly desirable. To estimate the soil volume a mass-to-volume ratio is used. For this reason, the mass-to-volume ratio of the sand must be pre-calibrated by letting the sand fall from a similar height and at a similar rate of flow as in the procedure of measuring bulk density. Thus:

Equation 2:

$$\text{Soil sample volume (cm}^3\text{)} = \text{Mass of the sand (g)} / \text{Density of the sand (g cm}^{-3}\text{)}$$

Core size (=sampled volume): the suitable sample size will depend on soil bulk density and size and characteristics of the coarse fraction. Therefore, it is difficult to standardize sample size. Sample sizes used to determine the bulk density of soils containing only or mainly fine earth are typically 100 cm³. Since coarse fragments are usually underrepresented in small samples. Thus, small samples will likely lead to sub-estimation of the bulk density of gravelly soils.

To determine the bulk density of the fine-earth fraction of soil layers that contain many coarse fragments (around 30%), Vincent and Chadwick (1994) suggested that representative field-sample volume may be smaller than 0.1 dm³, but for gravelly to extremely gravelly soils field samples between 0.2 and 1 dm³ were recommended. In fact, for a soil horizon containing around 30% coarse fragments by volume, the same authors reported representative sample volumes of 4 dm³ or larger and, for a soil horizon containing around 50% coarse fragment by volume, the representative volume was at least 5 dm³. Typically, core diameter will be greater than 50 mm (smaller than this and collection of coarse roots and gravel may be hampered) and less than 100 mm (larger than this and problems associated with machinery, logistics, site disruption become insurmountable).

Indirect methods of determining bulk density may be useful after suitable calibration. Among those are radiation methods, for example gamma radiation transmission or scattering techniques, requiring special equipment (gamma source and detector), and pedotransfer functions (PTFs).

Pedotransfer functions (PTFs) are based on the fact that soil bulk density is influenced by several other soil properties. To reduce time and costs, PTFs use more easily measurable soil properties, i.e. soil clay content and SOC content to predict soil bulk density (e.g. de Vos *et al.*, 2005; Benites *et al.*, 2007; Shiri *et al.*, 2017). They are usually developed based on existing datasets. Using PTFs often increases the variance and uncertainty of estimated SOC stocks if the error associated with the application of the function is not correctly accounted for. This may lead to a systematic bias of calculated SOC stock (Schrumpf *et al.*, 2011) and high uncertainty in SOC estimation at regional scales (Xu *et al.*, 2015).

RECOMMENDATION 9. Soil bulk density should be determined in the same core in which SOC concentration is measured. For estimating bulk density, direct measurement methods should be used, specifically the undisturbed (intact) core method and the excavation method, because these can provide the most accurate determination of bulk density. The clod method should not be used because for SOC stock measurements the bulk density of soil layers or horizons has to be represented.

Bulk density and the calculation of SOC stocks

There are three different approaches to calculate SOC stock (Mg C ha⁻¹), depending on the basis for estimating bulk density:

- 1) Using the bulk density of the whole soil:

Equation 3:

$$SOC_i \text{ stock [Mg C ha}^{-1}] = OC_i \times BD_i \times (1 - gG_i) \times t_i \times 0.1$$

where,

SOC_i (Mg C ha⁻¹) is the soil organic carbon stock of depth increment i

OC_i (mg C g⁻¹ fine earth) is the organic carbon content of the fine earth fraction (< 2 mm) of the depth increment i

BD_i (g soil cm⁻³ soil) is the mass of soil per total volume of the soil sample of the depth increment i

gG_i (g coarse fragment g⁻¹ soil) is the mass fraction of coarse mineral fragment, thus (1- gG_i) is the mass fraction fine earth (g fine earth g⁻¹ soil) of the depth increment i

t_i is the thickness (depth, in cm) of the depth increment i

0.1 is a factor for converting mg C cm⁻² to Mg C ha⁻¹

- 2) Using the bulk density of the fine earth (BD_{fine1}), as in IPCC (2003, p. 90) and Equation 1 of the present guidelines:

Equation 4:

$$SOC_i \text{ stock (Mg C ha}^{-1}) = OC_i \times BD_{fine1_i} \times (1 - vG_i) \times t_i \times 0.1$$

where,

SOC_i (Mg C ha⁻¹) is the soil organic carbon stock of depth increment i

OC_i (mg C g⁻¹ fine earth) is the organic carbon content of the fine earth fraction (< 2 mm) in the depth increment i

BD_{fine1_i} (g fine earth cm⁻³ fine earth) is the mass of fine earth per volume of fine earth = (dry soil mass [g] – coarse fragment mass [g]) / (soil sample volume [cm³] – coarse fragment volume [cm³]) in the depth increment i

volume fraction fine earth (cm³ fine earth cm⁻³ soil) = 1 – volume fraction coarse fragment [cm³ coarse fragment cm⁻³ soil]

t is the thickness (depth, in cm) of the depth increment i

0.1 is a factor for converting mg C cm⁻² to Mg C ha⁻¹

- 3) Using bulk density of the fine earth expressed per total volume of the soil sample (BD_{fine2}), as in Poepflau (*et al.*, 2017):

Equation 5:

$$SOC_i \text{ stock (Mg C ha}^{-1}) = OC_i \times BD_{fine2_i} \times t_i \times 0.1$$

where,

SOC_i (Mg C ha⁻¹) is the soil organic carbon stock of depth increment i

OC_i (mg C g⁻¹ fine earth) is the organic carbon content of the fine earth fraction (< 2 mm) in the depth increment i

BD_{fine2_i} (g fine earth cm⁻³ soil) is the mass of fine earth per total volume of the soil sample = mass (g) of fine earth / total volume of soil sample (cm³) in the depth increment i

t_i is the thickness (depth, in cm) of the depth increment i

0.1 is a factor for converting mg C cm⁻² to Mg C ha⁻¹

It is recommended to use the well-known IPCC formula described in Equation 4. However, Equation 5 is a simpler calculation for which fewer measurements are needed and less uncertainty is involved, as there is no need to determine or assume the volume of the coarse fraction. A disadvantage is that the user may still want to know the 'regular' bulk density as a diagnostic soil property. In this case, weighing the soil before and after sieving away the stones, BD, BD_{fine1} and BD_{fine2} can be calculated. Importantly, uncertainties must be properly propagated through the calculations.

Coarse mineral fraction and fine earth masses: The coarse mineral fraction (e.g. gravel, stones, boulders or artifacts) is any mineral particle that has a diameter > 2 mm (FAO, 2006); the fine earth fraction is all material < 2 mm. The coarse fraction of the soil has negligible capacity to store carbon, therefore, it is removed before analysis and SOC content is measured in the fine-earth fraction. Therefore, the fine earth and coarse fractions shall be separated before SOC content analysis. This is done by removing particles larger than 2 mm from the sample by wet screening. The coarse fraction should be washed to remove fine earth (secondary carbonate rinds shall not be removed), oven-dried until constant weight, and then weighed.

Coarse mineral fraction volume: To determine the volume of the coarse fraction the following procedure can be followed. The oven-dried coarse fraction is submerged under water inside a bell jar that was placed under vacuum for 40 h. After the pores within the coarse fraction are saturated by this procedure, the surface of the coarse fraction should be dried using a towel and then it should be quickly weighed and placed into a calibrated container for volume determination. The saturation of pores assures precise measurement of the bulk volume of the coarse fragment (Vincent and Chadwick, 1994). This method is accurate but very time demanding. The volume of the coarse fraction may also be estimated by assuming a certain bulk density of the coarse fraction. Thus, volume coarse fraction = mass of the coarse fraction / assumed bulk density of the coarse fraction.

Artifacts: In specific cases very fine artifacts with diameters < 2 mm may be present in the soil (e.g. Anthrosols or Technosols). Artifacts do not play role in SOC accumulation and storage. Hence, if making up more than 5 % of the total soil mass, artifacts should be quantified to correct fine soil mass.

2.4.3 Coarse fraction of belowground organic carbon

Soil C stock in the coarse (> 2mm) belowground biomass may be estimated by using the same soil cores with known volume extracted for estimating SOC stocks in the fine soil fraction. The biomass retained in the 2 mm sieve (mostly roots, rhizomes, and bulbs) should be cleaned from attached soil, dried at 60 °C to 80 °C, and then weighed. The C content of this fraction can be measured by using the dry combustion technique (see below) after grinding and homogenizing or estimated by assuming a C concentration taken from the literature. The carbon stock in the coarse fraction of belowground organic carbon (for simplicity, referred here as "Root C") shall be calculated by using the following formula (adapted from Poeplau *et al.*, 2017):

Equation 6:

$$\text{Root } C_i = \text{Root } OC_i \times \text{Root } M_i \times t_i / V_i \times 0.1$$

where,

Root C_i is the root organic stock of the depth increment i , in Mg C ha⁻¹

Root OC_i is the carbon content, as mg C g^{-1} of oven dry root mass, for the depth increment i

Root M_i is the oven dry mass of roots in the depth increment i , in g

t_i is the thickness of the depth increment i , in cm

V_i is the volume of the soil sample from which roots were extracted, in cm^3

2.4.4 Inorganic carbon

The soil C pool is composed of two major compartments, SOC and SIC. The SIC forms are primarily carbonates derived from geologic or soil parent material sources. The two most common carbonate minerals found in soils and sediments are the slightly soluble calcite (CaCO_3) and dolomite [$\text{CaMg}(\text{CO}_3)_2$] although other forms may also be present (e.g., siderite, FeCO_3) depending on where the soils were formed or where the sediment source was located. Dissolved carbonate can be found in higher concentrations in sodic soils (Na_2CO_3) or in microenvironments of high microbial activity (Loeppert and Suarez, 1996).

Soil organic carbon (SOC) is considered the more active and most abundant terrestrial C pool. However, calcareous soils (soils high in CaCO_3) cover over 30% of the Earth's land surface, mainly in arid and semi-arid regions. Besides, soils that contain sodium carbonates (e.g. Solonchaks, Solonetz) and other soil classes with variable CaCO_3 content (e.g. Chernozems) are also common. In soils of humid tropical regions (e.g. Ferralsols, Acrisols etc) the predominant form of carbon is organic, but they may also contain SIC, temporarily, for example if liming occurs.

SIC is no longer seen as a merely static C pool. Biological activities and climate change can impact the factors that control dissolution and precipitation of CaCO_3 and thus modify the equilibrium between the different dissolved, gaseous and solid inorganic carbon species leading to the emission of CO_2 or precipitation of calcite (Chevallier *et al.*, 2017). In soils in which SIC is predominant, quantifying it can render useful ancillary information. Quantitative methods for total carbonate determination were described by Loeppert and Suarez (1996).

If SOC is estimated by measuring total carbon of a sample, it is important to remove all SIC before analysis. To determine if carbonates are present, a test is performed by adding few drops of hydrochloric acid to the soil and observing effervescence.

If carbonates are to be eliminated as CO_2 by acidification, prior to analysis of remaining organic carbon, care must be taken to ensure a thorough reaction of all soil carbonates with the acid, while minimizing losses and dilution of SOC. A small-scale acidification approach using HCl, such as that described by Ellert and Rock (2008) is recommended because SOC remaining after acidification is related back to the original un-acidified subsample taken for dry combustion analysis. Acidification should not be required if wet oxidation (not recommended) without CO_2 determination is used. Loss-on-ignition techniques (also not recommended) are not reliable in carbonate-containing soils.

Carbonates can be removed by the following techniques:

- Adding hydrochloric acid (1M HCl) and waiting till effervescences stops. The limitation of this method is that HCl can destroy some of the organic carbon compounds and interference of Cl^- in case of wet oxidation techniques
- Adding a combination of H_2SO_4 and FeSO_4 (Nelson and Sommers, 1996).

RECOMMENDATION 10. To measure the SOC correctly, contributions from SIC shall be removed. A small-scale acidification technique using HCl followed by automated dry combustion is recommended. In some soils SIC could represent a significant and dynamic portion of soil carbon

(e.g. calcareous, irrigated, and amended soils), and may be quantified by direct determination of total inorganic carbon or by the difference between total soil C and SOC.

2.5 Analytical methods for total soil organic carbon determination

Soil organic carbon content is expressed as gravimetric percentage of dry (105 °C) soil [g SOC kg⁻¹ dry (105 °C) soil]. Standard procedures for the determination of soil moisture are available (see section 2.4.1). Soil organic carbon may be estimated as the difference between total carbon and inorganic carbon, directly after removal of inorganic carbon, or by dichromate oxidation-titration methods. In all cases, SOC content shall be quantified in the fine-earth fraction which is obtained by passing the soil through a 2 mm mesh size. In most cases, soil samples are further ground and reduced to powder (<0.2mm) to allow adequate homogenization.

To reduce analytical error to a minimum, soil sample preparation and analytical standard procedures should be set up, strictly followed, and be carried out by trained laboratory staff. Equipment should be regularly calibrated, including analytical balances of adequate precision. It is desirable that the laboratory that carries out SOC analyses participates in a quality control programme. Minimally, in-house quality control should be applied to ensure precision. For comparative purposes, the same method of SOC analysis shall always be used for all measurements and consistency control should be applied (see also section 2.4).

RECOMMENDATION 11. SOC content analysis shall be performed in a laboratory that has well established quality control and assurance systems.

The most important SOC methods are presented below.

2.5.1 Dry combustion method

Dry combustion is a direct chemical method to measure SOC content based on the combustion of soil samples containing carbon. It uses finely ground soils samples (<0.2 mm) burned at elevated temperatures, generally around 1000°C (Nelson and Sommers, 1996). The combustion of the soil sample is achieved in the presence of pure oxygen which ensures complete combustion of the sample and acts as a catalyst or accelerator. Other catalysts and accelerants are also used including vanadium pentoxide, Cu, CuO, and aluminium oxide. The end-product of the combustion (CO₂) is quantified by gas chromatography using a thermal conductivity or a flame ionization detector. Results from dry combustion are taken directly from the instrument readout and reported to three significant figures.

Since carbonates will also be measured, it is essential to remove them before SOC determination (see section 2.4.4). Some equipment is designed to measure total soil carbon in two steps; first SOC is quantified at 600°C, and then the rest of the carbon (basically inorganic carbon) is quantified at 1000 - 1400°C. Caution has to be taken when soils contain highly stable organic carbon compounds which decompose at temperatures higher than the temperature set in the first step, leading to underestimation of SOC (and overestimation of SIC). An example are soils that are submitted to natural or man-made fires resulting in the presence of recalcitrant carbon containing compounds in the fine earth fraction (e.g. charcoal/black carbon; Roscoe et al., 2001). In the Brazilian savanna for example, as much as 40% of SOC can be in the form of char (Jantalia *et al.*, 2007). Stable carbon containing soil amendments (e.g. biochar) may also lead to similar bias in SOC analysis.

The main advantages of the dry combustion method are that it: (i) ensures a complete combustion of all SOC present in the sample (in contrast to wet oxidation, see below) and, (ii) allows a relatively large number of samples to be processed per unit time. The main disadvantage of the dry combustion method is the high initial economic investment associated with the purchase of specific instruments (readily available on the market). A potential disadvantage may be very small sample mass that is analysed (from 8-10 mg to a few grams, depending on the equipment). Great attention has, therefore, to be given to adjust sample mass to the detection limits of the equipment and to ensure representative sample composition during sample preparation (see section 2.4.1).

Automated dry combustion using commercially available instruments is widely accepted as the standard method for soil C determination. Since most of these instruments also quantify total N simultaneously, there is potential for such instruments to provide additional crucial information.

2.5.2 Wet digestion/oxidation of organic carbon compounds by dichromate ions ($\text{Cr}_2\text{O}_7^{2-}$)

The wet oxidation method directly measures SOC concentration on finely ground soil (<0.2 mm) based on a rapid wet oxidation of organic C compounds by dichromate ions ($\text{Cr}_2\text{O}_7^{2-}$) followed by the determination of unreduced dichromate by oxidation-reduction titration with ferrous (Fe^{+2}) ammonium sulphate in the presence of common indicators, such as ortho-phenanthroline ferrous complex, barium diphenylamine sulfonate (Walkley and Black, 1934) or photometric determination of Cr^{3+} (Souza *et al.*, 2016). Potassium dichromate and concentrated sulphuric acid are used to extract organic carbon present in the soil. Orthophosphoric acid may be added to help eliminate interferences from the ferric iron that may be present in the sample.

The Walkley and Black (1934) procedure (and its modified versions) require minimal equipment, is simple and rapid to carry out, and it has thus been commonly used worldwide. Further, this method also requires relatively small sample mass (normally 0.3 to 0.5 grams of soil) that must be adjusted to the SOC content of the sample. However, the oxidation of SOC is incomplete, with a recovery rate of SOC ranging from 60 to 86 %. Average recovery is estimated to be 75 % (Walkley and Black, 1934) and, therefore, a correction factor of 1.33 is commonly used to adjust the results. Further, this method is labour-intensive, requires a great deal of analytical skill, employs strong oxidants and acids that must be heated, and generates hazardous waste (Essington, 2004).

Another disadvantage of this method is that, apart from recalcitrant material, such as charcoal, the presence of iron and manganese oxides in weathered soils can be source of errors. Depending on soil type and C content, underestimation can be large (Davis *et al.*, 2018). Where charcoal is present, comparison of soil C stocks between pristine areas and sown pasture in which soil is homogenised by ploughing can be misleading as correction factors may be erroneously established. Therefore, for weathered soils or when charcoal is present, the wet oxidation method is not recommended.

2.5.3 Loss-on-ignition method

The loss-on-ignition method gives an estimate of SOM content, but does not give direct information on SOC content, which is a proportion of SOM that ranges between 43 and 58 %. It is based on the oxidation of soil at temperatures close to 550°C for at least 3 hours. SOM content is the difference between the soil mass before and after ignition:

Equation 7:

$$\text{SOM (\%)} = (\text{soil mass at } 105^\circ\text{C} - \text{soil mass at } 550^\circ\text{C}) / \text{soil mass at } 105^\circ\text{C} \times 100$$

The main drawback of this method is that it overestimates the amount of organic matter due to the loss of structural water, mainly by hydrated aluminosilicates, because heating to temperatures above 150 °C drives off hygroscopic H₂O and intercrystalline H₂O from crystalline clays and allophane. Potential overestimation errors are also due to CO₂ release from the decomposition of carbonate minerals and some hydrated salts and from the loss of H₂O from hydroxyl groups in sesquioxides (Goldin, 1987). A clay correction factor should always be used, to avoid overestimating the SOM content by correcting for structural water loss.

Samples should be left to equilibrate with ambient temperature in a desiccator to avoid uptake of moisture before weighing. An analytical balance with a precision of 0.1 mg should be used to weigh the samples.

Analytical errors are dependent on differences in important soil properties, such as the amount and type of clay and the amount of carbonates and sesquioxides. Such differences make the standardization of the loss-on-ignition method quite difficult. For instance, special precautions should be taken when the method is applied to strongly carbonaceous soils and soils containing free iron. Hoogsteen *et al.* (2015) found that different furnace types (in terms of pre-heating air) did not influence results for a variety of soils representing a large range of clay content and different clay minerals. Turning soil trays halfway through the analysis reduced variability associated with uneven heating and overcame the effects on heat losses near the furnace door (Hoogsteen *et al.*, 2015).

The advantage of this method is that it only requires basic laboratory facilities: a furnace that reaches 600°C stable temperature and an analytical balance with a 0.1 mg precision. Further, loss-on-ignition measurements are simple to carry out and do not require the use of reagents, thus having low environmental impact with no need for laboratory waste treatment (Nelson and Sommers, 1996). Another advantage is that large sample masses can be analysed –40 to 2000 times larger than in dry combustion or wet oxidation– that may reduce analytical error due to more representative sample mass. Indeed, a sample mass of at least 20 g should be used to minimize variation in loss-on-ignition measurements.

Although the loss-on-ignition method does not provide direct measurement of SOC content, it could be used to assess SOC stock change *if the above-mentioned minimum criteria are observed and other methods are not available*

RECOMMENDATION 12. The dry combustion method shall be used for measuring SOC content when possible. If not available, wet oxidation may be used, except on weathered soils or when charcoal is present. If dry combustion is not available, loss-on-ignition may be used on organic soils.

2.5.4 Spectroscopic techniques for soil organic carbon determination

Soil organic carbon determination with the dry combustion and wet oxidation methods is often time and cost intensive and laborious, especially if large number of samples must be analysed. This can be the case in SOC stock change projects in livestock production systems that evaluate extensive land areas over years, or in long-term monitoring of soil properties. In fact, depending on the cost of the analysis and the number of samples necessary to detect SOC stock change, the viability of the project may be compromised. Having a large amount of SOC data could also help reduce measurement uncertainties due to high spatial variability in SOC content.

Spectroscopy offers a relatively rapid, low-cost, non-destructive alternative to conventional SOC testing (Reeves III, 2010; Bellon-Maurel and McBratney, 2011; Viscarra Rossel *et al.*, 2016). Soil spectroscopy uses the interaction of electromagnetic radiation with matter to characterize the

physical and biochemical composition of soil sample. The principle is that light is shone on a soil sample and properties of the reflected light (visible-near-infrared, near infrared, or mid-infrared) are representatives of molecular vibrations that respond to the mineral and organic composition of soils. Reflected or absorbed light is collected at different wavelengths by a detector. The resulting pattern is referred to as a spectrum (Figure 6). Spectral signatures thus provide both an integrated signal of functional properties as well as the ability to predict several conventionally measured soil properties (Nocita *et al.*, 2015).

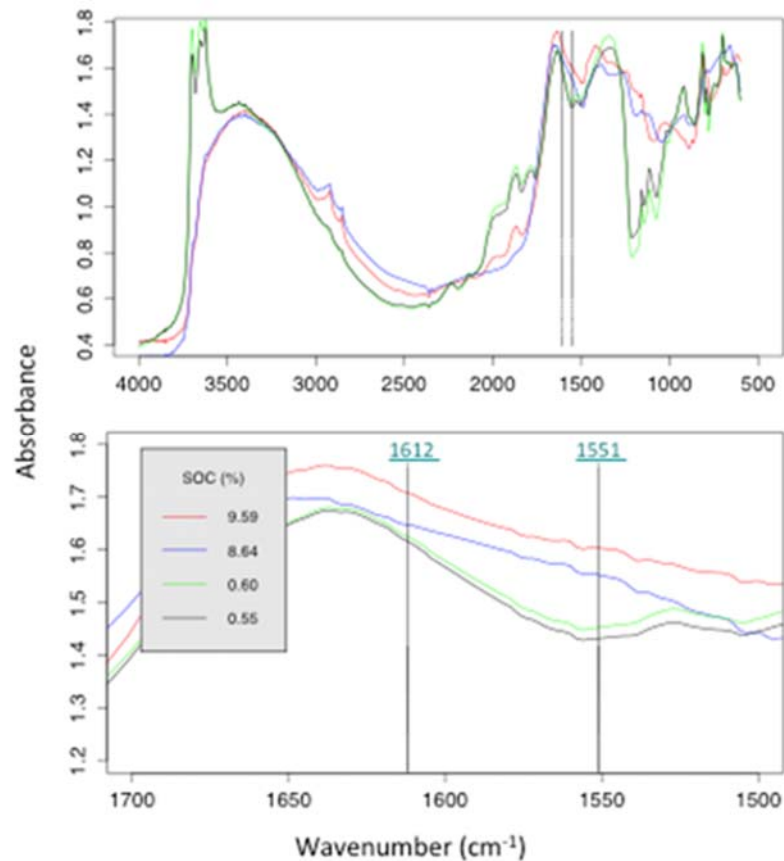


Figure 5. Example of soil spectral signatures of four samples from the Ethiopia LASER study with different levels of soil organic carbon.

There are numerous mathematical methods and their combinations that have been tested for the development of models that estimate SOC and other soil properties (Gobrecht *et al.*, 2014). Chemometric models can be developed for different scales, from regional to local, of SOC determination (Madari *et al.*, 2005; Clairotte *et al.*, 2016; Lucá *et al.*, 2017). Depending on the scale, representativeness of the calibration sample set, spectral pre-treatment and the chemometric methods and sampling approach (Jiang *et al.*, 2017; Guo *et al.*, 2017; Roudier *et al.*, 2017), an extra error will be included in the determination, the error of prediction. This error shall be considered when deciding on the SOC prediction method applied.

Other emerging and promising techniques are laser-induced breakdown spectroscopy (LIBS) (Senesi and Senesi, 2016; Knadel *et al.*, 2017) and neutron induced gamma-ray spectroscopy (Wielopolski *et al.*, 2010, 2011). LIBS is a cost-effective technique with potential for rapid analysis of elements present in the soil. It has been successfully tested for total carbon measurement in combination with multivariate calibration (da Silva *et al.*, 2008; Belkov *et al.*, 2009) as well as for

differentiating organic and inorganic carbon (Martin et al., 2013). Portable equipment is also available (da Silva *et al.*, 2008; Rakovský *et al.*, 2014).

RECOMMENDATION 13. Spectroscopic techniques -which show promise for estimating the SOC content and which enable the analysis of large numbers of samples- may be used when technical capacities for adequate chemometric calibration are available.

3. MONITORING SOIL ORGANIC CARBON STOCK CHANGES – REPEATED MEASUREMENTS AGAINST A BASE PERIOD, AND MEASUREMENTS AGAINST A BUSINESS-AS-USUAL BASELINE

Soil organic carbon is a controlling factor in ecosystems services and agricultural productivity, landscape function, and climate change (Bispo *et al.*, 2017; FAO, 2017a). There is now an extensive body of research demonstrating that human use of land for livestock production has affected SOC stocks. In much of this land, there are good opportunities for management practices to increase SOC stocks while maintaining or increasing productivity.

Increasing SOC stocks can contribute a range of benefits, including greenhouse gas (GHG) mitigation (e.g. Rumpel *et al.*, 2015; Paustian *et al.*, 2016; FAO, 2017b). However, implementing effective strategies to realise this potential requires the capacity to monitor SOC stock change with acceptable accuracy and uncertainty, and at an acceptable cost.

To quantify changes in SOC due to human management activities, it is necessary to monitor change in carbon stocks against a baseline through consistent measurement or modelling over time and space. This Chapter offers guidance for designing and implementing a sampling and measurement protocol. Chapter 6 provides guidance on modelling approaches.

3.1 Planning and implementing a monitoring strategy for soil organic carbon stock change

Selecting the method to monitor SOC stock change should consider the purpose of the investigation and the skills, capacity and budget available to the project. There are a range of objectives and scales possible for a SOC stock change study, for example:

- Global or regional accounting for GHG emissions and removals from the land sector as a component of climate change accounting
- Monitoring, Reporting and Verification (MRV) obligations for the United Nations Framework Convention on Climate Change (UNFCCC)
- Analysis of the climate change impact of livestock products
- Evaluation of the environmental impacts of grazing land management for animal agriculture
- Assessment of the mitigation potential of agricultural practices at an industry, region or farm scale
- Implementing mitigation options in an emissions trading or other market mechanism where payments for SOC sequestration depend on accurate and verifiable quantification
- Research into processes affecting SOC stocks and dynamics

After deciding on the goal and scope of the monitoring project, the proponent may answer a series of questions regarding existing data and knowledge, along with the skills and capacity available to guide planning. A decision framework is valuable to guide systematic decisions on the monitoring approach and requirements to achieve accuracy and consistency levels aligned to the goals of the study. Figure 6 depicts one such decision tree to guide the development of a sampling and measurement or modelling plan.

Decision tree for monitoring SOC change in livestock production systems

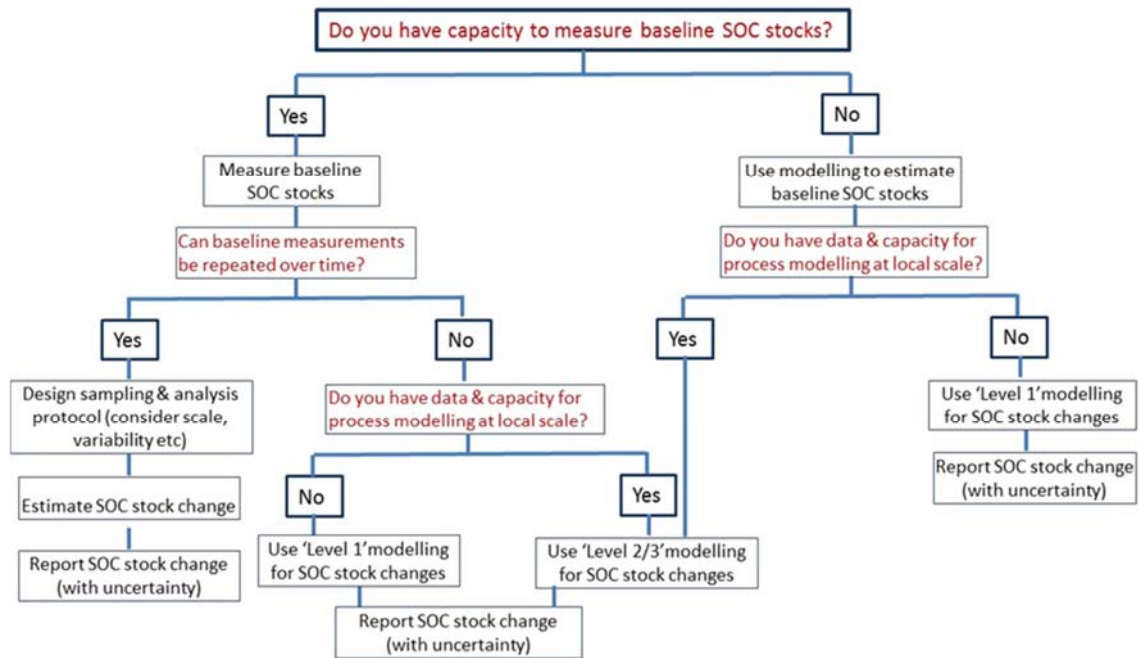


Figure 6. A decision tree to guide the selection of a SOC stock change monitoring approach. Level 1 refers to simple ‘empirical’ models; Level 2, to ‘soil’ models; and Level 3, to ‘ecosystem’ models, with model complexity and data demand increasing from Levels 1 to 3 (more detail on Levels 1 to 3 of the Modelling option are available in Chapter 6).

3.2 Introduction to soil organic carbon stock change assessment by measuring against a baseline

Where a measurement approach is used to assess changes in SOC stocks, planning the sampling and analysis protocol is critical. There are two types of change in SOC stocks that can be measured: a change over time relative to a base period (or reference period), or a change relative to an alternative scenario associated with a specific baseline. While the term ‘baseline’ will be used for both cases throughout these Guidelines, the type of baseline that should be used depends on the study (Brander, 2016).

If the study is an inventory of anthropogenic GHG emissions/removals, then it is necessary to account for changes in SOC stocks that occur naturally, and a ‘natural’ baseline is required (Figure 7). If the study is an assessment of the change in emissions/removals caused by a specified intervention, then the appropriate baseline is the business-as-usual scenario that would have occurred in the absence of the intervention in question.

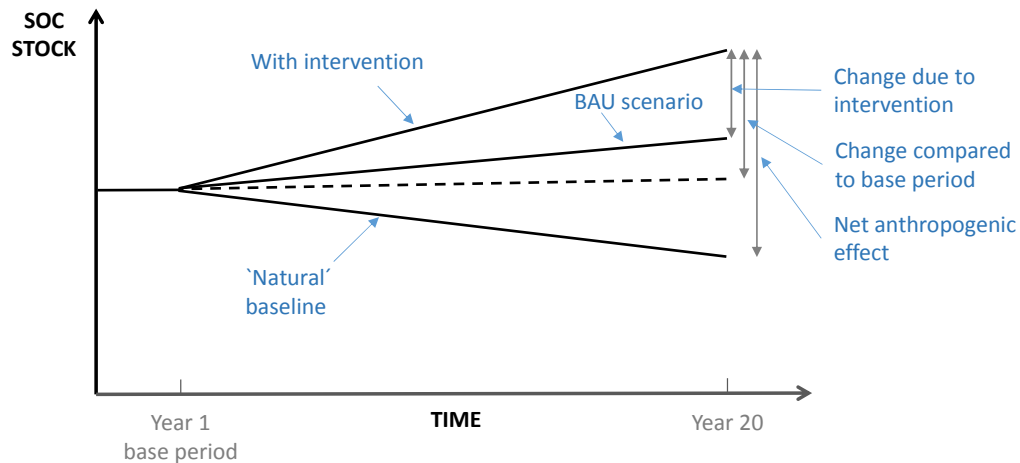


Figure 7. A schematic representation of the different SOC stock baselines and the associated changes that can be measured.

Repeated measurements over time against a measured base period. This approach is most suitable where sampling sites can be revisited every 1 to 10 years to monitor change and where additional data is available, such as seasonal climate and specific management practices. Results are commonly analysed as t_1 vs. base period (t_0) or using statistical tools such as regression analysis to detect trends in SOC stocks over time when several measurement times are available.

Point-in-time measurements against an assumed business-as-usual baseline. This approach does not require a 'before management change' baseline measurement. Instead, it compares SOC stocks at different sites at one single time after a contrasting management was implemented in one of them. The underlying assumption is that the business-as-usual site and the differently managed sites were the same prior to the change in management (e.g. in terms of soil type, climate, land use, productivity). Further, the interpretation of management effects is direct if SOC at t_0 was at a steady state. If SOC was on a trajectory from a prior management practice, the interpretation of management effects becomes less straightforward (Figure 8, see Van den Bygaart and Angers, 2006). These assumptions introduce uncertainty, as the lack of a 'before practice change' baseline means SOC stock change estimate will have lower confidence than repeated sampling over time with a known baseline. However, these scenarios are often encountered when farm management practices diverged sometime in the past but with no baseline data collected at that time, and the approach underpins approaches used in IPCC (2014) and UNFCCC (2014) accounting.

3.2.1 Sources of error and bias in soil organic carbon stock change monitoring

According to the Marrakesh Accords, uncertainties in measuring GHG in offsetting projects should be quantified and IPCC (2003) has recommended using confidence intervals as a quantitative estimate of uncertainty. Determining SOC stock changes associated with changes in management can be difficult because of the large spatial variability in SOC stock and uncertainties related to sampling and analytical error during field sampling, sample processing and laboratory measurements. Addressing these heterogeneities and uncertainties is a key challenge when monitoring changes to SOC stocks through measurements.

Uncertainties generally mean that monitoring needs to occur over long time periods, ideally decades. However, the overall design of a soil sampling strategy to estimate SOC stock changes is

often determined by time and budgetary constraints (Smith, 2004; De Gruijter *et al.*, 2006). Hence, a sampling strategy requires careful planning to ensure harmonized data collection (to gather relevant field information) and data processing (appropriate statistical method to analyse the data). De Gruijter *et al.* (2006) provide a detailed list of basic design criteria for site survey (baseline scenario) and monitoring of natural resources that includes balancing the sources of variation.

Chapter 2 provides a detailed account of sources of error when estimating SOC stocks and strategies to minimize these errors. Table 2 lists the major sources of uncertainties in measuring SOC (Vanguelova *et al.*, 2016). Here, the focus will be on SOC stock changes, including determining the minimum detectable difference (MDD), that is, the smallest difference, or change, that can be statistically detected. As MDD defines the difference between two means, increased errors result in disproportionately larger MDD values. All recommendations given in Chapter 2 are, therefore, relevant.

RECOMMENDATION 14. In planning a SOC stock change study, a process of identification of potential sources of error and bias in SOC stock estimation shall be undertaken and steps should be taken to minimise their impact, as described in Chapter 2. Consistent methodologies and practices should be used to minimise the minimum detectable difference (Eq. 9) and the number of samples required to obtain it (Eq. 10).

3.3 Sample size

3.3.1 Pre-sampling for soil organic carbon stocks and variability to guide sample size

Soil organic carbon stocks can have considerable spatial variation with increasing variation from field to regional, continental, and global extent (Minasny *et al.*, 2017). For instance, SOC stocks fluctuate with latitude, with greater stocks at higher latitudes due to the lower temperature regimes, decreases in the mid-latitudes, and increases in the humid tropics. When estimating SOC stock changes it is important to consider the likely variability in space and depth to determine the best sampling design and minimum detectable difference. To assist in the process of making decisions, pre-sampling may provide valuable guiding information.

Depending on the spatial scale at which SOC stock change is to be estimated (i.e. field, regional, landscape), a pre-sampling may comprise 5 to 10 soil cores per strata or area of interest to 30 cm depth and possibly up to a depth of 60 cm, taken along a transect or spaced several meters apart. To estimate the variance in SOC stocks per soil layer, several soil samples should be taken from each of multiple distinguished layers. If the IPCC procedure is to be followed, the 0-30 cm depth should be analysed separately.

RECOMMENDATION 15. To analyse lateral and vertical spatial variability of SOC stock, a pre-sampling (5 to 10 cores per strata) of the area of interest may be undertaken to get an indication of the SOC stocks mean value and variability in SOC stocks and, therefore, attainable minimum detectable difference for a given sampling effort. This information should be used to guide estimation of the number of samples needed to determine SOC stock change with an acceptable level of uncertainty. Based on estimated SOC stocks and variability from the pre-sampling and the maximum number of analyses that can be afforded, a decision on whether individual or composite sample cores are analysed should be made.

3.3.2 Using minimum detectable difference to determine sample size

Spatial variation of SOC is often large, making long monitoring periods or large sample sizes imperative for evaluating treatment effects on SOC stocks (Gregorich *et al.*, 1995; Smith, 2004; Yang *et al.*, 2008). A statistical approach to determine the smallest difference in SOC stock that can be detected as statistically significant between two monitoring moments in time or treatments is based on the minimum detectable difference (MDD) (Zar, 1999). This is to minimize the risk of Type II error, that is, the risk of not detecting a true difference because there was insufficient power (Van den Bygaart and Allen, 2011; Kravchenko and Robertson, 2011).

Power analysis can be conducted *a priori*, given a certain variance and α -level (i.e. significance level). The MDD for paired observations is calculated as following:

Equation 8:

$$MDD \geq \frac{S}{\sqrt{n}} \cdot (t_{\alpha, v} + t_{\beta, v})$$

where,

S is the standard deviation of the difference in SOC stocks between t_0 and t_1

n is the number of replicates

$v = n - 1$ is the degrees of freedom for the relevant t -distribution

t are the values of the t -distribution given a certain power level $(1-\beta)$ and α level.

The minimum number of samples required can then be determined as:

Equation 9:

$$n \geq \left(\frac{S \cdot (t_{\alpha} + t_{\beta})}{MDD} \right)^2$$

where,

n is the number of samples,

S is the estimated standard deviation,

MDD is the minimum detectable difference

t_{α} is the two-sided critical value of the t -distribution at a given significance level (α) frequently taken as 0.05 (5%), and

t_{β} is the one-sided quartile of the t -distribution corresponding to a probability of type II error β (e.g. 90%).

The following hypothetical case illustrates the calculation procedure:

In a 3-year field experiment the number of replicates is 5 and the initial SOC content varies from 40 to 46 Mg C ha⁻¹. Due to annual organic C additions, SOC is expected to increase by about 0.8 Mg C ha⁻¹ y⁻¹. Thus, after a period of 3 years the expected increase is 2.4 Mg C ha⁻¹. The initial standard deviation is 2.39 and after 3 years is 2.77. The standard deviation of the paired differences after an experimental period of 3 years is 1.34 (Table 3).

Table 3. Data for a hypothetical field experiment with a duration of 3 years to illustrate the calculation procedure of the minimum detectable difference.

Sample number	SOC stock at t_0 (Mg ha ⁻¹)	SOC stock at t_3 (Mg ha ⁻¹)	Change in SOC (Mg ha ⁻¹)
1	46	50	4
2	41	44	3
3	43	44	1
4	40	43	3
5	44	45	1
Average	42.80	45.20	2.40
S	2.39	2.77	1.34
S ²	5.70	7.70	1.80

If we set the chance of detecting a significant difference (the power) at 90 % and we use an α -level of 0.05, we find t values of 2.776 and 1.533 ($df = 4$). In that case, MDD would be:

$$\sqrt{\frac{1.34^2}{5}} \cdot (2.776 + 1.533) = 2.58$$

So, a sample number of 5 would be large enough to be able to detect differences in SOM of 2.58 Mg ha⁻¹ after a period of 3 years, with a probability of 90%. In this case, the MDD value is larger than the expected change of 2.4 Mg C ha⁻¹, thus the number of samples needs to be increased. With a sample number of 10, MDD would be:

$$\sqrt{\frac{1.34^2}{10}} \cdot (2.262 + 1.383) = 1.55$$

In this case, the MDD value is smaller than the expected change in SOC stock. Hence, a sample size of 10 would be large enough to be able to detect significant differences at the end of the experiment.

MDD increases with spatial scale for a fixed soil depth and with soil depth, for a fixed spatial scale (Figure 8; adapted from Maillard *et al.*, 2017). For example, for depth of 30cm MDD with $n = 50$ samples was 14, 16, 20 and 29 % at 0.1, 1, 10 and 10 000 km², respectively. Whereas for a fixed scale of 0.1 km² MDD as 12, 14 and 18 % for depths 0–10, 0–30 and 0–100 cm, respectively.

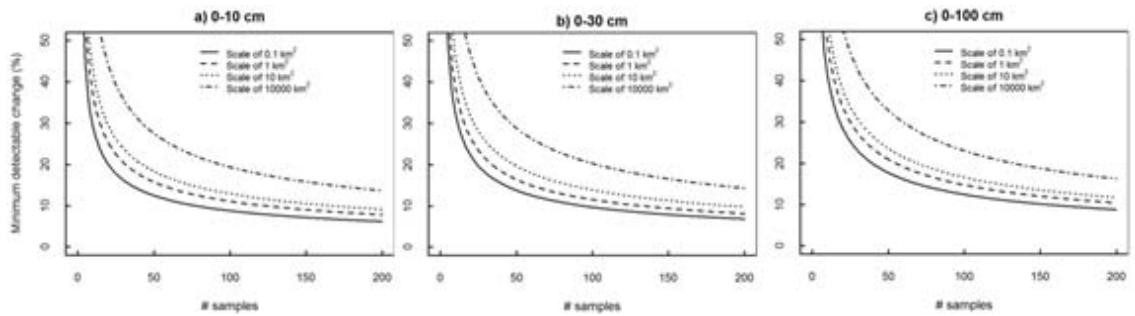


Figure 8. Relationship between sample points required (i.e. intensity) and minimum detectable difference (power of 90%, significant level of 0.05) as a function of spatial scales for the 0-10cm, 0-30cm and 0-100cm layer (adapted from Maillard *et al.*, 2017).

It is sobering to consider that with an initial SOC stock of 60 Mg C ha⁻¹ and a C sequestration rate of 0.5 Mg C ha⁻¹ y⁻¹, a statistically significant change after 5 years would be detected only with 516, 730, 1051, and 2260 samples at 0.1, 1, 10 and 10 000 km², respectively. At the same scales, 135, 190, 273, and 586 samples would be necessary to detect the change as statistically significant after 10 years. This highlights that it may be difficult and costly to detect significant changes within timescales of less than 10 years. A further case study example is given in BOX 2.

BOX 2. Monitoring SOC dynamics in temporary grasslands: how large should the sample size be to detect significant changes over time?

Overview: Grassland management options targeting increases in root biomass inputs could be a promising strategy to increase the soil organic carbon (SOC) content of grassland soils. Farmers can influence root biomass and thus SOC inputs by grazing management and plant species composition (Deinum, 1985; McNally *et al.*, 2015). Detecting significant changes is, however, a challenging exercise as spatial variation of SOC is often thought to be large. This makes long monitoring periods or a large number of replicates imperative for evaluating experimental treatment effects on C storage under field conditions (Smith *et al.*, 2004).

Approach: A statistical approach to determine the smallest significant difference in SOC that can be detected between two monitoring moments in time or between treatments gives the minimum detectable difference (MDD), (Zar, 1999). Power analysis can be conducted a priori, given a certain initial variation and α -level. The MDD for paired observations was calculated using Equation 8.

An example: Here we demonstrate how to calculate the MDD for a field experiment investigating the effects of different simulated stocking systems (continuous (CS), rotational (RS) and lenient (LS) strip stocking) on SOC dynamics in a five year field experiment on a sandy soil in The Netherlands (Hoogsteen *et al.*, unpublished). An α -level of 0.05 was chosen and the chance to detect a significant difference was set at 80%. The corresponding t values were 1.860 and 0,889 (n=9).

Stocking system	Initial SOC content	Final SOC content	Difference	SD	CV	MDD
CS	60.9	63.8	2.9	1.4	0.5	1.3
LS	60.7	63.8	3.1	2.1	0.7	1.9
RS	62.9	64.8	1.9	2.1	1.1	2.0

The MDD values of CS and LS were smaller than the measured differences between the initial and final SOC contents. Thus, a sample size of 9 was large enough to detect significant changes in SOC after a monitoring period of five years. However, in the case of RS the number of samples was not sufficient to detect a significant change. This is a consequence of the larger variability ($CV_{RS} > CV_{LS}, CV_{CS}$). The minimum number of required samples calculated using Equation 9 for the RS treatment was 10.

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

Zar, J.H. 1999. *Biostatistical Analysis*. Fourth Edition. Prentice-Hall, New Jersey.

RECOMMENDATION 16. Minimum detectable difference calculations shall be used to estimate the number of samples needed to detect the expected SOC stock change (or alternatively the number of years required for a given rate of change in SOC to produce a statistically detectable change). The number of samples may differ between sampling campaigns (repeated measurements with baseline at t_0) or treatments (paired plots with assumed business-as-usual baseline). This reduces sampling effort when the baseline was estimated with a large sampling size.

3.4 Sampling frequency

Determining sampling frequency is important when SOC stock changes are estimated by repeated measurements against a baseline obtained at the onset of land use or management change. More frequent sampling, that is shorter time periods between samplings, will increase the precision (as a larger number of samples will reduce sampling error) and will also allow detection of variations in the rate at which SOC stocks changes as it might not be constant.

In general, the expected change in SOC stock should be greater than the MDD, so lower rates of expected change will correspond to less frequent samplings, allowing more time for the change to occur. Likewise, methods that have greater precision will lower the detectable limit and will allow more frequent sampling. Similarly, fields with large variability may require longer time intervals between measurements to accurately assess changes in SOC stock.

It is common to let at least three years pass between the baseline and the first resampling or paired treatment (Donovan, 2013). More conservatively, Smith (2004) pointed out that if C inputs increase by a maximum of 20 to 25%, SOC stock changes could be detected with 90 % confidence only after 6 to 10 years. In addition to changes in C input, climate and seasonal weather can influence SOC accumulation or loss. Therefore, under variable weather conditions a longer time interval is recommended to increase the possibility of detecting SOC stock changes.

When measuring SOC changes over time, intra-annual variability of SOC stocks shall be considered and its impact on stock change assessment shall be minimised. Seasonal variability of SOC stocks is dependent on SOC decomposition and plant growth and organic matter inputs. In livestock

production systems, the intra-annual variability of organic matter input can be related to the grazing regime, forage harvesting, fertilizer application rate and dates but also to weather conditions. On the other hand, decomposition of SOC is affected by environmental conditions, mainly moisture and temperature (Paul, 2007). As these vary throughout the year, the decomposition conditions for SOC are not constant. For example, enhanced drying and shrinking of organo-mineral complexes in the summer can lead to higher SOC decomposition rates (Leinweber *et al.*, 1994). Water logging and cold temperatures may also hamper the activity of SOC decomposers (Paul, 2007).

Intra-annual variations shall be considered when sampling at two different years, especially when these are expected to be higher than the detectable change caused by management over a certain assessment period. This can be done by ensuring that repeated sampling in different years occurs during the same season (Allen *et al.*, 2010; Pringle *et al.*, 2011), or through monitoring of the SOC stocks throughout the year when comparing two or more years. When evaluating different management practices through a paired plot approach, the relationship between seasonality effects on SOC stocks and treatment should be verified (Wuest, 2014). In a grazing intensity study in Alberta (Canada), SOC stocks were measured at four seasons at two sites and for two grazing intensity treatments (Dormaar *et al.*, 1977). In five out of eight measurements, SOC stock differences were higher between two subsequent seasons than the differences between treatments.

RECOMMENDATION 17. For repeated measurements to capture SOC stock change related to management activities, sampling shall typically occur 4 to 5 years apart. Sampling strategies shall always consider the estimated minimum detectable difference (Eq. 9) and corresponding number of required samples (Eq. 10). A sampling campaign should take no longer than 60 days within the same season, i.e. all sampling should occur no more than 30 days before/after the median day and month of the baseline sampling round. The record of each sampling round shall include the day (or days), the month (or months), the year (or years), and the median day.

3.5 Calculating soil organic carbon stock change

3.5.1 Equivalent soil mass

Soil bulk density can change over time in response to climate and/or management, including mechanical (e.g. trampling from animals; Willat and Pullar, 1984; Zhao *et al.*, 2007), biophysical (e.g. soil moisture; Dasog *et al.*, 1988; Blanco-Canqui *et al.*, 2009) and/or chemical factors (e.g. change in SOC content; Périé and Ouimet, 2008). If changes in bulk density over time are not considered when estimating a temporal change in SOC stocks then the SOC stock change estimates will not be accurate (Figure 9).

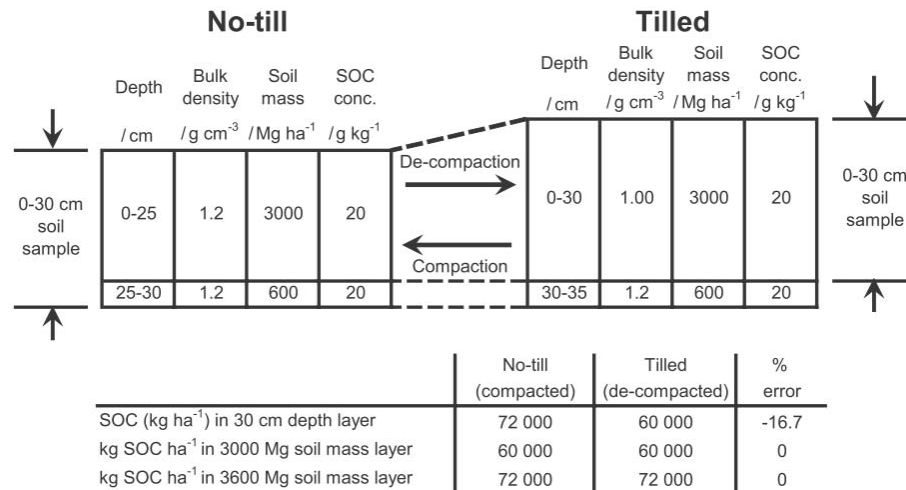


Figure 9. Example for the uses of equivalent mass and the error bias induced by quantifying soil SOC stocks at fixed depths when differences in bulk density occur (Wendt and Hauser 2013).

For example, if the carbon content of the soil remained the same but bulk density increased from 1.3 to 1.5 g cm⁻³ then a calculation to a nominated depth would show an increase of approximately 15% of the SOC stock. This increase merely reflects that there is now more soil in the volume sampled, not because SOC stocks increased. Hence, tracking changes in SOC stocks over time requires that the SOC stocks are compared for the same mass of soil, that is, by estimating SOC stocks on an equivalent soil mass (ESM) basis. The actual ESM selected is largely immaterial, so long as it is 0.3 Mg m⁻² or more.

Estimating SOC stocks for a fixed, uniform or equivalent soil mass will entail assumptions about how SOC content and bulk density change with increasing soil depth. If only one value for SOC content and bulk density is given for a given soil layer, the assumption must be that their distribution within the soil layer is homogeneous. Correcting the soil mass, i.e. mathematically reducing the sampling depth of a respective layer, poses the risk of over-correction. Thus, SOC and bulk density information from discrete, contiguous and successive soil layers will assure a more precise SOC stock correction (Poeplau and Don, 2013). This is especially true for grassland topsoils, in which steep SOC gradients are common. Thereby, only the lowermost layer shall be corrected using ESM. A detailed description on SOC stock correction with multiple soil layers along with an excel sheet to fit a spline function for minimizing the error associated with the above-mentioned assumption was published by Wendt and Hauser (2013). However, multiple layer sampling might not always be affordable and the problem minimizes with increasing sampling depth.

In general, several methods for calculating SOC stock changes on an ESM basis are available that differ in their approach to the calculation of the reference mass and/or the depth at which the mass of soil is adjusted (Wendt and Hauser, 2013; Gifford and Roderick, 2003; Ellert and Bettany, 1995; Sisti *et al.*, 2004). The method provided here uses the soil mass of the baseline as the reference to correct SOC stocks of subsequent samplings. The equations are constructed so that users can correct SOC stocks for any depth.

If the sampled area is stratified or uses a sampling design where points or areas in space are represented (see section 2.2.1), then ESM shall only be adjusted for samples that represent the same point or area (Murphy *et al.*, 2013). This can be done by aggregating samples either by physically compositing samples in the field or through data calculations. The calculations use the

sum of the masses and volumes of the samples for a point or area to calculate the ESM used to correct SOC stocks. This is because the volume of the implement used to collect soil samples may change between sampling periods, or the numbers of samples for a given point or area may change over time.

The equation for calculating the ESM to correct SOC stocks is:

Equation 10:

$$ESM = \frac{1}{n} \times \frac{\sum M_{bi}}{\sum V_{bi}} \times t_i \times 100$$

Where:

ESM (Mg soil ha⁻¹) is the equivalent soil mass (to be used in Equation 11)

n is the number of samples being aggregated

$\sum M_{bi}$ (Mg) is the sum of the masses of all samples being aggregated

$\sum V_{bi}$ (m³) is the sum of the volumes of all samples being aggregated

t_i (cm) is the thickness of the samples

RECOMMENDATION 18. To consider possible changes in bulk density over time or due to management, comparisons of SOC stocks shall be made on an equivalent soil mass basis (ESM). Samples from at least three discrete, contiguous and successive soil layers should be available to describe how bulk density and SOC concentrations change from the surface layer downward. Only the lowermost layer in any nominated ESM must be based on assumed rather than directly measured bulk density and SOC concentration. An exception may be made only when estimating SOC stock changes for a relatively small and uniform area without stratification, in which case ESM may be neglected and the lowest mass of all samples may be taken at baseline. When using ESM for repeated SOC measurements or point-in-time comparisons, estimates shall be made for the same point (i.e. spatial and depth) or area over time. For sampling schemes where individual samples are taken, these should be aggregated to ensure they represent the same point or area. The method for calculating ESM shall remain consistent across all sampling times.

3.5.2 Calculating soil organic carbon stock changes

To calculate the change in SOC stocks, samples of soil shall be collected and analysed consistently with the baseline sampling protocol described in Chapter 2. SOC stock estimation, and a measure of the variance in the estimate, shall also be carried out in accordance with methods described in Chapter 2.

Changes in SOC stocks can be estimated either (a) between a base period established at t_0 and another sampling at t_1 , or (b) between paired-plots assuming a business-as-usual baseline. In both cases, three steps are involved:

Step 1. Calculating the soil organic carbon stocks in a sample

Volumetric SOC stocks may be calculated for any layer represented by a discrete sample. The SOC for each aggregated sample i that represent a point or area in space is calculated as:

Equation 11:

$$SOC_i \text{ (in Mg C ha}^{-1}\text{)} = OC_i \times ESM \times (1 - vG_i) \times 1,000,000$$

Where:

OC_i (mg C g⁻¹ soil) is the organic carbon content of the soil fine fraction of sample i (see Chapter 2)

ESM (in Mg soil ha⁻¹) is the equivalent soil mass calculated for each study area (see Equation 10)

vG_i is the volumetric coarse fragment content of the sample layer of the sample i , as a percentage of oven dry soil mass (see Chapter 2).

Step 2. Calculating the soil organic carbon stocks and variance in a study area

If IPCC recommendations are followed (see section 2.2.3), the average SOC stock should be calculated separately for the 0 – 30 cm soil layer. The average SOC stock for the study area, and corresponding sampling variance, for each relevant area and each sampling round shall be calculated as described below.

Where equal area strata and compositing of samples apply, SOC stocks for a stratum are calculated as:

Equation 12:

$$SOC_{Aij} = SOC_i \times A_j$$

where,

SOC_{Aij} is the SOC stock for the depth increment i , for strata with area j

SOC_i is the ESM adjusted SOC stock for the depth increment i

A_j is the area of strata j

Where strata are of equal area, the SOC stock for the “carbon estimated area” is calculated as:

Equation 13:

$$\overline{SOC_{CEA}} = (\sum SOC_{Aij}) / n$$

where,

$\overline{SOC_{CEA}}$ is the mean SOC stock for the “carbon estimation area”

SOC_{Aij} is the carbon stock for strata j of area A , for the depth increment i

n is the number of strata in the CEA

The between strata variance is then calculated by:

Equation 14:

$$S^2 SOC_{CEA} = [\sum (SOC_{Aij} - \overline{SOC_{CEA}})^2] / (n - 1)$$

Where:

$S^2 SOC_{CEA}$ is the sample variance for SOC stock of the “carbon estimated area”

n is the number of strata

Where strata are of unequal area, the weighted mean SOC stocks for the “carbon estimation area” shall be calculated as:

Equation 15:

$$\overline{\text{SOC}}_{\text{CEA}} = [\sum(A_j/A_t \times \text{SOC}_{\text{Aij}})] / n$$

where,

$\overline{\text{SOC}}_{\text{CEA}}$ is the mean SOC stock for the “carbon estimation area”

SOC_{Aij} is the carbon stock for strata j of area A , for the depth increment i

A_j is the area of stratum j

A_t is the total area of the “carbon estimation area”

The variance is then calculated as:

Equation 16:

$$S^2 \text{SOC}_{\text{CEA}} = [\sum(A_j/A_t \times (\text{SOC}_{\text{Aij}} - \overline{\text{SOC}}_{\text{CEA}})^2)] / (n - 1)$$

Step 3. Calculating the soil organic carbon stock change

Several statistical tests (t -test, mixed effects models, etc.) exist to determine whether the SOC stocks are different: (a) between t_0 and t_1 when using repeated measurements over time and, (b) at carbon estimation areas 1 and 2 (at a time x) when using paired-plot comparison against a business-as-usual baseline.

(a) repeated measurements at t_0 and t_1

The Welch’s t -test shall be used to test whether the SOC stocks at t_0 and t_1 are different. To do this, the t -statistic of the difference between the SOC stocks is calculated as:

Equation 17:

$$t_{\Delta \text{SOC}} = (\text{SOC}_{\text{CEA at } t_0} - \text{SOC}_{\text{CEA at } t_1}) / \sqrt{[(S^2 \text{SOC}_{\text{CEA at } t_0} + S^2 \text{SOC}_{\text{CEA at } t_1})/n]}$$

where:

$t_{\Delta \text{SOC}}$ is the Welch’s t -test statistics

$\text{SOC}_{\text{CEA at } t_0}$ is the total SOC stock for the “carbon estimation area” as baseline

$\text{SOC}_{\text{CEA at } t_1}$ is the total ESM-corrected SOC stock for the sampling period compared back to the baseline

$S^2 \text{SOC}_{\text{CEA at } t_0}$ is the variance of SOC stock for the “carbon estimation area” baseline

$S^2 \text{SOC}_{\text{CEA at } t_1}$ is the variance of ESM-corrected SOC stock for the sampling period compared back to the baseline

n is the number of strata in the “carbon estimation area”

The degrees of freedom (*df*) of the Welch's *t*-statistic are calculated as:

Equation 18:

$$df = \{[(S^2 \text{SOC}_{\text{CEA at } t_0} + S^2 \text{SOC}_{\text{CEA at } t_1})/n]^2\} / \{[(S^2 \text{SOC}_{\text{CEA at } t_0})^2 + (S^2 \text{SOC}_{\text{CEA at } t_1})^2]/(n-1)\}$$

The respective *t* value ($t_{\alpha(df)}$) for an appropriate alpha level (e.g. 0.9) for the calculated *df* needs to be derived from an appropriate table. If $|t_{\Delta \text{SOC}}| > t_{\alpha(df)}$, then we can consider that the observed change in SOC stocks is statistically significant.

(b) paired-plot comparison against an assumed business-as-usual baseline

When using paired-plot comparison against a business-as-usual baseline, SOC_{CEA} at t_0 and t_1 are replaced by SOC_{CEA1} and SOC_{CEA2} , which are the total EMS-corrected SOC for the “carbon estimation area” of the business-as-usual treatment and the plot of comparison, respectively (both measured at t_x , the year of measurement after the implementation of contrasting management). This assumes that at t_0 the SOC of both plots was identical. Further, the interpretation of treatment effects is direct if SOC at t_0 was at a steady state. If SOC was on a trajectory from a prior management practice, the interpretation of the effect of the new management becomes less straightforward (see Van den Bygaart and Angers, 2006).

RECOMMENDATION 19. To calculate changes in SOC stock, soil samples shall be collected and analysed with a consistent sampling protocol (Chapter 2). Further, a baseline that corresponds to the aim of the study should be chosen using Figure 8. (i) Changes in SOC stocks estimated over time shall be calculated in accordance with recommended methods and use of statistical tools (e.g. regression analysis), and in some cases knowing the ‘natural’ baseline might be necessary. (ii) Changes in SOC stocks estimated from paired-plot comparisons of new land use or management conditions against a business-as-usual baseline shall only be made when the starting point is consistent (i.e. same soil properties, climate, and prior land use and management); the conditions defining the land use or management states shall be thoroughly described. In both cases, estimated relationships should not be extrapolated beyond the period of the last measurement, as changes in SOC cannot be assumed to be constant over time.

BOX 3. The effects of grazing in mountains of southern Norway on soil carbon stocks

Overview: In Norway, approximately 2.2 million sheep graze in mountains during the summer. Sheep grazing has a strong impact on plant ecology and biomass, therefore possibly affecting soil C stocks.

Approach: Long-term experiments with different levels of sheep grazing (decreased; 0 sheep km^{-2} , maintained; 25 sheep km^{-2} and increased; 80 sheep km^{-2}) were conducted in a non-fertilized alpine pasture of moderate productivity in southern Norway. Soil was sampled by genetic horizon and C-stocks calculated by multiplying horizon depth, bulk density and C concentration (Martinsen *et al.*, 2011). Total ecosystem C-stocks were calculated including C in vegetation and surface soil horizon.

Impact of grazing on C stocks: After seven years, soil organic C stocks in surface horizons were lowest at sites with increased sheep density (Martinsen *et al.*, 2011). In contrast, maintained sheep density caused a slight increase in soil C stocks. The set of studies also showed that C

sequestration in the alpine landscape in S. Norway is strongly affected by the tree-line, which in addition to climatic conditions, is determined by the management of herbivore densities (Austrheim *et al.*, 2016).

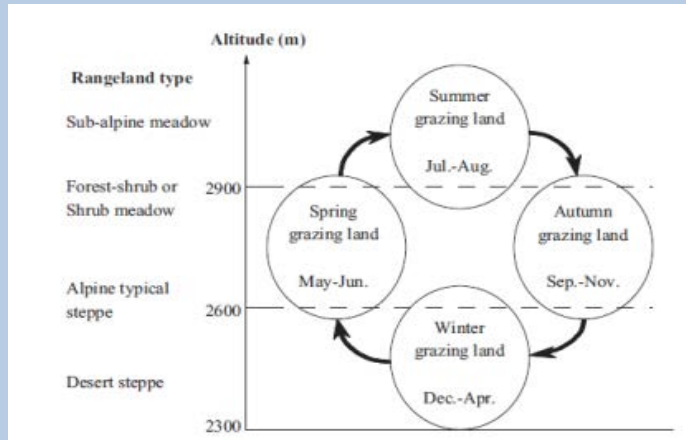


Austrheim *et al.*, 2016. Synergies and trade-offs between ecosystem services in an alpine ecosystem grazed by sheep—an experimental approach. *Basic and Applied Ecology* 17, 596-608

Martinsen *et al.*, 2011. Carbon storage in low-alpine grassland soils: effects of different grazing intensities of sheep. *European Journal of Soil Science* 62, 822-833.

BOX 4. SOC stocks under two grazing patterns in alpine meadows of Qilian Mountain, China.

Overview: Increased grazing intensity can correlate with depletion of SOC, so the long-term impact of grazing pattern and management on SOC stocks was estimated. The study area was in Gansu Province, China (38.8°N, 99.6°E), where grassland is classified as Alpine Typical Steppe. Livestock farming here has a history of more than a thousand years, with seasonal grazing being important to local herdsman.



Schematic diagram of the seasonal grazing rotation. Animals are moved to higher altitude pastures in summer and lower pastures in winter, with spring and autumn at intermediate altitudes.

Approach: Fifteen Wapiti deer (5–6 years old) grazed in winter pasture (WP) and in spring and in autumn pastures (SAP). Soil samples for depths of 0-10, 10-20, 20-30, and 30-40 cm were collected in 1999 and 2012. Gravel, loose vegetative debris and visible roots were removed, soil samples were air dried, sieved, and soil organic carbon (SOC) was determined using the Walkley–Black method (Nelson and Sommers, 1996).

What the study showed: SOC content was strongly reduced with increasing grazing intensity under two grazing patterns, and more strongly on SAP than WP. Soil organic carbon stock changes responded to grazing activity, there is no lower threshold of grazing intensity below which SOC loss does not occur.

SOC stock to 40 cm (Mg/ha) affected by distance from night pen under two grazing patterns in the Qilian mountain, Qinghai Tibetan Plateau

Grazing season	Year	distance from night pen (m)		
		0	1200	1500
Spring and Autumn pasture (SAP)	1999	225	428	446
	2012	196	363	370
Winter pasture (WP)	1999	156	163	167
	2012	138	145	152

Summary : The evidence based on this case study helps in determination of a sustainable stock rate setting for a longer scale in a high attitude and cold environment.

Yuan, H. and Hou, F. 2015. Grazing intensity and soil depth effects on soil properties in alpine meadow pastures of Qilian Mountain in northwest China. *Acta Agriculturae Scandinavica*, 65: 222–232.

4. DATA MANAGEMENT AND REPORTING. SAMPLE ARCHIVING

4.1 Handling data

A plan for research data handling specifies how data will be acquired, processed and stored within the scope of research projects. It should ensure the integrity of research data and a high quality and accessible dataset. Data handling addresses concerns related to confidentiality, security, and preservation/retention of research data. Proper planning for data handling results in efficient and economical storage and retrieval of data. In the case of data handled electronically, data integrity is a primary concern to ensure that recorded data is not altered, erased, lost or accessed by unauthorized users.

Data traceability, error checking and data quality, storage and backup are all integral parts of data handling. Data handling should be considered when planning field soil sampling, sample preparation and analysis, and anticipate the expected reports once final results are generated. Thus, data handling requires adequate planning, development of procedures that simplify data management, as well as training and supervision of research staff to ensure that data is stored and archived in a safe and secure manner.

4.1.1 Data gathering

Data gathering for assessing SOC stock change starts with field sampling, then processing and analysis and finally recording the results of analyses in a spreadsheet or database. Some equipment will export data directly to computers for storage. All other data should be initially recorded in notebooks (i.e. neither post-it notes nor loose pieces of paper), then manually entered into a computer for data handling. To promote data standardization and ensure that experiments are fully described, sampling protocols and a spreadsheet-based data-entry template should be developed.

In addition to SOC measurements, Del Grosso *et al.* (2014) suggested that additional data, such as site descriptors (e.g. weather, soil class, spatial attributes), experimental design (e.g. factors manipulated, measurements performed, plot layouts), management information (e.g. planting and harvesting schedules, fertilizer types and amounts, biomass harvested, grazing intensity, pest and weed controls), should also be recorded. Documenting the geographical coordinates of the position where the sample was taken is always recommended, as it is indispensable information for any (additional) kind of spatial analysis, including digital soil mapping.

Such complementary data is often needed for modelling, inventory, interpretation and reporting. The type and level of detail of field complementary data depends on the level of complexity of the approach to be used when assessing SOC stock change. For Tier 1 models (e.g. IPCC) the relative stock change factors are based on land use, land management and climatic region. Tier 2 and simple soil models (e.g. ROTH-C) require monthly weather data (monthly rainfall, evaporation and air temperature) and field data such as soil cover (0 or 1), monthly input of plant residues and livestock dung/manure. The net primary production (NPP) can be used to estimate the monthly plant residue input, while the type and number of livestock on a grazed pasture can be used to estimate the livestock dung/input. Tier 2 and 3 approaches use country-specific coefficients and/or finer scale area disaggregation (e.g. high-resolution activity data at sub-national to fine grid scales), which will reduce uncertainty in estimates. Depending on the selected model for the assessment, complementary data such as root biomass, SOC fractions for model initialization, carbon to nitrogen ratio (C:N) and soil moisture may be required. For fodder crop systems,

information such as whether crop residues are retained in the field will improve estimates of C input.

When studying SOC stock changes, nitrogen dynamics is often an important driver of change because the nitrogen availability often determines biomass production and rates of SOC decomposition (Piñeiro *et al.*, 2010). Therefore, quantification of soil nitrogen stocks may be of use depending on the purpose of the assessment. The presented recommendations in this Chapter apply in the same way when sampling to measure nitrogen stocks.

RECOMMENDATION 20. The geographical coordinates of the sampling location and of the boundaries of the represented area shall always be documented. When planning the assessment of SOC stock changes, possible complementary data from the field, such as net primary productivity, soil texture and pedoclimatic data, should be considered and collected as required.

4.1.2 Data processing

Most data can be processed and stored in a spreadsheet (e.g., Microsoft Excel, OpenOffice, LibreOffice). Larger and more complex datasets may require the use of a relational database (e.g. Microsoft Access, Oracle, MySQL). In both cases, unique identifiers should be attached to all items (e.g. each soil sample). Unique identifiers are crucial to ensure data traceability and error checking and so are integral to proper database design.

Proper data storage in spreadsheets begins with using a logical name for each workbook and sheet within the workbook, or for the database and its tables, queries, and reports. Each workbook shall have metadata (e.g. a “readme sheet”). The metadata should note: a brief description of the data, equipment used for analysis, brief description of analytical method, dates when samples were collected and analysed, names of persons who collected, prepared, analysed or entered the data, and anything else pertinent (mistakes or equipment problems). Each sheet shall have column titles and units (if applicable). Data in workbooks shall show calculation flows and checks and be cross-referenced with reference logbooks (which indicate usage of instruments/equipment). Finally, data should be in formats that will make later retrieval and analysis efficient. This includes using commonly available software formats (e.g. .xlsx, .accdb) or even comma separated value (.csv) files. There may be opportunities decades in the future to compare results and to present findings.

4.1.3 Data storage and retrieval

Storing data is very important to ensure that all the information needed for interpretation is available and can be retrieved in a variety of ways. Without proper data storage, reporting and publishing will be difficult in the future. Most projects start with storing data in a spreadsheet (e.g. Microsoft Excel). An example of SOC stock change after cultivated crops were converted to native pasture is provided in Annex 4.1. When data collected exceeds the capacity of an Excel workbook, databases are typically used to store large data sets. Databases can also handle more complex relationships among data tables and offer better reporting capabilities than spreadsheets.

Soil carbon databases exist for countries and are being developed globally. An example of a soil carbon database is the Northern Circumpolar Soil Organic Carbon Database, which can be found at sis.agr.gc.ca/cansis/interpretations/carbon/index.html. The databases are in .dbf format, using the old dBASE PC program, but Microsoft Access can import the tables.

Stored data should be backed-up regularly, either using an organization's internal system or with an online external data storage company (often referred to as "storage in the cloud"). Personal backups (e.g. taking a copy home after work on a USB drive) are insufficient. Further, it may violate organizational policies if the data is considered confidential. USB sticks and DVDs seem ubiquitous today, but fifty years ago data was stored on computer cards and tapes that are very difficult to read today. Dedicated backup services minimize problems associated with technological change.

Whatever backup method is used, it should be sufficiently well documented that even in an extreme case (e.g. all team members leave the project) someone can find and access the backup and understand how to interpret the data. Some countries have policies allowing accounting and human resources data to be deleted after a certain period, but that policy should not be applied to research data.

"Open Notebook Science" (en.wikipedia.org/wiki/Open_notebook_science), proposed by Jean-Claude Bradley, advocates not only that scientific data should be preserved but that it must be publicly available so that "all of the information available to the researchers to make their conclusions is equally available to the rest of the world".

4.1.4 Data quality control

To ensure the integrity of the data collected, standard operating procedures shall be followed at every step with proper Quality Control/Quality Assurances in place. Soil organic carbon may be estimated by different methods. To obtain accurate and comparable data, the use of standardized protocols and instruments which have undergone Quality Assurance and Quality Control are recommended. Quality Control uses established protocols to achieve standards of measurement based on the three principle components of quality: precision, accuracy and reliability. Quality Assurance is a system of activities designed to better ensure that the Quality Control is done properly. As part of the SOC stock assessment, laboratories that analyse soil samples should have their Quality Assurance/Quality Control in place to ensure that data quality and integrity is achieved. A good example of Quality Assurance/Quality Control can be found in the UC Davis Analytical Lab Quality Manual (UC Davis, 2017, anlab.ucdavis.edu/forms-and-guides/files/qual-manual.pdf). While using an International Organization for Standardization (ISO/IEC 17025:2005 General requirements for the competence of testing and calibration laboratories) certified laboratory for soil analyses is preferred, quite often the laboratory QA/QC practices of academic and research organizations will meet or exceed the ISO standard despite not being ISO certified.

Hand-written data must be neat and readable (not always easy under field conditions). The data should be entered into a computer as soon as practical, and particularly while the person who made the entries remains available to answer any questions. Data entry can be a boring job and prone to high error rates, so double entry with an independent comparison and resolution of any differences is worthwhile if resources permit. If possible, limiting data entry activity to one-hour periods with other activities in-between can be helpful to limit boredom fatigue. Very large projects might consider using dedicated data entry staff or even optical character recognition (OCR) to improve accuracy and efficiency. Databases and spreadsheets facilitate basic validity checks for errors (e.g. a quantity of 5r.3 is clearly incorrect) or reasonableness. For example, if the pH value in an experiment is expected to be between 4.0 and 7.0 at least 95% of the time, the exceptions can be flagged and checked to ensure they are valid. When the analysis generates unexpected results, this may also indicate data quality issues.

RECOMMENDATION 21. Data shall be stored in a suitable format, such as the template (tab- or comma-delimited text, .txt. csv), and include all necessary data for identification (e.g., year, field,

replicates, soil layers, etc.), variables for estimates (coarse fragment, roots, residual humidity), sample treatments (CaCO₃, sieving, drying, etc.).

In cases, where spreadsheets are not enough for the purpose, relational databases should be used to store data. In addition to collecting the data required for physical determination of SOC stock, all relevant metadata from sampling sites shall be preserved. These include the sites' past history (fertilisation, sowing, grazing, tillage, manure, etc.) and georeferenced location.

4.2 Reporting results

The level and scope of data/results reporting depends on for whom the final report is intended, e.g., funders, scientific community, the public, etc. All key members of the team involved in the data collection and analyses should have a chance to carefully review and discuss the reports.

Results can be presented in several different ways, including graphs, tables, maps, etc. They should always be accompanied by estimates of error. Reporting results shall include a description of methods used in data collection and data processing, as well as storage location of data and metadata (along with contacts). Every part of the process should be described, not just the statistical, sampling or lab procedures.

It is good practice to log all data from the exercise in an internal or public archive. This allows the project to keep data secure for follow up and allows others to make use of it for further analyses and to link it with other data.

RECOMMENDATION 22. Data/results reporting shall include a detailed description of methods including site of stored data and metadata. Reported results should be accompanied by an estimate of error or uncertainty.

5. MONITORING SOIL ORGANIC CARBON CHANGES – NET BALANCE OF ATMOSPHERIC CARBON FLUXES

An alternative to the physical determination of C stocks at repeated times, is to draw up a full carbon budget. Such an 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 or net ecosystem production, and further C inputs and outputs to and from the system. Measurements of the net balance of C fluxes exchanged (i.e. estimating net ecosystem exchange) can be achieved by chamber measurements or by the eddy covariance method (Aubinet *et al.*, 2012). Both these approaches are used more as research tools than for routine monitoring as both are relatively labour intensive and, in the case of eddy-covariance highly specialised and expensive to operate.

Soil chambers are the simplest method of measuring uptake and soil efflux but have a small spatial footprint, cannot be used for long-term studies and, if manual, may suffer from poor temporal resolution (see Schmitt *et al.*, 2010). Due to these constraints, chamber measurements of net ecosystem exchange should be limited to plot scale only. Ideally, CO₂ fluxes should be measured dynamically, allowing several measurements to be recorded during the day and night and periods of optimal vegetation growth (e.g. Mitchell *et al.*, 2016).

The eddy covariance method can measure the net exchange of CO₂ over areas of several hundred square metres to hectares depending on the sensor height (i.e. 2-3m over grassland) and horizontal wind speed, and provides a high temporal resolution allowing detection of SOC stock changes within one year (Ammann *et al.*, 2007; Klumpp *et al.*, 2011).

The eddy covariance technique analyses the covariance between rapid fluctuations in vertical wind-speed measured with a three-dimensional ultrasonic anemometer and simultaneous measurements of the rapid fluctuations (10-20 Hz) in the CO₂ concentration, as measured by a fast-response gas analyser (Aubinet *et al.*, 2012, Figure 10).

The main limitations of the eddy covariance technique are related to the fact that this is a point-in-space measurement. Thus, the relationship between this point measurement of a flux and the upwind measure area (i.e. footprint) requires certain atmospheric conditions to be considered at set up of the tower. These involve: (i) well-developed and continuous turbulence, (ii) stationary wind field and turbulence conditions and, (iii) a homogeneous distribution of sources and sinks of CO₂ in the footprint area.

The eddy covariance provides the most robust measure of not only net ecosystem exchange but also allows for the partitioning into GPP and total ecosystem respiration. GPP is not easily measured at large scales but can be estimated from the net ecosystem exchange measured by eddy covariance, by extrapolating night-time ecosystem respiration (see Reichstein *et al.*, 2005).

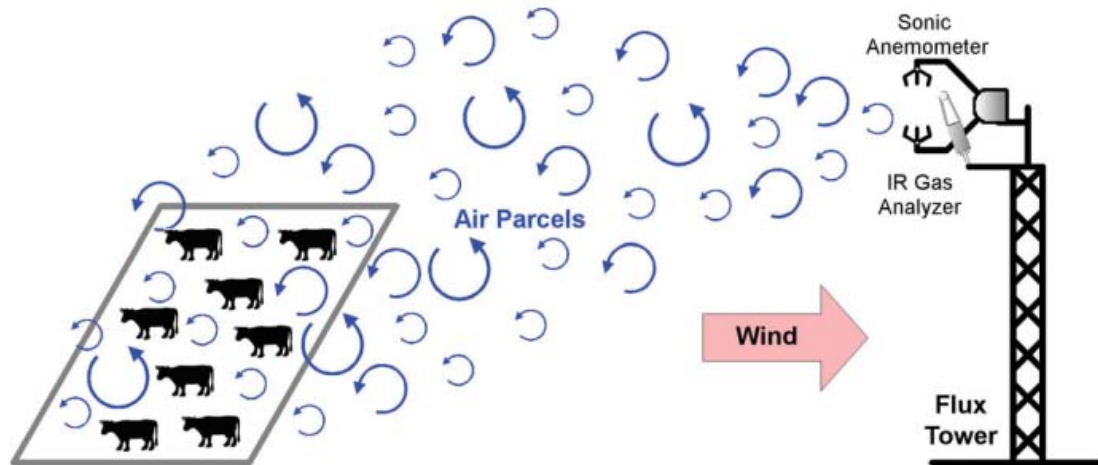


Figure 10. Measurement principle of the eddy covariance method (Hu et al., 2014).

To determine the net carbon storage (NCS) via the eddy covariance technique, further C inputs and outputs to the field need to be considered (see Soussana *et al.*, 2010). These include: (i) trace gases comprising C compounds exchanged with the atmosphere (i.e. CH₄, volatile organic compounds, VOC, and emissions during fires), (ii) organic C imports (manures) and exports (harvests, animal products), (iii) dissolved C lost in waters (dissolved organic and inorganic C) and lateral transport of soil C through erosion. By considering these variables, NCS (g C m⁻² per year) is the mass balance of these fluxes (Equation 8):

Equation 19:

$$\text{NCS} = (F_{\text{CO}_2} - F_{\text{CH}_4\text{-C}} - F_{\text{VOC}} - F_{\text{fire}}) + (F_{\text{manure}} - F_{\text{harvest}} - F_{\text{animal-products}}) - (F_{\text{leach}} + F_{\text{erosion}})$$

Where:

F_{CO_2} is the net ecosystem exchange of CO₂ between the ecosystem (plant and soil) and the atmosphere, including CO₂ (digestive + metabolic CO₂) from grazing animal. F_{CO_2} is conventionally positive for a C gain by the ecosystem.

$F_{\text{CH}_4\text{-C}}$, F_{VOC} and F_{fire} are trace gas C losses from the ecosystem as methane, volatile organic compounds and through fire, respectively (g C m⁻² y⁻¹).

F_{manure} , F_{harvest} and $F_{\text{animal-products}}$ are lateral organic C fluxes which are either imported or exported from the system (g C m⁻² y⁻¹).

F_{leach} and F_{erosion} are organic (and/or inorganic) C losses through leaching and erosion, respectively (g C m⁻² y⁻¹).

Depending on the studied system (i.e. climatic zone) and management, some of the fluxes in Equation 8 can be neglected for NCS calculations:

- Fire emissions (F_{fire}) by grasslands are very low in humid temperate regions (i.e. below 1 g C m⁻² per year over 1997-2004 in Europe), while they reach 10 and 100 g C m⁻² per year in Mediterranean and in tropical grasslands, respectively (Van der Werf *et al.*, 2006).
- Erosion (F_{erosion}) is rather insignificant in permanent grasslands (e.g. in Europe), but can be increased by tillage in the case of sown grasslands. The global map of F_{erosion} created by Van Oost *et al.* (2007) indicates that grassland C erosion rates are usually below 5 g C m⁻² per year, even in tropical, dry grasslands.

- Volatile Organic C emissions (F_{VOC}) by grassland systems are usually very small, and can thus be easily neglected (Davison *et al.*, 2008).

In many grasslands systems, equation 1 above can be simplified to (Allard *et al.*, 2007):

Equation 20:

$$\text{NCS} = (F_{\text{CO}_2} - F_{\text{CH}_4\text{-c}}) + (F_{\text{import}} - F_{\text{export}} - F_{\text{animal-products}}) - F_{\text{leach}}$$

Some studies have compared repeated SOC stock measurements with C balance obtained by the eddy covariance technique (e.g. Leifeld *et al.*, 2011; Skinner and Dell, 2014; Stahl *et al.*, 2017) showing that methods match well for long-term comparison (i.e. > 5yrs), but not in the short term due to the uncertainty of eddy covariance measurements linked to instrumentation and data processing. Nonetheless, the strength of this method compared to repeated SOC measurements, is that it allows for the annual assessment of C sinks and related principal drivers (e.g. management, climate) of source/sink strength to be elaborated (Jones and Donnelly, 2004; Skinner and Dell, 2014; Klumpp *et al.*, 2011). This may be the case for management systems that are newly imposed (less than ten years old). Even so, analysing net ecosystem exchanges is quite costly and labour intensive in terms of instrument set up, maintenance and data processing, making it necessary to dedicate a whole research team to this approach. A case study showing the strengths of the approach as well as the technology and expertise required by the eddy covariance technique is shown in BOX 6.

RECOMMENDATION 23. When using a full-system carbon budget approach as an alternative to repeated physical measurement methods to determine SOC stock changes, it shall firstly be established that adequate funds and equipment and a research team with the required expertise can be dedicated to the project. For eddy covariance measurements to determine SOC stock changes, assessment of site suitability shall be undertaken to determine that the spatial area is sufficiently large (4 to 8 hectares, minimum, depending of wind direction) to fully quantify contributions to fluxes of all material carbon sinks and sources (e.g. harvest, leaching, animal products). Established research groups and networks (e.g. Fluxnet, Ameriflux, NEON, ICOS) with experience in use of eddy covariance methods should be consulted when seeking to set up instrumentation and programs using full carbon budget methods.

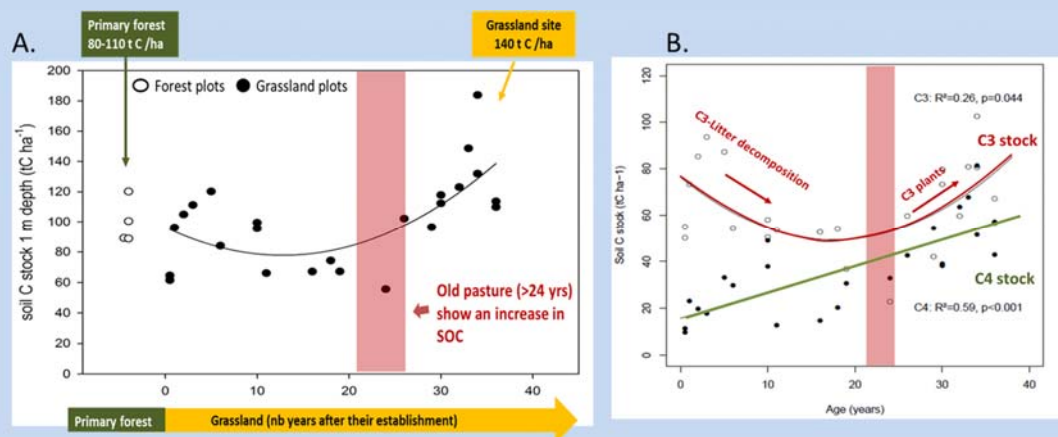
BOX 5. Soil carbon storage of old permanent pastures in Amazonia

Overview: Amazonian forests accumulate carbon (C) in biomass and in soil, representing a carbon sink of 0.42-0.65 Gt C yr⁻¹. In recent decades, more than 15% of Amazonian forests have been converted into pastures, resulting in net C emissions (~200 Mg C ha⁻¹) due to biomass burning and litter mineralization in the first years after deforestation. However, little is known about the capacity of tropical pastures to restore a forest C sink.

Approach: To estimate C stock changes of pastures and native forests in French Guiana, two independent approaches were applied: (i) a chronosequence study including the inventory of soil C and N stocks to a depth of 100 cm in 24 pastures from 0.5 to 36 years old and four native forests distributed across French Guiana and, (ii) measurement of NEE by eddy covariance in one young (4-year-old) and one old (33-year-old) pasture included in the chronosequence study, and one native forest.

What the study showed: The combination of chronosequence study and eddy covariance measurements showed that pastures stored between 1.3 ± 0.37 and $5.3 \pm 2.08 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ whilst the nearby native forest stored $3.2 \pm 0.65 \text{ tC ha}^{-1} \text{ yr}^{-1}$. Data showed that French Amazonia tropical pastures could partly restore the C stocks observed in native forest, when maintained longer than 24 years. Carbon was mainly sequestered in the humus of deep soil layers (20-100 cm), whereas no C storage was observed in the top 0-20 cm layer. C storage in C_4 tropical pasture was related to the installation and development of C_3 species (e.g. legumes, weeds), which increase either N input to the ecosystem or the C:N ratio of SOM.

Changes in soil carbon stocks to a depth of 1 metre under pastures ≤ 24 and ≥ 24 years old (A), and soil carbon stock changes originating from C_3 and C_4 plants (B), along the chronosequence. The C_4 plant (black circles) planted when the pastures were established. The C_3 plant signature (white circles) from C native forest and C from new plants such as shrubs legumes.



Summary: Efforts to curb deforestation in Amazonia remain an obvious priority to preserve forest C stocks and biodiversity. However, these results show that under sustainable management (avoiding fires and overgrazing, using a grazing rotation plan and a mixture of C_3 and C_4 species), tropical pastures can ensure a continuous C sequestration, which adds to the current C sink of Amazonian forests.

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

6. MODELLING SOIL ORGANIC CARBON CHANGES

6.1 Introduction

6.1.1 What is modelling and who is it intended for: decision support and reporting

Modelling is an approach used to infer SOC stocks and distributions in conditions where they have not been measured, such as: (1) under future climatic conditions, (2) at locations or for soil types or regions where no measurement exists, (3) for pasture management scenarios that have not yet been tested, e.g. use of new grass species or changes in fertilization or grazing regime. The inability to measure SOC stocks directly can have various causes, such as difficult access to representative sampling points, lack of equipment or that the number of samples needed to representatively cover a certain area of interest exceeds those affordable. Furthermore, the information obtained by direct measurements is not always sufficient to answer all relevant questions related to SOC stock and dynamics.

In the last decades, numerical models have been developed, including mathematical representations that quantitatively describe soil characteristics and processes. The breadth of these approaches can be illustrated by the recent compilation of 90 mathematical models describing SOC changes and biogeochemical related soil processes developed in the last 80 years (Falloon and Smith, 2009; Manzoni and Porporato, 2009, and Campbell and Paustian, 2015). However, according to their structure, number of input variables required and temporal and spatial resolution, not all available C models are suitable for all studies (Manzoni and Porporato, 2009). Additionally, due to bias in previous studies towards particular ecosystems, there are notable gaps in our understanding. For instance, currently, most of the modelling efforts have focused on forests and croplands, while grasslands have received less attention.

Grassland models have been developed with different research foci to model soil C, N, P, and S dynamics at monthly and daily time-steps (e.g. CENTURY, DayCent). Some have aimed at improving representation of biochemical, biophysical and ecosystem processes in natural grasslands (e.g. Grassland Ecosystem Model, GEM) or describing C, N and water cycles in grazed systems (e.g. Hurley Pasture Model of Thornley (1998), PaSim) or simulating multiple grass species which compete for water and nutrients (e.g. DNDC, Li et al., 2012) and other process-based models. Because modelling grassland systems is complex, both individual and ensemble models perform poorly in predicting above-ground grass production, whereas model ensembles perform adequately for predicting yields of annual crops (Ehrhardt *et al.*, 2018). Grassland systems are characterized by features that are absent in arable cropping systems. These add complexity to process-based modelling of grassland systems compared to annual cropping systems and thus present significant challenges to model developers and users. These features include: (i) pastures are botanically diverse (e.g. perennials, legumes, C3/C4 species); (ii) there are substantial interactions between management practices (e.g. grazing animals, grazing practices, fire regimes, fertilization, harvests, etc.) and vegetation responses and; (iii) the whole farm management is more complex and at the same time more important for grasslands than for arable systems.

Models of SOC in pasture systems, developed and tested by scientists, are used by extension specialists and consultants for making practical recommendations towards climate smart agricultural practices. Extension specialists use models to predict long-term changes in SOC for specific farms and communicate this information to farmers, in terms of best practices for grazing land management. Consultants and public sector advisors apply a similar approach, using models to evaluate the sustainability of grazing land management at different scales to facilitate decision making in public and private sectors. Decision makers are interested in identifying pasture management options that provide an optimal balance between carbon sequestration and

reduction in greenhouse gas emissions and broader effects on ecological health, resiliency and productivity.

Reporting is another main application of SOC models. Once there is a policy decision to sustainably increase carbon storage in pasture soils and measures to implement this have been agreed upon, there is a long-term requirement to report on progress towards this goal. Modelling can be an important tool in the reporting process, providing a method for estimating soil C gains resulting from the new management. Reporting can be performed at various scales, from the individual field to entire countries or continents. For example, a livestock farmer might need to report to funding agencies changes in SOC stocks due to crop rotations, stocking rates and fertilizer practices. He might not have the technical and financial capacity to conduct soil analyses after every cropping season, so a modelling approach is needed to account for potential changes. Also, many countries are obliged to report greenhouse gas emissions from different sectors in national inventory reports. Soil carbon stock changes can be an important part of such inventories in the agricultural sector. While some countries have measured baseline SOC stocks and some might even repeat measurements in certain intervals, models are commonly used to annually account for changes in SOC stocks on the national scale.

RECOMMENDATION 24. Models shall be used when the objective is to estimate or extrapolate changes in carbon stocks in or to conditions in which they have not been measured e.g. soil type, climate and management. As a guiding principle, the complexity of the model should be aligned to the context.

6.2 The different modelling approaches

Three modelling approaches are usually recognized, referred to here as three different levels of assessment. Following the 'tier' structure proposed by the IPCC (2003, 2006), a three (1-3) level approach is proposed to estimate SOC stocks and SOC dynamics using simulation models. The level and method selection will depend on the specific purpose of the study, the spatial scale, and data availability (see section 6.3), among other factors. Although the level structure is not hierarchical, moving to a higher level should improve the accuracy of the estimation and reduce uncertainties, as the complexity and data resources required for modelling SOC changes also increase. The approaches are not mutually exclusive, and a mix of approaches may be applied for different calculation needs or local circumstances. The following three levels represent different methodological modelling approaches and range from the use of default data and empirical equations to the use of more complex, specific, locally validated functional or mechanistic models. These three levels are:

- Level 1: 'Empirical' Models
- Level 2: 'Soil' Models
- Level 3: 'Ecosystem' Models

6.2.1 Level 1. Empirical models

SOC stocks and changes in this level may be estimated using an empirical approach, which usually represent the observed relationships between SOC stocks or SOC changes and defined environments, or environmental and management variables, such as soil clay content, temperature, precipitation or land use (Grigal and Berguson, 1998; Davidson and Janssens, 2006; Milne *et al.*, 2007).

One of the best-known empirical approaches is the computational method for estimating SOC stock changes developed by The Intergovernmental Panel on Climate Change (IPCC, 2003, 2006). This empirical approach computes projected net SOC stock changes over a 20 year period. This is assumed to be the default period for SOC stocks to attain a new steady state (referred to as 'equilibrium') although this may take much longer, even more than 100 years (e.g. Poulton et al 2018). This approach estimates change in SOC stocks by assigning a reference SOC stock value, which varies depending on climate, soil type and other factors. This reference value is then multiplied by factors representing the quantitative effect of changing grassland management on SOC storage. The method can use default climatic, soil and land use/management information given by the IPCC or, if available, country-specific data. For each period, SOC stocks are estimated for the first and last year, based on multiplying a reference C stock found under native vegetation (for a specific climate and soil type) by stock change factors (land use, management, organic matter inputs, and land area). Annual rates of carbon stock change are estimated as the difference in stocks at two points in time divided by the time dependence of the stock change factors. For an example of this approach, see the case study in BOX 6.

This approach may be used for systems with a limited availability of historic climatic data, soil databases, and/or productive registers (management practices and its effects on net primary production, or estimations of biomass returns and exports, etc.). These types of approach have been used to estimate C sequestration potentials for rangelands and pastures and the potential effects of management practices on SOC stocks and stock changes (Ogle *et al.*, 2004; Grace *et al.*, 2004; Easter *et al.*, 2007; Milne *et al.*, 2007; Kamoni *et al.*, 2007; Petri *et al.*, 2010; Berhongaray and Alvarez, 2013) at global, national and regional scales. The method may, however, have limitations for sub-national or sub-regional assessments (Milne *et al.*, 2007).

One main drawback of the IPCC approach is that it considers, as do other regression approaches, that SOC changes linearly (Milne *et al.*, 2007) and reaches equilibrium in 20 years (Goglio *et al.*, 2015). This may cause important deviations in some types of environment (Berhongaray and Alvarez, 2013). Another drawback is that much of the data available for deriving the empirical factors in the IPCC default approach are from studies in North America and Europe. For this reason, there is a significant lack of data from grasslands in other environments, which may result in bias of the estimations of default reference SOC values, or in land use or management factors (Petri *et al.*, 2010). An adjustment of these parameters with local data may be required to improve estimations (Berhongaray and Alvarez, 2013). Finally, regression-based estimates may be also limited in their ability to predict long-term soil C dynamics in a changing environment (Peng *et al.*, 1998).

Simple carbon balance equations, that consider decay and humification rates, developed for a specific region or environment based on empirical functions, may be included at this level. In these types of models, SOC decomposes according to first order kinetics with a rate constant represented by an empiric coefficient of mineralisation k_2 (year^{-1}), which is assumed to be a characteristic of soil and climatic conditions. The amount of carbon that becomes part of SOC stocks is estimated from plant carbon inputs (CI), as a function of another empiric parameter, k_1 or 'isohumic coefficient', which represents the yield of the transformation into humified carbon of the crop residues and is generally characteristic of the type of residues (Andriulo *et al.*, 1999). SOC changes in these models follow the Hénin and Dupuis (1945) two compartment approach, and may be summarised as:

Equation 21:

$$\Delta\text{SOC}/\Delta t = k_1 \times \text{CI} - k_2 \times \text{SOC}$$

BOX 6. Extending the lifetime of temporary sown grasslands to increase soil C sequestration – French case study

Overview: Soil C sequestration by the world’s grasslands could offset GHG emissions. These offsets can be partly achieved by grazing management and restoration of degraded lands. However, there are considerable effects of climate and management linked to C sequestration potential. In grasslands C accumulation mainly happens in the top soil layers (first 30cm), which account for 80 to 90% of the variations in the stock. Thus, the nature, frequency and intensity of soil disturbance are key factors determining C sequestration potential. In France, cultivated grassland have become an important part of agricultural systems in recent decades (e.g. steady decline of permanent grasslands; 12.8 Mha permanent and 2.7 Mha temporary in 1980 compared to 7.4 Mha and 3.2 Mha in 2010). However, these grasslands submitted to frequent cultivation are more vulnerable to C losses compared to permanent grasslands; approximately 20–30% of top SOC (0-30cm) is susceptible to rapid losses due to tillage in the first years after grassland installation (0.6 to 1.2 Mg C ha⁻¹ year⁻¹ after ploughing). Limiting the frequency of grassland renewal may thus improve carbon sequestration by reducing soil disturbance.

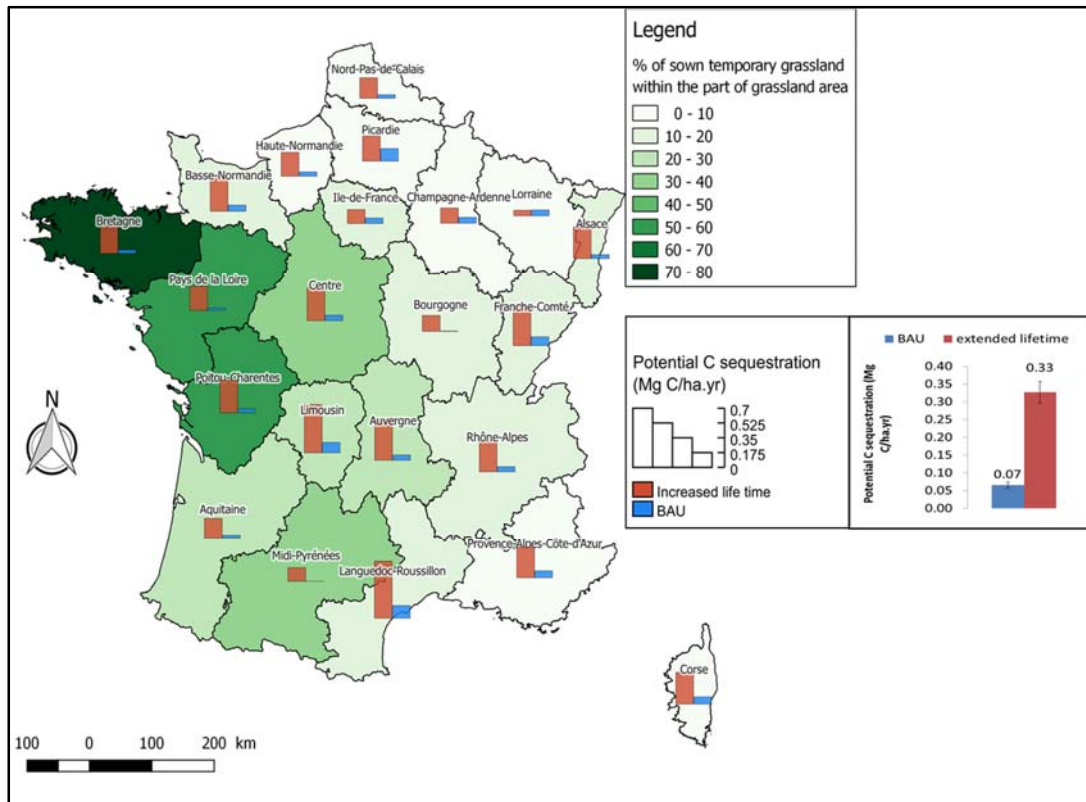
Approach: The C sequestration potential of temporary grasslands (TG) by extending "life time" to 5 years (Pellerin *et al.*, 2013) was estimated. At present, French temporary grasslands are divided into six age classes occupying 31% (1 year), 17% (2 year), 17% (3 year), 16% (4 year), 13% (5 year) and 6% (6 year) of the total TG area (3.14M ha vs. permanent 9.8Mha). Without increasing the surface area of TG, we increased TG life-time to five years, for all TGs >4 years, for 80% of the TG 3yrs, 65% of the TG 2 yrs and 50% of TG 1yrs. Potential C sequestration was estimated by using a Tier 2 (IPCC 2006, see also Dolle and Klumpp, 2015) approach for C stock changes (i.e. $SOC(t) = SOC_{ref} \times F_{LU} \times F_{MG}(t) \times F_i(t)$) in the 0-30 cm soil layer, where SOC_{ref} was the mean soil C stock of the French administrative region in 2013, F_{LU} is the land use factor (1 for temperate grassland), F_{MG} the management factor (0.7 to 1.14 from highly degraded to improved grassland) and F_i the input factor (1 to 1.11 for moderate to improved). To simulate an extension of "life time" mission factors ($F_{LU} \times F_{MG} \times F_i$) were combined varied according to grassland age (table below).

Combined "life time" mission factors ($F_{LU} \times F_{MG} \times F_i$) according to grassland age

Age	$F_{LU} \times F_{MG} \times F_i$	Management
1	0.95	Loss of C due to tillage
2	1	non-degraded grassland
3	1.05	non-degraded grassland + one or more improvements
4	1.097	Intensively used grassland (moderate degradation) + improvements
5	1.14	Sustainable grassland management

What the study showed: A lifetime extension of temporary grasslands (i.e. 16% of the TG area) increased mean C sequestration potential by 0.26±0.03 t C ha⁻¹yr⁻¹ (-0.002 to 0.5 tC ha⁻¹yr⁻¹ depending on regional initial SOC stock, % of sown grassland within the total grassland area and partitioning of grassland ages).

Pellerin *et al.*, 2013. Optimisation of grassland management. In: How can French agriculture contribute to reducing greenhouse gas emissions? Abatement potential and cost of ten technical measures. INRA, France. 92 pp.



These kinds of approaches are still widely used to describe or predict carbon evolution in different environments and scales (Minasny *et al.*, 2013), and have been the basis for other more complex models. However, it has long been recognized that SOC has many components or pools varying in stability and turnover rates, and that the value of the mineralisation and humification parameters change over time. Hence, the main drawback of using this empiric type of approach is that generally these equations are generated for specific conditions (soil, climate, management, type of carbon inputs), so they will not necessarily perform adequately in different environments or under changes in these variables.

RECOMMENDATION 25. Level 1 modelling without modification may provide a first indication to predict the magnitude or direction of carbon stock changes. Level 1 modelling should be used when there is access to data-based factors that have been specifically determined for the system of interest (e.g. IPCC factors that can be adapted based on region-specific experiments). Users should note that Level 1 models can be used for reporting or claims but the simplicity of these models translate into limited accuracy if region specific factors are not used.

6.2.2 Level 2. Soil process models

Soil organic carbon stocks and changes may be estimated at this level by using models that simulate SOC dynamics through time, considering the effects of climatic and soil factors together with land use and management variables. Models at this level take account of underlying dynamic processes and variables determining SOC stocks and changes by using mathematical functions

that describe in detail the physical and chemical processes involved, or by using robust empirical functions based on general physical-chemical principles to simulate and integrate different processes.

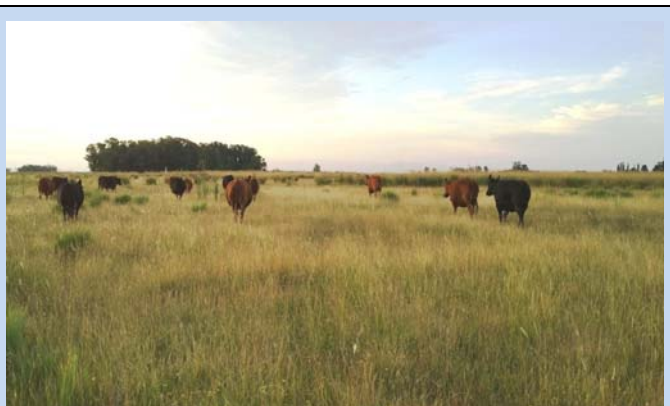
Many types of models can predict and integrate a variety of variables other than SOC (such as soil moisture and temperature) and simulate its impacts on SOC dynamics. They are generally used to predict SOC dynamics based on different conceptual C pools or compartments that vary in size via inputs, decomposition rates and stabilization mechanisms (each compartment or pool being a fraction of SOC with similar chemical and physical characteristics; Stockmann *et al.*, 2013). The flows of carbon within most of these models represent a sequence of carbon going from plant and animal debris to the microbial biomass, then to soil organic pools of increasing stability. The output flow from an organic pool is usually split and generally directed to some type of microbial biomass pool, another organic pool and, under aerobic conditions, to CO₂ (Falloon and Smith, 2009).

At this second level, dynamic, process-oriented, ‘soil-centred’ models are proposed. These models take into account previously mentioned SOC processes, but do not simulate other complex processes such as plant above or below ground biomass growth, or nutrient dynamics. So, in these cases, incoming carbon from plant and animal residues must be estimated elsewhere. YASSO (Liski *et al.*, 2005), ICBM (Andren and Kätterer, 1997) C-TOOL (Taghizadeh-Toosi *et al.*, 2014), CANDY (Franko *et al.*, 1997) or Roth-C (Jenkinson *et al.*, 1990; Coleman *et al.*, 1997) are some examples of this type of models. RothC has been one of the most widely used SOC models in the last 20 years (Campbell and Paustian, 2015). Although it was originally developed and parameterized to model the turnover of organic C in arable topsoils, it was later extended to model turnover in other biomes, and to operate in different soils and under different climates (Coleman *et al.*, 1997). It has been widely used to simulate C dynamics in livestock systems, including grasslands, pastures, savannas and shrublands (e.g. Falloon *et al.*, 1998; Cerri *et al.*, 2003, 2007; Martí-Roura *et al.*, 2011; Liu *et al.*, 2011)

Although these models are more complex than empirical approaches, they have relatively few data requirements and it is relatively easy to obtain climatic, soil and productivity data inputs to run them. Soil carbon inputs from plant residues and animal excreta need to be estimated, but they may be derived from above-ground net primary production, root: shoot ratios, livestock efficiencies and harvest, and plant material digestibility (Liu *et al.*, 2011; Poeplau, 2016). However, by excluding simulations of plant biomass growth, plant interactions with climatic variables, soil water budgets, nutrient dynamics, or GHG emissions other than CO₂, these models may have limitations for application to specific purposes. For an example of their use, see the case study in BOX 7.

BOX 7. Using Models to analyse management strategies in the Flooding Pampa, Argentina

Overview: The Flooding Pampa is the main beef cattle breeding region of Argentina, occupying 9 Million hectares of grasslands, characterized by a mild, temperate humid climate. This lowland region is covered mainly by different kind of saline sodic soils, which remain waterlogged during winter-spring and often experience summer droughts. Vegetation consists of native

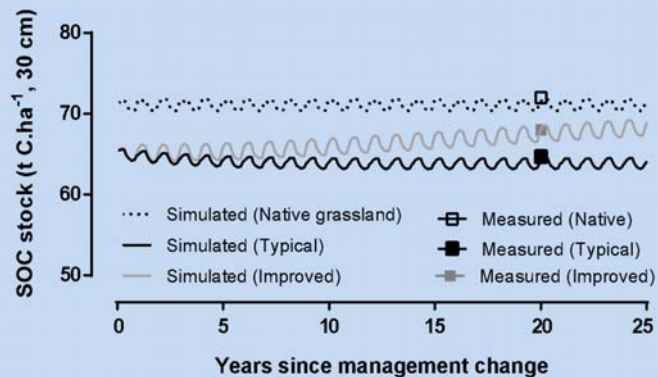


grassland extensively and continuously grazed by cattle. SOC levels as high as 60 -75 t C ha⁻¹ can be found in the top 30 cm in pristine situations or by long term grazing exclusion (enclosures). Since the introduction of cattle more than 400 years ago, it has been estimated that SOC stocks have decreased by 15-30% (Piñeiro *et al.*, 2006). With appropriate grazing systems established, not only is plant community structure improved, but NPP is also increased in these grassland soils (Di Bella *et al.*, 2015). Grazing management could be a viable option to improve soil quality and SOC stocks in the region.

Approach: A combination of SOC measurements and simulation models was used to analyse current and possible future trends in SOC levels under different management strategies at a field scale in these ecosystems. Production data (easily accessible to farmers) were used to estimate carbon inputs (Soussana and Lemaire, 2014; Liu *et al.*, 2011) for the Roth-C Model, which simulated expected SOC stock changes under different management regimes.

What the study showed: The figure shows simulated SOC evolution after 20 years under native vegetation (a typical livestock system), and 'improved' management (with phosphorus addition and a grazing-legume rotation).

Average SOC levels in Natraquoll soils, measured in commercial production farms are shown as a reference. After increasing NPP, 'improved' systems may raise C stocks by nearly 160 kg C ha⁻¹ y⁻¹, even when grazed at high stocking rates. However, at a broader scale, this kind of approach should be complemented with Life Cycle Assessment (LCA) methods whenever possible, to properly account for CO₂ and other GHG flows associated with each management regime.



Soil organic carbon (SOC) evolution under different management regimes, as simulated with the Roth C model. The squares show the average SOC level measured in a series of farmer's fields with different management.

Di Bella, C. *et al.*, 2015. Impact of cattle grazing on temperate coastal salt marsh soils. *Soil use and management* 31, 299-307.

Soussana, J.-F. & Lemaire, G. 2014. Coupling carbon and nitrogen cycles for environmentally sustainable intensification of grasslands and crop-livestock systems. *Agriculture, Ecosystems and Environment* 190, 9-17

Liu, D. *et al.*, 2011. Simulation of soil organic carbon dynamics under different pasture managements using the RothC carbon model. *Geoderma* 165, 69-77.

Piñeiro, G. *et al.* 2006. Potential long-term impacts of livestock introduction on carbon and nitrogen cycling in grasslands of Southern South America. *Global Change Biology* 12, 1267-1284.

RECOMMENDATION 26. Level 2 modelling should be used when regional factors for SOC change and factors affecting the change (e.g. humification coefficients) are not available, but data about plant carbon inputs and environmental parameters affecting carbon losses, that are needed to feed the model, are available.

6.2.3 Level 3. Ecosystem models

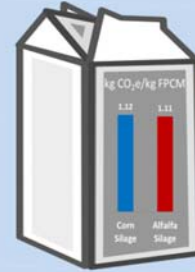
At this level, the use of dynamic, process oriented, more complex and locally calibrated SOC models is proposed. As in 'level 2' models, SOC changes in time are simulated considering the effects of climate, soil, land use and management variables on SOC dynamics. However, 'Ecosystem Models' also integrate these variables to simulate soil processes other than carbon turnover that may have a direct or indirect impact on SOC dynamics. Thus, 'Ecosystem Models', using different sub-models, simulate above and belowground plant biomass growth and carbon inputs, soil water dynamics, nutrient dynamics and their interactions. Models at this level generally simulate carbon fluxes through different organic pools in the soil: soil active carbon (plant litter or residues, microbial biomass), slow organic carbon and passive or inert carbon. Each pool has different specific decomposition rates, regulated by the pool size, soil characteristics, nutrient availability, soil temperature, and soil moisture, which in turn depend on the plant growth, soil water budget and nutrient dynamics simulated by the model.

There are a range of existing Ecosystem models for estimating SOC including: EPIC (Williams *et al.*, 1984), CENTURY (Parton, 1996), DNDC (Li, 1996), DAISY (Svendsen *et al.*, 1995) and SOCRATES (Grace *et al.*, 2006). There are also examples of 'level 2' models which have been incorporated into ecosystem or farm models, such as ICBM in HOLOS (Kröbel *et al.*, 2016), which was developed to estimate SOC changes and whole-farm greenhouse gas emissions (see case study in BOX 8). Other widespread ecosystem models like DSSAT (Jones *et al.*, 2003) and APSIM (McCown *et al.*, 1996) have also incorporated SOC subroutines. Finally, there are different examples of ecosystem simulation models, specifically oriented to livestock systems, able to simulate SOC dynamics, such as the ECOMOD Suit (including EcoMod, DairyMod, and SGS Pasture models; Johnson *et al.*, 2008) and PaSIM (Riedo *et al.*, 1998; 2000).

Tested using long-run data sets and locally calibrated, these 'ecosystem models' generally show a good ability for predicting SOC dynamics across a range of land use, soil types and climatic regions (Smith *et al.*, 1997). However, model calibration and validation of the different subroutines or parameters play a major role in influencing their predictive ability, but auxiliary data can sometimes be difficult to measure, costly, time consuming and highly variable. Models at this level have higher soil, climatic and management data requirements, which may be difficult to obtain. Moreover, carbon pools or compartments simulated by these models are usually theoretical without measurable counterparts, making it difficult to initialize the models and validate model-calculated results (Falloon and Smith, 2009). Ecosystem models offer the potential to simulate SOC stocks and SOC dynamics for a wide range of purposes, but they are not always the most appropriate tool, thereby requiring careful consideration when deciding on the approach.

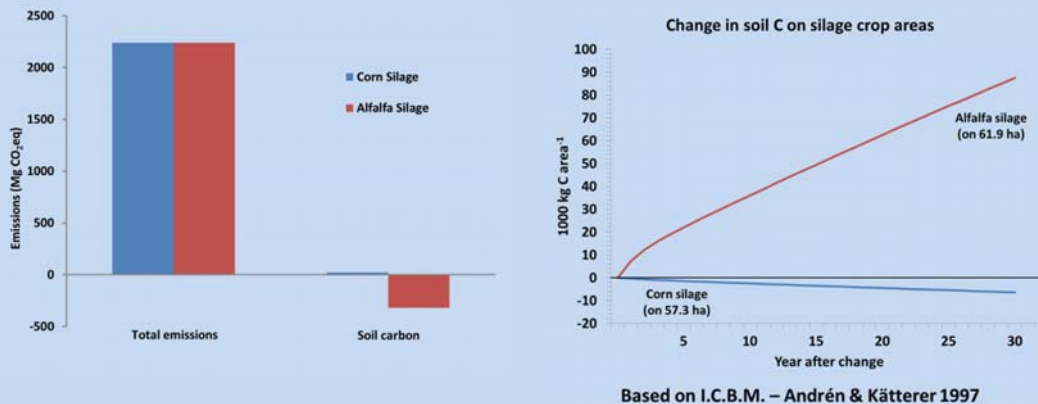
BOX 8. Including soil carbon change assessment in whole-system footprint analysis of a Canadian dairy farm

Overview: A new carbon model approach was used in a whole-farm dairy assessment to evaluate the effect of forage source on the GHG intensity of milk production (Little *et al.*, 2017). In a companion research study, feeding corn silage rather than alfalfa silage to dairy cows lowered enteric CH₄ emissions. This prompted us to investigate the net effects of a change in forage management on total GHG emissions for a 60 cow dairy farm. Holos, a whole-farm GHG model developed by Agriculture and Agri-Food Canada (<http://www.agr.gc.ca/holos-ghg>), was used to estimate net emissions of CO₂, CH₄, and N₂O (in CO₂ equivalents).



Approach: To estimate effects on soil carbon change, we used the Introductory Carbon Balance model (Andrén and Kätker, 1997) with carbon simulations beginning at equilibrium (in 1985 before Canadian cropping systems started to diversify), thus providing an estimate for the effect of the management decision.

What the study showed: The study showed that total GHG emissions were slightly greater with corn silage, and thus milk GHG intensity was slightly lower with alfalfa than with corn silage (1.11 vs. 1.12 kg CO₂e/kg fat and protein corrected milk, respectively). However, alfalfa silage required 5 ha more land. When taking the carbon modelling approach into account (comparing 4 year corn silage – 4 year mixed hay versus 4 year alfalfa silage – 1 year barley silage rotations), the corn silage based system kept losing soil carbon (~2000 kg C ha⁻¹ 30yr⁻¹), thus adding about ~23 Mg CO₂e yr⁻¹ to the >2000 Mg CO₂e yr⁻¹ whole-farm GHG emissions. The alfalfa silage system, however, stored carbon (~1.9 Mg C ha⁻¹ 30yr⁻¹), thus reducing the whole-farm GHG emissions by ~320 Mg CO₂e yr⁻¹ (16%).



This simulated carbon change will, however, diminish over time, which is why it is reported separately from the total of GHG emissions.

Andrén, O. and Kätker T. 1997. ICBM: The Introductory Carbon Balance Model for Exploration of Soil Carbon Balances. *Ecological Applications*, 7,1226-1236
 Little, S.M., Benchaar, C., Janzen, H.H., Kröbel, R., McGeough E. J., & Beauchemin, K.A. 2017. Demonstrating the effect of forage source on the carbon footprint of a Canadian dairy farm using whole-systems analysis and the Holos Model: Alfalfa silage vs. Corn silage. *Climate* 5, 87

RECOMMENDATION 27. Level 3 modelling shall be used when the objective is to integrate the feedbacks from multiple soil-plant-atmospheric processes on SOC dynamics. They should be used to investigate multiple impacts between agricultural management, crops and soils and to estimate the impacts of climate change feedbacks between crop productivity and SOC dynamics. They may be used to estimate the trade-offs between SOC change and other environmental indicators.

6.3 Deciding on the approach

In general, the choice for a specific modelling approach may depend on the purpose, available resources (time, computer capacity and data) and expertise of the agent. Most models are freely downloadable or can be obtained from the developer, usually together with useful handbooks. Thus, the model as such should not be a limiting factor. As a rule, the level of complexity of the chosen modelling approach chosen should be aligned with the overall context. For example, if SOC is only one component that needs to be considered in holistic multi-component budgets, such as whole-farm greenhouse gas budgets (see the case study of the Holos model in BOX 8) (Bolinder *et al.*, 2006), a level 3 approach might not be the most feasible solution. This is because: (i) SOC stock changes are not the major part in such a budget and thus less accurate prediction of SOC stock changes might not be critical for the overall budget and, (ii) the level of detail of input data in the overall context is most likely not good enough to achieve more realistic results using a level 3 approach as compared to lower level approaches.

Level 3 approaches have the potential to be most accurate, but for that they require detailed site-specific calibration data. In many cases, this will not be available. Therefore, often a level 2 approach may be more suitable. On the other hand, one major feature of level 3 approaches is indispensable in certain situations: the ability to simulate vegetation dynamics. In general, as a stand-alone, only level 3 approaches can simulate climate change scenarios, since not only processes in the soil are modified by climate, but also responses of the vegetation need to be considered (Parton *et al.*, 1995). For the same reason, it may make sense to use a level 3 model when trends in SOC dynamics are to be estimated without having any information on the productivity, i.e. plant-derived carbon inputs to the soils, at a specific site. Again, filling such essential data gaps with simulations should however only be considered when sufficient data (for example climate and soil data) are available to parameterize the ecosystem model. Otherwise a rough estimate of carbon inputs, i.e. derived from agricultural statistics in combination with average allocation coefficients might be just as accurate (Andr n *et al.*, 2004).

The following two tables provide guidance in deciding which modelling approach might be most suitable for a certain purpose at a certain scale. In the first table, several purposes, which might be the most relevant, are listed. For each purpose, a measure of validity of the modelling approach is assigned to each of the three levels of complexity.

In Table 4, red indicates that the respective level should not be considered at all, yellow indicates a general validity of the level with limited accuracy and potentially limited acceptance and green indicates that the level is valid and common practice for the respective purpose.

For both level 2 and level 3 approaches, it should be noted that the most commonly applied models (as listed in Table 4) were parameterized and calibrated in a temperate climate, often only at one experimental site. Thus, especially when applied in a subtropical or tropical context, the user should ensure that the model has been validated for those conditions, by searching for alternative parameter sets or recalibrating and/or validating the model. As an example, (Shirato *et al.*, 2004) changed the decomposition rate of one SOC pool of the RothC model to improve the model performance for Japanese Andosols. More detailed guidance on model calibration, validation and uncertainty, notably with the use of Monte Carlo approaches, can be found in the

appendix 2. Recently, Brilli *et al.* (2017) have reviewed the strength and weaknesses of many agro-ecosystem models and give additional guidance for deciding on the approach.

Table 4. List of modelling purposes with the validity of the three modelling approaches (levels) indicated by different colours. Red= invalid, yellow= limited accuracy and limited acceptance, green= valid and common practice.

Model purpose	Level 1	Level 2	Level 3
National accounting	Green	Green	Green
Comparing management practices	Yellow	Green	Green
Optimizing ecosystem services	Yellow	Yellow	Green
Climate change Scenarios	Red	Red	Green
Benchmarking	Green	Green	Green
Life Cycle Assessments	Yellow	Green	Green
Cross Compliance (including other GHGs)	Red	Red	Green
2-3D modelling (depth profile, lateral fluxes)	Red	Red	Yellow
Upscaling	Green	Green	Green
Commercial farm assessment	Green	Yellow	Red

RECOMMENDATION 28. The choice of modelling approach should consider the purpose and spatial scale of the study, as well as the availability of quality data to run the model. The complexity of the model should be aligned to the context, but the simplest, locally validated model is preferred. Internal calibration of a model (based on region-specific data), where model “factors” are adapted based on experiments, leads to more accurate results, regardless of the level of assessment.

Table 5 summarizes frequently-applied spatial scales and uses of well-known SOC models used for livestock systems, as well as their data requirements, as a guide for the decisions on the approach. More information on the advantages, potential uses, and disadvantages / limitations of each type of approach is mentioned in sections 6.2.1 and sections 6.2.3.

Table 5. An overview of the most common models used in livestock systems, the spatial scale at which the different approaches are usually applied and a summary of the minimum data requirements for running the models.

	Level 1 approach: Empirical models	Level 2 approach: Soil process models	Level 3 approach: Ecosystem models
Models used in livestock systems	IPCC (Tiers 1-2)	ROTH- C ICBM CANDY C-TOOL	CENTURY-DAYCENT DNDC EPIC-APEX DAISY SOCRATES APSIM

			PASIM
Frequently used spatial scale	Farm	Research plots	Research plots
	Regional	Field/Farm	Field/Farm (experimental)
	National	Regional	Landscape
	Global	National	Regional National
General data requirements	<u>Climatic Region</u> <u>Soil type</u> <u>Land use</u> (management coefficient or factors) <u>Initial SOC stock</u> (may be estimated)	<u>Climatic variables</u> (e.g. monthly precipitation, air temperature, PAN evaporation). <u>Basic Soil parameters</u> (e.g. % Clay, bulk density) <u>Initial SOC stock</u> (may be estimated) <u>Management variables</u> (e.g. carbon inputs, residue quality, soil cover, manure inputs, type of tillage).	<u>Climatic variables</u> (e.g. rainfall, max /min air temperature). <u>Soil parameters</u> (e.g. % clay, silt, sand, bulk density, pH. Some models may require water constants and CEC). <u>Initial SOC stock</u> (may be estimated), <u>Initial nitrogen or other nutrient contents</u> . <u>Management variables</u> (e.g. rotation, tillage, fertilizers, manure, irrigation, residue management / crop cover, grazing management).

6.3.1 Technical capacity and activity data

A model of a system must balance the conceptual understanding the model is intended to represent, the mathematical approach that best represents that understanding and the data available to inform and evaluate how the model functions, within the constraints of available computational capacity (Campbell and Paustian, 2015). Precision of models relies heavily on the quality and quantity of data used in executing them. Often, the datasets for running models are not collected for that specific purpose but taken from previous or ongoing studies. In many cases the format and amount of data may be inappropriate for the models. A lot of data are collected that cannot be integrated to support testing models, partly because they are collected at different times and are not available to other parties. The absence of meta-data in most datasets, make it near impossible to use beyond the project it was intended for.

Availability of data notwithstanding, there are situations where data shortages can be addressed by using proxy data variables. The technical capacity to identify and process these alternative sources of data is a frequent limitation. Modelling requires complex and often expensive software, which limits interest and capacity in conducting modelling studies. In many developing economies, power outages can make it difficult for researchers to execute modelling operations. This is further compounded by the tendency to make policy decisions that give no priority to data. This makes funding for data collection extremely difficult and hence the tendency to rely on secondary data sources.

Networks for collaborative data sharing can improve data access and, therefore, model predictions. North-South collaborative programmes between experts and young scientists can offset some of the limitations associated with inappropriate data from different studies or locations.

RECOMMENDATION 29. Significant investment should be made in improving and engaging existing modelling expertise in making decisions for validation, calibration and implementation of selected models. This includes setting up input data to reduce uncertainty for sound scientific practice for the specific application. Users should recognise that without this investment, using a model carries a large risk that project results will not be accepted upon professional review.

6.4 Implementation

6.4.1 Data availability

Several international soil and climate databases are available for model input. A few key examples are provided in Table 6. Availability of data is an important factor to consider when deciding on implementing a modelling approach for terrestrial ecosystems. For some situations, local data may be available.

Table 6. A few international soil and climate databases are available for model input.

Type of data	Source	Web link	Comments
Soil data	ISRIC – Global Soil Data Facility	https://www.soilgrids.org/#!/?layer=TAXNWRB_250m&vector=1	Web app that provide free access to soil data across borders
Soil data	The World Soil Information Service (WoSIS)	http://isric.org/explore/wosis/accusing-wosis-derived-datasets	WoSIS aims to serve the user with a selection of standardised/ harmonised soil data
		http://data.isric.org/geoserver/wosis_snapshot/wfs http://data.isric.org/geoserver/wosis_latest/wfs	Links to the data

Soil data	Harmonized World Soil Databases	http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/	A 30 arc-second raster database with over 15,000 soil mapping units combining existing regional and national updates of soil information worldwide (SOTER, ESD, Soil Map of China, WISE) with the information contained within the 1:5 000 000 scale FAO-UNESCO Soil Map of the World
Soil data	FAO: Global Soil Organic Carbon Map (GSOC)	http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data/global-soil-organic-carbon-gsoc-map/en/	
Climate data	NASA	https://catalog.data.gov/dataset?groups=climate5434&#topic=climate_navigation	A very large repository of dataset sorted by themes
Climate data	FAO CLIMWAT Databases	http://www.fao.org/land-water/databases-and-software/climwat-for-cropwat/en/	A climatic database to be used in combination with the computer program CROPWAT allowing the calculation of crop water requirements and irrigation scheduling for various crops for a range of climatological stations worldwide. CLIMWAT provides long-term monthly mean values of seven climatic parameters
Climate data	Cru (Climate Research Unit) databases	http://www.cru.uea.ac.uk/data	Gives monthly gridded data on temperature and precipitation at global scale or the period 1901-2016 (temperature since 1850) on a 0.5° * 0.5° grid basis

Guidance on the different types of data that will be needed should be considered. Some categories are listed below.

1. **Input data.** The input data, sometimes referred to as forcing data (referencing climate forcing), are the data that a model is fed with to predict an outcome.

a. **Environmental data.** The most obvious set of environmental data is meteorological forcing data, with another main one being spatially explicit soil properties. One must consider if there are sufficient meteorological data for a given model application. Registered meteorological data may be incomplete and so implementing gap-filling procedures may be necessary. The model may also be used in predictive mode, in which case simulated climate data from General

Circulation Models must be downscaled to the proper spatial and temporal resolution before being used in models (e.g. Rasse *et al.*, 2001). Therefore, environmental input data may be either directly measured, or gap-filled with simpler models, or simulated.

b. **Management Data.** In the case of managed ecosystems, the history of site management is crucial for accurate simulation of environmental responses. Are C fluxes and stocks in equilibrium with current management practices? For example, recent land-use change will have a critical impact for many years on the C dynamics of grasslands. Similarly, scenario/data on the planned future management of the grasslands shall be clearly defined for predictive simulation exercises. Management data specific to pasture include e.g., first date of grazing, grazing frequency, proportion left ungrazed at each grazing event, animal stocking rate (i.e. LSU/ha, heads/area), fertilization rate, fertilizer type (mineral vs organic) and harvest dates (if mown).

c. **Initialization data.** Dynamic mechanistic models are generally based on simulating the evolution of “pools”, e.g. C pools (SOC in each horizon, root C, above-ground biomass, etc.). In most cases, when a simulation is conducted, these pools need to be given an initial value. It is, therefore, critical that these pools are correctly quantified for initializing the simulations.

2. **Parameters** are data needed to adapt the model equations to describe the ecosystem. In practice, different grass species (i.e. fertile productive to poor unproductive, tall grass vs short grass, legume fraction, C4/C3) and cultivars grow differently under the same set of environmental conditions. A classic example of the need for parameterization of model equations is the photosynthesis model of Farquhar *et al.* (1980). This model, and its later refinements (de Pury and Farquhar, 1997), describe photosynthetic CO₂ uptake as a function of a mechanistic understanding of photosynthesis at the molecular level as it happens in the leaf. This model, quoted more than 4300 times as of 2017, is the CO₂ uptake engine of numerous ecosystem models. However, specific parameters are needed for individual species and possibly for local populations. For example, Rasse *et al.* (2003) modelling the effects of elevated CO₂ on wetland vegetation in Maryland needed 19 parameters for parameterizing the photosynthesis model, out of which 7 were from general literature and 12 specifically measured at the site. In practice, the question is generally to assess if the predefined parameters in the model are sufficient to generate accurate simulations of plant and soil C pools. If not, specific model parameters might need to be measured, or more generally, fitted with existing calibration data.

3. **Test data** are the data being predicted by the model, in our case SOC stock and changes. Test data may be divided into calibration data that have been used in the parameter estimation and validation data that are independent and different from calibration data. Both data are of the same type but may be for different sites or periods. To sufficiently calibrate a model, it is important that the calibration data be chosen carefully to cover the range of conditions/stresses over which the model will be used, for instance the range of seasonal precipitation or temperature. When satisfactory calibration runs are obtained, the model needs to be validated on an independent dataset.

Availability of any of these three main categories of data may be the limiting element in applying a given modelling approach. Application of a full ecosystem model for pasture with the aim of modelling soil C requires an interdisciplinary approach where data from different sources are used. In many instances, meteorological data and soil-property maps may be available, but parameters may not be available for plant growth and biomass production for local varieties of the pasture species. A minimum amount of soil carbon data are also necessary to calibrate and

validate the model before it can be safely used to extrapolate the effect of pasture management on soil carbon content in the farm / region / country of interest.

RECOMMENDATION 30. Data availability for both model input parameters and to test model outputs shall be investigated before choosing a modelling approach.

6.4.2 Initialization of the model

6.4.2.1 Initialisation challenges and approaches

Initialisation refers to setting the initial SOC condition at the start of the period over which SOC stocks will be estimated for level 2 and 3 models. The goal of initialisation is to have the appropriate SOC amount at the start of the simulation so that further simulated results are a realistic estimate of SOC stock in response to the input vegetation characteristics, land management and weather.

When the initial SOC amount is known, either from measurement or from assumptions based on soil survey or other soil information, model initialisation involves having the model start with the known initial SOC. For common models, one does not know the exact distribution of initial SOC among the different pools in the model. If the pools are not in coherent proportion with past SOC dynamics, there will be rapid changes to SOC while the pools adjust to a coherent proportion. To avoid this artefact of initialization, the standard procedure is to have a spin-up (or warm-up) period of model operation so the pools are in approximate equilibrium with the initial conditions regarding vegetation and land management. The length of the spin-up period needed to approach a steady state pool distribution varies depending on the model but typically is from 10 to 100s of simulated years. If the SOC after the spin-up period is substantially different from the known initial SOC, then some calibration is warranted. Often, the C input is adjusted so that the modelled initial SOC matches known SOC. Available information of C input from the vegetation from similar situations is useful to help set the limits of possible C inputs. If adjusting C input is not successful, the next option is to calibrate the fundamental model parameters affecting C dynamics so that modelled initial SOC equals known SOC. Calibration of C-dynamics parameters is more challenging. If the model C-parameters are changed, these new values shall be used for further modelling from that initial SOC and would warrant further validation.

If the initial SOC is not known, the only option is to have the model estimate the initial SOC. In this case, the spin-up period will typically be 1000s of years. The estimated C input will be critical to determining the modelled SOC amount. Therefore, available information of C input from the vegetation from similar situations is useful to help either set the C input (level 2 model) or adjust the vegetation growth parameters to match C input for the modelled situation (level 3 model).

An assumption of the above initialization schemes is that the baseline condition is at or approaching steady state. However, the soil may not be near steady state in the baseline condition (Wutzler and Reichstein, 2007). Basso *et al.* (2011) advocated using C inputs and land management to follow known land use and management history. These may be most practically estimated from general historical information and expert opinion (Ogle *et al.*, 2007). Knowledge of distant history is likely limited, but it is the more recent history that is of greater importance to pool sizes. Therefore, an option is to initialise with a multi-thousand-year equilibrium model spin-up based on estimated historic land use conditions to the point in time when there is sufficient knowledge of land use change and management history to include in the later period of the spin-up modelling until reaching the desired baseline year.

Finally, in some cases it can make sense to initialize the model with measured SOC pools as obtained by means of SOC fractionation (Wiesmeier *et al.*, 2016). This has the advantage, that the steady-state assumption is not necessary, but has the disadvantages that i) obtaining the initial pool distribution is very elaborate and can only be performed for a limited number of samples and ii) a direct ‘functional’ link between measured and modelled does not exist for many models (Zimmermann *et al.*, 2007).

Further details of approaches to model initialization are given in Appendix One.

RECOMMENDATION 31. The amount and type of SOC shall be used to initialise the model to produce reliable estimates of SOC amount over the simulation period. Good estimates of the SOC and C input from the vegetation and land use and conditions for many decades prior to the simulation period should be used to improve the ability to accurately predict the initial SOC, by calibrating model parameters where needed.

6.4.3 Validation of results

Model validation is the process of determining the degree to which a simulation model is capable of accurately representing the real world for a set of model applications. Thus, the term validation is used here for the comparison of model output with measurements. A valid model is one that generates predictions that are consistent with real-world observations (Oreskes *et al.* 1994) or lies within acceptable limits or errors (Refsgaard *et al.*, 2005). Validation of models is a continuous process in which the model is checked in different conditions, with newly developed knowledge and needs. Bellocchi *et al.* (2010) identified the following issues to be considered when performing the model validation:

1. **Validation purpose:** there may be different purposes for model validation. These could include the assessment of the accuracy of the estimates with respect to the reality, how confident we can be in model results, or the behaviour of the model in specific applications (e.g. how the model responds if we change conditions of simulation).

2. **Model predictions:** the use of models for prediction involves a series of problems for validation, as data required to quantify the accuracy of the estimates do not yet exist. Predictions become increasingly uncertain as we look at a time horizon in the distant future. Nonetheless, predictive models can be validated if they explain past events (ex-post validation) (Bellocchi *et al.*, 2010). Validation assumes a fundamental importance in the definition of the limits and conditions in which the model can be confidently applied.

3. **Model complexity:** the level of complexity of the models influences the type of assessment that can be carried out. Often the comparison of the model with the measured data only applies to certain output (e.g., yield or SOC). However, when the complexity of the model is high, and it consists of many sub-models, each of which simulates a part of the process, the assessment should take account of this and the individual sub-models should be validated. The other way to deal with this is to give models a penalty for each variable (e.g., Akaike information criterion). Validating all sub-models could be very onerous and is not recommended.

4. **Data accuracy and quality:** accurate data is a fundamental requirement in modelling. In fact, the confidence in simulation results depends not only on the accuracy with which the algorithms of the model are able to predict the behaviour of the studied process, but also on the quality of both the input data and the data used for validation of outputs. Random errors arise from data sampling, i.e. data may not adequately represent temporal and spatial variability, and sample handling. Systematic errors may be due to incorrect calibration of instruments used to collect

input data, inadequate sampling design (i.e. lack of representativeness of data) or using proximal data. All these factors shall be considered in the process of validation.

5. **Robustness of model results:** the capability of a model to preserve its accuracy under different experimental conditions.

Common measures of model performance used for validation include the coefficient of determination (R^2), the Nash-Sutcliffe model efficiency (ME) (Nash and Sutcliffe, 1970), the d -index of agreement (Willmott, 1982), average relative error fraction (ARE), and the root mean square error ($RMSE$) determined using Equations 23-27:

Equation 22:

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O}) \cdot (P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (P_i - \bar{P})^2 \cdot \sum_{i=1}^n (O_i - \bar{O})^2}} \right)^2$$

Equation 23:

$$ME = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

Equation 24:

$$d = \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (|P_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

Equation 25:

$$ARE = \frac{\sum_{i=1}^n (P_i - O_i)}{n \cdot \bar{O}}$$

Equation 26:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - P_i)^2}{n}}$$

Where:

P_j is the predicted (modelled) value,

O_j is the observed value,

n is the number of measured values,

\bar{O} is the average of the observed values, and

\bar{P} is the average of the predicted values.

Frequently, several measures are considered together for validation:

- The R^2 is a representation of the success of predicting the dependent variable from the independent variables using regression analysis (Nagelkerke, 1991).
- The ME has a maximum value of one (perfect agreement), and a value below zero indicates that the model does not explain any part of the initial variance.
- The d -index is a dimensionless measure between 0 and 1 and with the following recommended criteria: $d \geq 0.9$ indicates there is “very good” agreement; $0.8 \leq d < 0.9$ is considered as “good” agreement; $0.7 \leq d < 0.8$ equates to “moderate” agreement; and, $d < 0.7$ suggests there is “poor” agreement between measured and predicted values (Willmott and Matsuura, 2005).
- $ARE\%$ can be used to determine whether the model overestimates or underestimates measured values (Yang *et al.*, 2014).
- The $RMSE$ is useful to compare the divergence between model-produced estimates with independent, reliable observations and is one of the most widely reported error measures in environmental literature (Willmott and Matsuura, 2005). The $RMSE$, expressed as percentage of the mean of the observed values, should be within the 95% confidence interval from the measurement. If the simulation is within this interval, the accuracy of the model can be considered good. If the $RMSE\%$ is outside the 95% confidence interval, the model should be improved.

The model performance for the data used to calibrate model parameters or inputs (see section 6.5.3) is invariably affected by adjustment of the parameter values to account for the idiosyncrasies of specific site characteristics, as well as those of the measured input and output data. Therefore, the model performance against the calibration data is considered biased positively. To protect against the potential bias of better model performance for observations used for calibration observations, it is common practice to use only part of the available data for calibration. The remainder of the data is used for validation only, to assess quality of the model performance and to estimate its uncertainty. Where there is limited observed data (such as when data from only one site are available), then the observed data may be divided into one period for calibration and another period for validation. Furthermore, uncertainties of the measured values used for validation are often neglected and modelled values are validated against measured means. Guest *et al.* 2017 thus proposed to account for measurement uncertainty when evaluating model performance.

RECOMMENDATION 32. Before any other evaluation, preliminary model results should be graphed to see if they look approximately similar to the measured values. Once the model output appears to give a good simulation of the measured data, a full evaluation should be performed.

6.5 Uncertainty and sensitivity analysis

6.5.1 Sensitivity and uncertainty - Introduction

A model is an abstraction of the real world. Therefore, imprecision in input and within the model itself leads to estimation uncertainty. There are two main sources of uncertainty: uncertainty of modelled system inputs and model uncertainty.

Uncertainty of modelled system inputs can be quantified as the deviation between a “true” input value (that we don’t usually know with certainty) and the value used for input. This uncertainty

includes measurement error and natural variability. Due to natural variability we have imprecise knowledge of the value of natural inputs (weather, plant growth, animal behaviour, etc.) throughout the physical and time dimensions of the modelled system. Consequently, the input data has inevitable uncertainty. Our knowledge comes from measurements but there are errors in those measurements. These errors may not always be random, so that our knowledge from measurements can be biased. Similarly, we have imperfect knowledge of the initial system state (SOC, vegetation, animals, etc.) that is an important input to model the real system.

Model uncertainty can be quantified as the deviation between “true” output value (that we don’t usually know with certainty) and the estimated output value from the model with all inputs without error. This uncertainty arises from model structural uncertainty and from model parameter value uncertainty. Structural uncertainty is the imperfect knowledge that the real system is adequately represented in the model conceptualization. Parameter value uncertainty is the imprecise knowledge of the correct value for the parameters that determine that model estimations. Observed system behaviour, such as SOC stocks over time, that is used for model parameterization also has an uncertainty. Observed system outputs are subject to both measurement error and natural variability. Output uncertainty contributes to the imprecision in our knowledge of model performance and so is a component of model uncertainty (Ogle *et al.*, 2010).

Structural uncertainty is the most troubling uncertainty because, if the processes are not correctly represented, reducing the uncertainty of inputs will not substantively improve the estimation. Parameter calibration alone cannot be expected to overcome incorrect process representations for all potential model applications. In practice, there is no way to know exactly the amount of structural uncertainty. The model computer code can be verified to determine that it truthfully implements the model as conceptualized, but that does not verify the truthfulness of the conceptualization itself (Refsgaard and Henriksen, 2004). The conceptualization, as represented by the parameterized model, can be validated to the extent that it has been substantiated that the “model, within its domain of applicability, possesses a satisfactory range of accuracy consistent with the intended application of the model” (Refsgaard and Henriksen, 2004). Therefore, the decision as to whether a model has been successfully validated is inherently subjective. Further, there is no universal validation for all potential model applications, only for specific domains. The degree of confidence in the credibility of the model increases with the number of successful site validations that meet or exceed the desired performance criteria for the desired domain of application (Hansen *et al.*, 2012). Therefore, all other considerations equal, it is best to use the model that has the most successful site validations for conditions similar to the intended domain of model application.

Model prediction uncertainty includes all sources of uncertainty that affect predictions, including model structural uncertainty and input data uncertainties, including those of initial conditions.

A particular concern for applying SOC models to grazing systems is that our estimates of C inputs are typically uncertain. Using the RothC model, it has recently been demonstrated for grasslands that plant-derived carbon input is the most uncertain parameter and the parameter to which the model is most sensitive (Poeplau, 2016). The major part of plant-derived carbon inputs in grassland systems is derived from roots. Due to difficulties in determining this parameter directly, it has to be estimated, which is usually done by literature-derived, above-ground yield-based allocation coefficients (Bolinder *et al.*, 2007). However, yield or aboveground net primary production is a typically highly uncertain parameter in grassland ecosystems. In a global modelling study, the performance of models was tested for simulating NPP of grasslands and it was found that the model ensemble was highly uncertain, in part due to uncertainty of observations (Ehrhardt *et al.*, 2018) but also due to the difficulty in characterizing diverse grassland systems. In contrast to croplands, farmers are usually not specifically interested in grassland yields. Furthermore, the coefficients to estimate belowground carbon allocation in relation to

aboveground carbon allocation can strongly vary and are thus highly uncertain. Finally, the proportion of belowground biomass that turns over annually, as well as the amount of carbon that is released by roots as exudates, are highly uncertain. The grazing management effects are also not always easy to quantify but may stimulate or damage plant growth, and/or change the species composition of the pasture. The grazing regime itself can also change the amount of NPP and its partitioning and this effect is hard to include in C input estimates for level 2 models or for vegetation growth characteristics for level 3 models. Thus, the probability of estimating correct C inputs is very low, even if data for aboveground NPP is present. In turn, carbon inputs do strongly determine simulated trends in SOC stocks. Calibration of C inputs during initialization, so that a known amount of initial SOC is modelled may be a useful means to improve estimates of C input (see Appendix 1), or at least can improve the estimated amount of C input relative to the modelled C losses from decomposition. An important consequence of the relatively poorer information on C input for grazing systems than cropping systems is that SOC models well validated for modelling cropping systems cannot be assumed to be valid for modelling nearby grazing systems.

Figure 11 depicts uncertainty of, and model sensitivity to, basic parameters needed to run most SOC turnover models. An intermediate spatial scale such as one or several farms was chosen, for which initial SOC stocks have been determined at representative points. It indicates, that not all parameters that are highly uncertain necessarily have a high potential to cause misfits. The different colours were chosen to illustrate the relevance of the combination of uncertainty and sensitivity for the model result with red being very relevant, yellow being intermediately relevant and green being less relevant. An example might be the timing of carbon input. Most models need this information, while especially for livestock systems it might not be available (high uncertainty). However, the long-term trend in SOC stocks (>1 year) is not influenced by how the total carbon input is distributed between months. Therefore, this highly uncertain parameter is not very relevant for the model result. The opposite example is climate data. Depending on the area, the nearest weather station might be within a few kilometres, so data that come close to the actual site conditions can be obtained. The uncertainty of climate data is thus relatively small, while the model sensitivity to climate parameters is very high. Together with carbon inputs and climate data, SOC models are most sensitive to initial SOC stocks. In the example, the latter have been measured as a baseline. If this is not the case, this parameter would be shifted into the “red area”.

Technical guidance on advanced Monte Carlo methods to estimate the uncertainty of model predictions can be found in Appendix two.

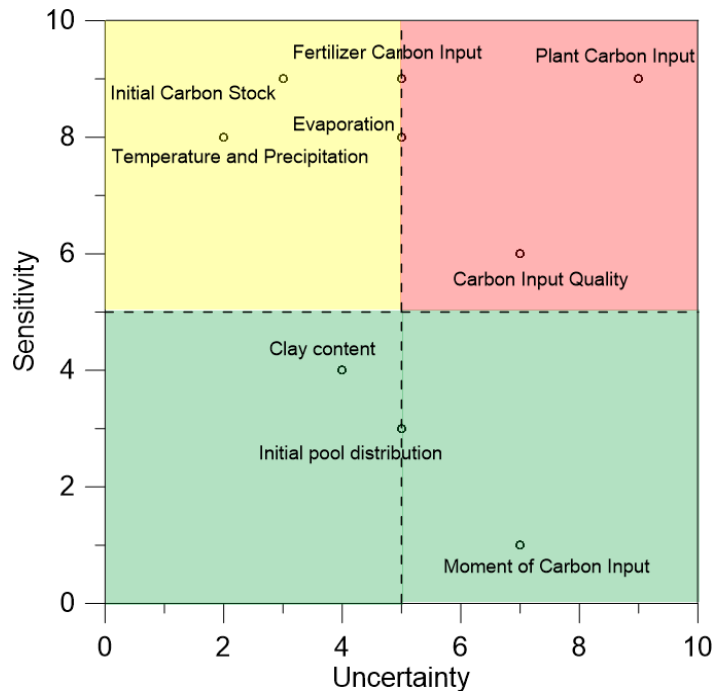


Figure 11. Scatter plot showing uncertainty of, and model sensitivity to, basic parameters needed to run most soil organic carbon turnover models. In the scale from one to ten, one indicates very low, ten indicates very high. Parameters in the green fields are thereby most often less problematic, while parameters in the red area are often problematic due to high uncertainty and high model sensitivity. Model sensitivity estimation is based on the RothC model (modified from Poeplau, 2016).

RECOMMENDATION 33. To minimize model uncertainty, the model shall be validated for the conditions (e.g.: country or climatic zone) in which it will be applied when possible. If a model is not validated for the region of interest, the model should be calibrated using local time series of SOC stocks. Thereby, only a limited number of parameters should be modified and only those that do not have many interdependencies with other parameters. Guidance on model calibration and validation and advanced methods of sensitivity and uncertainty analysis can be found in the appendix of this document. Because soil carbon turnover models are most sensitive to initial SOC stocks and carbon inputs, a measured baseline of SOC stock shall be used whenever available, and C inputs should be estimated as accurately as possible.

6.5.2 Sensitivity analysis

Sensitivity analysis is usually done initially using the one-at-a-time (OAT) approach where only one variable is changed and all others held constant at their assumed most representative value (Wang *et al.*, 2016). Sensitivity analysis by OAT is useful to identify the subset of most influential variables and parameters for further analysis.

Sensitivity analysis requires that model output is produced over the range of the variation in input or parameters. If the variation is overestimated, the sensitivity will also typically be overestimated while underestimation of the range underestimates the sensitivity. Therefore, care is needed in selecting the range. For input variables that are widely measured, such as meteorological variables, there is often a good understanding of the expected variation. Consequently, the sensitivity analysis forces the model user to describe the uncertainty of those variables. The more

uncertain variables and parameters have a higher relative variation, though that does not necessarily infer that the model is most sensitive to more uncertain variables and parameters. For example, processes that are supply limited, such as total annual decomposition of very labile organic matter, may have an uncertain rate constant over short periods but the annual C stock estimate may be quite insensitive to that rate constant. The range of values for many model parameters is often poorly understood because they are not easily measured. Inspection of those parameter values that were used in other studies with the model is a good starting point to estimate parameter uncertainty. The population of expected values can be estimated from the parameter values used across a range of successful site validations combined with expert knowledge. Soliciting advice for experienced users of the model can also provide suggestions for the reasonable range of these target parameters values. This range is also useful to set up the range over which to calibrate a parameter.

6.5.3 Calibration

Some of the uncertainty of an uncalibrated model can be reduced by calibrating influential model parameters. Frequently, a limited number of parameters are manually calibrated to improve model fit, based on criteria such as minimizing root mean square error or maximizing modelling efficiency. Judgement is required in deciding which parameters to calibrate and order of calibration. For established models, there is invariably experience regarding which of the sensitive parameters are most effective to calibrate to improve model performance. Generally, it is sound practice to calibrate the parameters that affect independent responses before calibrating those for responses that have many interdependencies. For example, vegetation growth is less dependent on total SOC than total SOC is on vegetation growth, so it is recommended to calibrate the vegetation growth parameters before SOC parameters.

6.5.4 Uncertainty estimates from calibration and validation

As described above (Section 6.4.3) model validation compares model estimates with observation and, thereby, provides an important assessment of inaccuracy or uncertainty of the model. Inspection of the fit between estimates and observations provides important insight into model structural problems such as greater apparent problems simulating some conditions than others. If there appear to be serious deficiencies in model performance such as grossly over- or underestimating effects that cannot be rectified with calibrated parameters, the model user needs to decide if the model, as it will be applied to the modelling domain, is appropriate (i.e. uncertainty is acceptable) for using at all.

The calibration procedure provides validation for the observed situations used for calibration. Since the uncertainty from input conditions and the parameters optimize model performance for those conditions, the deviation between predictions and observations provides a useful estimate of model uncertainty. If the model is to be only applied to a prediction domain that closely adheres to conditions used for parameter calibration (e.g. using a model to estimate a SOC value within a time-series of measured SOC values for single paddock), the model performance against the data used for calibration may be considered a valid estimate of prediction uncertainty.

RECOMMENDATION 34. A model sensitivity analysis and uncertainty assessment should be conducted to inform decisions about the suitability of the model, and provide valuable information on which model inputs and processes are most important.

6.5.5 Model prediction uncertainty

In using models to estimate SOC for life cycle assessment purposes, it is the model prediction uncertainty over the application domain that is of greatest importance. This requires validation using the types of input data and initialization data derived from the sources and methods that will be used for prediction. In prediction mode, the model inputs may not be measured on site and will be estimated. For example, application does not rely on measured data at the site and could, for example, have C inputs estimated from general empirical relationships, soils data derived from coarse-resolution soil maps, and meteorological data extracted from a location nearby but not at the site to be modelled.

Validation comparing observations for an actual site but using inputs and initial values that would be used if there had been no observation provides a fairer assessment of model prediction uncertainty than validation using site measurements for inputs and initial values.

Several approaches can be used to estimate prediction uncertainty, including Monte Carlo methods. Further details are given in Appendix 2.

6.5.6 General guidance

The uncertainty of SOC models for grazed grassland will likely be large, probably larger than for models applied to cropland (Ehrhardt *et al.*, 2018). Therefore, it is important to carefully estimate the prediction uncertainty to determine if the model is appropriate for the use and, if appropriate, then to properly interpret model results. The recommended steps for sensitivity and uncertainty analysis are:

- Conduct a sensitivity of model input variables, initial variable values, and parameters to identify the most influential variables and parameters.
- Calibrate influential model parameters, identified from sensitivity analysis (and expert model users when possible) for the model application domain
- Validate the calibrated model for the intended application domain to gain understanding of uncertainty including evidence of structural problems. Unless the model application domain coincides exactly with the calibration data, the validation should not be based on solely the calibration dataset.
- Estimate the model prediction uncertainty for the method and data that will be used for its application domain.

In BOX 9 a case study that combines measurements and modelling is shown.

BOX 9. Effects of improved management on SOC stocks using a combined measurement and modelling approach

Overview: The study site was a 250 ha self-replacing sheep farming enterprise in south-eastern Australia (34_570S, 149_100E) with an average annual rainfall of 625 mm. The farm specialises in ultrafine Merino wool, with supplementary income from grazing beef cattle and farm forestry (Ive and Ive, 2007). Since settlement in 1860, loss of soil organic carbon and land degradation has occurred due to unsuitable management practices. Clearing of the original *Eucalyptus spp.* woodlands and over-grazing led to erosion, dryland salinity with poor pasture growth and plant survival until 1980 when new owners started regenerative management practices. This case study discusses the improvement in farm carbon balance for the period 1980 to 2012.

Soil carbon stock change approach: On-farm soil C measurements were used in combination with modelling with the Roth-C based FullCAM model used in the Australian National Greenhouse Gas Inventory to determine soil organic carbon (SOC) stocks and stock change. The combined approach gave a more accurate site-specific 1980 baseline to assess SOC stock change under management change. Measurements under pasture areas for 0 – 30 cm depth gave SOC of 0.8% in 1980 and 1.4% in 2011 and these measured values were used to tune the model. Although the approach in this study did not allow full statistical analysis, insights of the management impacts were gained from comparisons between the long-term average model output for the 50-year period from 1963 to 2012 and the period from 1980 to 2012 since commencement of improved practices. SOC stocks in a dry year (2006) and a high rainfall year (2012) were also compared to examine climate impacts.

What the case study showed: The model indicated that between 1980 and 2012 there was a total increase in SOC stocks (0 – 30 cm) equivalent to sequestration of 11800 Mg CO₂e across the farm. Over the same period re-establishment of trees on previously cleared land sequestered an additional 19300 Mg CO₂e. The research estimated that increase in soil carbon stocks alone was sufficient to offset all greenhouse gas emissions from livestock and farm activities on the case study farm.



Time sequence images showing the impact of seasonal conditions (e.g. dry in 2006; wet in 2007) and improved management on the case study farm. SOC stocks showed an overall farm average increase from 0.8% in 1980 to 1.4% in 2011.

Summary: This case study used long-term modelling and soil carbon measurements at two times more than 30 years apart, to show that substantial gains can be made in SOC stocks where initial soil carbon is depleted due to degradation and topsoil erosion. Practices to improve land condition included introduction of perennial pastures, strategic tree plantings and managing stocking rate, increased SOC stocks under pastures and enhanced livestock productivity.

Ive, J. & Ive, R. 2007. Achieving production and environmental benefits in a challenging landscape. In: Proceedings of the 22nd annual conference of the Grassland Society of NSW, Queanbeyan, NSW'. (Eds D Garden, H Dove, T Bolger) pp. 26–33.

7. SPATIAL INTERPRETATION AND UPSCALING OF SOC

7.1 Introduction

Spatial analysis is the process by which we turn raw data into useful information. Spatial analysis deals with two different types of information: one concerns the attribute of the spatial object (e.g. SOC content) and the other concerns location information (position on map or geographic coordinates). The spatial objects concerned in most analysis are polygons (i.e. zones, statistical census areas) or sampling points. Spatial analysis deals with the degree to which attributes are similar to those located nearby. If objects similar in location are also similar in attributes, then there is a spatial autocorrelation or association (spatial patterns due to cluster of high and low values), whilst the opposite situation indicates that there is not a pattern linked with the position.

Soil properties are characterized by strong spatial heterogeneity and spatial dependence, at a great range of scales. Emergence of Geographic Information Systems (GIS) and geostatistical modelling approaches (Burgess and Webster, 1980; Chiles and Delfiner, 1999; López-Granados *et al.*, 2005) has improved our predictive capacity for soil properties over larger scales, especially the continuous variables such as SOC. To understand how SOC stocks and environmental factors are connected, the characterization of their spatial variability is essential. Any sampling in a finite number of locations will inevitably give an incomplete description of natural variations. Thus, to produce a continuous map of soil properties we need to use an interpolation method to estimate them in un-sampled points, that is, a model of spatial dependence of soil data is necessary (Goovaerts, 1998).

The concept of scale - or resolution, in case of digital mapping - is central to geography; some mappers rely on data obtained from satellites, yet others depend on data regarding soil particles obtained through electronic microscopes. Hence, the need to address spatial problems from multiple scales and resolutions is always of primary importance. This variation in scales can be regarded both as a strength and weakness of the spatialization procedure. Analyzing spatial phenomena using a range of scales offers a special view and methodology enhancing mapping's strength. To the contrary, the massive amount of data needed for analysis of spatial phenomena at various scales, coupled with the possibility of applying an inappropriate methodology, often leads to a meaningless study (Lam and Quattrochi, 1992). With appropriate methodology and sufficient attention to the problem of scale, the spatial perspective derived from analyses using different scales can contribute in many ways to an understanding of various spatial phenomena, such as SOC content.

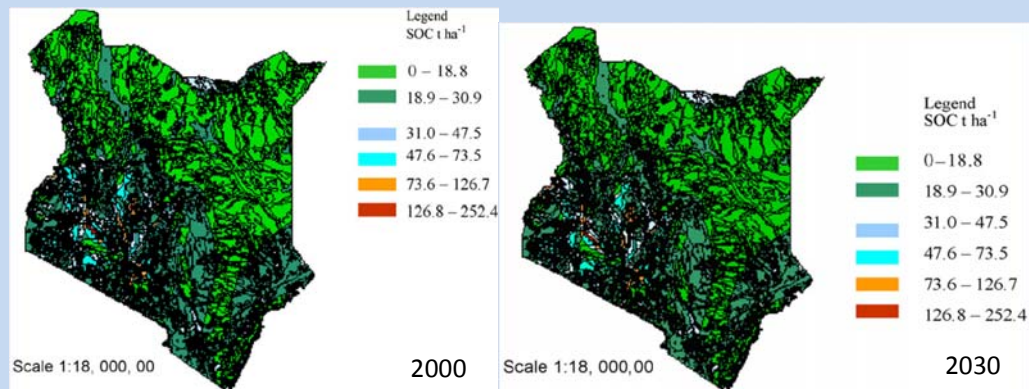
With regards to SOC, estimates of stocks and their variability at different spatial scales are essential to identify the potential C sink capacity of different land uses and management and the more promising sequestration strategies. Some modelling approaches such as CENTURY and RothC can provide relatively good estimates of soil properties into the landscape. However, the accuracy and reliability of these estimates can be significantly improved by integrating spatial information in the modelling. Therefore, coupling conventional C models with geospatial information is a powerful approach for upscaling SOC measurements. In BOX 10 a case study that illustrates this modelling approach is shown.

BOX 10. Application of Carbon Models to estimate SOC changes in grazing lands in Kenya

Overview: Kamoni *et al.* (2007) used the Global Environment Facility Soil Organic Carbon (GEFSOC) System, which links the CENTURY and the RothC models to a GIS to estimate national C stock changes for Kenya. They simulated grasslands, savannas, and shrub/grasslands as tropical grassland dominated by C₄ grasses. The aim of the study was to provide estimates of changes in SOC to contribute to the national GHG emissions accounting.

Approach: Estimates of SOC stocks and changes were made for grasslands, savannas, and shrub/grasslands in Kenya using the GEFSOC Modelling System. The tool couples Century general ecosystem model, RothC soil C decomposition model and the IPCC method for assessing SOC at regional scales. Datasets of measured SOC were used to evaluate and refine the simulation capacity of Roth-C and CENTURY models. Data from these models were coupled to a soils, climate and land-use GIS data at national and sub national level. The GIS interpolated the data over un-sampled locations and developed SOC coverage needed to run the GEFSOC Modelling System.

What the study showed: The study estimated a decline in SOC stocks for Kenya 1,415 Tg in 2000 to 1,311 Tg in 2030, suggesting a predicted national loss of 104 Tg C. When the estimates were made using each of the models separately, comparable results were obtained.



SOC stocks changes for Kenya between 2000-2030, estimated using Century output from the GEFSOC Modelling System. Adapted from Kamoni, et al., 2007.

Summary: The study shows how large-scale (national and even regional) SOC changes can be estimated to support GHG inventory. Using this approach can significantly reduce sampling efforts but needs to be supported with periodic field sampling to validate the results.

Kamoni, P.T. *et al.* 2007. Predicted soil organic carbon stocks and changes in Kenya between 1990 and 2030. *Agriculture, Ecosystems and Environment* 122, 105-113.

7.2 Sampling for spatial interpolation

Inevitably, sampling will always be partial and will thus lead to an imperfect knowledge of reality; furthermore, any sampling is subject to different sources of error (sample collecting, measurement, recording, transfer function, modelling, spatialization and so on), which globally

produce a sampling error. The complexity and costs of most sampling projects require the definition of an optimum sampling design to obtain maximum information at a given cost.

In any realistic sampling design, the amount of information required, the type of data to be collected and the criterion of optimization to be used are fundamental parameters which depend on several factors, but above all on the specific objectives of the problem at hand. The location of sampling points is critical for subsequent analysis and several approaches can be used as shown in Figure 12. In principle, sampling for spatial analysis should follow the guidelines provided in Section 2.2. Ideally, for interpolation purposes, samples should be located evenly over the target area. A completely regular sampling network can be biased, however, if it coincides in frequency with a regular pattern in the landscape (e.g. regularly spaced drains). The drawbacks of completely random location of sample points are the large sampling effort and the likelihood of having uneven distribution of points unless a very large number of samples can be collected, which is usually limited by associated costs. Cluster (or nested) sampling can be used to examine spatial variation at several different scales. There is no general approach to sampling; therefore, it is important to clearly define the aims, the support and the resolution needed before sampling. If geostatistics are used as an interpolation method, sampling is a crucial topic for an accurate modelling.

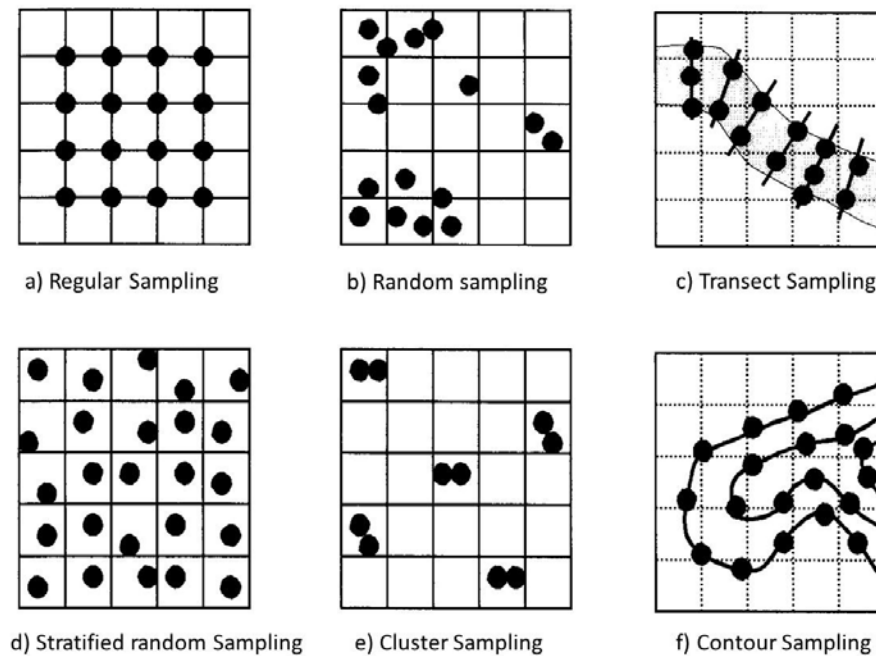


Figure 12. Different kinds of sampling nets used to collect spatial data from point locations. (Burrough and McDonnell, 1998; page 101)

RECOMMENDATION 35. There is no universally best sampling design approach. For geostatistical analyses, collecting samples on a regular grid allows directional variograms over several different directions to be calculated easily, mostly along the axes of the grid (for regular grids, where the lag distances and directions are known and the number of pairs per lag interval is a function of grid spacing). A *rule of thumb* is not to estimate semivariances for lags greater than half the maximum distance of the sampled area. The main disadvantage of regular grids is that resolution is limited by grid spacing. We strongly recommend adding more closely spaced pairs of points at

some randomly selected grid nodes, so that the form of the variogram at the most critical short distances and the nugget variance can both be better estimated.

7.3 Interpolating methods for soil organic carbon predictions

There is often a need to map soil properties at a location where the soil has not been sampled and the property measured. Interpolation involves either inference from an assumed similarity, given the biophysical environment (based on Boolean logic), or on mathematical functions (e.g. arithmetic, logarithmic, trigonometric, power functions, etc.). Estimation requires the application of certain models to the real world. There is a huge variety of models that can be grouped into two main sectors:

- Mechanistic models, physically based and deterministic in prediction;
- Statistical models, recognizing the intrinsic uncertainty associated with estimation.

Conventional soil mapping was originally developed as a means of spatially characterizing soil properties from discrete soil classes. Using these classes, average values of soil properties are applied spatially and as a result abrupt changes in properties occur at the soil class boundary (Watt and Palmer, 2012). This method has several weaknesses that often include poor correlation between soil properties and the mapped classes, the misrepresentation of gradual change by abrupt boundaries, and the treatment of within-class variation as spatially uncorrelated (Campbell *et al.*, 1989; Nortcliff, 1978). Furthermore, these techniques are also time-consuming and generally do not provide complete and updated information.

Interpolation involves: (i) Defining a search area or neighbourhood around a point, (ii) defining the point to be predicted, (iii) finding the data points within this neighbourhood, (iv) choosing a mathematical function to represent the variation over this limited number of points and, (v) evaluating the value for the point on a regular grid. Approaches for estimating soil properties in non-sampled locations using mathematical functions include the following (Figure 13):

- *Neighbourhood operations*: use data from surrounding locations to determine output value at corresponding location;
- *Zonal operations*: use a selection of one or more nearby data points
- *Global operations*: use all data points over the whole area.



Figure 13. Different approaches for estimating soil properties at non-sampled locations.

With global interpolation, all available data are used to provide predictions for the whole area of interest. Global interpolators are not usually used for direct interpolation, but for examining and possibly removing the effects of large-scale (global) variations, caused by major trends or the presence of various classes of land that may indicate areas that have different average values. Once the global effects have been taken care of, the residuals from the global variation can be interpolated locally. These global interpolation techniques are described below.

A relatively simple global approach is trend surface analysis, whereby polynomial and sometimes trigonometric functions are fitted by least squares regression on the spatial coordinates used as predictors. It is commonly used as a preliminary step in the study of data structure before the application of advanced mathematical interpolation techniques for de-trending data and determining the stochastic residuals. This simple approach has several shortcomings:

- Distortion of the results owing to occurrence of data clusters and or outliers;
- Instability caused by outliers or observational errors or when enough terms are included in the function to retain local detail;
- Loss of detail because of powerful smoothing;
- Variation of one part of the region affecting the fit of the surface everywhere;
- Lack of physical meaning of the regression coefficients.

Among the local techniques, the simplest approach uses only one data point per interpolation point, which is considered as representative for an area delineated by a polygon. The assumption in such a method is that the environmental properties within the polygon are homogeneous and the values change abruptly at the polygon boundaries. If the variation of the data values is gradual, the results may be plausible. However, the only advantage of this method is that the amount of calculation is quite small (Castrignanò and Lopez, 2004).

A quite simple method is the drawing of Thiessen polygons, i.e. each interpolation point assumes the value of the nearest data point. If gradients of spatial variation are smooth and the data points are not too far apart, the method may be plausible enough. Nevertheless, when the data points are situated in different zones which differ due to their elevation, position to mountain ranges or to coast lines, type of soil and vegetation, climate and so on, this method creates fictitious, abrupt discontinuities.

An alternative to Thiessen polygons is location-specifying zoning, which is delineating a zone around each data point. This delineation is often drawn by eyeballing and is based on expert knowledge of the relationship between geography and landscape properties. Owing to its intuitive character, it is quite subjective and not reproducible, unless formal rules for zoning have been previously defined and then applied.

The basic prescription for moving average interpolation is to use all the data points within a circle centred on the interpolation point and the interpolated values are calculated as the average of these sample data. As the circle moves around over interpolation points, the selected data points change and depending on the radius of the circle the short-range variations can be emphasized or levelled off. The basic assumption is that for all interpolation points placed on a line between two sample points, the data values change continuously and smoothly. Variations to the approach are possible by introducing a weighing factor, a method called weighted moving averages. The advantage of this modification is that it allows us to give a different degree of influence on the interpolation point by the neighbouring data. The most commonly used weighing factor is inverse distance and inverse squared distance (Castrignanò and Lopez, 2004).

Thin plate splines depend on an *a priori* assumption of smoothness, which implies that the variable is not completely local - in the sense that the value at one location depends on nearby values. Splines have been widely applied in spatial statistics. The main reasons for this are that splines are computationally efficient and there are software packages available which implement them freely. Moreover, they are relatively robust and the smoothness parameter, which is the only parameter which can be adjusted on the splines, can be determined automatically. Nevertheless, splines are rather restrictive in the choice of basic functions.

Each of the interpolation methods described has its own disadvantages but the following ones apply to all traditional methods:

- Spatial dependence in data is assumed *a priori* and there is no statistical test to validate the assumption;
- It is not possible to describe and model the structure of spatial variation to take into account during interpolation;
- Many of the outcomes look rather crude and prone to fluctuation.

No theoretical estimation variance can be computed and so any evaluation of the interpolation must involve *a posteriori* validation. Even if trend surface analysis, which is a form of regression, seems to estimate error in interpolated values, it is, in fact, somewhat misleading. The reason is that the regression model assumes among other things that the residuals from the fitted surface are independent of each other; this assumption is almost always violated, so no true estimation variance can be calculated (Castrignanò and Lopez, 2004).

7.4 Geostatistics

As soil varies at both spatial and temporal scales with great complexity, we deem that no deterministic model can capture the full extension of its variations. Geostatistical methods for interpolation recognize that the spatial variation of any continuous attribute is often too irregular to be modelled by a simple, smooth mathematical function, and provide ways to deal with the limitations of deterministic interpolation methods. Estimation and simulation of probable scenarios using statistical models are adopted to deal with the limits and difficulties of traditional soil mapping. The power of geostatistics to derive relationships between soil and landscape properties can be used at various scales, from field to global, depending on the level of precision targeted.

Estimation of variables by geostatistical techniques through moving average interpolation has been applied extensively since the 1980s (Burgess and Webster, 1980). More recently, specific theories for soil science were developed (Goovaerts, 1997, 1999; Webster and Oliver, 2001). Classical geostatistical approaches allow modelling of the spatial variability of a target variable and to perform an estimation of non-sampled locations. Geostatistics is based on the spatial autocorrelation of data, providing an estimate of a variable in each point applying a well-defined model of spatial autocorrelation (Goovaerts, 1997; McBratney *et al.*, 2003). Basically, geostatistics recognizes the continuous nature of soils and can account for random variation through modelling the spatial correlation in soil properties often present in the landscape. Once the spatial behaviour and spatial distribution of a parameter is characterized, this information is used to predict the value of the variable between sampled points and to minimize estimation error (Webster and Oliver, 2001). Geostatistical approaches have generally improved our predictive capacity for soil properties, especially the continuous ones like SOC. The underlying principle is that values at points close together in space are more likely to be similar than points further apart. Geostatistical methods are optimal when data are: (i) normally-distributed and, (ii) stationary (mean and variance do not vary significantly in space).

Spatial variation of soil properties contains systematic and random components (Figure 16). Systematic variability is a gradual or distinct change (trend) in soil properties that can be understood in terms of soil-forming factors or processes at a given scale of observation (topography, lithology, climate, biological activity, age of soils, physical and chemical composition). In addition to this component of soil variation there are differences that cannot be related to a known cause. This unexplained heterogeneity is called random variability.

The theory of regionalized variables represents the basis of geostatistics. It assumes that a spatial variation of any variable can be expressed as the sum of three major components:

- A deterministic component associated with a constant mean value or a long-range trend;
- A spatially correlated random component;
- A white noise or residual error term that is spatially uncorrelated.

De-trending in geostatistics is used to satisfy the stationarity assumptions, meaning that modelling is conducted on the random short-range variation in the residuals. The trend is automatically added back before the final continuous surface is created, to obtain reasonable predictions.

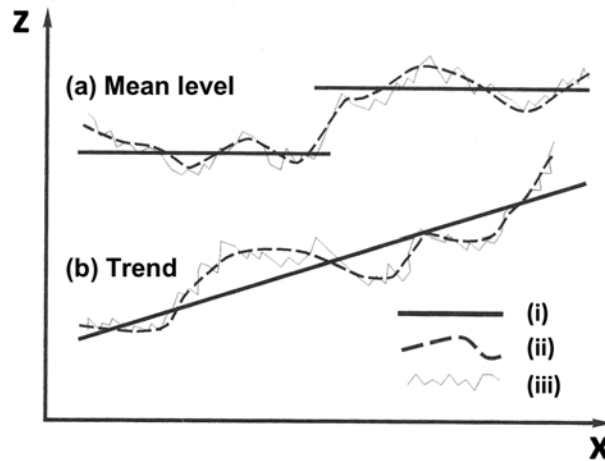


Figure 14. Elements of spatial variation: (a) mean, and (b) trend (from Burrough and McDonnell. 1998. Principles of GIS, Oxford University Press; p. 134)

Compared to the classical statistics which examine the statistical distribution of a set of sampled data, geostatistics incorporates both the statistical distribution of the sample data and the spatial correlation among the sample data. While in classical statistics, observations are assumed to be independent (no correlation between observations), information on spatial locations in geostatistics allows us to compute distances between observations and to model autocorrelation as a function of distance. Spatial autocorrelation is a defining feature of geostatistics: this spatial relationship is described by the semivariance. The semivariance $\gamma(h)$ describes the spatially dependent component of the random function Z . It is equal to the expected squared distance between sample values separated by given h .

Equation 27:

$$2\gamma(h) = \sum [Z_x - Z_{x+h}]^2$$

Where:

$\gamma(h)$ is the semivariance (as a function of h)

Z_x value of a random function Z at position x

Z_{x+h} value a random function Z at position $x+h$, where h is a distance

The semivariance for a given direction is usually displayed as a plot of semivariance $\gamma(h)$ versus distance h , called a semivariogram or simply variogram (Figure 17). A variogram cloud is produced plotting all the semivariances versus their distances, and an experimental variogram is obtained averaging the values for a standard distance (lag).

In the variogram the spatial dependence of the data is typically expressed by a monotonic increase from the origin with increasing lag distance; the variogram is hence a function of the spatial autocorrelation of the sample. The semivariances are typically smaller at shorter distance, and may reach, or asymptotically approach, an upper bound (sill) at a finite distance (range), beyond which there is no longer spatial autocorrelation (Heuvelink and Webster, 2001). In fact, the values of a target variable are more similar at a shorter distance, up to a certain distance where the differences between the pairs are equal to the global variance (Hengl, 2009).

Ideally, the experimental variogram should pass through the origin when the distance between the samples, and then variation, is zero. However, many soil properties have non-zero variance when h tends to zero. The nugget variance is a positive intercept on the ordinate, representing an uncorrelated component and indicator of short distance variation which includes measurement error, sampling error, inter-sample error and unexplained and inherent variability. The experimental variogram exhibits pure nugget effect when $\gamma(h)$ equals the sill at all values of h . It rises when there is a large point-to-point variation at short distances of separation and indicates a total absence of spatial correlation at the sampling scale used. It rarely signifies lack of spatial correlation. In fact, increasing the detail of sampling will often reveal structure in the apparently random effects of the pure nugget effect.

The experimental variogram is, by its construction, a series of discrete points. To obtain a smooth, continuous function, a model is to be fitted to these points (Goovaerts, 1997). Not any mathematical function can be used. A variogram model must fulfil the condition that no linear combination of variables can result in a negative variance of the derived variable. There are only a few models known to obey this condition. The most common ones are listed in standard texts, such as Webster and Oliver (2001): Spherical, Exponential, Gaussian, Power, Periodic, etc.

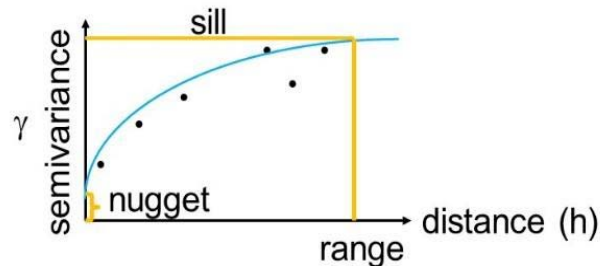


Figure 15. Theoretical semivariogram and its parameters.

The choice of variogram model is very important because each type yields quite different values for the nugget variance and range, both of which are critical parameters for interpolation. In fact, geostatistical interpolation uses the variogram to optimize prediction by kriging, using the parameters of the variogram model to assign optimal weights for interpolation.

Ordinary Kriging (OK) is by far the most common type of kriging, consisting in a form of weighted averaging, in which the unknown value in a point is predicted from the known values (Heuvelink and Webster, 2001). The weights are chosen in such a way that the estimator is unbiased. Kriging has many useful properties:

- The interpolated value is the most precise possible from the data available;
- The interpolated value can be used with a degree of confidence, because an error term is calculated together with the estimation;

- The estimation variance depends only on the variogram model and on the configuration of the data locations in relation to the interpolated point and not on the observed values themselves;
- The condition of unbiasedness ensures that kriging is an exact interpolator, because the estimated values are identical to the observed values when a kriged location coincides with a sample location. In this case, the weights within the neighbourhood are all zero and the estimation variance equals the nugget variance of the variogram model;
- Only the nearest few samples are spatially correlated to the kriged location and, therefore, they are the most weighted. Two important advantages become clear: firstly, the variogram needs to be accurate only on the first few lags; secondly, whatever is gained from introducing distant points is limited also because sample locations interposed between the kriged point and more distant samples screen the distant ones reducing their weights.

The appropriateness of the chosen variogram model and the kriging assumptions of unbiasedness and minimum estimation variance can be tested by cross-validation. This involves deleting each sample in turn and then kriging it independently from all other points in the estimation neighbourhood. In addition, the kriging procedure produces the variance of this estimation.

Considering the support of estimation, we can distinguish Point Kriging, applied to areas or volumes of the same size as that of the original sampling unit, and Block Kriging, applied to areas or volumes that are larger than the units that were originally sampled. Block kriging modifies punctual kriging equations to obtain an average estimate over a discrete area/volume or block. Both punctual and block estimates can be mapped. In the first case, values are kriged at numerous points on a fine grid through which contour lines are threaded to display the result. In block kriging the domain to be mapped is subdivided into small blocks and the estimates are displayed as blocks, or they are assigned to the centres of the blocks and contoured as for punctual kriging (Figure 18).

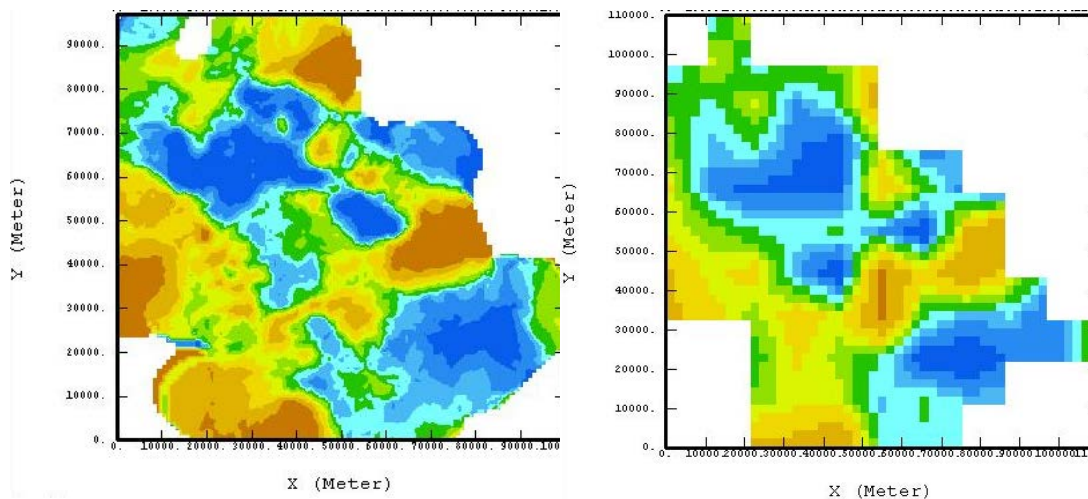


Figure 16. Example of punctual kriging map (left) and block kriging map (right) (Castrignanò A., personal communication).

Other commonly used Kriging algorithms are:

- Co-kriging, a kriging algorithm in which the distribution of a second, highly correlated variable (covariate) is used along with the primary variable to provide interpolation estimates. Co-kriging can improve estimates if the primary variable is difficult, impossible,

or expensive to measure, and the second variable is sampled more intensely than the primary variable.

- Universal Kriging (also called regression kriging), a kriging method often used on data with a significant spatial trend, such as a sloping surface. In universal kriging the expected values of the sampled points are modelled as a polynomial trend. Kriging is carried out on the difference between this trend and the values of the sampled points.
- Indicator Kriging (IK) is a non-parametric form of kriging, which uses a binary variable (0,1); predictions from IK can be interpreted as probabilities of the variable being 1 or being in the class that is indicated by 1. If a threshold was used to create the indicator variable, the resulting interpolation map would show the probabilities of exceeding (or being below) the threshold.
- Empirical Bayesian Kriging (EBK) is an interpolation method that accounts for the error in estimating the underlying variogram through repeated simulations. EBK creates a large number of variograms and the result is a distribution of variograms.

Differing from traditional methods of interpolation, kriging, with its probability model, allows us to calculate the uncertainty of predictions. In geostatistical practice, as we mentioned above, the usual method of testing is cross-validation. However, its results are actually biased and somewhat too optimistic (Creutin and Obled, 1982), because it retains the same variogram, whereas the variogram should be recomputed and fitted every time that an observation is removed (Laslett *et al.*, 1987). Moreover, cross-validation is not a true validation, because the same sample data set is used for both estimation and validation.

All these shortcomings can be avoided by using a separate independent set of data for validation. The values are estimated at the sites in the second data set and then the predicted and the measured values are compared. As for cross-validation, different indices can be computed from the observed and predicted values of the sites belonging to the validation sample. These are the:

- Mean error, which measures the bias of the prediction and should be close to 0 for unbiased methods;
- Mean square error, which measures the precision of the predictions and should be as small as possible;
- Variance of the standardised estimation error, which measures the goodness of the theoretical estimate - the better the estimate is, the closer it is on average to 1.

RECOMMENDATION 36. When using kriging to perform a geostatistical interpolation, it should be checked that the data used follows a normal distribution and are spatially auto-correlated.

7.5 Digital Soil Mapping

Geostatistical methods are based uniquely on the position of one point in respect to the others. This kind of estimation often tends to smooth the details of soil spatial variability and to underestimate the short-range variability to some extent (Curran and Atkinson, 1998; Ping and Dobermann, 2006). The quality of the estimation of soil properties can be improved and the spatial sampling intensities may be reduced by incorporating secondary information, provided that the primary and secondary variables are well correlated (McBratney *et al.*, 2003; Marchetti *et al.*, 2008), such as those derived from morphometry and remotely sensed data.

The use of environmental covariates has improved several aspects of soil surveying in many parts of the world (Boettinger, 2010). Thus, hybrid geostatistical procedures that account for

environmental correlation have become increasingly popular in recent years. These methods allow utilization of ancillary information that is often available at finer spatial resolution than the sampled values of a primary target variable (McBratney *et al.*, 2000).

Digital Soil Mapping (DSM) consists in a set of hybrid methods for producing digital estimated maps of soil properties through geostatistical regression techniques, using measured data combined with auxiliary information from environmentally based variables and remotely sensed images. DSM was developed as a substitute for the traditional polygon soil maps (McBratney *et al.*, 2003). The Working Group of the International Union of Soil Sciences on Digital Soil Mapping defines digital soil mapping as “the creation and the population of a geographically referenced soil database, generated at a given resolution by using field and laboratory observation methods coupled with environmental data through quantitative relationships” (see www.digitsoilmapping.org). According to Lagacherie and McBratney (2006) the input for digital soil mapping are field and laboratory observations (both legacy soil observation or maps and newly collected samples using statistical sampling techniques). Processing of data implies building statistical or mathematical models which relate soil observations with their environmental covariates to upscale point data to a full spatial extent. The ultimate output is an updatable spatial soil information system including raster representations of prediction along with the uncertainty of prediction. There is an increasing interest in using DSM to predict SOC worldwide, since this is an important issue to decrease costs and subjectivity of maps.

An efficient scaling up approach is Regression Kriging (RK), one of the most widely used hybrid spatial interpolation techniques, which generally produces realistic spatial representations, as the smoothing effect is much smaller than other interpolation methods. RK is a kind of Best Linear Unbiased Prediction (BLUP) technique for spatial data, which adds together the regression value of the covariates or exhaustive variables and the kriging value of the residuals of the regression (Sun *et al.*, 2012). BLUP assumes that the local mean varies continuously into each neighbourhood and can be estimated, using in association, both data from direct measurements and correlated auxiliary information (Goovaerts, 1997; Hengl *et al.*, 2007; Odeh *et al.*, 1994). Auxiliary information can be derived from the Digital Elevation Model (DEM), that is an optimal source of topographic information and an important data base for terrain attributes calculation, and from satellite imagery, easily available at relatively low cost.

In comparison with other methods, RK offers some advantages: analysis of representativeness of the plot inventory, analysis of uncertainties, regional soil C assessment and connections to other inventories, and allows the monitoring of land management factors. The strength of RK becomes better visible if high resolution data are available, reflecting the landscape scale predictors from the SOC distribution model. Accordingly, DSM offers a more accurate expression of the variation of a certain soil property, including a spatial quantification of the prediction error, which is why it is recommended, whenever possible (FAO 2017).

RECOMMENDATION 37. There is no spatial prediction method which is generally best for any case. The best method for SOC mapping should be selected on a case by case basis.

7.6 Practical application of interpolation techniques

As part of the activities of the Global Soil Partnership, a Global Soil Organic Carbon Map was released on December 5th 2017 (www.fao.org/global-soil-partnership/pillars-action/4-information-and-data/global-soil-organic-carbon-gsoc-map/en/). This map consists of nationally produced maps, developed as 1 km soil grids, covering a depth of 0-30 cm. Within this framework, a technical guideline to produce soil property grids by digital soil mapping techniques, based on local samplings and measurements, has been published (FAO, 2017). Reference is made to this

document for users, such as country representatives, who are engaged in e.g. determining SOC stock baselines. The instructions provide detailed guidance in preparing local soil data and environmental covariates, up-scaling data via regression-kriging and data mining and analysing uncertainties.

RECOMMENDATION 38. When up-scaling SOC stock change estimates, an overview of the data integration and spatial modelling procedure as well as the related uncertainty should be documented and reported together with the produced maps.

8. INTEGRATING CHANGES IN SOIL ORGANIC CARBON INTO LIFE CYCLE ASSESSMENT

8.1 Introduction

Life Cycle Assessment (LCA) is a tool that quantifies impacts associated with the provision of goods and services over their full life cycle. The LCA approach is comprehensive and has been formalized by ISO 14044:2006 (Environmental management - Life cycle assessment - Requirements and guidelines) and is generally accepted by the industry and stakeholders as being the most robust approach for comparing alternatives across their environmental impacts. Conversely, an alternative approach that does not consider the life cycle of a product could lead to burden shifting between life cycle phases – i.e. a decision made to reduce impact in manufacturing, for example, could lead to a change in materials which would ultimately cause more impact upstream in the material production phase.

There are two different types of LCA, attributional LCA and consequential LCA. UNEP/ SETAC (2011) defines attributional LCA as a “modelling approach in which inputs and outputs are attributed to the functional unit of a product system by linking and/or partitioning the unit processes of the system according to a normative rule”. Attributional LCA is, therefore, an inventory-type method, as it provides an inventory of emissions/removals within a defined inventory boundary. Consequential LCA is defined as a “modelling approach in which activities in a product system are linked so that activities are included in the product system to the extent that they are expected to change as a consequence of a change in demand for the functional unit”. Consequential LCA therefore provides an assessment of change in emissions/removals caused by a specified decision or intervention.

In terms of scope, LCA has traditionally focused on environmental impacts, but can also include economic and social impacts, particularly on human health (using endpoint LCA methods such as ReCiPe, Impact 2002+, etc.). Conducting an LCA involves creating an inventory, consisting of a balance sheet of estimated and measured emissions to air, soil and water which subsequently are classified into the impacts of interest, whose results are the product of applying pre-established characterisation factors that allow the summing of all flows (e.g. emissions) that contribute to an impact. For example, for the climate change impact category, kg of nitrous oxide and methane emissions will be converted into kg CO₂-equivalent emissions, so that a total impact on climate change can be estimated.

Changes in SOC levels are relevant to the environmental performance assessment of livestock product systems, primarily due to its effects on the balance of emissions of GHGs in the system, which affects climate change impacts. Moreover, SOC is an indicator for soil quality, reflecting its ability to provide ecosystem services, such as biotic production and climate change mitigation. Changes in SOC stock of grasslands supporting livestock production, as well as other LU and LUC directly or indirectly linked to livestock production (e.g. soybean) should be included in the evaluation, so that the industry’s impact can be estimated comprehensively, avoiding burden shifting.

LCA studies should follow the recommendations given in the ISO standards. The structure of an LCA report includes the sections illustrated in Figure 17: (i) goal and scope definition, (ii) life cycle inventory analysis, (iii) life cycle impact assessment and, (iv) interpretation.

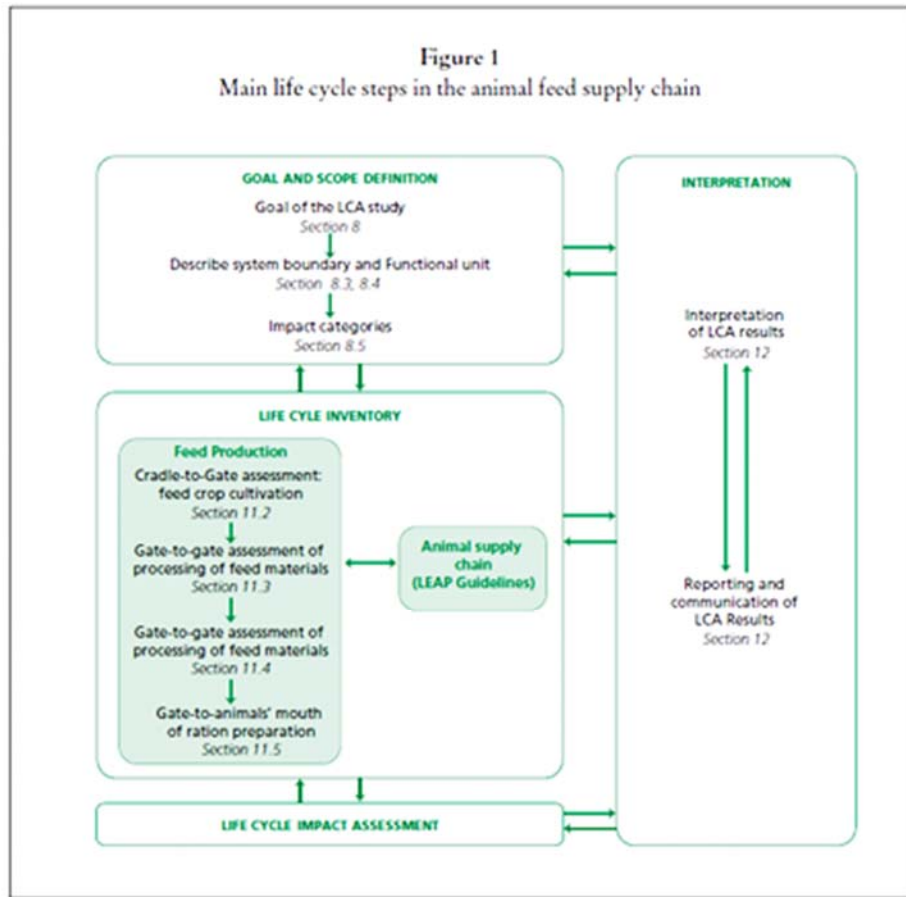


Figure 17. The structure of an LCA report adapted from the LEAP Guidelines for assessment of environmental performance of animal supply chains.

One of the most contentious issues with the inclusion of SOC stock changes in LCA is the temporal aspect. SOC levels in agricultural production systems are typically either steady-state (balanced inputs and outputs) or batch systems. In either system, the time reference of the production system does not usually present a challenge. In livestock production systems, a reference of one year is usually sufficient to account for temporal variations (e.g. related to variable feed composition throughout the year). The reference system may be extended when production (e.g. growth) happens over multiple years, in distinct phases (e.g. meat production from one animal over its full lifetime). Alternatively, one can look at a greater system with continuous inputs and outputs (e.g. meat production from one farm over a year).

However, when agricultural practices change, SOC levels will change accordingly. This change is usually rapid soon after the introduction of the new practice and eventually stabilises when a new equilibrium is approximated (Petersen et al., 2013). Since this process varies depending on the region's climate, soil type, agricultural practice or initial SOC levels, it is challenging to give an approximate indication of a representative time interval. Furthermore, SOC is known to follow a "slow in, fast out" pattern (Poeplau *et al.*, 2011), making the assumption of a same time horizon for sequestration and loss overly simplistic. Finally, determining an unambiguous SOC stock change associated with the new equilibrium also requires a decision that may be fraught with practical difficulties.

An approach used in other recommendations (IPCC, 2006; PAS 2050, 2011) is to allocate the benefits of carbon sequestration (or the burden of carbon emissions) linearly throughout a fixed period (e.g. equally over 20 years of production).

Petersen *et al.* (2013) showed that the choice of time perspective has a considerable impact upon the LCA results. While IPCC (2006) Tier 1 methodology proposes a time period of 20 years, as used in many LCA's modelling land use change, many have argued and shown (e.g. Vellinga *et al.*, 2013; Poepflau *et al.*, 2011) that carbon stocks may not reach an equilibrium after 20 years. In the methodology for the FeedPrint tool (Vellinga *et al.*, 2013), it is claimed that following 200 years after conversion, carbon is still accumulating in grasslands and decreasing in arable land. The time perspective should correspond to the time perspective most commonly used for the global warming potential in LCAs, which is 100 years (Petersen *et al.*, 2013).'

The calculation of a carbon footprint - a specific calculation for climate change impact with a life cycle approach - is reported in terms of CO₂-equivalents (all GHG are converted to CO₂-equivalents using Global Warming Potentials as characterisation factors) for a unit of reference. This reference usually is known as the Functional Unit in LCA, e.g. 1 tonne of milk. In this case, the carbon sequestered in and emitted from soils could be included in the balance of GHG emitted and sequestered if the methodology allows for it. The conversion from livestock reference (weight of meat or milk) to surface of grassland required shall also be made explicit.

8.2 Implications of including SOC stock changes in LCA

8.2.1 System boundaries and cut-off criteria

An LCA report requires a clearly defined and communicated system boundary that is relevant to the goal and scope of the study. For modelling climate change from land use and land use change, all GHG emissions should be included, not only carbon dioxide. Furthermore, when estimating the environmental impact of livestock production systems (in the LCA of beef or milk, for example), it is also necessary to account for effects of soil carbon changes elsewhere in the system. For example, SOC changes associated with additional feed crop production on arable land, or SOC changes due to the application of manure. An incomplete system boundary can generate burden shifting, where the benefits of the action of focus (e.g. change in management practice) cause a greater burden (e.g. emissions of CO₂) elsewhere in the supply chain. An assessment with limited boundaries can therefore be misleading and contrary to the rationale for using an LCA approach, which is to avoid shifting burdens.

Figure 18 shows a system boundary for livestock systems. All life cycle stages where material C and N flows occurs shall be accounted for, and other significant emissions for these stages shall also be estimated in a full LCA. Depending on the goal of the LCA study, one may also include additional steps of packaging, storage, distribution, retail, use (i.e. cooking) and waste management. These stages may be relevant for some intended uses only (e.g. for customer education but not for agricultural land management regulation).



Figure 18. Minimum Life Cycle Stages linked to livestock production in an LCA approach.

8.2.2 Representativeness and appropriateness of LCI data (SOC data or model)

In most LCA studies that include estimates of changes in SOC stocks, accounting is only for land use changes (see review of multiple LCA studies by Goglio *et al.*, 2015), either counting only direct or also including indirect land use change. Emission modelling is typically based on IPCC (2006) emission factor guidelines. This is in line with the European LCA framework (EU-JRC, 2010). While this highly applicable but low precision tool (Goglio *et al.*, 2015) is regarded as appropriate for large scale soil carbon changes occurring after a land use change, it is recommended to use a finer model (Level 2 or 3) to model emissions occurring because of land management change. Most dynamic crop-climate-soil models (Level 3) are considered of medium certainty (Goglio *et al.*, 2015), based on classification criteria derived from JRC (2011). BOX 11 shows a case study using models to include SOC stock changes in LCA. When a study context does not allow specific data collection, model Level 1 could be used with specific factors adapted to the production context to provide a first estimate of the expected SOC change direction or amplitude.

8.2.3 Types, quality and sources of required data and information

SOC stock changes can be estimated by measurements or modelling. Please refer to the relevant sections in this document for details (Chapters 3, 5 and 6).

At present time, little to no information concerning SOC stock changes is available or included in the databases usually used in LCA software and studies, except those related to LUC (especially for soybean meal from South America). Explicit mention of inclusion or exclusion of SOC changes should be made in the communication of results whenever possible, specifying if related to LUC only or LU as well.

8.2.4 Comparisons between systems

The inclusion of net soil carbon sequestration in the overall balance of GHG has the potential to reduce the overall footprint of a livestock product, until a new steady-state is achieved. The potential for carbon sequestration in grasslands used for livestock production depends on current SOC stocks and the history of management. More degraded land that has lost more carbon due to past poor management has the potential for higher carbon sequestration to approach the native SOC state. Hence, different rates of SOC stock change increase between farms at a point in time does not give a measure of the longer-term sustainability of farm management. The UNEP/SETAC Life Cycle Initiative has produced guidelines for conducting the Life Cycle Inventory analysis and Life Cycle Impact Assessment phases of an LCA study (See Koellner *et al.*, 2012; 2013).

For assessing the impacts of land use and land use change on climate change, see Müller-Wenk and Brandão (2010).

8.2.5 Identifying critical review needs

Since the inclusion of SOC in estimates of net GHGs emissions can have a significant importance to the results, a critical review should be made before reporting the results of a single or comparative LCA including this source. The goal of the review will be to assess if the model and data chosen are the best to represent the situation evaluated.

8.2.6 Emerging reporting requirements

Currently, common LCA reporting platforms refer to the importance of SOC without clearly including it in the overall balance (PAS 2050, PEF). The latest version of the PAS 2050 (2011) states: *“Soils are important in the carbon cycle, both as a source and a sink for carbon, and it is acknowledged that scientific understanding is improving regarding the impact of different techniques in agricultural systems. For this reason, provision is made for future supplementary requirement or revision to the PAS 2050 requirements that could facilitate the inclusion of emissions and removals arising from changes in soil carbon”*.

The EU’s Product Environmental Footprint (PEF) rules suggest an ad-hoc calculation for C sequestration that can be mentioned separately from the total (in line with ISO 14067:2013 Carbon footprint of products). Meanwhile, it is also deemed by many stakeholders to be an important mitigation method that should be included in the balance of emissions, which would provide the holistic view that is characteristic of LCA. For this reason, it is expected that once consensus is reached on a method of estimating and reporting SOC changes, they could rapidly be accepted within the boundaries of life cycle carbon foot printing.

BOX 11. Quantifying SOC sequestration in a LCA study of a livestock system

Overview: Practices to manage native vegetation and to improve soil health and carbon stocks are increasingly being adopted for production and environmental benefits on Australian pastoral lands. However, the greenhouse gas (GHG) benefits of these activities are commonly overlooked in life cycle assessment (LCA) studies, affecting the accuracy of climate change impact assessment. This case study sought to estimate sequestration in soils and vegetation in a cradle to farm-gate LCA study (Henry *et al.*, 2015) of the potential climate change impact of wool production in the region around Armidale (30°31’S, 151°40’E), Australia.

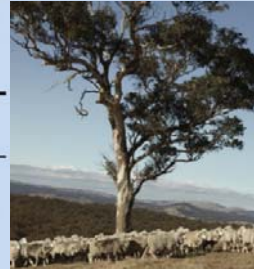
Approach: The life cycle inventory used regional production data and on-farm surveys to model the net greenhouse gas emissions per kg greasy wool at the farm-gate. A simple Tier 2 approach used a Level 1 model to estimate SOC stock change due to pasture management. Emission factors were derived from regionally relevant research conducted over the past ten years. A conservative approach was adopted with zero SOC stock change assumed for activities where research results were variable and/or close to zero. In the study region, where nutrient deficiency was addressed through application of phosphate fertiliser and introduction of legumes, more consistent gains in SOC stocks had been measured and an average rate of sequestration of 0.1 Mg C ha⁻¹ year⁻¹ was modelled in the LCA. Net annual GHG emissions per kg wool was calculated as total farm emissions less sequestration in vegetation and soil

annualised over two timeframes, 20 years and 100 years, used in LCA studies and national accounts. Impacts were allocated between wool and sheep-meat using a biophysical approach.

What the case study showed: While the rate of SOC per hectare was low, over the large area of farm production in this region the increase in carbon stocks in soils was close to that in tree biomass. Over a 100-year period, total sequestration offset about 10% of all farm emissions.

Carbon sequestration for reforestation and soil management in a sheep grazing region, calculated using an LCA approach and expressed as equivalent CO₂ (kg CO₂-e) per kg greasy wool produced at the farm gate, assuming a 100-year amortisation period to simulate permanent sequestration.

Sequestration Activity	Cradle to farm-gate LCA modelling scenario	GHG intensity (kg CO ₂ -e/kg greasy wool)*
Biomass (Mixed native & exotic tree planting)	National inventory model	-1.6
Biomass (Mixed native & exotic tree planting) plus SOC stock change under fertilised pasture)	National inventory model SOC stock change = 0.1 tC ha ⁻¹ yr ⁻¹)	-2.4



* A negative value indicates CO₂ removals from the atmosphere

Summary: This case study illustrates an approach for assessing sequestration in SOC and vegetation biomass using modelling and survey information and including results in livestock LCA. The LCA results demonstrated that land use and direct land-use change practices on sheep farms may result in significant and quantifiable GHG removals. Modelling SOC stock change in LCA is important for accurate impact assessment, and to recognise and encourage good practice.

Henry B. *et al.* 2015. Quantifying carbon sequestration on land managed for sheep grazing in Australia in life cycle assessment studies. *Rangelands Journal* 37, 379-388.

9. APPENDIX ONE: Technical information on model initialization

9.1 Initialisation Challenges and Approaches

Peltoniemi *et al.* (2006) studied effects of various factors on modelled SOC changes and found that soil initial state has the greatest impact on subsequent modelled values. Initialisation of SOC in levels 2 and 3 models is inherently complex because it involves subdividing total SOC into various largely conceptual SOC pools that differ in rates of turnover. Figure 19 illustrates some of the problems that arise from incorrect initial pool sizes using the simple level 2 Introductory Carbon Balance Model.

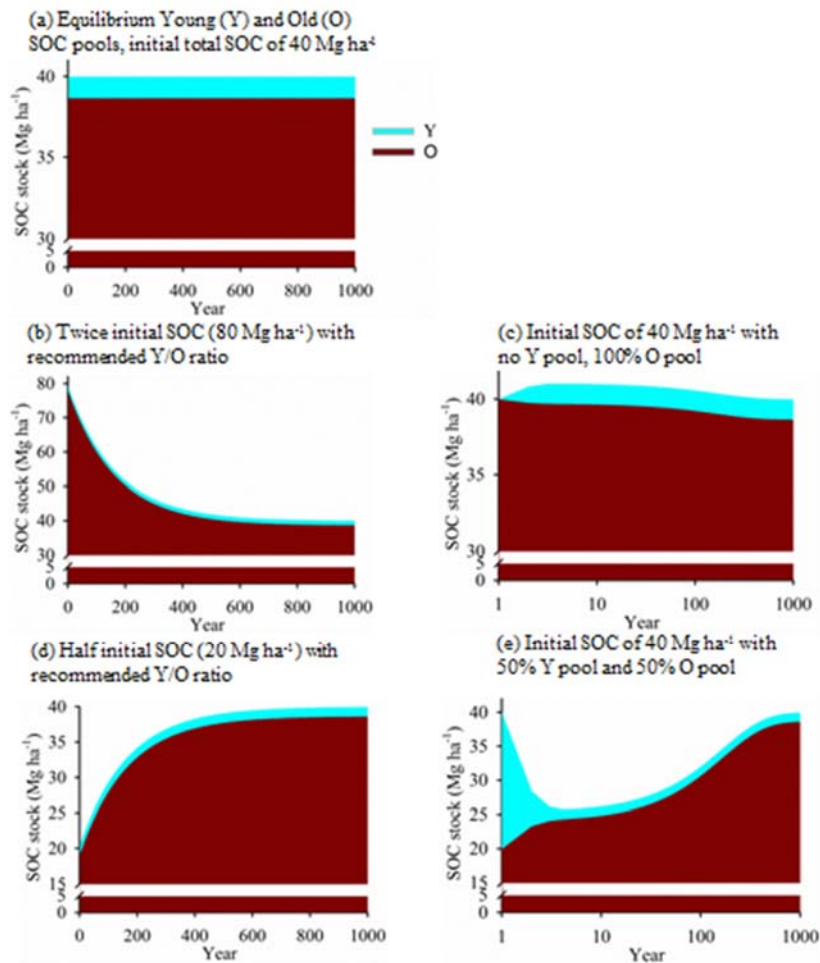


Figure 19. Example using Introductory Carbon Balance Model (with C input aboveground = 0.54 Mg ha⁻¹, belowground = 0.54 Mg ha⁻¹; climate factor, $r_e=1$; humification factor above ground = 0.125, belowground = 0.310; decomposition rate Young pool (Y) = 0.8 yr⁻¹, Old pool (O) = 0.00605 yr⁻¹) of SOC trend with different types of disequilibrium for initial SOC.

Compared to continual equilibrium (Figure 19a), overestimating baseline SOC (Figure 19b) imposes a disequilibrium that forces SOC to decrease from baseline over time while the disequilibrium from underestimating baseline SOC Figure 19d will force SOC to increase.

Underestimating or overestimating the proportion of C in model C pools with fast turnover (Figure 19c and Figure 19e, respectively) causes rapid changes in these pools over few years but it reaches values similar to equilibrium within 10 years. Conversely, underestimating or overestimating the proportion of C in model C pools with slow turnover (Figure 19e and Figure 19c, respectively) introduces slow changes to SOC that requires many centuries to reach equilibrium values.

The two most frequently used schemes are to have a spin-up (or warm-up) period for the model to estimate the pool sizes at steady state. The modelled situation for the spin-up period is that representing the baseline condition. The first option, scheme 1, runs the soil to equilibrium over a long spin-up period of up to 10,000 years. With such long spin-up the model not only estimates the relative pool distribution but also the total SOC, as it will be essentially unaffected by the initial input SOC values. The second option, scheme 2, is to use general ratios to partition known total SOC. Then from these input pools, a shorter spin-up period of 10 to 30 years is used to let the model modify the pool sizes to be more consistent with modelled SOC behaviour for the modelled baseline condition. For pools with fast turnover, such as the decomposable plant material and slow and fast biomass pools in RothC, the model will estimate the steady values within a few years of spin-up. Skjemstad *et al.* (2004) found that initialising these values to small non-zero values had no effect on pool size after model spin-up of just two years.

There are several variants to the above two initialisation schemes that involve some calibration of the model. One variant of scheme 1, for the level 2 RothC model, adjusted C-input so equilibrium C matched measured total SOC at the end of the spin-up period (Jenkinson *et al.*, 1999; Nemo *et al.*, 2017). This variant is useful for grassland systems where exact C input may be uncertain. Another effective variant for scheme 1 for the RothC model was to calibrate the change rate of slowest carbon pool so that the modelled total SOC stock matches the measured value at the end of the long spin-up period (Hansen *et al.*, 2012). Paustian *et al.* (1992) used the scheme 2 for level 3 Century modelling but modified the initial ratios for original pool partition of total SOC so that the modelled C dynamics better matched observations.

An assumption of the above initialization schemes is that the baseline condition is at or approaching steady state. However, the soil may not be near steady state in the baseline condition (Wutzler and Reichstein, 2007). Basso *et al.* (2011) advocated using C inputs and land management to follow known land use and management history. These may be most practically estimated from general historical information and expert opinion (Ogle *et al.*, 2007). Knowledge of distant history is likely limited and it is the most recent history that is most important to pool sizes. Therefore, an option is to initialise with a multi-thousand-year equilibrium model spin-up. This approach uses estimated earlier land use conditions until there is enough knowledge of land use change and management history to include in the later period of the spin-up modelling.

Several process models, most notably RothC, allow for an inert organic matter pool that does not change in the scale of several centuries. Coleman *et al.* (1997) used the 1960 ¹⁴C pulse from atmospheric nuclear weapon testing to develop an estimate of inert organic matter. Falloon *et al.* (1998) developed an empirical relationship of inert organic matter from total SOC for RothC.

There has been a continual drive to match model SOC pools with measureable pools. Then initial SOC pools could be input from measurements. Smith *et al.* (2002) argue that measurable pools not only have to be shown to match the modelled pools but must also be unique and non-composite (i.e. cannot be divided into different sub-pools). They found that these conditions were difficult to achieve in practice. Having long-term experimental results to test and/or validate results is necessary to knowing how well the modelled results using measured pool initialization match observed performance.

Skjemstad *et al.* (2004) developed a procedure that matched the largest modelled C pools in RothC with measured pools. However, they changed the turnover rate of the resistant plant material pool based on calibration to have a good fit of modelled to measure SOC for sites in Australia.

Zimmermann *et al.* (2007) developed a procedure for matching RothC pools to measured pools. They could not subdivide the resistant and decomposable plant material pools so split a measured plant material pool into these two pools based on the pool ratios from a 1000-year spin-up equilibrium model run. They had a good relationship between measured pools and modelled pools for a range of land uses in Switzerland. Xu *et al.* (2011) also used the pool differentiation procedure of Zimmerman *et al.* (2007) and found that the resistant plant material pool was underestimated compared to measured value. This was attributed to wet soil conditions in Irish grasslands. Shirato *et al.* (2013) used a similar scheme to that of Zimmerman *et al.* (2007). They used $\delta^{14}\text{C}$ values to estimate the amount of inert organic matter. Although they were able to obtain good estimates of total SOC over a time scale of decades, the $\delta^{14}\text{C}$ did not agree with observations. They cautioned that the accuracy of long-term (multi-century) modelled results is suspect.

Other procedures for initialisation rely on probabilistic calibration. Yeluripati *et al.* (2009) used Bayesian calibration (Van Oijen *et al.*, 2005) to estimate the variability of pool sizes and model parameters for the level 3 Daycent model. Kwon and Grunwald (2015) deconstructed level 3 Century and rewrote the SOC estimation portion into statistical software and performed inverse modelling to fit observed CO_2 evolution from incubation studies to initialise soil SOC state and calibrate model parameters.

9.2 Initialisation of soil pool sizes is less important for comparisons between two or more concurrent scenarios

Initialisation of soil pool sizes is less important for comparisons between two or more concurrent scenarios. For some uses, the information required is the difference in SOC between a baseline condition and a modified condition over the same period. A GHG offset is an example, because standards such as ISO 14064:2006 (Greenhouse Gases) only require the difference between the SOC stocks over time for the offset action and those for the business-as-usual management. A comparative LCA may be constructed so only the difference in SOC change between compared systems is required. Similarly, a consequential LCA to investigate the effect of a change to a system may be constructed so it only needs the difference between the SOC stock changes for the modified system compared with those for the original system.

For level 2 models where there is no modelled feedback between SOC change and C input, the initial soil pool sizes generally do not have a large effect on the difference between two different concurrent scenarios. For example, using the Introductory Carbon Balance Model, the difference in total SOC stocks between baseline C input for and stocks for a 10% increase in C input scenario was essentially identical for all the five initial SOC cases (Figure 19). However, when the level 2 model parameters are changed in a scenario, then there may be important deviations between the modified and baseline scenario depending on initial soil states. Figure 20 shows the difference for changing the model parameters of humification factor for above and below ground for the five initial SOC cases described in Figure 19. The variation of modified humification and the baseline scenario was substantively different for case (e) of Figure 19 where the initial model C pool ratio deviated markedly from typical equilibrium values.

For level 3 models (such as Century) there is usually a feedback between SOC change and plant C input. A substantial disequilibrium between the baseline condition and initial SOC pool sizes will cause rapid changes in SOC, in turn causing either a source or sink of mineral N that will affect plant growth and, thereby, C input. Nevertheless, the comparison between two concurrent scenarios will not be affected greatly by various reasonable initial soil C pool states.

The recommended method remains to have the initial SOC pools as close as can be judged to appropriate values for actual initial soil conditions to provide the best estimate of the difference

between two concurrent scenarios. However, the initial soil state for the above will not be required with the same accuracy as for a model use, such as for SOC stock change for attributional LCA, where the SOC trend for single scenario needs to be estimated as accurately as possible. Importantly, the relative insensitivity for initial SOC state for comparing concurrent scenarios does not extend to model parameters such as rate constants for which SOC stock change remains very sensitive to inaccuracies.

It is recommended not to change model C fate parameters for initialisation unless changes are done as part of broader calibration exercise.

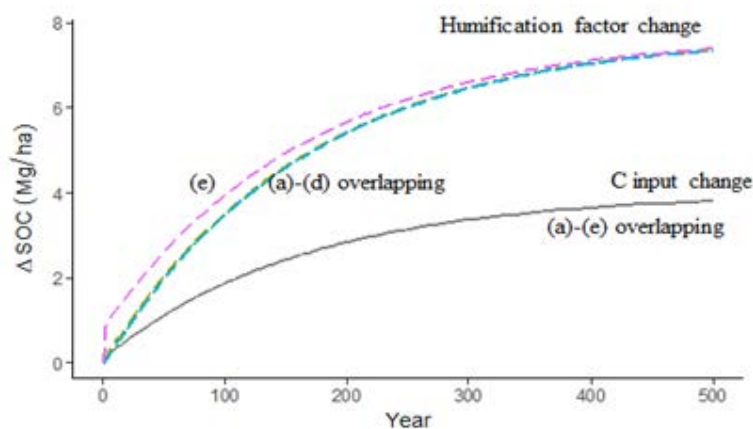


Figure 20. Difference from baseline conditions for a modified scenarios of 10% increase in above and below ground C input and of 20% increase in above ground and below ground humification factors as estimated by the Introductory Carbon Balance Model (Andrén and Kätker, 1997). Cases (a) to (e) refer to descriptions in Figure 19.

9.3 Guidance for Initialisation

If there is limited knowledge regarding baseline SOC, including no estimate of initial total SOC, the best option is to use scheme 1 model spin-up to equilibrium for the baseline conditions. If it is judged that there are good estimates of C inputs, then level 2 models can be used. Good estimates of C inputs can also be used to help parameterize vegetation growth in level 3 models so modelled C input matches known C input. If there is limited knowledge of C inputs, then level 3 models that estimate plant growth can provide initial estimates of SOC stock based on the input data including vegetation growth parameters and site variables such as weather and soil texture. Without knowledge of the C inputs, the accuracy of vegetation growth parameters will be critical so it is important to choose a parameter set that has been shown to perform well for similar vegetation characteristics and growing conditions to the modelled situation. If there is good knowledge of past land use and management history, particularly histories that would likely cause baseline soil to be not at steady state, then including that history for the last years of the model spin-up is recommended. This requires the availability of good estimates of C input for level 2 models or vegetation growth parameters and soil erosion for level 3 models for that history. Checking initial SOC stock estimates with any available SOC data, such as general soil information from soil surveys, is useful to determine if the model estimated SOC values are reasonable.

If there is knowledge of baseline total SOC, then scheme 2 of partitioning total SOC into pools based on generic or modelled equilibrium C pool ratios followed by a spin-up period of 10-30 years is a feasible option. The option exists to calibrate either carbon input or pool turnover rates to improve match between initial modelled and measured total SOC. If there is knowledge of past

land use and management history, particularly histories that would likely cause the baseline soil to not be far from steady state, then including the effects of that in initial C pool ratios at start of the model spin-up is recommended good practice. This would be done by using the initial pool ratio from a scheme 1 spin-up that includes that history for the last years of the model spin-up providing it is judged there are good estimate for the C input for level 2 models or vegetation growth parameters and soil erosion for level 3 models for that history.

If the primary purpose of model use is to estimate the difference between two concurrent scenarios, additional effort beyond the above options may not improve the results significantly. However, if a SOC stock change for a single scenario is needed then the additional effort for initialisation should be considered.

If there is detailed fractionation of SOC for baseline condition and confidence that the measured pools will match model pools for the modelled situations, and then the initial pool sizes can be adjusted based on measured fractions for scheme 2 initialisation outlined above. Testing the suitability of this modification against a range of soil data relevant to the modelled situations and/or for long term measured SOC stock time series is recommended before application.

If there are good measurements of SOC over many years, preferably several decades for a site with conditions similar to the modelling objective, then there is an opportunity to calibrate C input and/or model parameters to provide a good match between observed and modelled SOC. The calibrated values can then be used to make estimates of initial soil SOC through:

1. scheme 1 as outlined above where there is no knowledge of baseline SOC
2. scheme 2 as outlined above where there is knowledge of initial total SOC.

It is a large investment in time to calibrate a process SOC model. Some reviewers of calibrated modelling may require rigorous documentation of the calibration procedure to show that the model was not deliberately or inadvertently calibrated to produce a particular result when used to make an estimate of SOC stocks for the target model application. If no calibration is done, it is recommended that long-term data be used to assess the appropriateness of the chosen soil C pool initialisation method and model parameters.

10. APPENDIX TWO: Technical details of model calibration and uncertainty evaluation using Monte Carlo approaches

Monte Carlo methods, that draw random values from the probability distribution functions for inputs and parameters, are an efficient and flexible way to estimate the whole uncertainty of the modelled estimation, including those from input and model uncertainty (VandenBygaart *et al.*, 2004; Stamati *et al.*, 2013). It also does not require the use of a data set of observed system performance. The major reluctance to use this approach is the challenge of selecting justifiable probability distribution functions of influential inputs and parameters (Verbeeck *et al.*, 2006).

As an example of the Monte Carlo approach, Ogle *et al.* (2010) made an estimate of structural uncertainty of the Century model. Their study included a Monte Carlo implementation of an empirical mixed model of fixed effects for major factors of SOC change and random effects to include the spatiotemporal dependencies in the United States (Ogle *et al.*, 2007). They found that there were systematic errors for Century regarding the effect of tillage and the effect of soil texture on SOC stock. Through Monte Carlo simulation this empirical model was used to estimate the uncertainty in SOC stocks that arises from the use of Century. This allowed the authors to make SOC stock estimates for these fixed effects, for application in the United States (for which the empirical model is valid).

The variables and parameters that make the greatest contribution to model-estimated output uncertainty are those with the largest combinations of their own uncertainty and modelled output sensitivity. It is difficult to know which is most important. Several procedures are available to subdivide total model output variance into components to gain an understanding of uncertainty from individual factors and their variance. The simplest of these use the most sensitive variables from OAT analysis in form suitable for Monte Carlo estimation. The results are structured for Analysis of Variance (ANOVA) with uncertain variable as factors and with model output as the response variable (Wang *et al.*, 2006; Tang *et al.*, 2007; Nishina *et al.*, 2015). Interactions between influential factors are also included. The variable contributing most to the variance are those having greatest impact on uncertainty.

A more-advanced method to use a Monte Carlo approach is to condition the parameter uncertainties, based on differences between observation and modelled outputs. The Markov Chain Monte Carlo is a powerful and computationally efficient method, that uses random selection to continually improve the likelihood of the probability distribution function of variables and parameters based on comparing model output with observed values (Ricciuto *et al.*, 2008; Tuomi *et al.*, 2009; Ren *et al.*, 2013). The General Linearized Uncertainty Estimation (GLUE) is a related method to Markov Chain Monte Carlo, in that it also uses Monte Carlo methods and Bayesian inference to simultaneously estimate the uncertainty of parameters and of the model estimation (Wang *et al.*, 2005; Causarano *et al.*, 2007; Juston *et al.*, 2010; Salazar *et al.*, 2011). These methods provide good characterization of the uncertainty and the contribution of different inputs and parameters to that uncertainty. However, to provide good estimates of model prediction uncertainty, the observations to which the model output is compared need to represent the range of conditions in the application domain. This can be a limitation for applying these advanced methods to estimate the model prediction uncertainty for grazed grassland systems as there are usually few studies with observations of SOC.

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