Food and Agriculture
Organization of the
United Nations

Global Soil Organic Carbon Sequestration Potential Map

GSOCseq v1.1

Technical report

International
Network of Soil
Information
Institutions
(INSII)

GLOBAL SOIL PARTNERSHIP

Global Soil Organic Carbon Sequestration Potential Map (GSOCseq v.1.1) Technical report

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P4WG Pillar 4 Working Group

INSII International Network of Soil Information Institutions

ITPS Intergovernmental Technical Panel on Soils

4per1000 SCT 4 per 1000 Scientific and Technical Committee

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UNCCD-SPI The UNCCD Science-Policy Interface

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Abbreviations and acronyms

BAU Business as usual

BIO Microbial Biomass

Ceq Estimated annual C input at equilibrium

Ct Annual carbon inputs for a specific year

CO_2 Carbon dioxide

DM Dry matter

DPM Decomposable plant material (C pool)

GHG Greenhouse gases

GSOCmap Global Soil Organic Carbon Map

GSOCseq Global Soil Organic Carbon Sequestration Potential Map

GSP Global Soil Partnership

HUM Humified soil organic matter (C pool)

HWSD Harmonized World Soil Database

INSII International Network of Soil Information Institutions

IOM Inert organic matter (C pool)

IPCC Intergovernmental Panel on Climate Change

ITPS Intergovernmental Technical Panel on Soils

NDVI Normalized difference in vegetation index

NPP Net Primary Production

P4WG Pillar 4 Working Group

QA/QC Quality Assurance/Quality Check

RMSE Root mean square error

RPM Resistant plant material (C pool)

SOC Soil organic carbon

SOCmeas Measured soil organic carbon (as in GSOC map)

SOCseq Soil organic carbon sequestration

SOCsim Simulated soil organic carbon after the first equilibrium run

SOM Soil organic matter

SSM Sustainable soil management

SSM1 Low carbon inputs sustainable soil management scenario

SSM2 Medium carbon inputs sustainable soil management scenario

SSM3 High carbon inputs sustainable soil management scenario

VGSSM Voluntary Guidelines for Sustainable Soil Management

Preface

This document presents the technical details of the first ever country-driven Global Soil Organic Carbon Sequestration Potential Map (GSOCseq). This map allows for the estimation of top (0–30 cm) soil organic carbon (SOC) sequestration potential in agricultural areas under a business as usual and three sustainable soil management scenarios. The untapped potential of sequestering SOC in agricultural lands as one of the most effective nature-based solutions for climate change mitigation and adaptation has been widely described in recent years. However, unlocking this potential relies on the establishment of reliable, transparent and cost-effective mechanisms to monitor, report and verify (MRV) changes in SOC stocks. Globally, there exists a tangible divide between countries with enough resources and technical expertise to establish such mechanisms and those still lagging these capacities. The Global Soil Organic Carbon Sequestration Potential Map (GSOCseq) stands out as a game-changing programme aimed at bridging this divide by raising technical expertise on SOC sequestration potential modeling and mapping while relying on a uniquely participatory and iterative process. The GSOCseq v1.1 was developed based on the submissions of national experts appointed by the Food and Agriculture Organization of the United Nations (FAO) Member countries. Each of the appointed National Experts generated national maps following a bottom-up approach that was facilitated and coordinated by the Secretariat of FAO's Global Soil Partnership (GSP). Starting in November of 2020, an extensive capacity-building program was launched, reaching over 500 participants from 119 countries through seven regional online training sessions. To further support National Experts in applying the method- ology to their own country database, a remote technical support platform was established as well. The methodology is based on the process-based Rothamsted Carbon Model (RothC), made freely available through the open source R software and the R package SoilR. Countries have been using this software to model their national SOC sequestration potential for agricultural areas by predicting changes in SOC stocks over a period of 20 years under a business as usual (BAU) scenario and three Sustainable Soil Management (SSM) scenarios that vary in the degree of carbon inputs to the soil. Alongside of this standardized approach, countries are encouraged to further refine and adapt the methodology to better suit their environmental condition and available database. By fostering and leveraging local expertise, the methodology of the GSOCseq is constantly being extended, improved and updated to better characterize local SOC dynamics.

Chapter 1

Background, objectives and significance

1.1 Soil carbon

Soils constitute the largest terrestrial carbon (C) pool. Total soil carbon (C) stock comprises soil organic C (SOC) and soil inorganic C (SIC) components. 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). The global SOC stock of ice-free land contains about 1500–2400 Pg C (1 Pg = 1 Gt) in the top 1 m, and about 2200–3000 Pg C in the top 3 m (Batjes, 1996; Scharlemann *et al.*, 2014; Tifafi *et al.*, 2018; Lorenz and Lal, 2018). This represents more than the sum of carbon contained in the atmosphere and vegetation (Smith *et al.*, 2020). Soil inorganic C comprises pedogenic carbonates and bicarbonates, which are particularly abundant in arid regions and in alkaline soils. The SIC stock is estimated at 700–1700 Pg C in the top 1 m soil layer (Lorenz and Lal, 2018) and is believed to occur predominantly in the deeper layers of temperate soils. Although soils contribute to a major share of agricultural greenhouse gas emissions (GHGs), due to the size of the soil carbon pool, even small increments in the net soil C storage represent a substantial C sink potential (Paustian *et al.*, 2016). Carbon sequestration implies transferring atmospheric CO_2 into long-lived C pools that is not immediately reemitted (Lal *et al.*, 2018). Thus, soil C sequestration means increasing SOC and SIC stocks through judicious land use and sustainable soil management (SSM) / sustainable land management (SLM) practices. Throughout this report the terms sustainable soil management and sustainable land management will be used interchangeably. Due to the knowledge limitation regarding the SIC contributions to soil C sequestration (Ontl and Schulte, 2012), the GSOCseq program focused only on SOC sequestration potential, as its size, dynamics and global distribution are better understood.

1.2 Soil organic carbon sequestration

The basic process of SOC sequestration in the terrestrial biosphere involves transfer of atmospheric CO_2 into plant biomass and conversion of the biomass into stable SOC through formation of organo-mineral complexes (Lal *et al.*, 2018). Thus, soil carbon sequestration relies on plant photosynthesis to carry out the initial step of capturing CO_2 from the atmosphere. Major advantages of scaling up soil C sequestration as a nature based solution are that, because SOC stocks are most depleted on lands currently under agricultural management, this approach does not require land use conversions (e.g., to forests) or increase competition for land resources, and additionally the implementation of SSM can increase SOC stocks which is crucial to soil health and fertility, securing the delivery of ecosystem services and enhancing system resilience and adaptation capacity to climate change (Paustian *et al.*, 2019).

1.3 Factors affecting soil organic carbon sequestration

SOC storage is governed by the balance between the rate of C added to the soil from plant residues (including roots) and organic amendments (e.g., manure, compost, biochar), and the rate of C lost from the soils, which is mainly as CO_2 from decomposition processes (i.e., heterotrophic soil respiration). Organic C can also be lost in the form of CH_4 in anaerobic (e.g. flooded) conditions and to a lesser extent through leaching of dissolved organic C (Sanderman and Amundson, 2009). Also, soil erosion can greatly affect C stocks at a particular location, but at larger scales erosion may not represent a loss process per se but rather a redistribution of soil C (VandenBygaart *et al.*, 2012). Similarly, manure and compost application may only represent a redistribution of C in the landscape rather than a net SOC sequestration, if the alternative use of the biomass was not burning (Powlson et al. 2011). Decomposition rates are controlled by a variety of factors including soil temperature and moisture, soil cover, drainage (impacting soil O_2 availability) and pH (Paustian *et al.*, 2019). Soil physical characteristics such as texture and clay mineralogy also impact the potential to sequester C, and the longevity and persistence (i.e., mean residence time) of the sequestered C, by affecting organic matter stabilization processes, through mineral-organic matter associations (Schmidt *et al.*, 2011; Paustian *et al.*, 2019). In native ecosystems the rate of C inputs is a function of the vegetation type (e.g., annual vs. perennial, woody vs. herbaceous) and productivity of the vegetation, largely governed by climate (mainly temperature and precipitation) but also nutrient availability and other growth determining factors. In managed ecosystems such as cropland and grazing land both the rate of C input as well as the rate of soil C loss via decomposition are impacted by the soil and crop management practices applied. There is no one universal management practice to increase SOC sequestration (Lal *et al.*, 2018), but in general, soil C stocks can be increased by: (a) increasing the rate of C inputs into the soil (e.g. Fujisaki *et al.*, 2018), which removes CO_2 from the atmosphere, and/or (b) reducing the relative rate of loss (as CO_2) via decomposition, which reduces emissions to the atmosphere that would otherwise occur (Paustian *et al.*, 2019). Three key aspects need to be considered regarding the pattern of gains or losses of soil C and hence SOC sequestration (Paustian *et al.*, 2019). The first is that with increased C inputs and/or decreased decomposition rates, soil C stocks tend toward a new equilibrium state and thus after a few decades C gains attenuates, becoming increasingly small over time (Poulton *et al.*, 2018). Secondly, although sequestered SOC can be highly stable, changes in management that lead to C gains are potentially reversible, i.e., if management reverts to its previous condition, much or all gained C can be lost (Badgery *et al.*, 2020). Thus, practices that led to increased soil C need to be maintained in a long term. Climate change (even when management remains constant) is also a potential cause of reversibility, and thus risk (Badgery *et al.*, 2020). Third, mineral soils (i.e., non-peat soils) have an upper limit or “saturation level” of soil C regulated by intrinsic soil properties such as clay concentration and mineralogy, representing a limited capacity to stabilize organic C (Hassink, 1997; Six *et al.*., 2002).

While this maximum soil C concentration is well above the observed C concentration of most croplands, carbon rich mineral soils that already have very high SOC levels (e.g., >5 percent C by mass) may have a low propensity for further C gains over time. At the same time, carbon rich mineral soils which are losing SOC under current conditions, may still exhibit important SOC sequestration potential when compared to business as usual SOC sequestration trends.

1.4 Estimating and mapping soil organic carbon sequestration potential

Taking into account the above mentioned factors, SOC sequestration potential after the adoption of SSM practices can be expressed in different ways depending on the establishment of a SOC stock baseline and time towards a new equilibrium state. SOC changes can be assessed as: an 'absolute SOC change or difference', expressed as the changes in SOC stocks over time relative to a base period (t0 baseline); and a 'relative SOC change or difference, expressed as the changes in SOC stocks over time relative to business as usual SOC stocks (Fig. 1.1). Thus, the 'absolute' SOC changes can be determined for business as usual (BAU) and SSM practices, and can be either positive, neutral or negative:

$$\Delta SOC_{ABS} tCha^{-1} = SOC_{SSM\ or\ BAU\ t} - SOC_{t0} \tag{1.1}$$

where SOC $SOC_{SSM/BAU\ t}$ refers to the final SOC stocks after a defined period of time (e.g. 20 years), and SOC_{t0} refers to the initial or base period SOC stocks (t=0). The 'relative' attainable SOC sequestration is either neutral or positive, can be determined as:

$$\Delta SOC_{REL} tCha^{-1} = SOC_{SSM\ t} - SOC_{BAU\ t} \tag{1.2}$$

where $SOC_{SSM\ t}$ refers to the final SOC stocks after a defined period of time (e.g. 20 years) after SSM practices are implemented, and $SOC_{BAU\ t}$ refers to the final SOC stocks under business as usual (BAU) practices at the end of the same considered period. Mean annual SOC sequestration rates (t C ha^{-1} yr^{-1}; absolute or relative) can be determined by dividing SOC changes by the duration of the defined period.

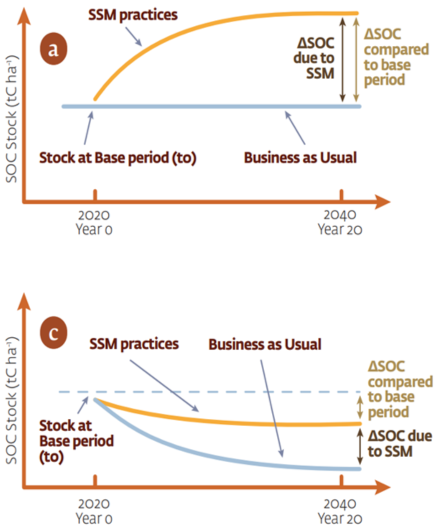


Figure 1.1: Soil organic carbon theoretical evolutions under business-as-usual (BAU) practices and after the adoption of sustainable soil management (SSM) practices. This depicts: a) lands where SOC levels have reached equilibrium and it is possible to increase levels through SSM; b) lands where SOC is increasing but can be further increased through SSM; and lands where SOC is decreasing and it is possible to stop or mitigate losses in SOC levels (c), or even reverse this fall through SSM (d)

Thus, agricultural lands can show potential for improvement in their SOC stocks after the implementation of SSM practices (compared to business as usual practices), by either gaining or maintaining SOC content. Four situations are possible: a) lands where SOC stocks have reached equilibrium or steady state and it is possible to increase those stocks through SSM (Fig. 1.1.a); b) lands where the SOC is increasing but can be further increased through SSM (Fig. 1.1.b); c) lands where SOC is declining and it is possible to stop or mitigate losses in SOC stocks through SSM (Fig. 1.1.c); and d) lands where SOC is declining and it is possible to reverse this fall through SSM (Fig. 1.1.d). Throughout this report, the SOC sequestration potential will be represented by the estimated relative SOC changes (20 year relative difference and annual average relative SOC change rate RSR, as compared to BAU management). Estimating SOC sequestration of SSM by comparing SOC changes against BAU SOC stocks provides multiple advantages. It better reflects the amount of additional SOC that could be sequestered by SSM measures compared to other approaches. It also allows users to compare and validate results with ground data from sites with contrasting historic management (especially in countries lacking long term studies of SOC dynamics). By this approach, the results can also be linked to emerging carbon crediting programs in which CO_2 removals are estimated by comparing SOC stocks changes against business as usual practices. It has been estimated that the widespread adoption of site/biome-specific SSM practices can harness the large C sink capacity of the agricultural systems at a global scale: 0.4–1.2 Pg C yr^{-1} (Lal, 2004); 1.0–1.32 Pg C yr^{-1} (Smith *et al.*, 2008); 0.4–1.1Pg C yr^{-1} (De Vries, 2018); 0.32–1.01 Pg C yr^{-1} (Batjes *et al.*, 2019). However, the extent and rates of SOC sequestration in agricultural lands may vary greatly depending on the different land uses and practices, soil characteristics, vegetation, topography and climate, among other soil forming factors and processes (Smith *et al.*, 2008; Minasny *et al.*, 2017; Lal *et al.*, 2018; Batjes *et al.*, 2019). SOC sequestration rates due to management practices in croplands and grasslands show a great variability, often ranging from 0.1 to over 1.0 t C ha^{-1} yr^{-1} (Poepleau and Don, 2015; Wertebach *et al.*, 2017; Minasny *et al.*, 2017; Conant *et al.*, 2017; Paustian *et al.*, 2016; Paustian *et al.*, 2019). It is therefore relevant to identify which regions, environments, agricultural systems and practices have a greater potential to increase SOC stocks and establish priorities for research and implementation of private and public policies. In this regard, coupling SOC models to GIS (Geographic Information Systems) platforms enables the transition from site-specific SOC stocks estimations to spatial simulations and projections (e.g. Smith *et al.* 2005; Milne *et al.*, 2007; Kamoni *et al.*, 2007), allowing for the identification of environmental and management conditions that increase the SOC sequestration potential. Several different studies combined empirical or process oriented SOC models with spatial datasets to project and map SOC dynamics and the SOC potential in agricultural lands at country, regional and global scales (e.g. Smith *et al.*, 2005; Gottschalk *et al.*, 2012; Lugato *et al.*, 2014; Wiesmeier *et al.*, 2014; Zomer *et al.*, 2017; Chen *et al.*, 2018; Morais *et al.*, 2019). However, the multiplicity of environmental and management variables regulating SOC dynamics at the global scale demands a 'made for purpose' Global Soil Organic Carbon Sequestration Potential (GSOCseq) map that is developed and validated applying local expertise, and using standardized procedures and the best available local databases. Moreover, a country-driven (bottom-up) participatory and inclusive approach, involving local experts from different fields and institutions within each participating country, will allow such a map to become a trustful and useful tool to design public and private policies, drive financial investment to the agricultural sector, establish priorities for research, and ultimately to promote and realize the implementation of SSM practices on the ground.

1.5 Objectives

Taking into account the above-mentioned considerations, the objectives of the Global Soil Organic Carbon Sequestration Potential Map (GSOCseq) initiative are:

a) to identify and prioritize areas that have high SOC sequestration potential for the implementation of SSM projects;
b) to set attainable and evidence based national targets for carbon sequestration;
c) to set up and improve local technical capacities on sustainable soil management, soil data management and use, digital soil mapping and modelling.

In order to achieve these objectives, an intensive capacity development program on SOC sequestration potential through the use of modeling and mapping techniques was implemented (see Chapter 3). A first version of a global map (GSOCseq v1.1) depicting the projected SOC stocks and SOC sequestration potential in agricultural soils after the adoption of sustainable soil management practices, compared to business as usual management, was generated from national SOCseq maps. In GSOCseq v1.1, SOC sequestration estimates focused on mineral soils in croplands (including annual and perennial crops) and grazing lands (including grasslands, rangelands, savannas and shrublands), (see Chapter 4. Product Specifications and Chapter 5.Methodology, for further details). The objective of this Technical report is to summarize the approach and results of GSOCseq v1.1.

1.6 Significance

Soils are the foundation for food production and many essential ecosystem services. As mentioned before, soils have become one of the key resources for climate change mitigation and adaptation. The Paris Agreement, the Koronivia Joint Work in Agriculture, the International Resource Panel (IRP) Report (UNEP, 2016) and the recent Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate and Land (IPCC, 2019), have also led to the development of an enabling political-institutional environment that will allow the support and adoption of sustainable management practices based on SOC maintenance and/or sequestration. Different global policy frameworks, including the UN Sustainable Development Goals (SDGs), directly or indirectly address soil, sustainable soil management and SOC sequestration. In the context of the SDGs, a sustainable global food system must foster a sustainable environment in which agriculture, biodiversity conservation and climate change adaptation and mitigation can thrive, but also co-exist and complement each other (FAO, 2017). As recently stated by Lal *et al.* (2021), sustainable soil management can contribute to achieve several SDGs, including: SDG 1 (End Poverty), 2 (Zero Hunger), 3 (Good Health and Wellbeing), 5 (Gender Equality), 6 (Clean Water and Sanitation), 7 (Affordable and Clean Energy), 9 (Industry Innovation and Infrastructure), 11 (Sustainable Cities and Communities), 12 (Responsible Consumption and Production), 13 (Climate Action), and 15 (Life on Land). Moreover, sustainable soil management and SOC are closely linked to SDG 15, as the SDG indicator 15.3.1 “Proportion of land that is degraded over total land area” is based on three sub-indicators and associated metrics: land cover (land cover change), land productivity (land productivity dynamics) and carbon stocks (soil organic carbon stocks). As indicated in the IRP report (UNEP, 2016), the development and integration of tools and indicators to assess the long-term potential of agricultural lands to generate ecosystem services in a sustainable way, constitutes a fundamental basis for the successful achievement of several of the UN SDGs. In this sense, and responding to a request from the Global Soil Partnership (GSP) Member countries for support in addressing the SDGs Indicators, especially indicator 15.3, the Global Soil Partnership (GSP) Plenary Assembly in 2020 instructed the Intergovernmental Technical Panel on Soils (ITPS) and the GSP Secretariat to develop the Global Soil Organic Carbon Sequestration Potential map (GSOCseq map), following the same country-driven approach developed for the Global Soil Organic Carbon map (GSOCmap). This 'bottom-up' approach is expected to generate a GSOCseq map from national SOCseq maps, developed and validated by local experts, based on the implementation of SOC models using standardized procedures and by leveraging the best available local data.

Chapter 2

Data policy

2.1 Data sharing principles

The GSP Data Policy was endorsed during the 5th GSP Plenary Assembly in June 2017 (FAO and GSP, 2017b) in order to promote and govern soil data sharing for data products including GSOCseq contributions, and applying data harmonization and interoperability principles. The GSP data policy ensures that:

- all existing data ownership rights to shared soil data are respected and applied;
- the specific level of access and the conditions for data sharing are clearly and detailed specified;
- the ownership of each data set and web service are properly acknowledged and well-referenced;
- the data owners are protected against any liability arising from the use of their original and/or derived data.

For more information please visit the following link containing the latest version of the GSP Data Policy (FAO, 2017, http://www.fao.org/3/bs975e/bs975e.pdf).

Chapter 3

Capacity building programme

3.1 Workshops on SOC sequestration potential modeling and mapping

Considering the request from partners to support them by providing training on state-of-the-art techniques for SOC modeling and mapping, the GSP- Secretariat designed a capacity development program following an on-the-job training model. The aim of the GSP capacity development program has been to support the exchange of knowledge on techniques on modeling SOC sequestration potential to and among the officially mandated National Experts. The National Experts were appointed directly by the national representatives of the International Network of Soil Information Institutions (INSII) and by the GSP Focal Points. This in turn allowed for a hybrid model of on-the-job workshops in which the trainees could themselves exchange local expertise on the topic SOC sequestration modeling. The establishment of a platform for the exchange of expertise played a crucial role throughout the implementation of the GSOCseq and especially to tailor the proposed methodology to country specific realities and environments. In response to travel restrictions linked to the COVID-19 pandemic in 2020, the training sessions were held online via Zoom and organized regionally to accommodate time-zone differences. Starting from the last quarter of 2020, seven regional and three national online training sessions were organized and offered by the GSP-Secretariat. Figure 3.1 illustrates the extensive outreach of this training campaign. Through seven regional and three national online training sessions 119 countries out of the 197 FAO Member countries were represented. More than 500 people attended the workshop in its entirety.

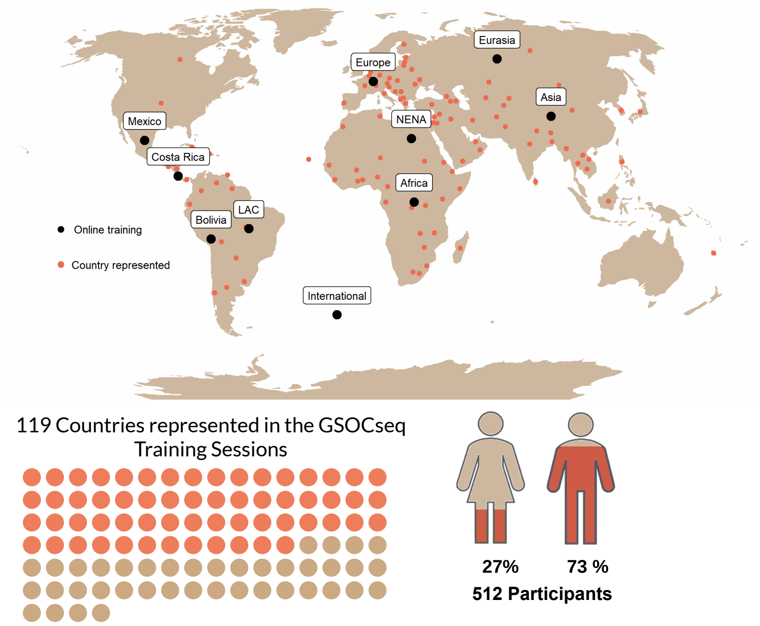


Figure 3.1: The GSOCseq Capacity Development Program in Numbers

The contents of the workshops included: introduction to the RothC model (Coleman and Jenkinson, 1996; see section 5.3), introduction to the open source programming language R, QGIS and Google Earth Engine, preparation of the input data (including monthly climatic, soil properties, land cover and vegetation cover data) and finally the training on modeling SOC sequestration potential using a spatialized version of RothC in R based on the SOILR package (Sierra *et al.*, 2012).

3.2 GSP remote support platform

To support the officially mandated national experts further in applying the methodology, a remote technical support platform was established during the national SOCseq maps generation phase. An online platform was created, allowing national experts to request virtual meetings with the GSP Secretariat working in two different time zones. To date, 60 countries have used this service. The post-training support service allowed the GSP Secretariat to address any feedback, questions, or doubts that countries´ representatives encountered. The GSP Remote support platform played a crucial role in the collection and registration of relevant feedback that was translated into ad hoc extensions of the methodology (e.g. the inclusion of an alternative approach to complete the Spin up phase, based on an analytical solution) and or will be included in future updates of the GSOCseq.

3.3 Technical manual: Global Soil Organic Carbon Sequestration Potential Map (GSOCseq v1.1)

The Technical Manual: Global Soil Organic Carbon Sequestration Potential Map (GSOCseq v1.1) (Peralta *et al.*, 2022) has been developed by the GSP Secretariat to provide technical steps and basic knowledge for modeling and mapping SOC sequestration potential. The Technical Manual used in combination with the provided sample dataset and scripts can be used as a step-by-step guide, which covers data preparation and harmonization, modeling potential soil organic carbon sequestration, converting the results to 1 x 1 km grids, estimating the uncertainty and finally data sharing and reporting. The GSOCseq Technical Manual supplements the GSP Guidelines for sharing national data/information to compile a national GSOCseq product. The GSOCseq Technical Manual was published in a GitHub Page (https://fao-gsp.github.io/GSOCseq) to ease the access to the R codes as well as the inclusion of updates.

Chapter 4

Product specifications

GSOCseq is a country-driven global product which depicts the projected Soil Organic Carbon (SOC) stocks (in t C ha^{-1}) 20 years into the future, in current agricultural lands under different soil management scenarios that vary in the degree of carbon inputs to the soil (See below and Chapter 5 for further details), at a 0-30 depth and 1 x 1 km spatial resolution.

A 20-year period was assumed to be the predetermined period of time after which SOC stocks approach a new steady state. This period has been highlighted in the IPCC Guidelines (IPCC, 2006; 2019) as a predetermined time interval in which SOC stocks can reach a new equilibrium after the introduction of land use and management practices. Although it is known that carbon stabilization can take much longer (i.e., 100 years or more) under certain environmental conditions (e.g., Poulton *et al.*, 2018), the 20-year period is selected to allow comparisons between different modeling approaches (e.g., IPCC Tier 1 method) and better harmonization of results between different regions and countries.

Although SOC is responsive to land management changes in soil layers deeper than the first 30 cm (e.g. Follett *et al.*, 2013; Poeplau and Don, 2013; Schmer *et al.*, 2014), the 0–30 cm is selected because: it is most responsive to land management changes; allows the use of GSOCmap as a baseline for SOC stocks; allows for better harmonization with national greenhouse gas inventories, and allows validation of selected models with available ground data (mostly generated at 0–30cm depth).

Due to the important potential role of agricultural lands in SOC sequestration (see sections 1.1 and 1.4), GSOCseq v1.1 estimates focus on the effects of increased C inputs on SOC stocks from mineral soils in current (by 2020) croplands (including annual and perennial crops) and grazing lands (including grasslands, rangelands, savannas, and shrublands) (see Chapter 5, Methodology, for details). Land use change projections are not considered in GSOCseq v1.1.

As changes in C inputs have been identified as one of the factors influencing SOC changes (e.g. Fujisaki *et al.*, 2018), and one of the factors to which models are most sensitive when projecting changes in SOC stocks (FAO, 2019), GSOCseq v1.1 considers the effects of SSM practices that directly affect C inputs to the soil. These practices include those highlighted in Technical Manual of Recommended Management Practices for Recarbonizing Global Soils (FAO, 2021), such as the inclusion of cover crops, improved crop rotations, grazing management, application of manure and organic fertilizers (if their destiny was other than being applied to soils), among other practices. Given the multiplicity and possible combination of those practices in the different production systems around the world, three SSM scenarios were considered in which C inputs are increased from Business As usual (BAU) C inputs. Based on Smith (2004), Wiesmeier *et al.* (2016), and FAO (2021), the expected effects (percent increase in C inputs vs. BAU C inputs) of the three scenarios were conservatively set at:

- Low (SSM1): 5 percent increase in C inputs
- Medium (SSM2): 10 percent increase C inputs
- High (SSM3): 20 percent increase in C inputs. (Refer to Chapter 5 for further details on the approach)

GSOCseq v1.1 also depicts SOC sequestration potential of soils under these three SSM scenarios compared to BAU practices, expressed as an annual relative SOC sequestration rate (in t C ha^{-1} y^{-1}). The projections are based on a spatialized version of the process-based Rothamsted Carbon Model (RothC; Coleman & Jenkinson, 1996), made available through the open-source R software. GSOCseq v1.1 includes 7 main products with their associated uncertainties (available online at the GSOCseq Data Platform - http://www.fao.org/global-soil-partnership/gsocseq-map/en/). These main products are described in the following sections.

4.1 Projected SOC stocks

4.1.1 Initial SOC stocks (GSOCseq_T0_Map030)

This map represents an estimate of current soil organic carbon stocks (in t C ha^{-1}) in 2020 (stocks at time 0; t0), at a soil depth of 0-30 cm. The best available national datasets collected over the years from the different countries were used to derive the 2020 baseline stocks (See section 5.3).

4.2 Projected SOC stocks

4.2.1 Final SOC stocks under business as usual scenario (GSOCseq_finalSOC_BAU_Map030)

This map represents the projected soil organic carbon stocks (in t C ha^{-1}) in 2040 (t20), after 20 years of business as usual (BAU) management, at a soil depth of 0-30 cm.

4.2.2 Final SOC stocks under sustainable soil management scenario 1 (GSOCseq_finalSOC_SSM1_Map030)

This map represents the projected soil organic carbon stocks (in t C ha^{-1}) in 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 5 percent increase in carbon inputs (SSM Scenario 1), at a soil depth of 0-30 cm.

4.2.3 Final SOC stocks under sustainable soil management scenario 2 (GSOCseq_finalSOC_SSM2_Map030)

This map represents the projected soil organic carbon stocks (in t C ha^{-1}) in 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 10 percent increase in carbon inputs (Scenario 2), at a soil depth of 0-30 cm.

4.2.4 Final SOC stocks under sustainable soil management scenario 3 (GSOCseq_finalSOC_SSM3_Map030)

This map represents the projected soil organic carbon stocks (in t C ha^{-1}) in 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 20 percent increase in carbon inputs (Scenario 3), at a soil depth of 0-30 centimeters.

4.2.5 SOC stocks uncertainties

The Initial SOC stocks (stocks at time 0, t0) and the final SOC stocks under the BAU and three SSM scenarios are accompanied by three uncertainty maps. Uncertainties in GSOCseq v1.1 represent the forward propagation of plausible uncertainty ranges of input layers (see section 5.6). These uncertainties do not include the model structural uncertainties. The uncertainties maps of the SOC stocks include the following products:

GSOCseq_T0_UncertaintyMap030: uncertainty of initial SOC stocks (stocks at time 0; T0)
This map represents the uncertainties (in percent) in the estimate of initial soil organic carbon stocks in 2020, due to the uncertainties of the input layers.

GSOCseq_BAU_UncertaintyMap030: uncertainty of final SOC stocks under business as usual scenario
This map represents the uncertainties (in percent) in the estimate of the projected soil organic carbon stocks after 20 years of business as usual (BAU) management, due to the uncertainties of the input layers.

GSOCseq_SSM_UncertaintyMap030: uncertainty of final SOC stocks under sustainable soil management scenarios
This map represents the uncertainties (in percent) in the estimate of the projected soil organic carbon stocks after 20 years of sustainable soil management practices, due to the uncertainties of the input layers.

4.3 SOC sequestration potential

These maps are expressed as the annual average sequestration rates compared to BAU management (relative sequestration rates RSR).

4.3.1 Relative SOC sequestration rate under sustainable soil management scenario 1 (GSOCseq_RSR_SSM1_Map030)

This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) after 20 years of implementation of sustainable soil management (SSM) practices that generate a 5 percent increase in carbon inputs (SSM Scenario 1) compared to business as usual (BAU) management, at a soil depth of 0-30 cm.

4.3.2 Relative SOC sequestration rate under sustainable soil management scenario 2 (GSOCseq_RSR_SSM2_Map030)

This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) after 20 years of implementation of sustainable soil management (SSM) practices that generate a 10 percent increase in carbon inputs (SSM Scenario 2) compared to business as usual (BAU) management, at a soil depth of 0-30 cm.

4.3.3 Relative SOC sequestration rate under sustainable soil management scenario 3 (GSOCseq_RSR_SSM3_Map030)

This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) after 20 years of implementation of sustainable soil management (SSM) practices that generate a 20 percent increase in carbon inputs (SSM Scenario 3) compared to business as usual (BAU) management, at a soil depth of 0-30 cm.

4.4 SOC sequestration uncertainties

The Relative SOC sequestration rates are accompanied by their corresponding uncertainty maps (%). Uncertainties in GSOCseq v1.1 were estimated by forward propagation of plausible uncertainty ranges of input layers (see section 5.6), and do not include the model structural uncertainties. The uncertainties maps include:

GSOCseq_RSR_SSM1_Uncertainty_Map030: uncertainty of relative sequestration rates under sustainable soil management scenario 1
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 1) compared to business as usual practices, due to the uncertainties of the input layers.

GSOCseq_RSR_SSM2_Uncertainty_Map030: uncertainty of relative sequestration rates under sustainable soil management scenario 2
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 2) compared to business as usual practices, due to the uncertainties of the input layers.

GSOCseq_RSR_SSM3_Uncertainty_Map030: uncertainty of relative sequestration rates under sustainable soil management scenario 3
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 3) compared to business as usual practices, due to the uncertainties of the input layers.

4.5 Additional products

The GSOCseq v1.1 procedure also generated intermediate products which can be useful for potential users, available upon request. These products are described in the following sections.

4.5.1 Relative differences

GSOCseq_RelDiff_SSM1_Map030: Relative SOC stock difference under sustainable soil management scenario 1
This map represents soil organic carbon stock differences (in t C ha^{-1}) between projected SOC stocks after 20 years of implementation of sustainable soil management (SSM) practices that generate a 5 percent increase in carbon inputs (SSM Scenario 1) and projected SOC stocks after 20 years of business as usual (BAU) management, at a soil depth of 0- 30 cm.

GSOCseq_RelDiff_SSM2_Map030: Relative SOC stock difference under sustainable soil management scenario 2
This map represents soil organic carbon stock differences (in t C ha^{-1}) between projected SOC stocks after 20 years of implementation of sustainable soil management (SSM) practices that generate a 10 percent increase in carbon inputs (SSM Scenario 2) and projected SOC stocks after 20 years of business as usual (BAU) management, at a soil depth of 0-30 cm.

GSOCseq_RelDiff_SSM3_Map030: Relative SOC stock difference under sustainable soil management scenario 3
This map represents soil organic carbon stock differences (in t C ha^{-1}) between projected SOC stocks after 20 years of implementation of sustainable soil management (SSM) practices that generate a 20 percent increase in carbon inputs (SSM Scenario 3) and projected SOC stocks after 20 years of business as usual (BAU) manage- ment, at a soil depth of 0-30 cm.

4.5.2 Absolute differences

GSOCseq_AbsDiff_BAU_Map030: Absolute SOC stock difference under business as usual scenario
This map represents the projected soil organic car- bon stock change (in t C ha^{-1}) from 2020 initial stocks, after 20 years of business as usual (BAU) management, at a soil depth of 0-30 cm.

GSOCseq_AbsDiff_SSM1_Map030: Absolute SOC stock difference under sustainable soil management scenario 1
This map represents the projected soil organic carbon stock change (in t C ha^{-1}) from 2020 initial stocks, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 5 percent increase in carbon inputs (SSM Scenario 1), at a soil depth of 0-30 cm.

GSOCseq_AbsDiff_SSM2_Map030: Absolute SOC stock difference under sustainable soil management scenario 2
This map represents the projected soil organic carbon stock change (in t C ha^{-1}) from 2020 initial stocks, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 10 percent increase in carbon inputs (SSM Scenario 2), at a soil depth of 0-30 cm.

GSOCseq_AbsDiff_SSM3_Map030: Absolute SOC stock difference under sustainable soil management scenario 3 This map represents the projected soil organic carbon stock change (in t C ha^{-1}) from 2020 initial stocks, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 20 percent increase in carbon inputs (SSM Scenario 3), at a soil depth of 0-30 cm.

4.5.3 Absolute SOC stock change rates

GSOCseq_ASR_BAU_Map030: Absolute SOC stock change rate under business as usual scenario
This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) from 2020 to 2040, after 20 years of business as usual (BAU) management, at a soil depth of 0-30 cm.

GSOCseq_ASR_SSM1_Map030: Absolute SOC stock change rate under sustainable soil management scenario 1 This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) from 2020 to 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 5 percent increase in carbon inputs (SSM Scenario 1), at a soil depth of 0- 30 cm.

GSOCseq_ASR_SSM2_Map030: Absolute SOC stock change rate under sustainable soil management scenario 2 This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) from 2020 to 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 10 percent increase in carbon inputs (SSM Scenario 2), at a soil depth of 0-30 cm.

GSOCseq_ASR_SSM3_Map030: Absolute SOC stock change rate under sustainable soil management scenario 3
This map represents the average annual rate of soil organic carbon stock change (in t C ha^{-1} yr^{-1}) from 2020 to 2040, after 20 years of implementation of sustainable soil management (SSM) practices that generate a 20 percent increase in carbon inputs (SSM Scenario 3), at a soil depth of 0-30 cm.

4.5.4 Other uncertainties

GSOCseq_ASR_BAU_Uncertainty_Map030: uncertainty of absolute SOC stock change rate under business as usual scenario
This map represents the uncertainties (in percent) in the estimate of the average

annual rate of soil organic carbon stock change after 20 years of business as usual (BAU) management, due to the uncertainties of the input layers.

GSOCseq_ASR_SSM1_Uncertainty_Map030: uncertainty of absolute SOC stock change rate under sustainable soil management scenario 1
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 1), due to the uncertainties of the input layers.

GSOCseq_ASR_SSM2_Uncertainty_Map030: uncertainty of absolute SOC stock change rate under sustainable soil management scenario 2
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 2), due to the uncertainties of the input layers.

GSOCseq_ASR_SSM3_Uncertainty_Map030: uncertainty of absolute SOC stock change rate under sustainable soil management scenario 3
This map represents the uncertainties (in percent) in the estimate of the average annual rate of soil organic carbon stock change after 20 years of implementation of sustainable soil management practices (Scenario 3), due to the uncertainties of the input layers.

Chapter 5

Methodology

5.1 Scope

SOC sequestration estimates are focused on croplands and grazing lands in GSOCseq v1.1. As defined by IPCC (2006; 2019), croplands include: all annual crops (cereals, oils seeds, vegetables, paddy rice, root crops and forages); perennial crops (including trees and shrubs, orchards, vineyards and plantations such as cocoa, coffee, tea, oil palm, coconut, rubber trees, and bananas), and their combination with herbaceous crops (e.g. agroforestry); cropland which is normally used for cultivation of annual crops, but which is temporarily used for forage crops or grazing as part of an annual crop-pasture rotation (mixed system), was included under croplands. Grazing lands typically included different land uses permanently dedicated to livestock production with a predominant herbaceous cover, including grasslands, rangelands, savannas, and shrublands. Short-term pastures were included under croplands or grazing lands depending on the quality of the plant material (see section 5.4.3). All other land uses were excluded.

5.2 SOC sequestration estimates

SOC stocks in 0-30 cm of mineral soils were projected over a 20-year period starting from year 2020 (t0), under business as usual land use and management, and after adoption of sustained SSM Practices represented by increased C inputs to soils (See section 5.3), in all agricultural lands (croplands and grazing lands by 2020). Thus, the SOC sequestration potential quantified in GSOCseq v1.1 represents a biophysical potential rather than a technical or economic one defined by the technological, cultural, financial or political barriers that may limit the adoption of SSM practices within each country and region (Amundson and Biardeau, 2018).A 20-year period was assumed to be the default period during which SOC stocks approach a new steady state (e.g. IPCC, 2006 Tier 1-2; IPCC, 2019). SOC changes were estimated in absolute and relative terms (See section 1.4) for that period. As mentioned in the previous sections, the SOC sequestration potential is represented in this report by the estimated relative SOC sequestration (20 year difference - REL DIFF; and annual average SOC sequestration rate - RSR). GHG mitigation potential from SOC sequestration was derived from relative sequestration rates, and expressed in CO_2 equivalent units yr^{-1} (IPCC, 2019). Additional emissions resulting from an increase in C input to the soil were not considered in this analysis. GHG mitigation potential was compared to total yearly agricultural emissions, derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The FAOSTAT domain Agricultural Emissions Totals contain GHG emissions including CH_4, N_2O and CO_2 emissions from crop and livestock activities.

5.3 Modeling approach

The modeling approach was based on the studies by Smith *et al.* (2005; 2006; 2007) and Gottschalk *et al.* (2012). A spatial version of the RothC model (Coleman and Jenkinson, 1996) was developed by GSP Secretariat in R-language based on SOILR functions (Sierra *et al.*, 2012). RothC is a model for the turnover of organic carbon that includes the effects of soil type, temperature, moisture content and plant cover on the turnover process, with a monthly time step. RothC was originally developed and parameterized to model the turnover of organic C in arable topsoils in temperate climates (Jenkinson *et al.*, 1990), and it was later extended to model turnover in paddy fields, grasslands, savannas and woodlands, and to operate in different soils and under different climates.

However, there is relatively less available data of the parametrization and performance of the RothC model under volcanic soils (Shirato *et al.*, 2004; Takata *et al.*, 2011), salt affected soils (Setia *et al.*, 2013), tropical soils (Cerri *et al.*, 2007; Kaonga and Coleman, 2008; Bhattacharyya *et al.*, 2012), and arid and semi-arid conditions (Farina *et al.*, 2013; Azad *et al.*, 2019).

Although carbon saturation theory suggests that soils have a limited capacity to stabilize organic C regulated by intrinsic soil properties such as clay concentration and mineralogy (Hassink, 1997; Six *et al.*., 2002), no upper limit or "saturation limit" of soil C was included in RothC functions in GSOCseq v1.1, due to the limited evidence of the model performance under different environmental conditions with such modifications (Heitkamp *et al.*, 2012). Modifications to the original functions were introduced in GSOCseq v1.1 to include well documented rate modifying factors for paddy rice (e.g. Shirato and Yokozawa, 2005; Jiang *et al.*., 2013; Shirato, 2020) following the functions originally developed by Shirato and Yokozawa, 2005). The vegetation cover factor estimation was based on MODIS NDVI products (see section 4.2). Since the proposed standardized methodology and the defined model are neither parameterized nor recommended for use on organic soils, soils with SOC stocks higher than 200 t C ha^{-1} at 0–30 cm depth at t0 were excluded from the global results in this first version (following Gottschalk *et al.*, 2012).

The spatial RothC model was run for mineral soils in the selected target land uses at a 1 x 1 km resolution. To initialize the model, RothC was run iteratively to equilibrium to calculate the size of the annual carbon inputs (C_{eq}) required to reach initial SOC stocks. A first equilibrium run for a minimum of 500-year period was performed, considering constant climatic conditions as the average of historic climate data from 1980 to 2000 (see section 4.2.1, Climate datasets), clay contents 0-30 cm (see section 4.2.2, soil datasets) and land use representative of those of year 2000 (see section 4.2.3.). Annual plant C input was initially assumed to be 1 t C ha^{-1} yr^{-1} and then adjusted based on Smith *et al.*, 2007 and Mondini *et al.*, 2017:

$$C_{eq} = C_i \times \frac{SOC_{GSOCmap} - IOM}{SOC_{sim} - IOM} \tag{5.1}$$

where C_{eq} is the estimated annual C input at equilibrium, C_i is the initial annual C addition (C input in the first equilibrium run), $SOC_{GSOCmap}$ is the estimated soil C given in GSOCmap, SOC_{sim} is the simulated soil C after the first equilibrium run, and IOM is the C content of the inert organic matter fraction in the soil (all in t C ha^{-1}) estimated following Falloon *et al.* (1998). SOC stocks for the different SOC pools of the RothC model were estimated following the functions developed by Weihermüller *et al.* (2013). Since FAO-ITPS GSOCmap SOC was generated from individual SOC measurements taken over different decades (i.e. 1960s to 2000s), a temporal harmonization of SOC stocks was performed as a second initialization step to minimize differences in current SOC stocks at year 0 (i.e. initial SOC stocks at year 2020). SOC stocks from the GSOCmap were considered to be representative of the stocks twenty years prior to the simulation (t = -20 y; i.e. year 2000).

A 20-year 'short spin-up' run was performed to adjust for major deviations among different measurement periods on the GSOCmap using year-to-year climatic conditions for the period 2001-2020 (section 3.3.1, Climate datasets), and land use during the 2000-2020 period (or representative land use). Year-to-year C inputs over the period 2001-2020 were adjusted considering year-to-year changes in estimated Net Primary Production (NPP) following Smith *et al.* (2005; 2007). NPP was estimated from annual average temperature and the annual sum of precipitation using the MIAMI model (Lieth, 1975). Changes in NPP due to land use change over the period 2000-2020 were adjusted considering biomass removal coefficients from Schulze *et al.* (2010). If recent (2015-2020) national SOC monitoring campaigns have been undertaken to generate the latest version of the FAO-IPS GSOCmap, the SOC stocks from the GSOCmap were considered as the current stocks (t = 0 y; i.e. year 2020), and the 'short spin-up' phase was not performed.

After the equilibrium and 'short spin-up' runs, SOC sequestration due to SSM practices was projected for 20 years, using average mean monthly climate variables (2001-2020), land use representative of year 2020 (no land use changes assumed) and C inputs estimated from the above mentioned modeling phases. SOC stocks were simulated from 2020 (t=0) to 2040 (t = +20) for a business as usual (BAU) scenario and three scenarios that included the implementation of SSM practices. The SSM practices considered in this approach were practices that directly affect C inputs to the soil, as changes in C inputs have been identified as one of the factors to which models are most sensitive when projecting changes in SOC stocks (FAO, 2019). Annual BAU C inputs were estimated from the C inputs at equilibrium and the annual adjustments (2000-2020) mentioned above. The C inputs of the SSM scenarios were estimated as a percent increase from BAU C inputs. The use of predefined percentages in C input increase allowed the global application of the RothC model without complex configuration. Based on Smith (2004) and Wiesmeier *et al.* (2016) the expected effects (percent increase in C inputs vs. BAU C inputs) of three scenarios were conservatively set at:

- Low (SSM1): 5 percent increase in C inputs
- Medium (SSM2): 10 percent increase C inputs
- High (SSM3): 20 percent increase in C inputs

5.4 Input data

Following a country-driven approach, countries were encouraged to use: a) National Sources or preferred regional data source as a first option, following harmonization procedures detailed in the Technical specifications and Country Guidelines for the Global Soil Organic Carbon Sequestration Potential Map (GSOCseq)(FAO, 2020); b) Default global data sets, when national or regional gridded data sets were not available. The following sections describe the required input data and default global datasets. The datasets used by each country are detailed in Annex A.

5.4.1 Climate data

The following variables (1980-2020 series, monthly data, year to year) were required to run the model at 1 x 1 km spatial resolution: monthly average air temperature (°C), monthly precipitation (mm), monthly potential evapotranspiration (Penman-Monteith; mm). Two global datasets were provided to be used as default datasets to be used by countries in the absence of national data: Climate Research Unit (CRU) and TerraClimate. CRU TS v. 4.03 dataset (https://crudata.uea.ac.uk/c ru/data/hrg/cru_ts_4.03/cr uts.1905011326.v4.03/) was developed by the University of East Anglia, United Kingdom (Harris *et al.*, 2014) at a resolution of 0.5° (~50 x 50 km). TerraCimate (http://www.climatologylab.org/terraclimate.html) dataset was developed at a 0.042° (~4 x 4 km) spatial resolution by combining high-spatial resolution climatological normals from the WorldClim data set, with coarser spatial resolution, but time-varying data from CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55) (Abatzoglou *et al.*, 2018). See Annex A for the climate layer used by each country.

5.4.2 Soil data

Initial total SOC stocks to 30cm depth (in t C ha^{-1}) were obtained from the GSOCmap (30 arc seconds; ~ 1 x 1 km resolution grid), latest revised version (V.1.5 or higher; http://54.229.242.119/GSOCmap/; FAO-ITPS, 2019). Clay content (0-30 cm, percent mass fraction; 1 x 1 km resolution) was provided from the SoilGrids 2018 database developed by the International Soil Reference and Information Centre (ISRIC) (https://data.isric.org/geonetwork/srv/spa/catalog.search#/metadata/20f6245e-40bc-4ade-aff3-a87d3e4fcc26), if national or regional data were not available. Average clay contents over a 0-30 cm depth interval were derived by taking a weighted average of the predictions over the depth interval using numerical integration (Hengl *et al.*, 2017). See Annex A for the soil data layers used by each country.

5.4.3 Land cover/Land use and soil management data

Since land cover may vary substantially between data sources and estimates of past and current land cover may have important deviations from real land cover and land use, countries were encouraged to estimate land use from the national, regional or global source that best reflects national and subnational conditions for the 2000-2020 period (See Annex A for the land cover layer used by each country). The ESA (European Space Agency, http://www.esa-landcover-cci.org/) land cover Global dataset (2000-2019) was provided as the default global dataset if national or regional data were not available. ESA land cover classes were reclassified into FAO Global Land Cover - SHARE (GLC-SHARE) classes (Table 1). FAO Cropland class was further disaggregated into two additional classes (paddy rice and tree-crops) in order to provide the alternative to modify model parameters for these classes (i.e., decomposition rates, decomposability of incoming plant material). Default values for the DPM/RPM ratio (decomposability of incoming plant material) obtained from Coleman and Jenkinson (1996) were provided for each class (Table 5.1). In the case of tree crops, as this class can include a wide range of crops from banana plantations to vineyards, the DPM/RPM value proposed by Morais *et al.* (2019) at the global scale was provided as default. In all cases, country experts were able to modify DPM/RPM ratios for the different land covers based on local data.

Table 5.1: Default ESA Land Cover classes aggregation and reclassification scheme to FAO land cover classes, and default decomposable to resistant plant material ratios (DPM/RPM)

ESA Land Cover Class	FAO Land Cover Class	Default DPM/RPM
0	0 No Data	-
190	1 Artificial	-
10 11 30 40	2 Croplands	1.44
130	3 Grassland (unimproved)	0.67
50 60 61 62 70 71 72 80 81 82 90 100 110	4 Tree Covered	0.25
120 121 122	5 Shrubs Covered	0.67
160 180	6 Herbaceous vegetation flooded	0.67
170	7 Mangroves	-
150 151 152 153	8 Sparse Vegetation	0.67
200 201 202	9 Baresoil	-
220	10 Snow and Glaciers	-
210	11 Waterbodies	-
12	12 Treecrops-orchards	1.44
20	13 Paddy fields(rice/ flooded crops)	1.44

Annual carbon inputs were estimated for the BAU and SSM scenarios following the approach detailed in section 5.3. In the absence of national data, monthly vegetation cover was derived from MODIS ('MODIS/006/MOD13A2) NDVI products (global normalized difference in vegetation index; 1 x 1 km). Estimating the probability of exceeding a specified NDVI threshold, e.g. NDVI>0.2-0.3 vegetated vs. bare soil; NDVI>0.5-0.6 fully vegetated/covered can be used to identify trends linked to vegetation cover and SSM management (Sobrino *et al.*, 2002). The proportion of images P_{veg} with NDVI values greater than a specified threshold (NDVI=0.5 provided as default), indicating active vegetation growth, within a representative time series (e.g. 2015-2020), was estimated for each month as:

$$P_{veg} = \frac{Number\ of\ images\ NDVI > 0.5}{Total\ images} \tag{5.2}$$

Then for each target month, NDVI probability of exceeding a threshold (0=bare to 1=always covered) was linearly transformed into the RothC vegetation cover factor (1.0=bare to 0.6= fully covered).

5.5 Gap filling

For the first version of the GSOCseq, countries lacking the technical capacity and/or human resources to undertake the task asked the GSP Secretariat to generate national maps. The gap filling of these countries (refer to Annex A for details for each country) was developed following the general modeling approach explained in sections 5.3. For the spin up modeling phase, an alternative approach using the analytic solution of the RothC model (Dechow *et al.*, 2019) was implemented to estimate initial carbon inputs and initial SOC pools, requiring lower computational capacity (FAO, 2020). All other procedures followed the procedures described in section 5.3. Soil, and land use and management input data layers corresponded to the default global datasets described in section 5.4. Except for Brazil and Indonesia for which the climatic dataset TerraClimate was used, all other non-participating countries were gap-filled by relying on the CRU climatic dataset (section 5.4). The model was run over a 5 km point grid for the GSOCseq target areas. The output layers were subsequently downscaled to a 1 km resolution using a weighted Generalized Additive Model (GAM) model following the approach described by Malone *et al.*, (2012).

5.6 Uncertainties

Uncertainties in GSOCseq v1.1 represent the uncertainties of input data layers and their effects on SOC projections. For each simulated scenario, uncertainties (U) were estimated at 1 x 1 km as:

$$U\% = \frac{100 \times (UL - LL)}{2 \times SOC_{av}} \tag{5.3}$$

where UL corresponds to the upper limit of the estimated SOC stock at the end of the simulation (in t C ha^{-1}), LL corresponds to the lower limit of the estimated SOC stock at the end of the simulation (in t C ha^{-1}); and SOCav the average of the estimated SOC at the end of the simulation (t C ha^{-1}), after 20 years of the forward modeling, for each scenario. To estimate uncertainties of the sequestration rates (uncertain quantities are combined by subtraction, e.g. $\Delta SOC = StocksSSM - SOCstocksBAU$), the uncertainty expressed in percentage terms was estimated by the following equation (IPCC, 2019):

$$Ut = \frac{\sqrt{((U1X1)^2 + ... + (UnXn)^2)}}{|X1 + ... + Xn|} \tag{5.4}$$

where Ut is the percentage uncertainty in the subtraction of the quantities, $X1, ...Xn$ represent the quantities to be combined (e.g. Stocks SSM and SOC stocks BAU at the end of the forward simulation), and U1,. . . Un is the percentage uncertainties associated with each of the quantities (as estimated from equation 5.3). As well-known methods to estimate uncertainties such as Monte Carlo and related simulations (e.g. Markov Chain-Monte Carlo method, as in Hararuk et al., 2014; GLUE method, as in Salazar et al., 2011) usually require considerable computational capacity, especially for long spin-up runs (>500 years), an alternative approach was developed, to calculate uncertainties considering minimum and maximum values (corresponding to the limits of a 95% confidence interval) of a set of predefined input parameters. Maximum and minimum values were estimated for the input layers considered to have the greatest influence in RothC modeling results (initial SOC, Carbon inputs, and soil and climatic variables). Thus, uncertainties were estimated for each modeling unit and for each scenario by estimating the maximum (upper limit) and minimum (lower limit) SOC simulated values (UL and LL; similarly to VCS, 2012) using a predefined arrangement of inputs:

$$SOC_{max} = Model(SOC_{i\ max}, C_{i\ max}, Temp_{max}, Pp_{max}, Clay_{max}) \tag{5.5}$$

$$SOC_{min} = Model(SOC_{i\ min}, C_{i\ min}, Temp_{min}, Pp_{min}, Clay_{min}) \tag{5.6}$$

where SOC_{min} and SOC_{max} are respectively the minimum and maximum value for the simulated SOC stocks; $SOC_{i\ min}$ and $SOC_{i\ max}$ are respectively the minimum and maximum value for the initial SOC stocks (estimated at the 95% confidence interval);$C_{i\ min}$ and $C_{i\ max}$ are respectively the minimum and the maximum value for the annual carbon inputs (estimated at the 95% confidence interval); $Temp_{min}$ and $Temp_{max}$ are respectively the minimum and maximum value for the average monthly air temperature (estimated at the 95% confidence interval); Pp_{min} and Pp_{max} are respectively the minimum and maximum value for the average monthly precipitation (estimated at the 95 percent confidence interval); and $Clay_{min}$ and $Clay_{max}$ are respectively the minimum and maximum value for the soil clay content (0-30 cm) (estimated at the 95 percent confidence interval). The arrangement of variables to generate minimum and maximum SOC stocks was generated considering the effects of each variable on NPP, decomposition rates, and overall carbon dynamics (Chapter 5). If no local estimate of the maximum and minimum value for these parameters was available, those values were estimated using general uncertainty coefficients reported from global modeling exercises by Gottschalk et al. (2007) and Hastings et al. (2010). Average uncertainties for these parameters are summarized in Table 5.1. The model was run two more times for each modeling unit and scenario in the different modeling phases using the selection of values to obtain a maximum and minimum projected SOC stock (eq 5.5-5.6).

Table 5.1 General uncertainties of main parameters affecting SOC dynamics. Derived from Gottschalk et al. (2007) and Hastings et al. (2010).

Parameter	Uncertainty in the input	Minimum value	Maximum value
Temperature	± 2 %	Monthly Temp x 0.98	Monthly Temp x 1.02
Precipitation	± 5 %	Monthly PP x 0.95	Monthly PP x 1.05
Clay content	± 10 %	Clay x 0.90	Clay x 1.10
FAO SOC	± 20 %	SOC FAO x0.8	SOC FAO x 1.2
C input increase in SSM scenario	± 15 %	C eq x (SSM1 % increase - 15%)	C eq x (SSM % increase + 15%)

5.7 GSOCseq scripts - GitHub repository

The scripts used for the country-driven implementation of the GSOCseq initiative are open-source and available in the following GitHub repository: https://github.com/FAO-GSP/GSOCseq-scripts

Chapter 6

Results

The GSOCseq Version 1.1 is comprised to date of 50 National Submissions. Figure 6.1 illustrates the distribution of national submissions. Country specific details on the submission status and input data used can be found in Annex A. The 50 countries that submitted GSOCseq maps based on the best available national data represent 55 percent of the total target agricultural area. Countries that agreed to take part in the GSOCseq initiative, but could not submit a national product were gap-filled using globally available data sets and represent 37 percent of the target GSOCseq area. Countries that indicated their preference to be left out blank for the first version of the GSOCseq represent 8 percent of the target GSOCseq area (Figure 6.2). It is important to note that the GSOCseq is constantly being extended to accommodate improved and/or new national products. The following section summarizes the most relevant findings that can be derived from Version 1.1 of the GSOCseq. The results are representative for countries that participated in the initiative by either submitting a national product or that agreed to being temporarily gap-filled (92 percent of the total target agricultural area). Countries that wished to remain blank on the current version of the product were not included in this analysis.

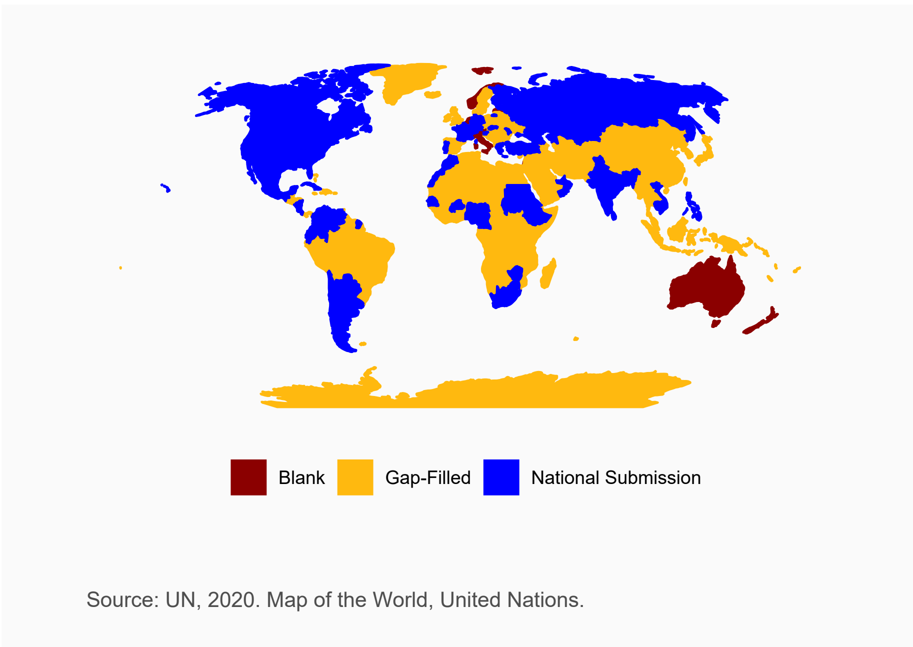


Figure 6.1: Overview of Countries that submitted a National GSOCseq.

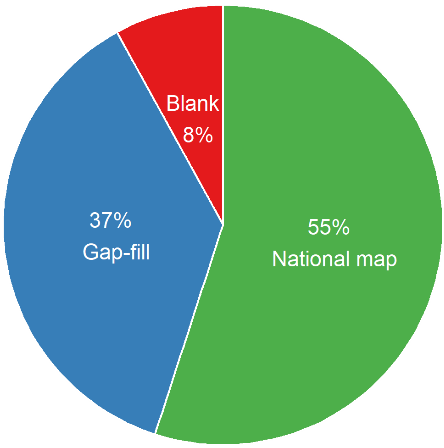


Figure 6.2: Share of national products submitted to the GSOCseq V1.1, expressed as a percentage of the global agricultural area

6.1 Global soil organic carbon sequestration potential

6.1.1 Soil organic carbon sequestration potential sustainable soil management vs business as usual

Figure 6.3 highlights the global distribution of Soil Organic Carbon Sequestration Potential in terms of the average annual sequestration rate in t C ha^{-1} yr^{-1} under SSM3 scenario compared to the BAU scenario. Figure 6.4 shows a comparison of the average annual sequestration rate (RSR, t C ha^{-1} yr^{-1}) between all SSM1, SSM2 and SSM3 scenarios with 5 percent, 10 percent and 20 percent C input increase respectively alongside its corresponding uncertainty estimations (Figure 6.5).

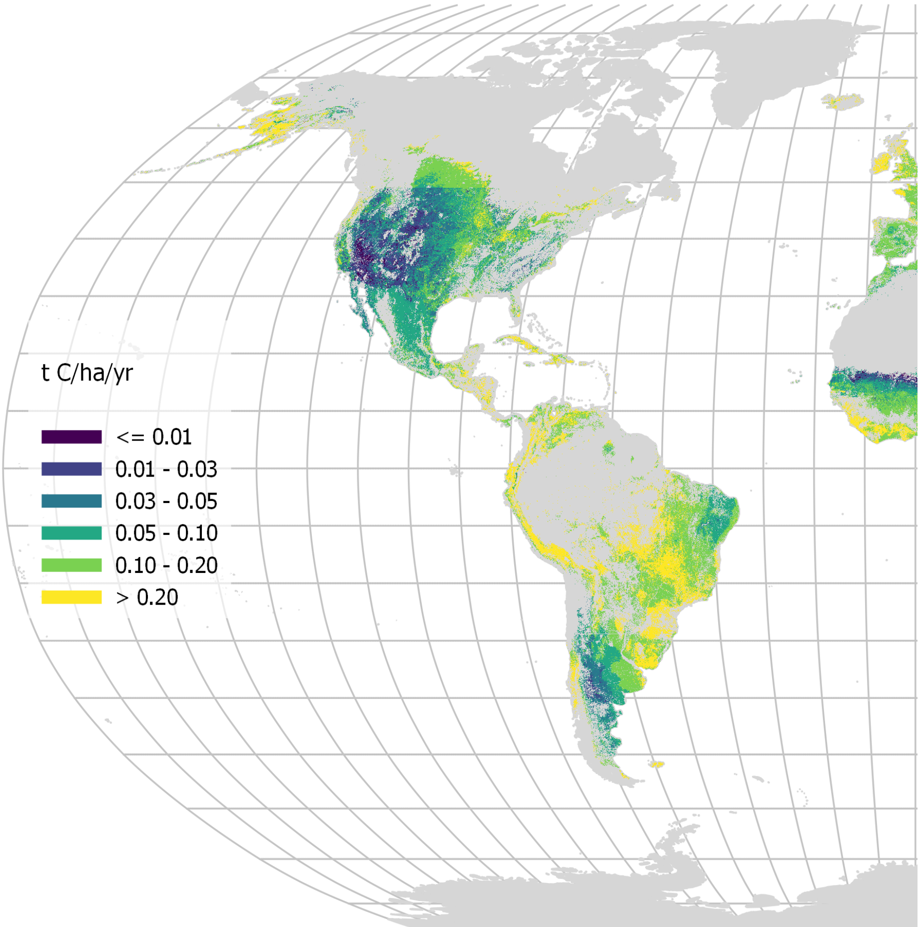
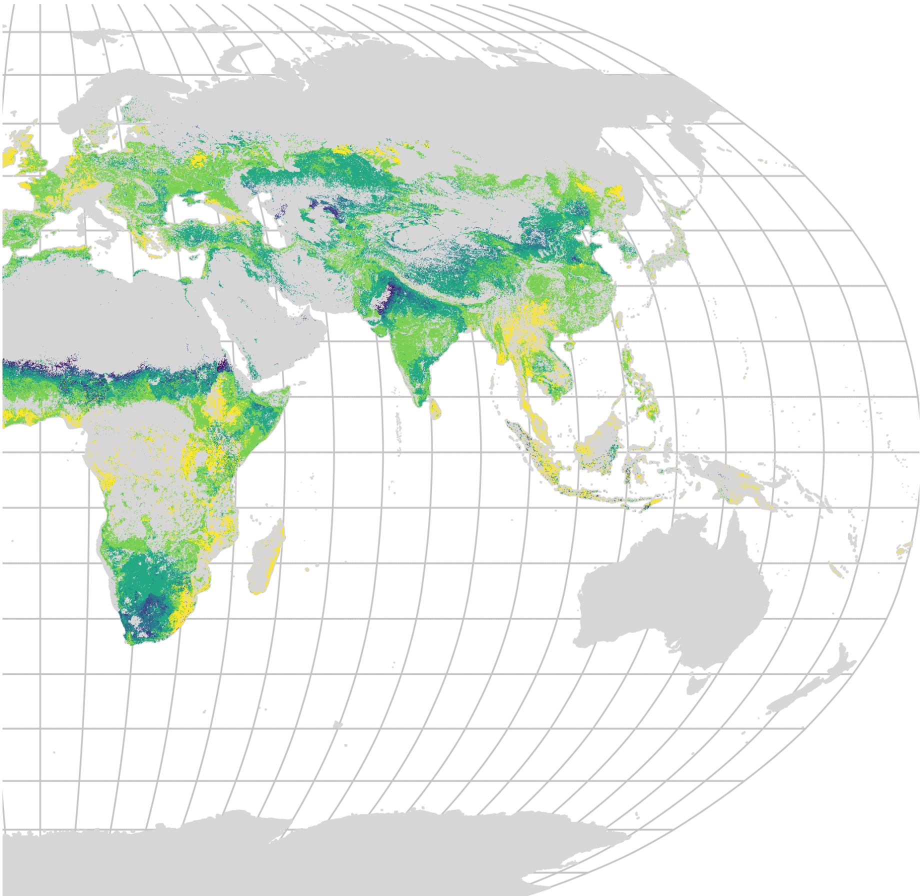


Figure 6.3: Relative Soil Organic Carbon Sequestration Rates under the SSM3 scenario. Gray areas represent non agricultural lands according to national submissions or gap-filling process.



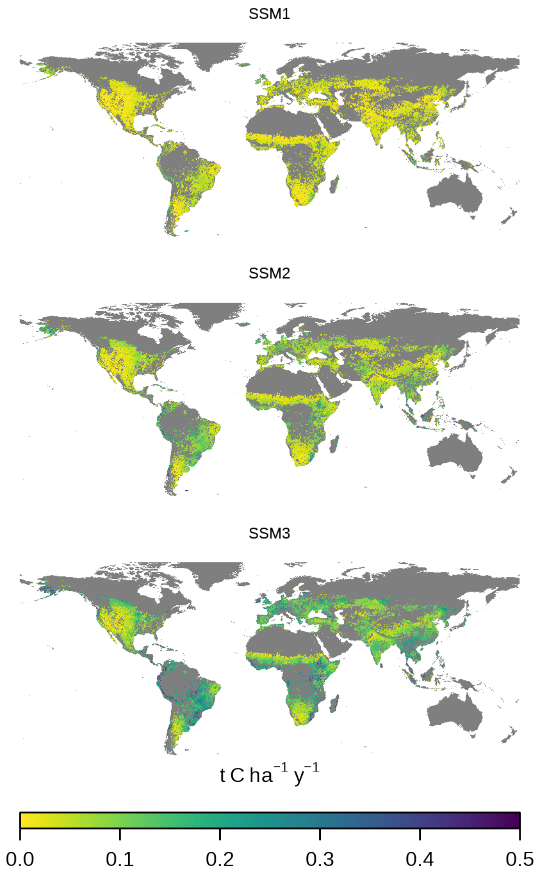


Figure 6.4: Relative Soil Organic Carbon Sequestration Rates. Gray areas represent non agricultural lands according to national submissions or gap-filling process.

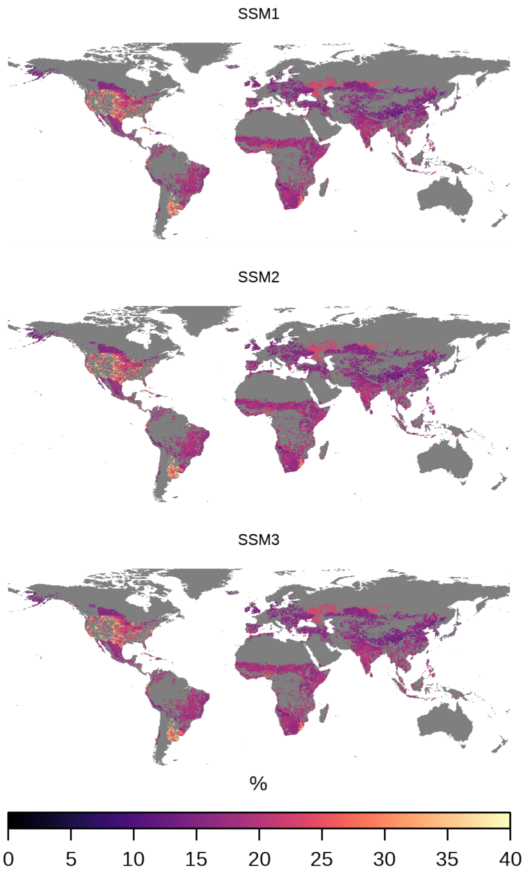


Figure 6.5: Uncertainty estimation of Relative Soil Organic Carbon Sequestration Rates. Uncertainties were dervied from the input data considering minimum and maximum values of initial SOC, Carbon inputs, and soil and climatic variables. Gray areas represent non agricultural lands according to national submissions or gap-filling process.

Table 6.1 summarizes the annual global sequestration potential in terms of yearly SOC increases. Up to 0.3 percent additional carbon could be sequestered globally, compared to the BAU scenario (SSM3). Thus, up to 11.31 Pg of additional C could be sequestered by 2040 if a 20 percent increment in C returns would be inputted to the soil (SSM3 scenario).

Figure 6.6 breaks down the potential relative sequestration rates according to the three scenarios. In terms of C potentially sequestered on a yearly basis, 0.14±0.05 Pg yr^{-1}, 0.29±0.1 Pg yr^{-1}, 0.57±0.19 Pg yr^{-1} could be sequestered under the SSM1 (5 percent C input increase), SSM2 (10 percent C input increase) and SSM3 (20 percent C input increase) scenarios respectively. As shown in table 6.2 the results from SSM3 scenario are in line with previous estimations for agricultural lands (Paustian *et al.*, 2004; Smith *et al.*, 2008; Sommer and Bossio, 2014; Batjes *et al.*, 2019), although in the lower range of those estimates. The results from SSM1 and SSM2 scenarios are in the same order of magnitude but smaller than those estimates from previous studies.

Table 6.1: Summary of estimates of total global Relative SOC sequestration rates Pg yr^{-1} and average global Relative SOC sequestration rates in tha^{-1}.

Layer	Scenario	sum		mean		Change *
		PG C yr^{-1}	± PG C yr^{-1}	$t\ C\ ha^{-1}$	$\pm\ t\ C\ ha^{-1}$	%
RSR	SSM1	0.143	0.05	0.042	0.01	0.076
RSR	SSM2	0.289	0.10	0.090	0.01	0.153
RSR	SSM3	0.566	0.19	0.173	0.02	0.300

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks. The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95 percent confidence interval) of selected input layers.

Table 6.2: Previous estimations of Soil Organic Carbon Sequestration Potential.

Source	Sequestration Rate Pg C/yr
Paustian et al (2004)	0.44 - 0.88
Smith et al (2008)	0.44 - 1.15
Sommer and Bossio (2014) (Croplands+grasslands+rangelands)	0.37 - 0.74
Batjes et al (2019)	0.32 - 1.01
Lal et al (2018) (Croplands+grasslands-rangelands)	0.48 - 1.93

Table 6.3 and Figure 6.7 show total relative sequestration rates in Pg of CO_2

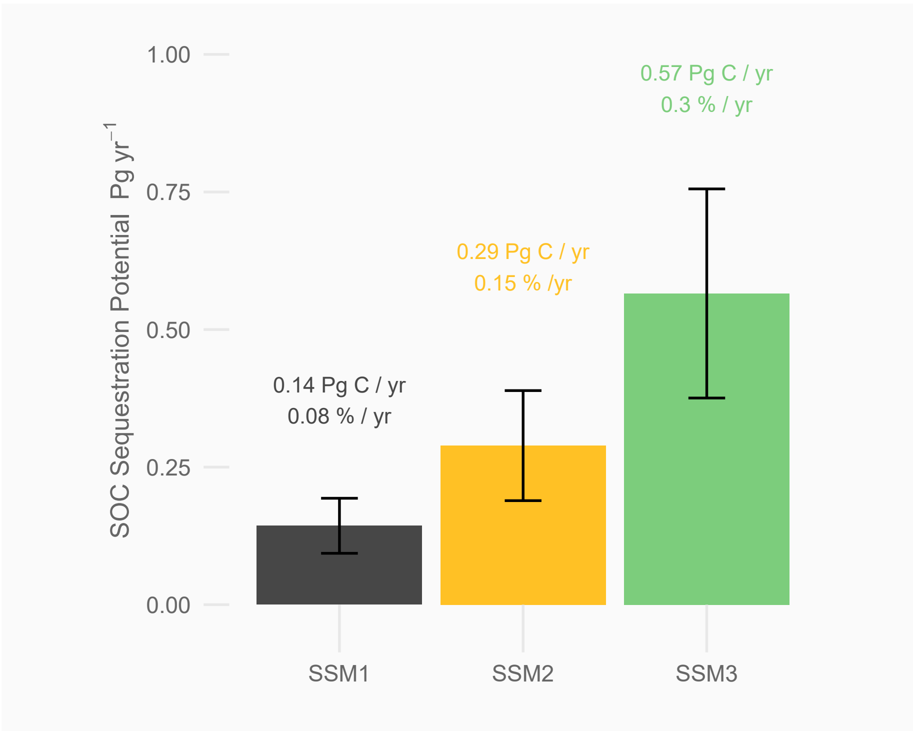


Figure 6.6: Soil Organic Carbon Sequestration Potential: sustainable soil management Scenarios (SSM1, SSM2 and SSM3) vs business as usual (BAU) scenario.

yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead a yearly mitigation of 0.52 - 2.08 Pg CO_2-eq yr^{-1}, representing 7.9 - 31.3 % of total agricultural net emissions.

Table 6.3: Potential Mitigation of Agricultural Net Emissions in Pg of CO_2 equivalent (Pg $CO_2 - eq/yr^{-1}$)

Total Agricultural Emissions.. CO_2-eq Pg yr^{-1}	Scenario	C sequestered CO_2-eq Pg yr^{-1}	Mitigation share %
6.63	SSM1	0.525	7.92
6.63	SSM2	1.061	16.00
6.63	SSM3	2.077	31.33

* Total Agricultural Net Emissions are based on the item *Agriculture Total* from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5)

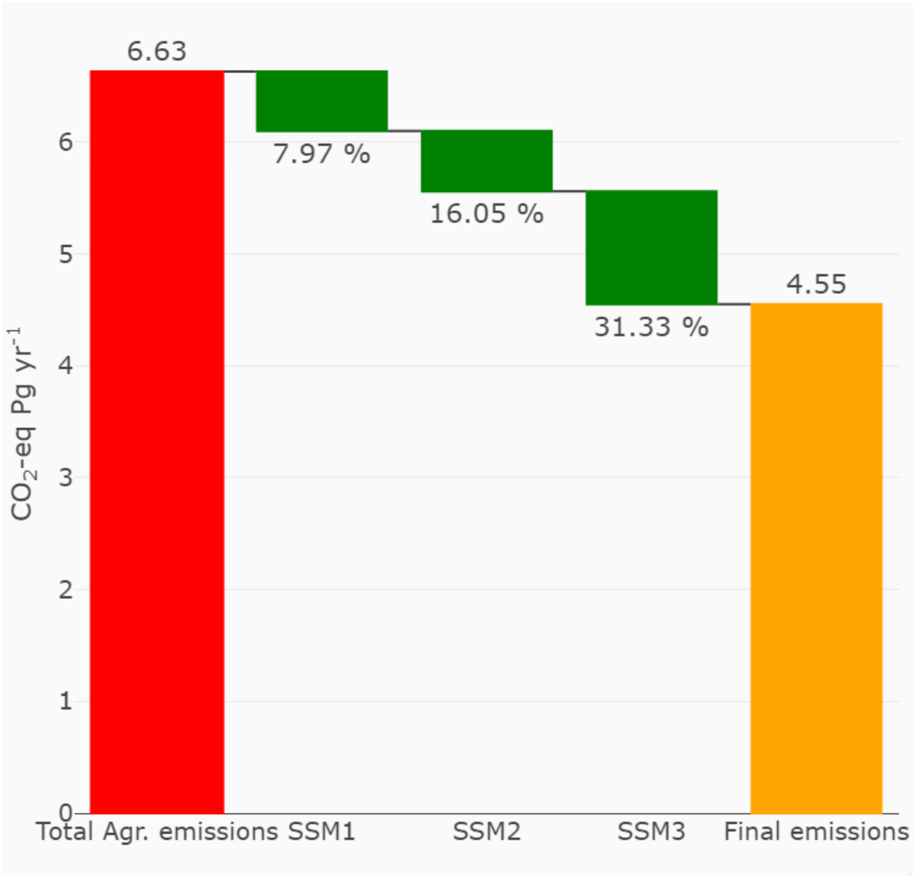


Figure 6.7: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1}

6.2 Statistics for countries (GSOCseq V.1.1)

Statistics based on countries were calculated using the United Nations Administrative Boundaries map for 2020 as the source for national boundaries. Over 57 percent of the total yearly relative SOC sequestration potential at 30 cm is shared by agricultural soils in the following 15 countries: Brazil, China, United

States of America, India, Russian Federation, Argentina, Indonesia, Ethiopia, Kazakhstan, South Africa, Canada, Mexico, Peru, United Republic of Tanzania and Colombia (Table 6.4).

Figure 6.8 shows the top 15 countries with the highest mean SOC sequestration potential that could sequester at least one Mt C on a yearly basis.

Table 6.4: Top 15 countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Brazil	71.54 ± 16.21	0.18 ± 0.03	12.7	Gap-filled
China	52.89 ± 15.77	0.12 ± 0.02	9.4	Gap-filled
United States of America (the)	45.57 ± 7.6	0.14 ± 0.03	8.1	National Submission
India	21.54 ± 1.93	0.1 ± 0.02	3.8	National Submission
Russian Federation (the)	16.64 ± 6.7	0.17 ± 0.03	2.9	National Submission
Argentina	16.61 ± 3.96	0.1 ± 0.05	2.9	National Submission
Indonesia	14.65 ± 11.31	0.27 ± 0.05	2.6	Gap-filled
Ethiopia	13.97 ± 1.69	0.17 ± 0.02	2.5	National Submission
Kazakhstan	12.31 ± 2.08	0.07 ± 0.01	2.2	National Submission
South Africa	11.41 ± 0.91	0.09 ± 0.02	2.0	National Submission
Canada	10.72 ± 5.19	0.24 ± 0.01	1.9	National Submission
Mexico	9.88 ± 2.13	0.09 ± 0.01	1.7	National Submission
Peru	8.42 ± 4.67	0.25 ± 0.06	1.5	Gap-filled
United Republic of Tanzania (the)	7.93 ± 2.54	0.18 ± 0.03	1.4	Gap-filled
Colombia	7.73 ± 3.94	0.25 ± 0.04	1.4	National Submission

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.5 shows the top 15 countries with the highest mean Relative Sequestration Rates (RSR) (t C ha^{-1} yr^{-1}) that could at least sequester one Mt yr^{-1} under the SSM3 scenario. Annex B shows the results for all participating countries.

Figure 6.8: Top 15 Countries with the highest total and mean yearly Soil Organic Carbon Sequestration for the three sustainable soil management (SSM) scenarios that could at least sequester one Mt of Carbon on a yearly basis (A; Total RSR in Mt C/yr, B; Mean RSR in t C/ha yr)

Table 6.5: Top 15 countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could at least sequester 1 Mt of SOC a year.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Sri Lanka	1.46 ± 1.02	0.46 ± 0.14	0.3	National Submission
Malaysia	3.51 ± 2.89	0.44 ± 0.07	0.6	Gap-filled
Papua New Guinea	1.9 ± 1.79	0.41 ± 0.16	0.3	Gap-filled
Chile	3.17 ± 1.8	0.37 ± 0.04	0.6	National Submission
Madagascar	2.62 ± 1.99	0.33 ± 0.06	0.5	Gap-filled
Georgia	1.27 ± 0.94	0.33 ± 0.02	0.2	National Submission
Ecuador	3.19 ± 1.74	0.32 ± 0.03	0.6	National Submission
Cuba	1.65 ± 1.61	0.28 ± 0.09	0.3	National Submission
Congo (the)	1.36 ± 1.19	0.28 ± 0.04	0.2	Gap-filled
Ireland	1.27 ± 0.54	0.28 ± 0.03	0.2	Gap-filled
Indonesia	14.65 ± 11.31	0.27 ± 0.05	2.6	Gap-filled
Sierra Leone	1.32 ± 0.71	0.27 ± 0.05	0.2	Gap-filled
Uruguay	3.84 ± 0.03	0.26 ± 0.06	0.7	National Submission
Peru	8.42 ± 4.67	0.25 ± 0.06	1.5	Gap-filled
Colombia	7.73 ± 3.94	0.25 ± 0.04	1.4	National Submission

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

6.3 Statistics for climate zones and land cover types

To estimate the relationship between SOC sequestration potential and climate, the layer with Relative Sequestration Rates globally under the SSM3 scenario, compared to the BAU scenario, was spatially intersected with the IPCC, 2019 climate regions layer. The zones are defined by a set of rules based on annual mean daily temperature, total annual precipitation, total annual Potential Evapotranspiration (PET) and elevation. The highest mean sequestration potential rates per area (t C ha-1 yr-1) are observed in Moist Climates (Table 6.6). Figure 6.9 further breaks down these results according to the respective SSM1-3 scenarios. Considering total agricultural area from each climate zone, the highest sequestration potential (Mt C yr^{-1}) is expected in Tropical Moist and Subtropical Moist zones.

Table 6.6: Relative Soil Organic Carbon Sequestration Rates by IPCC climate regions

IPCC Climate Region	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %
Subtropical Moist	77.1 ± 26.9	0.241 ± 0.039	14.2
Warm Temperate Moist	57.5 ± 18.4	0.233 ± 0.064	10.6
Cool Temperate Moist	59.8 ± 28.7	0.233 ± 0.03	11.0
Tropical Moist	95 ± 53.4	0.231 ± 0.028	17.5
Boreal Moist	6.9 ± 4.7	0.153 ± 0.053	1.3
Tropical Dry	71.9 ± 10.1	0.149 ± 0.024	13.2
Subtropical Dry	60.3 ± 13.7	0.127 ± 0.017	11.1
Warm Temperate Dry	51.4 ± 13.4	0.116 ± 0.02	9.5
Boreal Dry	6.8 ± 3.9	0.115 ± 0.042	1.3
Cool Temperate Dry	56.1 ± 13.2	0.115 ± 0.024	10.3

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.7: Relative Soil Organic Carbon Sequestration Rates by land cover class

Land cover	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %
Cropland	295.1 ± 106.7	0.18 ± 0.02	55.4
Shrubland	108.3 ± 27.4	0.16 ± 0.02	20.3
Grassland	104.9 ± 32.8	0.19 ± 0.05	19.7
Paddy fields	21.7 ± 6.5	0.16 ± 0.02	4.1
Tree crops	2.6 ± 1.4	0.3 ± 0.03	0.5

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

The same approach was used to compare the total Relative Sequestration Rates under the SSM3 scenario, compared to the BAU scenario, to land cover data (Figure 6.10). The land covers were based on the ESA (European Space Agency) product reclassified into the FAO GSOCseq classes. The following land cover classes were considered: Cropland, Grassland, Paddy fields and Tree Crops. The greatest share of SOC Sequestration Potential is found within Croplands

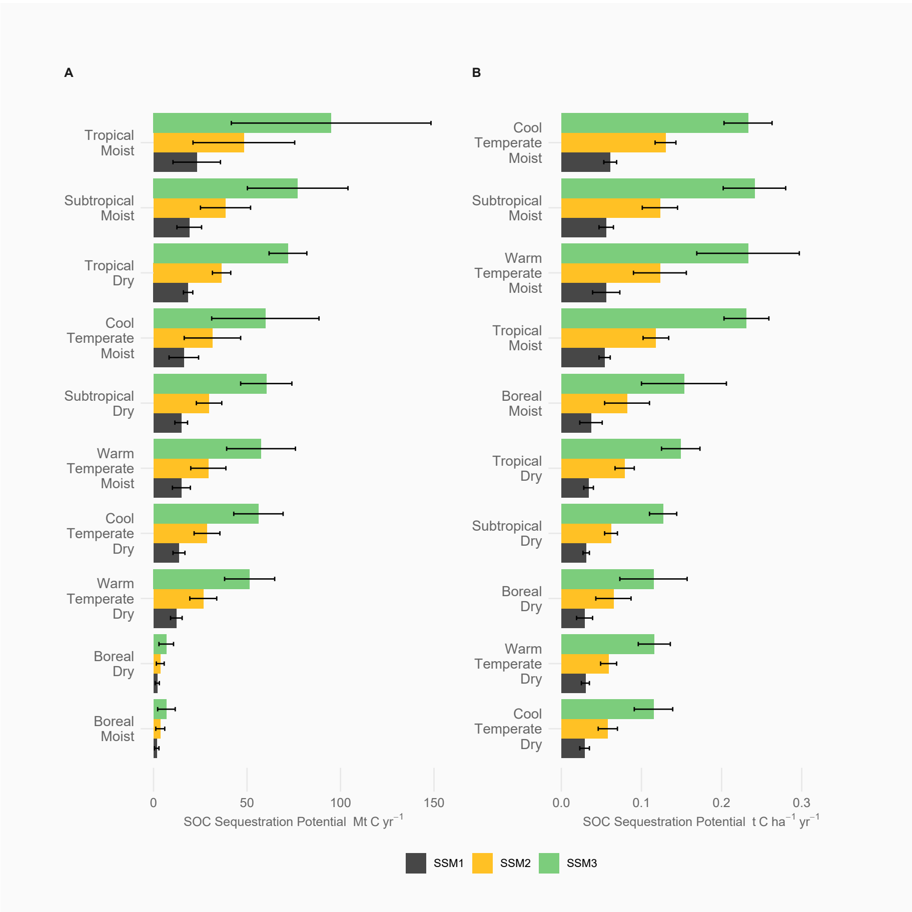


Figure 6.9: Relative Soil Organic Carbon Sequestration Rates by land IPCC climate zone for the three sustainable soil management (SSM) scenarios (A; Total RSR in Mt C/yr, B Mean RSR in t C/ha yr).

(52.4 percent) followed by Shrublands and Grasslands (20.2 percent and 19.9 percent). The highest mean SOC Sequestration Potential in t C ha^{-1} yr^{-1} are found in Tree Crops with 0.22 t C ha^{-1} yr^{-1}. In this exercise Tree Crops represent Orchards and Agroforestry systems (Table 6.7).

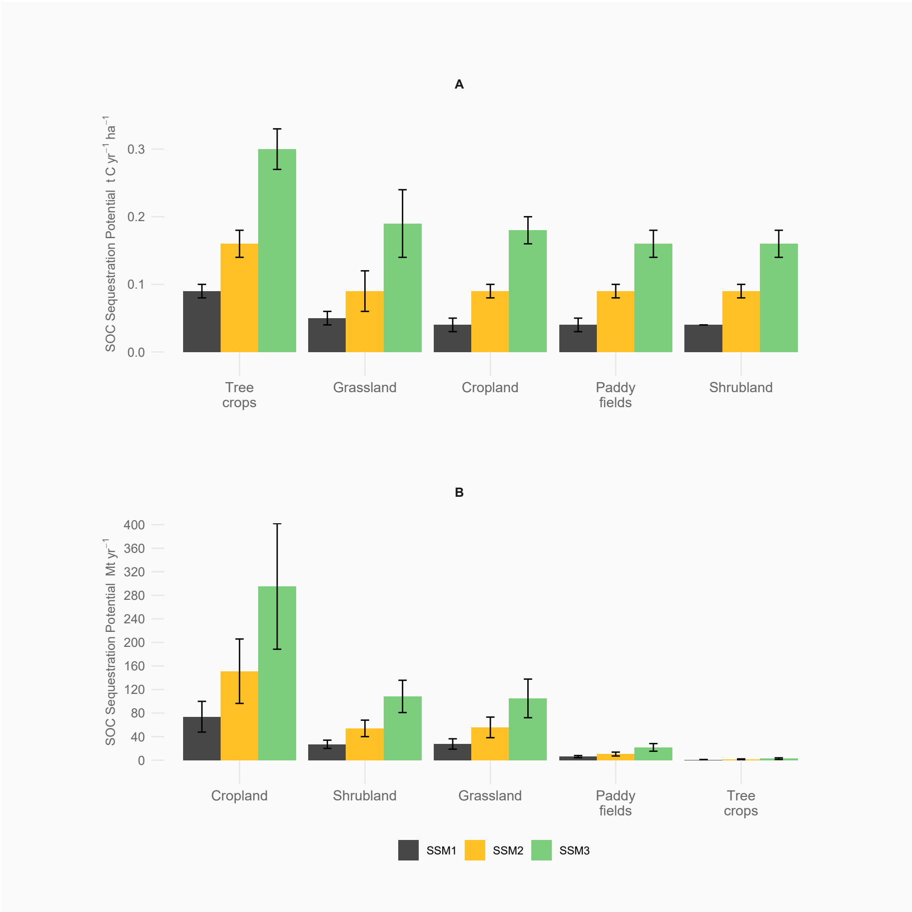


Figure 6.10: Relative Soil Organic Carbon Sequestration Rates by land cover class for the three sustainable soil management (SSM) scenarios (A; Mean RSR in t C/ha yr, B; Total RSR in Mt C/yr).

6.4 Statistics for the GSP regions

The following section summarizes the most relevant findings that can be derived from Version 1.1 of the GSOCseq according to the GSP regions. The results are representative for countries that participated in the initiative by either submitting a national product or that agreed to being temporarily gap-filled. Results are presented in detail for the following GSP regions:

- Africa
- Latin America and the Caribbean (LAC)
- Asia
- Europe and Eurasia
- North America
- North Africa and Near East (NENA)

Figure 6.11 shows the results according to the respective SSM1-3 scenarios for each GSP region while Table 6.8 further breaks down the results in terms of total and average yearly sequestration rates under the SMM3 scenario compared to the BAU scenario.

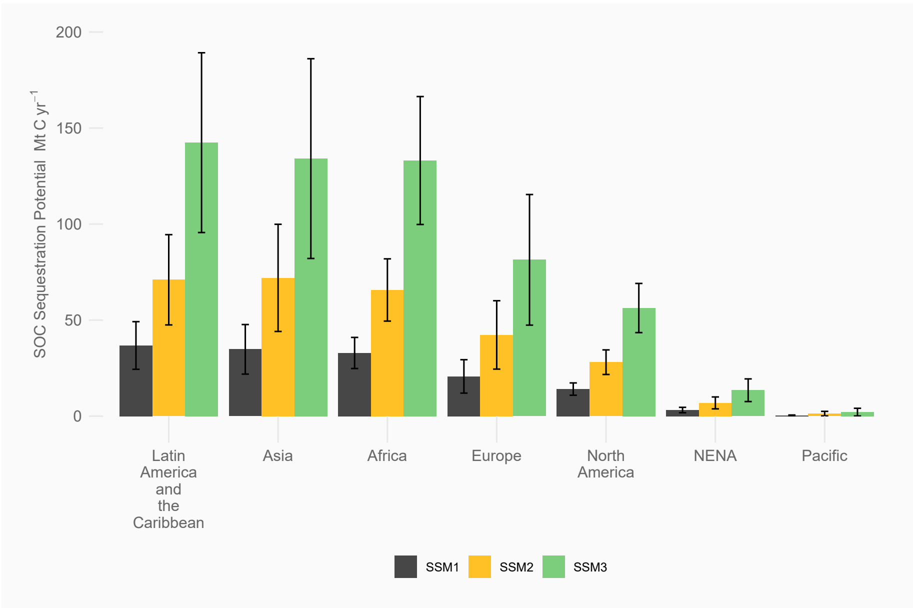


Figure 6.11: Soil Organic Carbon Sequestration Potential for the GSP regions under the three sustainable soil management Scenarios (SSM1, SSM2 and SSM3) vs business as usual (BAU) scenario. Results for the Pacific regions do not include Australia and New Zealand.

Table 6.8: Yearly Relative Soil Organic Carbon Sequestration Rates by GSP region.

GSP Region	Total RSR SSM3 $Mt\ C\ yr^{-1}$	Mean RSR SSM3 $t\ C\ ha^{-1}\ yr^{-1}$	Share SSM3 %
Latin America and the Caribbean	142.4 ± 46.8	0.18 ± 0.03	25.2
Asia	134.1 ± 52	0.17 ± 0.02	23.7
Africa	133.1 ± 33.3	0.13 ± 0.01	23.6
Europe	81.4 ± 34	0.13 ± 0.02	14.4
North America	56.3 ± 12.8	0.16 ± 0.03	10.0
NENA	13.5 ± 5.9	0.1 ± 0.01	2.4
Pacific	2.1 ± 2	0.41 ± 0.15	0.4

Results for the Pacific region do not include Australia and New Zealand. The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

6.4.1 Africa

Figure 6.12 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead a yearly mitigation of 13-55 percent of total agricultural net emissions in the African region.

As summarized in Table 6.9 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU scenario, an additional 2.6 Pg of C could be sequestered by 2040. Table 6.9 shows the results in terms of yearly increases. Under the SSM3 scenario 0.42 percent additional carbon compared to the BAU scenario could be sequestered on a yearly basis. Table 6.10 and 6.11 show the top 5 countries in order of total and mean SOC sequestration potential under the SSM3 scenario respectively.

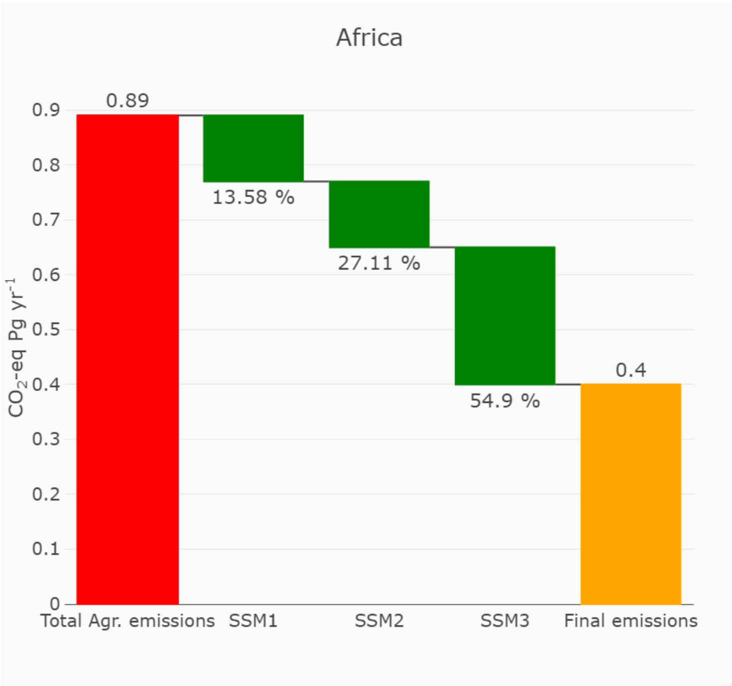


Figure 6.12: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} for the African GSP region.

Table 6.9: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the African GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	31.9±6.8	31.44±5.47	
SOC stocks 2040	SSM1	32.5±5.7	32.09±7.49	0.6
SOC stocks 2040	SSM2	33.2±5.8	32.73±7.63	1.3
SOC stocks 2040	SSM3	34.5±6	34.06±7.9	2.6
SOC stocks 2020	T0	31.7±6.9	31.28±5.23	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.10: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the African GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	32.9±32.9	0.03±0	0.10
SSM2	65.7±65.7	0.06±0.01	0.21
SSM3	133.1±133.1	0.13±0.01	0.42

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.11: Top 5 African countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Ethiopia	13.97 ± 1.69	0.17 ± 0.02	2.5	National Submission
South Africa	11.41 ± 0.91	0.09 ± 0.02	2.0	National Submission
United Republic of Tanzania (the)	7.93 ± 2.54	0.18 ± 0.03	1.4	Gap-filled
Democratic Republic of the Congo (the)	7.33 ± 5.62	0.23 ± 0.06	1.3	Gap-filled
Nigeria	7.18 ± 0.91	0.11 ± 0.01	1.3	National Submission

Table 6.12: Top 5 African countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could sequester at least 0.5 Mt of C.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Rwanda	0.7 ± 0.1	0.35 ± 0.03	0.1	Gap-filled
Madagascar	2.62 ± 1.99	0.33 ± 0.06	0.5	Gap-filled
Gabon	0.59 ± 0.55	0.32 ± 0.07	0.1	Gap-filled
Burundi	0.67 ± 0.03	0.3 ± 0.06	0.1	Gap-filled
Congo (the)	1.36 ± 1.19	0.28 ± 0.04	0.2	Gap-filled

6.4.2 Latin America and the Caribbean (LAC)

Figure 6.13 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead a yearly mitigation of 12-48 percent of total agricultural net emissions in the LAC region.

As summarized in Table 6.13 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU scenario, an additional 2.8 Pg of C could be sequestered by 2040. Table 6.14 shows the results in terms of yearly increases. Under the SSM3 scenario, 0.40 percent additional carbon compared to the BAU scenario could be sequestered. Table 6.15 and 6.16 show the top 5 countries in order of total and mean SOC sequestration potential under the SSM3 scenario respectively.

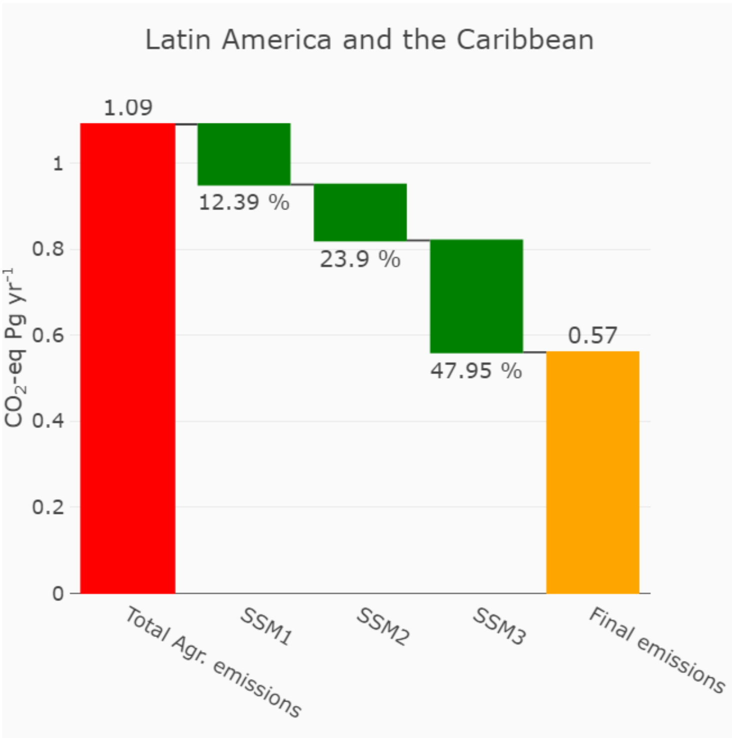


Figure 6.13: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} for the LAC GSP region.

Table 6.13: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the LAC GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	35.6±8.7	43.67±9.29	
SOC stocks 2040	SSM1	36.3±9.4	44.58±12.99	0.7
SOC stocks 2040	SSM2	37±9.6	45.4±13.22	1.4
SOC stocks 2040	SSM3	38.4±10	47.22±13.74	2.8
SOC stocks 2020	T0	36.2±8.8	44.05±9.19	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.14: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the LAC GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	36.8±36.8	0.046±0.006	0.1
SSM2	71±71	0.087±0.013	0.2
SSM3	142.4±142.4	0.178±0.027	0.4

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.15: Top 5 LAC countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SM3 Pg C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Brazil	71.54 ± 16.21	0.18 ± 0.03	12.7	Gap-filled
Argentina	16.61 ± 3.96	0.1 ± 0.05	2.9	National Submission
Mexico	9.88 ± 2.13	0.09 ± 0.01	1.7	National Submission
Peru	8.42 ± 4.67	0.25 ± 0.06	1.5	Gap-filled
Colombia	7.73 ± 3.94	0.25 ± 0.04	1.4	National Submission

Table 6.16: Top 5 LAC countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could sequester at least 0.5 Pg of C.

Country	Total RSR SM3 Pg C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Chile	3.17 ± 1.8	0.37 ± 0.04	0.6	National Submission
Ecuador	3.19 ± 1.74	0.32 ± 0.03	0.6	National Submission
Dominican Republic (the)	0.59 ± 0.51	0.3 ± 0.23	0.1	Gap-filled
Cuba	1.65 ± 1.61	0.28 ± 0.09	0.3	National Submission
Uruguay	3.84 ± 0.03	0.26 ± 0.06	0.7	National Submission

6.4.3 Asia

Figure 6.14 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead to a yearly mitigation of 6–21 percent of total agricultural net emissions in the Asian region.

As summarized in Table 6.17 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU , an additional 2.6 Pg of C could be sequestered by 2040. Table 6.18 shows the results in terms of yearly increases. Under the SSM3 scenario, 0.30 percent additional carbon compared to the BAU scenario could be sequestered. Table 6.19 and 6.21 show the top 5 countries in order of total and mean SOC sequestration potential under the SSM3 scenario respectively.

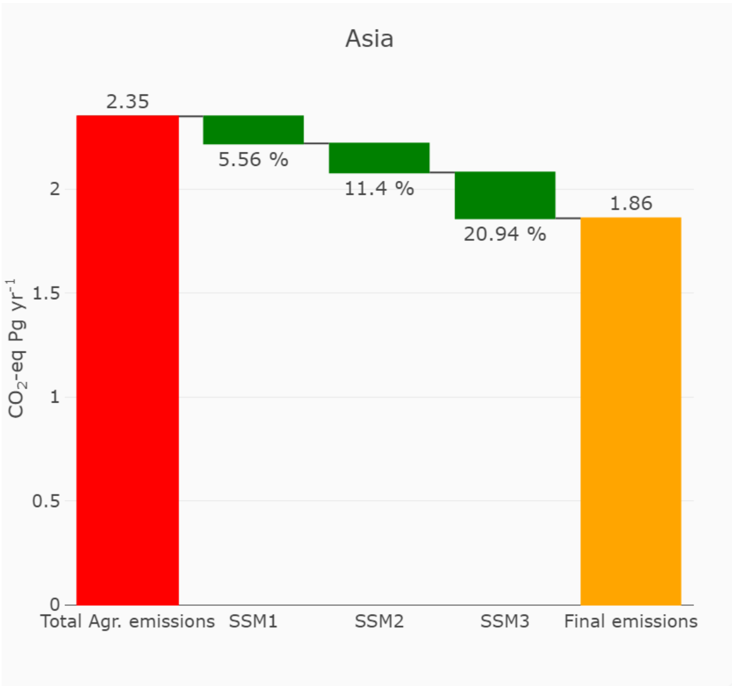


Figure 6.14: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} for the Asian GSP region.

Table 6.17: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the Asian GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	44.8±14.3	47.96±6.56	
SOC stocks 2040	SSM1	45.5±13.6	48.79±8.24	0.7
SOC stocks 2040	SSM2	46.2±13.9	49.88±8.46	1.4
SOC stocks 2040	SSM3	47.4±14.3	51.42±8.7	2.6
SOC stocks 2020	T0	44.2±14.3	47.5±6.36	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.18: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the Asian GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	34.8±34.8	0.04±0	0.08
SSM2	72±72	0.1±0.01	0.16
SSM3	134.1±134.1	0.17±0.02	0.30

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.19: Top 5 Asian countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SM3 $Mt\ C\ yr^{-1}$	Mean RSR SSM3 $t\ C\ ha^{-1}\ yr^{-1}$	Share SSM3 %	Map Source
China	52.89 ± 15.77	0.12 ± 0.02	9.4	Gap-filled
India	21.54 ± 1.93	0.1 ± 0.02	3.8	National Submission
Indonesia	14.65 ± 11.31	0.27 ± 0.05	2.6	Gap-filled
Thailand	6.48 ± 2.54	0.21 ± 0.02	1.1	Gap-filled
Myanmar	6.15 ± 2.72	0.2 ± 0.04	1.1	Gap-filled

Table 6.20: Top 5 Asian countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could sequester at least 0.5 Mt of C.

Country	Total RSR SM3 $Mt\ C\ yr^{-1}$	Mean RSR SSM3 $t\ C\ ha^{-1}\ yr^{-1}$	Share SSM3 %	Map Source
Sri Lanka	1.46 ± 1.02	0.46 ± 0.14	0.3	National Submission
Malaysia	3.51 ± 2.89	0.44 ± 0.07	0.6	Gap-filled
Timor-Leste	0.51 ± 0.5	0.42 ± 0.08	0.1	Gap-filled
Indonesia	14.65 ± 11.31	0.27 ± 0.05	2.6	Gap-filled
Thailand	6.48 ± 2.54	0.21 ± 0.02	1.1	Gap-filled

6.4.4 Europe and Eurasia

Figure 6.15 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead to a yearly mitigation of 10–39 percent of total agricultural net emissions in the European and Eurasian region.

As summarized in Table 6.21 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU scenario, an additional 1.6 Pg of C could be sequestered by 2040. Table 6.22 shows the results in terms of yearly increases. Under the SSM3 scenario, 0.20 percent additional carbon compared to the BAU scenario could be sequestered. Table 6.23 and 6.24 show the top 5 countries in order of total and mean SOC sequestration potential under the SSM3 scenario respectively.

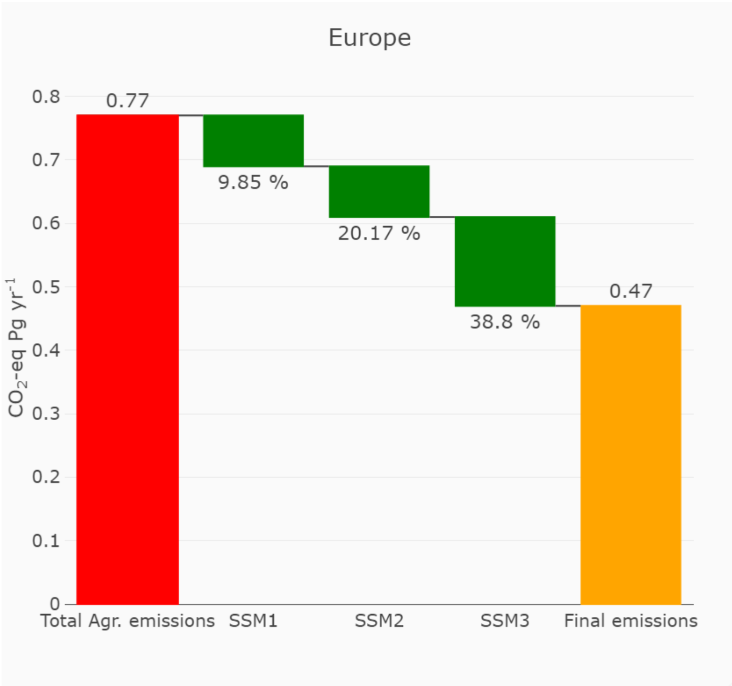


Figure 6.15: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} Eurasian GSP region.

Table 6.21: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the European and Eurasian GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	40.9±15.1	62.12±9.19	
SOC stocks 2040	SSM1	41.3±14.8	62.67±10.72	0.4
SOC stocks 2040	SSM2	41.7±15	63.36±10.87	0.8
SOC stocks 2040	SSM3	42.5±15.3	64.72±11.09	1.6
SOC stocks 2020	T0	40.5±15.3	61.69±9.21	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.22: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the European and Eurasian GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	20.7±20.7	0.03±0	0.05
SSM2	42.3±42.3	0.06±0.01	0.10
SSM3	81.4±81.4	0.13±0.02	0.20

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.23: Top 5 European and Eurasian countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Russian Federation (the)	16.64 ± 6.7	0.17 ± 0.03	2.9	National Submission
Kazakhstan	12.31 ± 2.08	0.07 ± 0.01	2.2	National Submission
France	6.28 ± 6.1	0.17 ± 0.02	1.1	National Submission
Ukraine	5.89 ± 0.83	0.13 ± 0.02	1.0	Gap-filled
Turkey	5.23 ± 1.88	0.1 ± 0.01	0.9	National Submission

Table 6.24: Top 5 European and Eurasian countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could sequester at least 0.5 Mt of C.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Georgia	1.27 ± 0.94	0.33 ± 0.02	0.2	National Submission
Ireland	1.27 ± 0.54	0.28 ± 0.03	0.2	Gap-filled
Greece	1.92 ± 1.04	0.22 ± 0.03	0.3	National Submission
United Kingdom of Great Britain and Northern Ireland (the)	3.28 ± 1.79	0.21 ± 0.01	0.6	Gap-filled
Germany	4.59 ± 1.42	0.18 ± 0.03	0.8	National Submission

6.4.5 North America

Figure 6.16 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead to a yearly mitigation of 12–47 percent of total agricultural net emissions in the North American region.

As summarized in Table 6.25 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU scenario,an additional 1.1 Pg of C could be sequestered by 2040. Table 6.26 shows the results in terms of yearly increases. Under the SSM3 scenario, 0.19 percent additional carbon compared to the BAU scenario could be sequestered. Table 6.27 shows total and mean SOC sequestration potential under the SSM3 scenario for the United States and Canada.

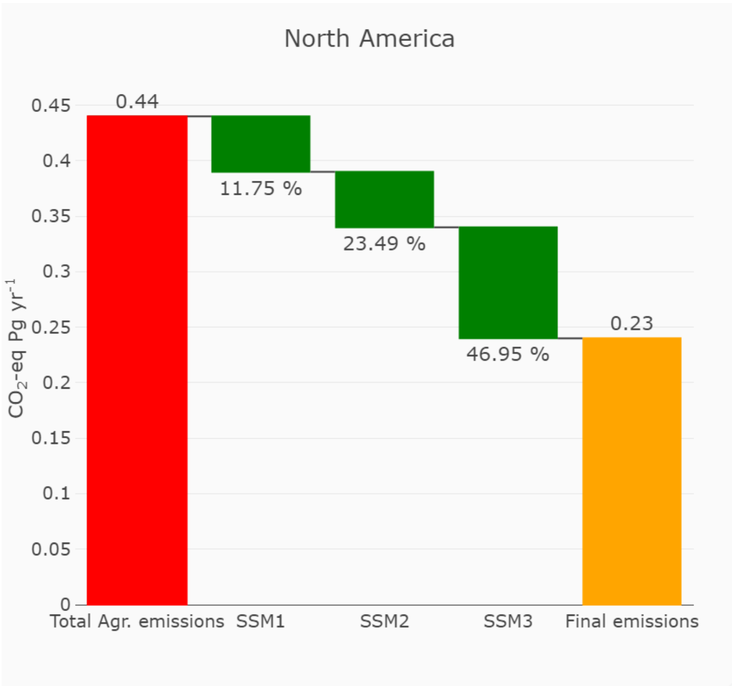


Figure 6.16: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} for the North American GSP region.

Table 6.25: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the North American GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	29.7±7.2	79.54±17.94	
SOC stocks 2040	SSM1	29.9±7.5	80.32±20.56	0.2
SOC stocks 2040	SSM2	30.2±7.5	81.11±20.77	0.5
SOC stocks 2040	SSM3	30.8±7.6	82.67±21.23	1.1
SOC stocks 2020	T0	29.2±8	79.34±22.13	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.26: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the North American GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	14.1±14.1	0.04±0.01	0.05
SSM2	28.1±28.1	0.08±0.01	0.09
SSM3	56.3±56.3	0.16±0.03	0.19

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.27: North American countries with the highest total SOC Relative Sequestration under the SSM3 scenario vs BAU scenario.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
United States of America (the)	45.57 ± 7.6	0.14 ± 0.03	8.1	National Submission
Canada	10.72 ± 5.19	0.24 ± 0.01	1.9	National Submission

6.4.6 Near East and North Africa (NENA)

Figure 6.17 shows total relative sequestration rates in Pg of CO_2 yr^{-1} in relation to total yearly agricultural net emissions derived from FAOSTAT (2017) according to the IPCC Fifth Assessment Report (AR5). The GSOCseq shows that the adoption of SSM practices could potentially lead to a yearly mitigation of 5–22 percent of total agricultural net emissions in the NENA region.

As summarized in Table 6.28 if 20 percent C would be inputted to the soil (SSM3 scenario) compared to the BAU scenario, an additional 0.3 Pg of C could be sequestered by 2040. Table 6.29 shows the results in terms of yearly increases. Under the SSM3 scenario, 0.29 percent additional carbon compared to the BAU scenario could be sequestered. Table 6.30 and 6.31 show the top 5 countries in order of total and mean SOC sequestration potential under the SSM3 scenario respectively.

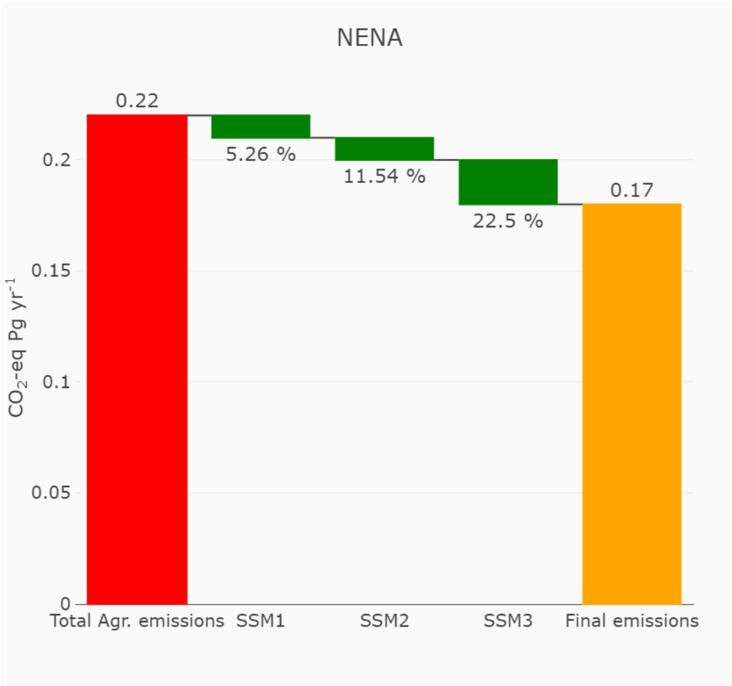


Figure 6.17: Potential Mitigation of Agricultural Emissions through SOC sequestration in gigagrams of CO_2 eq yr^{-1} for the NENA GSP region.

Table 6.28: Summary of estimates of topsoil SOC stocks in Pg and average SOC content in tha^{-1} over four scenarios (SSM1-3: sustainable soil management; BAU: business as usual) and at the beginning of the simulation at time T0 (2020) for the NENA GSP region.

Layer	Scenario	sum	mean	Relative difference *
		Pg C	$t\ C\ ha^{-1}$	Pg C
SOC stocks 2040	BAU	4.6±2	35.32±4.34	
SOC stocks 2040	SSM1	4.7±1.9	35.76±6.07	0.1
SOC stocks 2040	SSM2	4.8±1.9	36.3±6.15	0.2
SOC stocks 2040	SSM3	4.9±2	37.34±6.42	0.3
SOC stocks 2020	T0	4.6±2	35.16±4.08	

* Relative differences indicate the difference between the SOC stocks after the adoption of SSM practices and SOC stocks after the BAU scenario.

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha for mean SOC content; Pg C for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers.

Table 6.29: Summary of estimates of total Relative SOC sequestration rates Mt yr^{-1} and average Relative SOC sequestration rates in tha^{-1} for the NENA GSP region.

Scenario	sum	mean	Change *
	Mt C yr^{-1}	$t\ C\ ha^{-1}$	%
SSM1	3.2±3.2	0.02±0	0.07
SSM2	6.9±6.9	0.05±0	0.15
SSM3	13.5±13.5	0.1±0.01	0.29

* The column Change indicates the yearly relative (when compared to the final stocks under the BAU scenario) change in percent in SOC stocks

Table 6.30: Top 5 NENA countries with the highest total SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Sudan (the)	4.29 ± 0.87	0.06 ± 0.02	0.8	National Submission
Iran (Islamic Republic of)	3.47 ± 1.48	0.09 ± 0.01	0.6	Gap-filled
Algeria	1.49 ± 1.25	0.13 ± 0.01	0.3	Gap-filled
Morocco	1.23 ± 0.77	0.12 ± 0.03	0.2	National Submission
Iraq	0.92 ± 0.24	0.1 ± 0.02	0.2	Gap-filled

Table 6.31: Top 5 NENA countries with the highest mean SOC Relative Sequestration Rates based on three sustainable soil management (SSM) scenarios that could sequester at least 0.5 Mt of C.

Country	Total RSR SM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Share SSM3 %	Map Source
Tunisia	0.64 ± 0.44	0.14 ± 0.01	0.1	Gap-filled
Algeria	1.49 ± 1.25	0.13 ± 0.01	0.3	Gap-filled
Morocco	1.23 ± 0.77	0.12 ± 0.03	0.2	National Submission
Iraq	0.92 ± 0.24	0.1 ± 0.02	0.2	Gap-filled
Iran (Islamic Republic of)	3.47 ± 1.48	0.09 ± 0.01	0.6	Gap-filled

Chapter 7

Discussion

7.1 Interpretation of results

In terms of C potentially sequestered by implementing SSM practices, the results of the GSOCseq v1.1 are in line with previous estimations for agricultural lands in different regions (Smith *et al.*, 2008) and at the global scale (Sommer and Bossio, 2014; Lal *et al.*, 2018; Batjes *et al.*, 2019), particularly for the SSM3 scenario, although in the lower range of those estimates. GSOCseq v1.1 covers around 90 percent of global agricultural area, and the estimated figures can be expected to increase once all agricultural areas are included in following versions. National submissions also excluded non-agricultural areas (such as natural reserves and protected areas) and other non-managed areas according to national expert opinion, areas that may have been included in previous top-down approaches showing higher estimates.

Due to their extensive total agricultural area, the results from GSOCseq v1.1 show that the highest sequestration potential (in terms of Mt C yr^{-1}) is expected in tropical moist and subtropical moist climatic zones, and in the GSP regions: Latin America, Asia and Africa . Considering all global agricultural lands, the results suggest that SOC sequestration may play a relevant role in climate change mitigation: yearly agricultural global net emissions could be cut by up to 34 percent by implementing practices oriented to increase C inputs. However, this also implies that, even without considering the technical, cultural and economical barriers to adopt SSM practices in all the selected lands, SOC sequestration alone will not be enough to reduce agricultural net emissions to zero. It will be necessary to implement other practices oriented to reduce GHG net emissions from nutrient management, rice cultivation, manure management and enteric fermentation, among others (Smith *et al.*, 2008).

As stated by Sykes *et al.* (2020), it is worthy to consider that SOC sequestration is finite and time-limited, but it can nonetheless play a crucial role as an interim measure until the implementation of other practices or the deployment higher potential greenhouse gas removal technologies can be realized. Considering the three main agricultural greenhouse gases (CO_2, N_2O and CH_4) and the combined effect of different potential management strategies in agricultural lands, including SOC sequestration, the global technical mitigation potential from agriculture has been estimated to be ca. 5.5– 6 Gt CO_2-eq. yr-1 by 2030 (Smith *et al.*, 2012). This would represent a mitigation of nearly all current agricultural net emissions (6.05 Gt CO_2-eq. yr-1; FAOSTAT, 2019). The estimated economic potentials from the different agricultural practices are smaller (1.5-4.3 Gt CO_2-eq. yr-1 depending on carbon prices; Smith *et al.*, 2012), but still reflect the significant potential contribution of the agricultural sector to cut down GHG net emissions. Moreover, recent estimates show that transforming the complete land sector and deploying measures in agriculture, forestry, wetlands, bioenergy, diet shifts and food waste, could contribute about 15 Gt CO_2-eq. yr-1 or 30 percent of the global mitigation needed in 2050 to deliver on the 1.5 °C target from the Paris Agreement (Roe *et al.*, 2019), stressing that no single strategy, sector or region will be sufficient to deliver on the mitigation objective. As stated by Paustian *et al.* (2019), there are no single solutions to achieving GHG emission reductions and CO_2 removal targets, and many strategies, each contributing a modest (5-10 percent) part of the solution, will be required.

7.2 Limitations and way forward

The harmonization (or standardization) on the estimation of SOC sequestration and its GHG mitigation potential among countries, regions, and productive systems was not a straightforward task and there are different contentious issues and limitations that must be outlined, in order to refine the results of future versions.

7.2.1 Selected sustainable soil management scenarios and carbon inputs

In GSOCseq v1.1, the effects of SSM practices were represented by three-fixed standard percent increases in current C inputs, and BAU C inputs were derived from equilibrium C inputs at year 2000, derived in turn from initial SOC stocks, and then yearly adjusted by land use and climatic conditions in the 2000-2020 period. This allowed harmonizing results on a global map including countries lacking complete local land use and management data, without complex configuration. The spatial distribution of sequestration potentials is thus strongly driven by the initial SOC stock map: higher C inputs are therefore estimated in areas with higher initial SOC stocks, and depending on the edapho-climatic variables considered in the model, these areas may exhibit higher sequestration rates. At the global scale, arid and semi arid regions, characterized by lower SOC contents and lower C inputs, exhibited lower rates compared to more humid climates with higher SOC stocks and higher C inputs (see Fig.6.4 and 6.10). However, the results should be interpreted with caution, as sites with high SOC stocks may already be receiving high C inputs and may be close to their sequestration potential. Therefore, increasing C inputs and SOC stocks will not always be technically possible in these conditions. As mentioned in Chapter 5, the SOC sequestration potential quantified in GSOCseq v1.1 represents a biophysical potential rather than a technical or economic one (Amundson and Biardeau, 2018).

On the other hand, the fixed percent increases in C inputs may be low for some areas with depleted SOC stocks but with the technical feasibility to further increase residue returns and SOC sequestration. In consequence, in future versions, the regional determination of sequestration potentials should be refined based on the regional feasibility of management options, unlinked from initial SOC stocks, instead of using fixed percent increases for all land uses and regions. The use of local and country-specific scenarios, based on national expertise and local data, including a more detailed description of regional agricultural practices and current and attainable C inputs (e.g. derived from crops and yield statistics, e.g. Smith *et al.*, 2006; Riggers *et al.*, 2021), will require a great coordinated effort, but it is essential to improve the estimates within each region and country in future versions. Guidelines on how to estimate C inputs from yield data and how to estimate the effects of SSM practices on C inputs in a standardized manner will contribute to generating local scenarios.

7.2.2 Projected climatic conditions

In the current approach, climate conditions for the period of 20 years 2020-2040 are estimated from the average value from 2000-2020. Temperature is expected to increase in the next 20-50 years, especially after 2050 (IPCC, 2018) and this may impact in a longer term the SOC dynamics. Recent national projections show that high OC input increases with drastic changes in agricultural management may be required to compensate for SOC losses under climate change scenarios up to 2099 (Riggers *et al.*, 2021). The proposed methodology allows to incorporate climate change scenarios for longer term projections in future versions, and analyze their impact on SOC sequestration, once standardized climatic scenarios are defined. Terraclimate spatialized datasets (http://www.climatologylab.org/terraclimate.html) provide two projected global climate scenarios (+2°C; +4°C) and datasets which could be used in future versions.

7.2.3 Target areas

Current agricultural lands (croplands and grazing lands) were selected as target areas to estimate SOC sequestration potential in GSOCseq v1.1. These lands have been highlighted among the options with greater potential to accumulate SOC and mitigate GHG emissions through improved management practices (Smith *et al.*, 2008; Lal *et al.*, 2018). Furthermore, most of the information regarding the SOC dynamics has been developed for these productive systems, and most SOC carbon models have been successfully calibrated and validated under these conditions (FAO, 2019). However, other lands such as managed forests, degraded lands, wetlands and peatlands can have a major contribution on global SOC sequestration potential (Lal *et al.*, 2018). Future versions of the GSOCseq map may include other land uses, depending on national demands.

7.2.4 Target soil depth

The proposed approach estimates SOC changes in the first 30 cm and SOC but sequestration estimates can be higher if considering changes at deeper layers. The 0-30 cm depth was selected in GSOC v1.1 because: a) this depth is widely considered the most responsive layer to land management changes; b) it allows the use of GSOCmap as a baseline for SOC stocks; c) it allows for harmonization with national greenhouse gas inventories, and d) it allows validation of selected models with available ground data (often generated at 0-30cm depth). However, SOC at deeper soil layers can be also responsive to land management changes (e.g. Follett *et al.*, 2013; Poeplau and Don, 2013; Schmer *et al.*, 2014). New models and adaptations of known models have been developed to account for SOC dynamics in deep layers with different approaches (see Campbell and Paustian, 2015). For example, the DAYCENT model was modified to simulate deeper soil C dynamics by slowing SOC pool turnover and increasing allocation to passive soil C, without separating soil layers (Wieder *et al.*, 2014). Jenkinson and Coleman (2008) modified RothC to RothPC-1 to predict the turnover of organic C in subsoils up to 1 m of depth using multiple layers and introduced two additional parameters, one that transports organic C down the soil profile by an advective process, and one that reduces decomposition processes of SOC with depth. However, there is still a strong necessity for additional data to confirm or refute hypotheses suggested by the different modeling approaches of SOC in deep layers (Campbell and Paustian, 2015). As new information is generated, future versions of the GSOC and GSOCseq maps will be able to incorporate SOC stocks and SOC changes at deeper layers.

7.2.5 Selected soil organic carbon model

In order to obtain repeatable, consistent, standardized and harmonized results, and allow comparisons between countries and regions, and due to differences in computational, technical capacities and data availability, the use of RothC as a common 'process-oriented' SOC model, following the proposed methodology, was used in GSOCseq v1.1. Ideally, SOC models should account for all major SOC-controlling factors, such as soil mineralogy, climate conditions, litter quality, biota activity and composition, land use and management. However, even the full multidimensional development of a single element of a model can rarely, if ever, be predicted precisely, and the actual consequence is that it is impossible to create "universal" models (Sinclair and Seligman, 1996). At some level of analysis all known process-oriented SOC models, including RothC, include empirical functions, so they are expected to perform best when operating in situations similar to those for which they were originally parameterized, which tend to be croplands and grasslands from the temperate zone (Jenkinson *et al.*, 1990; Petri *et al.*, 2009).

Current SOC models, including RothC, can be limited in their applicability beyond these conditions, due to differences in soil fauna and their effects on SOC dynamics, the much faster turnover of slow and passive SOM, different temperature and moisture relationships with microbial activity, and differences in mineralogy (Shang and Tiessen, 1998; Tiessen *et al.*, 1998) and solution chemistry (Parton *et al.*, 1989). The inability to account for cation availability or aluminium (Al) toxicity can also limit SOC model predictions in tropical soils (Parton *et al.*, 1989; Shang and Tiessen, 1998). Although, as mentioned in section 5.3, the RothC model has been tested under volcanic soils (Shirato *et al.*, 2004; Takata *et al.*, 2011), salt affected soils (Setia *et al.*, 2013), tropical soils (Cerri *et al.*, 2007; Kaonga and Coleman, 2008; Bhattacharyya *et al.*, 2011), and arid and semi-arid conditions (Farina *et al.*, 2013; Azad *et al.*, 2019), there is relatively less available data of the parametrization and performance of the model under these conditions.

The interpretation of results within these areas should be carried out with caution. Future versions of the GSOCseq will need to include modifications in the used SOC model/s and functions, as more national ground data is gathered and made available, in order to improve the predictions of SOC dynamics under these and other conditions.

7.2.6 Estimation of uncertainties

The uncertainties in GSOCseq v1.1 were estimated by forward propagation of plausible uncertainty ranges of input layers. However, evaluating model applications using long-term observations of soil carbon stocks showed that model structural uncertainties and uncertainties of carbon input estimation methods affected total model uncertainties most (Dechow *et al.*, 2019, Riggers *et al.* 2019). Thus, the reported uncertainties in GSOCseq v1.1 may vastly underestimate the uncertainties associated with the actual implementation of practices and their associated SOC stock changes. Further improvements could imply the application of a multi-model ensemble approach (e.g. Riggers *et al.*, 2019; 2021; Lehtonen *et al.*, 2020) to improve the prediction accuracy and consider the structural model uncertainty. The SoilR package (Sierra *et al.*, 2012) used in the current approach, which already includes other SOC models like CENTURY, YASSO and ICBM, will allow the use of a multi-model approach following already generated scripts and procedures.

7.2.7 Data quality, data availability and resolution

The precision of models relies heavily on the quality, quantity and availability of data used in executing and validating them (FAO, 2019). Careful harmonization of datasets and input estimation methodologies is essential to obtain consistent results across regions and countries. Ideally, driving data should match the scale of the model simulation. Countries submitted their products to generate GSOCseq v1.1 using the best available local data or global sources which better reflected local conditions. However, data limitations prompted the use of data of coarser resolution and/or mixing data of varying quality from different sources (e.g. climate data that usually occurs at coarser resolutions). Although data was re-scaled and harmonized at 1 x 1 km, datasets from different resolutions were used, and this may introduce uncertainties which are not currently accounted for. The selected resolution allowed for comparisons among countries at a global scale, but it may be too coarse for other specific purposes at national and subnational scales, especially at the farm scale, so the interpretation of results should be carried out with caution. However, the methodology allows modifying the target resolution based on the available input data in a simple and straightforward manner.

Data availability for model evaluation will also affect the assessment of model accuracy. Although there is a wealth of measured data from carefully monitored long-term agronomic experiments to evaluate SOC models, especially in the northern hemisphere and temperate climate conditions, there are comparatively few similar datasets in other regions (Falloon and Smith, 2003). Restricted accessibility to the already generated data can be also limit model improvement. Many countries are lacking already published and accessible datasets regarding the effects of SSM practices on SOC stocks. GSOCseq can constitute an opportunity for the different involved countries to establish long-term observatories following a standard protocol that will allow monitoring the effect of different management practices on SOC stocks and SOC sequestration under different environments, and this will in turn allow the improvement of model estimations.

7.3 Final comments

We acknowledge that consistency among inputs and results would be improved if there was only one actor involved in the entire process. However, the process highlighted that it is of most importance that information is locally generated and curated, involving local experts and institutions, building technical capacities in the process, as a fundamental step for iterative improvements. Moreover, the process allowed countries to gather the information that was scattered and to produce national spatial layers that will be useful for other projects. Despite the above mentioned limitations and considerations, GSOCseq v.1.1 allowed the involved countries to implement a robust technical approach to produce digital SOC sequestration maps using the best available national legacy data, process oriented SOC models and modern techniques of digital soil mapping. This approach allowed covering as many conditions and productive systems worldwide as possible, in a relatively simple, transparent, and standardized way, without complex configuration and restrictive computational capacities. GSOCseq v1.1 constitutes the first global effort to assess the projected SOC stock changes, SOC sequestration potential and associated GHG mitigation potential in global agricultural lands. It represents a key first step to identify and prioritize areas with greater potential to increase SOC stocks and mitigate GHG emissions through SOC sequestration in agricultural lands, set attainable and evidence based national targets for carbon sequestration, and facilitate the enhancement of local technical capacities, in order to unlock the potential of SOC sequestration as a Climate Change adaptation and mitigation strategy.

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Annex A | GSOCseq Submission Overview

A1: Afghanistan

GSOCseq layers source:
Gap-filling Layer

A2: Albania

GSOCseq layers source:
Gap-filling Layer

A3: Algeria

GSOCseq layers source:
Gap-filling Layer

A4: Andorra

GSOCseq layers source:
Gap-filling Layer

A5: Angola

GSOCseq layers source:
Gap-filling Layer

A6: Antigua and Barbuda

GSOCseq layers source:
Gap-filling Layer

A7: Argentina

GSOCseq layers source:
National Submission

National Expert(s):
Franco Daniel Frolla, Marcos Esteban Angelini, Marcelo Javier Beltrán, Guillermo Ezequiel Peralta, Luciano Elias Di Paolo, Darío Martín Rodríguez, Guillermo Andrés Schulz

Data-holding Institution(s):
INTA

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Franco Frolla

A8: Armenia

GSOCseq layers source:
Gap-filling Layer

A9: Azerbaijan

GSOCseq layers source:
Gap-filling Layer

A10: the Bahamas

GSOCseq layers source:
Gap-filling Layer

A11: Bahrain

GSOCseq layers source:
Gap-filling Layer

A12: Bangladesh

GSOCseq layers source:
National Submission

National Expert(s):
A. F. M. Manzurul Hoque; Mohammed Ruhul Islam

Data-holding Institution(s):
Soil Resource Development Institute

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
A. F. M. Manzurul Hoque

A13: Barbados

GSOCseq layers source:
Gap-filling Layer

A14: Belarus

GSOCseq layers source:
Gap-filling Layer

A15: Belize

GSOCseq layers source:
Gap-filling Layer

A16: Benin

GSOCseq layers source:
Gap-filling Layer

A17: Bhutan

GSOCseq layers source:
National Submission

National Expert(s):
Tsheten Dorji & Dawa Tashi

Data-holding Institution(s):
National Soil Services Centre

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)

Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
National Soil Services Centre

A18: Bolivia (Plurinational State of)

GSOCseq layers source:
Gap-filling Layer

A19: Bosnia and Herzegovina

GSOCseq layers source:
Gap-filling Layer

A20: Botswana

GSOCseq layers source:
Gap-filling Layer

A21: Brazil

GSOCseq layers source:
Gap-filling Layer

A22: Brunei Darussalam

GSOCseq layers source:
Gap-filling Layer

A23: Bulgaria

GSOCseq layers source:
Gap-filling Layer

A24: Burkina Faso

GSOCseq layers source:
National Submission

National Expert(s):
Desiré Kabore

Data-holding Institution(s):
FAO

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Desiré Kabore

A25: Burundi

GSOCseq layers source:
Gap-filling Layer

A26: Cambodia

GSOCseq layers source:
National Submission

National Expert(s):
Keo Nimol; Phy Chhin

Data-holding Institution(s):
General Directorate of Agriculture, MAFF

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Dr.Seng Vang

A27: Cameroon

GSOCseq layers source:
National Submission

National Expert(s):
Francis B. T. Silatsa; Serge S. Nanda; Martin Yemefack; Arlende F. Ngomeni

Data-holding Institution(s):
Sustainable Tropical Actions (STA)

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Dr Francis B. T. Silatsa

A28: Canada

GSOCseq layers source:
National Submission

National Expert(s):
Xiaoyuan Geng; Bert VandenBygaart; Juanxia He

Data-holding Institution(s):
Canadian Soil Information Service (CanSIS), AAFC

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Dr. Xiaoyuan Geng

A29: Cabo Verde

GSOCseq layers source:
National Submission

National Expert(s):
Jacques Tavares

Data-holding Institution(s):
INIDA

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Dr. Angela Moreno

A30: Central African Republic (the)

GSOCseq layers source:
Gap-filling Layer

A31: Chad

GSOCseq layers source:
Gap-filling Layer

A32: Chile

GSOCseq layers source:
National Submission

National Expert(s):
Rodrigo Osorio, Luis A. Reyes Rojas, Marco Pfeiffer, Fabio Corradini, en representación de José Padarian

Data-holding Institution(s):
Equipo Suelos FAO Chile

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Rodrigo Osorio

A33: China

GSOCseq layers source:
Gap-filling Layer

A34: Colombia

GSOCseq layers source:
National Submission

National Expert(s):
Gustavo A. Araujo-Carrillo; Viviana M. Varón-Ramírez; Douglas A. Gómez-Latorre; Reinaldo Sánchez L.; Helmer Guzmán L.; Eliana K. Fonseca G.; Maria J. Morales S.; Napoleón Ordoñez; Lady M. Rodríguez; Olga L. Ospina A.; Nelson E. Lozano C.; Blanca C. Medina P.; Sebastian Acosta T.; Claudia K. Ortíz V.; Jorge Gutierrez; Adriana Bolívar G.; Diego Pedroza C.

Data-holding Institution(s):
1 AGROSAVIA, Tibaitata Research Center, garaujo@agrosavia.co, vvaron@agrosavia.co, dagomez@agrosavia.co 2 Institute de Hydrology, Meteorology and Environmental Studies - IDEAM, A Office of the Deputy Director of Ecosystems and Environmental Information, rsanchez@ideam.gov.co, B Office of the Deputy Director of Meteorology, haguzman@ideam.gov.co, efonseca@ideam.gov.co, C Cooperation and International Affairs Office, mjmorales@ideam.gov.co 3 Agustin Codazzi Geographic Institute, Office of the Deputy Director of Agrology, nordonez@igac.gov.co, ladymarcela.rodriguez@igac.gov.co 4 Ministry of Environment and Sustainable Development of the Republic of Colombia, olospina@minambiente.gov.co 5 Ministry of Agriculture and Rural Development of the Republic of Colombia, nelson.lozano@minagricultura.gov.co, blanca.medina@minagricultura.gov.co 6 Ministry of Foreign Affairs of the Republic of Colombia, sebastian.acosta@cancilleria.gov.co, claudia.ortiz@cancilleria.gov.co 7 Food and Agriculture Organization of the United Nations – FAO, Office in Colombia, project CAEP II, jorge.gutierrez@fao.org, adriana.bolivargamboa@fao.org, diego.pedrozacastro@fao.org

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: IDEAM national hydrometeorological network

Contact Point:
Gustavo A. Araujo-Carrillo

A35: Comoros (the)

GSOCseq layers source:
Gap-filling Layer

A36: Congo (the)

GSOCseq layers source:
Gap-filling Layer

A37: Cook Islands (the)

GSOCseq layers source:
Gap-filling Layer

A38: Costa Rica

GSOCseq layers source:
National Submission

National Expert(s):
Mauricio Vega-Araya, Bryan Alemán, Floria Bertsch , Members of Mesa de Tierras-SIMOCUTE

Data-holding Institution(s):
National University, University of Costa Rica and Asociación Costarricense de Ciencias del Suelo

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: 2020 Sentinel 2 imagery classification
Clay: National Soil Clay Layer
Climate: CHIRPS and NCEP-CFSR

Contact Point:
mauricio.vega.araya@una.ac.cr

A39: Cote d'Ivoire

GSOCseq layers source:
Gap-filling Layer

A40: Croatia

GSOCseq layers source:
Gap-filling Layer

A41: Cuba

GSOCseq layers source:
National Submission

National Expert(s):
Mirelys Rodríguez

Data-holding Institution(s):
Istituto de Suelos

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Mirelys Rodríguez

A42: Cyprus

GSOCseq layers source:
Gap-filling Layer

A43: Czechia

GSOCseq layers source:
Gap-filling Layer

A44: Democratic People's Republic of Korea (the)

GSOCseq layers source:
Gap-filling Layer

A45: Democratic Republic of the Congo (the)

GSOCseq layers source:
Gap-filling Layer

A46: Denmark

GSOCseq layers source:
Gap-filling Layer

A47: Djibouti

GSOCseq layers source:
Gap-filling Layer

A48: Dominica

GSOCseq layers source:
Gap-filling Layer

A49: Dominican Republic (the)

GSOCseq layers source:
Gap-filling Layer

A50: Ecuador

GSOCseq layers source:
National Submission

National Expert(s):
Wilmer Antonio; Jimenez Merino

Data-holding Institution(s):
Ministry of Agriculture and Livestock of Ecuador (CGINA-DGGA)

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Wilmer Jimenez

A51: Egypt

GSOCseq layers source:
Gap-filling Layer

A52: El Salvador

GSOCseq layers source:
Gap-filling Layer

A53: Equatorial Guinea

GSOCseq layers source:
Gap-filling Layer

A54: Eritrea

GSOCseq layers source:
National Submission

National Expert(s):
Dermas S. Dainom

Data-holding Institution(s):
National Agricultural Research Institute (NARI)

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: CRU (Climate Research Unit)

Contact Point:
Dermas Sultan

A55: Estonia

GSOCseq layers source:
National Submission

National Expert(s):
Kadri Allik; Evelin Pihlap; Elsa Putku; Tambet Kikas; Ain Kull; Priit Penu; Karin Kauer; Alar Astover

Data-holding Institution(s):
Agricultural Research Centre, Estonian University of Life Sciences, University of Tartu

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: CORINE land cover
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Kadri Allik

A56: Eswatini

GSOCseq layers source:
Gap-filling Layer

A57: Ethiopia

GSOCseq layers source:
National Submission

National Expert(s):
Ephrem Mesfin

Data-holding Institution(s):
Ministry of Agriculture

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Addis Ababa

A58: Faroe Islands (the)

GSOCseq layers source:
Gap-filling Layer

A59: Fiji

GSOCseq layers source:
Gap-filling Layer

A60: Finland

GSOCseq layers source:
National Submission

National Expert(s):
Fulu Tao

Data-holding Institution(s):
Natural Resources Institute Finland (Luke)

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Finland

A61: France

GSOCseq layers source:
National Submission

National Expert(s):
Manuel Pascal Martin

Data-holding Institution(s):
INRAE

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: National Climate Layers

Contact Point:
Manuel Pascal Martin

A62: Gabon

GSOCseq layers source:
Gap-filling Layer

A63: the Gambia

GSOCseq layers source:
Gap-filling Layer

A64: Georgia

GSOCseq layers source:
National Submission

National Expert(s):
Giorgi Ghambashidze

Data-holding Institution(s):
Scientific-Research Centre of Agriculture

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Giorgi Ghambashidze

A65: Germany

GSOCseq layers source:
National Submission

National Expert(s):
Rene Dechow; Christopher Poeplau

Data-holding Institution(s):
Thünen Institute of Climate-Smart Agriculture

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: National Climate Layers

Contact Point:
Christopher Poeplau

A66: Ghana

GSOCseq layers source:
Gap-filling Layer

A67: Greece

GSOCseq layers source:
National Submission

National Expert(s):
Dimitris Triantakonstantis; Spyridon Detsikas

Data-holding Institution(s):
ELGO DIMITRA - Institute of Soil and Water Resources / Soil Science Department of Athens

Input layer specifications:
Soil Organic Carbon: An updated version (submitted to GSP-FAO) estimated the SOC stocks (tn / ha) in Greece for 0-30 cm depth at a resolution of 30-arc-seconds (~1x1 km resolution), using more than 2,400 up-to-date (2015-2020) soil data from all over the country (Triantakonstantis and Detsikas, 2021)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: ISRIC datasets at a resolution of 250x250 m
Climate: TerraClimate

Contact Point:
Dimitris Triantakonstantis

A68: Grenada

GSOCseq layers source:
Gap-filling Layer

A69: Guatemala

GSOCseq layers source:
Gap-filling Layer

A70: Guinea

GSOCseq layers source:
Gap-filling Layer

A71: Guinea-Bissau

GSOCseq layers source:
Gap-filling Layer

A72: Guyana

GSOCseq layers source:
Gap-filling Layer

A73: Haiti

GSOCseq layers source:
Gap-filling Layer

A74: Honduras

GSOCseq layers source:
Gap-filling Layer

A75: Hungary

GSOCseq layers source:
Gap-filling Layer

A76: Iceland

GSOCseq layers source:
Gap-filling Layer

A77: India

GSOCseq layers source:
National Submission

National Expert(s):
Nirmal Kumar

Data-holding Institution(s):
ICAR-Indian Council of Agricultural Research

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)

Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Nirmal Kumar

A78: Indonesia

GSOCseq layers source:
Gap-filling Layer

A79: Iran (Islamic Republic of)

GSOCseq layers source:
Gap-filling Layer

A80: Iraq

GSOCseq layers source:
Gap-filling Layer

A81: Ireland

GSOCseq layers source:
Gap-filling Layer

A82: Jamaica

GSOCseq layers source:
Gap-filling Layer

A83: Japan

GSOCseq layers source:
Gap-filling Layer

A84: Jordan

GSOCseq layers source:
Gap-filling Layer

A85: Kazakhstan

GSOCseq layers source:
National Submission

National Expert(s):
Azamat Yershibul

Data-holding Institution(s):
Ministry of Agriculture of the Republic of Kazakhstan

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Azamat Yershibul

A86: Kenya

GSOCseq layers source:
Gap-filling Layer

A87: Kiribati

GSOCseq layers source:
Gap-filling Layer

A88: Kuwait

GSOCseq layers source:
Gap-filling Layer

A89: Kyrgyzstan

GSOCseq layers source:
Gap-filling Layer

A90: Lao People's Democratic Republic (the)

GSOCseq layers source:
Gap-filling Layer

A91: Lebanon

GSOCseq layers source:
Gap-filling Layer

A92: Lesotho

GSOCseq layers source:
National Submission

National Expert(s):
Selebalo Ramakhanna; Koetlisi koetlisi; Polao Moepi; Thabo Motsoane; Khotso Mathafeng

Data-holding Institution(s):
LESIS

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Maseiso Hlongwane

A93: Liberia

GSOCseq layers source:
Gap-filling Layer

A94: Libya

GSOCseq layers source:
Gap-filling Layer

A95: Lithuania

GSOCseq layers source:
Gap-filling Layer

A96: Luxembourg

GSOCseq layers source:
Gap-filling Layer

A97: Madagascar

GSOCseq layers source:
Gap-filling Layer

A98: Malawi

GSOCseq layers source:
Gap-filling Layer

A99: Malaysia

GSOCseq layers source:
Gap-filling Layer

A100: Maldives

GSOCseq layers source:
Gap-filling Layer

A101: Mali

GSOCseq layers source:
Gap-filling Layer

A102: Malta

GSOCseq layers source:
Gap-filling Layer

A103: Marshall Islands (the)

GSOCseq layers source:
Gap-filling Layer

A104: Mauritania

GSOCseq layers source:
Gap-filling Layer

A105: Mauritius

GSOCseq layers source:
Gap-filling Layer

A106: Mexico

GSOCseq layers source:
National Submission

National Expert(s):
Villalobos, V.M.1, Arguello, S.1, Ortiz, S.1, Cerón A.1, Bunge, V.1, Reynoso, V.1, Velázquez, J.1, Biswas, A.2, Montano F.J.1, Guevara, M.3

Data-holding Institution(s):
ACRICULTURA MEXICO

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Combined - National for croplands; ESA for shrublands and grasslands
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
mguevara@geociencias.unam.mx

A107: Micronesia (Federated States of)

GSOCseq layers source:
Gap-filling Layer

A108: Monaco

GSOCseq layers source:
Gap-filling Layer

A109: Mongolia

GSOCseq layers source:
Gap-filling Layer

A110: Montenegro

GSOCseq layers source:
Gap-filling Layer

A111: Morocco

GSOCseq layers source:
National Submission

National Expert(s):
Moussadek Rachid; Hassani Kadiri Kenza

Data-holding Institution(s):
INRA

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)

Clay: National Soil Clay Layer
Climate: CRU (Climate Research Unit)

Contact Point:
Rachid Moussadek

A112: Mozambique

GSOCseq layers source:
Gap-filling Layer

A113: Myanmar

GSOCseq layers source:
Gap-filling Layer

A114: Namibia

GSOCseq layers source:
Gap-filling Layer

A115: Nauru

GSOCseq layers source:
Gap-filling Layer

A116: Nepal

GSOCseq layers source:
Gap-filling Layer

A117: Nicaragua

GSOCseq layers source:
National Submission

National Expert(s):
Wilmer Rodriguez ; Alfonso Martinuz Guerrero

Data-holding Institution(s):
NA

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: National Climate Layers

Contact Point:
Wilmer Rodriguez

A118: the Niger

GSOCseq layers source:
Gap-filling Layer

A119: Nigeria

GSOCseq layers source:
National Submission

National Expert(s):
O. James Jayeoba

Data-holding Institution(s):
Nigeria Institute of Soil Science (NISS)

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)

Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
NISS

A120: Niue

GSOCseq layers source:
Gap-filling Layer

A121: Oman

GSOCseq layers source:
National Submission

National Expert(s):
Saud Al Farsi

Data-holding Institution(s):
FAOOM

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Saud Al Farsi

A122: Pakistan

GSOCseq layers source:
Gap-filling Layer

A123: Palau

GSOCseq layers source:
Gap-filling Layer

A125: Panama

GSOCseq layers source:
Gap-filling Layer

A126: Papua New Guinea

GSOCseq layers source:
Gap-filling Layer

A127: Paraguay

GSOCseq layers source:
National Submission

National Expert(s):
Arnulfo Encina Rojas

Data-holding Institution(s):
Ministerio de Agricultura y Ganadería- Paraguay

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Arnulfo Encina Rojas

A128: Peru

GSOCseq layers source:
Gap-filling Layer

A129: Philippines (the)

GSOCseq layers source:
National Submission

National Expert(s):
Andrew B. Flores; Dominciano M. Ramos; Bertolio P. Arellano; Raquel R. Granil; Mark Anthony V. Posilero; Pablo M. Montalla

Data-holding Institution(s):
Bureau of Soils and Water Management

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
(+632)8920-4382

A130: Poland

GSOCseq layers source:
Gap-filling Layer

A131: Portugal

GSOCseq layers source:
National Submission

National Expert(s):
Guerrero, C.

Data-holding Institution(s):
Portuguese Partnership for Soil

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Dr. Rogério Lima Ferreira

A132: Qatar

GSOCseq layers source:
Gap-filling Layer

A133: Republic of Korea (the)

GSOCseq layers source:
Gap-filling Layer

A134: Republic of Moldova (the)

GSOCseq layers source:
National Submission

National Expert(s):
Rodica Sirbu

Data-holding Institution(s):
Institute of Pedology, Agrochemistry and Soil Protection “Nicolae Dimo”

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Rodica Sirbu

A135: Romania

GSOCseq layers source:
Gap-filling Layer

A136: Russian Federation (the)

GSOCseq layers source:
National Submission

National Expert(s):
Romanenkov Vladimir; Krenke Aleksandr; Golozubov Oleg; Meshalkina Julia; Gorbacheva Anna; Petrov Ivan; Rukhovich Dmitry; Litvinov Yuri; Nazarenko Olga

Data-holding Institution(s):
Lomonosov Moscow State University; Institute of Geography of the Russian Academy of Sciences; Analytical center of the Ministry of Agriculture of the Russian Federation; Dokuchaev Soil Science Institute; Academy of biology and biotechnology, Southern Federal University; Agrochemical Center "Rostovsky"

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: CRU (Climate Research Unit)

Contact Point:
Romanenkov Vladimir

A137: Rwanda

GSOCseq layers source:
Gap-filling Layer

A138: Saint Kitts and Nevis

GSOCseq layers source:
Gap-filling Layer

A139: Saint Lucia

GSOCseq layers source:
Gap-filling Layer

A140: Saint Vincent and the Grenadines

GSOCseq layers source:
Gap-filling Layer

A141: Samoa

GSOCseq layers source:
Gap-filling Layer

A142: San Marino

GSOCseq layers source:
Gap-filling Layer

A143: Sao Tome and Principe

GSOCseq layers source:
Gap-filling Layer

A144: Saudi Arabia

GSOCseq layers source:
Gap-filling Layer

A145: Senegal

GSOCseq layers source:
National Submission

National Expert(s):
LOUM Macoumba

Data-holding Institution(s):
Institut National Pédologie

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Macoumba LOUM

A146: Serbia

GSOCseq layers source:
Gap-filling Layer

A147: Seychelles

GSOCseq layers source:
Gap-filling Layer

A148: Sierra Leone

GSOCseq layers source:
Gap-filling Layer

A149: Singapore

GSOCseq layers source:
Gap-filling Layer

A150: Slovakia

GSOCseq layers source:
National Submission

National Expert(s):
Stefan Koco; Rastislav Skalsky; Gabriela Barancikova; Pavol Bezak

Data-holding Institution(s):
National Agricultrual and Food Centre - Soil Science and Conservation Research Institute

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Combination fo ESA CCI and national LPSI datasets
Clay: National Soil Clay Layer
Climate: National Climate Layers

Contact Point:
Stefan Koco

A151: Slovenia

GSOCseq layers source:
National Submission

National Expert(s):
Janez Bergant; Peter Kastelic; Borut Vrščaj

Data-holding Institution(s):
Ministry for Agriculture, Forestry and Food of Slovenia

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: National Climate Layers

Contact Point:
Petra Božic

A152: Solomon Islands

GSOCseq layers source:
Gap-filling Layer

A153: Somalia

GSOCseq layers source:
Gap-filling Layer

A154: South Africa

GSOCseq layers source:
National Submission

National Expert(s):
Dr Theunis Morgenthal, Ms Anneliza Collett; Mr Ramakgwale Mampholo and Mr Adolph Malatjie

Data-holding Institution(s):
Department of Agriculture, Land Reform and Rural Development

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
GSP Focal point

A155: South Sudan

GSOCseq layers source:
Gap-filling Layer

A156: Spain

GSOCseq layers source:
Gap-filling Layer

A157: Sri Lanka

GSOCseq layers source:
National Submission

National Expert(s):
Harsha Kumara Kadupitiya; Awanthi Iddawela, Dilshani Gunawardena, Wasala Bandara, Harshani Uduwerella, Ajith Hettiarachchi

Data-holding Institution(s):
Natural Resources Management Centre

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
No. 52, Sarasavi Mawatha, Peradeniya

A158: Sudan (the)

GSOCseq layers source:
National Submission

National Expert(s):
Abdelmagid Ali Elmobarak; Nuha Abdalla Mohamed; Faroog Elhadi; Maha Fethi

Data-holding Institution(s):
Land Evaluation Section, Land and Water Res. Centre, ARC

Input layer specifications:
Soil Organic Carbon: Other National Soil Organic Carbon Map
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: CRU (Climate Research Unit)

Contact Point:
Abdelmagid Ali Elmobarak

A159: Suriname

GSOCseq layers source:
Gap-filling Layer

A160: Sweden

GSOCseq layers source:
Gap-filling Layer

A161: Switzerland

GSOCseq layers source:
National Submission

National Expert(s):
Sonja G. Keel; Chloé Wüst

Data-holding Institution(s):
Agroscope

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: Default Dataset (SoilGrids)
Climate: National Climate Layers

Contact Point:
Chloé Wüst

A162: Syrian Arab Republic (the)

GSOCseq layers source:
Gap-filling Layer

A163: Tajikistan

GSOCseq layers source:
Gap-filling Layer

A164: United Republic of Tanzania (the)

GSOCseq layers source:
Gap-filling Layer

A165: Thailand

GSOCseq layers source:
Gap-filling Layer

A166: North Macedonia

GSOCseq layers source:
Gap-filling Layer

A167: Timor-Leste

GSOCseq layers source:
Gap-filling Layer

A168: Togo

GSOCseq layers source:
Gap-filling Layer

A169: Tokelau

GSOCseq layers source:
Gap-filling Layer

A170: Tonga

GSOCseq layers source:
Gap-filling Layer

A171: Trinidad and Tobago

GSOCseq layers source:
Gap-filling Layer

A172: Tunisia

GSOCseq layers source:
Gap-filling Layer

A173: Turkey

GSOCseq layers source:
National Submission

National Expert(s):
Muhammed Halil Koparan, Sevinc Madenoglu, Mehmet Gur, Mehmet Kececi, Bulent Sonmez

Data-holding Institution(s):
Republic of Turkey Ministry of Agriculture And Forestry General Directorate of Agricultural Research and Policies

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Muhammed Halil Koparan

A174: Turkmenistan

GSOCseq layers source:
Gap-filling Layer

A175: Tuvalu

GSOCseq layers source:
Gap-filling Layer

A176: Uganda

GSOCseq layers source:
Gap-filling Layer

A177: Ukraine

GSOCseq layers source:
Gap-filling Layer

A178: United Arab Emirates (the)

GSOCseq layers source:
National Submission

National Expert(s):
Bayan Mahmoud Athamneh; Rommel De Torres Pangilinan

Data-holding Institution(s):
Environment Agency - Abu Dhabi

Input layer specifications:
Soil Organic Carbon: National Soil Organic Carbon Map
Land Cover/ Land Use: National Land Cover Layer

Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Bayan Mahmoud Athamneh; Rommel De Torres Pangilinan

A179: United Kingdom of Great Britain and Northern Ireland (the)

GSOCseq layers source:
Gap-filling Layer

A180: United States of America (the)

GSOCseq layers source:
National Submission

National Expert(s):
Stephen Roecker;Suzann Kienast-Brown;Skye Wills;Charles Ferguson;David Lindbo

Data-holding Institution(s):
USDA-NRCS

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: National Soil Clay Layer
Climate: TerraClimate

Contact Point:
Stephen Roecker

A181: Uruguay

GSOCseq layers source:
National Submission

National Expert(s):
Gonzalo Pereira; Martin Dell´Acqua; Virginia Pravia; Adrian Cal; Fernando Fontes

Data-holding Institution(s):
DGRN-MGAP and INIA Gras

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: National Land Cover/Land Use Datasets
Clay: National Soil Clay Layer
Climate: CRU and National Climate Layers (2000 to 2020)

Contact Point:
Fernando Fontes

A182: Uzbekistan

GSOCseq layers source:
Gap-filling Layer

A183: Vanuatu

GSOCseq layers source:
Gap-filling Layer

A184: Venezuela (Bolivarian Republic of)

GSOCseq layers source:
National Submission

National Expert(s):
Juan Rey; Victor Sevilla

Data-holding Institution(s):
Instituto Nacional de Investigaciones Agrícolas

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Juan Rey

A185: Viet Nam

GSOCseq layers source:
National Submission

National Expert(s):
Vu Manh Quyet

Data-holding Institution(s):
Soils and Fertilizers Research Institute

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: SERVIR Mekong land cover dataset
Clay: Default Dataset (SoilGrids)
Climate: TerraClimate

Contact Point:
Vu Manh Quyet

A186: Yemen

GSOCseq layers source:
Gap-filling Layer

A187: Zambia

GSOCseq layers source:
Gap-filling Layer

A188: Zimbabwe

GSOCseq layers source:
National Submission

National Expert(s):
Shelter Mangwanya

Data-holding Institution(s):
Chemistry and Soil Research Institute

Input layer specifications:
Soil Organic Carbon: Default Dataset (GSOCmap)
Land Cover/ Land Use: Default Dataset provided by GSP (ESA CCI)
Clay: Default Dataset (SoilGrids)
Climate: CRU (Climate Research Unit)

Contact Point:
Shelter Mangwanya

Annex B | Results for all countries

Table A1 shows total and average Relative Sequestration Rates (RSR) for all participating countries (excluding countries that requested to remain blank for this current version of the GSOCseq v.1.1) in descending order, highest to lowest total RSR (Mt C yr^{-1}), under the SSM3 scenario.

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
Brazil	71.536 ± 16.207	0.181 ± 0.025	Gap-filled
China	52.893 ± 15.772	0.12 ± 0.019	Gap-filled
United States of America (the)	45.574 ± 7.6	0.142 ± 0.031	National Submission
India	21.543 ± 1.929	0.095 ± 0.015	National Submission
Russian Federation (the)	16.639 ± 6.703	0.169 ± 0.029	National Submission
Argentina	16.607 ± 3.964	0.101 ± 0.052	National Submission
Indonesia	14.654 ± 11.307	0.273 ± 0.049	Gap-filled
Ethiopia	13.97 ± 1.688	0.169 ± 0.023	National Submission
Kazakhstan	12.313 ± 2.082	0.073 ± 0.015	National Submission
South Africa	11.407 ± 0.907	0.089 ± 0.018	National Submission
Canada	10.717 ± 5.186	0.243 ± 0.015	National Submission
Mexico	9.884 ± 2.126	0.087 ± 0.01	National Submission
Peru	8.417 ± 4.669	0.247 ± 0.058	Gap-filled
United Republic of Tanzania (the)	7.935 ± 2.538	0.179 ± 0.029	Gap-filled

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 $Mt\ C\ yr^{-1}$	Mean RSR SSM3 $t\ C\ ha^{-1}\ yr^{-1}$	Map Source
Colombia	7.729 ± 3.938	0.247 ± 0.045	National Submission
Democratic Republic of the Congo (the)	7.327 ± 5.62	0.227 ± 0.059	Gap-filled
Nigeria	7.18 ± 0.912	0.11 ± 0.012	National Submission
Kenya	7.17 ± 1.1	0.177 ± 0.033	Gap-filled
Thailand	6.48 ± 2.535	0.207 ± 0.023	Gap-filled
Somalia	6.462 ± 1.155	0.137 ± 0.031	Gap-filled
Mozambique	6.315 ± 3.412	0.223 ± 0.044	Gap-filled
France	6.281 ± 6.096	0.167 ± 0.018	National Submission
Angola	6.235 ± 3.121	0.166 ± 0.028	Gap-filled
Myanmar	6.147 ± 2.722	0.201 ± 0.036	Gap-filled
Ukraine	5.895 ± 0.834	0.126 ± 0.021	Gap-filled
South Sudan	5.753 ± 0.439	0.168 ± 0.028	Gap-filled
Turkey	5.229 ± 1.88	0.102 ± 0.015	National Submission
Bolivia (Plurinational State of)	5.128 ± 3.369	0.211 ± 0.021	Gap-filled
Pakistan	5.059 ± 0.869	0.099 ± 0.015	Gap-filled
Venezuela (Bolivarian Republic of)	4.755 ± 2.876	0.195 ± 0.033	National Submission
Mongolia	4.691 ± 2.979	0.103 ± 0.013	Gap-filled
Namibia	4.639 ± 0.255	0.086 ± 0.012	Gap-filled
Germany	4.591 ± 1.418	0.181 ± 0.031	National Submission
Sudan (the)	4.289 ± 0.874	0.062 ± 0.016	National Submission
Chad	4.227 ± 0.144	0.092 ± 0.037	Gap-filled
Uruguay	3.843 ± 0.03	0.262 ± 0.063	National Submission
Spain	3.84 ± 1.715	0.123 ± 0.013	Gap-filled
Philippines (the)	3.632 ± 2.406	0.19 ± 0.014	National Submission
Zambia	3.568 ± 2.317	0.162 ± 0.028	Gap-filled
Malaysia	3.514 ± 2.888	0.436 ± 0.073	Gap-filled
Iran (Islamic Republic of)	3.473 ± 1.482	0.091 ± 0.012	Gap-filled
Afghanistan	3.447 ± 1.008	0.103 ± 0.015	Gap-filled
Botswana	3.44 ± 0.135	0.064 ± 0.012	Gap-filled
C“te d'Ivoire	3.433 ± 1.291	0.183 ± 0.016	Gap-filled
Mali	3.356 ± 0.163	0.075 ± 0.029	Gap-filled
Zimbabwe	3.336 ± 0.764	0.124 ± 0.025	National Submission
Uganda	3.281 ± 0.946	0.225 ± 0.046	Gap-filled
United Kingdom of Great Britain and Northern Ireland (the)	3.277 ± 1.791	0.209 ± 0.013	Gap-filled
Ecuador	3.185 ± 1.735	0.319 ± 0.034	National Submission

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
Chile	3.165 ± 1.799	0.372 ± 0.036	National Submission
Burkina Faso	2.784 ± 0.373	0.105 ± 0.024	National Submission
Madagascar	2.62 ± 1.994	0.327 ± 0.064	Gap-filled
Ghana	2.501 ± 0.754	0.181 ± 0.021	Gap-filled
Viet Nam	2.197 ± 0.982	0.154 ± 0.038	National Submission
Poland	2.173 ± 0.965	0.117 ± 0.016	Gap-filled
Paraguay	2.083 ± 1.02	0.157 ± 0.032	National Submission
Lao People's Democratic Republic (the)	1.918 ± 1.236	0.206 ± 0.039	Gap-filled
Greece	1.917 ± 1.038	0.219 ± 0.027	National Submission
Papua New Guinea	1.896 ± 1.786	0.413 ± 0.162	Gap-filled
Cambodia	1.754 ± 0.718	0.205 ± 0.025	National Submission
Cuba	1.651 ± 1.613	0.284 ± 0.094	National Submission
Guinea	1.635 ± 1.082	0.228 ± 0.007	Gap-filled
Romania	1.606 ± 0.599	0.121 ± 0.016	Gap-filled
Bangladesh	1.569 ± 1.215	0.152 ± 0.028	National Submission
Uzbekistan	1.563 ± 0.681	0.082 ± 0.013	Gap-filled
Algeria	1.495 ± 1.253	0.13 ± 0.011	Gap-filled
Sri Lanka	1.462 ± 1.018	0.461 ± 0.14	National Submission
Belarus	1.456 ± 0.702	0.128 ± 0.024	Gap-filled
Senegal	1.377 ± 0.176	0.088 ± 0.017	National Submission
Congo (the)	1.361 ± 1.19	0.28 ± 0.043	Gap-filled
Japan	1.336 ± 1.177	0.171 ± 0.017	Gap-filled
Sierra Leone	1.32 ± 0.709	0.273 ± 0.048	Gap-filled
Georgia	1.274 ± 0.942	0.335 ± 0.025	National Submission
Ireland	1.265 ± 0.543	0.278 ± 0.028	Gap-filled
Morocco	1.234 ± 0.774	0.12 ± 0.027	National Submission
Liberia	1.194 ± 0.51	0.234 ± 0.036	Gap-filled
Malawi	1.188 ± 0.488	0.177 ± 0.032	Gap-filled
Benin	1.086 ± 0.149	0.148 ± 0.019	Gap-filled
Turkmenistan	0.998 ± 0.593	0.086 ± 0.021	Gap-filled
Hungary	0.935 ± 0.28	0.139 ± 0.026	Gap-filled
Nicaragua	0.93 ± 0.551	0.243 ± 0.052	National Submission
the Niger	0.928 ± 0.442	0.039 ± 0.023	Gap-filled
Iraq	0.922 ± 0.236	0.095 ± 0.024	Gap-filled
Tajikistan	0.914 ± 0.228	0.107 ± 0.016	Gap-filled
Cameroon	0.89 ± 0.289	0.125 ± 0.007	National Submission
Honduras	0.7 ± 0.627	0.251 ± 0.054	Gap-filled
Rwanda	0.697 ± 0.105	0.348 ± 0.031	Gap-filled

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
Guatemala	0.684 ± 0.555	0.208 ± 0.03	Gap-filled
Serbia	0.684 ± 0.106	0.134 ± 0.021	Gap-filled
Czechia	0.668 ± 0.206	0.147 ± 0.023	Gap-filled
Burundi	0.666 ± 0.032	0.301 ± 0.064	Gap-filled
Lesotho	0.662 ± 0.108	0.227 ± 0.042	National Submission
Central African Republic (the)	0.655 ± 0.08	0.173 ± 0.023	Gap-filled
Bulgaria	0.653 ± 0.086	0.105 ± 0.017	Gap-filled
Sweden	0.641 ± 0.587	0.165 ± 0.012	Gap-filled
Tunisia	0.637 ± 0.436	0.141 ± 0.013	Gap-filled
Democratic People's Republic of Korea (the)	0.604 ± 0.452	0.15 ± 0.008	Gap-filled
Dominican Republic (the)	0.591 ± 0.513	0.303 ± 0.231	Gap-filled
Gabon	0.591 ± 0.551	0.32 ± 0.069	Gap-filled
Portugal	0.589 ± 0.346	0.151 ± 0.034	National Submission
Lithuania	0.576 ± 0.444	0.143 ± 0.01	Gap-filled
Nepal	0.564 ± 0.304	0.137 ± 0.031	Gap-filled
Kyrgyzstan	0.556 ± 0.189	0.111 ± 0.017	Gap-filled
Togo	0.556 ± 0.179	0.167 ± 0.017	Gap-filled
Falkland Islands (Malvinas) (the)	0.538 ± 0.538	0.546 ± 0	Gap-filled
Denmark	0.535 ± 0.393	0.178 ± 0.023	Gap-filled
Timor-Leste	0.509 ± 0.504	0.419 ± 0.079	Gap-filled
Haiti	0.486 ± 0.413	0.252 ± 0.074	Gap-filled
Slovakia	0.484 ± 0.166	0.157 ± 0.024	National Submission
Estonia	0.476 ± 0.374	0.251 ± 0.041	National Submission
Syrian Arab Republic (the)	0.475 ± 0.088	0.089 ± 0.014	Gap-filled
Iceland	0.456 ± 0.403	0.243 ± 0.04	Gap-filled
Azerbaijan	0.455 ± 0.284	0.094 ± 0.015	Gap-filled
Republic of Korea (the)	0.45 ± 0.268	0.104 ± 0.024	National Submission
Mauritania	0.434 ± 0.369	0.032 ± 0.005	Gap-filled
Croatia	0.411 ± 0.214	0.171 ± 0.025	Gap-filled
Eswatini	0.398 ± 0.014	0.382 ± 0.085	Gap-filled
Costa Rica	0.367 ± 0.237	0.384 ± 0.077	National Submission
Panama	0.353 ± 0.344	0.14 ± 0.003	Gap-filled
Bosnia and Herzegovina	0.331 ± 0.142	0.174 ± 0.027	Gap-filled

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
Finland	0.318 ± 0.291	0.118 ± 0.014	National Submission
Switzerland	0.317 ± 0.183	0.233 ± 0.025	National Submission
Egypt	0.311 ± 0.267	0.092 ± 0.011	Gap-filled
Albania	0.247 ± 0.15	0.15 ± 0.023	Gap-filled
Yemen	0.24 ± 0.169	0.072 ± 0.011	Gap-filled
Republic of Moldova (the)	0.232 ± 0.014	0.087 ± 0.013	National Submission
Taiwan Province of China	0.221 ± 0.192	0.229 ± 0.055	Gap-filled
North Macedonia	0.181 ± 0.101	0.175 ± 0.019	Gap-filled
the Gambia	0.169 ± 0.027	0.223 ± 0.041	Gap-filled
Fiji	0.161 ± 0.161	0.368 ± 0.024	Gap-filled
Guinea-Bissau	0.145 ± 0.079	0.2 ± 0.041	Gap-filled
Libya	0.141 ± 0.141	0.082 ± 0	Gap-filled
Slovenia	0.134 ± 0.134	0.229 ± 0.033	National Submission
New Caledonia	0.124 ± 0.124	0.376 ± 0	Gap-filled
Eritrea	0.113 ± 0.066	0.021 ± 0.009	National Submission
Saudi Arabia	0.113 ± 0.112	0.063 ± 0.008	Gap-filled
El Salvador	0.107 ± 0.078	0.256 ± 0.049	Gap-filled
Bhutan	0.091 ± 0.006	0.18 ± 0.022	National Submission
Armenia	0.085 ± 0.021	0.129 ± 0.022	Gap-filled
Guyana	0.082 ± 0.061	0.133 ± 0.018	Gap-filled
Lebanon	0.081 ± 0.064	0.109 ± 0.013	Gap-filled
Montenegro	0.067 ± 0.046	0.196 ± 0.024	Gap-filled
Puerto Rico	0.066 ± 0.066	0.279 ± 0	Gap-filled
Palestine	0.066 ± 0.037	0.171 ± 0.004	Gap-filled
Equatorial Guinea	0.065 ± 0.058	0.326 ± 0.015	Gap-filled
Belize	0.061 ± 0.056	0.22 ± 0.034	Gap-filled
Jordan	0.052 ± 0.005	0.098 ± 0.019	Gap-filled
Jamaica	0.049 ± 0.049	0.203 ± 0	Gap-filled
Luxembourg	0.03 ± 0.017	0.221 ± 0.03	Gap-filled
R,union	0.028 ± 0.028	0.307 ± 0	Gap-filled
Cyprus	0.027 ± 0.019	0.082 ± 0.007	Gap-filled
Cabo Verde	0.023 ± 0.023	0.135 ± 0	National Submission
Brunei Darussalam	0.02 ± 0.02	0.441 ± 0	Gap-filled
Northern Mariana Islands (the)	0.014 ± 0.014	0.583 ± 0	Gap-filled
Oman	0.013 ± 0.013	0.05 ± 0.02	National Submission
Guadeloupe	0.012 ± 0.012	0.256 ± 0	Gap-filled
Guam	0.012 ± 0.012	0.33 ± 0	Gap-filled

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
United Arab Emirates (the)	0.009 ± 0.009	0.029 ± 0.012	National Submission
Isle of Man	0.009 ± 0.001	0.243 ± 0.045	Gap-filled
Solomon Islands	0.007 ± 0.007	0.398 ± 0	Gap-filled
Vanuatu	0.007 ± 0.007	0.383 ± 0	Gap-filled
Barbados	0.006 ± 0.006	0.252 ± 0	Gap-filled
Djibouti	0.006 ± 0.006	0.109 ± 0.033	Gap-filled
South Georgia and the South Sandwich Islands	0.006 ± 0.006	0.343 ± 0	Gap-filled
Comoros (the)	0.005 ± 0.005	0.298 ± 0	Gap-filled
Suriname	0.004 ± 0.004	0.129 ± 0	Gap-filled
Trinidad and Tobago	0.004 ± 0.004	0.165 ± 0	Gap-filled
Andorra	0.003 ± 0.003	0.253 ± 0	Gap-filled
Antigua and Barbuda	0.003 ± 0.003	0.234 ± 0	Gap-filled
Martinique	0.003 ± 0.003	0.259 ± 0	Gap-filled
Mauritius	0.003 ± 0.003	0.274 ± 0	Gap-filled
Singapore	0.003 ± 0.003	0.577 ± 0.115	Gap-filled
Ascension, Saint Helena and Tristan da Cunha	0.003 ± 0.003	0.366 ± 0	Gap-filled
United States Virgin Islands (the)	0.003 ± 0.003	0.232 ± 0	Gap-filled
Cura‡ao	0.002 ± 0.002	0.181 ± 0	Gap-filled
Jersey	0.002 ± 0.002	0.186 ± 0	Gap-filled
Malta	0.002 ± 0.002	0.145 ± 0	Gap-filled
Anguilla	0.001 ± 0.001	0.246 ± 0	Gap-filled
Cayman Islands (the)	0.001 ± 0.001	0.528 ± 0	Gap-filled
French Guiana	0.001 ± 0.001	0.158 ± 0	Gap-filled
Saint Kitts and Nevis	0.001 ± 0.001	0.261 ± 0	Gap-filled
Kuwait	0.001 ± 0.001	0.047 ± 0.003	Gap-filled
Liechtenstein	0.001 ± 0	0.239 ± 0.017	Gap-filled
San Marino	0.001 ± 0.001	0.124 ± 0	Gap-filled
Sao Tome and Principe	0.001 ± 0.001	0.281 ± 0	Gap-filled
Seychelles	0.001 ± 0.001	0.397 ± 0	Gap-filled
Turks and Caicos Islands (the)	0.001 ± 0.001	0.352 ± 0	Gap-filled

Table A1: Countries in descending order according to total SOC Relative Sequestration Rates based on the Sustainable Soil Management Scenario 3.

Country	Total RSR SSM3 Mt C yr^{-1}	Mean RSR SSM3 t C ha^{-1} yr^{-1}	Map Source
Bahrain	0 ± 0	0.065 ± 0	Gap-filled
the Bahamas	0 ± 0	0.04 ± 0	Gap-filled
Western Sahara	0 ± 0	0.068 ± 0	Gap-filled
Faroe Islands (the)	0 ± 0	0.326 ± 0	Gap-filled
Guernsey	0 ± 0	0.182 ± 0.018	Gap-filled
Grenada	0 ± 0	0.264 ± 0	Gap-filled
China, Hong Kong SAR	0 ± 0	0.132 ± 0.03	Gap-filled
Palau	0 ± 0	0.432 ± 0	Gap-filled
Qatar	0 ± 0	0.055 ± 0	Gap-filled
Saint Pierre and Miquelon	0 ± 0	0.167 ± 0	Gap-filled

The symbol '±' denotes the upper and lower limits of the estimated SOC stocks (t C/ha/yr for mean SOC content; Mt C/yr for total SOC stocks) derived from the uncertainty ranges (95% confidence interval) of selected input layers. ±0 inidicates values smaller than 1e-4 Mt C /yr and/or 1e-4 t C /ha/yr.

Office of Communications – April 2022

[Global Soil Organic Carbon Sequestration Potential Map – GSOCseq v.1.1 - Technical report]

Corrigendum

Updated on [11/04/2022]

The following corrections were made to the PDF after it went to print.

Page	Location	Text in printed PDF	Text in corrected PDF
44	6.2. Statistics for countries (GSOCseq V.1.1)	Figure 6.8 further breaks down these results into the respective SSM1-3 scenarios. Brazil (71.54 ± 16.21 Mt yr-1), China (52.89 ± 15.77 Mt yr-1), United States of America (character(0) Mt yr-1) and India (21.54 ± 1.93 Mt yr-1) with their extensive agricultural soils dominate the chart and represent 34 percent of the global potential carbon sequestration under the highest C input (SSM3. 20 percent) scenario.	Figure 6.8 shows the top 15 countries with the highest mean SOC sequestration potential that could sequester at least one Mt C on a yearly basis.
129	A136: Russian Federation (the)	GSOCseq layers source: National Submission National Expert(s): TBD Data-holding Institution(s): TBD Input layer specifications: Soil Organic Carbon: Default Dataset (GSOCmap) Land Cover/ Land Use: National Land Cover/Land Use Datasets Clay: National Soil Clay Layer Climate: CRU (Climate Research Unit) Contact Point:	GSOCseq layers source: National Submission National Expert(s): Romanenkov Vladimir; Krenke Aleksandr; Golozubov Oleg; Meshalkina Julia; Gorbacheva Anna; Petrov Ivan; Rukhovich Dmitry; Litvinov Yuri; Nazarenko Olga Data-holding Institution(s): Lomonosov Moscow State University; Institute of Geography of the Russian Academy of Sciences; Analytical center of the Ministry of Agriculture of the Russian Federation; Dokuchaev Soil Science Institute; Academy of biology and biotechnology, Southern Federal University; Agrochemical Center “Rostovsky” Input layer specifications: Soil Organic Carbon: Default Dataset (GSOCmap) Land Cover/ Land Use: National Land Cover/Land Use Datasets Clay: National Soil Clay Layer Climate: CRU (Climate Research Unit) Contact Point: Romanenkov Vladimir

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The Global Soil Partnership (GSP) is a globally recognized mechanism established in 2012. Our mission is to position soils in the Global Agenda through collective action. Our key objectives are to promote Sustainable Soil Management (SSM) and improve soil governance to guarantee healthy and productive soils, and support the provision of essential ecosystem services towards food security and improved nutrition, climate change adaptation and mitigation, and sustainable development.

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