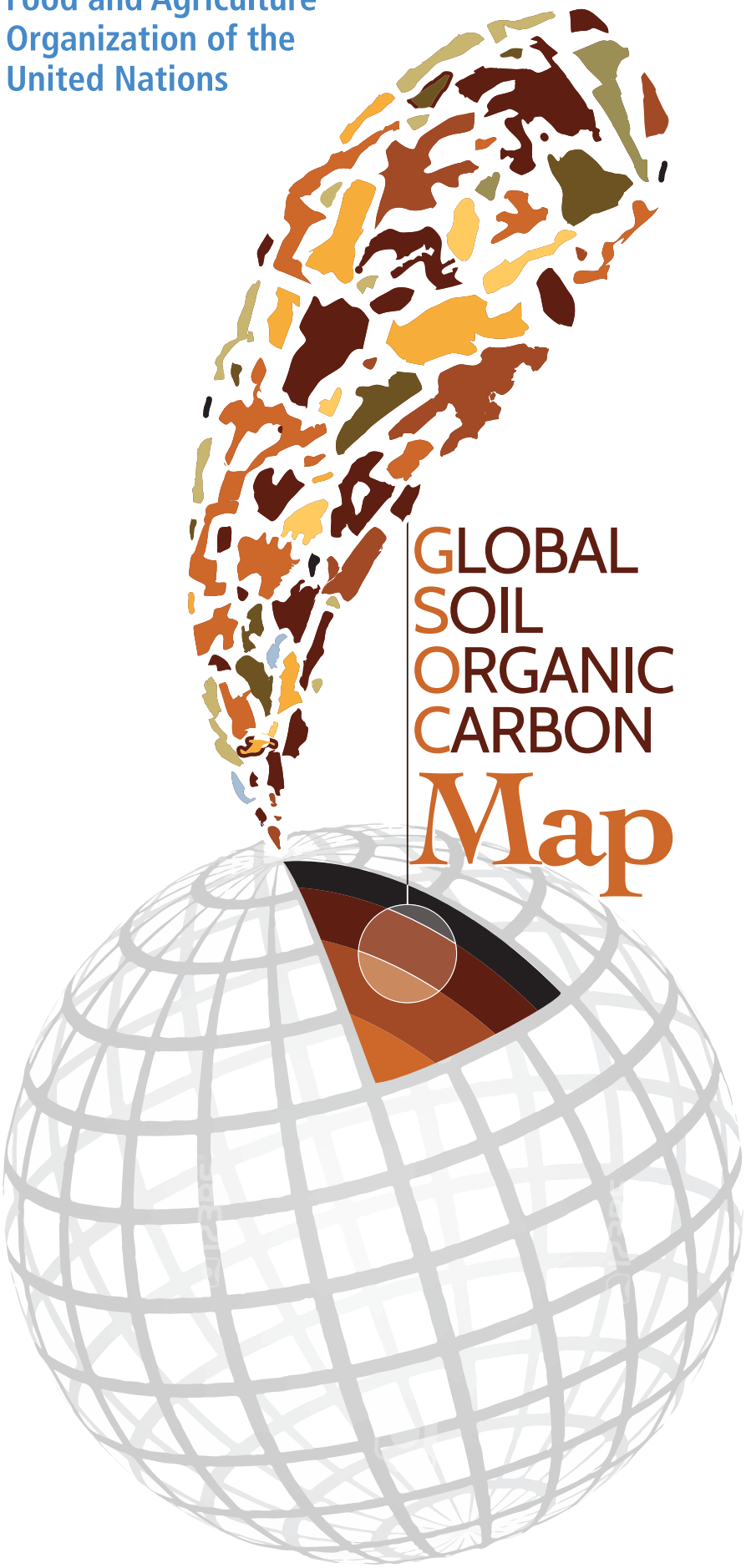
Food and Agriculture Organization of the United Nations



GLOBAL SOIL ORGANIC CARBON Map

TECHNICAL REPORT

GLOBAL SOIL PARTNERSHIP

Global Soil Organic Carbon Map
Technical report

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Contents

Figures

Tables

Foreword

This document presents the technical details of the first ever country-driven global soil organic carbon map (GSOCmap). This map allows the estimation of SOC stock from 0 to 30 cm. It represents a key contribution to the Sustainable Development Goal (SDG) indicator 15.3.1, which defines the area of degraded land. The novelty of this map is the fact that it is the first ever global soil organic carbon assessment which is produced through a participatory approach. Countries developed their capacities and stepped up efforts to compile or collect all available soil information at the national level.

The 5th GSP Plenary Assembly, in June 2017, approved the decision of member countries jointly developing a GSOCmap as a baseline for the amount and distribution of SOC soils. This map is part of the process of building a Global Soil Information System (GLOSIS) under the 4th pillar of the GSP, which aims to enhance the quantity and quality of soil data and information. This considerable effort, which led to the launch of the GSOCmap on World Soil Day 2017 (5 December), is paving the way to the establishment of national soil information systems and represents the first step toward introducing a soil monitoring program.

This technical report is aimed at scientists. It provides guidance on the process that led to the establishment of the GSOCmap and on how to use it. The map provides users with useful information to monitor the soil condition, identify degraded areas, set restoration targets, explore SOC sequestration potentials, support the greenhouse gas emission reporting under the UNFCCC. It also provides users with crucial information that is needed to make evidence based decisions to mitigate and adapt to climate change.

We can expect that the extensive data content of more than 1 million sampling points resulting from country contributions and the interactive nature of the GSOCmap will greatly assist in the process of building a global soil information system, which in turn will help contribute in the achievement of the sustainable development goals.

We are proud to make this very first edition of the global soil organic carbon map technical summary available for the international scientific community, and we hope that this map will be a major step in combating not only climate change which is directly linked to soil organic carbon, but also poverty, hunger and malnutrition.

The contributing institutions from the participating countries which submitted their maps or data are listed in Appendix A.

This technical report is a companion report to the GSOCmap V1.2.0. It presents methodologies and process of compiling the Global Soil organic Carbon Map.

Chapter 1

Background

1.1 The importance of soil organic carbon

Soil organic carbon (SOC) is the main component of soil organic matter (SOM) and is a crucial contributor to food production, mitigation and adaption to climate change, and the achievement of the Sustainable Development Goals (SDGs). SOC affects most of the processes relevant to soil functions and food production. A high SOM, and therefore SOC content provides plants with the nutrients and water they need by increasing soil fertility and water availability, which in turn improve food productivity. SOC has also long been used as an indicator of soil health, due to its capacity to improve soil structural stability, which affects porosity, aeration and water filtration capacities to supply clean water. However, SOC mineralization can be an important source of greenhouse gas (GHG) emissions. This means that changing SOM (and hence SOC) not only changes the provision of ecosystem services required for crop production, but also affects soils' capacity to buffer against environmental changes, as it regulates the resilience agricultural systems to climate change.

SOC has received great attention during the development of the greenhouse gas (GHG) reporting programme of the Intergovernmental Panel on Climate Change (IPCC) since the mid-nineties. This was done to address the contribution of intensive land management and the vast amount of degraded land to greenhouse gas emissions, since these have caused tremendous historic losses of SOC, resulting in high potentials for future carbon storage. Recently, an increasing number of authors have stressed the crucial role of healthy soils, with soil carbon being the most important indicator for food security and resilience against climate change. This has led to above and below ground carbon (SOC) becoming sub-indicators for the Sustainable Development Goals (SDG) target 15.3.1 (Proportion of land that is degraded over total land area).

The Status of the World's Soil Resources (SWRS) report highlights that, although more carbon is stored in the soil than in the atmosphere and plant life combined, a large portion (33%) of the world's soils are degraded, which has led to a major loss of global SOC reserves. The reversal of soil degradation through the buildup of SOM and the sustainable management of soils therefore offers large potential to contribute to climate change mitigation by sequestering atmospheric carbon into the soil. This emphasizes that soil can be a double-edged sword when it comes to carbon fluxes, as it can either be a net sink or a net source of GHGs depending on soil management practices.

Despite the current focus on SOC, knowledge about SOC baselines and changes, and the detection of vulnerable hot spots for SOC losses and gains under climate change and changed land management are still fairly limited. Accurate SOC baselines are still needed for many countries, and estimates about the role of soils in the global carbon cycle are currently only based on rough estimates, which results in large uncertainties. Global SOC estimates exist, but there is high variability in reported values among authors, caused by the diversity of different data sources and methodologies used to calculate and measure these estimates [Henry et al., 2009, Köchy et al., 2015].

1.2 Objectives of soil carbon mapping

The Intergovernmental Technical Panel on Soils (ITPS) and the GSP Secretariat were asked by the Science-Policy Interface (SPI) of the United Nations Convention to Combat Desertification (UNCCD) to share information about the possible pathways to support the SDG 15.3.1 indicator on SOC. During the 5th Session of the ITPS held during March 2016, collaboration between the ITPS and the SPI of the UNCCD, the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES), and the Intergovernmental Panel on Climate Change (IPCC) was discussed. The GSP/ITPS were requested to conduct a global SOC assessment based on country-level spatial soil data sets, combined into a new global SOC map. This task would directly relate to SDG 15.3.1, and would also support the endorsed metrics for the assessment of land degradation neutrality (LDN) [FAO and GSP, 2016b]. The preparation of the GSOCmap was discussed and supported to the 4th and 5th GSP Plenary Assembly [FAO and GSP, 2016a, 2017a].

As it was approved by the decision of the 5th GSP Plenary Assembly, June 2017 [FAO and GSP, 2017a], GSP members agreed to jointly develop a global SOC map as the zero status for the amount and distribution of SOC in soils around the world. This map was developed following the general GSP principle of being a country-driven initiative. It is a part of the process to build a Global Soil Information System under GSP Pillar 4 (Enhance the quantity and quality of soil data and information: data collection (generation), analysis, validation, reporting, monitoring and integration with other disciplines).

The development of a global soil organic carbon map using a country-driven approach provides and builds on synergies with ongoing and new reporting needs, data sharing obligations, and therefore benefits activities at national, regional and global levels. Particularly to:

- Enable training for countries in need of technical support (e.g. regarding the collection, statistical evaluation and modeling of SOC data);
- Develop data infrastructure to update the SWRS report on SOC through a country-driven baseline, and initiate future assessments of SOC changes;
- Support national GHG reporting: develop a valid, measurement-based inventory of reference SOC stocks for IPCC-Tier 2 assessments;
- Further utilize SOC mapping to estimate the soil carbon sequestration potentials (e.g. through modeling) and the vulnerability of soil functions under climate change (with SOC as an indicator);

- Contribute to the Sustainable Development Goals: by developing national SDG-15.3.1 Tier 3 data for the sub-indicator of soil carbon;

- Conduct harmonized assessments at different levels of action: GSP regional soil partnerships, FAO regional and country offices, national soil information institutions (GSP Pillar 4 INSII), national statistics offices (already involved with FAOSTAT), and GEOSS design principles for global data layers.

1.3 Data policy

1.3.1 Data sharing principles

The GSP Data Policy has been endorsed by partners of the Global Soil Partnership 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 GSOCmap contributions, and considering harmonization and interoperability requirements.

The GSP data policy aims to ensure that:

- every existing ownership right to shared soil data are respected;

- the specific level of access and the conditions for data sharing are clearly specified;

- the ownership of each dataset and web service are properly acknowledged and well-referenced;

- the data owners are protected from any liability arising from the use of their original and/or derived data.

It is recommended that data owners comply with the following open data principles:

a. Accessibility: the data shall be divulged through the Internet (web services).

b. Availability:the data is presented in a convenient, platform-independent and standards-conformant format (e.g. web feature service WFS).

c. License: the formal concession of the usage and access rights over the data shared.

d. Cost: data shall be shared free of cost, or at no more than a reasonable reproduction cost, preferably by downloading it from the Internet.

e. Re-use and Redistribution: data must be provided and licensed under terms that permit its reuse and redistribution, including intermixing with other data-sets.

f. Global benefit: any user must be able to access, use and redistribute data of the Global Soil Information System. However, inherited restrictions by national data policies shall be accepted.

g. Metadata: data describing the products of the Global Soil Information System will by default be open for access.

The data shared by the countries shall contain the relevant soil information representative for the area portrayed. The shared data-sets contain the best available information for a given area and topic, however, they are subject to potential restrictions based on the institutions' or countries' data policy.

The data shared by the countries should be quality controlled which means that the data have been technically evaluated to ensure data integrity, correctness, and completeness; errors and omissions are identified and, if possible, addressed.

1.3.2 Ownership, data rights and citation

In the case of original data, the rightful data owner keeps full ownership of it. All intellectual property rights (IPR) and copyrights pertaining to the data owner remain intact and are respected by the soil data facility (SDF) host. All data providers must communicate to the SDI host their IPR and data use policies. Thus, the ownership of all data made available through the GSP soil portal need to be clearly specified. This is an important prerequisite to allow this data to be accessible through the soil SDF.

In the case of derived data, the deriving institution becomes the rightful owner. However, all original data must be accredited and correctly cited. According to the Pillar 4 Implementation Plan, each global-level derived GSP data product will be quality-assured by the Pillar 4 Working Group. This includes agreements about the correct citation.

The data owner shall ensure that the data shared can be used and interpreted by the authorized users in general; this includes providing the proper citations, as well as providing information over the ownership of such data for acknowledgement purposes. Users shall acknowledge the source of data provided through the Global Soil Information System.

All providers of original data (data owners) are responsible to define and clarify the IPR and licensing. Any user of this data, such as the SDF host, has to respect the national data policies and/or licensing involved with the retrieval of the respective web services. In the case of data provided to the central repository, a bilateral agreement/license may be required (between the national data owner and SDF host), depending on and in conformity with national rules.

More information about the data policy can be accessed at FAO and GSP [2017b]

Chapter 2

GSP Capacity Development Programme

2.1 Training courses on Digital Soil Mapping

Considering the request from partners to support them by providing training on state of the art techniques for SOC mapping, the Secretariat designed a capacity development programme following an on-the-job training model. The aim of the GSP capacity development program has been to introduce recent concepts and techniques of digital soil mapping (DSM) to soil experts who work at national soil science institutes in soil mapping related activities. The impact of the trainings should be reflected on developing and updating national and regional soil information systems.

In order to support national capacities on digital soil organic carbon mapping, DSM workshops were organized by the GSP and the regional soil partnerships. The training workshops were already part of the GSP capacity development programme before the launch of the GSOCmap project (2012-2016). In 2017, the training focused more on digital soil organic carbon mapping to support countries with their GSOCmap contributions. After the launch of the GSOCmap project, additional training sessions were organized in different regions and eventually the capacity development program was able to reach 105 countries and 60% of the area coverage.

The contents of the workshops included: introduction to R; preparing spatial covariates using SAGA GIS; correlation analysis; regression-kriging; randomForest; support vector machines; uncertainties and validation. By the end of the training courses, participants were able to collect and rescue soil legacy data, compile and harmonize soil data for DSM applications, implement DSM, produce soil property maps and their uncertainties, and develop accurate digital soil maps for updating their national soil information systems.

2.2 GSP Remote Support Platform

A systematic process was by the GSP Secretariat to assist and provide technical support to soil experts after the training sessions (e.g., phone, video conferencing, email exchange). The

Table 2.1: GSP On-the-job Digital Soil Mapping Trainings

Date of training	Location	Participants	Participating countries
9 - 13 Jul/2012 †	Cali, Colombia		South American Soil Partnership
Set/2012 †	Rio de Janeiro, Brazil	18	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba El Salvador, Ecuador, Guatemala, Honduras, Nicaragua, Panama, Paraguay, Perú, Dominican Republic, Suriname, Uruguay, Venezuela
18 - 22 Mar/2013†	Rio de Janeiro, Brazil	20	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba El Salvador, Ecuador, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Perú, Dominican Republic, Uruguay, Venezuela
16 - 27 Mar/2015†	Accra, Ghana	21	Benin, Botswana, Burkina Faso, Cameroon, Cape Verde, Tchad, Djibuti, DRC, Gabon, Gambia, Ghana, Guinea Bissau,Guinea, Lesotho, Liberia, Malawi, Mauritius,Mozambique, Namibia, Niger, Nigeria, Rwanda,Senegal, South Africa, Swaziland, Tanzania, Togo, Uganda, Zambia
29 Nov - 07 Dec/2015†	Amman, Jordan	28	Algeria, Bahrain, Egypt, Iraq, Jordan, Kenya, Lebanon, Libya, Morocco, Palestine, Saudi Arabia, Sudan, Tunisia, Yemen
10 - 14 Oct/2016	Rabat, Morocco	11	Algeria, Egypt, Jordan, Lebanon, Morocco, Palestine, Tunisia
31 Oct - 4 Nov/2016	Almaty, Kazakhstan	17	Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine, Uzbekistan
24 - 29 Apr/2017	Bangkok, Thailand	16	Bangladesh, Bhutan, Bhutan, Cambodia, India, Indonesia, Japan, Laos , PDR, Malaysia, Mongolia, Myanmar, Nepal, Philippines, Sri Lanka, Thailand, Vietnam
6 - 23 Jun/2017	Wageningen, Netherlands	18	Bolivia, Costa Rica, Cuba, DRC, Egypt, Iraq, Kazakhstan, Mongolia, Mozambique, Nigeria, Paraguay, Ukraine,Uzbekistan, Tanzania, Tunisia, Zambia
26 - 30 Jun/2017	Aguascalientes, Mexico	17	Costa Rica, Cuba, Dominican Republic, El Salvador, Grenada, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Saint Lucia, Suriname, The Bahamas, Trinidad and Tobago
3 - 7 Jul/2017	Nairobi, Kenya	31	Burkina Faso, Lesotho, Malawi, Mauritius, Namibia, Nigeria, Uganda, Zambia, Zimbabwe, Benin, Rwanda, Gambia, Ghana, Ethiopia, Niger, Kenya, Cameroon, South Africa, Mozambique, Cabo Verde, Tanzania, Equatorial Guinea, Tchad, DRC, Swaziland, Djibouti, Guinea, Botswana, Eritrea, Senegal, Togo
21 - 25 Aug/2017	Izmir, Turkey	17	Turkey
28 Aug - 1 Sep/2017	Montevideo, Uruguay	23	Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, Venezuela
20 Jan - 24 Jan/2018	Tehran, Iran	32	Iran

†These training courses were part of the GSP Capacity Development Programme and were organized before the launch of the GSOCmap project.

Figure 2.1: GSP - Capacity Development Programme - Training Locations and Participated Countries

post-training support process allowed the GSP Secretariat toaddress any questions, doubts, or problems that countries faced.

2.3 Soil Organic Carbon Mapping Cookbook

The Soil Organic Carbon Mapping Cookbook [Yigini et al., 2017] has been developed by the ITPS and GSP Secretariat to provide generic methodologies and the technical steps for producing a SOC map. This includes step-by-step guidance for developing 1 km grids for SOC stocks, as well as for the preparation of local soil data, the compilation and pre-processing of ancillary spatial data sets, mapping methodologies, and uncertainty assessments.

Guidance is mainly specific to soil organic carbon data, but also contains many generic sections on soil grid development due to its relevance for other soil properties. The main focus of the guidance is on the mapping of SOC stocks in the GSOCmap and as such the cookbook supplements the GSP Guidelines for sharing national data/information to compile a Global Soil Organic Carbon (GSOC) map. It provides technical guidance to:

- Setting up the needed software environment
- Preparing ground data for soil organic carbon modeling
- Calculating SOC stocks from local samples to a target depth of 30 cm;
- Preparing spatial covariates for mapping
- Choosing and applying the best suitable mapping methodology.
- Evaluating the results and the outputs and providing guidance on validation and uncertainty assessments.

2.4 GSP-ISRIC Environmental Covariates data repository

A set of standardized national environmental covariates for digital soil mapping were provided by ISRIC World Soil Information (Table 2.2). The data can be accessed through ftp, all necessary credentials have been provided to the countries. The provided data sets fall within the following thematic fields:

- Geomorphometry i.e. Digital Elevation Models and derived land surface parameters and objects;
- Spectral and multispectral remote sensing imagery and derived parameters;
- Climatic and meteorological covariates;
- Land cover/ land use information,
- Parent material and soil-unit maps.

This data repository contains GIS raster layers of various biophysical earth surface properties for each territory in the world. These layers can, for example, be used as covariates in a digital soil mapping exercise.The territories and their boundaries are obtained from from the Global Administrative Unit Layers (GAUL) dataset [1]

Each folder contains three sub-folders:

- covs: GIS layers of various biophysical earth surface properties
- mask: an 'empty' grid file of the territory with territory boundary according to GAUL. This grid can for instance be used as a mapping mask.

Data Specifications
File format: GeoTiff
Coordinate system: WGS84, latitude-longitude in decimal degrees
Spatial resolution: 1km

Data Access: ftp://ftp.isric.org/ (user: gsp, pwd: gspisric)

Licence and Acknowledgement
The GIS layers can be freely used under the condition that proper credit should be given to the original data source in each publication or product derived from these layers. Licences, data sources, and data citations are indicated in the data description table.

Table 2.2: Layers prepared by ISRIC to be used as covariates in digital soil mapping

Name	Series	Attribute
DEMENV5	DEM-parameters	Land surface elevation
SLPMRG5	DEM-parameters	Terrain slope
CRVMRG5	DEM-parameters	Downslope Curvature
CRUMRG5	DEM-parameters	Local upslope Curvature

[1] http://www.fao.org/geonetwork/srv/en/metadata.show?id=12691

Table 2.2 continued from previous page

Name	Series	Attribute
CRDMRG5	DEM-parameters	Local downslope Curvature
VBFMRG5	DEM-parameters	Multiresolution Index of Valley Bottom Flatness
DVMMRG5	DEM-parameters	Deviation from Mean Value (surface roughness) x9
DV2MRG5	DEM-parameters	Deviation from Mean Value (surface roughness) x13
VDPMRG5	DEM-parameters	Valley depth
NEGMRG5	DEM-parameters	Negative Topographic Openness
POSMRG5	DEM-parameters	Positive Topographic Openness
MRNMRG5	DEM-parameters	Melton Ruggedness Number
TPIMRG5	DEM-parameters	Topographic Position Index
TWIMRG5	DEM-parameters	SAGA Wetness Index
EX1MOD5	MOD13Q1	Mean monthly MODIS EVI JanFeb
EX2MOD5	MOD13Q1	Mean monthly MODIS EVI MarApr
EX3MOD5	MOD13Q1	Mean monthly MODIS EVI MayJun
EX4MOD5	MOD13Q1	Mean monthly MODIS EVI JulAug
EX5MOD5	MOD13Q1	Mean monthly MODIS EVI SepOct
EX6MOD5	MOD13Q1	Mean monthly MODIS EVI NovDec
ES1MOD5	MOD13Q1	SD monthly MODIS EVI JanFeb
ES2MOD5	MOD13Q1	SD monthly MODIS EVI MarApr
ES3MOD5	MOD13Q1	SD monthly MODIS EVI MayJun
ES4MOD5	MOD13Q1	SD monthly MODIS EVI JulAug
ES5MOD5	MOD13Q1	SD monthly MODIS EVI SepOct
ES6MOD5	MOD13Q2	SD monthly MODIS EVI NovDec
I01MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Jan
I02MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Feb
I03MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Mar
I04MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Apr
I05MOD4	MCD43A4	Mean monthly MODIS NIR band 4 May
I06MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Jun
I07MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Jul
I08MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Aug
I09MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Sep
I10MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Oct
I11MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Nov
I12MOD4	MCD43A4	Mean monthly MODIS NIR band 4 Dec
M01MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Jan
M02MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Feb
M03MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Mar
M04MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Apr
M05MOD4	MCD43A4	Mean monthly MODIS MIR band 7 May
M06MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Jun
M07MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Jul
M08MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Aug
M09MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Sep
M10MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Oct
M11MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Nov
M12MOD4	MCD43A4	Mean monthly MODIS MIR band 7 Dec
T01MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Jan

Table 2.2 continued from previous page

Name	Series	Attribute
T02MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Feb
T03MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Mar
T04MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Apr
T05MOD3	MOD11A2	Mean monthly MODIS LST (daytime) May
T06MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Jun
T07MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Jul
T08MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Aug
T09MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Sep
T10MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Oct
T11MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Nov
T12MOD3	MOD11A2	Mean monthly MODIS LST (daytime) Dec
N01MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Jan
N02MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Feb
N03MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Mar
N04MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Apr
N05MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) May
N06MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Jun
N07MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Jul
N08MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Aug
N09MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Sep
N10MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Oct
N11MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Nov
N12MOD3	MOD11A2	Mean monthly MODIS LST (nighttime) Dec
T01MSD3	MOD11A2	SD monthly MODIS LST (daytime) Jan
T02MSD3	MOD11A2	SD monthly MODIS LST (daytime) Feb
T03MSD3	MOD11A2	SD monthly MODIS LST (daytime) Mar
T04MSD3	MOD11A2	SD monthly MODIS LST (daytime) Apr
T05MSD3	MOD11A2	SD monthly MODIS LST (daytime) May
T06MSD3	MOD11A2	SD monthly MODIS LST (daytime) Jun
T07MSD3	MOD11A2	SD monthly MODIS LST (daytime) Jul
T08MSD3	MOD11A2	SD monthly MODIS LST (daytime) Aug
T09MSD3	MOD11A2	SD monthly MODIS LST (daytime) Sep
T10MSD3	MOD11A2	SD monthly MODIS LST (daytime) Oct
T11MSD3	MOD11A2	SD monthly MODIS LST (daytime) Nov
T12MSD3	MOD11A2	SD monthly MODIS LST (daytime) Dec
N01MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Jan
N02MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Feb
N03MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Mar
N04MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Apr
N05MSD3	MOD11A2	SD monthly MODIS LST (nighttime) May
N06MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Jun
N07MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Jul
N08MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Aug
N09MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Sep
N10MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Oct
N11MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Nov
N12MSD3	MOD11A2	SD monthly MODIS LST (nighttime) Dec

Table 2.2 continued from previous page

Name	Series	Attribute
TMDMOD3	MOD11A2	Mean annual LST (daytime) MODIS
TMNMOD3	MOD11A2	Mean annual LST (nighttime) MODIS
P01CHE3	Global precipitation	Mean monthly precipitation at 1 km Jan
P02CHE3	Global precipitation	Mean monthly precipitation at 1 km Feb
P03CHE3	Global precipitation	Mean monthly precipitation at 1 km Mar
P04CHE3	Global precipitation	Mean monthly precipitation at 1 km Apr
P05CHE3	Global precipitation	Mean monthly precipitation at 1 km May
P06CHE3	Global precipitation	Mean monthly precipitation at 1 km Jun
P07CHE3	Global precipitation	Mean monthly precipitation at 1 km Jul
P08CHE3	Global precipitation	Mean monthly precipitation at 1 km Aug
P09CHE3	Global precipitation	Mean monthly precipitation at 1 km Sep
P10CHE3	Global precipitation	Mean monthly precipitation at 1 km Oct
P11CHE3	Global precipitation	Mean monthly precipitation at 1 km Nov
P12CHE3	Global precipitation	Mean monthly precipitation at 1 km Dec
PRSCHE3	Global precipitation	Total annual precipitation at 1 km
B02CHE3	Global precipitation	Mean diurnal range at 1 km
B04CHE3	Global precipitation	Temperature seasonality at 1 km
B07CHE3	Global precipitation	Temperature Annual Range at 1 km
B13CHE3	Global precipitation	Precipitation of wettest month [mm]
B14CHE3	Global precipitation	Precipitation of driest month [mm] at 1 km
F01USG5	Global Ecophysiography	Landform class: Breaks/Foothills
F02USG5	Global Ecophysiography	Landform class: Flat Plains
F03USG5	Global Ecophysiography	Landform class: High Mountains/Deep Canyons
F04USG5	Global Ecophysiography	Landform class: Hills
F05USG5	Global Ecophysiography	Landform class: Low Hills
F06USG5	Global Ecophysiography	Landform class: Low Mountains
F07USG5	Global Ecophysiography	Landform class: Smooth Plains
VW1MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor JanFeb
VW2MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor MarApr
VW3MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor MayJun
VW4MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor JulAug
VW5MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor SepOct
VW6MOD1	MOD05_L2	Monthly MODIS Precipitable Water Vapor NovDec
QUAUEA3	USGS Earthquake Archives	Density of earthquakes (5+)
LCEE10	ESA land cover	ESA land cover map 2010
MANMCF5	EarthEnv MODCF	Mean annual cloud cover
C01MCF5	EarthEnv MODCF	Mean monthly cloud cover Jan
C02MCF5	EarthEnv MODCF	Mean monthly cloud cover Feb
C03MCF5	EarthEnv MODCF	Mean monthly cloud cover Mar
C04MCF5	EarthEnv MODCF	Mean monthly cloud cover Apr
C05MCF5	EarthEnv MODCF	Mean monthly cloud cover May
C06MCF5	EarthEnv MODCF	Mean monthly cloud cover Jun
C07MCF5	EarthEnv MODCF	Mean monthly cloud cover Jul
C08MCF5	EarthEnv MODCF	Mean monthly cloud cover Aug
C09MCF5	EarthEnv MODCF	Mean monthly cloud cover Sep
C10MCF5	EarthEnv MODCF	Mean monthly cloud cover Oct
C11MCF5	EarthEnv MODCF	Mean monthly cloud cover Nov

Table 2.2 continued from previous page

Name	Series	Attribute
C12MCF5	EarthEnv MODCF	Mean monthly cloud cover Dec
RANENV3	EarthEnv Global Habitat Heterogeneity	Range MODIS EVI
MAXENV3	EarthEnv Global Habitat Heterogeneity	Maximum MODIS EVI
EVEENV3	EarthEnv Global Habitat Heterogeneity	Evenness of MODIS EVI
ENTENV3	EarthEnv Global Habitat Heterogeneity	Entropy MODIS
REDL00	Global Forest Change	Landsat Band 3 (red) for year 2000
NIRL00	Global Forest Change	Landsat Band 4 (NIR) for year 2000
SW1L00	Global Forest Change	Landsat Band 5 (SWIR) for year 2000
SW2L00	Global Forest Change	Landsat Band 7 (SWIR) for year 2000
REDL14	Global Forest Change	Landsat Band 3 (red) for year 2014
NIRL14	Global Forest Change	Landsat Band 4 (NIR) for year 2014
SW1L14	Global Forest Change	Landsat Band 5 (SWIR) for year 2014
SW2L14	Global Forest Change	Landsat Band 7 (SWIR) for year 2014
OCCGSW7	Global Surface Water	Occurrence probability
CHAGSW7	Global Surface Water	Surface water change
EXTGSW7	Global Surface Water	Global surface water maximum extent
BARL10	30 Meter Global Land Cover	Global 30m Bare Ground
TREL10	31 Meter Global Land Cover	Global 30m Tree Cover
S03ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Mar
S04ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Apr
S05ESA4	ESACCI	Mean monthly snowfall prob. at 500 m May
S06ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Jun
S07ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Jul
S08ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Aug
S09ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Sep
S10ESA4	ESACCI	Mean monthly snowfall prob. at 500 m Oct

Chapter 3

Product Specifications

3.1 Generic target specification

A global layer of harmonized national soil carbon stock maps has been developed according to the following specification:

- Grid at 30 arc-seconds resolution (approximately 1 x 1 km). Generic grid has been provided by ISRIC World Soil Information.
- Various SOC analysis methods and measurements are acceptable.
- 0-30 cm depth, including national increments and/or higher (deeper) depths where applicable.
- SOC stock [t/ha]: bulk density (BD) [kg/m3] and stone content [%] can be estimated or measured.
- Mapping/upscaling: various approaches possible (including country-specific stratification and custom resolution finer than 1x1 km).

More information about the product specification can be accessed at FAO - GSP [2017].

3.2 Metadata specifications

In order to ensure that the national layers metadata would be sufficient for quality assessment and possible harmonization, the countries were required to share information about their original data according to the following principles:

1. Share auxiliary information about the national data sources, e.g. type of sampling (soil profile or auger), density of sampling points in the country, sampling design (distribution and sampling depth/s), time of sampling (year), selection criteria (if subset of soil profiles is selected from a larger national database).
2. Provide as much metadata as possible in order to estimate the quality of the global SOC map. For example, SOC method(s) of analysis.
3. Share metadata about SOC stocks calculation in terms of:

Table 3.1: GSOCmap components

Product	Depth	Description
Map of Global SOC stocks 1 km resolution	0-30 cm depth (mandatory) Forests (optional): Litter layer Peat (optional): 30 cm peat depth (<100 cm - optional)	- Depth class 0-30 cm: in addition, subdivisions in thinner depth slices, or extensions beyond 30 cm depth are acceptable, depending on national sampling strategies and available data. - In the case of forests, the litter layer may be included if national data allow. There are two options: 1. A separate model/map for the forest floor organic layer (L, F and H) is produced, and later added to the national SOC stocks 0-30 cm. 2. Forest floor carbon stocks are modeled jointly with the mineral SOC stocks 0-30. - Peat: 0-30 cm is the mandatory mapping depth; a second layer with SOC stocks between 30 cm and up to 1 m depending on peat depth is recommended - Calculation of C stocks requires data about the SOC concentration, bulk density and for non-organic soils - stone content.
Uncertainties	Qualitative assessment Quantitative assessment, e.g. standard deviation	Based on reported metadata and documentation. If digital soil mapping is used, the spatial prediction error can be quantified depending on the density of soil profiles/samples

- Describing how SOC stocks for the target depth 0-30 cm have been calculated; if there are any deviations from this specification, provide an explanation.
- Quantifying the amount of carbon stored in litter (organic layer of forest floors)
- If data allow, stratifying the national soil databases according to organic (peat) and inorganic soils, and estimate the SOC stock for peat soils to 1 m depth
- Providing a description of the method used for bulk density measurements or estimations.
- Providing a description of the method used for coarse fragments measurements or estimations.

4. Share details about the upscaling approach:

   - mapping method (description, citation)
   - Input data/covariates, grid, soil maps, etc.

5. In order to consider the temporal dimension of the SOC map, it is important to share the sampling date as metadata. If the national data situation allows, pre- 1990 or post-1990 sub data sets might be defined. However, it will be an important asset of this SOC map to demonstrate the density of existing soil carbon data sets. The more data points are used, the better the reliability and accuracy of the global product. Subsequent steps to improve the temporal dimension, will be considered at a later stage.

Chapter 4

Data collection and processing

4.1 Different scenarios of country-driven action

The GSP Secretariat facilitated the process where countries were asked to deliver the following data and information;

- National Soil Organic Carbon Stock Map
- Uncertainty Assessment a) Qualitative assessment (Conventional Mapping) and/or b) Quantitative (Digital Soil mapping)
- Metadata: The data shared by the counties are extensively documented to enable quality and uncertainty assessments. This will allow insights into the quality of the SOC maps, remaining gaps and harmonization needs.Countries were required to provide detailed metadata documented in the GSOCmap Guidelines [FAO - GSP, 2017].
- One-page-report: A brief report describes the current status of the national SOC data, data collection, preparation and harmonization efforts, selection of the method(s), challenges and assessment of the results.

The GSP Secretariat organized the data collection depending on national capacities, data availability/usability (Fig. 4.1):

- Country Submissions: Countries produced and delivered their GSOCmap contributions to the GSP Secretariat.
- Joint Efforts: The GSP Secretariat worked with the soil experts from the member countries to produce their GSOCmap contributions.
- GSP gapfilling: The Secretariat produced or used publicly available point or raster data for the countries that were not able to contribute to the current version of the product.

4.1.1 Delivery of the maps produced by the countries

The GSP Secretariat contacted countries about their potential contributions to the GSOCmap project and informed countries about the process and the procedure.

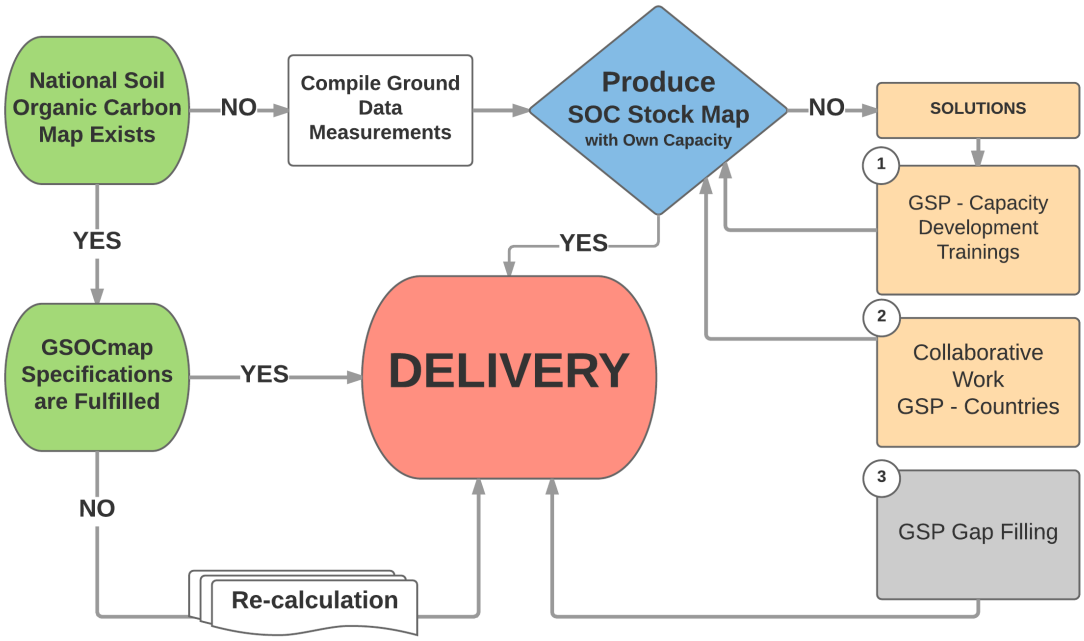

Figure 4.1: Country-driven action depending on national capacity

Countries already having national SOC maps that meet the specifications of this project, shared their data with the GSP Secretariat. If a national SOC map exists, and if not all requirements were met, adjustments to the existing SOC map were implemented (e.g. recalculation according to target depth).

Countries which did not yet have a national SOC map, developed such a map based on the specifications. Where needed, the GSP Secretariat supported such national activities by organising training sessions.

Upon receiving the national maps, the GSP Secretariat undertook the preliminary data quality checks. Whenever the national maps were inconsistent with the GSOC specifications, the GSP Secretariat worked in close collaboration with the institutions that provided the national data to resolve the existing issues.

67 countries submitted their maps as a contribution to the GSOCmap. This represents 63% of the world area (Table 4.1).

Data submission form

To deliver their data, countries were required to use the online data submission tool. The tool realized a guided delivery process which required the submitter to upload the map along with a 1-page report, and to answer questions about the methodology according to the metadata specifications. The questionnaire can be found in Annex B.

This questionnaire and the report were used to create the country-specific metadata for the map. A summary of this data can be found in Annex A and chapter 5.

4.1.2 Joint efforts

If the in-country development of a SOC map was not possible due to insufficient capacity, the original SOC measurements were shared with the GSP secretariat which would then execute the mapping in close cooperation with the national GSP-focal points and/or institutional data providers.

For the mapping, the GSP Secretariat used state-of-the-art digital soil mapping techniques and publicly available layers of environmental covariates (ISRIC, ftp service). The data were then evaluated by the national experts who made the final decision regarding the results of the joint mapping procedure and the final submission of the map. 8 country maps were prepared with joint efforts between the GSP and the countries (Table 4.1).

4.1.3 GSP gapfilling

For the countries that could not provide a SOC map or any original measurements, the GSP Secretariat used one of the two gap-filling approaches: spatial modeling using publicly available data or, in the case of absence or insufficient amount of data, using publicly available SOC stock maps.

The gap filling procedure involved producing maps for 121 countries. 74 country maps (30.2% of the world area) were done using available data; and 47 country maps (1.9% of the world area) were filled using `soilgrids.org` data.

Spatial modeling using publicly available data

For the countries where publicly available data of SOC measurements were sufficient for SOC mapping, the GSP Secretariat used digital soil mapping techniques to create the maps. The following data sources used for this purpose:

- WOSIS [Batjes et al., 2017]
- LUCAS soil (European Union - EU27) [Toth et al., 2013]
- AfSIS (Africa Soil Information Service) [Walsh, M.G. et al., 2009]

Publicly available layers of environmental covariates (`WorldGrids.org`) were used for the spatial modeling. Example scripts similar to the ones used by GSP for building these maps can be found in Annex D.

Using publicly available SOC stock maps

For the countries lacking any publicly available data of SOC measurements, the maps were produced using SoilGrids 250m product [Hengl et al., 2017] resampled according to the GSOC specifications.

4.2 Data processing and compilation of the GSOCmap

In order to compile a Global Soil Organic Carbon Map from the national contributions, the GSP Secretariat conducted basic data processing aimed to standardize the individual layers with minimal or no changes to the data provided by the countries. The processing steps included:

Table 4.1: Sources of the country maps included in the GSOCmap v1

Contribution	n	Area (km2)	% world area
Country submission	67	81631765	63.3
Joint Effort with GSP	8	5971255	4.6
GSP Gap-Filling	74	38978088	30.2
External dataset: soilgrids.org	47	2523628	1.9

- Reprojecting data to coordinate system lon/lat WGS84 with spatial resolution of 30 arc second using 'nearest neighbour' method (where necessary);
- Resampling the data to 30 arcsec grid resolution using bilinear interpolation (in case the cell size of the original data was different)
- Converting SOC stock values to tonnes/ha (where necessary).
- Mosaicking individual maps of the countries to acquire the global layer using 'nearest neighbour' method for resampling.
- Filling NoData values at national borderlines (in case the countries didn't use suggested empty grids) using GDAL gapfilling algorithm which interpolates values for all designated NoData pixels using inverse distance weighting and a four direction conic search to find values to interpolate from. A mask compiled from a 5-km buffer around country borders (excluding water bodies and coastlines) was used as a gap-filling procedure in order to make sure that only border gaps are filled and the NoData values provided by countries because of lack of information are preserved.
- Applying a global mask of water bodies (World Water Bodies - Esri, Garmin International).

Chapter 5

Metadata

The GSOCmap is a compilation of soil organic carbon stock maps produced by the countries in accordance with the GSOCmap Guidelines [FAO - GSP, 2017]. The total number of profiles/sampling locations used to create the global product is: 1002562. The number of sampling plots was calculated from the meta-data provided by the member countries.

5.1 Sampling Density

The metadata allows to assess the density of sampling points per country as shown in figure 5.1. It varies greatly and reflects the differences in the soil data coverage between countries and regions. This information can be used as an assessment of the current status of the available soil information in the world and to identify the regions where additional sampling is most needed.

However, aggregation of the data at the country level does not allow to accurately represent the sampling density in case of uneven distribution.

5.2 Temporal dimension

The metadata on the period of sampling was analyzed against the suggested baseline date 1990. 11% of the countries did not provide information about the temporal dimension. Besides, data about the temporal dimension for the 25% of the countries with data from external datasets, like `soilgrids.org`, were not available. The other 65% is divided: 15% with data from before 1990; 25% with a mix of data before and after 1990 and only 25% with all the data surveyed after 1990.

The results show that most countries had to include observationsfrom before 1990 to develop a dataset representing all their territory (Fig. 5.2). This means that the GSOCmap can be used as a baseline for SOC monitoring only for the countries with all the submitted data originating from recent soil surveys. However, the GSOCmap can be viewed as a baselinemap, as it contains the best available estimation of SOC at the country level (see Validation and comparison with existing products), making it an important tool for identifying SOC deficient areas within the countries and subsequently for planning the soil-protecting, sampling and monitoring activities.

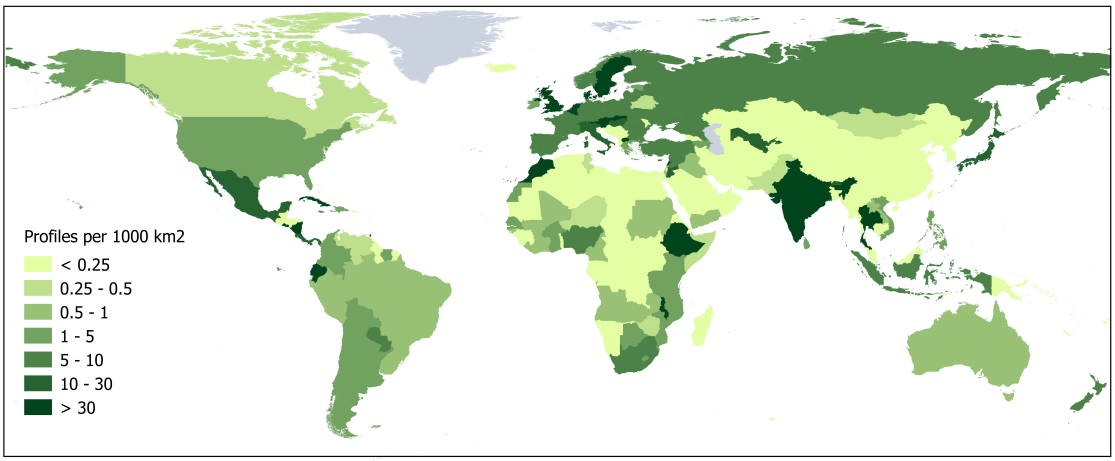

Figure 5.1: Density of point data (per country)

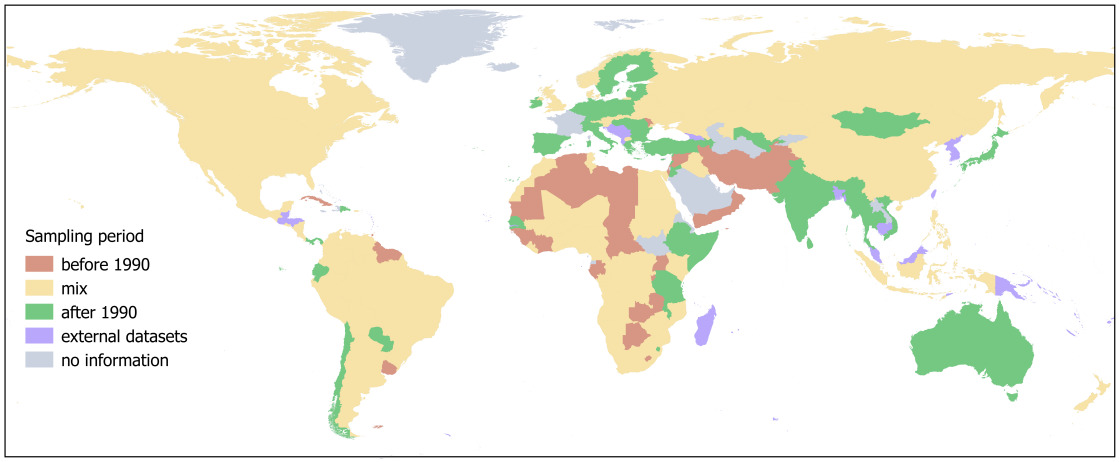

Figure 5.2: Sampling period

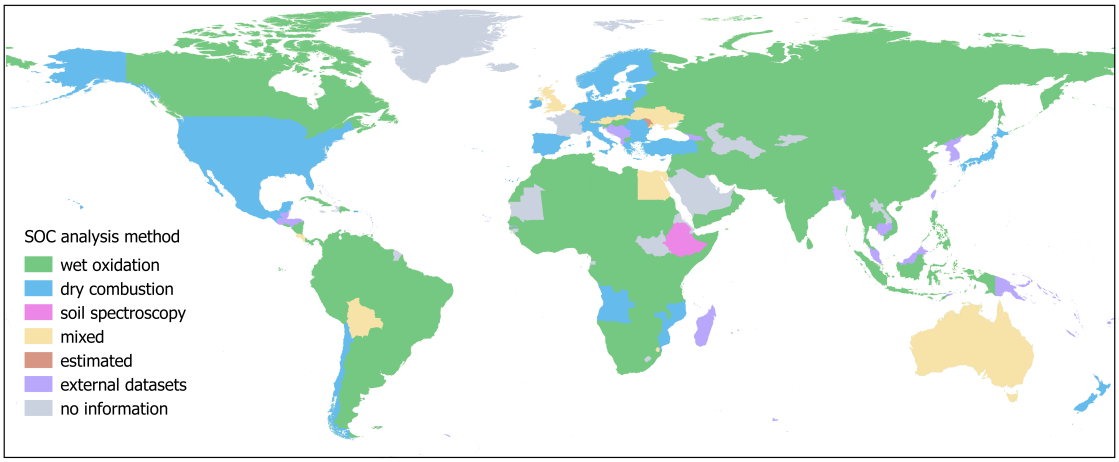

Figure 5.3: SOC analysis methods

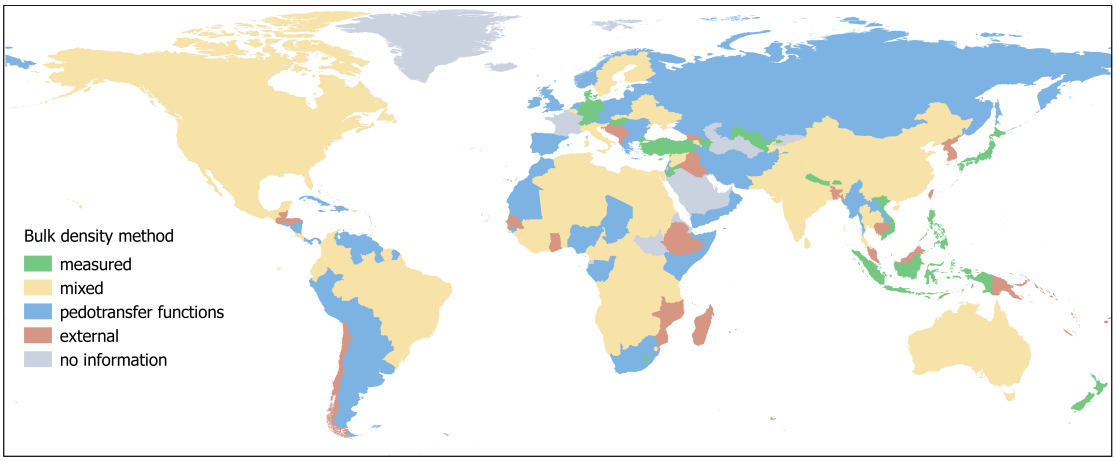

Figure 5.4: Bulk density analysis methods

5.3 Soil organic carbon

Concerning the SOC analysis method, 42% of the countries used wet oxidation, and 14% used dry combustion. The number of countries using soil spectroscopy is less than 1%.

The metadata shows differences in the methods used throughout the world for determining SOC (Fig. 5.3). This is valuable information for investigating the possibility of further harmonization of national data. One of the known issues is the difference in measured carbon values between Ethiopia and the surrounding countries, which could be caused by the difference in SOC analysis method since Ethiopia was the only country to use soil spectroscopy measurements as its primary data source.

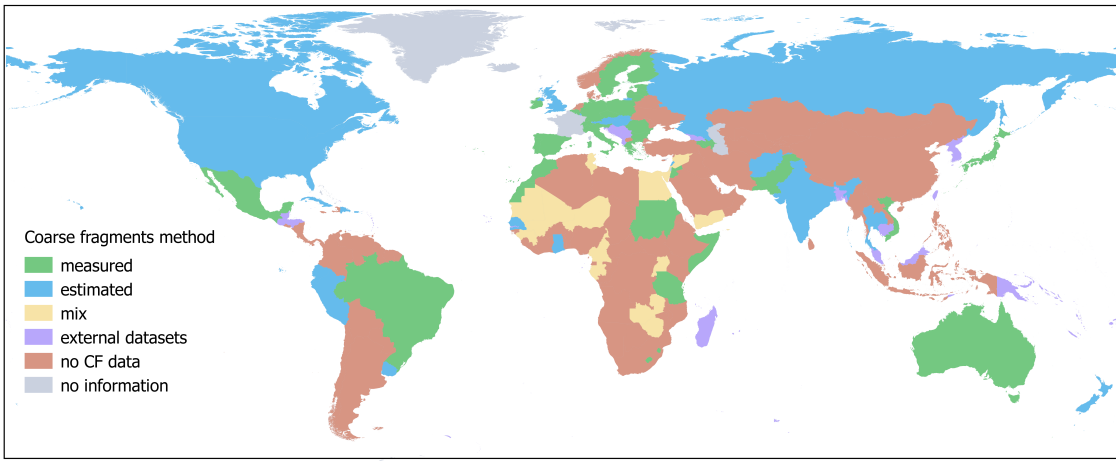

Figure 5.5: Coarse fragments methods

5.4 Bulk density

Measurements of bulk density were not available in many countries, thus different strategies were used to overcome this limitation (Fig. 5.4).

1. Using nationally developed pedotransfer functions
2. Using pedotransfer functions suggested in the cookbook manual
3. Using the values from publicly available data-sets (such as Harmonized World Soil Database [FAO et al., 2012] and SoilGrids [Hengl et al., 2017])

Only 8% of the countries used only measured bulk density data to estimate the Organic Carbon Stock. 27% submitted measured values for some profiles, but had to use pedotransfer functions for others. 28% relied only on pedotransfer functions. And external datasets like soilgrids.org or the HWSD were used for 28% of the countries. 9% of the countries did not provide information about the source of their bulk density data.

The estimation of bulk density is a potential source of high uncertainty in the calculation of carbon stocks, especially in soils with high stoniness [Poeplau et al., 2017]. According to our findings, more than 55% of the countries used pedotranfer functions, but only 25% used locally fitted pedotranfer functions. With a high percentage of countries using the pedotransfer functions suggested in [Yigini et al., 2017].

5.5 Coarse fragments

The metadata show that the majority of the countries had limited data on the coarse fragment content which could be a source of uncertainty in the calculation of organic carbon stocks, especially in mountainous areas (Fig. 5.5). Only 17% of the countries had measured data for the amount of coarse fragments. 10% used estimated values and 7% used a mix between estimated and measured values. Almost 40% of the countries did not use any information about the coarse fragments fraction for the organic carbon stock estimation.

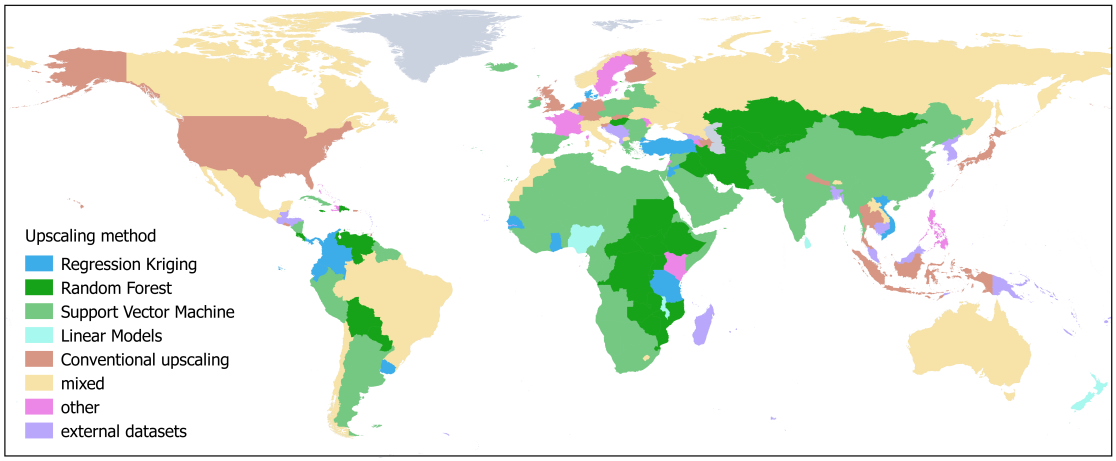

Figure 5.6: Mapping methods

5.6 Mapping methods

Various mapping methods were used by the countries depending on the capacity, data availability, and the specific features of the local soil cover, including but not limited to:

- Conventional Upscaling: Geo-matching, Class-matching;
- Digital Soil Mapping methods: Multiple linear regression, Regression Kriging, Multivariate adaptive regression splines, Generalized Linear Models, Generalized Additive Models, etc.
- Machine learning techniques: Random Forest, Support Vector Machine, Neural Networks, Regression trees, Bayesian trees, etc.
- Ensemble models combining different DSM methods;
- Geostatistical methods: Ordinary Kriging, IDW.

Figure 5.6 shows that most countries (66%) were able to use the state-of-the-art digital soil mapping techniques which demonstrates the overall success of the capacity building program undertaken by the FAO/GSP. Only 7% of the countries used conventional upscaling.

The heterogeneity of the mapping techniques could be one of the sources of uncertainty and 'border effects' between national products. However, the map shows that the difference in mapping methods is not the primary source of border inconsistency. As shown in the Figure 5.7, in many cases, the maps produced with different mapping methods have comparable values and form a continuous surface of organic carbon distribution with acceptable differences. Besides, there is no best mapping method for digital soil mapping, and testing and selection has to be done for every data scenario [Guevara et al., 2018].
The primary source of uncertainty and border inconsistencies appears to be in the original point data quality and representativity. The difference at the borders between the countries occurs when the adjacent region is not covered with soil sampling data and the values are extrapolated using a model from a different area or assigned on the basis of expert knowledge. Therefore, it is suggested that the work on improving the global consistency should be primarily focused

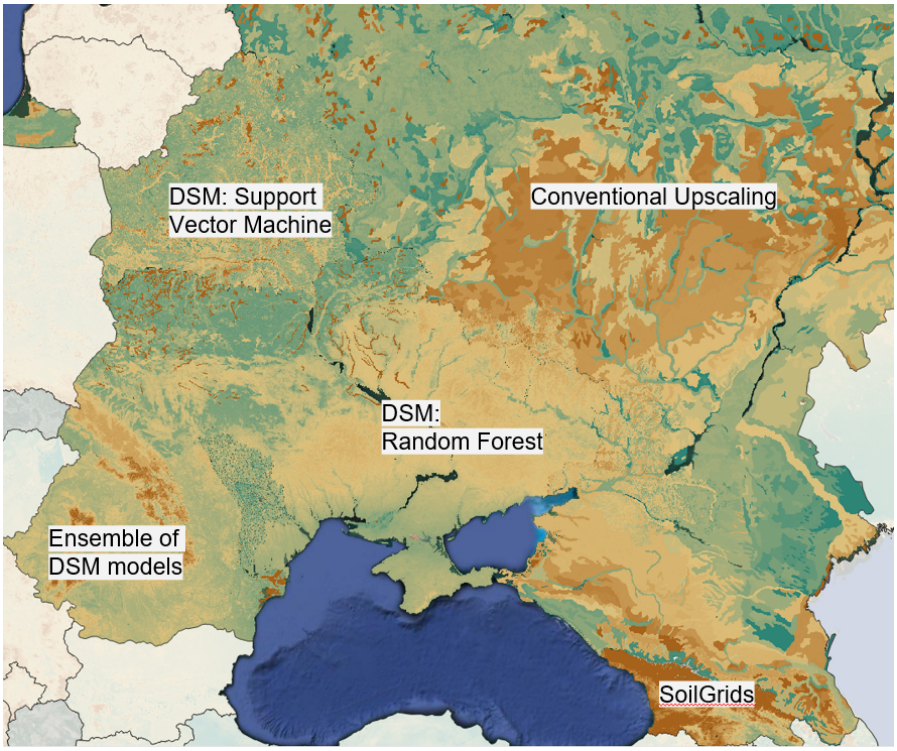

Figure 5.7: Fragment of the GSOCmap with different techniques used for mapping at country level

on acquiring additional data in the under sampled regions and capacity development aimed at ensuring that an appropriate mapping method was used based on the data distribution and representativity.

Chapter 6

Results

6.1 Total Global Soil Organic Carbon Stock

Global Soil Organic Carbon Stock for topsoil (0 to 30 cm) is **680** Petagrams. This value is 3.2% lower than the value for the HWSDa [Köchy et al., 2015] (Table 6.1).

The global figure has been calculated using the pseudo cylindrical Mollweide projection (1km) that preserves area measures. Mollweide projection was created by Karl B. Mollweide in 1805. It is an equal-area projection designed for small-scale maps. Figure 6.1 shows that the distortion is minimal with the Mollweide Projection.

6.1.1 Statistics for countries (GSOCmap V.1.2.0

Statistics for the countries were calculated based on the Global Administrative Units layer as the source for country boundaries. Over 70% of the global SOC stocks at 30cm is held by 14 countries: the Russian Federation (147.9 Pg - 21.9%), Canada (80.2 Pg - 11.9%), the United States of America (54.4 Pg - 8.0%), China (45.2 Pg - 6.7%), Brazil (35.4 Pg - 5.2%), Indonesia (22.6 Pg - 3.3%), Australia (22.6 Pg - 3.3%), Argentina (12.6 Pg - 1.9%), Kazakhstan (12.0 Pg - 1.8%), Peru (10.1 Pg - 1.5%), the Democratic Republic of Congo (9.4 Pg - 1.4%), Papua New Guinea (8.5 Pg - 1.3%), Mongolia (8.2 Pg - 1.2%), and India (8.2 Pg - 1.2%). Among these countries, Papua New Guinea and Indonesia have the highest mean SOC stocks (183.6 and 121.4 t/ha respectively) indicating a high concentration of carbon stocks in the tropical part of South-East Asia and Pacific.

6.1.2 Statistics for soil types, land use and climate zones

To estimate the relationship between SOC and climate, the result layer was spatially intersected with climate data. The climate data used was the thermal climate from the FAO available at

Table 6.1: Summary of estimates of Global SOC Stocks in topsoil in Pg from different sources. Adapted and expanded from Hiederer, R. and M. Kochy [2011]

GSOCmap	HWSD	HWSDa	FAO2007	WISE	DSMW	soilgrids 250m
680	967	699	710	504	574	1267

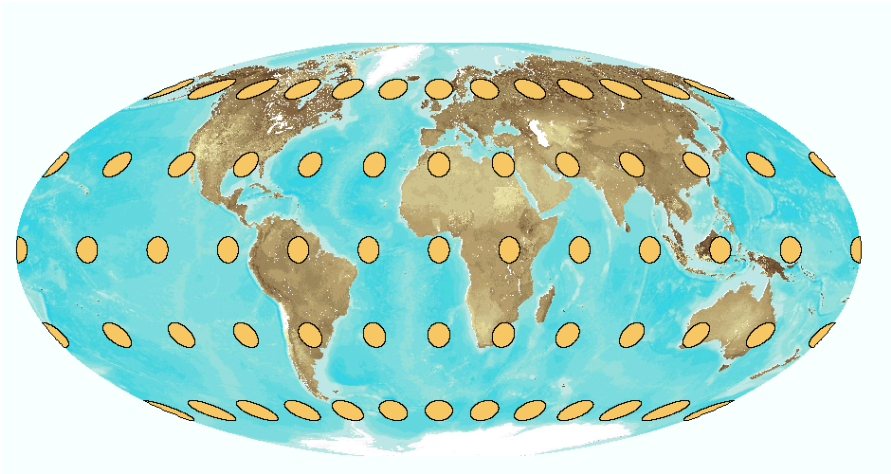

Figure 6.1: Tissot's Indicatrices with the Mollweide Projection

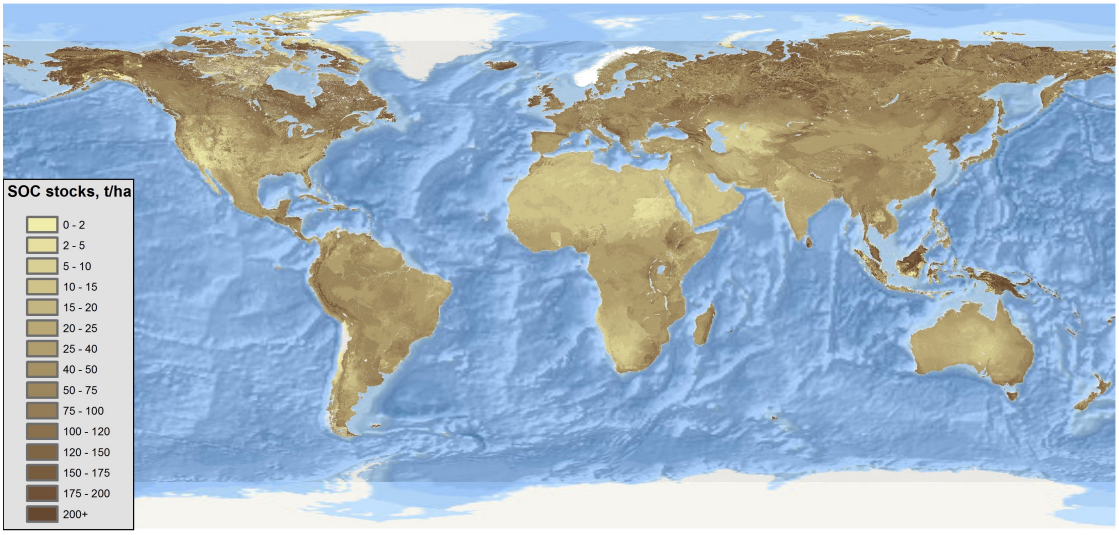

Figure 6.2: GSOCmap version 1.2.0

http://www.fao.org/geonetwork/srv/en/metadata.show?id=30589. The raster dataset of thermal climates has a spatial resolution of 5 * 5 arc minutes and is in geographic projection. Information with regard to thermal climates was obtained from the "Derived Soil Properties" of the FAO-UNESCO Soil Map of the World which contains raster information on soil properties. The thermal climates were obtained through classifying monthly temperatures corrected to sea level. The thermal climates distinguished in global AEZ are the following: tropics, subtropics (2 subtypes), temperate (3subtypes), boreal (3 subtypes) and polar/arctic.

The largest carbon pool is located in the tropical climate zone closely followed by the temperate zone (Table 6.2).

Table 6.2: Global SOC stocks per climate zones

Climate Zone	**SOC Stocks, Pg**	**Percentage of global stocks**
Tropics	208	31%
Temperate	191	29%
Boreal	140	21%
Subtropics	102	15%
Arctic	20	3%

The same approach was used to compare the GSOCmap to land cover data. The land cover layer used is the MODIS Land Cover Type [Friedl et al., 2002]. The MODIS Land Cover Type product contains 5 classification schemes, which describe land cover properties derived from observations spanning a year's input of Terra- and Aqua-MODIS data. The primary land cover scheme identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP), which includes 11 natural vegetation classes, 3 developed and mosaicked land classes, and 3 non-vegetated land classes.

The MODIS Terra + Aqua Land Cover Type Yearly L3 Global 500 m SIN Grid product incorporates five different land cover classification schemes, derived through a supervised decision-tree classification method:

- Land Cover Type 1: IGBP global vegetation classification scheme
- Land Cover Type 2: University of Maryland (UMD) scheme
- Land Cover Type 3: MODIS-derived LAI/fPAR scheme
- Land Cover Type 4: MODIS-derived Net Primary Production (NPP) scheme
- Land Cover Type 5: Plant Functional Type (PFT) scheme

For further details, please consult Friedl et al. [2010].

Nearly one third of the global SOC stocks is located in forested areas (Table 6.3) which further confirms the role of forests, especially tropical forests, in carbon sequestration and accumulation.

The relationship with soil types was explored using the Harmonized World Soil Database (HWSD) [FAO/IIASA/ISRIC/ISSCAS/JRC, 2012]. The HWSD is a 30 arc-second raster database with over 16,000 different soil mapping units that combines existing regional and national updates of soil information worldwide (SOTER, ESD, Soil Map of China, WISE) with the information

Table 6.3: Global SOC stocks per land cover classes

Landcover class	SOC stock, Pg	Percentage of global stocks
Forests	216	33%
Savannas and shrublands	197	30%
Croplands and grasslands	155	24%
Mosaic of natural vegetation, croplands and grasslands	39	6%
Barren or sparsely vegetated lands	33	5%
Permanent wetlands	11	2%

Table 6.4: Mean SOC stocks per WRB soil types

Soil Type	SOC, t/ha	Soil Type	SOC, t/ha	Soil Type	SOC, t/ha
Histosol	132.12	Regosol	57.32	Ferralsol	42.9
Chernozem	89.07	Fluvisol	57.12	Solonetz	40.55
Gleysol	88.36	Alisol	51.29	Anthrosol	40.2
Podzol	80.59	Nitisol	50.26	Lixisol	37.19
Andosol	76.16	Leptosol	49.63	Vertisol	30.68
Cambisol	62.94	Planosol	47.72	Gypsisol	24.26
Phaeozem	61.2	Kastanozem	47.59	Arenosol	24.17
Albeluvisol	60.73	Luvisol	44.71	Solonchak	22.01
Acrisol	58.87	Plinthosol	43.01	Calcisol	21.22

contained within the 1:5,000,000 scale FAO-UNESCO Soil Map of the World (FAO, 1971-1981).

Although the soils richest in organic carbon are Histosols and Chernozems, most of the carbon in the world is stored in Leptosols and Cambisols due to their larger area coverage (Tables 6.4 and 6.5).

6.2 Validation and comparison with existing products

Table 6.5: Total SOC stocks per WRB soil types

Soil Type	SOC, Pg	Soil Type	SOC, Pg	Soil Type	SOC, Pg
Leptosol	78.24	Arenosol	23.17	Solonetz	8.26
Cambisol	67.54	Calcisol	21.35	Nitisol	7.3
Gleysol	54.61	Fluvisol	20.12	Andosol	7.06
Podzol	53.01	Chernozem	19.74	Plinthosol	5.87
Acrisol	47.14	Phaeozem	18	Planosol	4.33
Regosol	40.97	Kastanozem	16.97	Gypsisol	3.1
Luvisol	36.22	Albeluvisol	14.45	Solonchak	2.71
Ferralsol	35.29	Vertisol	9.36	Alisol	2.31
Histosol	34.38	Lixisol	8.94	Anthrosol	2.26

6.2.1 Validation of the GSOCmap using available data

The validation of the map was done by comparison with available data. For this purpose, several available soil databases were merged. The final database contains 312122 soil samples. One of the sources used was the static dataset of the WoSIS Soil Profile Database. This dataset contains 63,009 soil profiles with information about SOC content. For the profiles without bulk density information, pedotransfer functions were used. Then, mass preserving spline functions were applied to estimate the carbon content of a standardized horizon of 0 to 30 cm. Finally, the organic carbon stock was estimated using the GSIF R package. These values were compared with the values in the GSOCmap.

For running the validation analysis, three different subsets were prepared from the full database. One including all the soil samples ('all data'), a second one only including samples with less than 150 $Mg \cdot ha$, ('mineral soils'), and the last one including samples with more than 150 $Mg \cdot ha$, ('carbon-rich soils').

The results of the validation analysis are shown in table 6.6. Different information criteria were used. The *mean error* is the mean error; *me mean* is the mean error divided by the mean of the observed values, a measure for how large the mean_error is in contrast to the mean of the dataset; *MAE* is the mean absolute error, *MSE* is the mean squared error; *cor obspred* is the correlation between observed and predicted values; *cor predres* is the correlation between predicted and residuals; *RMSE* is the root mean squared error; *RMSE sd* is the RMSE divided by the standard deviation of the observed values, a measure of how much the residuals vary from the total variation in the dataset and *iqr* is the interquartile range.

The mean error shows that the map, as an average, overestimates the value of the SOC in 1.6 $Mg \cdot ha$. However, if we only consider the soils with less than 150 $Mg \cdot ha$ ('mineral soils', in the table), the map overestimates the value by 4.585 $Mg \cdot ha$. For the 'carbon-rich soils', the GSOCmap underestimates the value by 165.2 $Mg \cdot ha$. According to the reports submitted by the countries, in few cases were the peats and other carbon-rich soils modeled independently. One reason for that is that not all the countries have detailed information on the spatial extent of these soils. In many cases, if these soils are modeled together with mineral soils, the result could be the underestimation of the value. The same trend could be observed in the RMSE: the value was 36.57 $Mg \cdot ha$ when using all the samples, 24.66 $Mg \cdot ha$ for the 'mineral soils' and 205.9 $Mg \cdot ha$ for the 'carbon-rich' soils.

6.2.2 Uncertainty analysis

Uncertainty analysis aims at quantifying possible deviations of SOC stock estimation on the maps from the real values. SOC map uncertainties come from the soil sampling, measurements of soil properties, and mapping techniques.

Although the GSP Secretariat asked the countries to provide information about the uncertainty of their contributed maps, not many countries were able to provide it. Besides, the layers contributed from the countries which could deliver, were generated using different and not comparable methodologies. The different methodologies used included: confidence intervals for the SOC values; standard deviation from regression kriging; standard deviation from an ensemble of different DSM models, and uncertainties as percentage based on expert knowledge. Therefore, a

Table 6.6: Validation criteria using available soil samples from WOSIS Soil Profile Database and countries data. Results from three different datasets.

	all data	mineral soils	carbon-rich soils
mean error	-1.621	-4.585	165.2
me mean	-0.044	-0.141	0.622
MAE	17.2	14.5	167.9
MSE	1338	608.1	42390
cor obspred	0.4496	0.4174	0.0247
cor predres	-0.207	-0.590	-0.425
RMSE	36.57	24.66	205.9
RMSE sd	0.91	1.14	1.85
iqr	15.3	15.02	171

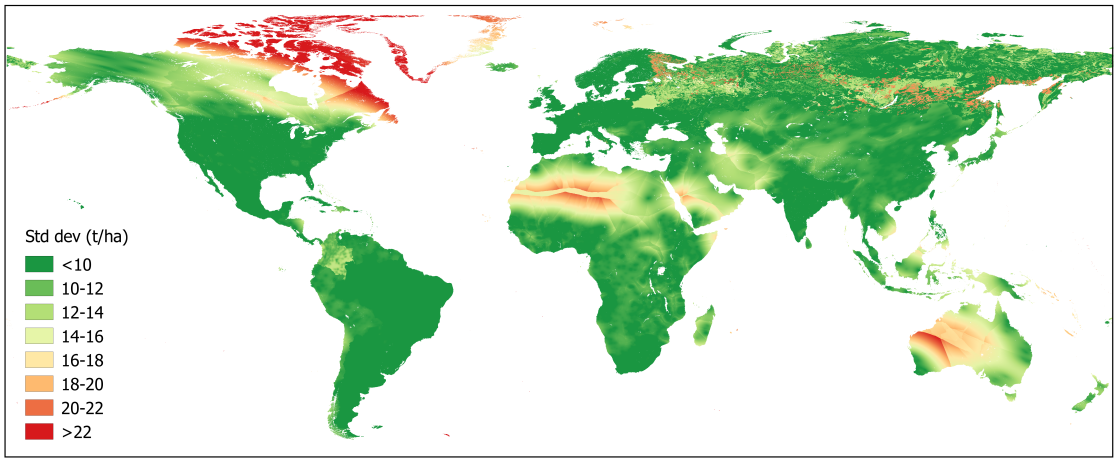

Figure 6.3: Map of standard deviations

global approach for estimating uncertainties was required.

A global uncertainty assessment was produced using the available database presented in Sect. 6.2.1. This database of 312,122 points was used to calculate the residuals of the maps. The residuals were estimated as the difference between the measured and predicted values by the GSOCmap. The current map presented in Fig. 6.3 is the result of the interpolation using ordinary kriging of the residuals. For the countries which provided their uncertainty layers in the form of standard deviations, the country layers were used instead of global interpolated values.

The current assessment shows highest uncertainty values in the tropical desert and arctic desert areas, due to insufficient number of soil samples from these regions. The difference in uncertainties between the countries in non-desert areas is mainly associated with the density of soil sampling and with the choice of mapping techniques. The global uncertainty assessment will be improved after the harmonization of the uncertainties maps delivered by the countries.

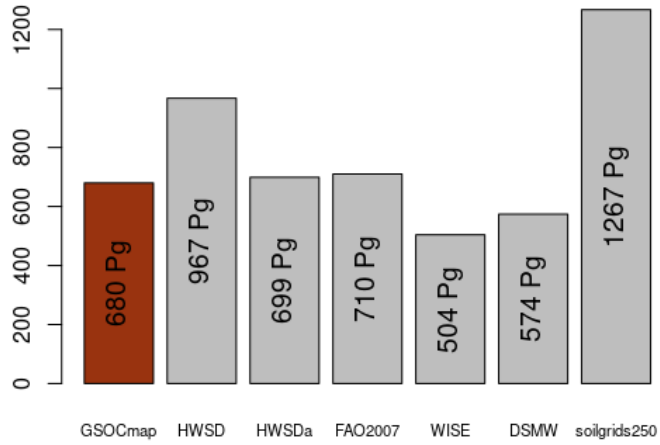

Figure 6.4: Comparison between the different estimates of Global SOC Stocks in topsoil

6.2.3 Comparison of the GSOCmap with other global data

The spatial distribution of soil organic carbon (SOC) represents one of the largest uncertainties in the carbon cycle. High resolution gridded data-sets of SOC are increasingly important for global modeling efforts and validation strategies [Jackson et al., 2017]. Validation experiments (e.g. across borders), the comparison of different approaches to predict soil carbon and the continuous calibration of country-specific-to- regional-to-global models are required to provide reliable estimates and enable the monitoring of SOC stocks. To compare and test different approaches (e.g. modeling and geo-matching), to map SOC stocks is relevant to reduce the current levels of uncertainty regarding the spatial variability and distribution of SOC, because they will work differently for the same objective. Using the same dataset, different approaches to map SOC will share bias derived from the quality of the data and the data characteristics that allow to meet modeling assumptions, or provide certainty to the soil mapper delineating a soil carbon polygon unit.

The objective of this section is to quantify the major differences of the country-specific GSOCmap and two global recent products of SOC, one derived from the SoilGrids initiative based on machine learning and environmental correlation [Hengl et al., 2017] and a second product derived from the Harmonized World Soil Database, based on soil type polygon units [Köchy et al., 2015]. The new knowledge will enhance updated versions of the GSOCmap because it will provide information about the spatial distribution and hotspots of discrepancy between the analyzed products.

The three SOC maps were re-sampled from their original resolution to a 1x1km grid and centered on the same spatial extent. The WoSIS dataset [Batjes et al., 2017] was used as a reference to analyze the changes from one map to another at the data collection points.

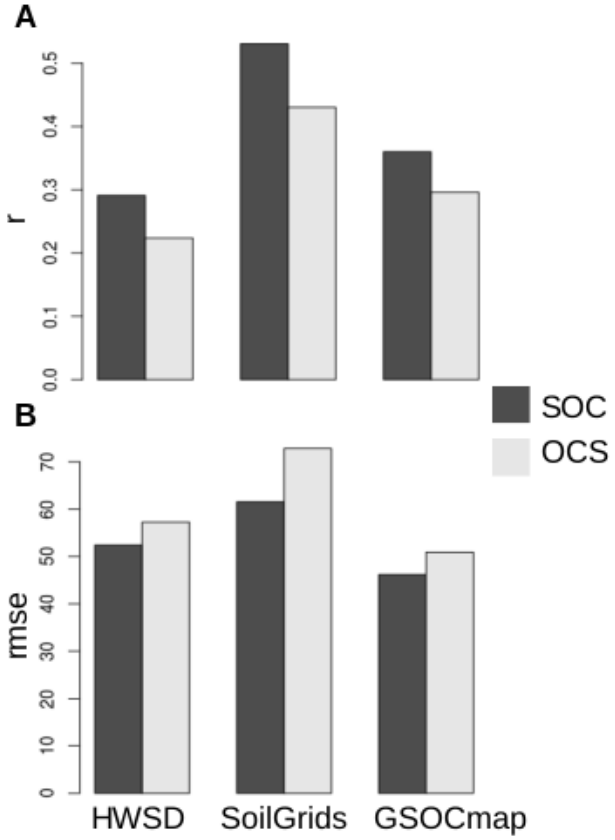

Figure 6.5: Correlation and rmse between the WoSIS dataset and the three analyzed products. These analysis were based on the SOC density (SOC, g/kg and with the calculated SOC stock, OCS kg/m).

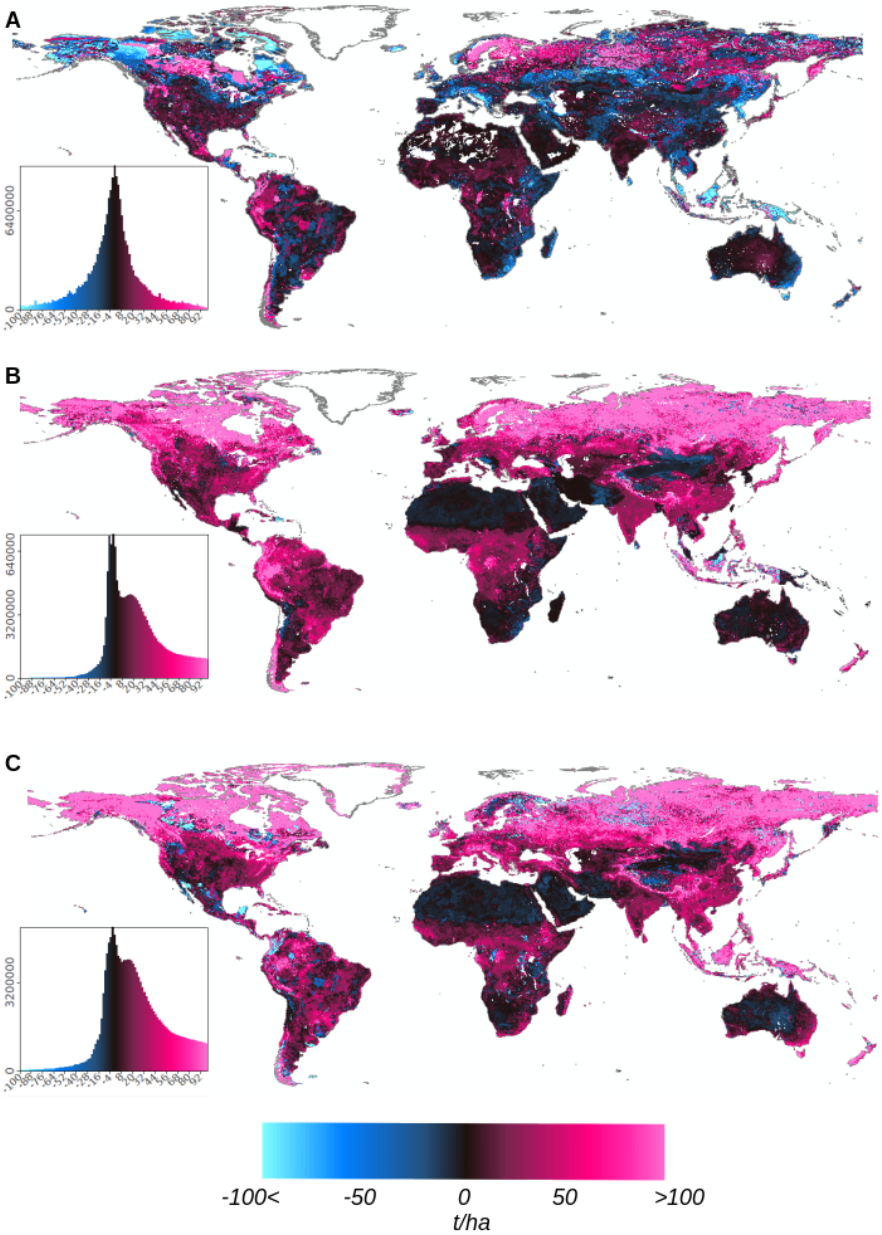

Figure 6.6: Change vector maps. Derived from a standardized confusion matrix, the map in A shows the changes from the GSOCmap to the HWSD, the map in B shows the changes from the GSOCmap to SoilGrids and the map in C we show the change from HWSD to SoilGrids.

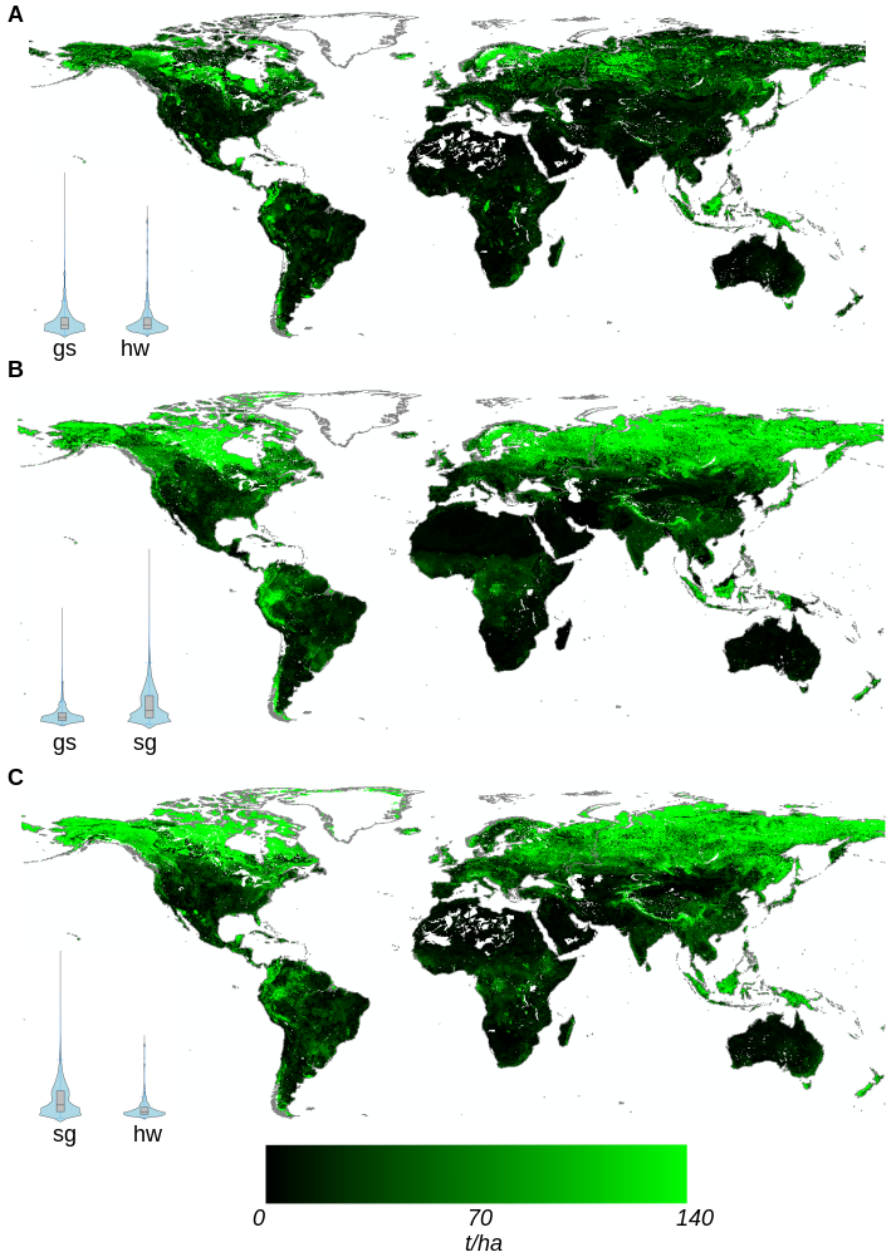

Figure 6.7: Mean absolute difference between the three SOC products. The insets violin plots are useful to visualize that the larger amount of SOC was predicted by the SoilGrids estimate. Larger discrepancy between the HWSD and the GSOCmap was found across northern latitudes, Indonesia and Central America

It was found that a) the HWSD generated the lowest correlations and the larger error, b) the SoilGrids system generated the higher correlation but also the higher error and c) the lowest error rate was found with the GSOCmap, as is shown in Fig. 6.5. The three methods/maps used a majority (in the case of SoilGrids) or a portion of the data collection included in the Wosis system (in the case of the GSOCmap and HWSD). These comparisons can therefore not represent a robust validation, because validation can only provide summary measures of uncertainty, and it is best conducted using probability sampling of independent observations of the soil property of interest [Heuvelink, G.B.M., 2014]. Yet the results are useful to identify and quantify differences among products that can be used to inform the development of future versions of country-specific and global SOC mapping efforts.

Conditional quantiles are a useful statistical approach of considering model performance against observations for continuous measurements [Wilks, 2011]. The conditional quantiles were plotted using splits of the data into evenly spaced bins, and for each predicted range, the corresponding values of the observations were identified in a percentile (quantile) basis as explained in the openair R manual [Carslaw and Ropkins, 2012].

For the global comparisons, the analysis based on numerical confusion matrices derived at the pixel level on SAGA GIS [Conrad et al., 2015]. A confusion matrix is a specific table layout that allows visualization of the main changes from a reference map (initial state) to another (final state). Thus, it quantifies the absolute difference and the direction of change comparing the GSOCmap with the HWSD, the GSOCmap with SoilGrids and the HWSD with SoilGrids. A map of (positive and negative) changes is derived for each iteration (between the reference and the final state), where values close to 0 represent areas of high agreement between the two compared products. It was found that there is a larger agreement between the GSOCmap and the HWSD than between the GSOCmap and the SoilGrids (Fig. 6.6A). While positive and negative changes from the GSOCmap the HWSD are irregularly distributed, the changes from the GSOCmap to the SoilGrids products tend to be positive, suggesting a major carbon pool predicted by the machine learning approach (Fig. 6.6B). A similar pattern was found by analyzing the changes from the HWSD to the SoilGrids map (Fig. 6.6C).

The standardized distances of the SOC maps comparison is provided, in order to detect major hotspots of discrepancy among the country specific and the global products (Fig. 6.7).

6.3 GSOCmap Web Services

The GSOCmap Web Services portal is operational with minimum functionality and advanced features are currently under development (Fig. 6.8). The map will be available online with functionality allowing to view, query and download the data, including the metadata acknowledging all organizations which contributed to the map (Fig. 6.9).

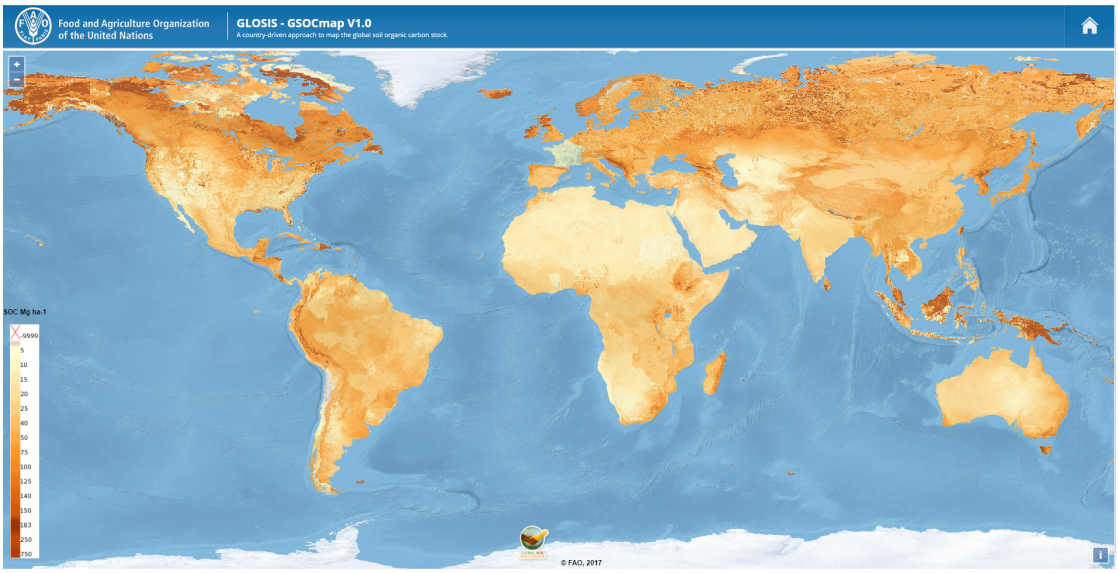

Figure 6.8: Accessing the GSOCmap on the web

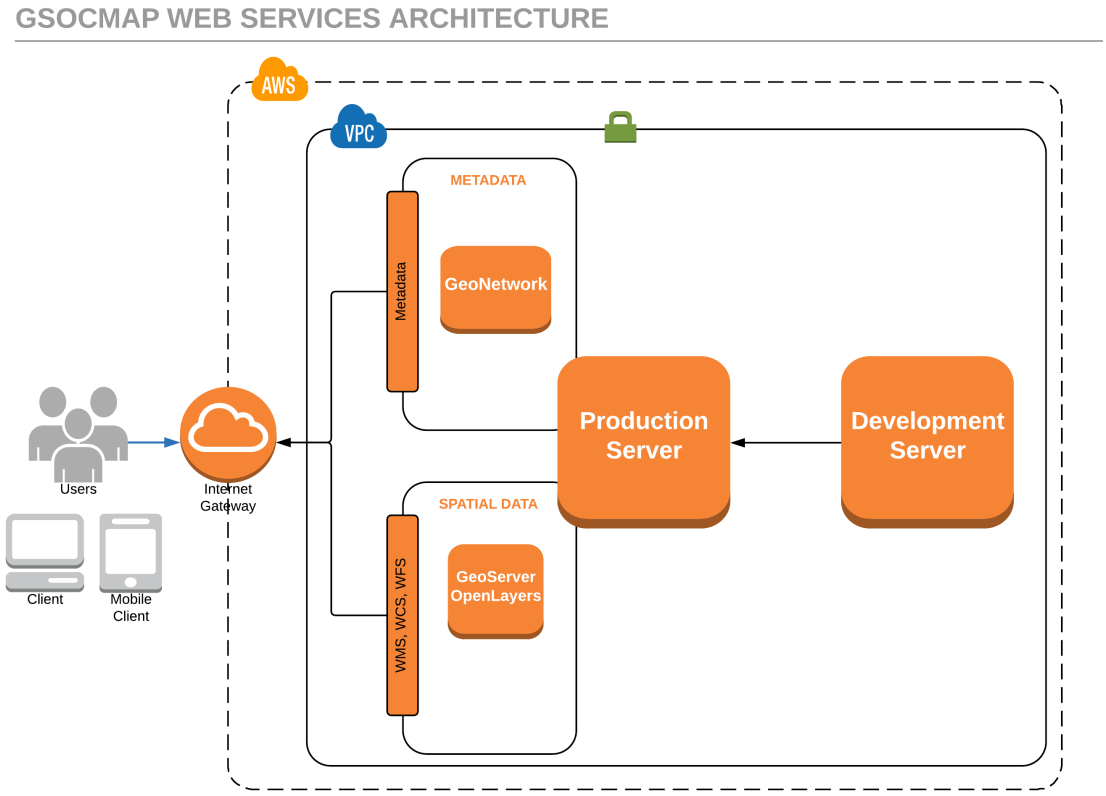

Figure 6.9: GSOCmap Web Services Architecture

Chapter 7

Conclusions and the way forward

The GSOCmap is a product of global efforts made to bring together the existing knowledge about soil organic carbon from all over the world. The map is currently based on more than 1 million profiles, most of the area is covered by original maps produced by the countries. This ensures that the GSOCmap is a global product which is consistent with the national soil knowledge and gives the best available estimation of SOC stocks at the country level.

The known issues are the differences at the borders between certain countries and overestimation of SOC stocks for the countries where external datasets were used for gap filling. These issues will be gradually addressed as more data is collected by countries which will allow to improve national maps and replace gap filling with original data.

The GSOCmap is to be continuously improved as the countries gather more data to improve their maps. The versioning system is being implemented which implies publishing the latest version of the map and keeping all previous versions available upon request.

7.1 Versioning system

The GSOCmap is a living product and will be updated as soon as more and better information is available. The GSP uses semantic versioning at certain level so that there is a standard pattern to data releases. Semantic versioning is widely used in the software development world and helps developers having a standardized way of versioning software releases. It follows the format of MAJOR.MINOR.PATCH.

The product released on World Soil Day 2017,(5 December) as V1.0.0 was recently updated to V1.2.0 with minor updates. Change-log is also to be released along with the data with each public release. The current changelog is persented in Annex C. The future releases will be using the following logic:

Major Major version will be incremented with substantial updates.

Minor Minor version will be incremented with new country submissions, replacements

Patch Patch version will be incremented with error fixes (i.e. removing outliers, fixing calculation errors, etc.)

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Appendix A

Country data in the GSOCmap

A.1 Afghanistan

Map source: GSP Gap-Filling

Point data

Number of samples: 17
Sampling period: 1962
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.2 Albania

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.3 Algeria

Map source: GSP Gap-Filling

Point data

Number of samples: 16
Sampling period: 1971-1972
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.4 Andorra

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.5 Angola

Map source: GSP Gap-Filling

Point data

Number of samples: 962
Sampling period: 1946-1991
SOC analysis method: dry oxidation (such as element analyzer), temperature = controlled, at 960 deg Celsius and higher (assumed: element analyzer), detection = sensoric (in element analyzer), calculation = complete recovery (assumed); wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Angola, Botswana and Namibia
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.6 Antigua and Barbuda

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.7 Argentina

Map source: Country submission

Point data

Number of samples: 4255
Sampling period: 1970-2015
SOC analysis method: Walkey Black
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Support Vector Machines and kriging of the residuals
Validation statistics: RMSE=1.6, corr predicted vs observed= 0.47

Contact

Data Holder: Instituto Nacional de Tecnologia Agropecuaria (INTA)
Contact: Guillermo Federico Olmedo olmedo.guillermo@inta.gob.ar
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A.8 Armenia

Map source: Country submission

Point data

Number of samples: 40
Sampling period: 2015-2017
SOC analysis method: Tyurin method
BD analysis method: No Data

Mapping method

Mapping method details: linear spectral unmixing pixel based classification
Validation statistics: No Data

Contact

Data Holder: Soil Science, Melioration and Agrochemistry Scientific Center named after H. Petrosyan
Contact: Sahakyan Samvel ssahakyan@yandex.ru

A.9 Australia

Map source: Country submission

Point data

Number of samples: 5588
Sampling period: 2000-2013
SOC analysis method: Dry combustion Dumas elemental analyser (4572 sites)
BD analysis method: Predominantly undisturbed cores with some using in situ water-replacement or Saran coating.

Mapping method

Mapping method details: Combination of decision trees with piecewise regression on environmental variables and geostatistical modelling of residuals.
Validation statistics: Refer to Viscarra Rossel et al. (2014) for detailed analysis of errors and confidence intervals. The total stock of organic C in the 0-30 cm layer of soil for Australia is 24.97 Gt with 95% confidence limits of 19.04 and 31.83 Gt. See maps of the 5% and 95% confidence limits for geographical variation across the continent. Further information on errors can be provided on request.

Contact

Data Holder: CSIRO Agriculture and Food
Contact: Mike Grundy mike.grundy@csiro.au
Citation: Viscarra Rossel RA, Webster R, Bui EN, Baldock JA (2014). Baseline map of organic carbon in Australian soil to support national carbon accounting and monitoring under climate change. Global Change Biology 20, 2953-2970. doi: 10.1111/gcb.12569

A.10 Austria

Map source: Country submission

Point data

Number of samples: 150511
Sampling period: 1950-2015
SOC analysis method: Agricultural map: Walkley-De Leenheer method (wet oxidation), Soil taxation survey: dry combustion, Forest monitoring data: dry combustion (ONORM L 1080)
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Dpt. for forest ecology and soil
Contact: Federal research and training center for forest, natural hazards and landscape Austria michael.englisch@bfw.gv.at
Citation: FBVA (Ed.) "Osterreichische Waldboden-Zustandsinventur". Mitteilungen der Forstlichen Bundesversuchsanstalt 168 (1992).

A.11 Azerbaijan

Map source: Country submission

Point data

Number of samples: 430
Sampling period: 2005-2017
SOC analysis method: Tyurin's Method
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Institute of Soil Science and Agrochemistry of ANAS
Contact: Amin Ismayilov amin_ismayilov@mail.ru ; amin.ismayil@gmail.com

A.12 Bahamas

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: data extracted from themodel for Central America based on WOSIS data
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.13 Bahrain

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.14 Bangladesh

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.15 Barbados

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.16 Belarus

Map source: GSP Gap-Filling

Point data

Number of samples: 88
Sampling period: 1958-1996
SOC analysis method: Wet oxidation (Tyurin Method)
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.17 Belgium

Map source: Country submission

Point data

Number of samples: 2457
Sampling period: Agricultural land (Flanders): 2004-2008, Agricultural land (Wallonia): 2005-2014, Forest (Flanders): 1997-2002, Forest (Wallonia): 2004-2014
SOC analysis method: Agricultural land (Flanders): Walkley & Black method, a correction factor of 1.33 was applied; Agricultural land (Wallonia): i/ 434 sites were analyzed by dichromate oxydation (Walkley and Black, 1934). 100 of these samples were also analyzed for SOC content by dry combustion method (see ii/ below) and used for fitting a linear regression between the results of both methods (Walkley & Black and dry combustion - corrected from inorganic carbon content). This linear regression was used to correct results of Walkley & black method from incomplete oxydation and making them comparable to the results obtained by dry combustion method corrected from inorganic carbon content (Chartin et al., 2017). ii/ 158 sites were

analyzed by dry combustion (Variomax CN, Elementar GmbH, Germany), and then corrected from inorganic carbon content. Forest (Flanders): Carbon analysis was performed using various methods: 88% of the samples were analysed by Loss-on-ignition (LOI), 35% by total analyser (TOC) and 6% by unmodified Walkley & Black method (WBC). A quarter of all samples were assessed both by TOC and LOI, to calibrate regression functions as described in De Vos et al. (2005). TOC was analysed according to ISO10694 with a Shimadzu TC analyser. The applied Walkley an Black method is described in De Vos et al. 2007; Forest (Wallonia): All the samples were analyzed by dichromate oxydation (Modified Springer & Klee Method; Springer & Klee , 1954).
BD analysis method: Agricultural land (Wallonia): 3 intact cores of 100cm3 (diameter of 5.3cm) were taken on the middle of each horizon within the 4m raduis circles investigated. Measurements were corrected from stone contents in order to obtain bulk density of fine earth only (¡ 2mm); Forest (Flanders): bulk density was sampled together with mineral soil sampling. A Riverside auger (Eijkelkamp, the Netherlands) was used in combination with a ring holder (Eijkelkamp, the Netherlands) for collecting undisturbed sample cores for bulk density determination. Standard sharpened steel cylinders (type Kopecky) of 100 cc volume (d = 53 mm, h = 50 mm) were used. Bulk density was measured after determination of the soil moisture retention curve at 8 matric potentials (determination of soil water retention curves). The samples were oven dried (105 C) till constant weight (¿ 24 h). Method described in De Vos et al. (2005b).

Mapping method

Mapping method details: Agricultural land (Flanders): The following empirical regression model was derived based on a dataset of 352 profiles. %SOC = LandUse + a.clay + b.H2Omin + c.LandUse.Clay + d.LandUse.H2Omi.n Based on the Belgian soil map and the VITO land use map (Poelmans, 2014), this regression equation was applied to the entire territory of Flanders. Agricultural land (Wallonia): i/A Generalized Additive Model (GAM; Wood, 2001) was fitted on 2/3 of the dataset. Spatialized environmental covariates (40m x 40m) were used as inputs on the model to map SOC stocks over croplands and grasslands in Wallonia (Southern Belgium).; Forest (Flanders): The average soil carbon stock in the upper 30 cm (Cs, in t C/ha) is computed per texture-drainage class of the Belgian soil map. This value is pasted into the 10x10 m2 grid of the land use map. ; Forest (Wallonia): i/A Generalized Additive Model (GAM; Wood, 2001) was fitted on 2/3 of the dataset. Spatialized environmental covariates (40m x 40m) were used as inputs on the model to map SOC stocks over forest in Wallonia (Southern Belgium).
Validation statistics: Agricultural land (Flanders): The uncertainty reported is the model uncertainty on point estimates for each data point, in which the estimated model parameters are simulated 1000 times, under the assumption that they are independent and normally distributed variables, using their model estimation and standard error as distribution parameters. (Goidts, 2009 and Meersmans, 2011); Agricultural land (Wallonia): The external validation (on the remaining 1/3 of the dataset) gave a R2 of 0.64 and a RMSE of 16 Mg C / ha. ii/ The computation of the prediction uncertainty accounts for the errors associated to both the estimations of i) SOC stocks and ii) parameters of the spatial model (GAM). Hence, two consecutive stochastic simulations (Monte-Carlo method) were used to produce 10,000 (i.e., 100 x 100) independent spatialized datasets. Based on these 10,000 individuals, mean SOC stocks and standard deviation (SD) were computed for each pixel. (Chartin et al., 2017) Forest (Flanders): The uncertainty of the mean (precision) is based on the margin of error (ME) derived from half the 95% confidence interval (CI95%). CI95% are estimated based on bias corrected and accelerated (BCa) percentiles at 2.5 and 97.5% determined by bootstrapping (B = 5000 resamples). Forest (Wallonia):The external validation (on the remaining 1/3 of the dataset) gave a R2 of 0.41, a mean error of 0.3 Mg C

/ha, a MAE of 16 Mg C /ha and a RMSE of 18.2 Mg C / ha. ii/ The computation of the prediction uncertainty (standard deviation, SD) accounts only for the errors associated to the estimation of the parameters of the spatial model (GAM). The mgcv package in R provides a Bayesian approach to compute standard errors for the predictions (Wood, 2001).

Contact

Data Holder: Data Holders: Vlaamse overheid and Service Public de Wallonie; Data Handlers: 1) Georges Lemaitre Centre for Earth and Climate Research, Earth and Life Institute, Universite Catholique de Louvain, 1348 Louvain-la-Neuve, Belgium 2) Environment and Climate unit, Research Institute for Nature and Forest, 1070 Brussels, Belgium 3) Vlaams Planbureau voor Omgeving, Departement Omgeving, Vlaamse overheid, 1000 Brussel, Belgium 4) Service Public de Wallonie, Direction Generale de l'Agriculture, des Ressources Naturelles et de l'Environnement (DGO3), 5100 Namur, Belgium
Contact: Data Holders: Katrien Oorts and Patrick Engels; Data Handlers: Caroline Chartin1, Suzanna Lettens2, Pieter Verschelde2, Sabine Buyle3, Katrien Oorts3*, Patrick Engels4, Martien Swerts3, Bruno De Vos2, Bas van Wesemael1, * Corresponding author Flanders: katrien.oorts@vlaanderen.be; Wallonia: patrick.engels@spw.wallonie.be
Citation: C. Chartin, S. Lettens, P. Verschelde, S. Buyle, K. Oorts, P. Engels, M. Swerts, B. De Vos, B. van Wesemael, 2017. The Belgian contribution to the Global Soil Organic Carbon Stock map, Proceedings of 'Soil Resources Mapping: past, present and future', Thematic Day 2017 of the Soil Science Society of Belgium. Spatial analysis of soil organic carbon evolution in Belgian croplands and grasslands, 1960-2006. Global Change Biology 17(1): 466-479.

A.18 Belize

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.19 Benin

Map source: GSP Gap-Filling

Point data

Number of samples: 714
Sampling period: 1968-1997
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent),

measurement condition = oven dry; natural clod; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.20 Bhutan

Map source: Country submission

Point data

Number of samples: 993
Sampling period: after 1997
SOC analysis method: Wet oxidation based on Walkley and Black
BD analysis method: undisturbed samples

Mapping method

Mapping method details: Regression tree using cubist and R Kriging using Vesper
Validation statistics: ME 0.05; RMSE 1.63 R2 0.63

Contact

Data Holder: National Soil Services Centre, Department of Agriculture, Ministry of Agriculture & Forests
Contact: Tsheten Dorji & Dr Tshering Dorji tshetendorji08@gmail.com & tsericdoji@gmail.com

A.21 Bolivia (Plurinational State of)

Map source: Country submission

Point data

Number of samples: 4788
Sampling period: 1960-2016
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest
Validation statistics: R2 = 0.287

Contact

Data Holder: Viceministerio de Tierras
Contact: Hernan Figueredo Ticona hernan.figueredo@yahoo.com

A.22 Bosnia and Herzegovina

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.23 Botswana

Map source: GSP Gap-Filling

Point data

Number of samples: 839
Sampling period: 1970-1986
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; samples: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Angola, Botswana and Namibia
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.24 Brazil

Map source: Country submission

Point data

Number of samples: 6998
Sampling period: 1958-2010
SOC analysis method: Wet oxidation
BD analysis method: Undisturbed sampling

Mapping method

Mapping method details: Ensemble model combining nine methods (stepwise multiple linear regression, elastic net, principal components regression, partial least squares regression, multivariate adaptive regression splines, cubist, regression tree, random forest and extreme gradient boosting)
Validation statistics: Training: ME = 1.55 t/ha, RMSE = 21.93 t/ha; Validation: ME = 5.82 t/ha, RMSE = 54.05 t/ha

Contact

Data Holder: Embrapa Solos
Contact: Gustavo M. Vasques gustavo.vasques@embrapa.br

A.25 Brunei Darussalam

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda,

M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.26 Bulgaria

Map source: GSP Gap-Filling

Point data

Number of samples: 664
Sampling period: 2012
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.27 Burkina Faso

Map source: GSP Gap-Filling

Point data

Number of samples: 532
Sampling period: 1966-2000
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; natural clod; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.28 Burundi

Map source: GSP Gap-Filling

Point data

Number of samples: 34
Sampling period: 1951-1984
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.29 Cabo Verde

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.30 Cambodia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.31 Cameroon

Map source: GSP Gap-Filling

Point data

Number of samples: 454
Sampling period: 1938-1999
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: natural clod

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Cameroon, Congo Gabon and Guinea
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.32 Canada

Map source: Country submission

Point data

Number of samples: 3000
Sampling period: 1960-2015
SOC analysis method: various: dry combustion, LOI, a few wet oxidation
BD analysis method: cores, excavation method

Mapping method

Mapping method details: ensemble map from 11 contributions using conventional upscaling, RF, and other algorithms
Validation statistics: We provide a sd based on the variation between overlapping contributions. Error rates for the individual contributions varied from none (polygon averages), low reliability for some maps (10% concordance), and some had better results (30 % or higher). Final map reliability estimates await the development of a national validation dataset (in progress).

Contact

Data Holder: Agriculture and Agri-Food Canada
Contact: Bert VandenBygaart bert.vandenbygaart@agr.gc.ca

A.33 Central African Republic

Map source: GSP Gap-Filling

Point data

Number of samples: 83
Sampling period: 1960-1978
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.34 Chad

Map source: GSP Gap-Filling

Point data

Number of samples: 5
Sampling period: 1968
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.35 Chile

Map source: Country submission

Point data

Number of samples: 1885
Sampling period: 2010-2015
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: super virtual machine, random forest y R Krigging
Validation statistics: ME: 0.4994 rmse:0.6341

Contact

Data Holder: Departamento De Suelos
Contact: Servicio Agricola y Ganadero nelson.bustamante@sag.gob.cl

A.36 China

Map source: GSP Gap-Filling

Point data

Number of samples: 1487
Sampling period: 1978-1993
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; natural clod; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.37 Colombia

Map source: Country submission

Point data

Number of samples: 4329
Sampling period: 1980-2012
SOC analysis method: Walkley-Black Method
BD analysis method: Samples made by the methods of the clod and cylinder, taken in the horizons of the modal profiles of the cartographic soil units

Mapping method

Mapping method details: Regression-kriging spatial interpolation technique that combines a regression of the dependent variable (target variable) over the predictors (i.e., the environmental covariates) with kriging of the prediction residuals.
Validation statistics: ME: 0.0006705, MAE: 0.5582, RMSE: 0.7416, R2 : 0.5843

Contact

Data Holder: Instituto Geografico Agustin Codazzi
Contact: German Dario Alvarez Lucero german.alvarez@igac.gov.co

A.38 Comoros

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.39 Congo

Map source: GSP Gap-Filling

Point data

Number of samples: 68
Sampling period: 1956-1998
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Cameroon, Congo Gabon and Guinea
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.40 Cook Islands

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.41 Costa Rica

Map source: Country submission

Point data

Number of samples: 1518
Sampling period: 1973-2013
SOC analysis method: Dry combustion and walkley-black
BD analysis method: Undisturbed sampling

Mapping method

Mapping method details: Random forest
Validation statistics: ME= 8.33, MAE = 2.88, RMSE=3.49, R2=0.265

Contact

Data Holder: INTA/UCR
Contact: Alban Rosales Ibarra/Bryan Aleman Montes arosaarosales@inta.go.cr/bryan.aleman@ucr.ac.cr

A.42 Cote d'Ivoire

Map source: GSP Gap-Filling

Point data

Number of samples: 250
Sampling period: 1966-1977
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: natural clod

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.43 Croatia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.44 Cuba

Map source: Country submission

Point data

Number of samples: 15738
Sampling period: 1975-1985
SOC analysis method: Walkley and Black volumetric method (Jackson, M, L. (1975). Soil Chemical Analysis, Ed. Omega, S.A., Barcelona, 662 p.)
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Instituto de Suelos, Ministerio de Agricultura
Contact: Dr. Luis A. Gomez Jorrin (General Director), Dr. Luis B. Rivero Ramos (Project Leader) director@isuelos.co.cu
Citation:

A.45 Cyprus

Map source: GSP Gap-Filling

Point data

Number of samples: 90
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support vector machine
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.46 Czechia

Map source: GSP Gap-Filling

Point data

Number of samples: 431
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.47 Democratic People's Republic of Korea

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.48 Democratic Republic of the Congo

Map source: GSP Gap-Filling

Point data

Number of samples: 374
Sampling period: 1954-2005
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.49 Denmark

Map source: Country submission

Point data

Number of samples: 46850
Sampling period: 1974-2010
SOC analysis method: Dry combustrion
BD analysis method: undisturbed rings

Mapping method

Mapping method details: Regression kriging
Validation statistics: For the 0-5 cm layer, the mean error was 1.1 g/kg

Contact

Data Holder: Agroecology, Aarhus University
Contact: Mogens H Greve, Mette B Greve mogensh.greve@agro.au.dk
Citation: Adhikari K, Hartemink AE, Minasny B, Bou Kheir R, Greve MB, et al. (2014) Digital Mapping of Soil Organic Carbon Contents and Stocks in Denmark. PLoS ONE 9(8): e105519. doi:10.1371/journal.pone.0105519

A.50 Djibouti

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.51 Dominica

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.52 Dominican Republic

Map source: Joint Effort with GSP

Point data

Number of samples: 120
Sampling period: 2015-2016
SOC analysis method: wet oxidation
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Ministerio De Medio Ambiente y Recursos Naturales
Contact: Rafael Antonio Rivera rafantoniorive@gmail.com
Institution: Ministerio De Medio Ambiente y Recursos Naturales

A.53 Ecuador

Map source: Country submission

Point data

Number of samples: 12861
Sampling period: 2009-2016
SOC analysis method: Wet Oxidation (WALKLEY & BLACK)
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: R Kriging
Validation statistics: ME: 0.0016; MAE:0.396; RMSE: 0.534; R2: 0.628

Contact

Data Holder: Ministerio de Agricultura y Ganaderia del Ecuador
Contact: Veronica Loayza, Wilmer Jimenez veronica_loayza@yahoo.es/wjimenez@mag.gob.ec/nloayza@mag.gob.e

A.54 Egypt

Map source: GSP Gap-Filling

Point data

Number of samples: 22
Sampling period: 1987-1992
SOC analysis method: 16 samples: dry oxidation (such as element analyzer), temperature = controlled, at 960 deg Celsius and higher (assumed: element analyzer), detection = sensoric (in element analyzer), calculation = complete recovery (assumed); 3 samples: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: 12 samples: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; 3 samples: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.55 El Salvador

Map source: Country submission

Point data

Number of samples: 866
Sampling period: 1960-2016

SOC analysis method: Walkley-Black
BD analysis method: Undisturbed sampling

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Ministerio de Medio Ambiente y Recursos Naturales (MARN)/ Centro Nacional de Tecnologia Agropecuaria y Forestal (CENTA)
Contact: Sol Munoz/ Rene Arevalo smunoz@marn.gob.sv / rene.arevalo@centa.gob.sv

A.56 Equatorial Guinea

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Cameroon, Congo Gabon and Guinea
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.57 Eritrea

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.58 Estonia

Map source: GSP Gap-Filling

Point data

Number of samples: 220
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.59 Ethiopia

Map source: Country submission

Point data

Number of samples: 58957
Sampling period: 2012-2017
SOC analysis method: soil spectroscopy
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest
Validation statistics: ME = 0.004104367, RMSE = 1.87978, and R2 = 0.5431023

Contact

Data Holder: Ministry of Agriculture and Natural Resources
Contact: Kiflu Gudeta gkiflu@gmail.com

A.60 Faroe Islands (Associate Member)

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.61 Fiji

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.62 Finland

Map source: Country submission

Point data

Number of samples: 2237
Sampling period: 2007-2009
SOC analysis method: Dry combustion
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Random Forest
Validation statistics: No Data

Contact

Data Holder: Natural Resources Institute Finland
Contact: Harri Lilja harri.lilja@luke.fi
Citation: Biosoil: https://doi.org/10.5194/gmd-9-4169-2016, 2016, Lucas: https://doi.org/10.1016/j.geoderma.20
Soil Database: https://doi.org/10.1016/S0166-2481(06)31005-7

A.63 France

Map source: Country submission

Point data

Number of samples: 2952
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: Estimated

Mapping method

Mapping method details: Cubist
Validation statistics: No Data

Contact

Data Holder: Institut National de la Recherche Agronomique (INRA)
Contact: Manuel Martin manuel.martin@inra.fr
Citation: France carbon soil map - INRA (with data provided by GIS Sol) - M. Martin, D. Arrouays, V.L. Mulder, M. Lacoste, A.C.Richer-de-Forges, M. Bardy and A. Bispo. 2017 - Updated 1/12/2017 Mulder, V.L., Lacoste, M., Richer-de-Forges, A.C., Martin, M.P., Arrouays, D., 2016. National versus global modelling the 3D distribution of soil organic carbon in mainland France. Geoderma 263, 16 - 34. https://doi.org/10.1016/j.geoderma.2015.08.035

A.64 Gabon

Map source: GSP Gap-Filling

Point data

Number of samples: 46
Sampling period: 1959-1984
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Cameroon, Congo Gabon and Guinea
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.65 Gambia

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Institution: ISRIC World Soil Information
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.66 Georgia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.67 Germany

Map source: Country submission

Point data

Number of samples: 3300
Sampling period: forest: 2006-2008, agricutural soils: 2011-2016
SOC analysis method: dry combustion
BD analysis method: undisturbed sampling with cube (100cm3)

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Thunen-Insitute of Forests Ecosystems, Thunen-Institutes of Climate-Smart Agriculture
Contact: Wellbrock nicole.wellbrock@thuenen.de, anna.jacobs@thuenen.de
Citation: Groneberg, E.; Ziche, D.; Wellbrock, N. (2014): Organic carbon stocks and sequestration rates of forests soils in Germany. Globalchange Biology. Vol. 20, Issue 8, 2644-2662. DOI:

10.1111/gcb.12558. ; https://www.thuenen.de/en/ak/projects/agricultural-soil-inventory-bze-lw/; https://www.thuenen.de/en/wo/projects/forest-monitoring/projekte-bodenzustandserhebung/national-forest-soil-inventory-in-germany-data-quality-and-data-management/

A.68 Ghana

Map source: Country submission

Point data

Number of samples: 751
Sampling period: 1945-2003
SOC analysis method: Walkley-Black Titrimetry (Wet Oxidation), samples were air dried, crushed and sieved (2-mm). The fine earth fraction (¡2mm) was used for laboratory analysis. wet ox agents:10ml K2Cr2O7 solution, 20ml conc. H2SO4, 85% H3PO4, 0.2g of NaF, 0.5ml ferrous solution, and 1mL of diphenylamine indicator.
BD analysis method: Bulk density layers (kg/m3) for Ghana were downloaded from soilgrids.org. (ISRIC)

Mapping method

Mapping method details: Multiple linear regression and R Kriging
Validation statistics: ME = -0.00035; MAE = 0.48; RMSE = 0.63; R2 = 0.12

Contact

Data Holder: CSIR-Soil Research Institute, Kwadaso-Kumasi, Ghana.
Contact: Stephen Owusu s.owusu@csir-soilresearch.org ; stephenowusu41@yahoo.com

A.69 Greece

Map source: GSP Gap-Filling

Point data

Number of samples: 491
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.70 Grenada

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.71 Guatemala

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.72 Guinea

Map source: GSP Gap-Filling

Point data

Number of samples: 61
Sampling period: 1962-1969
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry;

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.73 Guinea-Bissau

Map source: GSP Gap-Filling

Point data

Number of samples: 17
Sampling period: 1982-1983
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.74 Guyana

Map source: GSP Gap-Filling

Point data

Number of samples: 43
Sampling period: 1965-1966
SOC analysis method: wet oxidation
BD analysis method: No Data

Mapping method

Mapping method details: ensemble of different SVM models based on 238 points from the region
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.75 Haiti

Map source: GSP Gap-Filling

Point data

Number of samples: 135
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Bayesian Regression where the response variable is observational data from Haiti and the explanatory
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.76 Honduras

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.77 Hungary

Map source: Country submission

Point data

Number of samples: 1236
Sampling period: 1992-1993
SOC analysis method: wet oxidation
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Quantile regression forest
Validation statistics: ME= -1.72, MAE= 17.08, RMSE= 23.18

Contact

Data Holder: Institute for Soil Sciences and Agricultural Chemistry, Centre for Agricultural Research, Hungarian Academy of Sciences
Contact: Lazlo Pasztor pasztor@rissac.hu

A.78 Iceland

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.79 India

Map source: Joint Effort with GSP

Point data

Number of samples: 175993
Sampling period: 2000-2015
SOC analysis method: Wet digestion ((Walkley and Black 1934)
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Support Vector Machine
Validation statistics: ME (0.0002269), RMSE (0.8383869), R2 (0.53)

Contact

Data Holder: National Bureau of Soil Survey and Land Use Planning, Nagpur; Indian Institute of soil Science, Bhopal
Contact: S. K. Singh, A.K. Patra skcssri@gmail.com, patraak@gmail.com
Institution: National Bureau of Soil Survey and Land Use Planning, Nagpur; Indian Institute of soil Science, Bhopal

A.80 Indonesia

Map source: Country submission

Point data

Number of samples: 15750
Sampling period: 1980-2017
SOC analysis method: wet oxidation
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Indonesian Center for Agricultural Land Resource Research and Development
Contact: YIYI SULAEMAN y.sulaeman@gmail.com
Citation: Sulaeman et al. 2012 Sulaeman et al. 2013, 2014, 2015, 2016

A.81 Iran (Islamic Republic of)

Map source: GSP Gap-Filling

Point data

Number of samples: 6
Sampling period: 1964
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.82 Iraq

Map source: Country submission

Point data

Number of samples: 400
Sampling period: 1980s-2000
SOC analysis method: Walkley-Black
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Ministry of Agriculture
Contact: Dr Eman eman_sahib@yahoo.com

A.83 Ireland

Map source: GSP Gap-Filling

Point data

Number of samples: 233
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.84 Israel

Map source: GSP Gap-Filling

Point data

Number of samples: 12
Sampling period: 1976-1986
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.85 Italy

Map source: Country submission

Point data

Number of samples: 6748
Sampling period: 1990-2013
SOC analysis method: SOC values obtained with the Springer and Klee and 'flash combustion elemental analyser' methods were retained for elaborations. Uncorrected values obtained by the Walkey and Black method were corrected with an empirical linear equation, based on previous studies and as recommended by the Italian official methods.
BD analysis method: Undisturbed sampling, core method and pit method

Mapping method

Mapping method details: Neural Networks and GLM, according to soil region
Validation statistics: Mean Error (ME) of the prediction is 1.688 Mg/ha, MAE 25.57 Mg/ha, Root Mean Squared Error (RMSE) is 36.24 Mg/ha.

Contact

Data Holder: Research centre for agriculture and environment
Contact: CREA Consiglio per la ricerca in agricoltura e l'analisi dell'economia agraria edoardo.costantini@crea.gov.it

A.86 Jamaica

Map source: GSP Gap-Filling

Point data

Number of samples: 77
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Quantile Regression Forest
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.87 Japan

Map source: Country submission

Point data

Number of samples: 6254
Sampling period: cropland: 2008-2012, forest: 2006-2011
SOC analysis method: Dry combustion method
BD analysis method: Cropland: 100mL cylinder Forests: 400 mL cylinder (100 cm2 area, 4 cm depth),

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Cropland:Institute for Agro-Environmental Sciences, NARO, Forests:Forestry and Forest Products Research Insitute
Contact: Cropland: Hiroshi Obara, Forests:Shigehiro Ishizuka Cropland: obara@affrc.go.jp, Forest: ishiz03@ffpri.affrc.go.jp

A.88 Jordan

Map source: Country submission

Point data

Number of samples: 1072
Sampling period: 1993, 2013
SOC analysis method: No Data
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Multiple linear regression, Kriging
Validation statistics: R2 (0.92)

Contact

Data Holder: MOA
Contact: Mahmoud alfraihat Mahmoudalfrehat@gmail.com

A.89 Kazakhstan

Map source: Country submission

Point data

Number of samples: 502
Sampling period: 1960-2016
SOC analysis method: The samples SOM content was measured using Tyurin method
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: Kazakh Research Institute of Soil Science and Agrochemistry named after U.U. Uspanov
Contact: Maira madgu@inbox.ru

A.90 Kenya

Map source: Country submission

Point data

Number of samples: 2059
Sampling period: 1976-2017
SOC analysis method: organic C in the soil sample is oxidized by acidified dichromate at 1500Cfor 30 minutes to ensure complete oxidation (Anderson and Ingram, 1993). Barium chloride is added to the cooled digest, mixed thoroughly and the digest allowed to stand overnight. The C concentration is read on the spectrophotometer.
BD analysis method: No Data

Mapping method

Mapping method details: Environmental Correlation
Validation statistics: RMSE=39.721202 ;AC=0.657806; MAE=28.957822; SDOV=36.117432; ME=1.090813 Where: RMSE is root mean square error; AC is agreement coefficient; MAE is mean absolute error; SDOV is standard deviation of observed values; ME is mean error.

Contact

Data Holder: Kenya Agricultural and Livestock Research Organization
Contact: Peter Kamoni, Matolo Nyamai Peter kamoni(pkamoni@gmail.com) Matolo Nyamai(matolonyamai@gmai
Citation: Anderson, J. M. and J. S. I. Ingram (eds). 1993. Tropical Soil Biology and Fertility. A handbook of Methods. C.A.B. International, Wallingford, UK. Hinga G., Muchena F.N. and Njihia C.M., (ed 1980). Physical and Chemical methods of soil analysis. National Agricultural Laboratories, Nairobi Zhu AX., Liud J., Dud f., Zhang SJ., Qin CZ., Burtd J., Behrense T., and Scholtene T. Predictive soil mapping with limited sample data. European Journal of Soil Science, May 2015, 66, 535-547.

A.91 Kiribati

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.92 Kuwait

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.93 Kyrgyzstan

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.94 Lao People's Democratic Republic

Map source: Joint Effort with GSP

Point data

Number of samples: 155
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Caret ensemble of Random Forest, Cubist, KKNN, Bayesian trees, Partial Least Squares Regression, Principal Components Regression
Validation statistics: No Data

Contact

Data Holder: Ministry of Agriculture and Forestry of Laos
Contact: http://www.maf.gov.la/
Institution: Ministry of Agriculture and Forestry of Laos

A.95 Latvia

Map source: GSP Gap-Filling

Point data

Number of samples: 349
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.96 Lebanon

Map source: Country submission

Point data

Number of samples: 450
Sampling period: 1952-1953 and 1997-2001
SOC analysis method: Wet oxidation
BD analysis method: No Data

Mapping method

Mapping method details: Kriging
Validation statistics: No Data

Contact

Data Holder: Handler Institute: National Council for Scientific Research CNRS Lebanon
Contact: Talal Darwish tdarwich@cnrs.edu.lb; tlldarwish@gmail.com
Citation: Darwish T., Khawlie M., Jomaa M., Awad M. Abou Daher and P. Zdruli (2002). A survey to upgrade information for soil mapping and management in Lebanon. Options Mediterraneennes, Series A: Mediterranean Seminars, number 50: 57-71.

A.97 Lesotho

Map source: Country submission

Point data

Number of samples: 74
Sampling period: 1965-1979
SOC analysis method: Records not accessible. Analyses were conducted in accordance with procedures outlined in: 1.. Soil Survey Laboratory Methods and Procedures for Collecting Soil Samples (Soil Conservation Service, USDA, Washington, D. C., 1972). 2.. Physical and Chemical Methods of Soil and Water Analysis (J. Dewis, F. Freitas: FAO., Rome, 1970)
BD analysis method: Records not accessible. Analyses were conducted in accordance with procedures outlined in: 1.. Soil Survey Laboratory Methods and Procedures for Collecting Soil Samples (Soil Conservation Service, USDA, Washington, D. C., 1972). 2.. Physical and Chemical Methods of Soil and Water Analysis (J. Dewis, F. Freitas: FAO., Rome, 1970)

Mapping method

Mapping method details: Multiple linear regression, R Kriging, Random Forest
Validation statistics: No Data

Contact

Data Holder: Ministry of Forestry, Range and Soil Conservation
Contact: Koetlisi Koetlisi koetlisika@email.com and lesis2017@gmail.com
Citation: Cauley, P. M., 1986. Benchmark soils of Lesotho: their classification, interpretation, use, and management. Maseru, Lesotho.

A.98 Liberia

Map source: GSP Gap-Filling

Point data

Number of samples: 48
Sampling period: 1974-2008
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied

BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry;

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.99 Libya

Map source: GSP Gap-Filling

Point data

Number of samples: 14
Sampling period: 1980
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; 15 samples: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.100 Lithuania

Map source: GSP Gap-Filling

Point data

Number of samples: 356
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.101 Luxembourg

Map source: Country submission

Point data

Number of samples: 3492
Sampling period: agricultural land: 2012-2013, forest: 1998-2001
SOC analysis method: Dry Combustion (DC) ISO 10694 - 1995, Measure of TIC (by CO2) after treatment by phosphoric acid 40% ; TOC = TC -TIC
BD analysis method: No Data

Mapping method

Mapping method details: Generalized Additive Models (covariates: Land use, Elevation, precipitation, temperature, C factor, % Clay (80x80m))
Validation statistics: For cropland soils: R2 = 0.66, RMSE = 5.5 g C kg-1

Contact

Data Holder: Administration of agricultural technical services - Soil department
Contact: Marx Simone simone.marx@asta.etat.lu

A.102 Madagascar

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.103 Malawi

Map source: Country submission

Point data

Number of samples: 4922
Sampling period: 2010-2014
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Multiple linear regression
Validation statistics: No Data

Contact

Data Holder: Department of Land Resources Conservation, Ministry of Agriculture, Irrigation and Water Development,
Contact: Kefasi Kamoyo/ John Mussa kamokefa@yahoo.com/ mussajj@gmail.com

A.104 Malaysia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.105 Maldives

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.106 Mali

Map source: GSP Gap-Filling

Point data

Number of samples: 667
Sampling period: 1955-2001
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: 10 samples: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa; 1 sample: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry;

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.107 Malta

Map source: GSP Gap-Filling

Point data

Number of samples: 19
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.108 Marshall Islands

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.109 Mauritania

Map source: GSP Gap-Filling

Point data

Number of samples: 11
Sampling period: 1983
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.110 Mauritius

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.111 Mexico

Map source: Country submission

Point data

Number of samples: 36015
Sampling period: soil profiles: 1968-2016, augers: 2015-2016
SOC analysis method: Walkley Black (1968-2009) and Combustion Total (2010-2016)
BD analysis method: To spatially represent SOC information we use regionalization models that represent changes in average SOC values as a function of changes in factors of soil formation (or loss); such as gravity, climate, vegetation, land use, water erosion, deforestation, degradation and recovery. Each logical relationship has both exception rules and quantitative trend graphs for the continuous range of carbon values, which is established from the available cartographic information. Digital soil mapping techniques are also used to build statistical models and spatial predictions of SOC and depth. The ongoing development and the implementation of a national soil spatial inference engine assisted with high performance computing techniques will allow to periodically provide wall-to-wall SOC estimates at relevant scales for natural resources management.

Mapping method

Mapping method details: Mixed. Iterative Calibration map and Linear Regression. To spatially represent SOC information we use regionalization models that represent changes in average SOC values as a function of changes in factors of soil formation (or loss); such as gravity (inclination), climate, vegetation, land use, water erosion, deforestation, degradation and recovery. Each logical relationship has both exception rules and quantitative trend graphs for the continuous range of carbon values, which is established from the available cartographic information. Digital soil mapping techniques are also used to build statistical models and spatial predictions of SOC and depth. The ongoing development and the implementation of a national soil spatial inference engine assisted with high performance computing techniques will allow to periodically provide wall-to-wall SOC estimates at relevant scales for natural resources management.
Validation statistics: Four error factors are considered: (1) Disaggregation or level of detail in the available data. (2) Density or number of field observations per study surface. (3) Dispersion or heterogeneity represented by the coefficient of variation (Cv) obtained from the quotient of the standard deviation and the mean of each covariate of organic carbon (relief, geology, climate, vegetation, human management and various soil processes), and (4) Representation or congruence (qualitative evaluation of expert) between the study sites (points) and the carbon magnitude polygons represented. For the estimation of uncertainties follows the good practices suggestions from the IPCC (2003) through the use of the inverse of variance and R2.

Contact

Data Holder: 1 Instituto Nacional de Estadistica y Geografia. INEGI. omar.cruz@inegi.org.mx 2 Comision Nacional Forestal. CONAFOR. 3 Instituto Nacional de Investigaciones Forestales Agricolas y Pecuarias. INIFAP. 4 Red Nacional de Laboratorios para el Analisis, Uso, Conservacion y Manejo del Suelo. REDLABs. 5 Colegio de Postgraduados. COLPOS. 6 Colegio de la Frontera Sur. ECOSUR. 7 Organizacion de las Naciones Unidas para la Agricultura y la Alimentacion. FAO. 8 University of Delaware, UDEL. 9 Programa de las Naciones Unidas para el Desarrollo. PNUD.
Contact: Carlos Cruz-Gaistardo omar.cruz@inegi.org.mx
Citation: Soil Organic Carbon Map 2017. Mexico.

A.112 Micronesia (Federated States of)

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.113 Monaco

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. "'LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.114 Mongolia

Map source: Country submission

Point data

Number of samples: 512
Sampling period: 2010-2017
SOC analysis method: Tyurin's Method
BD analysis method: No Data

Mapping method

Mapping method details: Random forest model
Validation statistics: ME= 0.1, MAE=2.26, RMSE=3.0, R2=0.36

Contact

Data Holder: Institue of Plant and Agriculture Science
Contact: Bayarsukh Noov bayar67@yahoo.com

A.115 Montenegro

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.116 Morocco

Map source: Country submission

Point data

Number of samples: 24000
Sampling period: 1980-2016
SOC analysis method: Walkley-Black
BD analysis method: No Data

Mapping method

Mapping method details: esoter appraoch for soil unit and idw for regression
Validation statistics: No Data

Contact

Data Holder: INRA Morocco
Contact: Dr Rachid Moussadek rachidmoussadek@yahoo.fr

A.117 Mozambique

Map source: Country submission

Point data

Number of samples: 2427
Sampling period: 1960-2000
SOC analysis method: Loss ignition, dry combustion
BD analysis method: Sampling was done across all horizons of the profile

Mapping method

Mapping method details: Random Forest Method
Validation statistics: ME=4.4, R2=0.31

Contact

Data Holder: Mozambique Agrarian Reserch Institute
Contact: Orlando Inacio Jalane ojalane@gmail.com

A.118 Myanmar

Map source: Joint Effort with GSP

Point data

Number of samples: 115
Sampling period: 2009-2015
SOC analysis method: Tyurin's Method
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Ministry of Agriculture, Livestock and Irrigation (MoALI)
Contact: Su Su Win ¡susuwinmyanmar@gmail.com¿
Institution: Ministry of Agriculture, Livestock and Irrigation (MoALI)

A.119 Namibia

Map source: GSP Gap-Filling

Point data

Number of samples: 56
Sampling period: 1973-2000
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Angola, Botswana and Namibia
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.120 Nauru

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.121 Nepal

Map source: Country submission

Point data

Number of samples: 6000
Sampling period: 1990-2000
SOC analysis method: Wet Oxidation
BD analysis method: Undisturbed sampling

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Nepal Agricultural Research Council
Contact: Soil Science Division matobigyan@gmail.com

A.122 Netherlands

Map source: Country submission

Point data

Number of samples: 21210
Sampling period: 1990-2013
SOC analysis method: dry combustion by loss on ignition
BD analysis method: No Data

Mapping method

Mapping method details: R Kriging
Validation statistics: No Data

Contact

Data Holder: Wageningen University & Research, The Netherlands
Contact: Dennis Walvoort & Tom Hoogland https://www.wur.nl/en.htm
Citation: Hoogland, T. D. J. Brus, and D.J.J. Walvoort, (2017, in prep.). 3D-geostatistical interpolation of soil organic matter in the Netherlands.

A.123 New Zealand

Map source: Country submission

Point data

Number of samples: 2050
Sampling period: 1950-2010
SOC analysis method: Dry combustion (different methods over time)
BD analysis method: Disturbed (for soil physical/chemical parameters) and undisturbed (bulk density)

Mapping method

Mapping method details: generalized linear model (GLM)
Validation statistics: A test of the measured and predicted soil carbon stocks using the LENZ level 4 environmental classification model (the best of the four developed) indicates a residual standard error of 24.4t/ha using a robust Gaussian fit of the model residuals.

Contact

Data Holder: Landcare Research
Contact: Stephen McNeill mcneills@landcareresearch.co.nz
Citation: McNeill S., Golubiewski N., Barringer J. (2014): Development and calibration of a soil carbon inventory model for New Zealand. Soil Research 52: 789-804; http://dx.doi.org/10.1071/SR14020

A.124 Nicaragua

Map source: Country submission

Point data

Number of samples: 4000
Sampling period: 1972-2017
SOC analysis method: Walkley-Black
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest and Support Vector Machine
Validation statistics: No Data

Contact

Data Holder: Universidad Nacional Agraria
Contact: Fernando J Mendoza Jara fmendoza@ci.una.edu.ni

A.125 Niger

Map source: GSP Gap-Filling

Point data

Number of samples: 478
Sampling period: 1979-1998
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; natural clod; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.126 Nigeria

Map source: Country submission

Point data

Number of samples: 5545
Sampling period: 1970-2015
SOC analysis method: walkley Black Method,
BD analysis method: No Data

Mapping method

Mapping method details: Multiple linear regression
Validation statistics: RMSE 18.9, R2; 0.529, ME; 9.18

Contact

Data Holder: Federal department of Agricultural Lands and Climate Change Management Service
Contact: Oshadiya Pekun oshadiyapekun@gmail.com

A.127 Niue

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.128 Norway

Map source: GSP Gap-Filling

Point data

Number of samples: 3218
Sampling period: 1980-2016
SOC analysis method: Dry combustion (after ISO 10694)
BD analysis method: No Data

Mapping method

Mapping method details: ensemble of 6 models: random forest, cubist, kernels, decision trees, principal components and partial least square regression
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.129 Oman

Map source: GSP Gap-Filling

Point data

Number of samples: 9
Sampling period: 1982-1989
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.130 Pakistan

Map source: GSP Gap-Filling

Point data

Number of samples: 337
Sampling period: 1969-1989
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.131 Palau

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.132 Panama

Map source: Country submission

Point data

Number of samples: 837
Sampling period: 2010-2015
SOC analysis method: Wet Oxidation
BD analysis method: No Data

Mapping method

Mapping method details: R Kriging
Validation statistics: No Data

Contact

Data Holder: IDIAP
Contact: Ivan Ramos iarz1103@gmail.com

A.133 Papua New Guinea

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.134 Paraguay

Map source: Country submission

Point data

Number of samples: 2768
Sampling period: 1993-2017
SOC analysis method: potassium Dichromate - titulation
BD analysis method: no available

Mapping method

Mapping method details: Random Forest
Validation statistics: (ME) 1.66 Kg/m2 (MAE) 3.39 Kg/m2 RMSE 3.12 Kg/m2 R2 0.1416

Contact

Data Holder: Secretary of Environment SEAM
Contact: Minisry of Agriculture MAG no available

A.135 Peru

Map source: Country submission

Point data

Number of samples: 1010
Sampling period: 1980-2015
SOC analysis method: No Data
BD analysis method: estimated by a method ps / vs

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Ministerio de Agricultura y Riego
Contact: Honnan Denis Ponte Saldana hponte1410@Gmail.com, hponte@minagri.gob.pe

A.136 Philippines

Map source: Country submission

Point data

Number of samples: 500
Sampling period: 1979-2015
SOC analysis method: Walkley-Black
BD analysis method: No Data

Mapping method

Mapping method details: Kriging
Validation statistics: RMSE = 0.48

Contact

Data Holder: Bureau of Soils and Water Management
Contact: Baldwin Morales Pine baldwinmp@gmail.com/rodelcarating@yahoo.com/angelenriquez.bswm@gmail.com

A.137 Poland

Map source: GSP Gap-Filling

Point data

Number of samples: 1648
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.138 Portugal

Map source: GSP Gap-Filling

Point data

Number of samples: 476
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.139 Qatar

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.140 Republic of Korea

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.141 Republic of Moldova

Map source: Country submission

Point data

Number of samples: 0
Sampling period: 1980
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Institute of Pedology, Agrochemistry and Soil Protection "N. Dimo", Moldova
Contact: Iurii Rozloga iu.rozloga@gmail.com

A.142 Romania

Map source: GSP Gap-Filling

Point data

Number of samples: 1384
Sampling period: 2012
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.143 Russian Federation

Map source: Country submission

Point data

Number of samples: 150000
Sampling period: 1965-2016
SOC analysis method: Wet Oxidation , Turin's method
BD analysis method: No Data

Mapping method

Mapping method details: Used both conventional upscaling and DSM. For DSM: regression equations, IWD and kriging, fuzzi sets depending on area of country and sample density
Validation statistics: Under development yet

Contact

Data Holder: MSU soil data center
Contact: Oleg Golozubov oleggolozubov@gmail.com
Citation: Golozubov O.M., Chernova O.V. Using multi-scale old and modern maps combined with current soil monitoring data for online mapping the soil organic carbon stocks // International Conference "Global Soil Map 2017" Moscow, Russia, July 4-6, 2017. Materials of conference. p. 36.

A.144 Rwanda

Map source: GSP Gap-Filling

Point data

Number of samples: 88
Sampling period: 1963-1993
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry;

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.145 Saint Kitts and Nevis

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.146 Saint Lucia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.147 Saint Vincent and the Grenadines

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.148 Samoa

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.149 San Marino

Map source: GSP Gap-Filling

Point data

Number of samples: No Data
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: No Data
Contact: No Data
Institution: No Data

A.150 Sao Tome and Principe

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.151 Saudi Arabia

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.152 Senegal

Map source: Country submission

Point data

Number of samples: 678
Sampling period: 1990-2017
SOC analysis method: Wet Oxidation
BD analysis method: No Data

Mapping method

Mapping method details: R Kriging
Validation statistics: ME (-0,0038), MAE (0,42), RMSE (0,57), R2 (0,67)

Contact

Data Holder: Institut National de Pedologie
Contact: Macoumba Loum macoumbaloum@yahoo.fr

A.153 Serbia

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.154 Seychelles

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.155 Sierra Leone

Map source: GSP Gap-Filling

Point data

Number of samples: 11
Sampling period: 1968-1974
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: natural clod; undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.156 Singapore

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.157 Slovakia

Map source: Country submission

Point data

Number of samples: 16748
Sampling period: agricultural soils: 1961 - 1970, forest soils: 2006
SOC analysis method: Wet oxidation (Tyurin method) for agricultural soils, dry combustion for forest soils
BD analysis method: undisturbed sampling (cylinders)

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: National Agricultural and Food Centre, Soil Science and Conservation Research Institute (agricultural soils); National Forestry Centre, Forestry Research Institute (forest soils)
Contact: Rastislav Skalsky (agricultural soils); Pavel Pavlenda (forest soils) r.skalsky@vupop.sk; pavlenda@nlcsk.org

A.158 Slovenia

Map source: Country submission

Point data

Number of samples: 1681
Sampling period: 1980-2003
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Agricultural institute of Slovenia
Contact: Borut Vrscaj borut.vrscaj@kis.si

A.159 Solomon Islands

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.160 Somalia

Map source: Joint Effort with GSP

Point data

Number of samples: 257
Sampling period: 2007
SOC analysis method: wet oxidation
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.161 South Africa

Map source: Joint Effort with GSP

Point data

Number of samples: 11257
Sampling period: 1972-2014
SOC analysis method: Walkley Black
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: Soil, Climate and Water (ARC-SCW)
Contact: Dr. Maila scwinfo@arc.gis.za
Institution: Soil, Climate and Water (ARC-SCW)

A.162 South Sudan

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.163 Spain

Map source: GSP Gap-Filling

Point data

Number of samples: 2696
Sampling period: 2009
SOC analysis method: dry combustion
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machine model based on LUCAS data
Validation statistics: No Data

Contact

Data Holder: European Soil Data Centre (ESDAC)
Contact: esdac@jrc.ec.europa.eu
Institution: European Soil Data Centre (ESDAC)
Citation: Toth, G., Jones, A., Montanarella, L. (eds.) 2013. '"LUCAS Topsoil Survey. Methodology, data and results. JRC Technical Reports. Luxembourg. Publications Office of the European Union, EUR26102 - Scientific and Technical Research series - ISSN 1831-9424 (online); ISBN 978-92-79-32542-7; doi: 10.2788/97922"

A.164 Sri Lanka

Map source: Country submission

Point data

Number of samples: 233
Sampling period: 2000 - 2005
SOC analysis method: Walkley-Black
BD analysis method: Undisturbed core sampling

Mapping method

Mapping method details: Multiple linear regression
Validation statistics: No Data

Contact

Data Holder: Natural Resources Management Centre, Department of Agriculture
Contact: Dr. Ajantha de Silva ajandes@gmail.com

A.165 Sudan

Map source: Country submission

Point data

Number of samples: 1584
Sampling period: 1960-2015
SOC analysis method: Walkley-Black
BD analysis method: paraffin coating

Mapping method

Mapping method details: Random Forest
Validation statistics: STATISTICS_MAXIMUM=4.8131771087646 STATISTICS_MEAN=1.1700157773579 STATISTICS_MINIMUM=0.001964766299352 STATISTICS_STDDEV=0.71722792069521

Contact

Data Holder: Land and Water Research Centre,
Contact: Abdelmagid Ali Elmobarak melmobarak2012@gmail.com

A.166 Suriname

Map source: GSP Gap-Filling

Point data

Number of samples: 178
Sampling period: 1958-1983
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: natural clod

Mapping method

Mapping method details: Support Vector Machine
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.167 Swaziland

Map source: Country submission

Point data

Number of samples: 91
Sampling period: 1997-2014
SOC analysis method: Loss ignition , Wet Oxidation , Dry combustion, Infrared reflectance
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: Random forest regression
Validation statistics: RMSE, R2

Contact

Data Holder: Department of Geography, Environmental Science and Planning, University of Swaziland
Contact: Dr. Wisdom M. Dlamini mwdlamini@gmail.com, wdlamini@uniswa.sz

A.168 Sweden

Map source: Country submission

Point data

Number of samples: 19097
Sampling period: Swedish Forest Soil Inventory: 2003-2012, Cropland samples: 2001-2012
SOC analysis method: Dry combustion (forest and part of cropland)/LOI (part of cropland)
BD analysis method: Undisturbed sampling (O-layer, topsoil on forest soils)

Mapping method

Mapping method details: Multivariate adaptive regression splines (MARSplines)
Validation statistics: No Data

Contact

Data Holder: Dep of Soil and Environment, SLU
Contact: Johan Stendahl johan.stendahl@slu.se
Citation: Stendahl, J., Johansson, M.B., Eriksson, E., Nilsson, A., Langvall, O., 2010. Soil Organic Carbon in Swedish Spruce and Pine Forests - Differences in Stock Levels and Regional Patterns. Silva Fennica 44, 5-21. https://doi.org/10.14214/sf.159

A.169 Switzerland

Map source: Joint Effort with GSP

Point data

Number of samples: 1175
Sampling period: 2010-2014
SOC analysis method: Dry combustion; TruSpec CN (Leco) at 950 degrees Celsius, in calcareous soils inorganic carbon determined by adding hydrochloric acid and measuring the acid gas, Organic carbon result of total carbon minus 12% of the total calcium carbonate
BD analysis method: Mass dry fine earth (2 mm) divided by the volume of the fine earth. Therefore, the mass of the coarse fraction (¿ 2 mm) and the volume of this fraction had to be determined.

Mapping method

Mapping method details: Caret ensemble of Random Forest, Cubist, KKNN, Bayesian trees, Partial Least Squares Regression, Principal Components Regression
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.170 Syrian Arab Republic

Map source: Joint Effort with GSP

Point data

Number of samples: 1220
Sampling period: 1965-1984
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; natural clod; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines
Validation statistics: No Data

Contact

Data Holder: General Commission for Scientific Agriculture Research
Contact: Syrian Arab Republic, Damascus, Al-Hyjazz Square, General Commission for Scientific Agriculture Research
Institution: General Commission for Scientific Agriculture Research

A.171 Tajikistan

Map source: GSP Gap-Filling

Point data

Number of samples: 21
Sampling period: 1974
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: natural clod

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.172 Thailand

Map source: Country submission

Point data

Number of samples: 70000
Sampling period: 2015
SOC analysis method: Walkey and Black method
BD analysis method: undisturbed sampling

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Land Development Department
Contact: Suradesh Tiewtrakool dgldd@ldd.go.th

A.173 The former Yugoslav Republic of Macedonia

Map source: GSP Gap-Filling

Point data

Number of samples: 3301
Sampling period: 1951-2013
SOC analysis method: wet oxidation
BD analysis method: No Data

Mapping method

Mapping method details: Caret ensemble of Random Forest, Cubist, KKNN, Bayesian trees, Partial Least Squares Regression, Principal Components Regression
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.174 Timor-Leste

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.175 Togo

Map source: GSP Gap-Filling

Point data

Number of samples: 9
Sampling period: 1985-1997
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied;
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry;

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Benin, Burkina Faso, Cote d'Ivoire, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Nigeria, Senegal, Sierra Leone, Togo
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.176 Tokelau (Associate Member)

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.177 Tonga

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.178 Trinidad and Tobago

Map source: Joint Effort with GSP

Point data

Number of samples: 122
Sampling period: 1967-1972
SOC analysis method: wet oxidation
BD analysis method: cores

Mapping method

Mapping method details: Support vector machine based on statistical simulation of the position of sampling points
Validation statistics: No Data

Contact

Data Holder: University of The West Indies
Contact: Ronald Roopnarine. Gaius Eudoxie ronald.roopnarine@sta.uwi.edu
Institution: University of The West Indies

A.179 Tunisia

Map source: GSP Gap-Filling

Point data

Number of samples: 58
Sampling period: 1965-2004
SOC analysis method: No Data
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.180 Turkey

Map source: Country submission

Point data

Number of samples: 7742
Sampling period: 2008-2009
SOC analysis method: Total Organic Carbon Analyzer (Dry combustion)
BD analysis method: paraffin coating

Mapping method

Mapping method details: Multiple Regression Kriging
Validation statistics: No Data

Contact

Data Holder: General Directorate of Agricultural Research And Policies, Soil, Fertilizer and Water Resources Central Research Institute Ankara, TURKEY
Contact: Dr. Bulent Sonmez, Doc. Dr. Aynur Ozbance bulent.sonmez@tarim.gov.tr, aynur.ozbahce@tarim.gov.tr
Citation: National Geospatial Soil Fertility and Soil Organic Carbon Information System (UTF/TUR/057/TUR)

A.181 Turkmenistan

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.182 Tuvalu

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.183 Uganda

Map source: GSP Gap-Filling

Point data

Number of samples: 12
Sampling period: 1988
SOC analysis method: No Data
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.184 Ukraine

Map source: Country submission

Point data

Number of samples: 3931
Sampling period: 1964-2016
SOC analysis method: Most of the samples: Tyurin method (ISO 10694:1995), 5 samples: mid-infrared spectrometry, peat samples: Zeydelman method (based on ash content)
BD analysis method: Measures in the field, ISO 11272:1998

Mapping method

Mapping method details: Random Forest
Validation statistics: For mineral soils: ME=0.01, MAE=1.32 RMSE=1.82, R2=0.56. For peat soils: ME=-0.12, MAE=1.87, RMSE=2.45, R2=0.22.

Contact

Data Holder: National Scientific Center "Institute for Soil Science and Agrochemistry Research named after O.N. Sokolovsky" (NSC ISSAR)
Contact: Sviatoslav Baliuk pochva@meta.ua

A.185 United Arab Emirates

Map source: GSP Gap-Filling

Point data

Number of samples: 0
Sampling period: No Data
SOC analysis method: No Data
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.186 United Kingdom

Map source: Country submission

Point data

Number of samples: 17421
Sampling period: England and Wales: 1979-1983, Scotland: 1947-1988, Northern Ireland: 1988-1997
SOC analysis method: Organic carbon was measured by loss-on-ignition for soils estimated to contain more than about 20% organic carbon, or by dichromate digestion
BD analysis method: Measured bulk density sampled using tin cores

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Cranfield University
Contact: Caroline Keay c.keay@cranfield.ac.uk
Citation: Bradley, R.I., Milne, R., Bell, J., Lilly, A., Jordan, C. and Higgins, A. (2005), A soil carbon and land use database for the United Kingdom. Soil Use and Management, 21: 363-369. doi:10.1079/SUM2005351

A.187 United Republic of Tanzania

Map source: Country submission

Point data

Number of samples: 3215
Sampling period: after 1992
SOC analysis method: Wet oxidation
BD analysis method: Undisturbed sampling

Mapping method

Mapping method details: R. Kriging, Random Forest
Validation statistics: ME: -0.00, MAE: 1.23, RMSE: 1.8, R2: 0.53

Contact

Data Holder: Agricultural Research Institute Mlingano
Contact: Joseph D. Mbogoni jdjmbogoni@gmail.com
Citation: Kempen, B. 2016. Development of a soil carbon map for the United Republic of Tanzania. ISRIC, Wageningen.

A.188 United States of America

Map source: Country submission

Point data

Number of samples: 10000
Sampling period: 1950-2015
SOC analysis method: multiple methods over time - primarily dry combustion
BD analysis method: Bulk density measured on undisturbed clods coated in saran (KSSL, 2014

Mapping method

Mapping method details: No Data
Validation statistics: No Data

Contact

Data Holder: Natural Resource Conservation Service
Contact: Micheal Robotham michael.robotham@wdc.usda.gov

A.189 Uruguay

Map source: Country submission

Point data

Number of samples: 160
Sampling period: 1964-1982
SOC analysis method: Oxidation with potassium dichromate and sulfuric acid without external heat application (Walkey Black method) Factor 1.3 is used to estimate the total organic C from the C oxidized
BD analysis method: Imperturbed sampling with cylinders with 100 mL edge, with sampler Eijkelkamp. Expansion in water for 48 hours, adjust to the volume of 100mL dried in stove to 105 and weight the sample. Also in several profiles the apparent density was estimated with local pedotransference model (Fernandez 1979)

Mapping method

Mapping method details: Multiple linear regression, R Kriging,
Validation statistics: RMSE = 0.4566, MAE= 0.3558, me_mean= -0.0002158, R2=0.5549

Contact

Data Holder: Direccion General de Recursos Naturales
Contact: Martin Dell'Acqua Gonzalo Pereira Pablo Prieto Fernando Fontes Fabian Davila mdellacqua@mgap.gub.uy mdavila@mgap.gub.uy ffontes@mgap.gub.uy pprieto@mgap.gub.uy gpereira@mgap.gub.uy
Citation: Direccion General de Recursos Naturales-DGRN Ministerio de Ganaderia y Agricultura y Pesca-MGAP - Uruguay 2017

A.190 Uzbekistan

Map source: Country submission

Point data

Number of samples: 4969
Sampling period: 1998-2008
SOC analysis method: Tyurin method
BD analysis method: BD sampling provided in accordance with manuals of soil survey

Mapping method

Mapping method details: Random Forest model based on the ensemble globally available data from Afghanistan, Pakistan, Turkmenistan, Tajikistan, Kyrgyzstan and the original data provided by Kazakhstan and Uzbekistan.
Validation statistics: R2 =0.88, RMSE=10.5

Contact

Data Holder: UZGIP Design and Research Institute
Contact: Bakhodir Ruziboev uzgip_tas@umail.uz, uzgip@bk.ru

A.191 Vanuatu

Map source: External dataset: soilgrids.org

Contact

Data Holder: ISRIC World Soil Information
Contact: soilgrids.org
Citation: Hengl, T., Mendes de Jesus, J., Heuvelink, G. B.M., Ruiperez Gonzalez, M., Kilibarda, M. et al. (2017) SoilGrids250m: global gridded soil information based on Machine Learning. PLoS ONE 12(2): e0169748. doi:10.1371/journal.pone.0169748.

A.192 Venezuela (Bolivarian Republic of)

Map source: Country submission

Point data

Number of samples: 310
Sampling period: 1960-2000
SOC analysis method: Walkley Black
BD analysis method: No Data

Mapping method

Mapping method details: Random Forest
Validation statistics: RMSE = 4.11 kg/m2, R2 = 0.0272, Mean error = 1.28 kg/m2, Mean absolute error = 1.96 kg/m2

Contact

Data Holder: Sociedad Venezolana de la Ciencia del Suelo (SVCS)
Contact: Juan C.Rey svcs.org

A.193 Viet Nam

Map source: Country submission

Point data

Number of samples: 1024
Sampling period: 1990-2016
SOC analysis method: Walkley Black- Wet Oxidation
BD analysis method: Soil sample was collected at natural status by a 100 cubic centimeters metal tube/ cylinder plug directly into soil layer

Mapping method

Mapping method details: Regression Kriging
Validation statistics: ME: -0.000242; MAE: 0.286; RMSE: 0.3858; R: 0.511

Contact

Data Holder: Soils and Fertilizers Research Institute
Contact: Vu Manh Quyet quyetvm.sfri@mard.gov.vn; vmquyet@gmail.com

A.194 Yemen

Map source: GSP Gap-Filling

Point data

Number of samples: 270
Sampling period: 1969-1990
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: No Data

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Algeria, Chad, Egypt, Iraq, Jordan, Lebanon, Libya, Mali, Mauritania, Morocco, Niger, Oman, Qatar, Saudi Arabia, Sudan, Syrian Arab Republic, United Arab Emirates, Western Sahara and Yemen
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.195 Zambia

Map source: GSP Gap-Filling

Point data

Number of samples: 460
Sampling period: 1963-1984
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7]

(and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

A.196 Zimbabwe

Map source: GSP Gap-Filling

Point data

Number of samples: 179
Sampling period: 1964-2010
SOC analysis method: wet oxidation with Sulphuric acid [H2SO4] - Potassiumbichromate [K2Cr2O7] (and Phosphoric acid [H3PO4]) mixture, temperature = no external heat, detection = titrimetric, calculation = default (Walkley and Black) correction factor for recovery of 1.3 applied
BD analysis method: undisturbed soil in metal/PVC-ring (soil core) (soil sufficiently coherent), measurement condition = oven dry; clod reconstituted from ¡ 2 mm sample formed by wetting and dessication cycles that stimulate reconsolidating by water in a field setting, measurement condition = equilibrated at 33 kPa

Mapping method

Mapping method details: Support Vector Machines model based on the ensemble globally available data from Burundi, Central African Republic, Democratic Republic of Congo, Kenya, Rwanda, South Sudan, Tanzania, Uganda, Zambia and Zimbabwe
Validation statistics: No Data

Contact

Data Holder: Global Soil Partnership
Contact: http://www.fao.org/global-soil-partnership/en/
Institution: Global Soil Partnership

Appendix B

Metadata questionnaire

B.1 Source data

- Total number of soil profiles/sampling locations;
- Type of sampling (profiles/augers/topsoil);
- Number of locations for each sampling method;
- Sampling Period (e.g. 1980-2007);
- Georeferencing (GPS coordinates/Location names);
- Depth of sampling;
- Sampling design (e.g. transect, catena, land use etc.)

B.2 Analysis methods

- Methods of Soil Organic Carbon analysis;
- Methods of Bulk Density analysis (measured/estimated)
  - Details about the sampling;
  - Pedotransfer functions, default values, citations;
  - External data-sets (HWSD, SoilGrids.org);
- Methods of Coarse Fragments (measured/estimated/NA)
  - Coarse fragments unit (e.g. % volume / % weight)
- Peat (sampling and description method);

B.3 Mapping

- mapping method (DSM / Conventional upscaling)
  - The method(s) used (e.g. Multiple linear regression, Regression-Kriging, Random Forest. . .);
- Map quality measures (Digital Soil Mapping)
  - Mean error (ME), Mean absolute error , root mean squared error, amount of variance explained;
- Units (tonnes/ha, kg/m2);
- Resampling Method (if used)

B.4 Contact details

- Submitter contact details;
- Institute (Data Holder / Handler);
- Citation;
- Update Frequency;
- Comments, Remarks

Appendix C

Changelog file of the GSOCmap

```
GSOCmap:
change log. From 05/04/2018. Most recent changes first / on top.
-----------------------------------------------------------------

VERSION 1.2.0

* Country Submission: CHL, COL

VERSION 1.1.0 -> (Public)

* Improved Maps: CMR, KHM
* Country Submission: RWA

VERSION 0.14.2 -> VERSION 1.0.0 (Public)

* Major inland water Surfaces have been masked out from the map.

VERSION 0.14

* New Submissions: DOM, HTI
* FRA has been added to the map (Official Submission)
* Improved maps for ALB, BIH, VRI, CXR, FSM, HRV, MNP, NFK, PLW, SGP, SPM

VERSION 0.13b

* FRA has been added to the map (GSP gap Filling).

VERSION 0.13a

* Improved maps submitted by ECU, URU, PER
* FRA has been removed from the map "official request"

VERSION 0.12.1
```

```
* Corrected map submitted by DEU
* Improved maps for KAZ, UZB, TKM, TJK,

VERSION 0.12

* New country submissions: JOR, SVN
* Improved map of BRA submitted by the country
* Improved maps for KAZ, UZB, TKM, TJK, AFG and PAK using data provided by
  KAZ and UZB + WOSIS
* Improved GSP gapfilling maps for SVK, DEU and small EU countries: AND,
  CYP, FRO, GGY, GIB, IMN, JEY, LIE, MCO, VAT, XAD, XNC

VERSION 0.11.1

* New country submission: SDN
* Joint effort: improved map IND

VERSION 0.11

* Joint effort: IND, LAO
* Improved map MAR

VERSION 0.10

* Improved the procedure for filling the NA values between the country boarders:
 a 5km buffer along the boarders was used for gap-filling, excluding water
 bodies and coastlines; no inland water bodies or urban areas were gap-filled.

VERSION 0.9.1

* Joint effort: SYR
* Improved maps of ETH, ARM submitted by the countries

VERSION 0.9

* SWE Improved
* Gapfilling using LUCAS Soil (GSP): SVK, SVN, ISL and small EU
  countries: AND, CYP, FRO, GGY, GIB, IMN, JEY, LIE, MCO, VAT, XAD
* Gapfilling GSP for Carribean (BHS) and GUY, GUF
* Joint Effort: HTI, JAM
* New Submission: DNK, SWZ
* Updated Map: MOZ
* Gapfilling (SoilGrids): Small islands
* Removed No Data zones at borderlines (GDAL, gdal_fillnodata.py, This
  algorithm will interpolate values for all designated nodata pixels. For each
  pixel a four direction conic search is done to find values to interpolate from
  (using inverse distance weighting).
* Changed SoilGrids Source Data (1km to 250 m)
* Removed Outliers (USA, BRA, DNK)
```

```
* Applied global mask

VERSION 0.8

* new corrected map from PRY
* new version of MOZ map submitted by the country
* updated model for MLI
* improved estimation of 0-30 stocks for ESP, IRL, FRA, GRC, BGR, ROU,
   LTU, LVA, POL, CZE, EST

VERSION 0.7

* Improved bulk density estimation: CHN, BEN, BFA, CIV, GHA, GIN, GNB, LBR,
  MLI, NGA, SEN, SLE, TGO, BDI, CAF, COD, RWA, SSD, UGA, ZMB, ZWE

VERSION 0.5

* FIN and TZA replaced with the country data
* New Data: CHE, MKD, MLT
* Calculation errors fixed: CUB, IDN, MOZ, MWI
* Improved Model: ESP, IRL, FRA, GRC, BGR, ROU, LTU, LVA, POL, CZE, EST
* Gap Filling (SoilGrids): BGD, LAO, KHM, KOR, PRK, HND, GTM, JAM, HTI, BHS

VERSION 0.4

* Reduced size (VERSION 0.3 exported as Version 0.4 in R (raster pckg))

VERSION 0.3

* Removed reported outliers (above 2000) and minus values

VERSION 0.1

* First map combining the folowing 0.1 maps:
  [1] "pred/soilgrids/AFG.tif"                 "pred/soilgrids/ALB.tif"
  [3] "pred/soilgrids/BIH.tif"                 "pred/soilgrids/GEO.tif"
  [5] "pred/soilgrids/GUF.tif"                 "pred/soilgrids/GUY.tif"
  [7] "pred/soilgrids/HRV.tif"                 "pred/soilgrids/IRN.tif"
  [9] "pred/soilgrids/KGZ.tif"                 "pred/soilgrids/MDG.tif"
 [11] "pred/soilgrids/MNE.tif"                 "pred/soilgrids/PAK.tif"
 [13] "pred/soilgrids/PNG.tif"                 "pred/soilgrids/SRBXKO.tif"
 [15] "pred/soilgrids/TJK.tif"                 "pred/soilgrids/TKM.tif"
 [17] "pred/Joint-notsubmitted/CUB.tif"        "pred/Joint-notsubmitted/SUR.tif"
 [19] "pred/Joint-notsubmitted/TTO.tif"        "pred/GSP/AGO.tif"
 [21] "pred/GSP/ARE.tif"                       "pred/GSP/BDI.tif"
 [23] "pred/GSP/BEN.tif"                       "pred/GSP/BFA.tif"
 [25] "pred/GSP/BLR.tif"                       "pred/GSP/BWA.tif"
 [27] "pred/GSP/CAF.tif"                       "pred/GSP/CHN.tif"
 [29] "pred/GSP/CIV.tif"                       "pred/GSP/CMR.tif"
```

```
 [31] "pred/GSP/COD.tif"                        "pred/GSP/COG.tif"
 [33] "pred/GSP/DZA.tif"                        "pred/GSP/EGY.tif"
 [35] "pred/GSP/ERI.tif"                        "pred/GSP/ESH.tif"
 [37] "pred/GSP/GAB.tif"                        "pred/GSP/GHA.tif"
 [39] "pred/GSP/GIN.tif"                        "pred/GSP/GNB.tif"
 [41] "pred/GSP/GNQ.tif"                        "pred/GSP/IRQ.tif"
 [43] "pred/GSP/ISR.tif"                        "pred/GSP/JOR.tif"
 [45] "pred/GSP/KEN.tif"                        "pred/GSP/KWT.tif"
 [47] "pred/GSP/LBN.tif"                        "pred/GSP/LBR.tif"
 [49] "pred/GSP/LBY.tif"                        "pred/GSP/MAR.tif"
 [51] "pred/GSP/MLI.tif"                        "pred/GSP/MMR.tif"
 [53] "pred/GSP/MRT.tif"                        "pred/GSP/NAM.tif"
 [55] "pred/GSP/NER.tif"                        "pred/GSP/NGA.tif"
 [57] "pred/GSP/OMN.tif"                        "pred/GSP/QAT.tif"
 [59] "pred/GSP/RWA.tif"                        "pred/GSP/SAU.tif"
 [61] "pred/GSP/SDN.tif"                        "pred/GSP/SEN.tif"
 [63] "pred/GSP/SLE.tif"                        "pred/GSP/SOM.tif"
 [65] "pred/GSP/SSD.tif"                        "pred/GSP/SYR.tif"
 [67] "pred/GSP/TCD.tif"                        "pred/GSP/TGO.tif"
 [69] "pred/GSP/TUN.tif"                        "pred/GSP/TZA.tif"
 [71] "pred/GSP/UGA.tif"                        "pred/GSP/YEM.tif"
 [73] "pred/GSP/ZAF.tif"                        "pred/GSP/ZMB.tif"
 [75] "pred/GSP/ZWE.tif"                        "pred/own/ARG.tif"
 [77] "pred/own/ARM.tif"                        "pred/own/AUS.tif"
 [79] "pred/own/AUT.tif"                        "pred/own/AZE.tif"
 [81] "pred/own/BEL.tif"                        "pred/own/BOL.tif"
 [83] "pred/own/BRA.tif"                        "pred/own/BTN.tif"
 [85] "pred/own/CAN.tif"                        "pred/own/COL.tif"
 [87] "pred/own/CRI.tif"                        "pred/own/DEU.tif"
 [89] "pred/own/DOM.tif"                        "pred/own/ECU.tif"
 [91] "pred/own/ETH.tif"                        "pred/own/GBR.tif"
 [93] "pred/own/GHA.tif"                        "pred/own/HUN.tif"
 [95] "pred/own/IDN_BALI_STOCK.tif"             "pred/own/IDN_BANTEN_STOCK.tif"
 [97] "pred/own/IDN_GORONTALO_STOCK.tif"        "pred/own/IDN_JABAR_STOCK.tif"
 [99] "pred/own/IDN_JATENG_STOCK.tif"           "pred/own/IDN_JATIM_STOCK.tif"
[101] "pred/own/IDN_KALBAR_STOCK.tif"           "pred/own/IDN_KALSEL_STOCK.tif"
[103] "pred/own/IDN_KALTENG_STOCK.tif"          "pred/own/IDN_KALTIM_STOCK.tif"
[105] "pred/own/IDN_MALUKU_STOCK.tif"           "pred/own/IDN_MALUKU_UTARA_STOCK.tif"
[107] "pred/own/IDN_NTB_LOMBOK_STOCK.tif"       "pred/own/IDN_NTB_SUMBAWA_STOCK.tif"
[109] "pred/own/IDN_NTT_FLORES_STOCK.tif"       "pred/own/IDN_NTT_SUMBA_STOCK.tif"
[111] "pred/own/IDN_NTT_TIMOR_BARAT_STOCK.tif" "pred/own/IDN_PAPUA_BARAT_STOCK.tif"
[113] "pred/own/IDN_PAPUA_STOCK.tif"            "pred/own/IDN_SULBAR_STOCK.tif"
[115] "pred/own/IDN_SULSEL_STOCK.tif"           "pred/own/IDN_SULTENG_STOCK.tif"
[117] "pred/own/IDN_SULUT_STOCK.tif"            "pred/own/IDN_SUMATERA_SOC.tif"
[119] "pred/own/IND.tif"                        "pred/own/IRQ.tif"
[121] "pred/own/ITA.tif"                        "pred/own/JOR.tif"
[123] "pred/own/JPN.tif"                        "pred/own/KAZ.tif"
[125] "pred/own/KEN.tif"                        "pred/own/LBN.tif"
[127] "pred/own/LKA.tif"                        "pred/own/LSO.tif"
```

```
[129] "pred/own/LUX.tif"                    "pred/own/MAR.tif"
[131] "pred/own/MDA.tif"                    "pred/own/MEX.tif"
[133] "pred/own/MNG.tif"                    "pred/own/MOZ.tif"
[135] "pred/own/MWI.tif"                    "pred/own/NIC.tif"
[137] "pred/own/NLD.tif"                    "pred/own/NPL.tif"
[139] "pred/own/NZL.tif"                    "pred/own/PAN.tif"
[141] "pred/own/PER.tif"                    "pred/own/PHL.tif"
[143] "pred/own/PRY.tif"                    "pred/own/RUS.tif"
[145] "pred/own/SEN.tif"                    "pred/own/SLV.tif"
[147] "pred/own/SWE.tif"                    "pred/own/THA.tif"
[149] "pred/own/TUR.tif"                    "pred/own/UKR.tif"
[151] "pred/own/URY.tif"                    "pred/own/USA_ak.tif"
[153] "pred/own/USA_as.tif"                 "pred/own/USA_conus.tif"
[155] "pred/own/USA_hi.tif"                 "pred/own/USA_pac_basin.tif"
[157] "pred/own/USA_prvi.tif"               "pred/own/UZB.tif"
[159] "pred/own/VEN.tif"                    "pred/own/VNM.tif
```

Appendix D

Example scripts used in GSP gapfilling

The scripts used for the different maps prepared by the GSP Secretariat are based in the ones presented in the SOC Mapping Cookbook [Yigini et al., 2017].

D.1 Data preparation for soil profiles

```
dat <- read.csv(file = "data/horizons.csv")

# Explore the data
str(dat)
summary(dat)

dat_sites <- read.csv(file = "data/site-level.csv")

# Explore the data
str(dat_sites)

# summary of column CRF (Coarse Fragments) in the example data base
summary(dat$CRF)

# Convert NA's to 0
dat$CRF[is.na(dat$CRF)] <- 0

hist(dat$CRF)

# Creating a function in R to estimate BLD using the SOC
# SOC is the soil organic carbon content in \%
estimateBD <- function(SOC, method="Saini_1996"){
  OM <- SOC * 1.724
  if(method=="Saini_1996"){BD <- 1.62 - 0.06 * OM}
  if(method=="Drew_1973"){BD <- 1 / (0.6268 + 0.0361 * OM)}
  if(method=="Jeffrey_1979"){BD <- 1.482 - 0.6786 * (log(OM))}
```

```
  if(method=="Grigal_1989"){BD <- 0.669 + 0.941 * exp(1)^(-0.06 * OM)}
  if(method=="Adams_1973"){BD <- 100 / (OM /0.244 + (100 - OM)/2.65)}
  if(method=="Honeyset_Ratkowsky_1989"){BD <- 1/(0.564 + 0.0556 * OM)}
  return(BD)
}

# summary of BLD (bulk density) in the example data base
summary(dat$BLD)

# See the summary of values produced using the pedo-transfer
# function with one of the proposed methods.
summary(estimateBD(dat$SOC[is.na(dat$BLD)], m
                   ethod="Honeyset_Ratkowsky_1989"))

# Fill NA's using the pedotransfer function:
dat$BLD[is.na(dat$BLD)] <- estimateBD(dat$SOC[is.na(dat$BLD)],
                                      method="Grigal_1989")

# explore the results
boxplot(dat$BLD)

# Load aqp package
library(aqp)

# Promote to SoilProfileCollection
# The SoilProfileCollection is a object class in R designed to
# handle soil profiles
depths(dat) <- ProfID ~ top + bottom

# Merge the soil horizons information with the site-level
# information from dat_sites
site(dat) <- dat_sites

# Set spatial coordinates
coordinates(dat) <- ~ X + Y

# A summary of our SoilProfileCollection
dat

library(GSIF)

## Estimate 0-30 standard horizon usin mass preserving splines
try(SOC <- mpspline(dat, 'SOC', d = t(c(0,30))))
try(BLD <- mpspline(dat, 'BLD', d = t(c(0,30))))
try(CRFVOL <- mpspline(dat, 'CRF', d = t(c(0,30))))

## Prepare final data frame
dat <- data.frame(id = dat@site$ProfID,
```

```
                    Y = dat@sp@coords[,2],
                    X = dat@sp@coords[,1],
                    SOC = SOC$var.std[,1],
                    BLD = BLD$var.std[,1],
                    CRFVOL = CRFVOL$var.std[,1])

dat <- dat[complete.cases(dat),]

## Take a look to the results
head(dat)

# Estimate Organic Carbon Stock
# SOC must be in g/kg
# BLD in kg/m3
# CRF in percentage
OCSKGM <- OCSKGM(ORCDRC = dat$SOC, BLD = dat$BLD*1000,
                 CRFVOL = dat$CRFVOL, HSIZE = 30)

dat$OCSKGM <- OCSKGM
dat$meaERROR <- attr(OCSKGM,"measurementError")
dat <- dat[dat$OCSKGM>0,]
summary(dat)

## We can save our processed data as a table
write.csv(dat, "data/dataproc.csv")
```

D.2 Mixing covariates and soil points data

```
# Load the processed data. This table was prepared in the previous
# chapter.
dat <- read.csv("data/dataproc.csv")

files <- list.files(path = "covs", pattern = "tif$",
                    full.names = TRUE)

covs <- stack(files)

covs <- stack(covs, soilmap.r)

# correct the name for layer 14
names(covs)[14] <- "soilmap"

#mask the covariates with the country mask from the data repository
mask <- raster("data/mask.tif")

covs <- mask(x = covs, mask = mask)
```

```r
plot(covs)

#upgrade points data frame to SpatialPointsDataFrame
coordinates(dat) <- ~ X + Y

# extract values from covariates to the soil points
dat <- extract(x = covs, y = dat, sp = TRUE)

# LCEE10 and soilmap are categorical variables
dat@data$LCEE10 <- as.factor(dat@data$LCEE10)
dat@data$soilmap <- as.factor(dat@data$soilmap)

#levels(soilmap) <- Symbol.levels

summary(dat@data)

dat <- as.data.frame(dat)

# The points with NA values has to be removed
dat <- dat[complete.cases(dat),]

# export as a csv table
write.csv(dat, "data/MKD_RegMatrix.csv", row.names = FALSE)
```

D.3 Fitting a RK model to predict the OCS

```r
# load data
dat <- read.csv("data/MKD_RegMatrix.csv")

dat$LCEE10 <- as.factor(dat$LCEE10)
dat$soilmap <- as.factor(dat$soilmap)

# explore the data structure
str(dat)

library(sp)

# Promote to spatialPointsDataFrame
coordinates(dat) <- ~ X + Y

class(dat)

dat@proj4string <- CRS(projargs = "+init=epsg:4326")

dat@proj4string

library(raster)
```

```r
# list all the itf files in the folder covs/
files <- list.files(path = "covs", pattern = "tif$",
                    full.names = TRUE)

# load all the tif files in one rasterStack object
covs <- stack(files)

# load the vectorial version of the soil map
soilmap <- shapefile("MK_soilmap_simple.shp")

# rasterize using the Symbol layer
soilmap@data$Symbol <- as.factor(soilmap@data$Symbol)
soilmap.r <- rasterize(x = soilmap, y = covs[[1]], field = "Symbol")

# stack the soil map and the other covariates
covs <- stack(covs, soilmap.r)

# correct the name for layer 14
names(covs)[14] <- "soilmap"

# print the names of the 14 layers:
names(covs)

datdf <- dat@data

datdf <- datdf[, c("OCSKGM", names(covs))]

## Fit a multiple linear regression model between the log transformed values
## of OCS and the top 20 covariates
model.MLR <- lm(log(OCSKGM) ~ ., data = datdf)

## stepwise variable selection
model.MLR.step <- step(model.MLR, direction="both")

## summary and anova of the new model using stepwise covariates selection
summary(model.MLR.step)
anova(model.MLR.step)

## graphical diagnosis of the regression analysis
par(mfrow=c(2,2))
plot(model.MLR.step)
par(mfrow=c(1,1))

## collinearity test using variance inflation factors
library(car)
vif(model.MLR.step)

#problematic covariates should have sqrt(VIF) > 2
```

```r
sqrt(vif(model.MLR.step))

## Removing B07CHE3 from the stepwise model:
model.MLR.step <- update(model.MLR.step, . ~ . - B07CHE3)

# Test the vif again:
sqrt(vif(model.MLR.step))

## summary  of the new model using stepwise covariates selection
summary(model.MLR.step)

# outlier test using the Bonferroni test
outlierTest(model.MLR.step)

# Project point data.
dat <- spTransform(dat, CRS("+init=epsg:6204"))

# project covariates to VN-2000 UTM 48N
covs <- projectRaster(covs, crs = CRS("+init=epsg:6204"), method='ngb')
covs$LCEE10 <- as.factor(covs$LCEE10)
covs$soilmap <- as.factor(covs$soilmap)

## Promote covariates to spatial grid dataframe.
covs.sp <- as(covs, "SpatialGridDataFrame")
covs.sp$LCEE10 <- as.factor(covs.sp$LCEE10)
covs.sp$soilmap <- as.factor(covs.sp$soilmap)

### RK model
library(automap)


## Run regression kriging prediction. This step can take hours...!
OCS.krige <- autoKrige(formula = as.formula(model.MLR.step$call$formula),
                       input_data = dat,
                       new_data = covs.sp,
                       verbose = TRUE,
                       block = c(1000, 1000))

OCS.krige

## Convert prediction and standard deviation to rasters
## And back-tansform the vlaues
RKprediction <- exp(raster(OCS.krige$krige_output[1]))
RKpredsd <- exp(raster(OCS.krige$krige_output[3]))


plot(RKprediction)
```

```r
## Save results as tif files
writeRaster(RKprediction, filename = "results/MKD_OCSKGM_RK.tif")
writeRaster(RKpredsd, filename = "results/MKD_OCSKGM_RKpredsd.tif")

# save the model
saveRDS(model.MLR.step, file="results/RKmodel.Rds")
```

D.4 Fitting a random forest model to predict the OCS

```r
library(reshape)

# Correlation analysis to select covariates
names(dat)
COR <- cor(as.matrix(dat[,7]), as.matrix(dat[,-c(1:8)]))
COR
x <- subset(melt(COR), value != 1 | value != NA)
x <- x[with(x, order(-abs(x$value))),]
x[1:25,]

idx <- as.character(x$X2[1:25])

dat2 <- dat[c('OCSKGM', idx)]
names(dat2)

COVall <- COV
COV <- COV[[idx]]

plot(COV)


library(randomForest)

# Try different values of mtry and select the model with the optimal value
model <- tuneRF(dat[,c(names(COV))], dat$OCSKGM, stepFactor=1.5, doBest = TRUE,
                improve = 0.5)

# Use the model to predict the SOC in the covariates space
beginCluster()
start <- Sys.time()
pred <- clusterR(COV, predict, args=list(model))
print(Sys.time() - start)
endCluster()
```

D.5 Fitting a svm model to predict the OCS

```
# Correlation analysis to select covariates
names(dat)
COR <- cor(as.matrix(dat[,7]), as.matrix(dat[,-c(1:8)]))
COR
x <- subset(melt(COR), value != 1 | value != NA)
x <- x[with(x, order(-abs(x$value))),]
x[1:25,]

idx <- as.character(x$X2[1:25])

dat2 <- dat[c('OCSKGM', idx)]
names(dat2)

COVall <- COV
COV <- COV[[idx]]

plot(COV)


library(e1071)
library(caret)

#  Test different values of epsilon and cost
tuneResult <- tune(svm, OCSKGM ~.,  data = dat[,c("OCSKGM", names(COV))],
                   ranges = list(epsilon = seq(0,1,0.1),
                                 cost = c(.5,1,1.5,2,5,10))
)

# Choose the model with the best combination of epsilon and cost
tunedModel <- tuneResult$best.model

# Use the model to predict the SOC in the covariates space
beginCluster()
start <- Sys.time()
pred <- clusterR(COV, predict, args=list(tunedModel))
print(Sys.time() - start)
endCluster()
```

GLOBAL SOIL ORGANIC CARBON Map

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