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Developing the map of carbons sequestration by the different scenarios of land management

Methodical recommendations

Košice
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Developing the map of carbons sequestration by the different scenarios of land management. Methodical recommendations. Compilers: Cherlinka Vasyl, Gallay Michal. Košice: UPJS, 2023, 75 p.

This methodical recommendation provides technical specifications and guidance for the generation of Soil Organic Carbon Sequestration Potential (SOCseq) maps at 1 km resolution for agricultural lands, based on a ‘bottom-up’. SOC stocks 0-30 cm of mineral soils shall be projected over a 20-year period after adoption of Sustainable Soil Management (SSM) practices oriented to increase carbon inputs to cropland and grassland soils. In order to obtain consistent results and to allow comparisons between countries and regions, the use of RothC as a standard spatialized SOC model is requested. General modeling procedures, software, data requirements and data sources are briefly described.

The compilers have made efforts so that people without special training in the field of GIS and digital modeling can reproduce the process. Creation of a SOCseq map is shown on the example of a district of Ukraine.

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1. Introduction

1.1. Background and objectives

Soils constitute the largest active terrestrial carbon (C) pool: an estimated total of 1500-2400 Pg or Gt C up to 1m (Scharlemann et al., 2014; Batjes, 2016; Tifafi et al., 2017). Although soils contribute a major share of agricultural greenhouse gas (GHGs) emissions, due to their large size and long residence time, even small increments of net soil C storage represent a substantial C sink potential (Paustian et al., 2016; Smith et al., 2020). It has been suggested that soil C sequestration through improved soil/land management practices could be a significant greenhouse gas removal strategy (Smith et al, 2008; Lal et al., 2018; Smith et al., 2020). However, the extent and rates of soil organic carbon (SOC) sequestration under different land use and management practices can vary greatly depending on soil characteristics, topography and climate (Smith et al., 2008; Lal et al., 2018; Batjes et al., 2019). It is thus relevant to identify which regions, environments and agricultural systems present the greater potential for increasing SOC stocks, and to establish priorities for the implementation of public and private policies.

Coupling SOC models to GIS (Geographic Information Systems) platforms allows modeling to move from site-specific SOC stocks simulations to spatial simulations (e.g. Smith et al. 2005; Milne et al., 2007; Kamoni et al., 2007; Falloon et al., 2007; Gottschalk et al., 2013; Lugato et al., 2014), and thus to identify conditions with greater SOC sequestration potential. However, the use of GIS-based models may be restricted by the availability of quality local data, as well as technical and computational capacity (FAO, 2019a). In this sense, GSP-FAO has established the 'Global assessment of soil organic carbon sequestration potential initiative' (GSOCseq) (FAO, 2019b) which aims to build this capacity internationally. In the first stage, a 'top-down' empirical modeling approach was implemented to estimate SOC stock changes using IPCC default Tier 1 factors. A 'bottom-up' approach, driven by countries and including local expert knowledge was proposed as a second stage, based on harmonized and best available local data and the implementation of SOC process-oriented models.

Within the framework of the GSOCseq initiative, the objectives of these technical guidelines are to:

- Outline technical specifications for mapping of SOC sequestration potential using harmonized procedures.
- Giving a methodological recommendation for create a harmonized SOC sequestration potential (SOCseq) map.

1.2. General framework for mapping carbon sequestration potential

SOC sequestration estimates will focus on croplands and grazing lands for the current GSOCseq map version. As defined by IPCC (2006), croplands include: all annual and perennial crops (cereals, oils seeds, vegetables, root crops and forages); perennial crops (including trees and shrubs, orchards, vineyards), and their combination with herbaceous crops (e.g., agroforestry); arable land which is normally used for cultivation of annual crops, but which is temporarily used for forage crops or grazing as part of an annual crop-pasture rotation (mixed system), is to be included under croplands. Grazing lands include different land uses permanently dedicated to livestock production with a predominant herbaceous cover, including intensively managed permanent pastures and hay land, extensively managed grasslands and rangelands, savannahs, and shrublands.

Since the proposed standardized methodology and the defined model are neither parameterized nor recommended for use on organic, sandy, saline, and waterlogged soils, soils with SOC stocks higher than 200 t C ha⁻¹, sand contents higher than 90% and/or electrical conductivity higher than 4 dS m⁻¹ at 0-30 cm depth, paddy rice lands, peatlands and wetlands will be masked out from the global results in this map version. Excluded conditions and land uses can be included in future versions of the SOCseq map, as harmonized procedures for specific conditions are developed.

1.2.1. SOC sequestration estimates

In order to assess the SOC sequestration potential, SOC stocks in 0-30 cm of mineral soils shall be projected over a 20-year period, under business-as-usual land use and management, and after adoption of Sustainable Soil Management (SSM) Practices in croplands and

grazing lands. A 20-year period is assumed to be the default period during which SOC stocks are approaching a new steady state, to be able to compare results among regions and countries, and with other estimation methods (e.g., IPCC, 2006 Tier 1-2; IPCC, 2019). Nevertheless, users can project SOC stocks over 20, 50 or 100 years or more, and determine the stocks and the period at which a new steady state is attained according to local conditions, and produce additional sequestration maps.

SOC sequestration can be expressed in different ways, depending on the definition of SOC baseline stocks. These guidelines will refer to two types of SOC sequestration: an ‘absolute SOC sequestration’ (SOCseq abs), expressed as the change in SOC stocks over time relative to a base period (or reference period, t_0); and a ‘relative SOC sequestration’ (SOCseq rel), expressed as the change in SOC stocks over time relative to the business-as-usual scenario (Fig. 1). Thus, the ‘absolute’ attainable SOC sequestration can be determined for the business as usual and SSM practices, and can be either positive, neutral or negative:

$$\Delta \text{SOC}_{\text{ABS}} (\text{t C ha}^{-1}) = \text{SOC}_{\text{SSM/BAU } t} - \text{SOC}_{t_0} \quad (1)$$

where $\text{SOC}_{\text{ssm/bau } t}$ refers to the final SOC stocks after a 20-year period (year 2040, under the business as usual or SSM practices), and SOC_{t_0} refers to the initial or base period SOC stocks (e.g. as in year 2020). The ‘relative’ attainable SOC sequestration is either neutral or positive, can be determined as:

$$\Delta \text{SOC}_{\text{R}} (\text{t C ha}^{-1}) = \text{SOC}_{\text{SSM } t} - \text{SOC}_{\text{BAU } t} \quad (2)$$

where $\text{SOC}_{\text{ssM}t}$ refers to the final SOC stocks after a 20-year period of implementing SSM practices and $\text{SOC}_{\text{bau } t}$ refers to the final SOC stocks after a 20-year period under business as usual (BAU) practices. Mean annual SOC sequestration rates ($\text{t C ha}^{-1} \text{ yr}^{-1}$; absolute or relative) are to be determined by dividing SOC changes by 20 years.

1.2.2. Business as usual and SSM scenarios

The BAU scenario refers to the land use, land management, production practices or technologies that are currently being implemented (as in time = 0, or 2020) in croplands and grazing lands. BAU practices represent typical, prevailing practices in a specific agro-ecological zone and productive system. SSM practices refer to

management practices that are expected to remove CO₂ from the atmosphere and retain it as SOC, to enhance SOC accumulation, or to mitigate or reverse SOC losses compared to the BAU (Fig. 1.1). Although there is no universal soil management practice, basic principles are widely applicable, such as those identified in the Voluntary Guidelines for Sustainable Soil Management (VGSSM; FAO, 2017) for enhancing soil organic matter content:

- increasing biomass production and residue returns to the soil;
- using cover crops and/or vegetated fallows;
- implementing a balanced and integrated soil fertility management scheme;
- implementing crop rotations, combining legumes and pulses with high residue crops, or improving the crop-mix;
- effectively using organic amendments, manure, or other carbon-rich wastes (which are not currently applied to soils);
- promoting agro-forestry and alley cropping;
- managing crop residues and grazing to ensure optimum soil cover; among others.

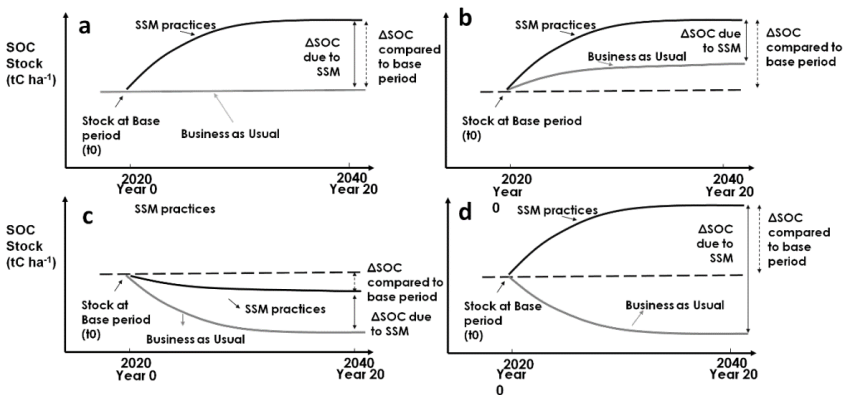


Fig. 1.1. Theoretical evolution in Soil Organic Carbon stock under a business as usual (BAU) scenario and after adoption of sustainable soil management practices: a) lands where SOC levels have reached equilibrium and where it is possible to increase levels under SSM; b) lands where SOC is increasing but can be further increased through SSM; c and d) lands where SOC is decreasing and where it is possible to mitigate (c) or reverse (d) this fall through SSM

A very wide range of management practices are currently being implemented and can potentially be introduced into the world's agricultural systems, depending on climatic, soil, socio-cultural and economic conditions. In turn, different SSM C-oriented practices are often combined, making it difficult to dissociate their effects on SOC dynamics. Thus, as a first step, and to harmonize the results on a global map, and because soil carbon turnover models are the most sensitive to carbon inputs, these guidelines propose to group SSM practices into three scenarios as a standard method, based on their expected relative effects on C inputs compared to BAU: Low, Medium and High increase in C inputs (referred as SSM1, SSM2, and SSM3 scenarios). National experts' opinion and local data are essential in order to accurately estimate or validate the target areas and carbon input levels for the different SSM scenarios.

1.3. Soil organic Carbon modeling

To obtain consistent results and to allow comparisons between countries and regions, the use of a standard 'process-oriented' SOC model is requested. Users are nevertheless encouraged to provide supplementary maps developed using alternative preferred SOC models.

For this first SOCseq version, the Rothamsted soil organic carbon model (RothC; Coleman & Jenkinson, 1996) is proposed as the standard comparison model, because:

- It has fewer data requirements due to the relative simplicity of obtaining input data compared to other process-oriented models
- It has been applied using data from long-term experiments across several ecosystems, climate conditions, soils and land use classes;
- It has been successfully applied at national, regional and global scales; e.g., Smith et al. (2005), Smith et al. (2007), Gottschalk et al. (2012), Wiesmeier et al. (2016), Farina et al. (2017), Mondini et al. (2018), Morais et al (2019);
- It (or its modified/derived version) has been used to estimate carbon dioxide emissions and removals in different national GHG inventories as a Tier 3 approach; according to the latest review by Smith et al. (2020): Australia (as part of the FullCam model, Japan

(modified RothC), Switzerland, and UK (CARBINE, RothC).

A spatially explicit version of the RothC model (e.g., Gottschalk et al., 2012; Mondini et al. 2018; Morais et al, 2019) is required to generate SocSeq maps. An open-source R version of the RothC model (embedded in the SoilR package) developed by Sierra et al. (2012) can be used for these purposes.

1.3.1. RothC: general model description

In the Roth-C model (Coleman and Jenkinson, 1996), SOC is split into four active compartments and a small amount of inert organic matter (IOM). The four active compartments are Decomposable Plant Material (DPM), Resistant Plant Material (RPM), Microbial Biomass (BIO) and Humified Organic Matter (HUM). The IOM compartment is resistant to decomposition. The structure of the model is shown in Fig. 1.2. Incoming plant carbon is split between DPM and RPM, depending on the DPM/RPM ratio of the particular incoming plant material. All incoming plant material passes through these two compartments only once. Both DPM and RPM decompose to form CO₂, BIO and HUM. The proportion that goes to CO₂ and to BIO + HUM is determined by the clay content of the soil. Each compartment decomposes by a first-order process with its own characteristic rate, which in turn is affected by the clay content of the soil, soil moisture, temperature, and soil cover. A more detailed description of the model and its processes can be found in Coleman and Jenkinson (1996), and Falloon and Smith (2009).

1.3.2 General procedures

Prior to the simulation of SOC stocks and sequestration under the different scenarios, model initialization is required to set the initial SOC condition (total SOC and partition of the different pools) at the start of the simulation period, and to adjust the C inputs estimates.

In a first initialization step, RothC shall be run iteratively to equilibrium to calculate the size of the SOC pools and the annual plant carbon inputs using constant environmental conditions (Phase 1, Fig. 1.3), for each grid cell on the map. A first equilibrium run for a standard 10 000-year period should be performed, considering constant climatic conditions as the average of historic climate data from 1980 to

2000, clay contents, and land use as in year. The total annual plant C input can be initially assumed to be $1 \text{ t C ha}^{-1} \text{ yr}^{-1}$ and the proportions of plant material added to the soil for each month are set to describe the typical input pattern for each land use class (Smith et al., 2007; Mondini et al., 2017).

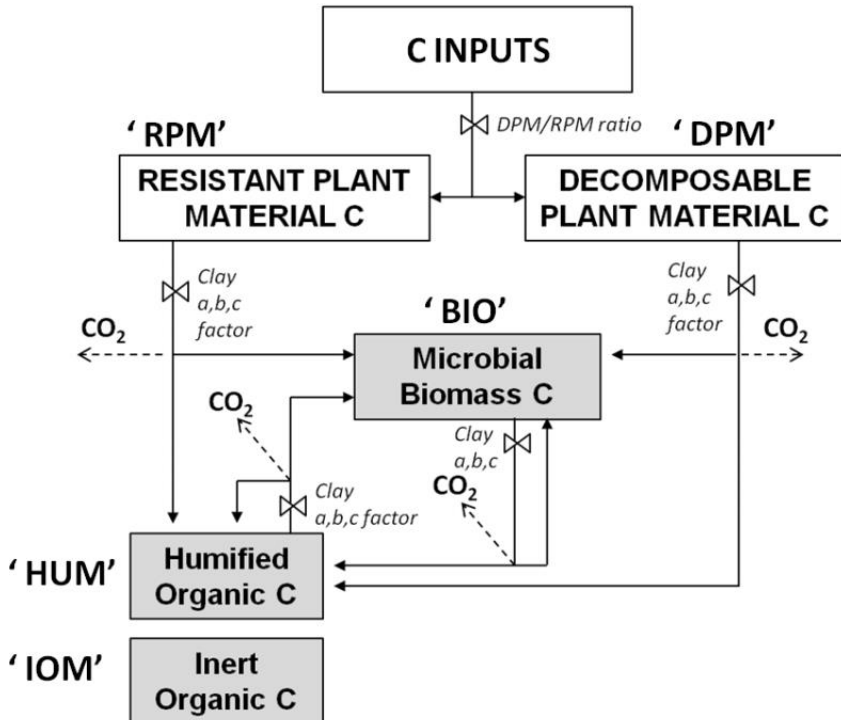


Fig. 1.2. Structure, pools, and flows of carbon in the Roth-C model, including major factors controlling the fluxes (a = multiplier for effects of temperature, b = multiplier for effects of moisture, c = multiplier for effects of soil cover; DPM/RPM = Decomposable/resistant plant material ratio). Source: redrawn from Coleman and Jenkinson (1996) and Falloon and Smith (2009)

After the first equilibrium run, the annual C input from plant residues needs to be optimized so that the results of the ‘long spin-up’ fit the estimates of total SOC stocks of 0–30 cm provided in the FAO-ITPS GSOC map. C equilibrium inputs can be adjusted using the

following equation (Smith et al., 2005):

$$C_{eq} = C_i \times [(SOC_{GSOCm} - IOM) / (SOC_{sim} - IOM)] \quad (3)$$

where C_{eq} is the estimated annual C input at equilibrium, C_i is the initial annual C addition (the sum of the proportions of the C input in the first equilibrium is 1), SOC_{csocm} is the estimated soil C given in FAO-ITPS GSOC map, SOC_{sim} is the simulated soil C after the first equilibrium run, and IOM is the C content of the inert organic matter fraction in the soil (all in $t C ha^{-1}$). The size of the IOM fraction ($t C ha^{-1}$) can be set according to the equation given by Falloon et al. (1998):

$$IOM = 0.049 \times (SOC_{GSOCm})^{1.139} \quad (4)$$

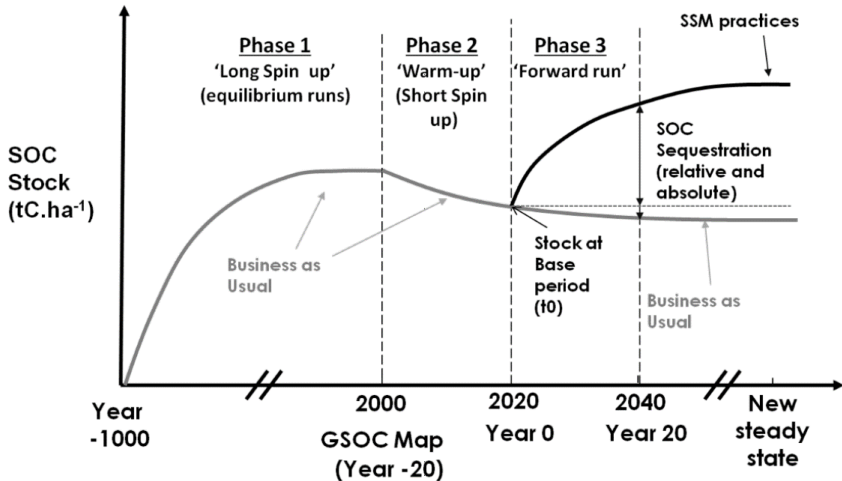


Fig. 1.3. SOC stocks simulated in the different phases according to the proposed general modeling procedure

A second long term (minimum 1000 years) equilibrium run shall be performed using the estimated C_{eq} , (under the same conditions as the first run), in order to obtain the size of the different SOC pools ($t C ha^{-1}$) at year 2000. Since FAO-ITPS GSOC map SOC was generated from individual SOC measurements taken over different decades (i.e., 1960s to 2000s), a temporal harmonization of SOC stocks can be performed as a second initialization step to minimize differences in current SOC stocks at year 0 (i.e., initial SOC stocks at year 2020):

- SOC stocks from the GSOC map shall be considered to be the stocks twenty years prior to the simulation ($t = -20$ y; i.e. year

- 2000).
- A 20-year ‘short spin-up’ run can be performed to adjust for major deviations among different measurement periods on the GSOC map (Fig. 1.3, Phase 2), using year-to-year climatic conditions for the period 2001-2020, clay contents, the stocks in the different SOC pools from the results of the ‘long spin-up’ run, and land use as in year 2020 (land use representative of the period 2001-2020; or yearly land use data shall be used when available).
 - Year-to-year C inputs over the period 2001-2020 should be adjusted considering year-to-year changes in estimated Net Primary Production (NPP). SOC stocks can either increase or decrease during this ‘short spin-up’ stage.

This ‘short spin-up’ period is intended to: reduce the effects of different time measurements in the GSOC map (over- or underestimation of current initial SOC stocks); minimize initialization effects (e.g. deviations in the estimation of initial pool sizes); and account for the effects of sub-regional, regional and global climatic and land use changes over the period 2001-2020 and their effects on NPP. If recent (2015-2020) national SOC monitoring campaigns have been undertaken to generate the latest version of the FAO-IPS GSOC map, the SOC stocks from the GSOC map can be considered as the current stocks ($t=0$ y; i.e. year 2020), and the ‘short spin-up’ phase is not required.

After the equilibrium and ‘short spin-up’ runs, SOC sequestration due to SSM practices can be estimated in a forward run (Fig. 1.3, phase 3). SOC stocks can be simulated from 2020 ($t=0$) to 2040 ($t=+20$) for the BAU and the three SSM scenarios, using average mean monthly climate variables (2001-2020), and C inputs, and land use as in year 2020.

It should be noted that global climatic changes are to be expected over the next 20 years (climate change projections diverge significantly in the second half of the century, after year 2050; IPCC, 2014; 2018). As it is not yet certain which climate projections will be used for future scenarios and prior agreement between countries is needed, and as significant divergences in climatic variables are expected from 2050 onwards, the use of monthly average climatic variables from 2001-2020 for the period 2020-2040 is set as the

standard for the forward run. However, the proposed methodology allows for the integration of climate change scenarios, especially for longer-term projections (i.e. + 2050) in future versions.

The attainable absolute SOC sequestration is to be estimated as the difference between the corresponding SOC stocks from the forward modeling at year +20 (2040) for the different scenarios and the estimated baseline SOC stocks for year 0 (year 2020; refer to equation 1). The attainable relative SOC sequestration is to be determined as the difference between the corresponding SOC stocks modeled forward at year +20 (2040) for the SSM scenarios and the simulated SOC stocks at year +20 (2020) for the BAU scenario (refer to equation 2).

The different modeling phases and their data requirements are summarized in Table 1.1.

Table 1.1. Summary of the different modeling phases and data requirements

Variables	Phase 1 Long spin up Equilibrium	Phase 2 Short spin up	Phase 3 Forward modeling
Time span	Minimum 500 years (using equilibrium runs procedure)	20 years	20 years
	Infinite (Analytical solution procedure)		
Climatic inputs	1980-2000 series monthly average:	2001-2020 year to year monthly data:	2001-2020 series monthly average:
	Rain, Temperature, Evaporation/	Rain, Temperature, Evaporation/	Rain, Temperature, Evaporation/
	Evapotranspiration	Evapotranspiration	Evapotranspiration
Soil inputs	Topsoil clay content	Topsoil clay content	Topsoil clay content
Initial SOC stocks and pools	Inert organic matter (IOM)	Inert organic matter (IOM)	Inert organic matter (IOM)
	“= 0” for all other fractions (when using equilibrium runs)	Other fractions equal to the final SOC pools modeled in phase 1	Other fractions equal to the final SOC pools modeled in phase 2
Carbon inputs	First run : 1tC.ha ⁻¹	NPP	NPP year-to year

	Adjusted C inputs (using equilibrium runs)	year-to year adjusted C inputs	adjusted C inputs for the BAU, Estimated from % increase vs. BAU for SSM scenarios
Vegetation cover	Monthly cover determined: by expert opinion, NDVI 2000-2020 or preferred spectral index	Monthly cover determined: by expert opinion, NDVI 2000-2020 or preferred spectral index	Monthly cover determined: by expert opinion, NDVI 2000-2020 or preferred spectral index
Land Use	Representative land use of the 1980-2000 period (or layer for year 2000; or best available layer)	Year to year Land use 2000-2020 (or representative land use of the period; or best available layer)	Last available land use layer (e.g. 2015, 2018; 2020) (or best available layer)
Modeled Scenarios	BAU	BAU	BAU
			SSM Low
			SSM Medium
			SSM High
Expected Results	C inputs at equilibrium	Total SOC and SOC pools at year t=0 (2020)	Total SOC and SOC pools at year t=+20 (2040) for the BAU, and SSMs scenarios
	Total SOC and SOC pools at year t=-20 (2000)		Absolute and relative Total Sequestration (3 SSMs)
			Absolute and relative Sequestration rates (3 SSMs)

2. Data sets and inputs

The sample data set provided with these Methodical recommendations was compiled to model and map the potential soil organic carbon sequestration for the Khmilnyk district of Vinnytsia region, Ukraine (Fig. 2.1). It covers an area of 3701 km² that is mainly dedicated to agriculture. The specialization of agricultural holdings in Khmilnyk district (shown by an arrow) is crop production (cereal winter crops), sugar beet, fodder crops, livestock.

These used in combination with the provided sample data set and scripts can be used as a step-by-step guide, which covers data preparation and harmonization, modeling potential soil organic carbon sequestration, rasterizing the results, estimating the uncertainty and finally data sharing.

The sample data set and scripts can be found in the following repository:

https://drive.google.com/file/d/1W35AJERw9PyHBsyCaBteKlcEmHtED98o/view?usp=share_link

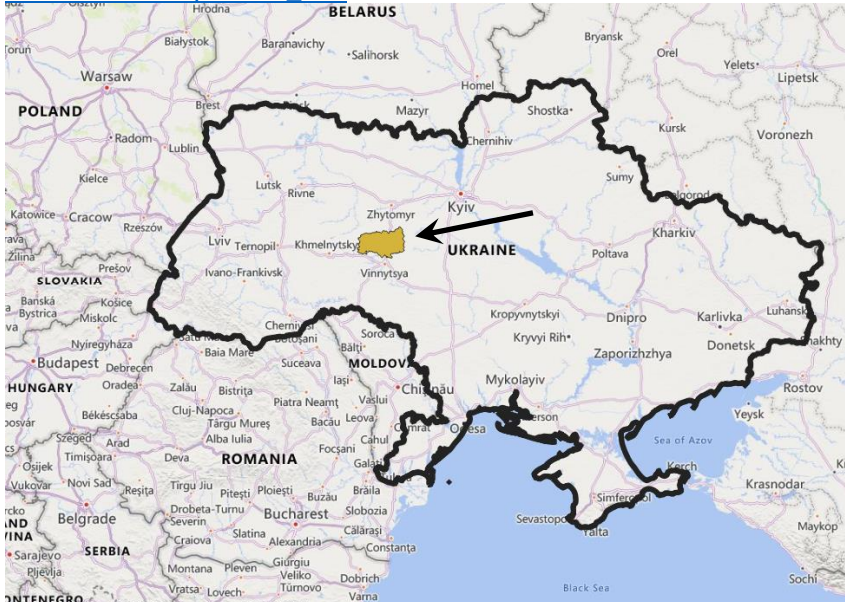


Fig. 2.1. Geographical location of the area of interest (AOI - Khmilnyk district of Vinnytsia region) within Ukraine; *Bing Map was used for the background

2.1. Climate data sets

Gridded climate data shall be obtained from:

- National Sources or a preferred regional data source;
- Global data sets, when national or regional gridded historical climate data sets are not available.

The dataset provided by the Climate Research Unit (CRU), developed by the University of East Anglia, United Kingdom (Harris et al., 2014) at a resolution of 0.5 degrees (~50x50 km) was initially recommended to be used as the standard global data set if national or regional gridded data is not available, or if the available national data is at a coarser resolution. To overcome limitations linked to the coarse resolution of the CRU products, this version of Methodical recommendations has identified and recommends the TerraClimate dataset as an improved global alternative. Since the map production phase for the implementation of the GSOCseq was initiated prior to the identification of the TerraClimate data set, this version of the Methodical recommendations still presents both data sets (CRU and TerraClimate) as viable global options.

The CRU 2019 dataset (CRU TS v. 4.03) covers the period 1901-2018, including precipitation (pre), average/minimum and maximum air temperatures (tmp, tmn, tmx), cloud cover percentage (cld), diurnal temperature range (dtr), vapor pressure (vap), number of rainy days (wet), frost days (frs), and potential evapotranspiration (pet); (See Table 2.1, data sets and download sources).

TerraClimate is a data set of monthly climate and climatic water balance for global terrestrial surfaces from 1958-2019. It has a monthly temporal resolution, a ~4x4 km spatial resolution and was created by combining high-spatial resolution climatological normals from the WorldClim data set, with coarser spatial resolution, but time-varying data from CRU Ts4.0 and the Japanese 55-year Reanalysis (JRA55) (Abatzoglou et al., 2018).

The following variables and data sets are required to run the model:

- Monthly average air temperature (°C),
- Monthly precipitation (mm),
- Monthly potential evapotranspiration (Penman-Monteith; mm),

Table 2.1. Summary of the input data requirements for the proposed modeling approach to generate SOCseq maps

Data	Variables	Time series	Units	Type	Resolution
Climatic data	Monthly air temperature	1980-2000; 2001-2020	°C	Raster	50 x 50 km or finer
		(or until last year available)			
	Monthly evapotranspiration/pan evaporation	1980-2000; 2001-2020	mm	Raster	50 x 50 km or finer
		(or until last year available)			
	Monthly precipitation + irrigation	1980-2000; 2001-2020	mm	Raster	50 x 50 km or finer
		(or until last year available)			
Soil data	Topsoil clay content (0-30 cm)		%	Raster	1 x 1 km
	Current Soil organic carbon stocks (0-30 cm)	Latest version of national FAO-GSOC map	tC ha ⁻¹	Raster	1 x 1 km
Land use/cover	Predominant land use/cover, re-classified into:	Minimum: 2000 and 2020 (or last year available)	01-mar	Raster	1 x 1 km
	Minimum: 3 default classes required by model: agricultural crops, grassland/shrubland/savannas and forestry	Optimum: annual land use 2000 to 2020	01-nov		
	Optimum: 13 classes defined in the FAO Global Land Cover - SHARE (GLC-SHARE)				
	Monthly vegetation cover.	Minimum: average 2000- 2020 (or last year available) Optimum: annual land use 2000 to 2020	0-1	Raster	1 x 1 km
	Obtained from national statistics/local expert knowledge; or derived from NDVI or spectral indexes (see section 3.3.4)				

- data sets: 1981-1990 (series average); 1991-2000 (series average); 2011-2010 (year to year); 2011-2018 (year to year).

The same data sources must be used in all modeling phases.

2.2. Soil data sets

2.2.1. Initial total SOC stocks

Initial total SOC stocks to 30cm depth (in t C ha⁻¹) are to be derived from the GSOCmap (30 arc seconds; 1km x 1km resolution grid), latest revised version (FAO-ITPS, 2019). Countries wishing to include an updated or improved estimate of current SOC stocks, compared to the latest version of the GSOCmap, are encouraged to submit their updated national SOCmap to the GSP Secretariat and use it for modeling. Since the GSOCmap was generated from national measurements taken between the 1960s and the 2000s, and no temporal corrections have been developed in many countries, GSOCmap values will represent SOC stocks for the year 2000. A short spin-up' model run (20 years) with climate variables and management forcing for the period 2000-2020 shall be performed to reduce the effect of temporal deviations. Thus, the simulated SOC content at 2020 after the 'short spin-up' run will represent the initial SOC stocks prior to implementation of SSM practices. If recent national SOC monitoring campaigns (2015-2020) have been undertaken to generate the latest version of the FAO-IPS GSOC map, the SOC stocks from the GSOCmap can be considered as the current stocks (t=0 y; i.e. year 2020), and the 'short spin-up' phase is not required.

2.2.2. Initial C pools

The initial C stocks in the different pools (in t C ha⁻¹) considered in the RothC model (DPM, RPM, BIO, HUM and IOM, Fig. 1.2) shall be estimated following the 'long spin-up' and 'short spin-up' procedure.

2.2.3. Soil texture: clay content

The average clay contents over 0-30 cm depth are to be obtained from gridded data (raster format) from:

- national Sources (1 km x 1 km resolution);
- global data sets, where national or regional data sets are not available.

The topsoil clay content (0-30 cm, % mass fraction; 1x1 Km resolution) from the Harmonized World Soil Database (HWSD) or SoilGrids developed by the- International Soil Reference and Information Centre (ISRIC) (see Table 2.1) shall be used as the standard global database if national or regional data is not available in the required format or resolution. Clay content can be averaged at finer resolutions to obtain 1 x 1 Km grids. However, countries are encouraged to produce their own texture and clay content maps to be used as inputs for the SOCseq map, following the digital soil mapping approaches described in the GSOCmap Cookbook (FAO, 2018). Average clay contents over a 0-30 cm depth interval can be derived by taking a weighted average of the predictions over the depth interval using numerical integration (Hengl et al., 2017).

2.3. Land cover data sets

The gridded land cover data layers shall be obtained from:

- national or regional sources;
- global data sets, where national or regional land use or land cover data sets are not available.

Since land cover may vary substantially between data sources and estimates of past and current land cover may have important deviations from real land cover and land use, users should estimate land use from the source that best reflects national and subnational conditions. Land cover data sets should cover the 2000-2020 (or approximate) period. The ESA (European Space Agency) land cover Global dataset (See Table 2.1), and its reclassification into FAO Global Land Cover - SHARE (GLC-SHARE; See Table 2.1) classes will be provided by the GSP Secretariat, if no national land use dataset is available. However, users should estimate land use from the source that best reflects national and subnational conditions. Other global and regional data sets are provided in Table 2.1. The land cover classes will affect the decomposability of the incoming plant material (DPM/RPM ratio). A spatialized R-version of RothC is provided by the GSP Secretariat and runs considering the 13 classes defined in the FAO Global Land Cover - SHARE (GLC-SHARE). A default DPM/RPM value is assigned to each class (Table 2.2). Thus, when using this spatialized R-version of RothC without modifying its scripts, the land use classes from the possible different data sets need to be re-classified into FAO Global Land Cover - SHARE (GLC-SHARE) land use classes. However, users can model alternative land use classes, and modify these default DPM/RPM values. If so, modifications in the R-version must be then introduced. Examples of land cover reclassification from the ESA land cover database

into the RothC land use categories are presented (Table 2.3). As a minimum, land use for the year 2000 and land use for the year 2020 (or last available year) at 1x1 km resolution shall be defined. The predominant land use category in each cell of the 1x1 km grid shall be selected if finer resolutions are available.

Table 2.2. FAO Land cover classes, land cover number and default DPM/RPM ratios. An extra land use class (*Tree-crops) is shown as an example of the disaggregation of a land use class.

FAO Land aggregated cover class	Land Cover code number	Default DPM RPM ratio
Artificial surfaces	1	/
Cropland	2	1.44
Grassland	3	0.67
Tree covered	4	0.25
Shrub covered	5	0.67
Herbaceous vegetation	6	0.67
Mangroves	7	/
Spare vegetation	8	0.67
Bare soil	9	/
Snow and Glaciers	10	/
Water bodies	11	/
Cropland-Tree crops*	12	1.44
Paddy fields	13	1.44

Table 2.3. Land cover aggregation schemes into RothC land use classes. Example from ESA

ESA Land Cover Class	ESA class Number	RothC Land Use type
Cropland rainfed	10	Agricultural crops/improved grassland
Cropland rainfed herbaceous cover	11	Agricultural crops/improved grassland
Mosaic Cropland > 50%	30	Agricultural crops/improved grassland
Cropland - Tree/shrub cover	12	Forest/Deciduous/tropical woodland
Cropland irrigated flooding	20	Waterlogged soils
Grasslands	130	-9999
Mosaic Natural vegetation herbaceous > 50% /cropland	40	Unimproved grassland and scrub (including Savanna)
Mosaic herbaceous cover >50%/trees-shrubs	110	Agricultural crops/improved grassland
Shrubland	120	Unimproved grassland and scrub/ Savanna
Shrubland evergreen	121	Unimproved grassland and scrub/ Savanna
Shrubland deciduous	122	Unimproved grassland and scrub/ Savanna
Tree cover broadleaved deciduous open 15-40%	62	Unimproved grassland and scrub/ Savanna

Tree cover needle leaved deciduous open 15-40%	82	Unimproved grassland and scrub/ Savanna
Tree cover broadleaved evergreen closed to open >15%	50	Unimproved grassland and scrub/ Savanna
Tree cover broadleaved deciduous closed to open >15%	60	Forest/Deciduous/tropical woodland
Tree cover broadleaved deciduous closed >40%	61	Forest/Deciduous/tropical woodland
Tree cover needle leaved evergreen closed to open >15%	70	Forest/Deciduous/tropical woodland
Tree cover needle leaved evergreen closed >40%	71	Forest/Deciduous/tropical woodland
Tree cover needle leaved evergreen open >40%	72	Forest/Deciduous/tropical woodland
Tree cover needle leaved deciduous closed to open >15%	80	Forest/Deciduous/tropical woodland
Tree cover needle leaved deciduous closed >40%	81	Forest/Deciduous/tropical woodland
Tree cover mixed leaf type	90	Forest/Deciduous/tropical woodland
Mosaic tree-shrub >50%/herbaceous cover	100	Forest/Deciduous/tropical woodland
Shrub or herbaceous flooded fresh/saline/brackish water	180	Forest/Deciduous/tropical woodland
Tree cover flooded fresh or brackish water	160	Waterlogged
Tree cover flooded saline water	170	-9999
Urban areas	190	-9999
Lichens and mosses	140	-9999
Bare areas	200	Others - No data-9999
Sparse vegetation tree-shrub-herbaceous (<15%)	150	Others - No data-9999
Sparse tree (<15%)	151	Others - No data-9999
Sparse Shrub (<15%)	152	Others - No data-9999
Sparse herbaceous (<15%)	153	Others - No data-9999
Consolidated bare areas	201	Others - No data-9999
Unconsolidated bare areas	202	Others - No data-9999
Permanent snow/ice	220	Others - No data-9999
Water bodies	210	Others - No data-9999
No data	0	Others - No data-9999

2.4. Monthly vegetation cover

It is required to indicate the approximate annual distribution of monthly vegetation cover for the simulations in order to:

- adjust the topsoil moisture deficit estimations (Fig. 1.2);
- consider the effects of soil cover on SOC decomposition rates (Fig. 1.2).

The annual distribution of vegetation cover can be derived from:

- public statistics of national and/or administrative units considering the predominant agricultural systems in a temporal series (2000-2020);
- derived from NDVI (normalized difference in vegetation index) values from historic satellite images (See data sets, Table 2.1).

The occurrence of plant cover can be assumed to be constant in grasslands, shrublands and savannas and during specific months (e.g. 1-6 months for croplands) (e.g. Smith et al., 2005; Smith et al., 2007). The following coefficients can be set for based on the specific land cover and/or land use:

- Perennial tree-crops, forests and grasslands ($c=0.6$);
- Months with predominantly bare soil and unvegetated fallows ($c=1$);
- Annual crops ($c=0.6$).

Considering a temporal series (2000-2020), the proportion of images with NDVI values greater than a specified threshold, indicating active vegetation growth, can be estimated (e.g. $NDVI > 0.6$). The monthly probability of being vegetated (P_{veg}) can be estimated for each cell grid and each month of the year (1-12), as:

$$P_{veg} = \frac{\text{Number of images } NDVI > 0.6}{\text{Total images}} \quad (2.1)$$

NDVI is proposed as an alternative for estimating vegetation cover when no vegetation cover data or local knowledge is available. The proposed threshold may vary according to local conditions. Global monthly vegetation cover data sets estimated by NDVI (2000-2020) will be provided by the GSP Secretariat.

However, NDVI may be a biased indicator in areas with low vegetation cover (e.g. drylands, shrublands), or high nubosity. In these cases, countries are encouraged to use other locally validated spectral indices to accurately estimate monthly vegetation cover (e.g. Multi Sensor Vegetation Index; Moradizadeh and Saradjian, 2016).

2.5. Monthly carbon inputs

2.5.1. C inputs under BAU practices

Carbon inputs for the BAU scenarios shall be estimated using the approach proposed by Smith et al. (2005: 2006: 2007) and Gottschalk et al. (2012). Total plant C inputs to the soil, which include plant litter, root exudates and fine root turnover, are rarely known. To overcome this problem, RothC shall be run in equilibrium mode' to calculate the initial plant carbon inputs to the soil (or 'equilibrium Carbon inputs', C_{eq}), which led to the initial SOC stocks (GSOCmap), under historic forcing conditions. The C_{eq} thus represents the historical average of annual carbon input of the BAU scenario up to the year 2000. For further details on the equilibrium run and initialization to estimate C_{eq} , refer to section 3.2 (General modeling procedures). Once these initial carbon inputs have been established (from the year 2000 onwards), year-to-year changes can be adjusted in accordance with changes in Net Primary Production (NPP), as changes in C inputs to the soil are assumed to be associated with changes in NPP (Smith et al., 2005). Thus, annual C inputs for the BAU scenario can be adjusted as:

$$BAU_{Ct} = C_{t-1} \times (NPP_{t-1}) - 1 \times NPP_t \quad (2.2)$$

where BAU_{Ct} is the annual carbon input of a specific year t . C_{t-1} is the annual carbon input of the previous year: NPP_t is the net primary production of year t . and NPP_{t-1} is the NPP of the previous year (in $tC\ ha^{-1}$). Thus, the average NPP over the initialization period shall be associated with C_{eq} and the annual C inputs for the BAU scenario can be adjusted as:

$$BAU_{Ct\ 2001} = C_{eq} \times NPP_{1980-2000}^{-1} \times NPP_{2001} \quad (2.3)$$

where $BAU_{Ct\ 2001}$ is the annual carbon input for the first year of the 'short spin-up' phase: C_{eq} is the estimated annual C input at equilibrium derived through the 'long spin-up' process: $NPP_{1980-2000}$ is the estimated average net primary production over the initialization period (1980-2000); and NPP_{2001} is the estimated annual net primary production for the first year of the 'short spin-up' phase. The annual C inputs for the BAU scenario can be then adjusted following equation 2.5, according to changes in the NPP. The estimation of NPP using the

MIAMI model (Lieth, 1975) is defined as the standard method in this document. It requires little input and is easily applicable worldwide, can be used to estimate NPP under future climatic conditions, and can act as a baseline for different NPP data sets or projections (e.g. Gottschalk et al., 2012). NPP estimated with the MIAMI model is computed with the following equations:

$$NPP_{MIAMI} = \min(NPP_T, NPP_P) \quad (2.4)$$

$$NPP_T_{MIAMI} = \frac{3000}{1 + e^{1.315 - 0.119 \times T}} \quad (2.5)$$

$$NPP_P_{MIAMI} = 3000 \times 1 - e^{-0.000664P} \quad (2.6)$$

where NPP is the climatic net primary production in dry matter (DM; g m⁻² yr⁻¹), NPP_T is the temperature dependency term of NPP, where T is the annual mean temperature (°C) and NPP_P is the moisture dependency term of NPP, where P is the mean annual sum of precipitation (mm). NPP is limited by either temperature or precipitation. MIAMI model NPP can be expressed in t C ha⁻¹ yr⁻¹ as:

$$NPP_{MIAMI} \text{ tC ha}^{-1} \text{ yr}^{-1} = NPP_{MIAMI}(\text{DM}; \text{g m}^{-2} \text{ yr}^{-1}) \times 0.01 \times 0.48 \quad (2.7)$$

The annual NPP_{MIAMI} shall be estimated for each grid cell from the climatic data sets described in section 6.1 for the different simulation periods (1981-1990; 1991-2000; 2001-2010; 2011-2020; 2021-2040). The NPP_{MIAMI} is used to estimate BAU carbon inputs under current and projected climatic conditions. The change in NPP is used as a surrogate for estimating the change in C input and assumes that a similar proportion remains in the field (e.g. Smith et al., 2005; Gottschalk et al., 2012). In a first instance, countries should focus on C inputs in agricultural lands in 2020, the use of which has not changed since the year 2000. Changes in land use and management over the period 2000-2020 and associated changes in C inputs can nevertheless be taken into account, if trends in biomass removal are known, in order to adjust C inputs (e.g. Schulze et al., 2010; Plutzer et al., 2016; Neumann and Smith, 2018). Thus, the annual changes in C inputs by equations 5 and 6 can be adjusted using annual land cover data. For example, by assuming and approving an NPP of 12, 28 and 47% for forests, grasslands and croplands (Schulze et al., 2010), the annual NPP of a specific year (NPP_T) can be adjusted using these coefficients

(equations 2.7 to 2.11), and the annual C inputs can then be estimated by equations 2.2 and 2.3:

$$NPPt_{forests} = NPP_{MIAMI} \times 0.88 \quad (2.9)$$

$$NPPt_{grasslands} = NPP_{MIAMI} \times 0.72 \quad (2.10)$$

$$NPPt_{croplands} = NPP_{MIAMI} \times 0.53 \quad (2.11)$$

2.5.2 C inputs under SSM practices

SSM practices shall be grouped into three scenarios as a standard method, based on their expected relative effects on C inputs compared to BAU: Low, Medium and High C inputs. The SSM practices considered in this approach are practices that affect C inputs to the soil, as changes in C inputs have been identified as one of the factors to which models are most sensitive when projecting changes in SOC stocks (FAO, 2019). As with estimates of BAU C inputs, total plant C inputs to the soil, including plant litter, root exudates and fine root turnover, are rarely known. Thus, C inputs of SSM scenarios will represent a % increase from BAU C inputs:

$$\Delta\%CSSM - BAU = (C_{inputs_{SSM}} - C_{inputs_{BAU}}) \times C_{inputs_{BAU}} \quad (2.12)$$

As a standard, the expected effects (% increase in C inputs) of 3 scenarios have been conservatively set at:

- **Low: 5 % increase in C inputs**
- **Medium: 10% increase C inputs**
- **High: 20 % increase in C inputs**

These percentages (based on Smith, 2004; Wiesmeier et al., 2016) shall be used to produce the mandatory maps for the global product. An additional ‘High increase’ scenario, considering a 30% increase in C inputs, can be modeled, to compare results with recent ‘top-down’ modeling approaches (e.g. CIRCASA). The use of default percentages in C input increase can be applied globally without complex configuration. However, countries should carefully check whether these scenarios are reasonable and under what type of management practices they are achievable. Countries are encouraged to produce and provide additional maps, taking into account their own estimates of the effects of different selected practices or land use changes, based on expert knowledge and local capacities. These effects can be

determined on the basis of expert opinion and available information at the country level. A metaanalysis should be conducted based on the latest available local and regional studies to estimate how agricultural practices affect average annual C inputs (and the % increase in C input compared to BAU practices). These practices may include, for example, the use of cover crops, rotation with high residue yielding crops or perennials, residue retention, grazing management, plant nutrition, species introduction, manure or organic amendment application, among others. If no data is directly provided in the compiled studies, carbon inputs and % increase in C inputs relative to BAU practices shall be estimated considering the framework proposed by Bolinder et al. (2007). The annual C inputs required to model the effects of SSM practices under 3 scenarios (Low, Medium, High) for each modeling unit (i.e. grid cells) shall be estimated from the annual BAU C inputs:

$$SSM_{Ct}Cha^{-1}yr^{-1} = BAU_{Ct} + \% \Delta CSSM_i - BAU \times BAU_{Ct} \quad (2.13)$$

where SSM_{Ct} represents the estimated annual C inputs for a specific scenario (i=Low, Medium, High) for year t. BAU_{Ct} represents the estimated annual C inputs for the BAU scenario for year t (determined from C inputs at equilibrium, as explained at the beginning of this section), and %ΔCSSM_i — BAU is the representative % increase in C inputs for a specific scenario (i=Low, Medium, High).

2.6. Residue decomposability: decomposable to resistant plant material ratio (DPM/RPM)

Default values for the DPM/RPM ratio (decomposability of incoming plant material) can be used (eg. 1.44 for crops and improved grasslands: 0.67 for unimproved grasslands and shrublands, and 0.25 for forests, woodlands and tree crops: Falloon and Smith, 2009). Table 2.2 (Land cover data sets) show default DPM/RPM for FAO land use classes. These default values can be modified according to region-specific data and local knowledge.

2.7. Required data sets and global data sources

The required data sets described in this chapter are summarized in Table 2.1. The proposed regional and global data sources to obtain the

required input data when no quality national or regional data is available are described in Table 2.4.

Table 2.4. Global and regional data sources to generate national SOCseq maps

Type	Source	Address	Resolution
Climatic monthly data	CRU – Climate Research Unit , University of East Anglia	https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.03/cruts.1905011326.v4_03/	4 km x 4 km
	TerraClimate	https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE	51 km x 50 km
SOC stocks 0-30 cm	GSOCmap - FAO-ITPS	http://54.229.242.119/GSOCmap/	1 x 1 km
Soil Texture	Harmonized World Soil Database v1.2	http://www.fao.org/soils-portal/	1 km (30 arc seconds by 30 arc seconds)
Soil Texture	OpenGeoHub Foundation - OpenLandMap	https://doi.org/10.5281/zenodo.1476854	250m
Soil texture, including uncertainties		http://soilgrids.isric.org	250 m
	Soil Grids -ISRIC		
NDVI- Historic images (2001-2020) every 16 days	MODIS - MOD13A2 datasets	https://lpdaac.usgs.gov/products/mod13a2v006/	1 x 1km
Land Cover	MODIS	https://modis.gsfc.nasa.gov/data/dataproduct/mod12.php	500 x 500m
	Land Cover Dynamics MCD12Q2		1 x 1 km
Land Cover	European Space Agency (ESA) Climate Change Initiative (CCI)- Copernicus Climate Change Service (C3S)	https://www.esa-landcover-cci.org/	300 x 300m
Land Cover – Land Use	FAO. Global Land Cover SHARE	http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1036355/	~1 x 1km
Land Cover	USGS Global Land Survey	https://lta.cr.usgs.gov/GLS	30 x 30m
Land Cover	CORINE land cover (Europe only)	https://land.copernicus.eu/pan-european/corine-land-cover	

3. Software environment and briefly overview of scripting process

A spatially explicit version of the RothC model (eg. Gottschalk et al., 2012; Mondini et al. 2017; Morais et al.; 2019) is required to generate national SOC sequestration maps. A spatialized version of the model was developed by the GSP Secretariat using an open-source R-environment, based on the SoilR package developed by Sierra et al. (2012). Users can use these and other alternative local adaptations of a spatialized RothC model by following the general procedures and input data described in previous chapters to obtain consistent results. This Chapter summarizes the steps required to set-up the software environment (R, RStudio, QGIS) to prepare the input data and run the spatialized R-version of the RothC model through scripts provided by the GSP. Additional supplementary scripts for QGIS and Google Earth Engine (GEE) are also provided. Users are required to download the following open-source software:

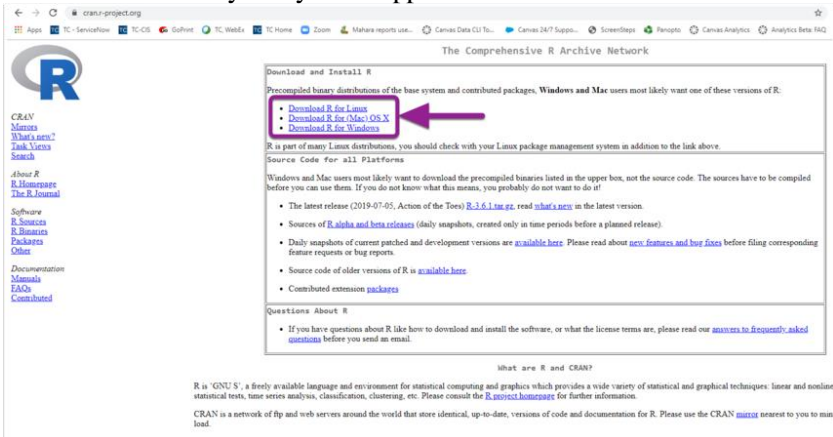
- R-language and environment for statistical computing and graphics (latest stable version, <https://cran.r-project.org/bin/windows/>)
- RStudio (latest stable version, <https://posit.co/downloads/>)
- QGIS (latest stable version, <https://qgis.org/en/site/forusers/download.html>)

In order to use Google Earth Engine users must register an account. The instructions in this Chapter will guide users through installing and manually configuring the software to be used for Microsoft Windows desktop platform.

3.1. Install R and R-Studio for Windows

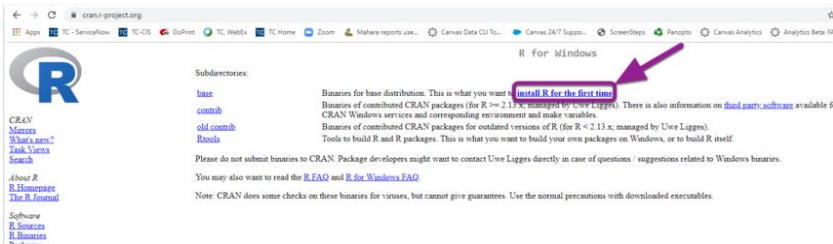
1. To install R, go to cran.r-project.org
2. Depending on your operating system, click Download R for (for us – Microsoft Windows version). R comes in both 32-bit and 64-bit versions. Which should you use? In most cases, it won't matter. Both versions use 32-bit integers, which means they compute numbers to the same numerical precision. The difference occurs in the way each version manages memory. 64-bit R uses 64-bit memory pointers, and 32-bit R uses 32-bit memory pointers. This means 64-bit R has a larger memory space to use (and search through). As a rule of thumb, 32-bit builds of R are faster than 64-bit builds, though not always. On the other hand, 64-

bit builds can handle larger files and data sets with fewer memory management problems. In either version, the maximum allowable vector size tops out at around 2 billion elements. If your operating system doesn't support 64-bit programs, or your RAM is less than 4 GB, 32-bit R is for you. The Windows and Mac installers will automatically install both versions if your system supports 64-bit R.



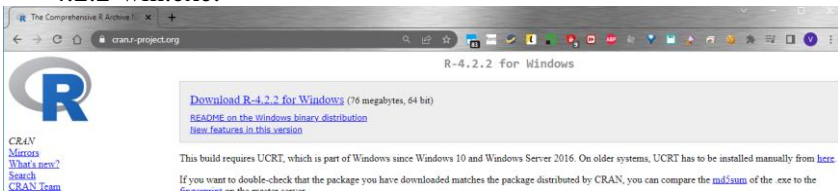
The screenshot shows the CRAN website's 'Download and Install R' page. The page title is 'The Comprehensive R Archive Network'. Under the heading 'Download and Install R', there is a section for 'Precompiled binary distributions of the base system and contributed packages. Windows and Mac users most likely want one of these versions of R:' with three bullet points: 'Download R for Linux', 'Download R for (Mac) OS X', and 'Download R for Windows'. A red box highlights these three links, and a red arrow points to the 'Download R for Windows' link. Below this, there is a section for 'R is part of many Linux distributions...' and another for 'Windows and Mac users most likely want to download the precompiled binaries...'. At the bottom, there is a section for 'What are R and CRAN?' and a paragraph explaining that R is GNU S, a freely available language and environment for statistical computing and graphics.

3. Click on install R for the first time:



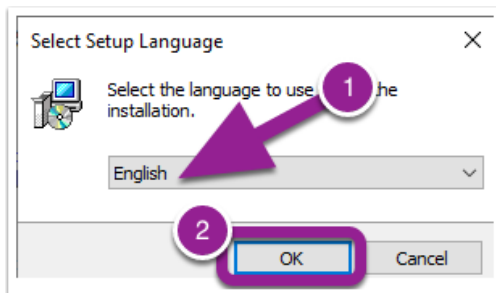
The screenshot shows the 'R for Windows' page on the CRAN website. The page title is 'R for Windows'. Under the heading 'Subdirectories:', there are several links: 'base', 'contrib', 'oldcontrib', and 'Rtools'. The 'base' link is highlighted with a red box, and a red arrow points to it. Below the subdirectories, there is a paragraph explaining that binaries for base distribution are available for Windows, and that there is also information on third-party software available for CRAN Windows services. There is also a section for 'Please do not submit binaries to CRAN...' and a note that CRAN does some checks on these binaries for viruses.

4. Click Download R for Windows. Open the downloaded file R-4.2.2-win.exe:

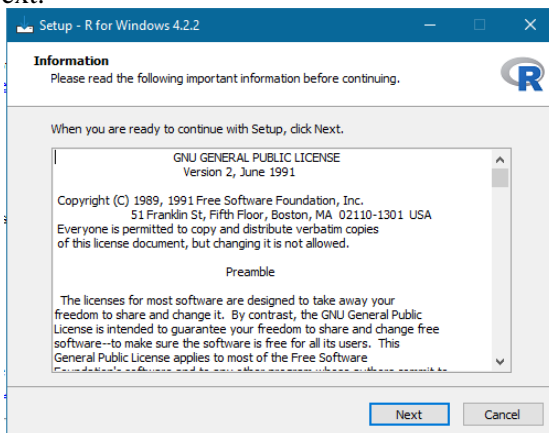


The screenshot shows the 'R-4.2.2 for Windows' page on the CRAN website. The page title is 'R-4.2.2 for Windows'. Under the heading 'Download R-4.2.2 for Windows (76 megabytes, 64 bit)', there is a link to 'Download R-4.2.2 for Windows'. A red box highlights this link, and a red arrow points to it. Below the link, there is a section for 'This build requires UCRT...' and a paragraph explaining that UCRT is part of Windows since Windows 10 and Windows Server 2016. On older systems, UCRT has to be installed manually from a link. There is also a section for 'If you want to double-check that the package you have downloaded matches the package distributed by CRAN...'.

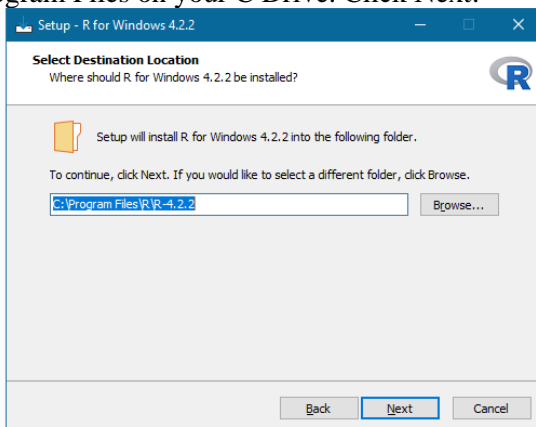
5. Select the language you would like to use during the installation. Then click OK:



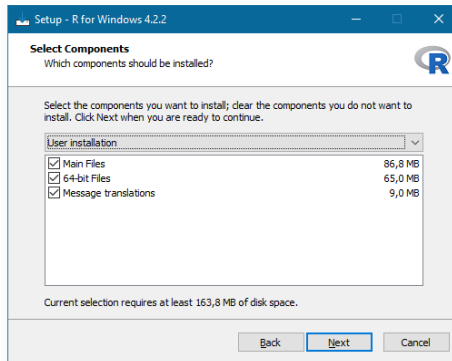
6. Click Next:



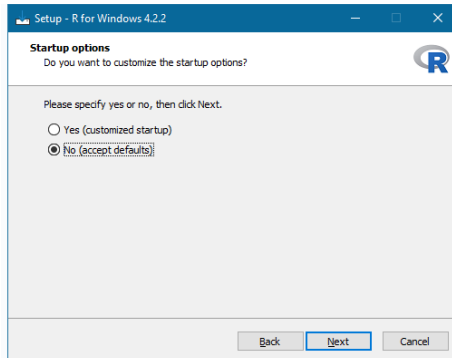
7. Select where you would like R to be installed. It will default to your Program Files on your C Drive. Click Next:



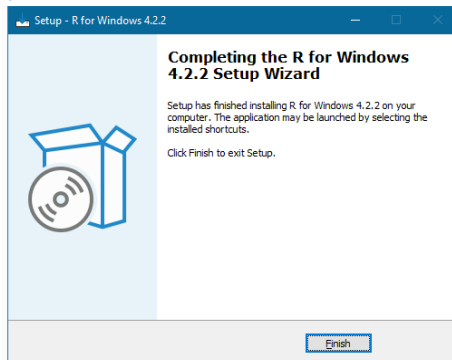
8. (Optional) If your computer is a 64-bit, you can choose the 64-bit User Installation. Then click Next.



9. Then specify if you want customized your startup or just use the defaults. Then click Next.



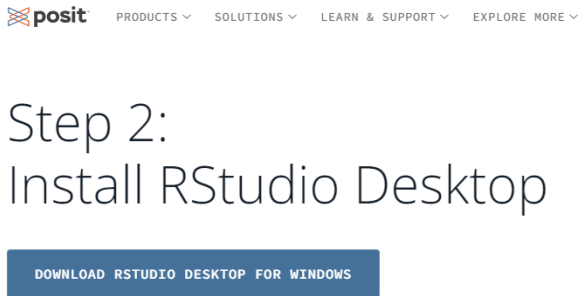
10. Click Finish:



11. Next, download RStudio. Go to <https://posit.co/downloads/>

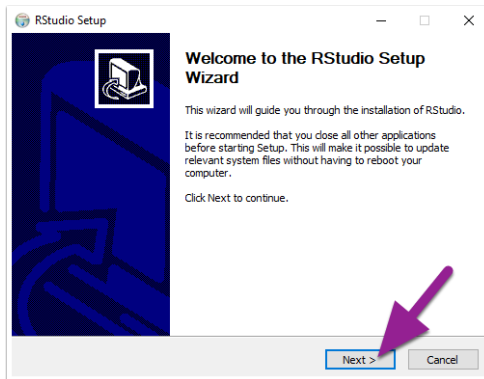


12. Click **DOWNLOAD RSTUDIO DESKTOP FOR WINDOWS**.

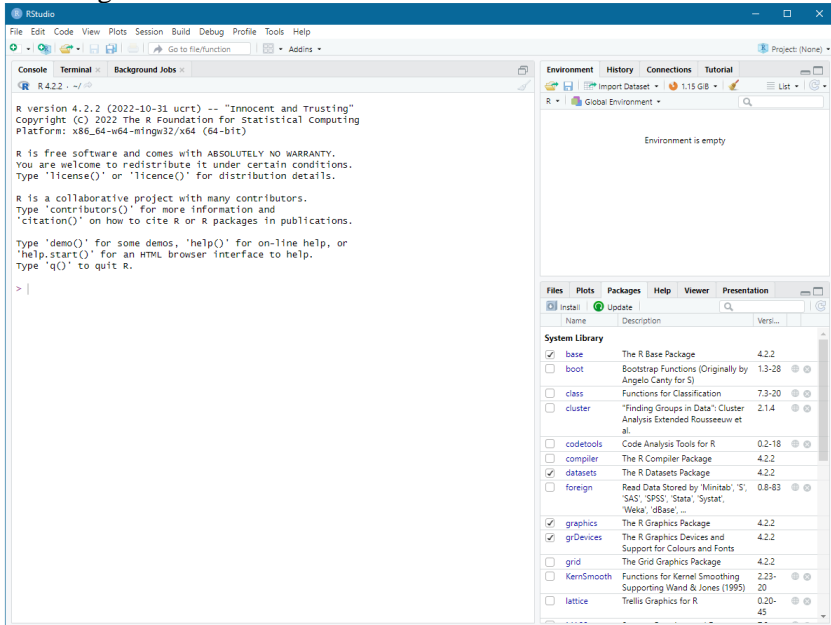


Size: 202.76MB | [SHA-256: FD8EA4B4](#) | Version: 2022.12.0+353 |
Released: 2022-12-15

13. The RStudio installation wizard will pop-up. Click Next and go through the installation steps:



14. Congratulations! You have now installed R and RStudio:



3.1.1. Getting started with R

One of the main benefits of using R is that this programming language relies on a wide and active community of developers and end-users. Several manuals, including the one found on ORAN below, guiding material, tutorials and web pages dedicated to debugging errors, such as stackoverflow (listed below) can be found online:

- R manuals: <http://cran.r-project.org/manuals.html>
- Contributed documentation: <http://cran.r-project.org/other-docs.html>
- Quick-R: <http://www.statmethods.net/index.html>
- Stackoverflow R community:
<https://stackoverflow.com/questions/tagged/r>

3.1.2. Some useful R-packages for the SOCseq maps

As mentioned previously, the main advantage of R is its extensibility. The scope of the possible implementations of R can be greatly increased with the vast collection of packages that extend its basic functionalities.

Packages are the equivalent of add-ons that developers can freely write and make available through the open-source platform that constitutes R.

R has a large and growing number of spatial data packages. We recommend taking a quick browse on R's official website to see the spatial packages available: <http://cran.r-project.org/web/views/Spatial.html>. Some of these packages that will be useful to generate the national SOCseq maps include:

- raster. Reading, writing, manipulating, analyzing and modeling of gridded spatial data. The package implements basic and high-level functions, processing of very large files is supported.
- rgdal: Provides bindings to the 'Geospatial' Data Abstraction Library ('GDAL') ($\geq 1.11.4$) and access to projection/transformation operations from the 'PROJ' library. Use is made of classes defined in the 'sp' package. Raster and vector map data can be imported into R, and raster and vector 'sp' objects exported.
- ncdf4. Provides a high-level R interface to data files written using unidata's netCDF library (version 4 or earlier), which are binary data files that are portable across platforms and include metadata information in addition to the data sets. Using this package, netCDF files (either version 4 or classic" version 3) can be opened and datasets read in easily.
- SoilR. This package contains functions for modeling Soil Organic Matter decomposition in terrestrial ecosystems. See <https://cran.r-project.org/web/packages/SoilR/SoilR.pdf>.
- abind: Combine multidimensional arrays into a single array. This is a generalization of cbind' and 'rbind'. Works with vectors, matrices, and higher-dimensional arrays. Also provides functions adrop', asub', and 'afill' for manipulating, extracting and replacing data in arrays.
- soilassessment. Soil assessment builds information for improved decision in soil management. It analyzes soil conditions with regard to agriculture crop suitability requirements (such as those given by FAO <http://www.fao.org/land-water/databases-and-software/crop-information/en/> soil fertility classes, soil erosion models and soil salinity classification. Suitability requirements are for crops grouped into cereal crops, nuts, legumes, fruits, vegetables, industrial crops, and root crops.

3.1.3. Installation of R-Packages used in this technical manual

The authors of this Technical Manual used a number of different R packages (summarized in Table 3.1). All required packages can be installed using the following code and the `install.packages()` function when starting a new SOC sequestration mapping project:

`install.packages("name_of_the_package")`

Alternatively, the code for the installation of the needed packages is included at the beginning of each script.

Table 3.1 Required R-packages for the national SOC sequestration potential maps using an R-environment

Protocol application area	R package	Reference
Import and export raster data	raster	Hijmans et col. (2020)
Import and export raster data	ncdf4	David Pierce (2019)
Import and export vector data	rgdal	Bivand et col (2019)
Harmonization	raster	Hijmans et col. (2020)
Harmonization	rgdal	Bivand et col (2019)
RothC model	SoilR	Sierra and Mueller (2014)
Data manipulation	abind	Plate (2016)
RothC model, NPP MIAMI model	soilassessment	Omuto (2020)

3.1.4. Considerations when using R

It is important to note the following points when using R:

- R is a case-sensitive scripting software. More than 90% of its commands are scripted in a text-editor and executed by running the line/script.
- Hash (#) denotes the beginning of a comment and is not executed by the software. Consequently, it can be used to insert comments in a line. All comments after hash (#) are colored green (like green traffic light) implying “pass” without execution.
- With the default editor theme errors and warnings are given in red, while functions and numbers are given in blue and commands and variables are given in black.
- When using RStudio text-editor, four panes are available in which the top left pane is the text editing window, top right pane is for the data environment, bottom right pane is for display and help, and the bottom left is the console for executing the scripts.
- Implemented scripts and reports (warning or errors) are shown in the

- console panel.
- Some commands may run for some time and patience is recommended to enable the software to progress to completion. During such time, a red icon will be shown at the top left corner of the console panel.
- The execution of a line or script can be stopped if necessary by clicking on the “STOP” button from the tools bar.

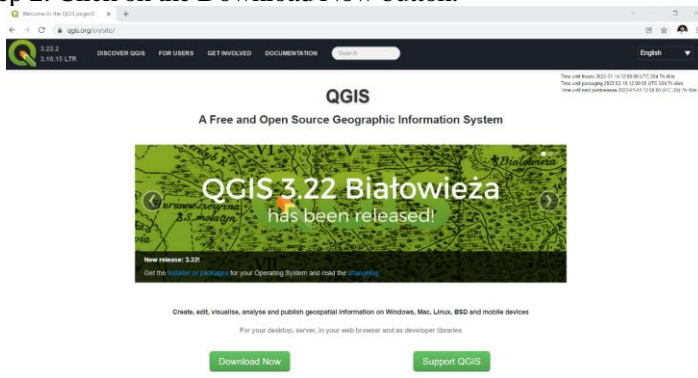
3.2. Install QGIS on Windows

To install QGIS on Windows follow the below steps:

Step 1: Visit the official website using the URL <https://www.qgis.org/en/site/> in any web browser.



Step 2: Click on the Download Now button.



Step 3: Next web screen open now click on QGIS standalone Installer version 3.22 to start downloading.


NOTE FOR EXISTING USERS: OSGeo4W v2 (previously known as testing) is now the regular repository. The latest QGIS release is only available here, as it already requires dependencies not available in the old repository. The long term release is additionally also available in the old repository using the same dependencies as before (see below). This also includes a 32-bit version, which OSGeo4W v2 does not support.

CAUTION: Upgrades of old setups using the new repository are not supported. You need to do a fresh install or use a different directory.


CAUTION: Windows 7 no longer works as we are now using Python 3.9, which dropped support for it.

Standalone installers (MSI) from OSGeo4W packages (recommended for new users)

Latest release (richest on features):

↓  [QGIS Standalone Installer Version 3.22](#) [sha256](#)

Long term release (most stable):

↓  [QGIS Standalone Installer Version 3.16](#) [sha256](#)

Note that the MSI installers are much bigger than the previous installers. This is because they include significant larger packages (eg. PROJ.B). The main reason for the switch to MSI were the size limits previously used NSIS has, which was blocking updates of dependencies.

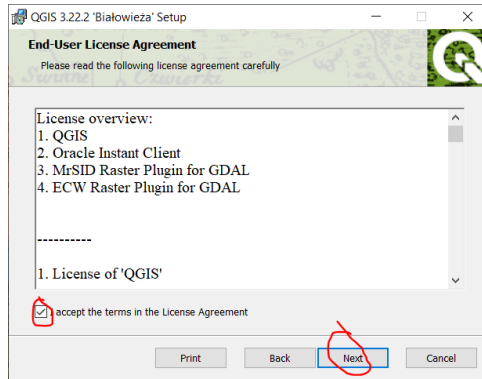
Step 4: Now check for the executable file in the downloads folder in your system and open it.



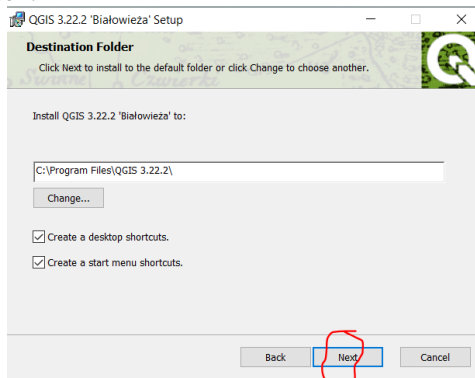
Step 5: Now the installation process is started click on the Next button.



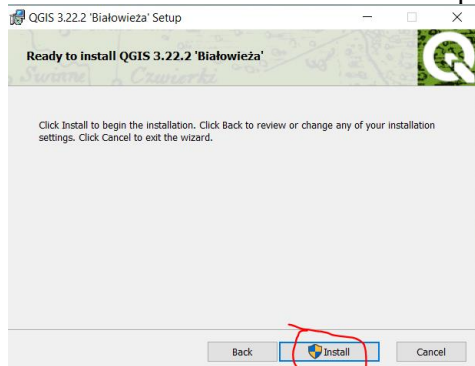
Step 6: The next screen will be of License Agreement; click on I accept the terms then click on Next button.



Step 7: The next window will be of installing location, so choose the drive which will have sufficient memory space for installation. Then click on the Next button.

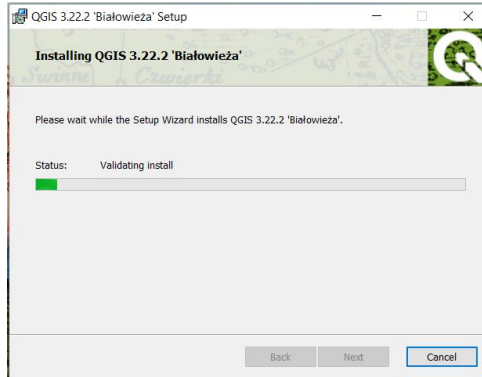


Step 8: Now click on the Install button to start the setup to install.

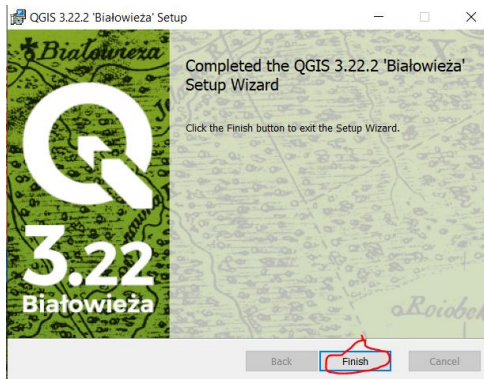


Step 9: It will prompt confirmation to make changes to your system. Click on Yes.

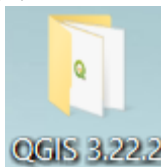
Step 10: After this installation process will start and it might take 8-12 minutes depending on your computer speed and specification to complete the installation.



Step 11: After the installation process is complete, click on the Finish button.

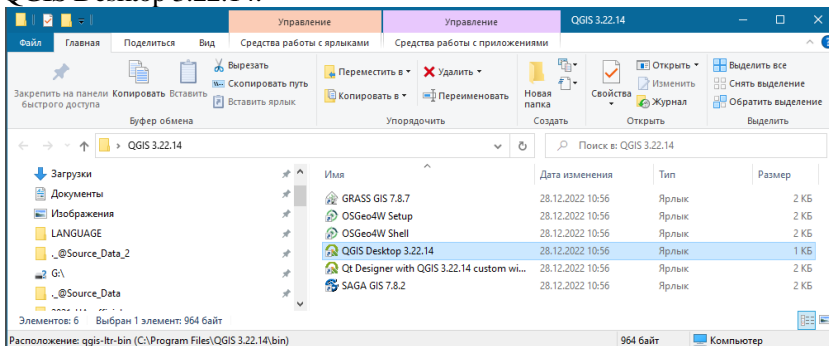


At this point, QGIS is successfully installed on the system and a folder will make on the desktop screen.

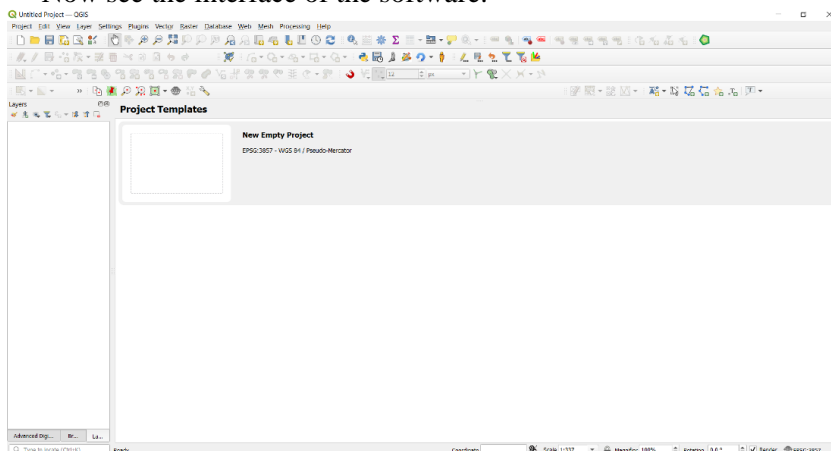


Now double click on the folder and you show many files but you choose

QGIS Desktop 3.22.14.



Now see the interface of the software.



Congratulations! At this point, you have successfully installed QGIS on your Windows system.

3.3. Running the scripts: overview

3.3.1. Summary of steps and scripts

The generation of national SOC sequestration potential maps using the spatially explicit R-version of the RothC model shall be divided in three stages (Figure 8.1.):

- Preparation and Harmonization of data (consists of eleven R

scripts, one QGIS model script, and one Google Earth Engine script);

- Running the model in three phases (three R scripts);
- Transformation of vector data to raster data (map generation, one R script)/

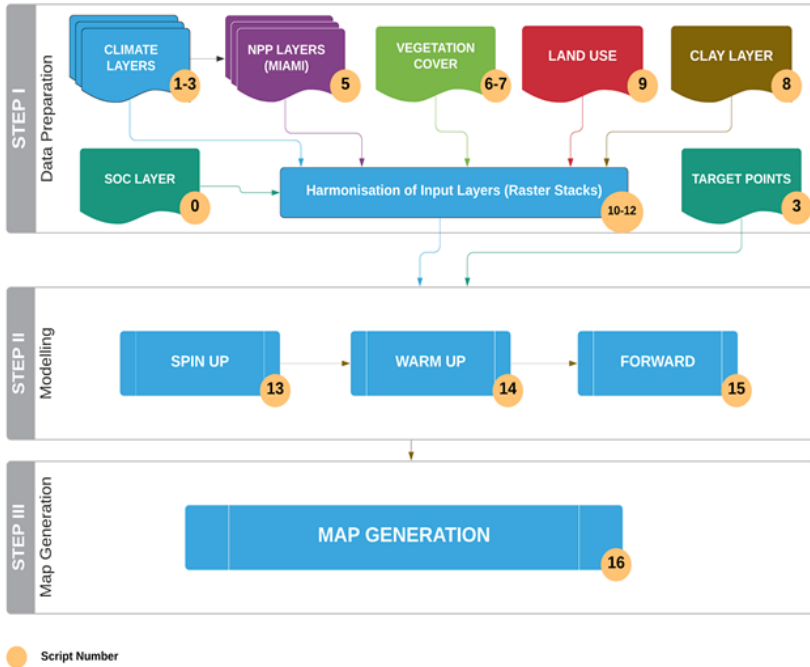


Fig. 3.1. Workflow for generating the national SOCseq layers

3.3.2. Stage 1: Preparation of data

Running the model over an area will require several spatial layers of information (climate, clay content, land use, vegetation cover, NPP layers) and defining target points where the model will be run. So before running the model, we will “harmonize” the different spatial layers, in order to have the same extent, same pixel size and same Coordinate Reference System (CRS). On the other hand, each modeling phase (spin up, short spin-up/warm up, forward runs) will require a different selection of layers for the different time series. So we will create ‘stacks’ of the different layers for the single modeling

phases. Land cover classes need to be re-classified into land use types that the model will recognize. We will reclassify land cover classes (like the ones provided by ESA; European Space Agency) to match the FAO land cover classes. At this stage, we will also create other input layers (like NPP and vegetation cover layers) which are necessary to run the model. Finally, we will create target points over the land use classes of interest (agricultural lands). These target points will become the modeling units (where the model is to be run).

So, the first step (Fig. 3.1) is aimed at:

- preparing, organizing and harmonizing all the required input data layers to run the model in the different phases;
- creating supplementary input data layers;
- creating target points for land use classes of interests/

Eleven R scripts, one QGIS script and one Google earth engine script are provided to complete these tasks (Table 3.1).

Table 3.1. Summary of the scripts for the complete modelling process

Type of Layer	Script	Objective
SOC layer	R- Script number 0	Cut the SOC layer by the area of interest polygon
Climate layers	R- Script number 1 R- Script number 2 R- Script number 3	Rearrangement of climate layers (CRU layers from .ncd to .tif)
NPP layers	R- Script number 5	Creation of NPP layers
Vegetation Cover (VC)	GEE Script number (Google Earth Engine) R- Script number 7	Creation of VC layers
Clay layers	R-Script number 8	Obtaining clay contents 0-30 cm from different depths (ISRIC)
Land Use layer	R-Script number 9	Re-classification into FAO land cover classes
STACK for SPIN UP	R-Script number 10	Stack input data layers for the spin up phase
STACK for WARM UP	R-Script number 11	Stack input data layers for the warm up phase
STACK for FORWARD	R-Script number 12	Stack input data layers for the forward phase
Target points	QGIS model script	Creation of target points
SPIN UP	R- Script number 13	Run long spin up phase
WARM UP	R- Script number 14	Run warm up phase
FORWARD	R- Script number 15	Run forward phase

POINTS TO RASTER	R- Script number 16	Rasterize points
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3.3.3. Stage 2: Running the model

Once the input data layers are prepared and stacked, we will run the spatialized RothC model at each target point using three specific scripts (Table 3.1):

1. Long spin up phase: the equilibrium carbon inputs (carbon inputs in $\text{tha}^{-1} \text{y}^{-1}$ required to reach SOC stocks in year 2000) and the initial stocks of the different SOC pools are calculated;
2. Short spin up or Warm Up phase: SOC stocks are adjusted for the 2000-2020 period;
3. “Forward” phase: SOC stocks are projected (2020 to 2040) under a “business as usual” scenario (no changes in carbon inputs), “low” scenario (5% increase in carbon inputs), “medium” scenario (10% increase in carbon inputs), and “high” scenario (20% increase in carbon inputs).

3.3.4. Stage 3: generation of the map

After the “forward” modeling phase, in the final step we will calculate the average absolute and relative SOC sequestration rates over a 20-years period for each scenario and for each target point. The vector target points will be then rasterized and saved to geotiff format to obtain the final product, using a specific R script. All the provided scripts are summarized in Table 3.1.

4. Developing the map of carbons sequestration by the different scenarios of land management

4.1. Stage 1: preparation of input data

This stage is aimed at:

- preparing, organizing and harmonizing all the required input data layers to run the model in the different phases;
- creating supplementary input data layers;
- creating target points for land use classes of interests.

During this stage we will need to arrange and prepare climate datasets for the different modelling phases, generate NPP estimates for each phase, generate vegetation cover data, prepare clay content data layers, and harmonize and stack all layers for each modelling phase. Finally, we will have to create target points to run the model. This stage requires the most effort and is the most time consuming of the entire process. Eleven R scripts, one QGIS script and one Google earth engine script are provided to complete these tasks.

Pay attention: since these methodological recommendations are mostly a simplified version and are largely based on the work: "*FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome*" <https://fao-gsp.github.io/GSOCseq/index.html>, then most of the necessary data for the territory of Ukraine we are already prepared for use by Ukrainian users. For more detailed information, please refer to the mentioned source.

By default, the AOI "District_Khmelnyk.shp" will be used. If desired, you can choose AOI from the following files:

"c:\TRAINING_MATERIALS\INPUTS\AOI_2021_UA_official\2021_UA_rajon_.shp"

(administrative districts)

"c:\TRAINING_MATERIALS\INPUTS\AOI_2021_UA_official\2021_UA_terhromady.shp"

(territorial communities)

"c:\TRAINING_MATERIALS\INPUTS\AOI_2021_UA_official\2021_UA_oblast.shp"

(regions).

In this case, you should change the AOI file names in the proposed scripts. All the necessary scripts are located in the corresponding folders along the path "c:\TRAINING_MATERIALS".

All source data for modeling are located in the corresponding folders along the path "c:\TRAINING_MATERIALS\INPUTS\".

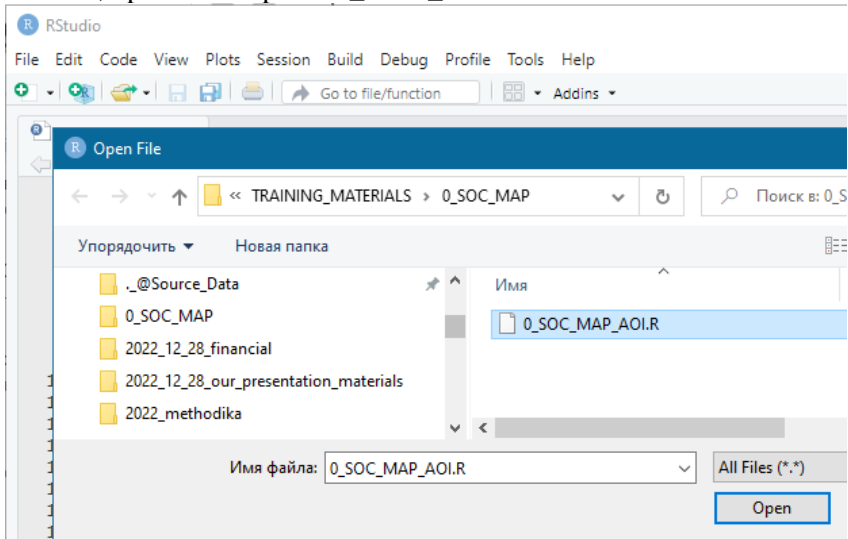
4.1.1. Preparation of SOC layer

As a default option, users are invited to use the GSOCmap to retrieve their SOC data for their area of interest (AOI). This can be achieved easily, by clipping the GSOCmap to the extent of a shapefile making up the borders of the chosen study area or country. All data sources can be found in Table 6.3 of Chapter 6.

Script Number 0. “SOC_MAP_AOIR”

Aim: Preparation of the Soil Organic Carbon SOC layer.

First, open the script SOC_MAP_AOIR.R in RStudio:



For RUN script: press “Ctrl+A” (select all script text) and Press “Ctrl+Enter”. All will work automatically. This procedure will need to be done for each script, unless otherwise specified.

4.1.2. Preparation of climate Layers

The climate variables needed for the three modeling phases are:

1. Monthly rainfall (mm/month):
2. Monthly Evapotranspiration (mm/month):
3. Average monthly mean air temperature (average °C/month).

We will need to arrange these climatic variables into three datasets:

- 1980-2000 (monthly average values for the complete series)

- 2001-2020 (year to year monthly values)
- 2001-2020 (monthly average values for the complete series)

Gridded climate data shall be obtained from either National Sources or regional or global datasets when national gridded historical climate datasets are not available. The recommended global data source of these layers are:

- The Climate Research Unit (<http://www.cru.uea.ac.uk/>)
- TerraClimate (readily available from the Google Earth Engine catalogue: https://developers.google.com/earth-engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE# citations)

For countries wanting to use the TerraClimate or the CRU data set, several scripts to obtain and to reformat the climate spatial layers to run the three modelling phases, will be presented. Users can prepare the necessary input climate data sets using other data sources. However, these scripts may still be helpful to guide the preparation process of other data sets, and as a guide of the required outputs that will be needed as inputs for the different modeling phases. Due to the coarse resolution of the CRU data set, small and/or coastal countries may encounter issues with the data set.

It is important to note that the CRU layers do not cover countries in their entirety. To overcome this, this revised version of the Technical Manual provides two options:

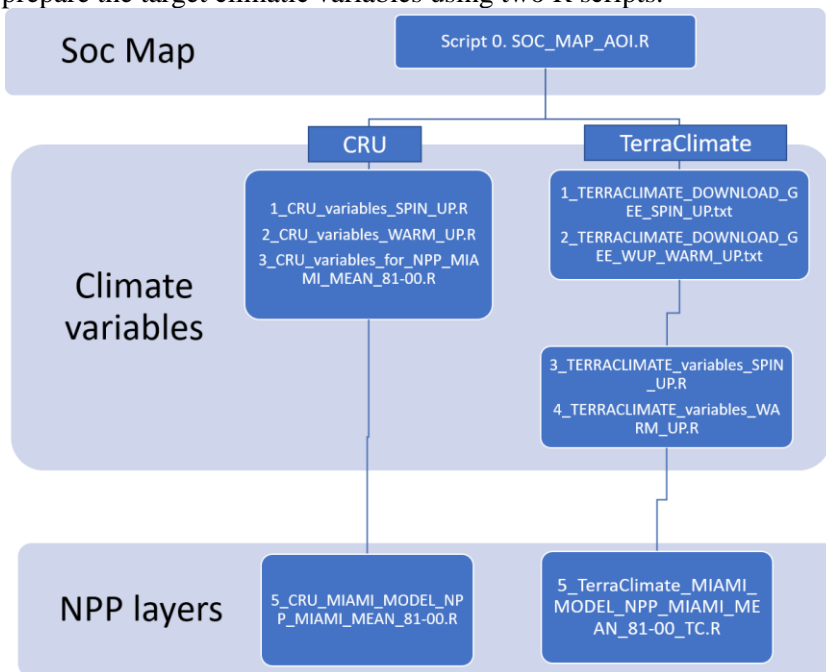
For countries wanting to use the TerraClimate or the CRU data set, several scripts to obtain and to reformat the climate spatial layers to run the three modelling phases, will be presented. Users can prepare the necessary input climate data sets using other data sources. However, these scripts may still be helpful to guide the preparation process of other data sets, and as a guide of the required outputs that will be needed as inputs for the different modeling phases. Due to the coarse resolution of the CRU data set, small and/or coastal countries may encounter issues with the data set.

It is important to note that the CRU layers do not cover countries in their entirety. To overcome this, this revised version of the Technical Manual provides two options:

1. Perform the whole procedure with higher resolution climate layers again for every point. We have provided scripts to download and prepare TerraClimate climatic layers.
2. Re-running the model only for those points that fall outside of the CRU layer using the provided scripts that include a line of code that fills NA values with the average of all surrounding pixel values.

For both cases a detailed step by step guideline is provided in: FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome.

The preparation of the climate data depending on whether a user selects the CRU (Option A) or TerraClimate (option B) data set is presented in the flowchart below. To make use of the TerraClimate dataset, users need to first download the data for the time periods 1980-2000 and 2001-2018 using two scripts for Google Earth Engine (GEE) and subsequently prepare the target climatic variables using two R scripts.



Script order to follow depending on whether CRU or TerraClimate data sets are selected

Option A: Preparation of the CRU climatic variables

Script Number 1. “CRU_variables_SPIN_UP.R”

For each modelling phase we will need a different selection of climate layers. For phase 1 (“Long Spin up”), we will need to stack 12 spatial layers

(the output file will be a multiband raster layer) for each climate variable mentioned above (temperature, precipitation and evapotranspiration). The time series for this initial phase goes from 1981 to 2000. The script number 1 (1_CRU_variables_SPIN_UP.R) will transform the downloaded CRU files to geotiff raster files and obtain monthly averages (temperature, precipitation, evapotranspiration) for the 1981-2000 series, ready to be used in the spin up modelling phase.

We have already prepared these files, so you do **NOT** need to run this script: **1_CRU_variables_SPIN_UP.R**

Script Number 2: “2_CRU_variables_WARM_UP.R”

The purpose of the “Warm up” phase is to adjust the initial SOC stock and initial pools for the “forward” phase. Once the input climate layers have been harmonized, the model will run for each year from 2001 to 2018/20, using the monthly climate data of each year of the series (for 216/240 values for each month of the time series). The script number 2 is prepared to arrange the necessary CRU climate files for this phase. We will need to generate one raster stack of 216/240 spatial layers for each climate variable mentioned above (216 spatial layers if we use just 18 years period instead of a 20 year period; from 2001 to 2018, depending on the available climate data). Each stack will have one layer for each month from 2001 to 2018/2020. For phase number 3, the “Forward” phase, we will need monthly averages of the time series 2001-2018/20. We will use the same arrangement as used in phase number one (one stack of 12 bands for each variable) but instead of using the averages of the 1981-2000 period we will use the climatic data of the 2001-2018/20 period. We will assume that there is no climate change in the next 20 years. Thus, script number 2 will also prepare the climate files for the “forward phase”.

We have already prepared these files, so you do **NOT** need to run this script: **2_CRU_variables_WARM_UP.R**

Script Number 3: “3_CRU_variables_for_NPP_MIAMI_MEAN_81-00.R”

Preparation of CRU files to estimate NPP 1981-2000. This script convert the CRU monthly climate data 1981-2000 into annual data to estimate annual NPP 1981-2000.

“3_CRU_variables_for_NPP_MIAMI_MEAN_81-00.R” will process the CRU files from the 1981-2000 series to generate the climate inputs files

required to estimate NPP by the MIAMI model. In this case, we have also already prepared these files, and therefore you do **NOT** need to run this script.

Script Number 4. “4_MIAMI_MODEL_NPP_MIAMI_MEAN_81-00.R”

To adjust yearly C inputs during the warm up phase according to annual NPP values, we will need to estimate an average annual NPP 1981-2000, that will be used as the starting point to adjust C inputs during the “warm up” phase. Script number 4 uses the climate raster outputs from script number 3 and estimates an annual NPP mean 1981-2000 value.

RUN script “4_MIAMI_MODEL_NPP_MIAMI_MEAN_81-00.R”. All will work automatically.

As we wrote above, there is **Option B for Preparation of the TerraClimate climatic variables**. If desired, you can read more about it in the manual: FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome.

Script Number 6. “6_Vegetation_Cover_GEE_copy_to_code_Editor_v2.txt” – vegetation cover from Google Earth Engine.

Script number 6 is a Google Earth Engine script. It is aimed at estimating an average vegetation cover status for each month of the year. Therefore: the script should be run twelve times, modifying the month number each time. It estimates, within a specified time series, the probability for each pixel to present NDVI values greater than a specified threshold, over which the soil is vegetated (for example $NDVI > 0.6$). The result will vary between 0 and 1. Users may modify the time series and NDVI threshold as desired and according to local knowledge. In this case, we have also already prepared these files, and therefore you do **NOT** need to run this script. If desired, you can read more about it in the manual: FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome.

Script Number 7. “7_Veg_Cov_stack.R”

The script number 7 is an R script that uses the monthly vegetation cover layers (0-1 values) created with the GEE script number 6 to create a raster stack. It also linearly rescales the values from “0 to 1” (proportion of vegetated pixels in a time series) to “1 to 0.6” (being 1 = bare soil and 0.6 = full vegetated pixel). This transformation will allow us to use the calculated values as modifying factors of the decomposition rates in the RothC model.

Because we have already downloaded the monthly vegetation cover layers for you for the entire territory of Ukraine, we will generate a stack of those layers. We will first open script “7_Veg_Cov_stack.R” and the required packages. Then, RUN script. All will work automatically.

Script Number 8. “8_Script_CLAY_from_ISRIC.R”

ISRIC clay layers represent the clay content (0-2 micrometer; in g/100g; w%) at four standard depths (S11=0-1cm; S12=1-5; S13=5-15cm; S14=15-30 cm) at a 250m resolution. The objective of this script is to aggregate the different layers into one layer by estimating the weighted average of the four depths.

We have already combined the data by layers for the entire territory of Ukraine, so when you run this script, it will only cut the data according to the AOI outlines.

4.1.3. Preparing the land use layer

The land use layer is one of the most important layers in the process, as it defines the target areas and production systems to be modeled. The land use layer will be needed:

- to account for major land use changes during the 2000-2020 period;
- to obtain the DPM/RPM ratios required in the RothC model;
- to define the modeling units/target points where the model is to be run (agricultural lands in 2020).

Each modeling phase will require specific land use layers. For the spin up’ phase, users should use a representative land use layer for the period 1980-2000 (e.g. land use layer as in year 2000), or best available land use layer. For the ‘warm-up’ phase, users can use year to year land use layers (2000 to 2020), or a representative land use layer for the period, depending on the available information. The ‘warm-up’ land use layer accounts for year-to-year changes in the land use during the period (for example a pixel

that changes from forest to cropland). The script will need a stack of land use layers, one layer for each year of the warm up phase. If the user does not want to model changes in the land use layer over the warm up phase, or information is not available, the same land use layer for each year can be used over the warm-up phase.

For the ‘forward’ phase, the latest best available land use layer should be used. As a minimum, the last available land use data at 1x1 km resolution shall be defined. The predominant land use category in each cell of the 1x1 km grid shall be selected if finer resolutions are available. The land use classes can be derived from land cover classes from different national, regional or global datasets which best correlate with national land use. The land use layers are used in the three modelling phases to generate a decomposition rate DR layer (generated through scripts 10, 11, and 12), that represents the above mentioned DPM/RPM ratios for the different land use classes. In scripts 10, 11 and 12, default DPM/RPM values are assigned to each FAO Global Land Cover (GLC-SHARE) class (See Table 2.2 and scripts 10, 11 and 12). For more information on this classification refer to FAO (2014) and to the FAO Land and Water site:

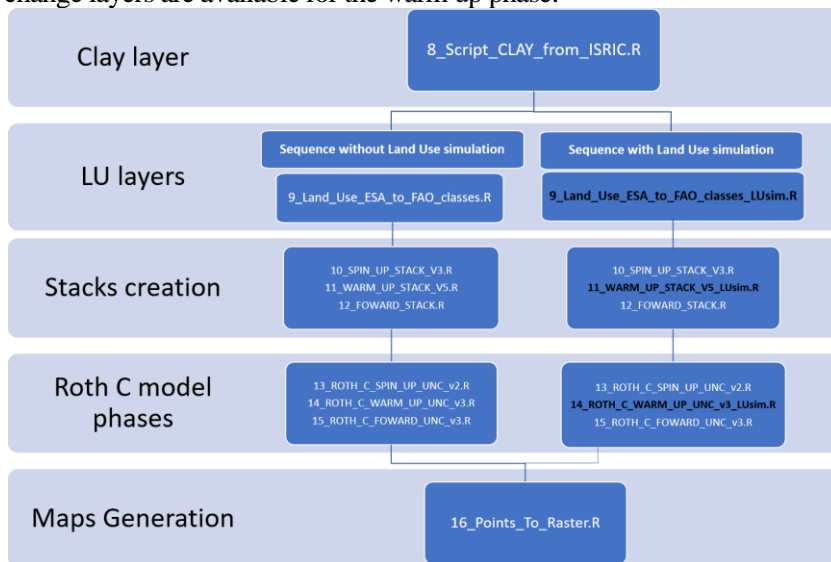
<http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1036355/>

Thus, land cover classes obtained from different datasets (e.g. European Space Agency - ESA) need to be re-classified into FAO land cover classes in a Geotiff format if the scripts 10, 11 and 12 are to be run with the default land classes and DPM/RPM ratios provided with the training material. In this section, we provide a script to transform ESA land use cover classes to FAO land use classes (script 9), which can be used as a model to convert and use classes from other datasets. Users can however modify the DPM/RPM default values (See Table 2.2) based on local knowledge and available information, create additional land use classes or disaggregate the FAO land use classes, and assign DPM/RPM ratios to those new classes by modifying the provided scripts. Users are encouraged to leverage available local knowledge and data to produce the most accurate SOCseq maps possible. With this in mind: if more detailed land use maps, i.e. containing information about the types of cropping systems present, and local data on the DPM/RPM for the specific land use types are easily accessible, the provided script should be edited accordingly.

Finally, the land use layer is also needed to define the target points where

the three phases of the protocol will be run. In next section we provide a QGIS model to generate the target points from the land use layer. Defining the target points out of the land use layer will allow us to run the model just in the pixels with the land use classes of interest.

Depending on whether yearly land use layers are available for the forward phase, technical manual (FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome) contains alternative scripts both for the data preparation phase (Scripts 9_Land_Use_ESA_to_FAO_classes_LUim.R and 11_WARM_UP_STACK_V5_LUim.R) and the modelling phase (Script 14_ROTH_C_WARM_UP_UNC_v3_LUim.R). Next figure illustrates the script sequence to be followed depending on whether yearly land use change layers are available for the warm up phase:



Script Number 9. “9_Land_Use_ESA_to_FAO_classes.R”: No land use change

Script number 9 transforms the ESA (European Space Agency 2015; 300 m resolution; ESA CCI Land cover website) land cover classes to the FAO land use classes. This script can be modified to be used with any other land use dataset.

RUN script “9_Land_Use_ESA_to_FAO_classes.R”. All will work automatically. An alternative way, when we conduct Land use change simulation, is not considered in these methodological recommendations.

4.1.4. Harmonization of soil, climate and vegetation layers

Once all soil, climate, vegetation and land use layers are created, they need to be harmonized in order to run the model. The harmonization of layers consists of three steps. First, if the model is to be run for an entire country/region/district, layers need to be harmonized to the extents of the AOI boundaries (AOI polygon layer extents). Second, a resampling process is required in order to match the spatial resolution to the master layer (SOC FAO layer). Finally, a masking process is required to cut the layer with the vector polygon boundaries. After the harmonization of all layers, we will generate a raster stack of all layers needed to run the model. The harmonization/stacking process will be performed three times (scripts 10, 11, 12), one for each modelling phase.

Script Number 10. “10_SPIN_UP_STACK_V3.R”

Script number 10 is intended to harmonize all layers needed to complete phase 1 (long spin-up) of the spatial RothC model. The result of this script is a simple raster stack which contains all the data to perform the spin-up phase. To generate the stack, we will need the SOC FAO layer (master layer), the clay layer (from script number 8), the three climate stacks (from script number 1), the land use layer (from script number 9), and the vegetation cover stack (from script number 7). The script creates a DR layer (DPM/RPM ratio). Here the DR layer is derived from the Land use layer, assigning default DPM/RPM ratios to each FAO land cover class. Users can modify these ratios according to local expertise and available local information.

RUN script. All will work automatically.

Script Number 11. “11_WARM_UP_STACK_V5.R” No Land use change!

Script number 11 is intended to harmonize all layers required to run the phase 2 (WARM UP) of the spatial RothC model. The result of this script is a simple raster stack which contains most of the layers needed for the warm-up phase. To generate the stack, we will need the latest version of SOC FAO layer (master layer), the clay layer (from script number 8), land use

layers (from script number 9), a land use stack (one land use layer per year), a vegetation cover stack (from script number 7) and the NPP stack (from script number 4). The climate layers and the NPP mean are additional layers that will be needed in the WARM UP phase but will not be part of this stack because of the final size of the output file.

RUN script. All will work automatically.

Script Number 12. “12_FOWARD_STACK.R”

Script number 12 harmonizes all layers needed to run phase 3 (forward) of the spatial Roth C model. The result of the script is a simple raster stack which contains the layers needed to perform the forward phase. To generate the stack, we will need the SOC FAO layer (master layer), the clay layer (from script number 8), the three climate stacks required for the forward phase (from script number 2), the land use layer or the forward phase (from script number 9), and the vegetation cover stack (from script number 7).

RUN script. All will work automatically.

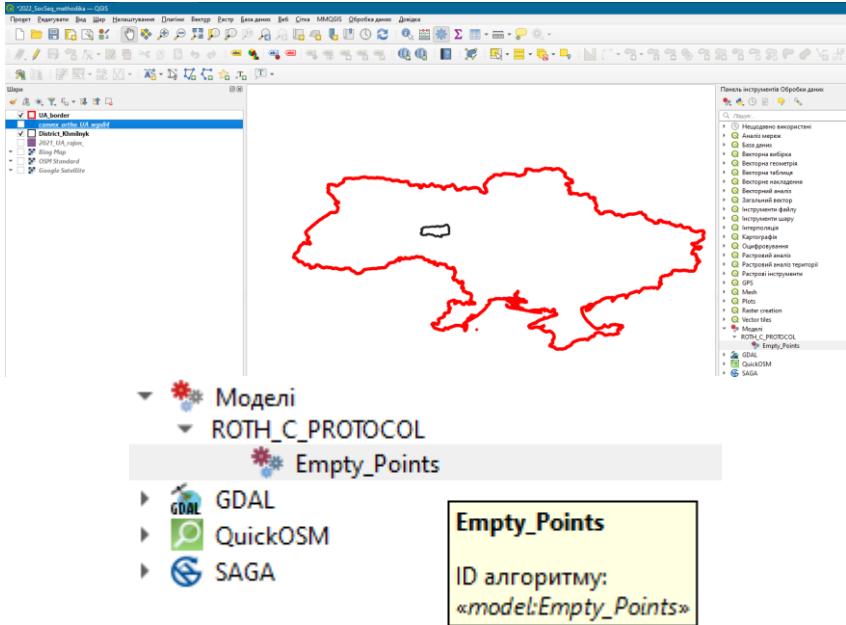
4.1.5. Defining target points to run the model

At this point we have three raster stacks for the different modelling phases. We need to create the points where those simulations will be run in order to accelerate the modelling process. These points will be the center of the pixels of the master layer (GSOCmap layer, script number 7). Later, we will convert the points containing the modelling output values back to a raster layer format.

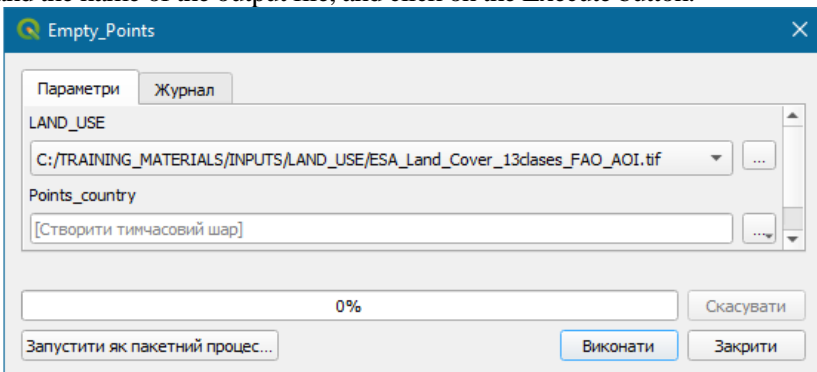
QGIS Procedure number 1 (model)

We will need the land use data of each pixel (we already corregistered the land use layer with the master layer at script number 7). Then we will use the land use layer of the country to generate the points. For this, we can use a QGIS model to create target points.

For these purposes we must open the QGIS, then go to the processing toolbox and click on the “open existing model” button. We will have to search for the model in the provided folder, called “4_Points_country”. We will have to load the model called “Qgis_Procedure_number_1.model3”. Once this is done, we can run the model from the processing toolbox.



We will click the `Empty_Points` button and a window will pop up. We will select the Land use layer created in script number 10 (already resampled to match the extent and pixel size of the GSOCmap), set the path and the name of the output file, and click on the Execute button.



This process will create vector points. Each point will be created in the centroid of each pixel of the land use layer. This vector will contain no fields. The scripts to run the model for each phase (SPIN_UP, WARM_UP,

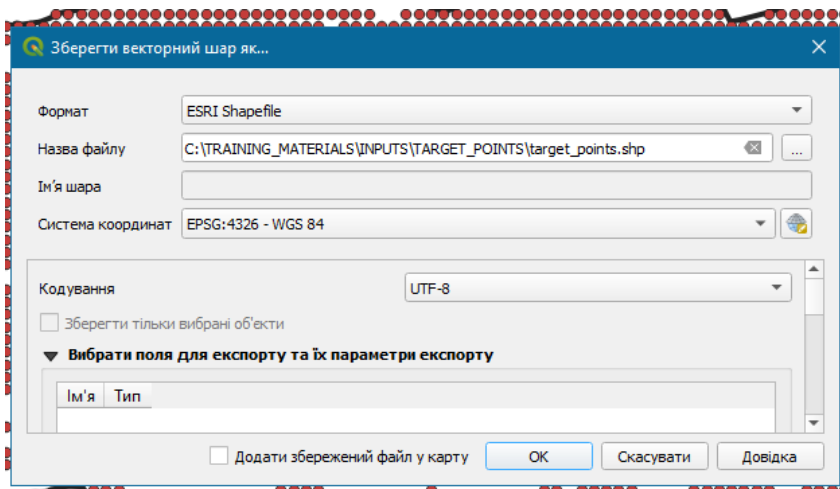
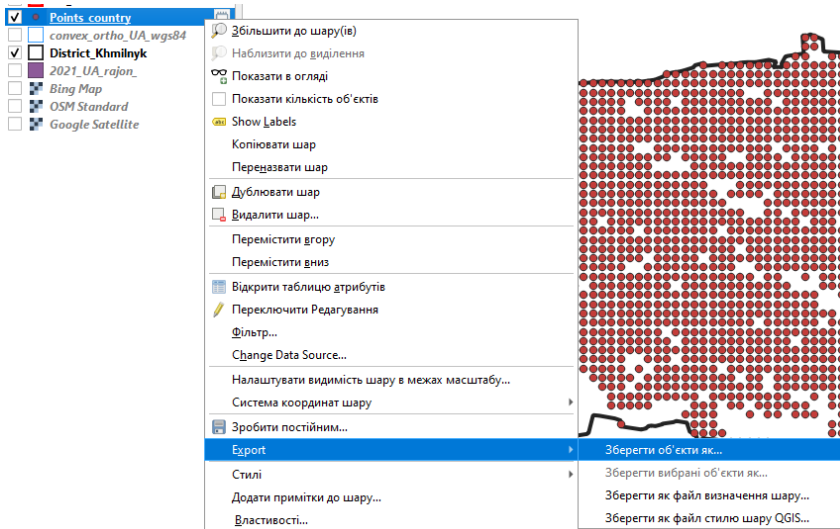
forward) will attach all the necessary data from the stacks (scripts number 10, 11 and 12) to each point.

The screenshot displays the QGIS Model Designer interface. The main workspace shows a workflow diagram with the following steps:

- LAND_USE** (Input)
- Píxeles ráster a puntos** (Raster to points)
- Select Croplands** (Filter)
- Select Grasslands** (Filter)
- Select Shrublands** (Filter)
- Select Treecrops** (Filter)
- Quitar campo(s)** (Remove field)
- Points_country** (Output)

Below the model, the QGIS map view shows a grid of points overlaid on a land use map of Slovakia. The points are concentrated in the agricultural areas. A small window titled 'Points_country - Features: Total: 5083, Filtered: 5083, Selected: 0' is visible at the bottom, showing a list of points with their coordinates.

Export points to:
 C:\TRAINING_MATERIALS\INPUTS\TARGET_POINTS\target_points.shp



4.2. Stage 2: running the model

Once all input layers are prepared, harmonized and stacked, we will run the three modeling phases (spin up, warm up and forward phase). At this stage, we will run the model three times, once for each phase using three different scripts (scripts 13A -equilibrium run or 13 B-analytical solution (this option is not considered in these methodological recommendations), 14 and 15), which use the same RothC function. For each script we will need the previously created raster stacks and target points. Each script will generate output vector points (containing the modeling results, i.e., SOC stocks of the different carbon pools of the RothC model). The output vector of each phase will be used as an input of the next modeling phase. Finally, after running the final modeling phase, the forward phase, we will obtain an output vector containing the SOC data for each projected scenario. This output vector will be used as input for the final script (script 16) to generate the raster files to build the sequestration potential maps.

4.2.1. Initialization – Spin up phase

To estimate initial carbon pools and equilibrium carbon inputs, we will be used first alternative. Users can run the initialization phase using the equilibrium procedure, implemented in Script 13A (e.g. Smith et al. 2005; 2006; 2007; Gottschalk et al., 2012). A minimum of 500 years is suggested to reach equilibrium with reduced computational time. However, it must be noted that spin up runs for 500 years may not necessarily end up in equilibrium SOC stocks, depending on soil, climate and land use conditions. Increasing the duration (1000-2000 years) will reduce deviations with the cost of additional computation time.

Script Number 13A. “13_ROTH_C_SPIN_UP_UNC_v2.R” (*equilibrium runs*)

Script number 13A implements the first modeling phase (spin up) using the original equilibrium run approach. In this script we will load the stack generated in script number 10 and the target points (QGIS model number 1). We will obtain an output vector containing our target points. This script runs the RothC model for a minimum of 500 years to calculate the equilibrium carbon inputs (the carbon inputs needed to reach the 2001 SOC stocks) and the SOC stocks for the different pools. It first runs using a standard C input of 1 tC ha⁻¹ yr⁻¹,

and then equilibrium inputs are estimated from the obtained results and GSOCmap stocks. In this script we will use pedotransfer functions to estimate the SOC stocks of the different pools from the total SOC stock (Weihermüller et al., 2013) to accelerate the spin up process. All that information will be saved to the output vector (shapefile file). The SPIN UP Phase will allow us to calculate two outputs that will be saved to a point vector layer called “C_INPUT_EQ.shp”: equilibrium carbon inputs (Ceq) and the carbon stocks of the different soil C pools to run the second phase (WARM UP phase).

RUN the script. All will work automatically.

4.2.2. Warm up phase

Script Number 14A. “14_ROTH_C_WARM_UP_UNC_v3.R” No Land use change

Script number 14 implements the second modeling phase (“Warm up” phase). In this script we will load the stack of different layers generated in script number 11 and the target points. We also will load the output vector of the phase 1 (spin up), the climate layers from script number 2, the NPP layer from script number 5, and the land use layer stack from script number 9. This script runs the Roth C model for 18 years (2000-2018) with the possibility to be modified to 20 years if data is available (2000-2020). The final outputs are SOC stocks of the five C pools of the RothC model (DPM, RPM, BIO, HUM and IOM), and the total SOC stock. This information will be saved to a shapefile vector. This script runs the spatial RothC model for the warm-up period (from 2001 to 2018). We will provide the script the target points (empty vector layer from Qgis procedure number 1), the Stack layer (from script number 11), the three NPP layers (from script number 5) and the three climate layers generated in script number 2. The output vector layer from script number 13 (Spin up phase) will also be needed.

RUN the script. All will work automatically.

Forward phase: Script Number 15. “15_ROTH_C_FOWARD_UNC_v3.R”

Script number 15 implements the third modeling phase (“forward” phase). We will need to load the stack of layers generated in script number 12 and the target points. We will also need to load the output vector of the phase 2 (“warm up”) as an input. This script will run the Roth C

model for 20 years, projecting SOC stocks for the 2020–2040 period under different management scenarios (“BAU” scenario and the three SSM scenarios: low, medium and high input carbon). C inputs will vary according to the SSM scenarios. Standard default values of 5-10-20% increase in C inputs is defined for the three SSM scenarios (low, medium, high, respectively). Users can modify these inputs based on local expertise and available information, and generate alternative maps using this data. The final outputs will be the final SOC stocks after 20 years for the different scenarios. This information will be saved to a shapefile.

The ‘Forward’ modeling phase requires (as in the previous phases) the target points (generated from the QGIS procedure number 1), the stack of layers (from script number 12), and the output vector from the previous phase (warm up). The ‘euler’ method can give some out-of-range results in some points, under specific combinations of climatic, soil and NPP variables. To avoid including those points in the maps we will remove any “out of range” value. Then, we will run the rest of the script, set the working directory, calculate the uncertainties and set the name of the output vector layer.

4.3. Stage 3: Map generation

Once the model is run through the three proposed phases, we have all the information required for generating the maps. We need to transform the output vector to raster layers. We will obtain the SOC stocks after 20 years of SSM practices for the three scenarios (low, medium and high carbon inputs increments), and SOC stocks under the business-as-usual scenario (no carbon input increment). We will estimate four absolute carbon sequestration rates (considering the 2018 or 2020 SOC as a baseline), and three relative carbon sequestration rates (considering the SOC stocks under the business as usual as the baseline).

Script Number 16: “Points_to_Raster.R”

We will use script number 16 to transform the output vector from script number 15 to raster layers. The inputs for this script are the output vector from script 15, the FAO SOC layer and the country boundary polygon. The outputs of the script number 16 are the SOC stocks for the future scenarios (20 years): BAU, low, medium and high carbon inputs, three relative

sequestration rates (SOC stock SSM scenario - BAU scenario)/20 , and four absolute sequestration rates: (SOC stock SSM or BAU scenario - SOC stocks 2018/20)/20.

Next, script will be transforming the vector points from the FORWARD phase of the model to raster files using the “rasterize” function. After this, script will calculate the absolute differences and the absolute rates (SSM - SOC 2018). Next, we will calculate the relative differences and rates (SSM - SOC BAU). Now, we will rasterize the values of the uncertainties of SOC BAU, SOC 2018 and one SSM (one for the three scenarios). This last step will transform this points to raster file, one for each required map

Now we will calculate the uncertainties for the absolute and relative rates.

4.4. Uncertainty and validation

Ideally, model prediction uncertainty provided in the SOCseq map should include all sources of uncertainty that affect predictions, including model structural uncertainty, model parameters’ and input data uncertainties. As a minimum, uncertainty should include input data uncertainties (e.g. Morais et al., 2019). There are different methods to estimate uncertainties in the results. Monte Carlo methods, that draw random values from the probability distribution functions for inputs and parameters, are an efficient way to estimate the whole uncertainty of the modeled estimation (Ogle et al., 2010; FAO, 2019b; Morais et al., 2019). In Monte Carlo simulation methods, parameter values of the model and input data (e.g. mean temperature, clay content, carbon inputs) shall be randomly chosen from hypothetical normal distributions with mean equal to the parameter value and the measured standard error around that mean. Once all the different parameter values for the model are generated from the hypothetical distributions, a model run shall be made. This process is to be repeated 100 or more times to produce a mean model prediction with a 95 percent confidence interval. The Monte Carlo simulation would generate an expected value of SOC stocks for the different scenarios and a 95 percent confidence interval. Uncertainty (U) shall be expressed as a percentage: half of the 95% confidence interval divided by the mean (Ogle et al., 2010). Thus, uncertainty can be estimated for each simulated scenario.

Uncertainties already generated in the SOCmap can be used to obtain the

min and max SOC FAO values. Uncertainties in C inputs and thus C_i max and min can be estimated from available data (e.g. meta-analysis). Temp max and Temp and PPmax and PPmin can be estimated from the average monthly values and confidence intervals of the climatic series to be modeled. Uncertainties in clay contents can be directly obtained from SOIL GRIDS (<https://soilgrids.org/>) if the ISRIC database is to be used for the clay content layers. If no estimate of clay variation is available for the used database, Clay max and clay min can be determined from clay content variation within the 1km x 1km grid cells (i.e. considering the values from 250 m x 250m resolution grids). If no estimate is available for these parameters, a maximum and minimum value can be estimated for these parameters, using general uncertainty coefficients, as those reported from global modelling exercises by Gottschalk et al. (2007) and Hastings et al. (2010). Average uncertainties for these parameters are summarized in Table 4.1.

Table 4.1 General uncertainties of main parameters affecting SOC dynamics. Derived from Gottschalk et al. (2007) and Hastings et al. (2010)

Parameter	Uncertainty in the input	Minimum value	Maximum value
Temperature	±2 %	Monthly Temp * 0.98	Monthly Temp * 1.02
Precipitation	±5%	Monthly PP * 0.95	Monthly PP * 1.05
Clay content	± 10%	Clay * 0.90	Clay * 1.10
FAO SOC	± 20 %	SOC FAO *0.8	SOC FAO *1.2
C input increase in SSM scenario	± 15%	C eq * (SSM1 % increase - 15%)	C eq * (SSM % increase + 15%)

The model should be validated for the conditions in which it will be applied when possible. The use of models for prediction involves a series of problems for validation, as data required to quantify the accuracy of the estimates do not yet exist. Nonetheless, predictive models can be validated if they explain past events (ex-post validation). If local results from different SSM practices on SOC stocks are available (a meta-analysis of local SSM practices can be conducted), and the collected activity data allow to perform simulations with these records, model-produced estimates shall be compared with the observed results. The RMSE shall be used to compare the divergence between model estimates and field observations.

Conclusion

So, this methodical recommendation provides technical specifications and guidance for the generation of Soil Organic Carbon Sequestration Potential (SOCseq) maps at 1 km resolution for agricultural lands, based on a 'bottom-up'. SOC stocks 0-30 cm of mineral soils shall be projected over a 20-year period after adoption of Sustainable Soil Management (SSM) practices oriented to increase carbon inputs to cropland and grassland soils. In order to obtain consistent results and to allow comparisons between countries and regions, the use of RothC as a standard spatialized SOC model is requested.

Using the study dataset within Ukraine, the end user will receive a complete set of necessary maps for assessing the potential of carbons sequestration by the different scenarios of land management, in particular:

Final SOC stocks (tC/ha)

Khmilnyk_SOCseq_T0_Map030.tif
 Khmilnyk_SOCseq_finalSOC_BAU_Map030.tif
 Khmilnyk_SOCseq_finalSOC_SSM1_Map030.tif
 Khmilnyk_SOCseq_finalSOC_SSM2_Map030.tif
 Khmilnyk_SOCseq_finalSOC_SSM3_Map030.tif

Uncertainties

Khmilnyk_SOCseq_T0_UncertaintyMap030.tif
 Khmilnyk_SOCseq_BAU_UncertaintyMap030.tif
 Khmilnyk_SOCseq_SSM_UncertaintyMap030.tif

SOC Absolute differences (SSM 1-3 – T0), In tC/ha

Khmilnyk_SOCseq_AbsDiff_BAU_Map030.tif
 Khmilnyk_SOCseq_AbsDiff_SSM1_Map030.tif
 Khmilnyk_SOCseq_AbsDiff_SSM2_Map030.tif
 Khmilnyk_SOCseq_AbsDiff_SSM3_Map030.tif

Absolute sequestration rates: Abs. Diff./20 years, In tC/ha/year

Khmilnyk_SOCseq_ASR_BAU_Map030.tif
 Khmilnyk_SOCseq_ASR_SSM1_Map030.tif
 Khmilnyk_SOCseq_ASR_SSM2_Map030.tif
 Khmilnyk_SOCseq_ASR_SSM3_Map030.tif

Uncertainties for the Absolute sequestration rates

Khmilnyk_SOCseq_ASR_BAU_UncertaintyMap030.tif

Khmilnyk_SOCseq_ASR_SSM1_UncertaintyMap030.tif

Khmilnyk_SOCseq_ASR_SSM2_UncertaintyMap030.tif

Khmilnyk_SOCseq_ASR_SSM3_UncertaintyMap030.tif

Relative sequestration rates: Relative Diff./20 years, In tC/ha/year

Khmilnyk_SOCseq_RSR_SSM1_Map030.tif

Khmilnyk_SOCseq_RSR_SSM2_Map030.tif

Khmilnyk_SOCseq_RSR_SSM3_Map030.tif

Uncertainties for the Relative difference

Khmilnyk_SOCseq_RSR_SSM1_UncertaintyMap030.tif

Khmilnyk_SOCseq_RSR_SSM2_UncertaintyMap030.tif

Khmilnyk_SOCseq_RSR_SSM3_UncertaintyMap030.tif

Relative difference SSM - SOCBAU

Khmilnyk_SOCseq_RelDiff_SSM1_Map030.tif

Khmilnyk_SOCseq_RelDiff_SSM2_Map030.tif

Khmilnyk_SOCseq_RelDiff_SSM3_Map030.tif

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References

1. Abberton, M.T., Conant, R.T. & Batello, C. 2010. *Grassland carbon sequestration: Management, policy and economics : proceedings of the Workshop on the role of grassland carbon sequestration in the mitigation of climate change*. Integrated crop management, 1020-4555. Rome, Food; Agriculture Organization of the United Nations, Plant Production; Protection Division; Food; Agriculture Organization of the United Nations.
2. Al-Adamat, R., Rawajfih, Z., Easter, M., Paustian, K., Coleman, K., Milne, E., Falloon, P., Powlson, D.S. & BATJES, N.H. 2007. Predicted soil organic carbon stocks and changes in Jordan between 2000 and 2030 made using the GEFSOC Modelling System. *Agriculture, Ecosystems & Environment*, 122(1): 35–45. <https://doi.org/10.1016/j.agee.2007.01.006>
3. Allen, M.R. & Stocker, T.F. 2014. Impact of delay in reducing carbon dioxide emissions. *Nature Climate Change*, 4(1): 23–26. <https://doi.org/10.1038/nclimate2077>
4. Anonymous. undated. Global Soil Organic Carbon (GSOC) Map | Global Soil Partnership | Food and Agriculture Organization of the United Nations. [Cited 26 November 2020]. <http://www.fao.org/global-soil-partnership/pillars-action/4-information-and-data-new/global-soil-organic-carbon-gsoc-map>
5. Bahn, M., Kutsch, W.L. & Heinemeyer, A. 2012. Synthesis: emerging issues and challenges for an integrated understanding of soil carbon fluxes. In W.L. Kutsch, ed. *Soil carbon dynamics*, pp. 257–271. Cambridge, Cambridge University Press.
6. Batjes, N.H. 1996. Total carbon and nitrogen in the soils of the world. *European Journal of Soil Science*, 47(2): 151–163. <https://doi.org/10.1111/j.1365-2389.1996.tb01386.x>
7. Beek, J. & Frissel, M.J. 1973. *Simulation of nitrogen behaviour in soils*. Simulation monographs. Wageningen, Pudoc. (also available at <http://eprints.icrisat.ac.in/13135/>).
8. Bolinder, M.A., Janzen, H.H., Gregorich, E.G., Angers, D.A. & VandenBygaart, A.J. 2007. An approach for estimating net primary productivity and annual carbon inputs to soil for common agricultural crops in Canada. *Agriculture, Ecosystems & Environment*, 118(1-4): 29–42. <https://doi.org/10.1016/j.agee.2006.05.013>
9. Campbell, E.E. & Paustian, K. 2015. Current developments in soil organic matter modeling and the expansion of model applications: a review. *Environmental Research Letters*, 10(12): 123004. <https://doi.org/10.1088/1748-9326/10/12/123004>
10. Clarholm, M. & Bergström, L., eds. 1989. *Ecology of Arable Land – Perspectives and Challenges: Proceeding of an International Symposium*, 9-

- 12 June 1987 Swedish University of Agricultural Sciences, Uppsala, Sweden. Developments in plant and soil sciences. Dordrecht, Springer Netherlands.
11. Coleman, K. & Jenkinson, D.S. 1996. RothC-26.3 - A Model for the turnover of carbon in soil. In D.S. Powlson, P. Smith & J.U. Smith, eds. *Evaluation of soil organic matter models*. pp. 237–246. NATO ASI series. Series i, global environmental change. Paper presented at, 1996, Berlin; New York.
 12. Easter, M., Paustian, K., Killian, K., Williams, S., Feng, T., Al-Adamat, R., BATJES, N.H., Bernoux, M., Bhattacharyya, T., Cerri, C.C., Cerri, C.E.P., Coleman, K., Falloon, P., Feller, C., Gicheru, P., Kamoni, P., Milne, E., Pal, D.K., Powlson, D.S., Rawajfih, Z., Sessay, M. & Wokabi, S. 2007. The GEFSOC soil carbon modelling system: A tool for conducting regional-scale soil carbon inventories and assessing the impacts of land use change on soil carbon. *Agriculture, Ecosystems & Environment*, 122(1): 13–25. <https://doi.org/10.1016/j.agee.2007.01.004>
 13. Eggleston, H.S., ed. 2006. *2006 IPCC guidelines for national greenhouse gas inventories*. Hayama, Japan, Institute for Global Environmental Strategies.
 14. Falloon, P.D., Smith, P., Smith, J.U., Szabó, J., Coleman, K. & Marshall, S. 1998. Regional estimates of carbon sequestration potential: linking the Rothamsted Carbon Model to GIS databases. *Biology and Fertility of Soils*, 27(3): 236–241. <https://doi.org/10.1007/s003740050426>
 15. Falloon, P., Jones, C.D., Cerri, C.E., Al-Adamat, R., Kamoni, P., Bhattacharyya, T., Easter, M., Paustian, K., Killian, K., Coleman, K. & Milne, E. 2007. Climate change and its impact on soil and vegetation carbon storage in Kenya, Jordan, India and Brazil. *Agriculture, Ecosystems & Environment*, 122(1): 114–124. <https://doi.org/10.1016/j.agee.2007.01.013>
 16. Falloon, P. & Smith, P. 2003. Accounting for changes in soil carbon under the Kyoto Protocol: need for improved long-term data sets to reduce uncertainty in model projections. *Soil Use and Management*, 19(3): 265–269. <https://doi.org/10.1111/j.1475-2743.2003.tb00313.x>
 17. FAO. 2020. GSOCseq Global Soil Organic Carbon Sequestration Potential Map Technical Manual. G. Peralta, L. Di Paolo, C. Omuto, K. Viatkin, I. Luotto, Y. Yigini, 1st Edition, Rome <https://faogsp.github.io/GSOCseq/index.html>
 18. Farina, R., Coleman, K. & Whitmore, A.P. 2013. Modification of the RothC model for simulations of soil organic C dynamics in dryland regions. *Geoderma*, 200–201: 18–30. <https://doi.org/10.1016/j.geoderma.2013.01.021>
 19. Farina, R., Marchetti, A., Francaviglia, R., Napoli, R. & Di Bene, C. 2017. Modeling regional soil C stocks and CO₂ emissions under Mediterranean cropping systems and soil types. *Agriculture, Ecosystems & Environment*, 320: 1–12. <https://doi.org/10.1016/j.agee.2017.05.010>

- Ecosystems & Environment*, 238: 128–141. <https://doi.org/10.1016/j.agee.2016.08.015>
20. Follett, R.F., Kimble, J.M., Pruessner, E.G., Samson-Liebig, S. & Waltman, S. 2009. Soil Organic Carbon Stocks with Depth and Land Use at Various U.S. Sites. In R. Lal & R.F. Follett, eds. *Soil carbon sequestration and the greenhouse effect*, pp. 29–46. SSSA special publication. Madison, WI, Soil Science Society of America, Inc.
 21. Food and Agriculture Organization of the United Nations. 2017. Voluntary Guidelines for Sustainable Soil Management. Rome, FAO. <http://www.fao.org/documents/card/en/c/5544358d-f11f-4e9f-90ef-a37c3bf52db7/>
 22. Franko, U. 1996. Modelling approaches of soil organic matter turnover within the CANDY system. In D.S. Powlson, P. Smith & J.U. Smith, eds. *Evaluation of soil organic matter models*. pp. 247–254. NATO ASI series. Series i, global environmental change. Paper presented at, 1996, Berlin; New York.
 23. Gilhespy, S.L., Anthony, S., Cardenas, L., Chadwick, D., Prado, A. del, Li, C., Misselbrook, T., Rees, R.M., Salas, W., Sanz-Cobena, A., Smith, P., Tilston, E.L., Topp, C.F.E., Vetter, S. & Yeluripati, J.B. 2014. First 20 years of DNDC (DeNitrification DeComposition): Model evolution. *Ecological Modelling*, 292: 51–62. <https://doi.org/10.1016/j.ecolmodel.2014.09.004>
 24. Gottschalk, P., Smith, J.U., Wattenbach, M., Bellarby, J., Stehfest, E., Arnell, N., Osborn, T.J., Jones, C. & Smith, P. 2012. How will organic carbon stocks in mineral soils evolve under future climate? Global projections using RothC for a range of climate change scenarios. *Biogeosciences*, 9(8): 3151–3171. <https://doi.org/10.5194/bg-9-3151-2012>
 25. Grace, P., Ladd, J., Robertson, G. & Gage, S. 2006. SOCRATES - A simple model for predicting long-term changes in soil organic carbon in terrestrial ecosystems. *Soil Biology and Biochemistry*, 38(5): 1172–1176. <https://doi.org/10.1016/j.soilbio.2005.09.013>
 26. Hadas, A., Parkin, T.B. & Stahl, P.D. 1998. Reduced CO₂ release from decomposing wheat straw under N-limiting conditions: simulation of carbon turnover. *European Journal of Soil Science*, 49(3): 487–494. <https://doi.org/10.1046/j.1365-2389.1998.4930487.x>
 27. Hansen, S., Jensen, H.E., Nielsen, N.E. & Svendsen, H. 1991. Simulation of nitrogen dynamics and biomass production in winter wheat using the Danish simulation model DAISY. *Fertilizer research*, 27(2-3): 245–259. <https://doi.org/10.1007/BF01051131>
 28. Hengl, T., Mendes de Jesus, J., Heuvelink, G.B.M., Ruiperez Gonzalez, M., Kilibarda, M., Blagotić, A., Shangquan, W., Wright, M.N., Geng, X., Bauer-Marschallinger, B., Guevara, M.A., Vargas, R., MacMillan, R.A., Batjes, N.H., Leenaars, J.G.B., Ribeiro, E., Wheeler, I., Mantel, S. & Kempen,

- B. 2017. SoilGrids250m: Global gridded soil information based on machine learning. *PLoS one*, 12(2): e0169748. <https://doi.org/10.1371/journal.pone.0169748>
29. IPCC. 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. <https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html>
 30. Jansson, C., Wullschleger, S.D., Kalluri, U.C. & Tuskan, G.A. 2010. Phytosequestration: Carbon Biosequestration by Plants and the Prospects of Genetic Engineering. *BioScience*, 60(9): 685–696. <https://doi.org/10.1525/bio.2010.60.9.6>
 31. Jenkinson, D.S., Adams, D.E. & Wild, A. 1991. Model estimates of CO2 emissions from soil in response to global warming. *Nature*, 351(6324): 304–306. <https://doi.org/10.1038/351304a0>
 32. Jenkinson, D.S. & Coleman, K. 2008. The turnover of organic carbon in subsoils. Part 2. Modelling carbon turnover. *European Journal of Soil Science*, 59(2): 400–413. <https://doi.org/10.1111/j.1365-2389.2008.01026.x>
 33. Jenkinson, D.S. & Rayner, J.H. 1977. The Turnover of Soil Organic Matter in Some of The Rothamsted Classical Experiments. *Soil Science*, 123(5): 298–305. <https://doi.org/10.1097/00010694-197705000-00005>
 34. Jenny, H. 1994. *Factors of soil formation: A system of quantitative pedology*. New York, Dover.
 35. Jenny, H., Gessel, S.P. & Bingham, F.T. 1949. Comparative Study of Decomposition Rates of Organic Matter in Temperate and Tropical Regions. *Soil Science*, 68(6): 419–432. <https://doi.org/10.1097/00010694-194912000-00001>
 36. Jo Smith, P.S., Jeannette Meyer, M.W., Sönke Zaehle, M.L., Robert J.A. Jones, R.H., Mark Rounsevell, L.M., REGINSTER, I. & Kankaanpää, S. 2006. Projected changes in mineral soil carbon of European forests, 1990–2100. *Canadian Journal of Soil Science*, 86(Special Issue): 159–169. <https://doi.org/10.4141/S05-078>
 37. Keenan, T.F., Carbone, M.S., Reichstein, M. & Richardson, A.D. 2011. The model-data fusion pitfall: assuming certainty in an uncertain world. *Oecologia*, 167(3): 587–597. <https://doi.org/10.1007/s00442-011-2106-x>
 38. Kutsch, W., Bahn, M. & Heinemeyer, A. 2016. *Soil carbon dynamics: An integrated methodology / edited by Werner L. Kutsch (Johann Heinrich von Thünen Institut, Braunschweig), Michael Bahn (Leopold-Franzens Universität Innsbruck), Andreas Heinemeyer (Stockholm Environment Institute, University of York)*. Reprinted with corrections edition. Cambridge, Cambridge University Press.
 39. Kutsch, W.L., ed. 2012. *Soil carbon dynamics: An integrated methodology*. Repr. with edition. Cambridge, Cambridge University Press.

40. Lal, R. 2004. Soil carbon sequestration impacts on global climate change and food security. *Science (New York, N.Y.)*, 304(5677): 1623–1627. <https://doi.org/10.1126/science.1097396>
41. Lal, R. & Follett, R.F., eds. 2009. *Soil carbon sequestration and the greenhouse effect*. Second edition. SSSA special publication. Madison, WI, Soil Science Society of America, Inc.
42. Lal, R., Smith, P., Jungkunst, H.F., Mitsch, W.J., Lehmann, J., Nair, P., Ramachandran, K., McBratney, A.B., de Moraes Sá, J.C., Schneider, J., Zinn, Y.L., Skorupa, A.L.A., Zhang, H.-L., Minasny, B., Srinivasrao, C. & Ravindranath, N.H. 2018. The carbon sequestration potential of terrestrial ecosystems. *Journal of Soil and Water Conservation*, 73(6): 145A—152A. <https://doi.org/10.2489/jswc.73.6.145A>
43. Lauenroth, W.K., Skogerboe, G.V. & Flug, M., eds. 1983. *Analysis of ecological systems: State-of-the-art in ecological modelling / edited by William K. Lauenroth, Gaylord V. Skogerboe, Marshall Flug ; proceedings of a symposium held from 24 to 28 May 1982 at Colorado State University, Fort Collins, Colorado, U.S.A. ; sponsored by the International Society for Ecological Modelling (ISEM) ; hosted by the Natural Resource Ecology Laboratory, Colorado State University*. Developments in environmental modelling. Armstrong; Oxford, Elsevier Scientific.
44. Lehtonen, A., Tupek, B., Nieminen, T.M., Balázs, A., Anjulo, A., Teshome, M., Tiruneh, Y. & Alm, J. 2020. Soil carbon stocks in Ethiopian forests and estimations of their future development under different forest use scenarios. *Land Degradation & Development*. <https://doi.org/10.1002/ldr.3647>
45. Li, C. 1996. The DNDC Model. In D.S. Powlson, P. Smith & J.U. Smith, eds. *Evaluation of soil organic matter models*. pp. 263–267. NATO ASI series. Series i, global environmental change. Paper presented at, 1996, Berlin; New York.
46. Lieth, H. 1975. Modeling the Primary Productivity of the World. In H. Lieth & R.H. Whittaker, eds. *Primary productivity of the biosphere*, pp. 237–263. Ecological studies, analysis and synthesis, 0070-8356. Berlin, Heidelberg, Springer Berlin Heidelberg.
47. Lieth, H. & Whittaker, R.H., eds. 1975. *Primary Productivity of the Biosphere*. Ecological studies, analysis and synthesis, 0070-8356. Berlin, Heidelberg, Springer Berlin Heidelberg.
48. Lorenz, K. & Lal, R. 2018. *Carbon sequestration in agricultural ecosystems*. Cham, Switzerland, Springer.
49. Lugato, E., Bampa, F., Panagos, P., Montanarella, L. & Jones, A. 2014. Potential carbon sequestration of European arable soils estimated by modelling a comprehensive set of management practices. *Global change biology*, 20(11): 3557–3567. <https://doi.org/10.1111/gcb.12551>

50. Manzoni, S. & Porporato, A. 2009. Soil carbon and nitrogen mineralization: Theory and models across scales. *Soil Biology and Biochemistry*, 41(7): 1355–1379. <https://doi.org/10.1016/j.soilbio.2009.02.031>
51. Martens, R. 1995. Current methods for measuring microbial biomass C in soil: Potentials and limitations. *Biology and Fertility of Soils*, 19(2-3): 87–99. <https://doi.org/10.1007/BF00336142>
52. Milne, E., Adamat, R.A., BATJES, N.H., Bernoux, M., Bhattacharyya, T., Cerri, C.C., Cerri, C.E.P., Coleman, K., Easter, M., Falloon, P., Feller, C., Gicheru, P., Kamoni, P., Killian, K., Pal, D.K., Paustian, K., Powlson, D.S., Rawajfeh, Z., Sessay, M., Williams, S. & Wokabi, S. 2007. National and sub-national assessments of soil organic carbon stocks and changes: The GEFSOC modelling system. *Agriculture, Ecosystems & Environment*, 122(1): 3–12. <https://doi.org/10.1016/j.agee.2007.01.002>
53. Minasny, B., Malone, B.P., McBratney, A.B., Angers, D.A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z.-S., Cheng, K., Das, B.S., Field, D.J., Gimona, A., Hedley, C.B., Hong, S.Y., Mandal, B., Marchant, B.P., Martin, M., McConkey, B.G., Mulder, V.L., O'Rourke, S., Richer-de-Forges, A.C., Odeh, I., Padarian, J., Paustian, K., Pan, G., Poggio, L., Savin, I., Stolbovoy, V., Stockmann, U., Sulaeman, Y., Tsui, C.-C., Vågen, T.-G., Wesemael, B. van & Winowiecki, L. 2017. Soil carbon 4 per mille. *Geoderma*, 292: 59–86. <https://doi.org/10.1016/j.geoderma.2017.01.002>
54. Mondini, C., Coleman, K. & Whitmore, A.P. 2012. Spatially explicit modelling of changes in soil organic C in agricultural soils in Italy, 2001–2100: Potential for compost amendment. *Agriculture, Ecosystems & Environment*, 153: 24–32. <https://doi.org/10.1016/j.agee.2012.02.020>
55. Moradzadeh, M. & Saradjian, M.R. 2016. Vegetation Effects Modeling in Soil Moisture Retrieval Using MSVI. *Photogrammetric Engineering & Remote Sensing*, 82(10): 803–810. <https://doi.org/10.14358/PERS.82.10.803>
56. Morais, T.G., Teixeira, R.F.M. & Domingos, T. 2019. Detailed global modelling of soil organic carbon in cropland, grassland and forest soils. *PLoS one*, 14(9): e0222604. <https://doi.org/10.1371/journal.pone.0222604>
57. Motavalli, P.P., Palm, C.A., Parton, W.J., Elliott, E.T. & Frey, S.D. 1995. Soil pH and organic C dynamics in tropical forest soils: Evidence from laboratory and simulation studies. *Soil Biology and Biochemistry*, 27(12): 1589–1599. [https://doi.org/10.1016/0038-0717\(95\)00082-P](https://doi.org/10.1016/0038-0717(95)00082-P)
58. Neumann, M. & Smith, P. 2018. Carbon uptake by European agricultural land is variable, and in many regions could be increased: Evidence from remote sensing, yield statistics and models of potential productivity. *The Science of*

- the total environment, 643: 902–911. <https://doi.org/10.1016/j.scitotenv.2018.06.268>
59. Palosuo, T., Foereid, B., Svensson, M., Shurpali, N., Lehtonen, A., Herbst, M., Linkosalo, T., Ortiz, C., Rampazzo Todorovic, G., Marcinkonis, S., Li, C. & Jandl, R. 2012. A multi-model comparison of soil carbon assessment of a coniferous forest stand. *Environmental Modelling & Software*, 35: 38–49. <https://doi.org/10.1016/j.envsoft.2012.02.004>
 60. Parshotam, A. & Hewitt, A.E. 1995. Application of the Rothamsted carbon turnover model to soils in degraded semi-arid land in New Zealand. *Environment International*, 21(5): 693–697. [https://doi.org/10.1016/0160-4120\(95\)00071-R](https://doi.org/10.1016/0160-4120(95)00071-R)
 61. Parton, W.J. 1996. The CENTURY model. In D.S. Powlson, P. Smith & J.U. Smith, eds. *Evaluation of soil organic matter models*. pp. 283–291. NATO ASI series. Series i, global environmental change. Paper presented at, 1996, Berlin; New York.
 62. Parton, W.J., Cole, C.V., Stewart, J.W.B., Ojima, D.S. & Schimel, D.S. 1989. Simulating regional patterns of soil C, N, and P dynamics in the U.S. central grasslands region. In M. Clarholm & L. Bergström, eds. *Ecology of arable land – perspectives and challenges*, pp. 99–108. Developments in plant and soil sciences. Dordrecht, Springer Netherlands.
 63. Paustian, K., Collier, S., Baldock, J., Burgess, R., Creque, J., DeLonge, M., Dungait, J., Ellert, B., Frank, S., Goddard, T., Govaerts, B., Grundy, M., Henning, M., Izaurralde, R.C., Madaras, M., McConkey, B., Porzig, E., Rice, C., Searle, R., Seavy, N., Skalsky, R., Mulhern, W. & Jahn, M. 2019. Quantifying carbon for agricultural soil management: from the current status toward a global soil information system. *Carbon Management*, 10(6): 567–587. <https://doi.org/10.1080/17583004.2019.1633231>
 64. Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G.P. & Smith, P. 2016. Climate-smart soils. *Nature*, 532(7597): 49–57. <https://doi.org/10.1038/nature17174>
 65. Petri, M., Batello, C., Villani, R. & Nachtergaele, F. 2009. *Carbon status and carbon sequestration potential in the world's grasslands*. FAO.
 66. Plutzer, C., Kraisleitner, C., Haberl, H., Fetzel, T., Bulgheroni, C., Beringer, T., Hostert, P., Kastner, T., Kuemmerle, T., Lauk, C., Levers, C., Lindner, M., Moser, D., Müller, D., Niedertscheider, M., Paracchini, M.L., Schaphoff, S., Verburg, P.H., Verkerk, P.J. & Erb, K.-H. 2016. Changes in the spatial patterns of human appropriation of net primary production (HANPP) in Europe 1990–2006. *Regional Environmental Change*, 16(5): 1225–1238. <https://doi.org/10.1007/s10113-015-0820-3>

67. Poeplau, Christopher and Don, Axel. 2012. Sensitivity of soil organic carbon stocks and fractions to different land-use changes across Europe. *Geoderma*, 192: 189–201. <https://doi.org/10.1016/j.geoderma.2012.08.003>
68. Poulton, P., Johnston, J., Macdonald, A., White, R. & Powlson, D. 2018. Major limitations to achieving "4 per 1000" increases in soil organic carbon stock in temperate regions: Evidence from long-term experiments at Rothamsted Research, United Kingdom. *Global change biology*, 24(6): 2563–2584. <https://doi.org/10.1111/gcb.14066>
69. Powlson, D.S., Smith, P. & Smith, J.U., eds. 1996. *Evaluation of soil organic matter models: Using existing long-term datasets*. NATO ASI series. Series i, global environmental change. Berlin; New York, NATO Advanced Research Workshop {\\textquotedbl}Evaluation of Soil Organic Matter Models Using Existing Long-term Datasets{\\textquotedbl}; Springer.
70. Richter, J. 1981. Simulation of nitrogen behaviour of soil-plant systems, Papers of a workshop Models for the behaviour of nitrogen in soil and uptake by plant. *Zeitschrift für Pflanzenernährung und Bodenkunde*, 144(4): 428–429. <https://doi.org/10.1002/jpln.19811440414>
71. Riggers, C., Poeplau, C., Don, A., Bamminger, C., Höper, H. & Dechow, R. 2019. Multi-model ensemble improved the prediction of trends in soil organic carbon stocks in German croplands. *Geoderma*, 345: 17–30. <https://doi.org/10.1016/j.geoderma.2019.03.014>
72. S., J.D. 1990. The turnover of organic carbon and nitrogen in soil. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 329(1255): 361–368. <https://doi.org/10.1098/rstb.1990.0177>
73. Sagar, S., Parshotam, A., Sparling, G.P., Feltham, C.W. & Hart, P.B.S. 1996. ¹⁴C-labelled ryegrass turnover and residence times in soils varying in clay content and mineralogy. *Soil Biology and Biochemistry*, 28(12): 1677–1686. [https://doi.org/10.1016/S0038-0717\(96\)00250-7](https://doi.org/10.1016/S0038-0717(96)00250-7)
74. Scharlemann, J.P.W., Tanner, E.V.J., Hiederer, R. & Kapos, V. 2014. Global soil carbon: understanding and managing the largest terrestrial carbon pool. *Carbon Management*, 5(1): 81–91. <https://doi.org/10.4155/cmt.13.77>
75. Schmer, M.R., Jin, V.L., Wienhold, B.J., Varvel, G.E. & Follett, R.F. 2014. Tillage and Residue Management Effects on Soil Carbon and Nitrogen Under Irrigated Continuous Corn. *Soil Science Society of America Journal*, 78(6): 1987–1996. <https://doi.org/10.2136/sssaj2014.04.0166>
76. Schmidt, M.W.I., Torn, M.S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I.A., Kleber, M., Kögel-Knabner, I., Lehmann, J., Manning, D.A.C., Nannipieri, P., Rasse, D.P., Weiner, S. & Trumbore, S.E. 2011. Persistence of soil organic matter as an ecosystem property. *Nature*, 478(7367): 49–56. <https://doi.org/10.1038/nature10386>

77. Schulze, E.D., Ciais, P., Luyssaert, S., Schrumppf, M., Janssens, I.A., Thiruchittampalam, B., Theloke, J., Saurat, M., Bringerzu, S., Lelieveld, J., Lohila, A., Rebmann, C., Jung, M., Bastviken, D., Abril, G., Grassi, G., Leip, A., Freibauer, A., Kutsch, W., Don, A., Nieschulze, J., Börner, A., Gash, J.H. & Dolman, A.J. 2010. The European carbon balance. Part 4: integration of carbon and other trace-gas fluxes. *Global change biology*, 16(5): 1451–1469. <https://doi.org/10.1111/j.1365-2486.2010.02215.x>
78. Shang, C. & Tiessen, H. 1998. Organic Matter Stabilization in Two Semiarid Tropical Soils: Size, Density, and Magnetic Separations. *Soil Science Society of America Journal*, 62(5): 1247–1257. <https://doi.org/10.2136/sssaj1998.03615995006200050015x>
79. Shirato, Y., Hakamata, T. & Taniyama, I. 2004. Modified rothamsted carbon model for andosols and its validation: changing humus decomposition rate constant with pyrophosphate-extractable Al. *Soil Science and Plant Nutrition*, 50(1): 149–158. <https://doi.org/10.1080/00380768.2004.10408463>
80. Shirato, Y. & Yokozawa, M. 2005. Applying the Rothamsted Carbon Model for Long-Term Experiments on Japanese Paddy Soils and Modifying It by Simple Tuning of the Decomposition Rate. *Soil Science and Plant Nutrition*, 51(3): 405–415. <https://doi.org/10.1111/j.1747-0765.2005.tb00046.x>
81. Sierra, C.A., Müller, M. & Trumbore, S.E. 2012. Models of soil organic matter decomposition: the SoilR package, version 1.0. *Geoscientific Model Development*, 5(4): 1045–1060. <https://doi.org/10.5194/gmd-5-1045-2012>
82. Sinclair, T.R. & Seligman, N.G. 1996. Crop Modeling: From Infancy to Maturity. *Agronomy Journal*, 88(5): 698–704. <https://doi.org/10.2134/agronj1996.00021962008800050004x>
83. Six, J., Conant, R.T., Paul, E.A. & Paustian, K. 2002. Stabilization Mechanisms of Soil Organic Matter: Implications for C-Saturation of Soils. *Plant and Soil*, 241(2): 155–176. <https://doi.org/10.1023/A:1016125726789>
84. Smith, J.O., Smith, P., Wattenbach, M., Zaehle, S., Hiederer, R., Jones, R.J.A., Montanarella, L., Rounsevell, M.D.A., Reginster, I. & Ewert, F. 2005. Projected changes in mineral soil carbon of European croplands and grasslands, 1990–2080. *Global Change Biology*, 11(12): 2141–2152. <https://doi.org/10.1111/j.1365-2486.2005.001075.x>
85. Smith, P. 2004. How long before a change in soil organic carbon can be detected? *Global Change Biology*, 10(11): 1878–1883. <https://doi.org/10.1111/j.1365-2486.2004.00854.x>
86. Smith, P., Andrén, O., Brussaard, L., Dangerfield, M., Ekschmitt, K., Lavelle, P. & Tate, K. 1998. Soil biota and global change at the ecosystem level: describing soil biota in mathematical models. *Global Change Biology*, 4(7): 773–784. <https://doi.org/10.1046/j.1365-2486.1998.00193.x>

87. Smith, P. & Falloon, P.D. 2000. Modelling refractory soil organic matter. *Biology and Fertility of Soils*, 30(5-6): 388–398. <https://doi.org/10.1007/s003740050019>
88. Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., Towprayoon, S., WATTENBACH, M. & Smith, J. 2008. Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 363(1492): 789–813. <https://doi.org/10.1098/rstb.2007.2184>
89. Smith, P., Smith, J.U., Franko, U., Kuka, K., Romanenkov, V.A., Shevtsova, L.K., Wattenbach, M., Gottschalk, P., Sirotenko, O.D., Rukhovich, D.I., Koroleva, P.V., Romanenko, I.A. & Lisovoi, N.V. 2007. Changes in mineral soil organic carbon stocks in the croplands of European Russia and the Ukraine, 1990–2070; comparison of three models and implications for climate mitigation. *Regional Environmental Change*, 7(2): 105–119. <https://doi.org/10.1007/s10113-007-0028-2>
90. Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., Coleman, K., Franko, U., Frolking, S., Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek, H., Komarov, A.S., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M. & Whitmore, A.P. 1997. A comparison of the performance of nine soil organic matter models using datasets from seven long-term experiments. *Geoderma*, 81(1-2): 153–225. [https://doi.org/10.1016/S0016-7061\(97\)00087-6](https://doi.org/10.1016/S0016-7061(97)00087-6)
91. Smith, P., Soussana, J.-F., Angers, D., Schipper, L., Chenu, C., Rasse, D.P., Batjes, N.H., Egmond, F. van, McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J.E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A. & Klumpp, K. 2020. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. *Global Change Biology*, 26(1): 219–241. <https://doi.org/10.1111/gcb.14815>
92. Tifafi, M., Guenet, B. & Hatté, C. 2018. Large Differences in Global and Regional Total Soil Carbon Stock Estimates Based on SoilGrids, HWSD, and NCSCD: Intercomparison and Evaluation Based on Field Data From USA, England, Wales, and France. *Global Biogeochemical Cycles*, 32(1): 42–56. <https://doi.org/10.1002/2017GB005678>
93. Vries, W. de. 2018. Soil carbon 4 per mille: a good initiative but let's manage not only the soil but also the expectations. *Geoderma*, 309: 111–112. <https://doi.org/10.1016/j.geoderma.2017.05.023>
94. Weihermüller, L., Graf, A., Herbst, M. & Vereecken, H. 2013. Simple pedotransfer functions to initialize reactive carbon pools of the RothC

- model. *European Journal of Soil Science*, 64(5): 567–575. <https://doi.org/10.1111/ejss.12036>
95. Wieder, W.R., Grandy, A.S., Kallenbach, C.M. & Bonan, G.B. 2014. Integrating microbial physiology and physio-chemical principles in soils with the MIncrobial-MIneral Carbon Stabilization (MIMICS) model. *Biogeosciences*, 11(14): 3899–3917. <https://doi.org/10.5194/bg-11-3899-2014>
 96. Wiesmeier, M., Poeplau, C., Sierra, C.A., Maier, H., Frühauf, C., Hübner, R., Kühnel, A., Spörlein, P., Geuß, U., Hangen, E., Schilling, B., Lützow, M. von & Kögel-Knabner, I. 2016. Projected loss of soil organic carbon in temperate agricultural soils in the 21(st) century: effects of climate change and carbon input trends. *Scientific reports*, 6: 32525. <https://doi.org/10.1038/srep32525>
 97. Wiesmeier, M., Schad, P., Lützow, M. von, Poeplau, C., Spörlein, P., Geuß, U., Hangen, E., Reischl, A., Schilling, B. & Kögel-Knabner, I. 2014. Quantification of functional soil organic carbon pools for major soil units and land uses in southeast Germany (Bavaria). *Agriculture, Ecosystems & Environment*, 185: 208–220. <https://doi.org/10.1016/j.agee.2013.12.028>
 98. Williams, J.R., Dyke, P.T. & Jones, C.A. 1983. Epic - a Model for Assessing the Effects of Erosion on Soil Productivity. In W.K. Lauenroth, G.V. Skogerboe & M. Flug, eds. *Analysis of ecological systems*, pp. 553–572. Developments in environmental modelling. Armstrong; Oxford, Elsevier Scientific.
 99. Yigini, Y., Olmedo, G.F., Reiter, S., Baritz, R., Viatkin, K. & Vargas, R. 2018. *Soil organic carbon mapping cookbook*. 2nd editio edition. Rome, FAO; FAO.

Developing the map of carbons sequestration by the different scenarios of land management.

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Methodical recommendations