Coordination of International Research Cooperation on soil CArbon Sequestration in Agriculture (CIRCASA)

Horizon 2020

Horizon 2020
European Union funding
for Research & Innovation

Call: H2020-SFS-2016-2017 (Sustainable Food Security – Resilient and resource-efficient value chains)

Type of action: CSA (Coordination and support action)

Grant Agreement: 774378-CIRCASA

DELIVERABLE NUMBER: D1.4

DELIVERABLE TYPE: Report

DELIVERABLE TITLE: International Knowledge Synthesis activities

Start date of the project: November 1, 2017

Submission date: M40

Organisation name of lead contractor: INRAE

Dissemination level: PU/~~PP~~/~~RE~~/~~CO~~

AUTHORS

Arias-Navarro C., Balkovič J., Batjes N., Bispo A., Bosma A., Ceschia E., Chenu C., de Sousa L., Deppermann, A., Folberth C., Frank S., Gurriaran L., Havlik P., Kim J. H., Kuhnert M., Martin M., Mendes de Jesus J., Montanarella L., Poggio L., Skalský R., Smith P., Soussana J.-F. , van Dijk M., Yogo W.

REQUIRED CITATION

CIRCASA 2021. Deliverable D1.4: *"International Knowledge Synthesis activities*." [Arias-Navarro C., Balkovič J., Batjes N., Bispo A., Bosma A., Ceschia E., Chenu C., de Sousa L., Deppermann, A., Folberth C., Frank S., Gurriaran L., Havlik P., Kim J. H., Kuhnert M., Martin M., Mendes de Jesus J., Montanarella L., Poggio L., Skalský R., Smith P., Soussana J.-F. , van Dijk M., Yogo W.] European Union's Horizon 2020 research and innovation programme grant agreement No 774378 - Coordination of International Research Cooperation on soil CArbon Sequestration in Agriculture. https://doi.org/10.15454/YWETVM

DISCLAIMER OF WARRANTIES

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement **No 774378**.

This document has been prepared by CIRCASA project partners as an account of work carried out within the framework of the EC-GA contract No 774378. Neither Project Coordinator, nor any signatory party of CIRCASA Project Consortium Agreement, nor any person acting on behalf of any of them:

a. makes any warranty or representation whatsoever, express or implied,

   I. with respect to the use of any information, apparatus, method, process, or similar item disclosed in this document, including merchantability and fitness for a particular purpose, or
   II. that such use does not infringe on or interfere with privately owned rights, including any party's intellectual property, or
   III. that this document is suitable to any particular user's circumstance; or

b. assumes responsibility for any damages or other liability whatsoever (including any consequential damages, even if Project Coordinator or any representative of a signatory party of the CIRCASA Project Consortium Agreement, has been advised of the possibility of such damages) resulting from your selection or use of this document or any information, apparatus, method, process, or similar item disclosed in this document.

TABLE OF CONTENTS

SUMMARY

The current state of our soils, as well as the opportunities and vulnerabilities that result from different land management practices, are of particular importance. Quantifying the optimal SOC storage capacity of soils would provide a benchmark to assess human impact on soils and help quantify potential benefits of altered soil management practices. In order to quantify potential SOC losses or sequestration at field, regional, and global scales, measurements for detecting changes in SOC are needed. Such measurements and soil-management best practices should be based on well established and emerging scientific understanding of processes of C stabilization and destabilization over various timescales, soil types, and spatial scales.

There are still large knowledge gaps at global scale on:

1. the current SOC stocks,
2. the baselines of soil organic C stocks under current practices,
3. the potential for increasing SOC stocks through changes in agricultural practices.

Here we address such knowledge gaps through the international knowledge synthesis activities providing:

1. **Geo-referenced data sets** from a range of sources concerning e.g. Climate, soil land use , land degradation, agricultural practices yields, crop residues, net primary productivity, etc.
2. **Data from models**
3. **Synthesis activities** and methodological guidelines.

In order to understand soil's contribution to ecosystem services, large-scale modelling and mapping soil properties and processes are needed. This increased global understanding will show how to tackle multiple land based challenges through agricultural SOC sequestration. This report is detailing the harmonized spatial data sets and their use to create knowledge synthesis on the potential for SOC sequestration in agriculture and on the role of SOC for agricultural productivity, climate change mitigation and adaptation.

The combination of these data will establish the **foundation for the knowledge information system (KIS) on SOC in agriculture** and will support the development of meta-analyses showing the role of soil carbon for food supply, climate change mitigation and adaptation in different agricultural systems, soil and climate conditions. Moreover, those data sets can further contribute to proposing and designing management practices to improve the status of agricultural soils, stop land degradation and better target policy interventions.

All data generated as part of this work is openly accessible via the CIRCASA Knowledge Information System https://www.ocp.circasa-project.eu/en/kis

FIGURES

Figure 13. Global MACCs for wheat and corn; NOT – no tillage, RED – reduced tillage. Both, rainfed and irrigated area considered, based on (IFPRI, 2019). Extreme values are limited to USD/t CO_{2eq} -1,000 and USD/t CO_{2eq} 1,000 respectively, to improve the visualization.

Figure 14. Number of studies returned on Web of Science searches of potentially carbon-sequestering agricultural practices. Keywords related to the topics were searched in conjunction with keywords related to soil carbon sequestration

Figure 15. Locations of studies in our net return dataset.

Figure 16. Differences in profit between no-till and conventional tillage plots. Boxes represent soil types (a) and crop types (b). Soil texture is listed from left to right in the order of decreasing sand content. Comparison of reduced and conventional tillage show similar trends for crop types (e.g. negative for fruits and vegetables and positive for fiber) but not for soil types (data not shown).

Figure 17. Global distributions of land use types and of individual land-based challenges.

Figure 18. Soil carbon debt for 0-30 com, 0-100 cm and 0-200 cm depths. Modified from (Sanderman et al., 2017).

Figure 19. Global distributions of (a) the number of overlapping land-based challenges (desertification and land degradation, climate change adaptation, chronic undernourishment, biodiversity, groundwater stress and water quality); (b) the Human Development Index (HDI) by country.

Figure 20. Components of a Monitoring, Reporting and Verification system for soil organic carbon (Smith, Soussana et al., 2019, Global Change Biology)

Figure 21. Global Inventory of Long-Term Soil-Ecosystem Experiments - LTSEs

Figure 22. Components of the Net Ecosystem Carbon Balance for a cropland ecosystem.

Figure 23. Soil carbon balance (ΔCsoil) as function of GPP. $\sigma\Delta C$ is represented by the error bars, in red when the parameters influencing $\sigma\Delta C$ where chosen to have the highest error, in grey for the reference scenario and in orange when the error was minimized. The red circle indicate the reference scenario, with GPP equal to 1760 gC.m−2.yr−1.

Figure 24. a) The red curve represents the MMD as a function of the percentage of change of the three parameters (Re, Obs and σ_k) controlling $\sigma_{GP\ P}$ and $\sigma_{NP\ P}$ and thus the error on ΔC for the fluxes method we developed. The value of these three parameters were changed all at once nine times, 10% in 10%, starting from the reference scenario. For Re and σ_k the value were diminished while it was increased for Obs. The black dashed line is the value of the MMD for the reference scenario. b) The blue curve represents the Minimable Detectable Difference (MMD) as a function of the number of samples for a soil analysis method (Schrumpf et al., 2011). The black dashed line is the value of the MMD for the reference scenario. The dashed-dotted line represents the value of the MMD for the soil analysis method with 10 samples. c) The pink curve represent the cumulated through time for a carbon storing rate of 1 ‰ with a baseline carbon stock of 5000 gC.m−2. The orange curve is for a carbon-storing rate of 4 ‰.

Figure A1. Wheat yield changes due to switching from conventional tillage systems to no-till (a) and reduced-till (b) systems in tons per hectare. Crop area based on (IFPRI, 2019)

Figure B1. Wheat mitigation effects from changing conventional tillage systems to no-till (a) and reduced-till (b) systems in tons CO_2 per hectare and year. Crop area based on (IFPRI, 2019) . Weighted average yields for rainfed and irrigation.

Figure C1. Changes in net-costs of wheat production [-(Δyield x price - Δproduction costs)] from changing conventional tillage systems to no-till (NOT) and reduced-till (RED) systems in $US2010 per hectare, for different assumptions on related changes of production costs (low, med, high, region; see Table 4). Crop area based on SPAM 2010 (IFPRI, 2019).

Figure C2. Changes in net-costs of corn production [-(Δyield x price - Δproduction costs)] from changing conventional tillage systems to no-till (NOT) and reduced-till (RED) systems in $US2010 per hectare, for different assumptions on related changes of production costs (low, med, high, region; see Table 5). Crop area based on SPAM 2010 (IFPRI, 2019).

Figure D1. Regional MACCs for wheat.

Figure D2. Regional MACCs for corn.

TABLES

1. Global maps at 250 m spatial resolution of SOC concentrations and SOC stocks

1.1 Introduction

Improved global soil organic carbon (SOC) stocks maps are paramount for reducing uncertainties in SOC sequestration potential at global scale. ISRIC's **SoilGrids** provides consistent, global maps of basic soil properties such as SOC concentration, pH, clay content, bulk density for six depth intervals (0-5 cm, 5-15 cm, 15-30 cm, 30-60 cm, 60-100 cm, 100-200 cm), as well as derived properties such as SOC stock and water holding capacity at 250 m spatial resolution. These layers can be used as inputs for environmental models such as RothC to assess SOC sequestration potential.

SoilGrids is a system for digital soil mapping based on state-of-the-art predictions methods based on machine learning approaches. SoilGrids was developed from ISRIC's soil sample data collection and an extensive stack of ancillary data ('covariates') in form of and products derived from satellite imagery and other environmental information including climate, land cover and terrain with global coverage. The sample data and covariates are combined in a machine learning framework. Machine learning models are used to elicit predictive relationships between soil samples and covariates. Once such a model is calibrated, it can be used to predict the soil property of interest for any location across the globe on basis of the covariate data at these locations. SoilGrids is a global modelling framework, meaning that for each soil property one machine learning model is calibrated using input data from across the globe.

Over the years, SoilGrids went through several phases of updating and improvement. Three years ago, ISRIC improved the spatial resolution from 1 km to 250 m, and changed from a geostatistical modelling framework to a machine learning framework, with improved predictions.

SoilGrids has evolved considerably since the previous release (2017), both in the methodologies employed as in the computation infrastructure and the data inputs. The following improvements can be highlighted:

- Wider selection of soil observations: more profile observations, increased quality assessment and improved and consistent standardisation across the different point datasets.
- Quantification of prediction uncertainty at pixel level with the 90% prediction interval using Quantile Random Forest.
- Improved model calibration and cross-validation procedure to better take into account the uneven spatial distribution of data points across the world.
- Improved covariates selection and model parameter tuning.
- Texture fractions modelled and mapped not independently from each other, but as compositional data with the sum of the fractions constrained to 100%.

This year (2019), ISRIC invested in a major update of the SoilGrids maps of basic soil properties (pH-H_2O, coarse fragments content, sand, silt and clay contents, cation exchange capacity, bulk density, SOC concentration, total nitrogen), with a strong focus on quality control. Improvements includes:

- Extension of the input datasets with soil observations: more data points, more focus on quality assessment of point data, improved standardization (following the standards of ISRIC's institutional soil database WOSIS) across the different point datasets.
- Quantification of prediction uncertainty at the pixel level with the 90% prediction interval.

- Improved model calibration and cross-validation procedure to better take into account the uneven spatial distribution of data points across the world.
- Improved covariates selection and model parameter tuning.
- Texture (sand, silt, clay) fractions modelled and mapped not independently from each other but as compositional data with the sum of the fractions constrained to 100%.

1.2 Soil Organic Carbon stock mapping

The 2019 update of SoilGrids focused on basic properties only, derived properties such as SOC stock were not considered initially. Because of obvious synergies between SoilGrids and CIRCASA with respect to the SOC domain and a smaller role for ISRIC on the KIS development as the existing platform DATAVERSE was selected, ISRIC's T 1.3 budget was partly used – after a plenary presentation and approval of CIRCASA leadership at the Cali project meeting (February 2019) – to support the **update of the SoilGrids SOC stock map** and expand this map with **quantified information about uncertainty** at the pixel level. The SOC stock map, together with SOC concentration map, can be used as inputs for CIRCASA's knowledge information system to support assessment of SOC sequestration potential with the RothC model. Here we will describe the tasks and (initial) results undertaken for this activity.

1.2.1 Bulk density and organic carbon density pedotransfer functions

SOC stock (kg m^{-3}) is a composite soil property that is computed from SOC concentration (g kg^{-1}), bulk density (kg m^{-3}) and coarse fragments (%). For a specific depth interval SOC stock (in kg m^{-2}) content as follows:

$$SOC\ stock\ (d) = SOC/1000 * BD\ * \left[1 - \left(\frac{CF}{100}\right)\right] * d$$

with *d* as the thickness of the depth layer of interest in m; e.g. 0.3 in case of mapping the 0-30 cm layer. Data on SOC concentration generally is well available; for SoilGrids for approximately 117,100 sites. Data on bulk density and coarse fragments is much scarcer. For bulk density data from 17,500 sites are available. Our *first* task was therefore to investigate if we could enlarge the bulk density dataset through the use of **pedotransfer functions** (PTF) that model and predict bulk density at sampling sites from other readily available soil properties such as SOC concentration, pH and clay content. We first explored the use of linear models for this purpose and tested different models (different sets of predictors, separate modelling of top- and subsoil layers). Results in terms of prediction accuracy were moderate; the best model explained 42% of the variation in the dataset (R^2 = 0.42). Furthermore, the models substantially over-estimated the relatively low bulk density values; which is undesirable because these will then heavily inflate SOC stock estimates. Next, we tested several more sophisticated models such as general additive models and random forest models. These models are better capable of modelling non-linear relationships between target property and the predictors. Results slightly improved (R^2 = 0.50).

The bulk density PTF results showed that the PTF-predicted bulk density at a sampling site is not always consistent with the SOC concentration measured at that site. There is a strong negative relationship between bulk density and SOC that must be retained for SOC stock modelling. We therefore decided to fit a pedotransfer function for the organic carbon density (OCD) instead of the bulk density, with OCD defined as: *OCD [kg m^{-3}] = SOC concentration [g kg^{-1}]/1000 * BD [kg m^{-3}]*. We used a random forest model with sand, silt and clay contents, pH-$H_2$0, SOC class and depth used as predictors. The model was calibrated using data from 17,500 sampling sites for which SOC and bulk density were both available. Cross-validation showed that this model performed reasonable well with an explained variation of about 70% (R^2 = 0.70). The PTF-predicted OCD was corrected for presence of coarse fragments (following the equation above). If a measured coarse fragments value was not available for a data point, then a predicted value from the SoilGrids coarse fragments map was taken instead.

1.2.2 SOC stock modelling and mapping

The *second* task was the modelling and mapping of global SOC stocks with the SoilGrids framework. Two different types of maps were created:

1. maps of SOC density (*OCD [kg m^{-3}] = SOC concentration [g kg^{-1}]/1000 * BD [kg m^{-2}] * 1-(CF/100) [%]*) for each of the six standard depths
2. maps of SOC stock density (*OCS [kg m^{-2}] = SOC concentration [g kg^{-1}]/1000 * BD [kg m^{-2}] * 1-(CF/100) [%] * d [m]*) for the 0-30 cm and 30-100 cm layers, which are typical layers used for SOC stock assessment and reporting. These layers can be simple summed to obtain stocks for the 0-100 cm layer.

Figure 1 shows a draft SOC stock map for the 0-30 cm layer. The total global stock on basis of this layer is estimated to be approximately 605 Pg. (Note that this estimate might still change since some final checks and verifications still need to be carried out). The 30-100 cm layer showed some unexpected spatial patterns of predicted SOC stocks that need to be further scrutinized before the map can be published. In particular correction by depth needs to be implemented and checked.

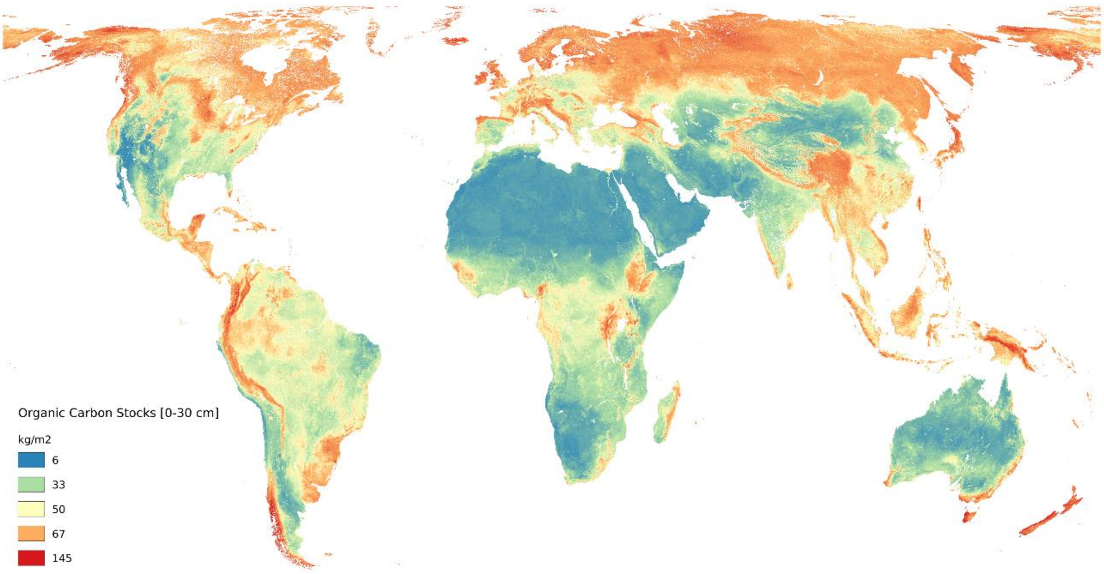


Figure 1: SoilGrids soil organic carbon stocks for the 0-30 cm layer (DRAFT).

The preview release of SoilGrids (December 2019) can be accessed through the following services:

- WMS: swift access for visualisation and data overview.
- WCS: best way to obtain map segments for specific regions in the world and to use SoilGrids as input to other modelling pipelines.
- WebDAV: download the complete global maps in VRT format.

1.3 Uncertainty

The *third* activity we undertook was modelling and mapping of prediction uncertainty at global level. Quantification of uncertainty at pixel level is new extension for SoilGrids. For previous SoilGrids versions this proved to be not feasible computationally. However, new methodological developments in the statistical software package R as well as the availability of powerful cloud computing allowed us to quantify pixel-level prediction uncertainty for this new SoilGrids version. We quantified the prediction uncertainty with the 90% prediction interval, following the specifications of the IUSS Global Soil Map Working Group.

SoilGrids uses the random forest to model the soil properties. Uncertainty of random forest predictions can be quantified with a method referred to as 'quantile random forest' (QRF). This method does not only give a predicted value as output but the full conditional distribution of the prediction. From this distribution the upper (95%) and lower boundary (5%) of the 90% interval can be derived. We developed a set of scripts to implement QRF on the High Performances Computing (HPC) facilities of the Wageningen University and generate maps of the 5% and 95% boundaries for all SOC layers. The same scripts were then applied to quantify the prediction uncertainty of the other soil properties.

1.4 Outlook

Based on the work done so far, we identified several activities to further improve the quality of the models and maps:

- Modelling and mapping of **soil depth**. The depth of the soil constrains the amount of carbon that can be stored. Having a good quality soil depth map will result in more realistic estimates of SOC stocks. Currently we have not yet taken soil depth into account for the global estimates of SOC stock. There is an experimental SoilGrids soil depth map available that was created in 2016. The methodology used to generate this map needs to be further developed.
- Assembling new and improved **covariates** for SOC stocks modelling with focus on high-resolution satellite imagery, for instance as supplied by ESA's Copernicus satellites.
- Enlarging the **soil sample database**. During 2019, ISRIC has obtained new SOC datasets from various territories in the world that were not yet included in the dataset used for modelling.
- Publication of a **peer-reviewed article** on global soil organic carbon stock mapping as a methodological quality control step.

In addition, modelling and mapping of **soil functions** at global level with specific focus on **carbon sequestration potential** with a machine learning framework and a global soil dataset could be worthwhile to further explore and develop as well.

2. Organic carbon inputs to soils and SOC balance in world arable systems

2.1. Introduction

Agricultural soils have been identified as having significant potential to sequester soil organic carbon (SOC) thereby mitigating climate change and maintaining soil productivity(Lal et al., 2007; Zhang et al., 2014). Significant efforts have been made to estimate the potential of agricultural soil to sequester C under diverse environmental and management conditions (Ogle et al., 2010; Smith et al., 2005; Wang et al., 2013; Yu et al., 2012).The actual amount sequestered depends on management strategies (e.g., residue retention and fertilizer application) and environmental conditions (Luo et al., 2010; Smith et al., 2008; West and Post, 2002). A detailed assessment of critical C input level targeting at certain soil C level will assist in designing effective management practices for C sequestration in agricultural soils and help different stakeholders assess the status of soil C under current farmers' C input level and future potential management and climate changes.

Regardless of management practices, increasing C input through residue retention and stimulating crop growth by nutrient intensification usually have to be achieved (Lal, 2004; Liu et al., 2014; Luo et al., 2014)

The objectives of this works are:

- Estimate the organic carbon inputs required for given local pedo-climate conditions to balance SOC losses and maintain the stock in an equilibrium under current climate conditions
- Estimate the organic inputs required to reach the aspirational 4 per 1000 target (0.4% annual increase in stock for 30 years) for SOC sequestration
- Produce a set of maps on global cropland NPP fraction returning to soil on annual basis for assumed scenarios of crop intensification levels.
- Analyze if the NPP fraction returning to soil ($tC.ha^{-1}.yr^{-1}$) is enough to sustain or to reach the 4 per 1000 target in agricultural soils.

This work was carried out based on data assembled by IIASA, and involved RothC simulations at INRA.

- The Rothamsted Carbon Model (RothC)(Coleman et al., 1997) model is one of the most commonly used soil models today (Coleman et al., 1997; Lark et al., 2019). The set of inputs required by RothC is a crucial advantage when compared with other process-based soil models that require more input data to drive the model (Morais et al., 2018). The range of dynamic SOC processes captured by RothC is lower, but the fact that it is a parsimonious model makes RothC a good candidate for global modelling exercises due to its manageability. However, few examples exist of continental or global-scale applications of RothC (Gottschalk et al., 2012; Smith et al., 2005).
- EPIC-IIASA provides a modelling framework, which integrates EPIC model with global-extent geographical data on all inputs necessary to run the model. Geographical data adds spatial component to otherwise field-scale simulation model making it suitable for large-scale applications (Balkovič et al., 2013)(Balkovič et al., 2014) (Mueller et al., 2012)(Folberth et al., 2019). Maps were interpreted from EPIC-IIASA model outputs for 17 major crops cultivated worldwide (Hypercube v1.0 dataset). The cropland NPP fraction estimates cover EPIC-IIASA simulation results for set of theoretical scenarios of crop intensification levels (subset of Hypercube v1.0 dataset) and additional assumptions on crop residue removal and irrigated land area fractions.

2.2. Methodological aspects

RothC simulations

Several datasets were gathered in order to yield the necessary input variables for the RothC runs. Among these, we used the HWSD soil database (running simulations on the dominant soil types only, and excluding organic soils), the AgMERRA climate dataset for years from 1980 to 2010 and the land cover as estimated for GEOBENE project from GLC2000 and SPAM datasets (Skalský et al., 2008)

The RothC model (Jenkinson et al., 1992) was originally developed to simulate changes in SOC stock in arable topsoils in the long-term field experiments at Rothamsted in the UK. It was then extended to model SOC turnover in grasslands and forests and evaluated in a variety of ecosystems in different climatic regions (Smith et al., 1997). The RothC model can be written as:

$$\frac{dSOC(t)}{dt} = F.SOC(t) + C_{in} \qquad (1)$$

where SOC is a dimension 4 vector composed of organic carbon content in four dynamic compartments, the resistant plant pool (RPM), the decomposable plant pool (DPM), the microbial pool (BIO) and the humic pool (HUM). C_{in} is a dimension 4 vector that indicates in which pools SOC inputs are incorporated, and F is a 4 x 4 matrix representing SOC mineralization and carbon flows between the four active carbon pools. The type of vegetation influences the distribution of C inputs into the RPM and DPM pools, hence the DPM:RPM ratio typically depends on the type of plant. In RothC, three plant types are available: croplands, unmanaged grasslands and forests with a DPM:RPM ratio of 1.44, 0.67 and 0.25 respectively.

The RothC model, like many other first-order kinetic SOC dynamic models, results in equilibrium SOC stocks in the long term, assuming that both SOC inputs and mineralization factors are constant or at least exhibit periodicity (Martin et al., 2007)

$$\lim_{t\to\infty} SOC(t) = SOC^*$$

SOC^* hereafter called the equilibrium state, can then be easily calculated and depends on OC input rates and the F matrix:

$$SOC^* = (I_4 - F)^{-1}C_{in} \qquad (2)$$

where I_4 is the identity matrix of dimension 4x4. Conversely, if estimates of SOC^* and F exist, C_{in} can in turn be estimated, assuming that the soil has reached equilibrium and that climatic conditions are constant. Note that SOC refers to SOC that is subject to SOC dynamics. For the RothC model, this dynamic SOC is a fraction of the total SOC.

$$SOC_{total} = SOC + IOM$$

where SOC_{total} is the total SOC, that can be measured in soils using for instance dry combustion analyzers, and IOM is the inert SOC fraction, which, according to RothC, is constant over time. IOM is usually estimated using the (Falloon et al., 1998) equation. Eq. 2 gives:

$$C_{in} = (I_4 - F)SOC^* \qquad (3)$$

Like in eq. 1, C_{in} is a dimension 4 vector. For the purpose of simplicity, C_{in} hereafter refers to total carbon inputs into the soil, i.e. the sum of the 4 components of this vector.

In the present study, we used the available analytical formulation of the RothC model to estimate

(i) the inputs of SOC that would be needed to maintain current SOC stocks, assuming these are at equilibrium state, and

(ii) the increased SOC inputs needed to reach SOC stocks in 30 years from now, assuming a constant yearly 4‰ rate of increase in SOC. More specifically, at each location, we performed the following algorithm, again assuming that SOC stocks were currently at equilibrium in each location:

Compute SOC_0 as $SOC_0^{total} - IOM = SOC_0^{total} - 0.049(SOC_0^{total})^{1.139}$ (Falloon et al., 1998)

Using eq. 2 and eq. 3

Split SOC among RPM, DPM, BIO and HUM

Calculate C_{in}^0 needed to have observed SOC^0

Compute SOC^{4p1000} as $SOC_0.(1.004)^{30}$ (a 30-years 4‰ increase)

Estimate C_{in}^{4p1000} needed to reach SOC^{4p1000}

From the C_{in}^{4p1000} estimate, the increase in SOC input is calculated as

$$\Delta C_{in} = C_{in}^{4p1000} - C_{in}^0$$

The RothC model was implemented in the RothC R package (Martin, 2018), GIS operations using GRASS GIS software (GRASS Development Team, 2018) and statistical analysis using R software (R Core Team, 2016)

EPIC-IIASA modelling framework

The Environmental Policy Integrated Climate (EPIC) model (Williams, 1995) is process-based field-scale simulation model of crop production developed in US. EPIC operates on daily time step integrating modules on weather, plant growth, nutrients cycling, and water balance. It requires input data on:

- weather (daily data on minimum/maximum temperature, sunshine hours, rainfall, and relative humidity),
- topography (position, slope inclination, slope length, and more),
- soil (soil profile depth, soil hydrological group, and for each layer sand, clay, stones, and organic carbon content, pH, cation exchange capacity, bulk density, and more),
- crop (planting, harvesting, cropping densities, and more),
- crop management (tillage operations, harvest operations, irrigation type and amount, fertilizer amount and timing, crop residue management, multi-cropping, mixed-cropping, crop rotations, and more).

Model provides daily, monthly, or yearly outputs for (among many more): crop biomass production (aboveground, below ground), crop yield, nutrient consumption (N, P), water balance elements (potential/actual evapotranspiration, irrigation water amount, surface/sub-surface runoff), soil organic carbon, crop residue decomposition rates, sediment transport, nutrient and soil organic carbon transport with sediments.

Geographical data (Table 1) integrated with EPIC-IIASA is organized within regular grid of 5’x5’ spatial resolution pixels covering global croplands. Individual pixels are organized within wider spatial domains (Simulation units – SimU). Each SimU groups one or more 5’x5’ pixels based on their similarity in topography and soil. It is further divided by country borders and 0.5°x0.5°spatial resolution grid. The 0.5°x0.5°spatial resolution grid keeps maximum size of each SimU constant and also serves for linking weather information (AgMERRA daily climate dataset). Size of SimU range between 5’x5’ and 0.5°x0.5°, actual size depending on physiographic heterogeneity of the area.

Table 1. Input datasets implemented with EPIC-IIASA at 5'x5' spatial resolution (for EPIC-IIASA Hypercube v1.0 product).

Input	Dataset	Spatial resolution	Temporal resolution	Source
Climate	AgMERRA Climate Forcing Dataset for Agricultural Modelling	0.5 arc-deg	1980-2010 (daily)	(Ruane et al., 2015)
Terrain	Shuttle Radar Topographic Mission Data (SRTM)	3 arc-sec	N/A	(Werner, 2001)
	Global 30 Arc Second Elevation Data (GTOPO)	30 arc-sec	N/A	https://www.usgs.gov/centers/eros
Soil	Digital Soil Map of the World	1:5 mil	N/A	http://www.fao.org/geonet
	World Inventory of Soil Emission Potential database (WISE)	5 arc-min	N/A	(Batjes, 2009)
Administrative units	Global Administrative Unit Layers (GAUL)	N/A	2007	http://www.fao.org/geonetwork
Land cover/Crop management	The Global Land Cover for year 2000 (GLC2000)	0.5 arc-min	Around 2000	(Bartholomé and Belward, 2005)
	Spatial Production and Allocation Model (SPAM) for physical and harvested crop areas	5 arc-min	Around 2000	(You et al., 2014)
	Crop calendar	30 arc-min	1990s	(Sacks et al., 2010)

Hypercube v1.0 dataset (further referred to as HC) is global-extent dataset which contains EPIC-IIASA simulated crop production characteristics and selected environmental externalities associated with crop production as assumed for selected crop intensification scenarios. HC scenarios cover qualitative and temporal dimensions including nutrient and water intensification gradients (Table 2).

Table 2. Data dimensions of the EPIC-IIASA Hypercube v1.0 dataset

Dimension	Points
Crop	17 major crops cultivated globally: barley, cassava, cotton, groundnut, corn, millet, potato, peas, beans, rape, rice, rye, sugar beet, sugar cane, sunflower, sorghum, soybean, and wheat
N fertilization rate	5 levels of nitrogen input: 0.1 $kg.ha^{-1}$, 25 $kg.ha^{-1}$, 100 $kg.ha^{-1}$, 200 $kg.ha^{-1}$, and 400 $kg.ha^{-1}$
P fertilization rate	1 level of phosphorous input: automatically balanced with N input
Irrigation	3 levels of irrigation water input: rainfed, moderately irrigated with 50 % water stress allowed for crops and maximum irrigation volume 300 mm, and fully irrigated with 20 % stress allowed for crops and maximum irrigation volume 2000 mm)
Time	30 individual years (1980-2010)

Annual HC outputs include dry matter yield ($t.ha^{-1}$), total biomass ($t.ha^{-1}$), below ground biomass ($t.ha^{-1}$), N application ($kg.ha^{-1}$), P application ($kg.ha^{-1}$), and irrigation water amount (mm). More than 100 variables are available in HC on monthly basis (crop production, nutrient and water inputs/consumption and environmental externalities).

2.3. Results

2.3.1 Simulated annual organic carbon (OC) inputs for SOC conservation and sequestration

Our analysis for arable crops shows that the distribution of organic carbon inputs to soils (

3) closely follows the distribution of SOC stocks worldwide (Figure 2

), but is modulated by SOM mineralization rates. RothC assumes that these rates are controlled both by soil properties and by climate. SOM mineralization increases with soil temperature and with soil moisture. Therefore, under tropical wet conditions the model calculates high mineralization rates per unit SOC. This results in large simulated demands of OC inputs to maintain the SOC stocks of arable crops in tropical wet regions.

Since RothC does not cover organic soils (SOC> 200 tC/ha) and these were excluded from the initial run. However, some soils – although not defined as organic – have large organic C stocks that may lead to unrealistic OC inputs values under tropical conditions, since for instance the model assumes a freely draining soil whereas soil anoxia may frequently happen in the wet tropics. Therefore, a more stringent filtering was used to exclude arable sites with SOC content > 100 tC/ha.

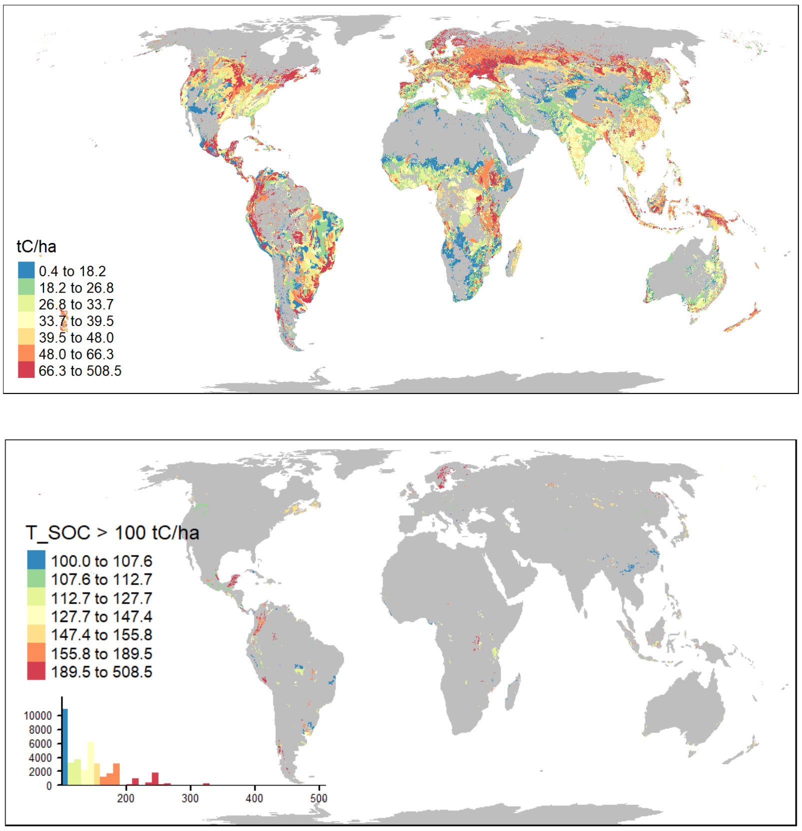


Figure 2: Current SOC stocks (0-30cm) in the dominant soil units (Top). Distribution of soils with more than 100 tC/ha (Bottom). Areas not used for crops and organic soils (SOC above 200 tC/ha) are masked in grey.

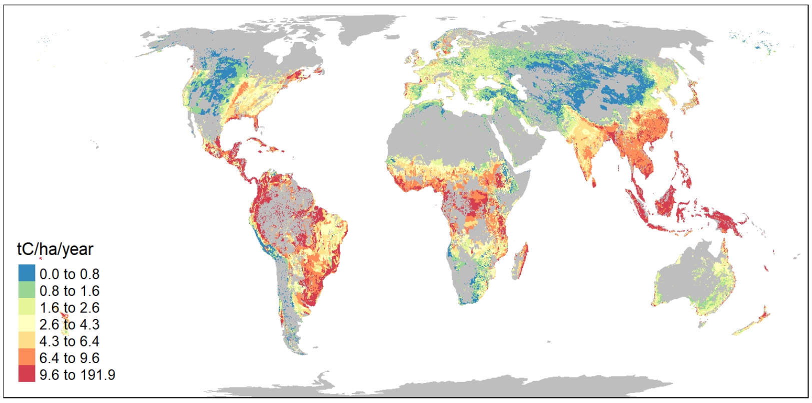


Figure 3: Simulated (RothC model) annual organic carbon inputs (in tC/ha/year) from crop residues and from organic fertilizer required to sustain current SOC stocks (0-30 cm) in cropped areas. Areas not used for crops, or with SOC stock above 100 tC/ha, are masked in grey. Note that the carbon content of dry organic matter (crop residues, organic fertilizers) is around 0.4.

Simulated annual OC inputs required for a steady state in SOC stocks of mineral soils from cropped areas range between low values (less than 0.8 tC/ha/yr) in cold and dry regions with SOC depleted soils (e.g. in parts of Northern Asia and Western North America) and much higher values (up to 10 tC/ha/yr) in equatorial and tropical regions with a wet climate (e.g. Central America, Central Africa, Indonesia). Intermediate values (around 1 tC/ha/yr) are simulated for temperate regions (e.g. Western and Central Europe, Eastern USA and Canada) and in dryer tropical conditions (e.g. Sahel, parts of Australia, North-East Brazil).

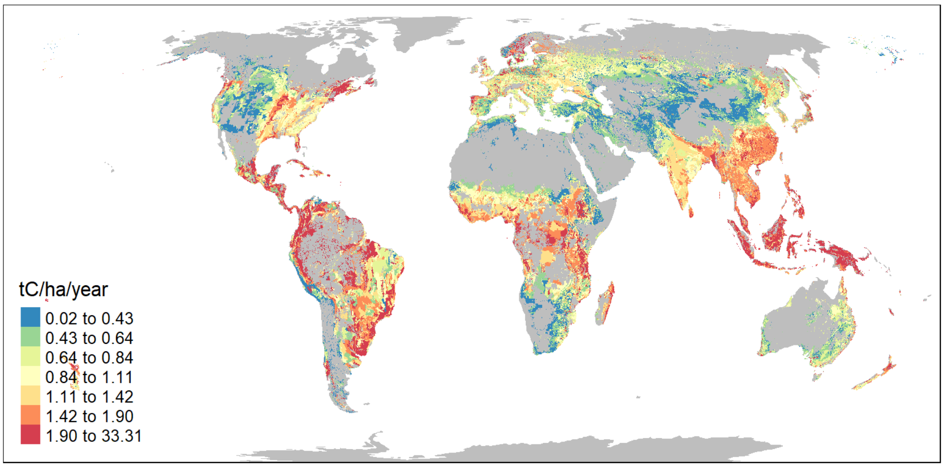


Figure 4: Simulated (RothC model) annual additional organic carbon inputs (in tC/ha/year) from crop residues and from organic fertilizer required to increase by 0.4% per year SOC stocks (0-30 cm) in cropped areas (assuming that SOC stocks are in a steady state). Areas not used for crops, or with SOC stock above 100 tC/ha, are masked in grey. Note that the carbon content of dry organic matter (crop residues, organic fertilizers) is around 0.4.

Compared to the assumption of OC inputs to soils maintaining SOC stocks in a steady state, we have also simulated additional OC inputs allowing to increase SOC stocks by 0.4% per year (i.e. the aspirational 4p1000 target, see Soussana et al., 2019) (Figure 4). Results show that the spatial distribution of additional inputs is closely correlated to the spatial distribution of OC inputs required for the maintenance of SOC stocks. Additional OC inputs to cropped soils required to reach the 4 per 1000 target are about 25-32% of the OC inputs required for a steady state in SOC stocks. Therefore, although after 30 years, compared to a steady state, the 0-30 cm SOC stock would be increased by 1.004^{30}, that is by 13% only, reaching this target demands a substantial increase (between one fourth and one third) in the annual return of organic matter to soils.

2.3.2 Simulation of annual organic carbon (OC) inputs to soils according to agricultural practices

Spatially explicit and SimU specific global cropland NPP fraction fraction returning to soil ($tC.ha^{-1}.yr^{-1}$) was interpreted from HC data with set of assumptions:

- business-as-usual (BAU) aboveground and belowground biomass production (with crop yield fraction subtracted) for each crop and irrigation scenario was estimated from two closest HC points based on spatially explicit and crop specific data on N fertilizer inputs at around 2000 (Mueller et al., 2012),
- irrigated and rainfed aboveground and belowground biomass production for N input level at 400 $kg.ha^{-1}.yr^{-1}$ (with crop yield fraction subtracted) was taken to represent potential (POT) production,
- national crop-specific residues removal and burning rates were taken from recent global report (Koeble, 2014) to account for plant residue removal with BAU nutrient input scenario and the removed fraction of crop residues was subtracted from BAU aboveground biomass production,
- organic C fraction of dry biomass was calculated for all crops and crop management intensification scenarios (BAU, POT, rainfed, fully irrigated) with coefficient 0.49 taken from (Bakker et al., 2013),
- NPP fractions ($tC.ha^{-1}.yr^{-1}$) were calculated across all crops using physical and harvested crop areas from SPAM dataset (You et al., 2014) ,
- irrigated and rainfed crop areas around the year 2000 from MIRCA2000 dataset (Portmann et al., 2010) were used for weighting irrigated and rainfed NPP fractions for combined rainfed and irrigated BAU or POT scenarios.

Overview of scenarios of cropland NPP fraction returning to soil ($tC.ha^{-1}.yr^{-1}$) and resulting datasets which were interpreted from HC data is provided in Table 3. Data visualizations for all scenarios are shown on Figure 5 and Figure 6

Table 3. Overview of data (5'x5'spatial resolution GeoTiff raster layers) produced for assumed scenarios of cropland NPP fraction (tC.ha-1.yr-1) returning to soil. Based on EPIC-IIASA simulated crop intensification levels and additional assumptions on crop residue removal and irrigated land fractions.

Data layer	File name	Description
BAU_firr	hc_c_per_ha_phys_bau_firr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input and fully irrigated production, weighted across all crops
BAU_firr_rem	hc_c_per_ha_phys_bau_firr_rem.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input and fully irrigated production, weighted across all crops, with crop residue removal
BAU_noirr	hc_c_per_ha_phys_bau_noirr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input and rainfed production, weighted across all crops
BAU_noirr_rem	hc_c_per_ha_phys_bau_noirr_rem.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input and rainfed production, weighted across all crops, with crop residue removal
BAU_wirr	hc_c_per_ha_phys_bau_wirr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input, weighted based on area share of irrigated production and across all crops
BAU_wirr_rem	hc_c_per_ha_phys_bau_wirr_rem.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for BAU nutrient input, weighted based on area share of rainfed and irrigated production and across all crops, with crop residue removal
POT_firr	hc_c_per_ha_phys_pot_firr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for unlimited nutrient input (yield potential) and fully irrigated production, weighted across all crops
POT_noirr	hc_c_per_ha_phys_pot_noirr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for unlimited nutrient input (yield potential) and rainfed production, weighted across all crops
POT_wirr	hc_c_per_ha_phys_pot_wirr.tif	Plant residue input ($tC.ha.yr^{-1}$) estimated for unlimited nutrient input (yield potential), weighted based on area share of rainfed and irrigated production and across all crops

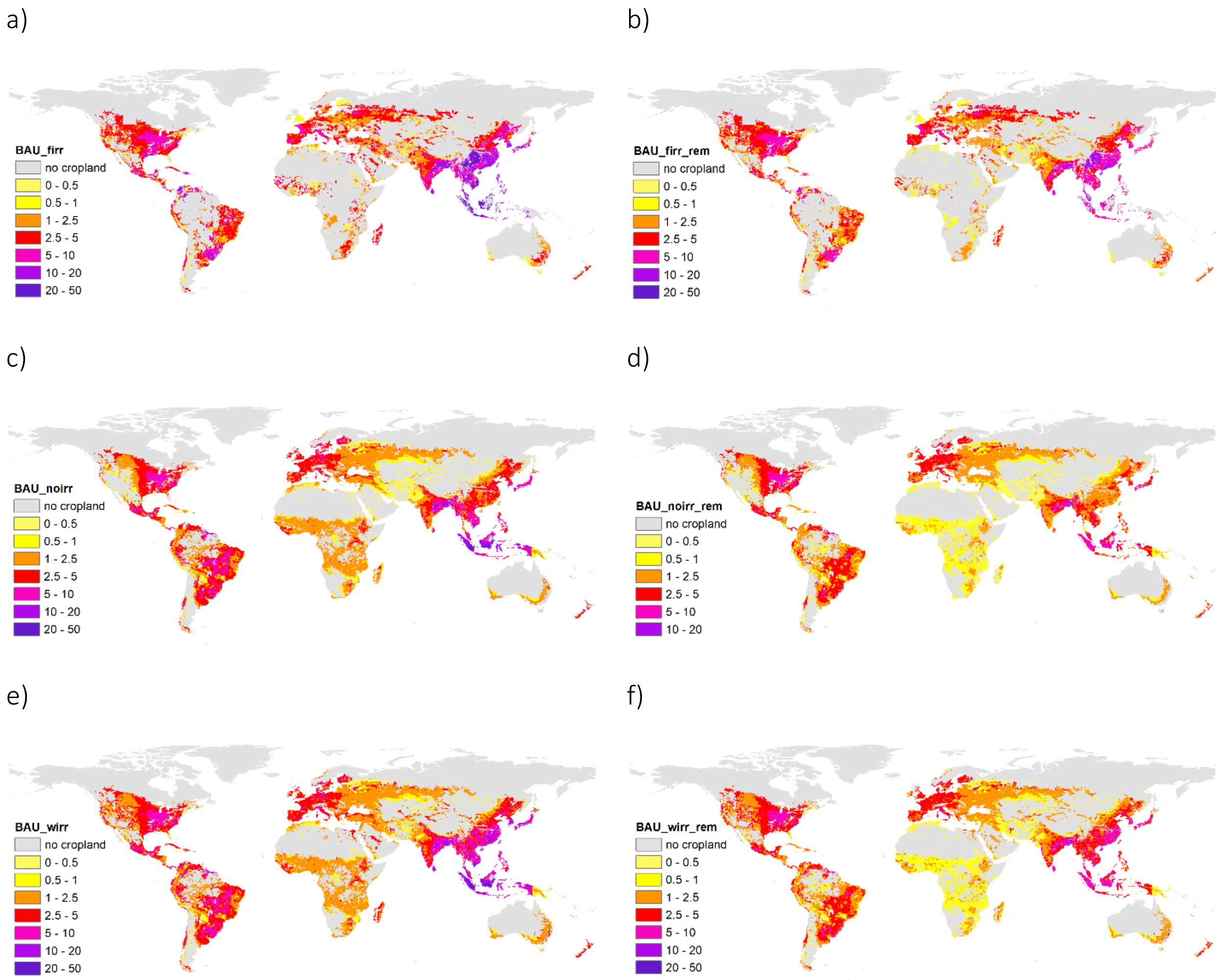


Figure 5. Cropland NPP flux returning to soil (litter, tC.ha-1.yr-1) for BAU crop management intensification scenarios. Fully irrigated (a, b), rainfed (c, d), and weighted (e, f) production without or with (b, d, f) plant residue removal.

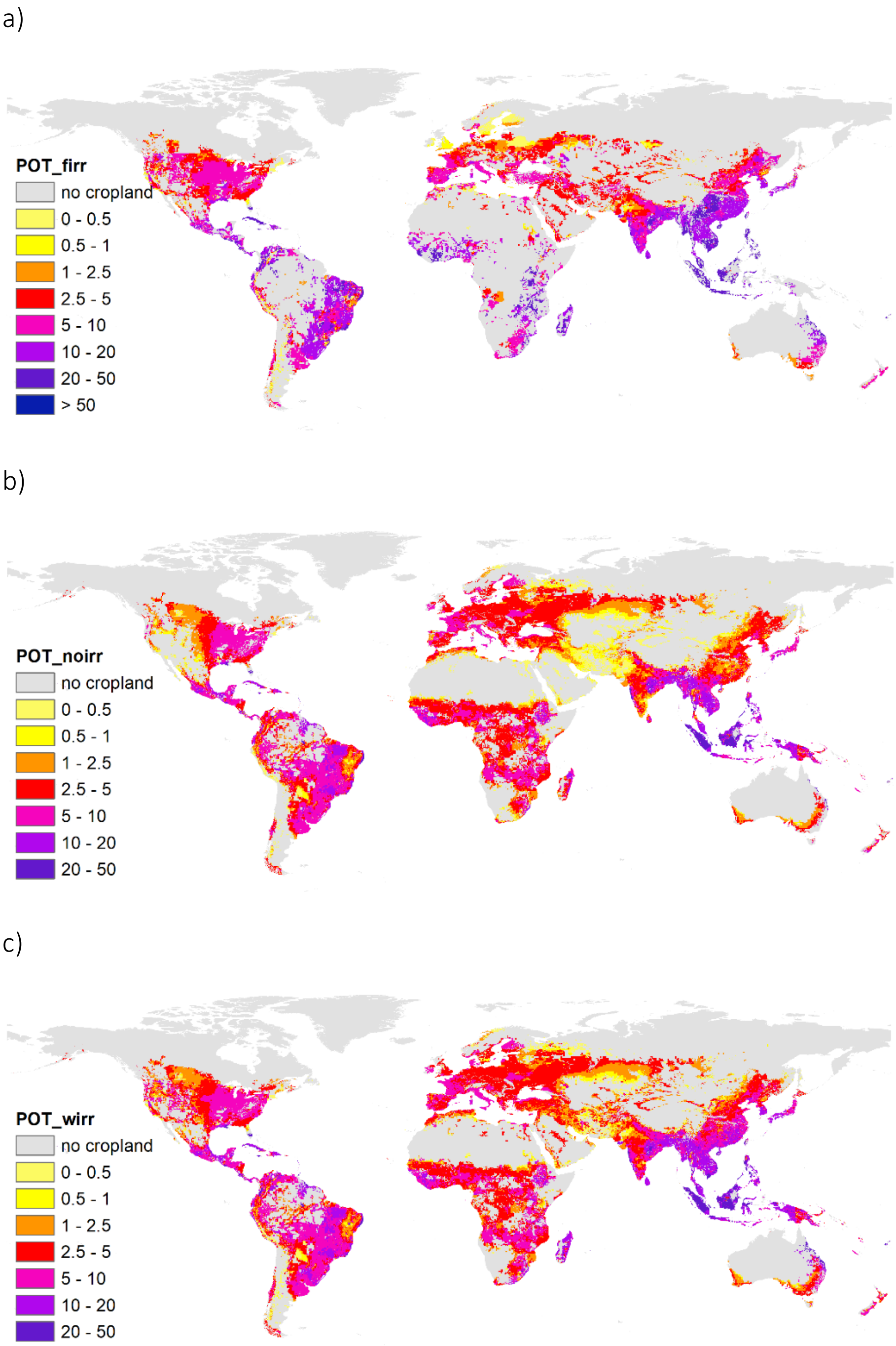


Figure 6. Cropland NPP returning to soil (litter, tC.ha^{-1}.yr^{-1}) for nutrient unlimited (potential) production crop management intensification scenarios. Fully irrigated (a), rainfed (b), and weighted (c) production without plant residue removal.

For soils under current climate conditions, the balance between C inputs by crop residues and inputs required for maintaining (Fig. 7) or increasing SOC stocks by 0.4% per year (Fig. 8) was calculated, considering the following crop management scenario: mean of all crops, BAU nutrient input, weighted rainfed and irrigated production and crop residue removal. It should be noted that crop residue removal (for use as feed and litter for livestock, as biomass for biogas production, etc.) and open burning of residues happen in many world regions. However, the fate of crop residues is not known global scale and there are no gridded data available showing crop residue use (although the GLEAM model by FAO[1], has gridded data on the feedbasket of livestock systems, including crop residues).

[1] http://www.fao.org/policy-support/tools-and-publications/resources-details/fr/c/1070783/ (accessed, Feb. 1, 2021)

When this C balance is positive, simulations estimate that the amount of crop litter going back to the soil exceeds the amount required to maintain SOC stock, or to increase it following the aspirational 4 per 1000 target. Such a positive C balance is simulated for most temperate regions of the Northern hemisphere. In contrast, in the intertropical latitudinal band, the C balance is on average negative, indicating that SOC stocks may decline (Fig. 7) and that they do not reach the aspirational 4 per 1000 target (Fig. 8). It should be noted that this C balance would be shifted upwards by considering an alternative scenario without removal of crop residues (since C inputs are higher without than with crop residues removal, see Figs. 5e and 5f, respectively).

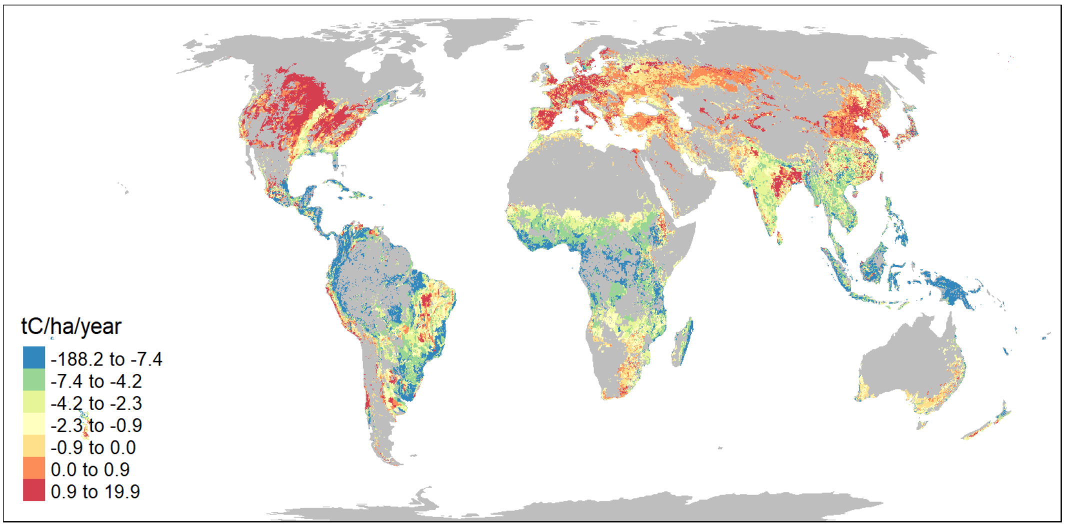


Figure 7 .Balance between crop litter input (tC.ha^{-1}.yr^{-1}) estimated for BAU nutrient input, weighted based on area share of rainfed and irrigated production and across all crops, with crop residue removal and carbon input needed to maintain current SOC stocks

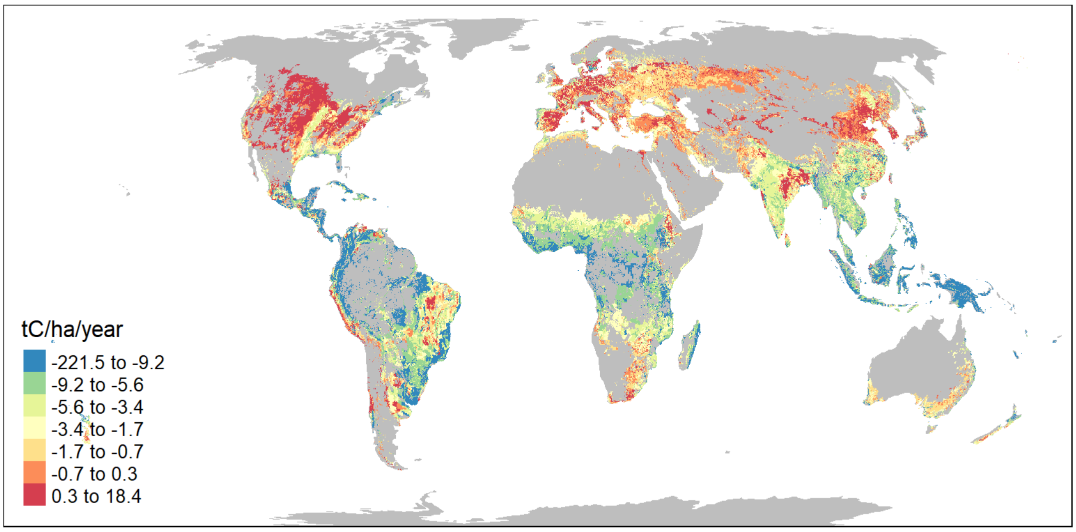


Figure 8 .Balance between crop litter input (tC.ha^{-1}.yr^{-1}) estimated for BAU nutrient input, weighted based on area share of rainfed and irrigated production and across all crops, with crop residue removal and the C input need to reach the 4p1000 target

2.4. Conclusion and Outlook

Increasing soil organic carbon (SOC) stock is a promising option to mitigate the increase in atmospheric CO_2 concentration (Minasny *et al.*, 2017; Soussana et al., 2019). At the field scale, changes in SOC stocks result from an imbalance between C inputs (crop residues, litterfall, root exudates, manure application, etc.) and C outputs due to harvests, mineralization of organic C, leaching or erosion (*e.g.* Lal, 2018). Although some farming practices may reduce mineralization rates (*e.g.* reduced tillage, see a recent review by Haddaway *et al.*, 2017), it is generally agreed that the most efficient way to increase soil C stocks is to increase C inputs (*e.g.* Virto *et al.*, 2012; Autret *et al.*, 2016; Fujisaki *et al.*, 2018). This can be achieved by increasing on-field biomass production and residue return (*e.g.* cover crops, Poeplau & Don, 2015), or by mobilizing and spreading external C resources such as manures or composts. Indeed, high C stock increases are often observed in experiments with high rates of organic fertilization (Poulton *et al.*, 2018; Maillard & Angers, 2014). However, as manures are often already applied to soils, they do not necessarily represent a potential source of additional soil C gain at global scale. In a context of increasing competition for C resources (e.g. for food, feed, fiber or energy production), the question arises of how much additional C is needed to reach the aspirational target of 4‰. Here, we have investigated with the RothC model (used in an inverse mode) the amount of additional C that is necessary for increasing the SOC stock by 4‰ per year during 30 years, and assessed the feasibility of the 4‰ target (increase the SOC stocks by 0.4% per year) in terms of available organic carbon flux going back to soils as litter (estimated by Global EPIC model) in current cropping systems worldwide.

We have identified methodological problems with the RothC model in some of the tropical areas, especially in hot and wet environments where the model overestimates SOC mineralization. High simulated values of carbon input in warm and wet tropical areas can be anticipated from RothC, as they result from the interplay of high carbon stocks, and high temperature (although < 30°C), high moisture content in soils leading to high mineralization rates. However, the following model limitations need to be considered when refining these first results:

- RothC is developed for mineral soils. In this study, we excluded organic soils, but not waterlogged soils and andosols (which have high SOC stocks). With Andosols, a modified version of RothC is needed as shown by Shirato et al. (2011) since there are strong interactions between decomposition and Al content.
- RothC does not simulate seasonal waterlogging of part or all of the soil profile although such conditions tend to reduce decomposition rates. Seasonal waterlogging may happen frequently under wet climatic conditions (precipitations exceeding ETP) especially in conditions (flat terrain, compacted soils, etc.) leading to low soil drainage).
- RothC has no maximum limitation of the temperature factor for soil OM decomposition. However, daily soil temperature exceeding 30 degrees are infrequent even in the tropics and such conditions usually come with a low soil moisture that suppresses decomposition through the soil water content factor of the model.
- The soil cover has also a direct impact on mineralization in RothC. This parameter was set to its default value of 4-month which is plausible in temperate cropping systems, but is likely to be underestimated in tropical cropping systems with more than one harvest per year. Increasing the simulated duration of the soil cover period in the tropical systems would lead to lower mineralization rates. In addition, as cropland systems are simulated on every dominant soil type, we might end up with unrealistic combinations, therefore it is needed to check the combinations of soil types and crop rotations when refining the simulations shown.
- The resolution of the climate data used is lower than that of the HWSD map. Some mismatch between climate data and soil data (especially concerning SOC stocks) might occur and could contribute to explain unrealistic values.
- To make progress, one option would be to set region specific maximum values for carbon input to soils in croplands. This could be based on known maximum NPP levels. These maximum values could be used a posteriori, to truncate simulations results.

The amount of SOC sequestered depends on management strategies (e.g., residue retention and fertilizer application) and environmental conditions. Regardless of management practices, increasing C input through residue retention and stimulating crop growth by nutrient intensification usually have to be achieved. Across space and time, the required C input levels to maintain or increase soil C stock may vary widely depending on local soil and climatic conditions. A detailed assessment of critical C input level targeting at certain soil C level will assist in designing effective management practices for C sequestration in agricultural soils and help different stakeholders assess the status of soil C under current farmers' C input level and future potential management and climate.

3. Costing strategies for crop and soil management in world arable systems

3.1. Introduction

Here we describe how we estimated spatially explicit impacts from changing agricultural management practices on soil organic carbon, yields, and production costs. Subsequently, the different data are combined to generate global marginal abatement cost curves (MACCs) for different practices of conservation agriculture. The analysis is done for two crops (corn and wheat) and two management systems (reduced tillage and no tillage) in comparison to conventional tillage, under rainfed and irrigated conditions.

3.2. Methodological aspects

In a first step, the global gridded version of the Environmental Policy Integrated Climate (EPIC) crop model, EPIC-IIASA (Balkovič et al., 2014; Izaurralde et al., 2006; Williams, 1990) was applied to simulate different management systems (conventional tillage, reduced tillage and no-tillage) for corn and wheat and the respective impacts on yield and soil organic carbon under rainfed conditions and irrigation.

The basic spatial resolution of the model is 5′ x 5′ (about 10 km x 10 km near the equator) at which soil and topographic data are provided. These are aggregated to homogenous response units and further intersected by country boundaries and with a 30′ x 30′ climate grid, the resolution at which global gridded climate data are available. This results in a total of 131,326 simulation units with a spatial resolution of 5′ to 30′ upon which the EPIC model was run. We used global daily weather data from the AgMERRA dataset for the years 1980-2010 (Ruane et al., 2015), at spatial resolution of 0.25° x 0.25°, soil information from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2009), and topography from USGS GTOPO30 (USGS, 1997). In the reduced and no-tillage scenarios, we decreased soil disturbance by reducing cultivation operations, tillage depth and surface roughness, and we increased the plant residues left in the field after harvest (Table 4).

Table 4: tillage management scenarios for maize and wheat cultivation.

	Conventional tillage	Reduced tillage	No-tillage
total cultivation operations	6 – 7	4 – 5	3
max. surface roughness	30 – 50 mm	20 mm	10 mm
max. tillage depth	150 mm	150 mm	40 – 60 mm
plant residues left	25 %	50 %	75 %
cover treatment class	straight	contoured	contoured & terraced

3.3. Preliminary results

3.3.1. Yield Impacts

Spatially explicit impacts on annual yields from changing the management systems from conventional tillage to (a) no tillage and (b) reduced tillage as described above, are calculated per simulation unit, based on average yields over 30 years (1980 to 2010).

Yield impacts for corn are presented in figure 9 and for wheat in Annex A.

Switching management from conventional tillage to no tillage has a negative impact on corn yields in large parts of Latin America, Eastern Europe, South Asia, Sub-Saharan-Africa (except for South Africa) and Australia. The strongest negative effects are estimated for the region around Ukraine and the European part of Russia. Western and Central Europe, China, Turkey, and large parts of USA are impacted slightly positive from switching to no tillage practices. With reduced tillage we observe similar geographic patterns but more moderate changes in yields.

For wheat (Annex A), strongest negative impacts are observed for Russia, Ukraine, but also for most parts of Europe and some parts of the USA, China and India. South America and Australia face mixed effects.

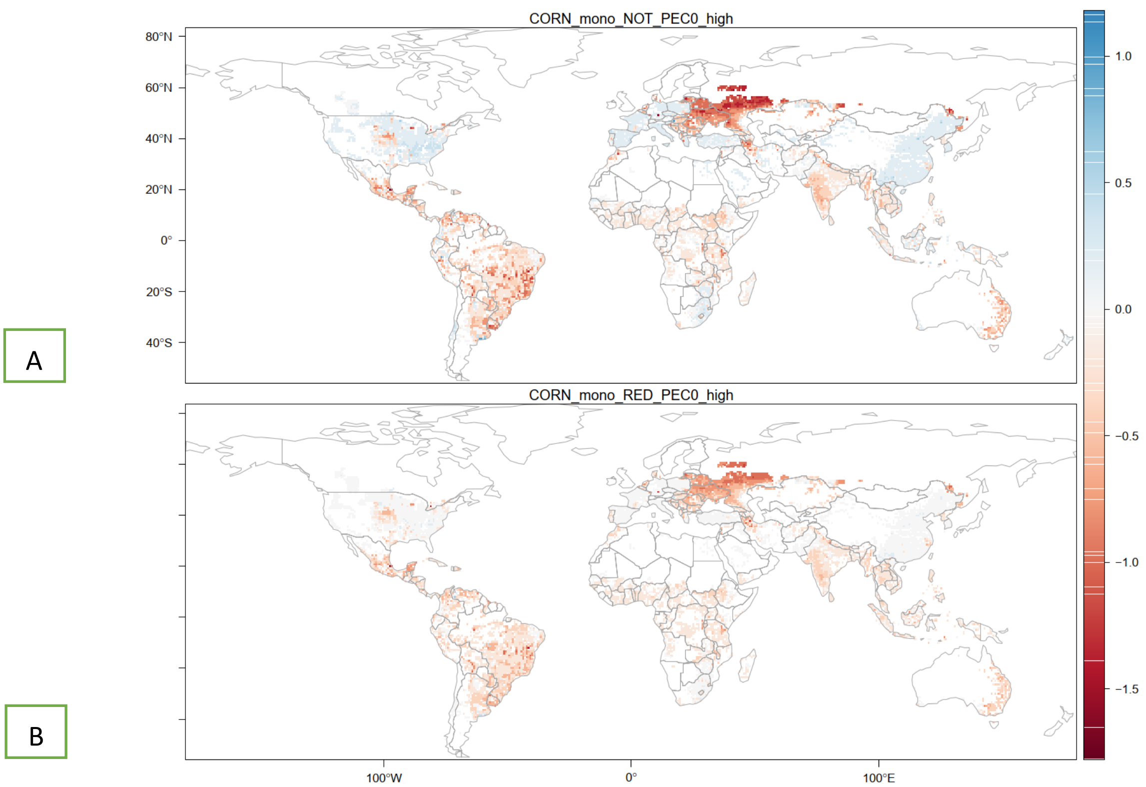


Figure 9. Average corn yield changes due to switching from conventional tillage systems to (a) no-till and (b) reduced-till systems in tons per hectare over a 30-year period. Crop area based on IFPRI (2019). Weighted average yields for rainfed and irrigation.

3.3.2. Mitigation effects

For the calculation of mitigation rates from shifting tillage management, in a first step the total organic carbon change (ΔOCPD) in each simulation unit after a simulation period of 21 years was calculated as:

$$\Delta OCPD = \frac{(Av\_OCPD_{2006-2010} - Av\_OCPD_{1990-1994})}{21},$$

where ΔOCPD is the total organic carbon change in tons of CO2 per hectare and year (tCO_2/ha/y) in the topsoil 0-30 cm, Av_OCPD2006-2010 is the average of total organic carbon over the last 5 years of the simulation; Av_OCPD1990-1994 is the average of total organic carbon over the first 5 years of the simulation. ΔOCPD was calculated for each crop management scenario. The so-called apparent CO_2 mitigation rate ΔCO_2 (in tCO2/ha/y) for the shift from conventional (baseline) to alternative crop management (x) in each grid is the difference between the ΔOCPD in the alternative and the conventional crop treatment: ΔCO2 = ΔOCPDx - ΔOCPDbaseline.

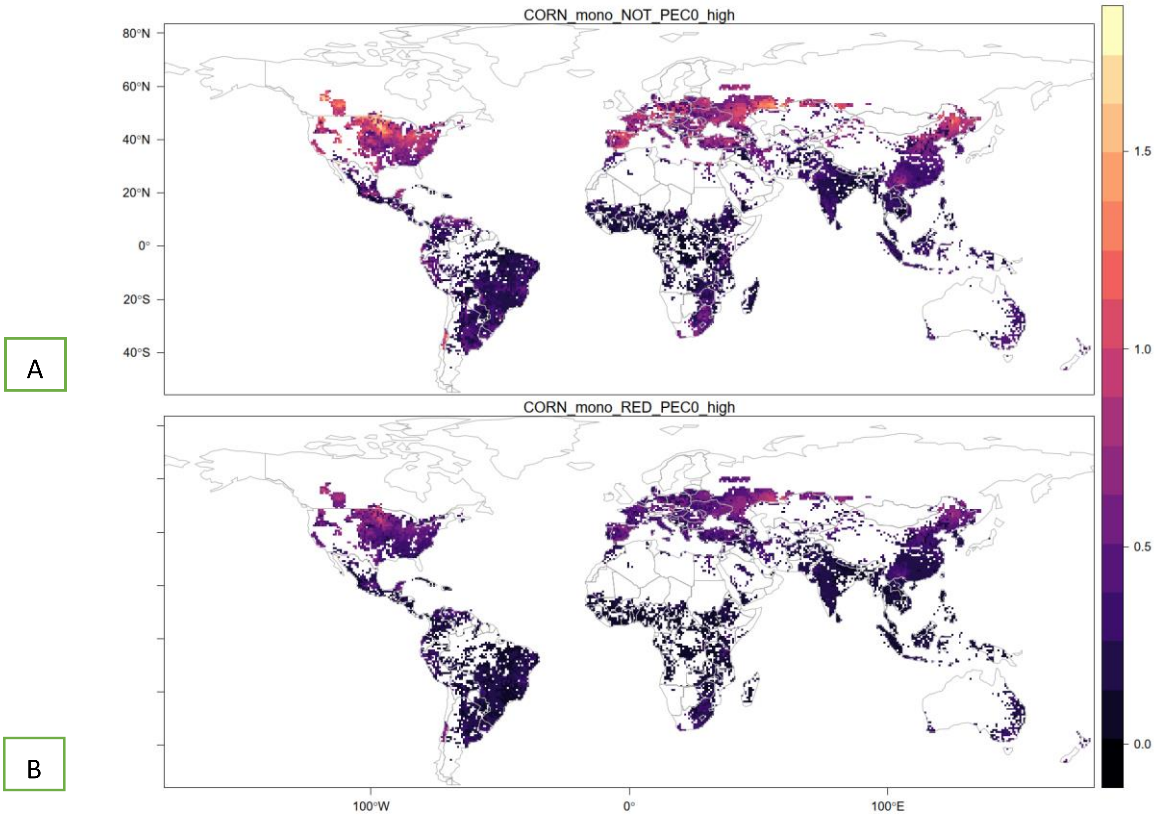


Figure 10. Corn mitigation effects from changing conventional tillage systems to no-till (a) and reduced-till (b) systems in tons CO2 per hectare and year. Crop area based on IFPRI (2019). Weighted average yields for rainfed and irrigation.

In most of the simulation units, changing the tillage systems to reduced or no tillage has a positive carbon mitigation effect (Figure 10). For corn, the strongest mitigation effects can be observed in the USA, Europe, Russia and South America. Positive but rather small effects are estimated for Latin America, SSA, large parts of Asia and Australia.

For wheat (Annex B), very low mitigation rates are observed in most parts of Africa and South America, mixed effects in India and positive effects in Europe, Russia, China and Middle Eastern countries.

3.3.3. Cost changes

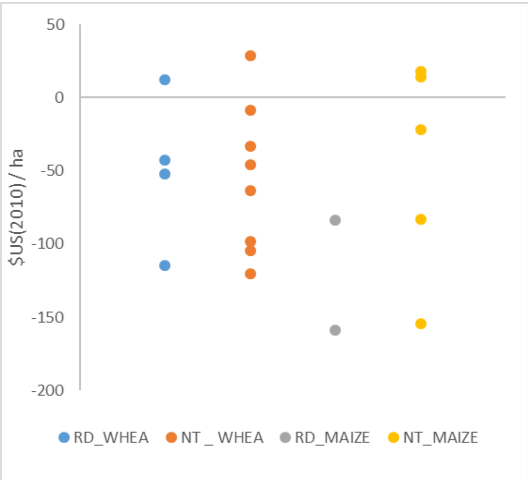
Based on a literature survey, impacts on production costs from switching from conventional tillage to no-till or reduced-till have been determined. These estimates only consider production costs, yield changes are not considered here. Furthermore, the opportunity costs of farming are not taken into account.

In many studies it is observed that labor, machinery and related costs are reduced because of reducing the number of field operations (Erenstein and Laxmi, 2008; Ribera et al., 2004). At the same time, the herbicide costs may increase when switching to reduced or no tillage systems (Janosky et al., 2002; Mattoso et al., 2001).

Overall, a very diverse picture of production cost changes emerges, depending on many farm specific attributes. (Epplin et al., 2005) find for Northwestern Oklahoma that the overall cost effect depends on the farm size and the assumptions made regarding machine selection and custom applications. In their study, conventional tillage appeared to be more economical for small farms, while for large farms no-till was found to be more economical, however, with overall relatively small differences in costs.

(Pannell et al., 2014) analyze different farms in Zimbabwe and find that for smallholders reducing the intensity of tillage operations only leads to labor savings when herbicides are used for weed control, but may increase labor demand when manual weeding is practiced.

Total production costs were found to decrease in most of the analyzed studies, however, in a few studies the overall cost of switching to reduced or not tillage systems are estimated to increase slightly when reducing the intensity of tillage (Figure 11).



	Wheat Reduced	Wheat No Till	Corn Reduced	Corn No Till	
			$US(2010)		
Austria	-52		-84		Bundesanstalt fuer Agrarwirtschaft, 2019
Brazil				14	Mattoso et al., 2001
China		-105*		-83*	Jin et al., 2007
Germany	-115	-120	-159	-154	Verch et al. 2009
Germany	-42	-98	-23		KTBL, 2019
India		-64			Erenstein and Laxmi, 2008
USA	12				Janosky et al., 2002
USA		-46			Riber et al., 2004
USA		-33			Epplin and Vitale, n.d.
USA		29			Epplin et al., 2005
USA		-9			Epplin et al., 2005
Zimbabwe				18	Panell et al., 2013
Zimbabwe				-22	Panell et al., 2013

* average of 4-year-noTill+1-year-subsoiling

Figure 11. Changes in overall production costs for wheat and corn for no-till and reduced-till in comparison to conventional tillage. Data found in comparison studies and cost databases (BAfA, 2019, KTBL, 2019), converted into Dollar and adjusted for inflation (based on data from the U.S. Bureau of Labor Statistics). Left panel: visualization of data presented in the right panel (RD – reduced tillage, NT – No-till).

Since the data are suggesting a large possible range of impacts on production costs (Figure 11), with some studies even disagreeing on the direction of the change, four different stylized scenarios were derived for the following analysis (Table 5).

Table 5: Assumptions on production cost scenarios (negative sign indicates a reduction of production costs).

<table>
<tr><th></th><th>low</th><th>med</th><th>high</th><th>region specific</th></tr>
<tr><td colspan="5">$US(2010)</td></tr>
<tr><td>Africa</td><td rowspan="7">0</td><td rowspan="7">-50</td><td rowspan="7">-100</td><td>0</td></tr>
<tr><td>Northern America</td><td>-50</td></tr>
<tr><td>Latin America</td><td>0</td></tr>
<tr><td>Europe</td><td>-100</td></tr>
<tr><td>Asia (except China & India)</td><td>0</td></tr>
<tr><td>- China and India</td><td>-80</td></tr>
<tr><td>Oceania</td><td>-50</td></tr>
</table>

3.3.4. Profits and MACCs

For an economic evaluation of switching from conservation tillage to no tillage or reduced tillage systems, we combine the yield effects with the changes in production costs.

To monetarize yield impacts, we multiply the estimated yield changes as presented above on a per hectare level with the respective product price of 2010 taken from the FAOstat database. For the subsequent construction of the MACC, we express all yield increases as a reduction in net-costs (with a negative sign) and decreasing yields as an increase in net-costs (with a positive sign). Additionally, the changes in production costs, as specified for respective scenarios (Table 5), are considered.

Like this, we calculate the changes in net-costs, with a negative sign indicating a profit increase and a positive sign indicating a decrease in profits:

$$\Delta \text{ net-costs} = -(\Delta \text{yield x crop price}_{2010} - \Delta \text{production costs}).$$

Spatially explicit impacts on per hectare net-costs are presented for the medium cost reduction scenario in Figure 12. Results for all combinations of management systems and production cost scenarios are presented in Annex C.

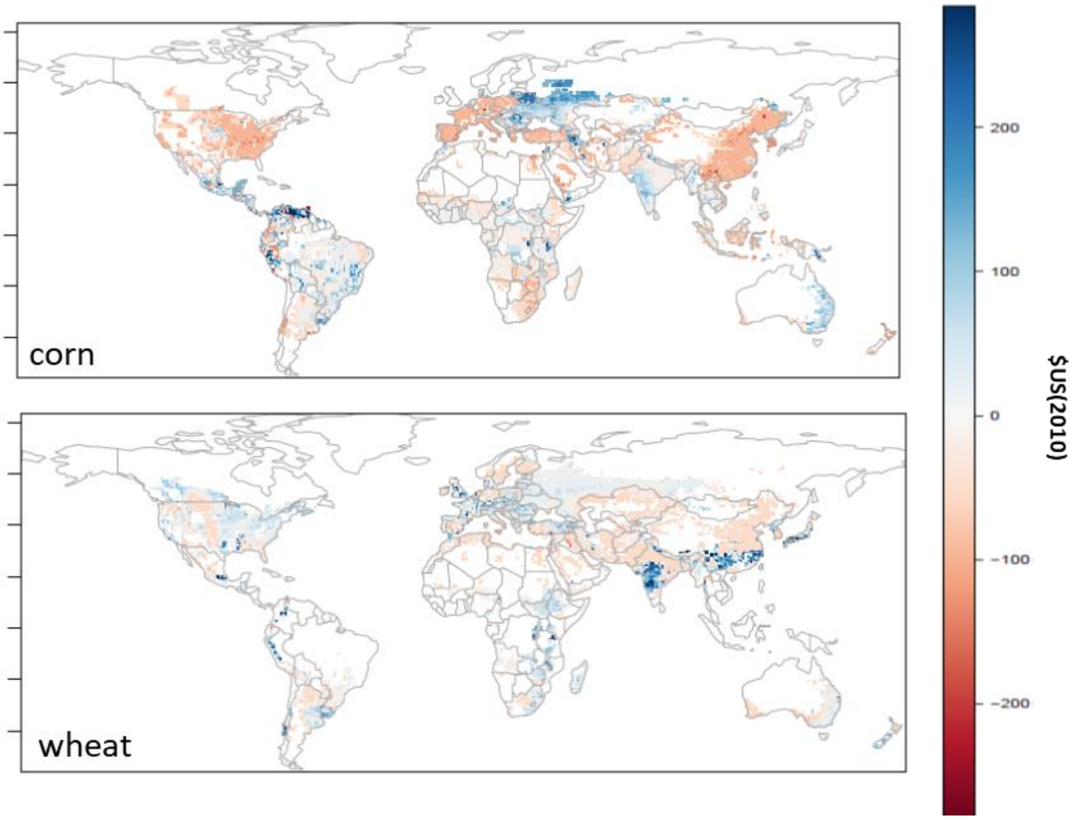


Figure 12. Net-cost changes [-(Δyield x crop price - Δproduction costs)] from changing conventional tillage systems to no-till systems in $US2010 per hectare, with a medium decrease in production costs (cost scenario: med). Crop area based on IFPRI (2019). Weighted average yields for rainfed and irrigation. Extreme values are limited to USD -250 and USD 250 respectively, to improve the visualization.

As a final step, marginal abatement cost curves are presented (Figure 13). For that purpose, net-cost changes have been calculated per ton of CO_2. Figure 13 presents global MACCs for different management systems and cost reduction scenarios for corn and wheat weighted by crop area (IFPRI, 2019). Regional MACCs are presented in Annex D.

The absolute mitigation potential for switching from conventional to no tillage (which likely is overestimated because we are not accounting for area that is already under alternative tillage systems) for corn and wheat together is estimated to be 205 Mt CO_2 per year, where 80 Mt CO_2 per year are coming from corn and 125 MT CO_2 per year from wheat production.

Depending on the cost reduction scenario, 20 – 100 Mt CO_2 per year could be mitigated in win-win situations (i.e, mitigation goes together with reducing net-costs of production) from wheat production and 55 – 70 Mt CO_2 per year from corn.

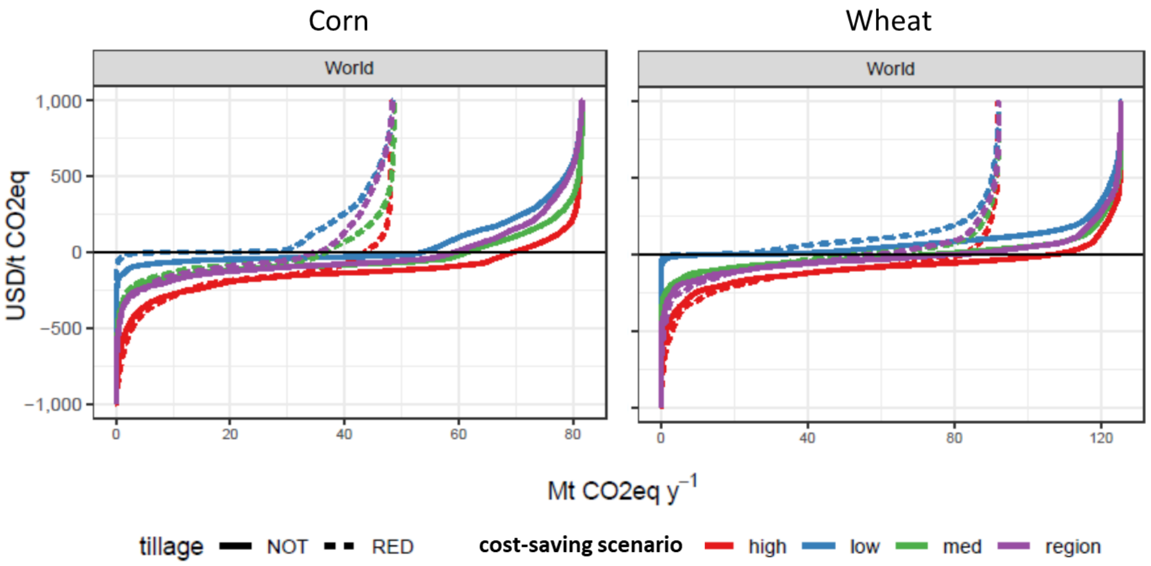


Figure 13. Global MACCs for wheat and corn; NOT – no tillage, RED – reduced tillage. Both, rainfed and irrigated area considered, based on (IFPRI, 2019). *Extreme values are limited to USD/t CO_{2eq} -1,000 and USD/t CO_{2eq} 1,000 respectively, to improve the visualization.*

3.4. Meta-analysis of tillage and crop rotations effects on yields and profit

We examined studies comparing net farm returns of different agricultural practices, identified using literature searches in the Web of Knowledge™ (Thomson Reuters, Philadelphia, PA; see Table 6 for search keywords). In addition, we used google scholar, websites of research organizations, and the bibliographies of relevant reviews, and contacted government agencies to identify relevant reports in the gray literature. Only English language search terms were used but all studies identified in other languages were included.

3.4.1 Methods

We identified the following as some of the most studied carbon-sequestering agricultural practices (CSAP): tillage, crop rotations, residue management, amendments, biochar, agroforestry, fertilizations and irrigation. Considering our goal of a global synthesis, we ultimately decided not to include topics that yielded small number of studies in our search (agroforestry, biochar; see Figure 14), or would have substantially high environmental costs if applied globally (irrigation, fertilization), or would have logistical or socioeconomic challenges over established alternative uses (residue, amendments), or lack of time and resources on our part (e.g. livestock). For example, due to already-large allocations of water to agriculture and worsening water scarcity or greenhouse gas emissions (CO_2, N_2O) associated with mineral fertilizer manufacturing and use, we did not think it would be meaningful to look to irrigation or increasing inorganic fertilizer application as means for carbon sequestration (Alvarez and Alvarez, 2005; West and Marland, 2002). Many existing alternative uses of crop residues or animal manure also indicate that addition of these materials to soils often does not represent carbon sequestration or would logistically challenging to achieve on a large scale (Kirkegaard et al., 2014; Powlson et al., 2011). Therefore, we limited our data entry efforts to studies comparing profits under different agricultural practices in the following two broad categories: tillage, and crop rotations. We saw these categories to represent agricultural practices with some of the largest potential for significant contributions to negative emissions and wide-scale adoption (Ogle et al., 2005; Poeplau and Don, 2015; West and Post, 2002). We excluded data from papers that did not report values based on physical observations.

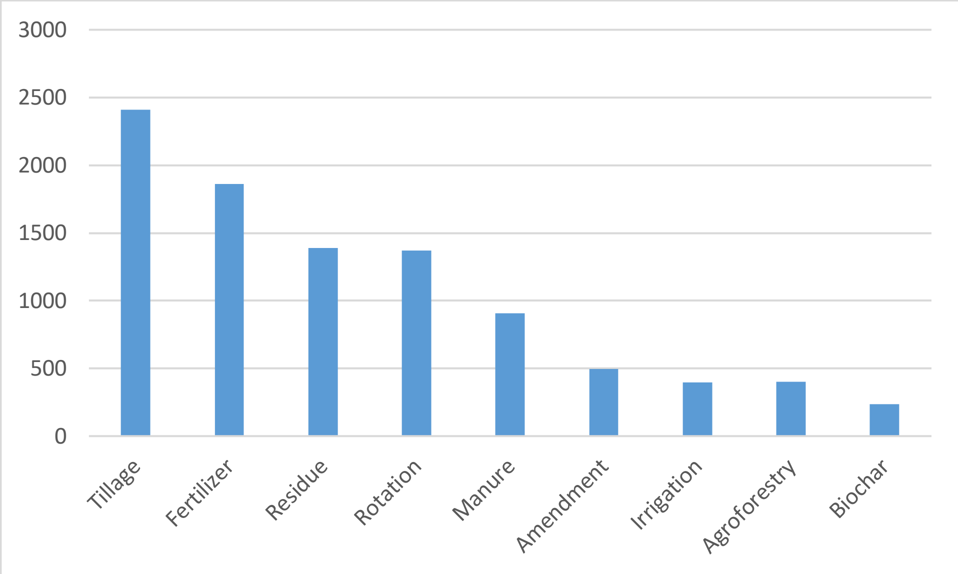


Figure 14. Number of studies returned on Web of Science searches of potentially carbon-sequestering agricultural practices. Keywords related to the topics were searched in conjunction with keywords related to soil carbon sequestration.

From tables, digitized graphs, and text, we recorded profits, yields, precipitation during the study period or the reported long-term mean (P), potential evapotranspiration (PET), soil texture (clay and sand contents and/or textural classes), tillage, crops, rotations, fertilizer, pesticide, irrigation, and any other management practices that differed such as liming, residue management when reported.

Most studies did not provide mean annual precipitation (MAP), potential evapotranspiration (PET) or temperature, and these variables were therefore obtained from the high spatial resolution (10' by 10') Climate Research Unit global data set, using locations of sites given in the studies {New, 2002 #74`; csi.cgiar.org/cru/index.asp}. We calculated PET using the Penman–Monteith equation from the monthly climate data set. Potential water excess (PWE) were calculated as MAP − PET to identify the climatic index with the strongest associations with farm profits and yields. To ensure that our estimates of precipitation were reasonable, we compared them with values of precipitation from the subset of studies where they were reported. When soil information was not reported, we looked for it in other studies describing the same experiment. Many studies did not report clay, silt and sand contents, so to increase the degrees of freedom in our analysis, we converted the reported soil texture classes into a continuous variable using the average clay + silt values of individual texture categories from the USDA texture triangle. We grouped crops into the following categories to simplify our analyses: corn, wheat, other cereals, legumes, oil-seeds, fruits and vegetables, and fiber.

We used a multiple regression model to compare the effects of management and biophysical variables on profit. Our response variable was the difference in profit or yield between conventional and CSAP:

$$y = \phi cs - \phi conv \qquad \text{Eq. 1}$$

where y is our response variable, ϕcs is profit or yield of CSAP, and ϕconv is that for conventional practice. Response ratios are commonly used to calculate effect size in meta-analysis. However, we used the differences because net returns in our database include values close to 0, making the interpretation of the ratio difficult. We compared between conventional (moldboard or disc plow or deep ripper) vs. reduced (subsoiler, chisel plow, field cultivator, ridge till, mulch tillage, stubble tillage, strip tillage and slot tillage) tillage and conventional vs. no-till (Reicosky, 2015). For crop rotations, we made the following comparisons: monoculture vs. monoculture + cover crop, single cropping vs. double- or multiple-cropping, monoculture vs. crop rotation, and less vs. more diverse crop rotations.

Our regression model tested for effects of precipitation, potential evapotranspiration, mean annual temperature, clay content, crop types, irrigation, machinery costs as fixed effects and the studies as random effects to control for intra-study correlation. Moreover, we tested for interactions based on previous studies. For example.(Matus et al., 1997) showed that no-till increased N-fixation of legume crops compared to conventional tillage.

Using our net return dataset, we also looked for corresponding studies on soil carbon sequestration for those with long-term data (>15 years) to estimate the cost of ASCS. We limited our search to this specific duration because SOC sequestration in agricultural has been shown to start to level off between 10-20 years (West and Post, 2002).

Table 6. Web of Knowledge^{TM} search keywords used in this study

WoS search keywords	
Profit	(net near/3 return*) or "return on" or "returns on" or "return over" or "returns over" or "returns to" or (econom* near/3 return*) or profit* or income* or revenue* or (gross near/3 margin*) or (net near/3 margin*)
Tillage	tillage or till* or plow* or plough* or "no till*" or "zero till*" or "reduced till*" or "direct drill*" or "conservation till*" or "minimum till*"
Crop rotations	(crop* and rotat*) and (divers* or sole* or mono*)
Cover crop	"cover crop*" "inter crop*" or inter-crop* or intercrop* or "mixed crop*" or "companion crop*" or "relay crop*"polycultur* or "multiple crop*" or multiple-crop* or polycrop* or doublecrop* or "double crop*" or "double-crop*"

3.4.2 Results and discussion

Our dataset on studies comparing profits under different tillage practices in croplands so far contain approximately 300 studies. The bulk of the data came from North America and Asia (Figure 15). We reached out to CIRCASA members to try to gain access to any government publications that might contain information on agricultural profit experiments, but thus far have been unsuccessful (except for Argentina). In this report, we present preliminary results comparing no-tillage vs. conventional tillage. About 120 studies remain to be added to the database, which will be cleaned and analysed for other CSAPs (cover crops, double-cropping, etc.).

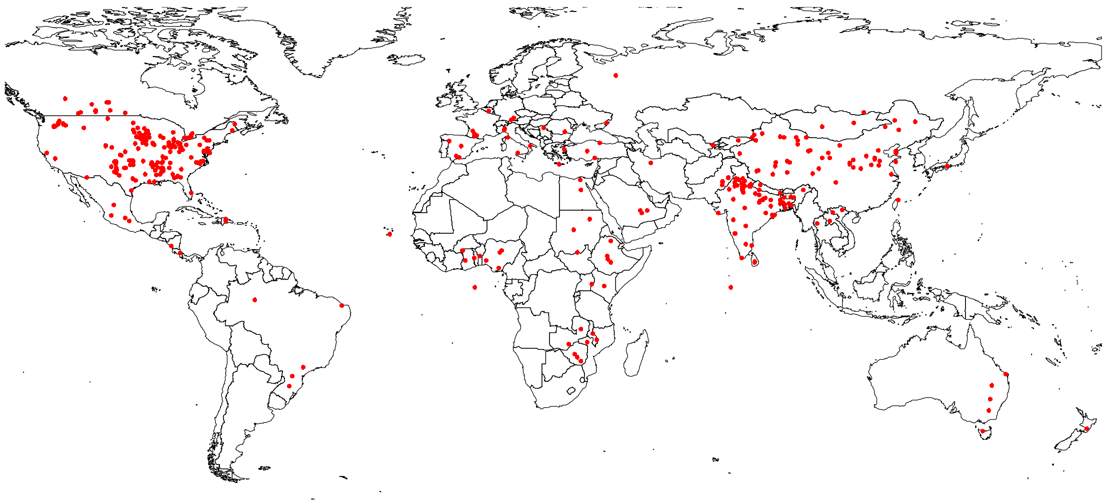


Figure 15. Locations of studies in our net return dataset.

Our multiple regression analysis showed that profits under no-tillage were higher than conventional tillage (positive intercept; Table 7) but yields were not (negative intercept), indicating some of the no-till profit gains are likely due to reduced fuel and equipment costs as opposed to yield increases. This also suggests that changes in profits and yields from adopting no-till may be at odds with one another, and that widespread adoption of no-tillage to sequester carbon could be problematic from food security perspective.

No-till was also more profitable in more humid and warmer climates where SOC gains are also expected to be greater with no-till compared to conventional tillage (Table 7; e.g. (Mangalassery et al., 2015; Reeves, 1997). Hence, switching to no-tillage in more humid and warmer regions may increase both profit and carbon sequestration relative to conventional tillage.

Table 7. Results from stepwise multiple regressions for net return and yield differences between conventional and no-till treatments. Adjusted R2 is ~0.40 for both response variables. '+' indicates positive effect of the term on the response variable. 'NS' denotes statistically not significant

Terms	Net return	P	Yield	P
Intercept	+	<0.00001	–	<0.00001
Humidity	+	<0.00001	NS	NS
Temperature	+	<0.0001	+	<0.02
Clay %	–	<0.0001	–	<0.0001
Irrigation	–	<0.00001	NS	NS
Fruits and vegetables	–	<0.00001	–	<0.00001
Corn	NS	NS	–	<0.0001
Year	NS	NS	+	<0.00001

The economic benefit of no-till was also higher in coarse-textured (sandier) soils (Table 7, Figure 16). This may be a reflection of the trend of no-till having greater agronomic benefits in coarser-textured soils, e.g. preventing loss of soil fertility, enhancing soil water storage, and reducing compaction.

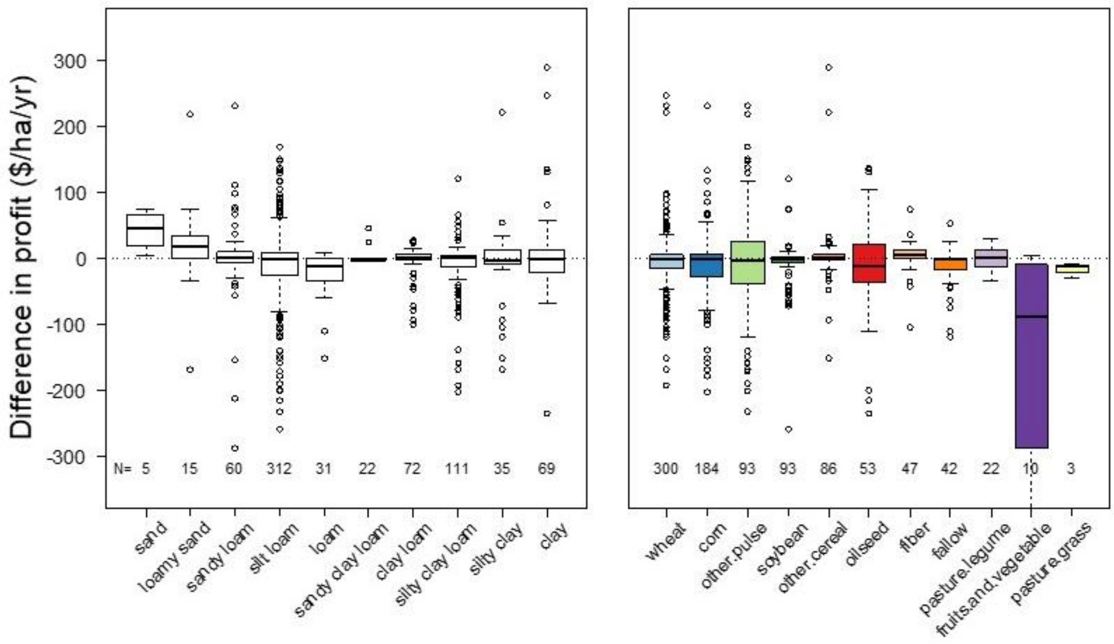


Figure 16. Differences in profit between no-till and conventional tillage plots. Boxes represent soil types (a) and crop types (b). Soil texture is listed from left to right in the order of decreasing sand content. Comparison of reduced and conventional tillage show similar trends for crop types (e.g. negative for fruits and vegetables and positive for fiber) but not for soil types (data not shown).

Long-term studies with both SOC and profit data showed that no-till or reduced tillage tend to increase net return while also increasing soil carbon storage compared to conventional tillage, suggesting a win-win scenario in terms of profit and carbon sequestration (Table 8). Because deeper sampling (~60 cm) has shown to reduce the differences in carbon storage between conventional and no-tillage (Baker et al., 2007; Luo et al., 2010), the shallow sampling depth (up to 15 to 40 cm) of these long-term studies indicate carbon sequestration potential is likely overstated. Moreover, decreases in crop yields for many of the rotations again present problems for future food security (Table 8) and suggests reducing or eliminating tillage may work in some regions against food security.

Table 8. Results from stepwise multiple regressions for net return and yield differences between conventional and no-till treatments. Adjusted R2 is ~0.40 for both response variables. '+' indicates positive effect of the term on the response variable. 'NS' denotes statistically not significant.

Study	Location	Period	Tillage	Crop	Δ net return	%Δ yield†	ΔSOC‡
					$/ha	Mg/ha	Mg C/ha
Fathelrahman 2011	Iowa, USA	1990-2003	CT→ NT	corn-soybean	22.05	-15, 0	2.7 (0-30)
Sánchez-Girón 2004	Madrid, Spain	1986-2001	CT→ NT	barley	10.88	-1	7.2 (0-40)
Sánchez-Girón 2004	Madrid, Spain	1986-2001	CT→ NT	wheat-vetch	44.09	5, 0	9.4 (0-40)
Sánchez-Girón 2004	Madrid, Spain	1986-2001	CT→ RT	barley	31.67	4	0 (0-40)
Sánchez-Girón 2004	Madrid, Spain	1986-2001	CT→ RT	wheat-vetch	6.19	5, -4	0.8 (0-40)
Ribera 2004	Texas, USA	1984-2001	CT→ NT	sorghum	-3.73	-10	4.2 (0-15)

Ribera 2004	Texas, USA	1984-2001 CT→ NT	sorghum-wheat/ soybean	13.5	-14, -6, 5	6.9 (0-15)
Ribera 2004	Texas, USA	1984-2001 CT→ NT	sorghum	-30.41	-23	8.2 (0-15)
Ribera 2004	Texas, USA	1984-2001 CT→ NT	wheat	33.72	-3	1.5 (0-15)
Ribera 2004	Texas, USA	1984-2001 CT→ NT	soybean/wheat	26.5	-8, 1	(0-15)

†Percent change in yield correspond to the crops listed in the Crop column.

‡Depths of soil examined for SOC in parentheses

As mentioned in the Methods section, we are adding more data on other SOC-sequestering farming practices such as cover crops and diversifying crop rotations. We will focus first on completing the tillage part of the study and hope to finish assembling the tillage database and a manuscript submitted by August 2021.

4. Relating soil carbon sequestration with land-based challenges

4.1. Introduction

Land-based systems are exposed to multiple overlapping challenges including climate change (adaptation and mitigation), land degradation and desertification, food insecurity, ground water stress (from over-abstraction), water pollution, biodiversity loss and declining nature's contribution to people (Smith et al., 2019a). Soil degradation is among the most crucial threats to ecosystem stability, and soil have recently gained more and more social and politically visibility. Land use and land cover change has resulted in substantial losses of carbon from soils globally, but credible estimates of how much soil carbon has been lost have been difficult to generate. Using a data-driven statistical model and the History Database of the Global Environment v3.2 historic land-use dataset (Sanderman et al., 2017) estimated that agricultural land uses have resulted in the loss of 133 Pg C from the soil. Importantly, the maps indicate hotspots of soil carbon loss, often associated with major cropping regions and degraded land.

We have assessed the spatial distribution of individual land-based challenges and soil carbon loss to show:

i) if SOC baselines are declining especially in world regions exposed to multiple overlapping challenges (e.g. land degradation and food insecurity) and
ii) how potential for SOC sequestration co-varies with land-based challenges.

4.2. Methods

Global maps have been standardized to a 5 arc-minute grid using longitude/latitude relative to the WGS84 datum.The spatial distribution of multiple challenges was calculated using the "raster" and "sp" R packages. We used the following challenges based on indices from recent published studies (Figure 17):

- Desertification attributed to land use is estimated from vegetation remote sensing, mean annual change in NDVImax < -0.001 (between 1982-2015) in dryland areas (Aridity Index > 0.65)
- Land degradation is based on a soil erosion proxy (annual erosion rate of 3 t ha^{-1} or above);
- The climate change challenge for adaptation is based on a dissimilarity index of monthly means of temperature and precipitation between current and end of century scenarios (dissimilarity index equal to 0.7 or above)
- The food security challenge is estimated as the prevalence of chronic undernourishment (higher or equal to 5%) by country in 2015 using FAO data.

- The biodiversity challenge uses threatened terrestrial biodiversity hotspots (areas where exceptional concentrations of endemic species are undergoing exceptional loss of habitat)
- The groundwater stress challenge is estimated as groundwater abstraction over recharge ratios above one in agricultural areas (croplands and villages);
- The water quality challenge is estimated as critical loads (higher or equal to 1000 kg N km^{-2} or 50 kg P km^{-2}) of nitrogen (N) and phosphorus (P).

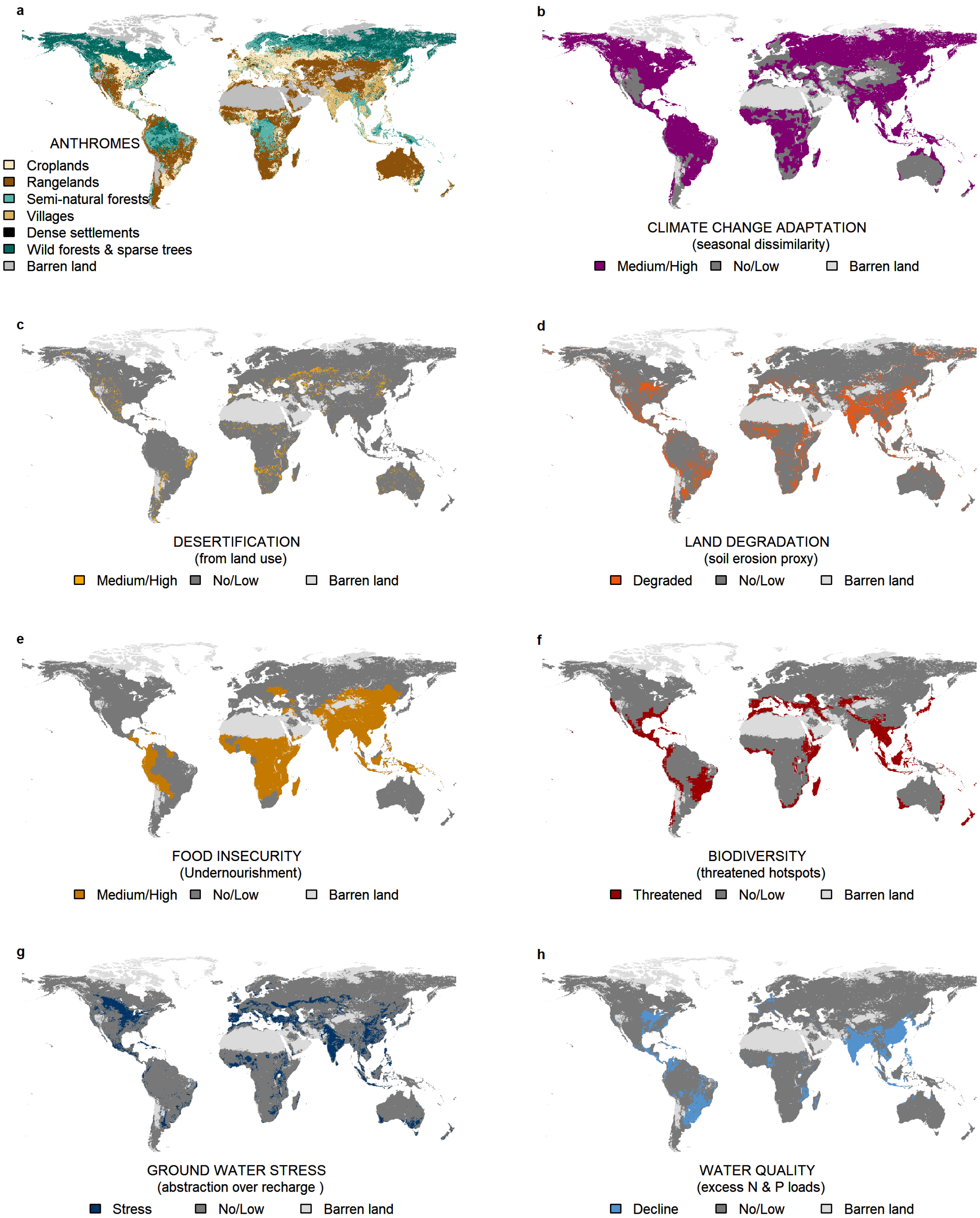


Figure 17. Global distributions of land use types and of individual land-based challenges. a, land use types (or anthromes(Ellis and Ramankutty, 2008)*); b, climate change adaptation challenge (estimated from dissimilarity between current and end of century climate scenarios*(Netzel and Stepinski, 2018)*); c, desertification challenge* (IPCC, 2019)*); d, land degradation challenge (estimated from a soil erosion proxy, one indicator of land degradation* (Borrelli et al., 2017)*; e, food security challenge (estimated from undernourishment, a component of food security* (FAO et al., 2015)*); f, biodiversity challenge (estimated from threatened biodiversity hotspots, a component of biodiversity* (Mittermeier et al., 2011)*); g, groundwater stress challenge (estimated from water over-abstraction* (Gassert et al., 2014)*); h, water quality challenge (estimated from critical N and P loads of water*

systems(Hua and Sadoff, 2017)*). Note that the mitigation challenge is not mapped as it applies to all land area. Also, note that desertification is land degradation in dry areas.*

Soil carbon debt maps (Figure 18) were calculated subtracting current (2010) SOC stocks from historic (NoLU) SOC stocks for 30 cm, 100cm, 200 cm (Sanderman et al., 2017). Negative values (gains) were excluded in order to make correlations with number challenges and Human Development Index (HDI). Results were masked to show agricultural land use (crop and rangeland).

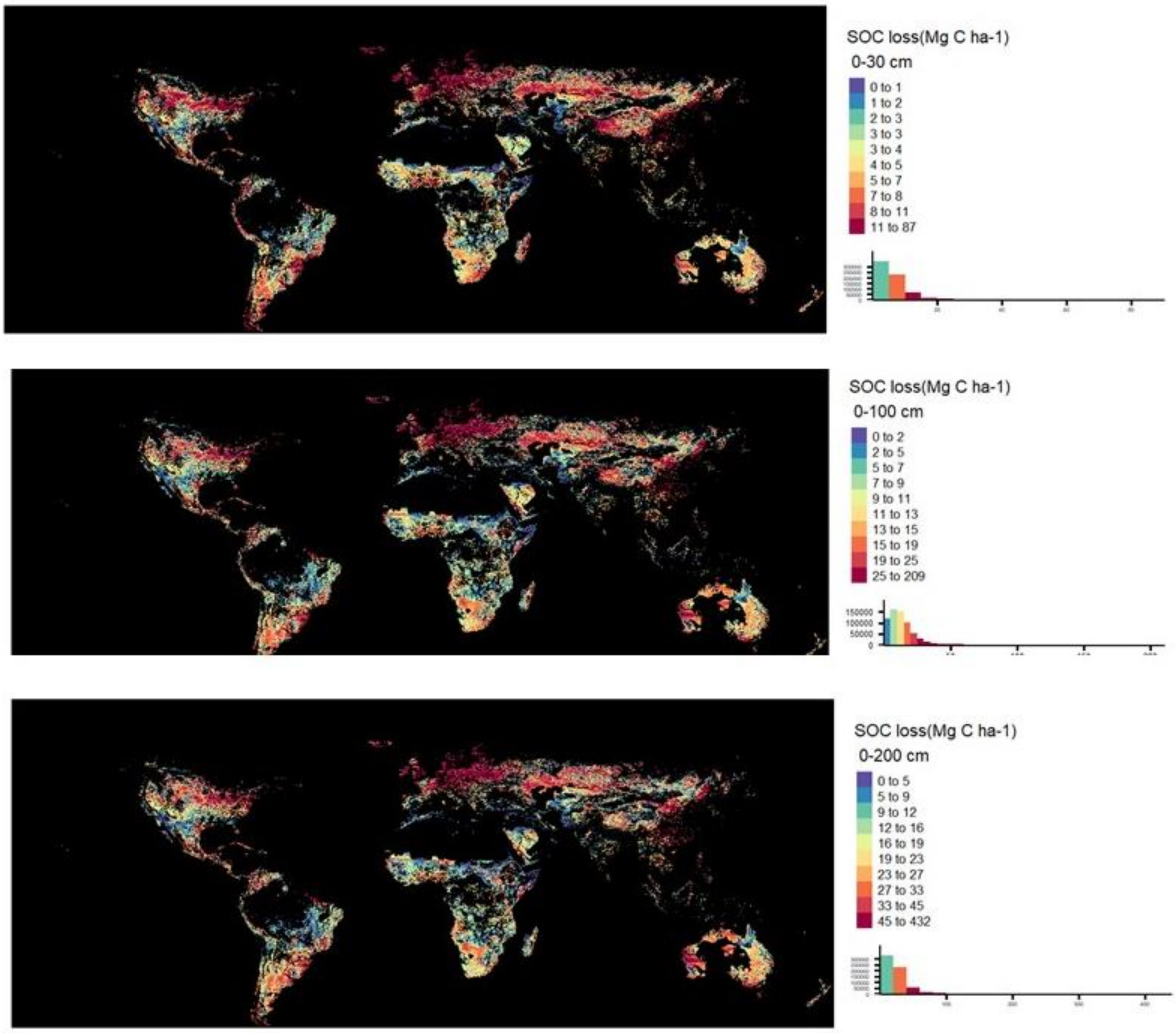


Figure 18. Soil carbon debt for 0-30 com, 0-100 cm and 0-200 cm depths. Modified from (Sanderman et al., 2017).

4.3. Results and discussion

On average, land used intensively (villages, croplands and rangelands, dense settlements) is exposed to more overlapping challenges than land least exposed to human use (barren lands and wild forests), with intermediate values for semi-natural forests. For instance, 76% of the village land area is exposed to 3 or more challenges and this percentage decreases to 42 and 32% for croplands and for dense settlements, and is below 20% for other land use types (Figure 18).

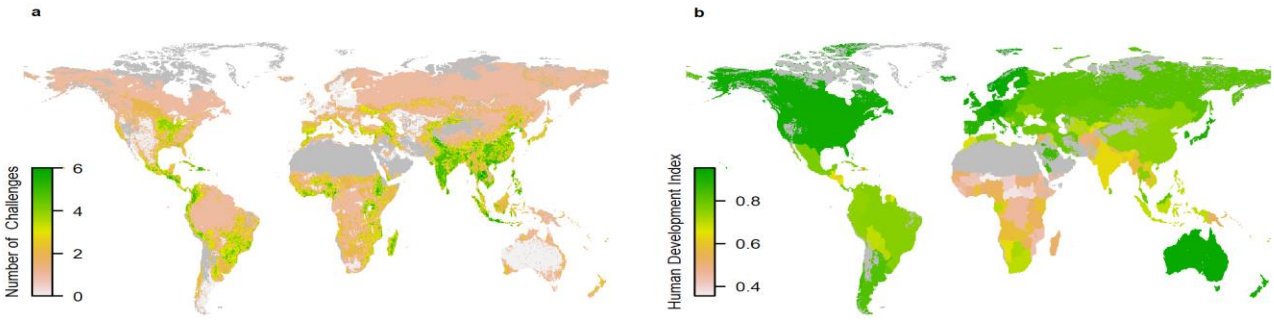


Figure 19. Global distributions of (a) the number of overlapping land-based challenges (desertification and land degradation, climate change adaptation, chronic undernourishment, biodiversity, groundwater stress and water quality); (b) the Human Development Index (HDI) by country. The more challenges, the smaller the HDI (Spearman's rank correlation, r=-0.16, p< 0.001) meaning that there is less capacity to adapt when there are more land-based challenges.

Correlations across (Spearman's rank correlation) variables, including SOC debt, individual land based challenges and the number of overlapping land challenges are shown in Table 9. Due to the large number of data, even small correlation coefficients tend to be significant.

*Table 9. Correlation matrix (Spearman's rank correlation). *, P<0.05; *, P<0.01; ***, P<0.001*

	n° of challenges	Groundwater stress	Critical P loads	Critical N loads	Food insecurity	Land degradation	Climate change adaptation
C Debt 0-30 cm	0.062***	-0.018**	0.13**	0.13**	0.11***	0.074***	0.084***
C Debt 0-100 cm	0.056***	0.072***	0.099***	0.12***	NS	NS	0.16***
C Debt 0-200 cm	0.057***	0.033***	0.087***	0.12***	-0.029***	-0.027***	0.19***

Results show that across soil depths, soil carbon debt is positively correlated with high loads of N and of P (which are markers of intensive agricultural land use), with a large climate change adaptation challenge and with a high total number of land based challenges. Therefore, it will be on average more difficult to cope with excess nutrients, climate change and a large number of overlapping land challenges since these tend, on average, to develop in land areas already strongly depleted in soil organic matter. Conversely, restoring soil organic carbon stocks where soil C debt is high would have a large potential for climate change mitigation and adaptation (through improved soil water retention) and for N and P immobilization thereby reducing critical loads to water bodies (Table 9).

With food insecurity, land degradation and groundwater stress, global correlations with soil C debt change sign with the soil depth considered. When selecting the stronger correlation across soil depths, we can see that on average a strong soil C debt is associated with groundwater stress, with food insecurity and with land degradation (Table 9). Here again, restoring soils depleted in organic carbon would therefore, on average, have large co-benefits for groundwater (through improved water retention and infiltration), land degradation, and food security (see Soussana et al., 2019).

Taken together, these results emphasize that large co-benefits for multiple land-based challenges can be expected from a strategy of SOC stock restoration focusing on soils that evidence a large historical soil C debt. This is also in agreement with the land degradation neutrality strategy of UNCCD and with SDG 15 Target 15.3 indicator on soil carbon, which focuses on restoring soil carbon when stocks are initially low.

5. SOC Monitoring, Reporting and Verification

5.1. Introduction

Since soil organic carbon content of soils cannot be easily measured, a key barrier to implementing programmes to increase soil organic carbon at large scale, is the need for credible and reliable measurement/monitoring, reporting and verification (MRV) platforms, both for national reporting and for emissions trading. Without such platforms, investments could be considered risky.

In (Smith et al., 2019b), we describe:

- how repeat soil surveys are used to estimate changes in SOC over time, and how long-term experiments and space-for-time-substitution sites can serve as sources of knowledge and can be used to test models, and as potential benchmark sites in global frameworks to estimate SOC change.
- We briefly consider models that can be used to simulate and project change in SOC and examine the MRV platforms for soil organic carbon change already in use in various countries / regions.
- In the final section, we bring together the various components described in this review, to describe a new vision for a global framework for MRV of soil organic carbon change, to support national and international initiatives seeking to effect change in the way we manage our soils.

We propose a vision for a global framework (Figure 19) to assess soil carbon change, based on a combination of mathematical models, spatial data to drive the models, short- and long-term data to evaluate the models, and a network of benchmarking sites to verify estimated changes in the light of the need to provide credible and robust MRV capabilities to support the growing International and National initiatives to increase SOC, such as the International "4p1000" initiative (Chabbi et al., 2017; Rumpel et al., 2019, 2018).

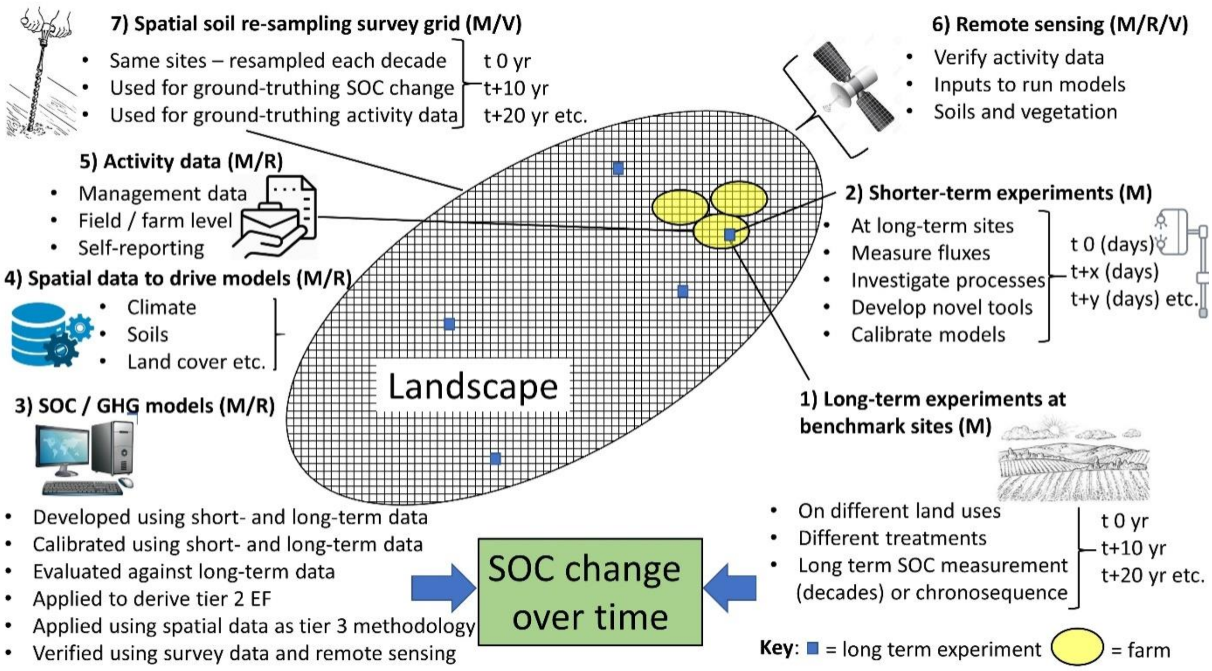


Figure 20. Components of a Monitoring, Reporting and Verification system for soil organic carbon (Smith, Soussana et al., 2019, Global Change Biology)

5.2. Design of an EU and global high-resolution dynamic soil organic carbon monitoring system for agricultural land

For applications ranging from carbon offsetting, to low carbon sourcing of agricultural commodities and low carbon policies in agriculture, soil carbon monitoring is required as well as the associated estimation of the GHG balance at field and farm scales. We focus here on soil carbon balance monitoring.

The goal is to monitor in Europe and globally soil organic carbon (SOC) balance at high spatial resolution e.g. 10 m) in agricultural lands with a target accuracy of less than 0.1 tC per ha and per yr (i.e. less than 0.2% of an average arable SOC stock of 50 tC/ha in the top 0-30 cm).

This is not possible at scale by directly measuring SOC stocks and their changes over time, since for a single field detecting within 5 yrs a 1% change in top soil SOC stock requires intensive soil coring and laboratory or spectrometry analysis and this comes with high costs. An alternative approach is to calculate the SOC balance as the difference between organic C inputs and C outputs from a field. A generic mass balance approach (Soussana et al., 2010, 2019) can be used:

$\Delta SOC=(NPP - Rh-\Delta AGC)+(Fmanure- Fharvest - Fanimal\text{-}products-FCH4\text{-}C)-(Ferosion+Ffire+Fleach+FVOC)$ (Eq. 1)

Where NPP is the net primary productivity, *Rh* is the heterotroph respiration from soils and from grazing livestock and ΔAGC is the change in above-ground vegetation C stock. All above fluxes are in g C m^{-2} yr^{-1}.

Eq. (1) shows the three categories of fluxes that govern ΔSOC at the ecosystem scale: the flux of organic carbon partitioned below-ground ($NPP- Rh\text{-}\Delta AGC$), the human appropriation of above-ground carbon ($Fmanure - Fharvest - Fanimal\text{-}products-FCH4\text{-}C$) and the carbon losses at ecosystem scale ($Ferosion+ Ffire+ Fleach +FVOC$).

This equation can be simplified (assuming that changes in above-ground C (AGC) and C emissions caused by fires, VOC compounds, macro-fauna and erosion can usually be neglected) as:

$$\Delta SOC = (NPP - R_{h\text{-}soil} - R_{h\text{-}livestock} - F_{CH4\text{-}C}) + (F_{manure} - F_{harvest} - F_{animal\text{-}products}) - F_{leach} \qquad \text{(Eq. 2)}$$

Without grazing (arable crops and mown grasslands) a further simplification applies (e.g. Béziat et al., 2009):

$$\Delta\ SOC= NPP - R_{h\text{-}soil} + F_{manure} - F_{harvest} - F_{leach} \qquad \text{(Eq. 3)}$$

$\Delta\ SOC$ in the above mass balance equations concern the full soil depth. In contrast, for practical reasons SOC stock direct measurements are often limited to the top soil (e.g. 0-30 cm).

5.2.1. Basic monitoring, reporting and verification (M,R,V) concepts

Main data sources are shown in Figure 20, with their M, R and V roles. An open-access database, where short- or long-term soil C measurements can be uploaded and shared (e.g. https://dataverse.org/ and the online collaborative platform as used in the CIRCASA project: https://www.circasa-project.eu/), would also be of great benefit for progressing a global MRV system.

Below is a list, to be completed especially for regions outside the EU, of data sources in these categories:

(1) **Long-term field experiments at benchmark sites** where ΔSOC can be monitored with intensive soil coring campaigns **(M).**

- CIRCASA and GRA/IRG work on a data repository part of the OCP (Open Collaborative Platform (www.ocp.circasa-project.eu)

- Global Inventory of Long-Term Soil-Ecosystem Experiments including nearly 250 LTSEs with metadata found on all continents, including Antarctica (Richter et al., 2007) (Figure 21). The metadata currently hosted by the International Soil Carbon Network (iscn.fluxdata.org/partner-networks/long-term-soil-experiments/)

- In Europe these sites will be based on the existing long-term experiments (http://iscn.fluxdata.org/partner-networks/long-term-soil-experiments/) and additional existing sites to be identified by the MS, but should also include the existing level 2 monitoring sites within ICP forest (http://icp-forests.net/page/level-ii).

Figure 21: Global Inventory of Long-Term Soil-Ecosystem Experiments - LTSEs

(2) **Shorter-term field experiments** where eddy flux covariance monitors NEE (Net Ecosystem Exchange), which is the balance between NPP and ($R_{h\text{-soi}}$+$R_{h\text{-livestock}}$) **(M)**

- EU data are organized by ICOS and international data by FluxNet (and other regional flux networks) (www.icos-cp.eu https://fluxnet.fluxdata.org)

(3) SOC/GHG models (M/R) to derive IPCC Tier 2 emission or SOC stock change factors, which are specific to the region and conditions represented within the region (e.g. Begum et al., 2018) or spatially over the whole landscape (or the entire land area of a country) using spatial databases of soil characteristics, and land cover, management and climate data, to directly simulate SOC change and GHG emissions, thereby delivering a Tier 3 methodology to report emissions (Table 10)

- An EU wide consistent modelling approach needs to be adopted avoiding duplication of efforts and competing/contradictory results. The EU Competence Centre on Modelling (CC-MOD) promotes a responsible, coherent and transparent use of modelling to support the evidence base for EU policies. (https://ec.europa.eu/knowledge4policy/modelling_en)

Table 10. Examples of models used in National GHG Inventories to estimate Carbon dioxide emissions and removals from the cropland remaining cropland soils component (Tier 3 method)

Country	Model		Reference
Australia	The Full Carbon Accounting Model (FullCAM)	Estimates emissions from soil through a process involving all on-site carbon pools (living biomass, dead organic matter and soil) on a pixel by pixel (25m x 25m) level.	(Richards, 2001)
Canada	CENTURY	process model used for estimating CO2 emissions and removals as influenced by management activities, based on the National Soil Database of the Canadian Soil Information System	(Parton et al., 1988, 1987)
Denmark	C-TOOL	3-pooled dynamic soil model parameterised and validated against long-term field experiments (100-150 years) conducted in Denmark, UK (Rothamsted) and Sweden and is "State-of-the-art".	(Taghizadeh-Toosi et al., 2014)
Finland	Yasso07 soil carbon model	The parameterisation of Yasso07 used in cropland was the one reported in (Tuomi et al., 2011)	(Palosuo et al., 2015)
Japan	Soil Carbon RothC model	In order to apply the model to Japanese agricultural conditions, the model was tested against long-term experimental data sets in Japanese agricultural lands (Shirato and Taniyama, 2003)	(Coleman and Jenkinson, 1987)
Sweden	Soil Carbon model ICBM-region	Calculate annual C balance of the soil based on national agricultural crop yield and manure statistics, and uses allometric functions to estimate the annual C inputs to soil from crop residues	(Andrén and Kätterer, 2001)
Switzerland	Soil Carbon RothC model	The implementation of RothC in the Swiss GHG inventory is described in detail in (Wüst-Galley et al., 2019)	(Coleman et al., 1997)
United Kingdom	CARBINE Soil Carbon Accounting model (CARBINE-SCA)	Simplified version of the ECOSSE model (Smith et al., 2010), coupled with a litter decomposition model derived from the ForClim-D model (Liski et al., 2002; Perruchoud et al., 1999).	(Matthews et al., 2014)
United States	DAYCENT biogeochemical model	Utilizes the soil C modelling framework developed in the Century model (Metherell et al., 1993; Parton et al., 1994, 1988, 1987), but has been refined to simulate dynamics at a daily time-step.	(Del Grosso et al., 2001; Del Grosso and Parton, 2011; Parton et al., 1998)

(4) **Spatial data** to drive models (climate, land cover, soil properties including top SOC content) **(M/R)**

- Climate data for agriculture are available from AgMIP (https://data.giss.nasa.gov/impacts/agmipcf/agmerra/) and other sources

- Soil interpolated maps are developed by ISRIC with support of the Global Soil Partnership and FAO (https://www.isric.org/explore/soilgrids) including the SOC content and its uncertainty for a 250 m resolution available on CIRCASA OCP.

- Other prominent data sources include for the EU LUCAS (https://esdac.jrc.ec.europa.eu/projects/lucas) also included in CIRCASA OCP concerning soil C (www.ocp.circasa-project.eu)

(5) **Activity data** (field and farm, management, self-reporting by farmers) **(M/R)**

- Remote sensing of land use (Corine LandCover, https://land.copernicus.eu/pan-european/corine-land-cover)

- Remote sensing of crop and grassland types by field (see Cropland products from COPERNICUS, to be released in 2021 for the EU)

- Remote sensing of phenology, NDVI, faPAR, fcover (see Phenology products from COPERNICUS, to be released in 2020 for the EU)

- Farmers activities are reported through the Land Parcel Identification System (LPIS) showing fields and their margins as part of the IACS of the Common Agricultural Policy (https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy/financing-cap/controls-and-transparency/managing-payments_en). Data about management practices adopted at farm scale in the EU are collected through the Farm Structure Survey https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Farm_structure_survey_-_methodological_articles

- However, for carbon monitoring purposes there are gaps in CAP declarations, including presence or not of cover crops and management of crop residues and of organic fertilizers)

(6) **Remote sensing** (verify activity data, soils and vegetation inputs to run models) **(M/R/V)**
Remote sensing tools as available within the COPERNICUS program can provide very valuable data for detecting SOC changes and for monitoring agricultural practices/land management practices. Extensive work done by ESA as well as the recently launched GEO initiative for monitoring land degradation in support to UNCCD and the related Land Degradation Neutrality target within SDG 15 can provide a lot of synergies in achieving an operational remote sensing component for MRV of SOC http://worldsoils2019.esa.int/

- Proxies of Net Primary Productivity (NPP) derived from (5)

- Proxies of Surface Soil Moisture (SSM) to constrain SOC modeling forthcoming at 1 km resolution (https://land.copernicus.eu/global/products/ssm)

- Surface SOC content (https://sentinels.copernicus.eu/web/sentinel/news/-/article/copernicus-sentinel-2-data-to-estimate-soil-organic-carbon-in-croplands)

(7) Spatial soil re-sampling survey grids (M/V)
The on-going LUCAS soil monitoring system based on a regular 2kmx2km grid is a solid base for the operational in-situ measurement of SOC across the EU. After 3 sampling campaigns (2009, 2015 and 2018)

it is by now a consolidated system providing regular monitoring data on soil properties in the EU https://esdac.jrc.ec.europa.eu/content/chemical-properties-european-scale-based-lucas-topsoil-data Further development of LUCAS needs to be fully adopted as the monitoring system at National scale on the basis of the same common grid.

- EU member state data to be harmonized by EJP soil (https://cordis.europa.eu/project/id/862695/fr)

- National gridded soil surveys in several EU countries (e.g. France: www.gissol.fr/le-gis/programmes/rmqs-34)

5.2.2. Dynamic soil carbon and GHG balance modeling

As shown in Figure 20, models (3) informed, constrained, calibrated and verified by the various data streams in Figure 20 are required to calculate *ΔSOC* and the GHG balance. Several approaches were used, noting however that soil carbon modelling is still evolving rapidly (e.g.(Woolf and Lehmann, 2019):

A. Land surface models including soil carbon and GHG emissions

Global land surface models (e.g. https://orchidee.ipsl.fr/) integrate biosphere, land use and land management and provide simulations of coupled carbon and water fluxes, including SOC balance (Camino-Serrano et al., 2017) and were also used to calculate SOC balance e.g. in global grasslands (Chang et al., 2015).

- Main application domains for soil carbon: climate change and land use projections and historical assessments at regional to global scales.

B. Crop and pasture models including soil carbon and GHG emissions

A recent intercomparison (Ehrhardt et al., 2018) , developed by Global Research Alliance, Integrative Research Group, GRA IRG) shows the potential of ensembles of crops and pasture models to simulate N_2O fluxes and yields at a range of long-term field sites. Simulations for soil carbon have been assessed by (Sándor et al., 2020) developed as well by GRA IRG.

Modeling platforms based on a single model are proposed, such as COMET farm a whole farm carbon and GHG accounting system (http://comet-farm.com/) which is based on the DayCent simulation model. Other examples in France include the STICS model, which has been used for nationwide tests of SOC sequestration potential for a range of changes in agricultural practices (https://www.inrae.fr/en/news/storing-4-1000-carbon-soils-potential-france)

- Main application domains for soil carbon: site based and farm based estimates of SOC change and GHG emissions. Note that these models are usually not coupled to data from remote sensing and that their calibration may be limited to certain crops only and to specific soil and climate conditions.

C. SOC models

SOC models and their ensembles can be used for predictions of organic carbon, despite uncertainties concerning the first order kinetics used for decomposition and the roles of microbial and stabilization processes (Menichetti et al., 2019; Woolf and Lehmann, 2019) and interactions with energy sources for microbes and soil nutrients. Some SOC models require prior information on SOM structure (e.g. aggregate structure, thermal stability as estimated by RockEval, (Poeplau et al., 2019)) which prevents their use on a large scale. However, spin-up runs based on steady state or on past land use have often been used to run these models (such as Century,(Dimassi et al., 2018), without further knowledge of SOM structure. Robust predictions from ensembles of SOC models are obtained in long-term bare fallow soils (Farina et al., in revision, developed by GRA IRG).

However, to predict *Δ SOC* in vegetated systems, carbon inputs to soils are required (see Eqs. 2-3). For instance in France (Simeos-AMG, www.simeos-amg.org), which is a commercial tool calibrated for main field crops and estimating crop residues based on allometry with yields. Well established SOC models such as RothC can be used in an inverse mode (e.g.(Meersmans et al., 2013), which allows to estimate e.g. the OC inputs required to maintain SOC in a steady-state (or to increase SOC by 0.4% per year, which is the aspirational target of the 4 per 1000 initiative (Soussana et al., 2019)). This inverse RothC approach has been used at global scale in the CIRCASA project (www.circasa-project.eu) by comparing OC input needs for SOC steady-state and for 4 per 1000 target with croplands OC inputs (Global EPIC simulations of crop residues https://iiasa.ac.at/web/home/research/researchPrograms/EcosystemsServicesandManagement/EPIC.en.html) and grasslands OC inputs (from GLEAM model, FAO, http://www.fao.org/gleam/en/). Results are available on the CIRCASA OCP (Section 2. Global maps of agricultural SOC stocks baselines and of technical sequestration potential)

- Main application domains for soil carbon: site to global scale, in direct mode forcing SOC models by OC inputs to soils and in inverse mode estimating OC inputs to soils required for an assumed baseline of SOC change. Note that these models are usually not coupled to data from remote sensing and from vegetation and that their calibration may be limited to certain soil and climate conditions. Note also that GHG emissions (e.g. N_2O) are not simulated.

5.2.3. Regional, national and project scale SOC monitoring systems

We distinguish three nested scales for SOC monitoring: international/regional, national and project.

Internationally, the UNFCCC Annex-I Parties are subject to the GHG accounting rules of that Convention and the IPCC Guidelines (see https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/). The IPCC Guidelines are designed to help estimate and report national inventories of anthropogenic GHG emission reductions including SOC. A tiered approach is proposed:

- Tier 1 or default method: simplest order of methods with the higher uncertainties. Reference carbon stocks are multiplied by Land use change factors.
- Tier 2: on the same principle as Tier 1 but with better accuracy taking into account country-specific data for land use change factors.
- Tier 3: lowest uncertainties order of method with the use of models, considering fluxes. For instance, Tier 3 methods are the only option to take into account the impact of soil erosion on C flows. Examples of model use (e.g. DayCent are provided in the 2019 refinement).

At national scale, diverse assessment methods, consistent with the international framework exist and are based on scientific advances and availability of input data from each country. For example, in the USA, COMET- Farm is the official GHG quantification tool of the USDA and developed in partnership with Colorado State University. The Methodology is a combination of process simulation models, empirical models and IPCC methodologies and peer-reviewed research results.

At project scale, MRV methods implemented for local emission reduction projects are aligned with specific frameworks respecting themselves national and international guidelines. For instance, the Australian Government's compliance offset program, the Emissions Reduction Fund (ERF), has currently two methodologies dedicated specifically to soil carbon sequestration: *Estimating Sequestration of Carbon in Soil Using Default Values* and *Measurement of Soil Carbon Sequestration in Agricultural Systems.*

The latest is the only one, which registered projects so far (44 of which one has issued Australian Carbon Credit Units in May 2019). *Measurement of Soil Carbon Sequestration in Agricultural Systems* methodology includes direct measurements, detailed sampling protocols and lab techniques as well as thermal analysis. Another example is Alberta Offset program in Canada, which is, based on the conservation Cropping Protocol, using Canada's National Emissions Tier 2 methodology based on country-specific sequestration coefficients (Paustian et al., 2019).

At national and project levels, a standardized, cost effective methodology is available to assess C benefits. The Carbon Benefits Project (CBP) provides tools for anyone wanting to estimate the impact of their activities on climate change mitigation (carbon stock changes and greenhouse gas (GHG) emissions). This includes agriculture, forestry or land management projects in simple or complex landscapes. The tools are freely available web-accessible system (https://banr.nrel.colostate.edu/CBP/) developed by Colorado State University and partners under a Global Environment Facility co-financed project implemented by the United Nations Environment Program. It offers tools for:

- Simple assessment for a quick estimate at any stage (including proposals) of C and GHG impacts;
- Detailed assessment for detailed analysis
- A Cost Benefit Analysis and a DPSIR (causal framework to describe interactions between society and the environment)

The H2020 NIVA project (https://cordis.europa.eu/project/id/842009/fr) aims to modernize the Integrated Administration and Control System (IACS) of the European CAP by making efficient use of digital solutions and e-tools. It will test a large scale implementation of environmental indicators calculated at plot scale by combining LPIS with Sentinel remote sensing data (Tier 1), eventually considering climate and/or soil and/or farmer's data (Tier 2) or relying on modeling approaches (Tier 3). Within this frame, in Tier 1 a proxy of the cropland carbon budget will be estimated based on a relationship between the net annual CO_2 fixation (NEE) and the duration of the periods with active vegetation (Ceschia et al., 2010), as estimated from remote sensing at plot scale. In Tier 2, a C budget will be calculated based on this approached combined with farmer's self-reporting on yield, straw management and organic fertilization and in Tier 3 C budget will be estimated based on the SAFY-CO2 crop model assimilating LAI derived from Sentinel 2 data (Pique et al. submitted).

5.2.4. Design principles for a high resolution EU and global dynamic SOC monitoring system

A global coverage at Tier 1, however with higher Tiers to be developed by members of the IRC (e.g. in some countries/regions, or by some corporates for their sourcing, carbon offsetting). For instance Tier 2, based on local to national data provided and verified by consortium members. A Tier 3, verifying systematically SOC change estimates from soil surveys and long-term fields sites, as well as eddy flux covariance.

A high spatial resolution (ca. 10 m to include small fields and small owners) based on remote sensing

A high accuracy target (detecting changes of less than 0.1% per year of top SOC stock) that will take several years to reach. A low initial accuracy is expected, but investment needs to attain high accuracy will be estimated each year.

An estimate of N_2O emissions and of the balance of other soil derived GHGs in CO_2 equivalents, noting that emissions from enteric fermentation and manure management cannot not be calculated with this approach.

A three pillar structure:

i) SOC pillar (soil science community, GSP, soil maps, remote sensing of surface soil),
ii) Vegetation pillar (remote sensing of vegetation, phenology and cropland/grassland COPERNICUS products to calculate NPP by crop/grassland types),
iii) Activity pillar (agricultural activities based on statistics or on self-reporting).

Land use change emissions could also be estimated in this way, however with substantial extensions in the monitoring system to cover deforestation areas (Quin et al., 2019) and the corresponding carbon balance (e.g. through LVOD, SMOS, Quin et al., submitted).

A modular structure, each pillar derives products that are coupled with other pillars products to derive gridded *Δ SOC* estimates with their associated uncertainties. Ensembles of calibrated models rather than single models could be used when possible.

A strong data infrastructure providing seamless access by multiple users and using the FAIR principles (www.go-fair.org/fair-principles). Initially, this data infrastructure could be hosted by CIRCASA's OCP. It would include options for self-reporting especially for activities currently not reported (e.g. organic fertilizers, crop residues, etc.) A gradual implementation, combining proxies at global scale in the first year (e.g. changes in annual duration of vegetation cover in arable systems could be used as a proxy of OC input to soil) and advanced implementation in pilot areas.

Provision of resources for ground truthing and for calibration data (e.g. calibration of NPP at eddy flux covariance sites, direct measurements of crop residues etc.).

The development cycles are anticipated to last 2 years, with 3 cycles:

- **2021-2023**: Design stage (all components designed and tested, implementation in 3-5 countries, including e.g. 2 countries outside the EU)
- **2023-2025**: Implementation stage 1. Targeting Tier 1 implementation at global scale, Tier 2 and Tier 3 implementation started in the EU)
- **2025-2027**: Implementation stage 2. Improved Tier 1 accuracy, Tier and Tier 3 implementation in the EU and in at least two other world regions.

5.2.5. Reporting and verifying SOC change estimates

Reporting would primarily be through gridded data extraction for any spatially defined entity (e.g. a field, a farm, a small region, the sourcing area of an industry, or a given crop type, a country etc.) and any time period (several months to decades).

All *Δ SOC* estimates would be provided in gC m^{-2} per time period selected. An uncertainty estimate would be provided (if possible as RMSE) systematically. Uncertainties would be calculated by reference with verification methods, noting however that reference methods are also uncertain.

Verification would be based on some of the data sources specified in Figure 20:

(1) Long-term experiments at benchmark sites

(7) Spatial soil re-sampling (surveys, grids, demonstration farms, etc.)

Verification would target a high accuracy estimate of *ΔSOC* over the full soil profile, with sampling and analytical methods limiting biases in final vs. initial SOC stock estimates. For instance, using the same sampling protocol and tools, using geo-referenced sampling points, using the same analytical procedure done in a single lab. The number of replicate soil samples in each site would be sufficiently high to provide a good accuracy (e.g. see CarboEurope soil sampling protocol at eddy flux sites). Therefore, part of the costs of the infrastructure would be caused by the increased measurement effort compared to classical soil surveys. Statistical studies will be required to optimize the design of the verification component.

Some countries will run a national soil C inventory based on stratified sampling of agricultural land with a design allowing to detect a change in national SOC stock above (in absolute value) a certain threshold. For instance, New Zealand is planning to detect an average change by 2 t C/ha/yr for the country with 500 sampling sites. This type of design would allow ground truthing of the carbon balance by the monitoring system.

Beyond traditional MRV, Artifical Intelligence approaches could be tested to optimize the predictive power of the monitoring based on calibration and verification data.

5.2.6. First assumptions for the three pillars in the EU

Activity pillar

- Corinne Land Cover for land use (available)

- Copernicus Cropland for crop types (2021)
- Sentinels for soil tillage and cover cropping
- For grasslands, permanent grasslands can be used

Vegetation pillar

- Climatic data (e.g. ERA5 for Europe on a 30 km grid, https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5)
- Copernicus Phenology (2020) coupled with Croplands for NDVI integral by crop cycle (2021), estimates available in near real time (providing Activity-Vegetation coupling)
- Simulate NPP from NDVI/LAI, partition NPP to shoots and roots and estimate leaf area increase and hence change in NDVI/LAI
- Assimilate NDVI/LAI change in the vegetation model for calibrating NPP (procedures that could be based on e.g. SAFY, (Claverie et al., 2012; Duchemin et al., 2008) or SAFYE CO2, Pique et al. submitted)
- Sentinels for soil moisture (see also Theia, https://www.theia-land.fr/product/humidite-du-sol-a-tres-haute-resolution-spatiale/ for soil moisture)
- Estimate crop yields, calibrate with statistical data, yield maps from combined harvester, with farmer's self-reporting etc.
- Estimate crop residues, calibrate with ground truthing, statistical data and farmer's self-reporting
- With grasslands, a similar approach can be used however with estimates of biomass exports by mowing and of herbage use by grazers.

SOC pillar

- LUCAS top soil survey coupled to ISRIC Soil Grids to provide first estimate of SOC stock
- Remote sensing of surface soil to derive SOC content, e.g. see (Castaldi et al., 2019; Vaudour et al., 2019) (and possibly soil nutrients and pH)
- Additional calibration data (from data sources (1) and (7) and from self-declaration by users)
- Modeling SOC balance through an ensemble of SOC models constrained by climatic data, soil type, initial SOC stock and OC inputs to soil (provided by Vegetation Pillar)

5.3. Assessing the uncertainty of soil carbon balance in croplands

To monitor the carbon content of a soil and its variations, two fundamentally different methods can be distinguished. The traditional way is to carry out soil analysis, where the SOC content is directly measured in soil samples. For example, the European Commission's LUCAS program was aimed to sample and analyse topsoil properties in European Union countries. Thus 19, 967 location were sampled in 23 countries (Tóth et al., 2013). To have a sufficient tem- poral and spatial resolution to detect changes in SOC content, material and financial costs can be very high, up to several million euros per site (Mäkipää et al., 2008), making this method difficult to systematize. Furthermore, this method is not devoid of uncertainties. In a study led by Schrumpf et al. (2011), the Minimable Detectable Difference (MMD) is thus estimated to 105 ± 28 $gC.m^{-2}$ in croplands with 100 measurements per site, which is a lot of work and a big financial investment.

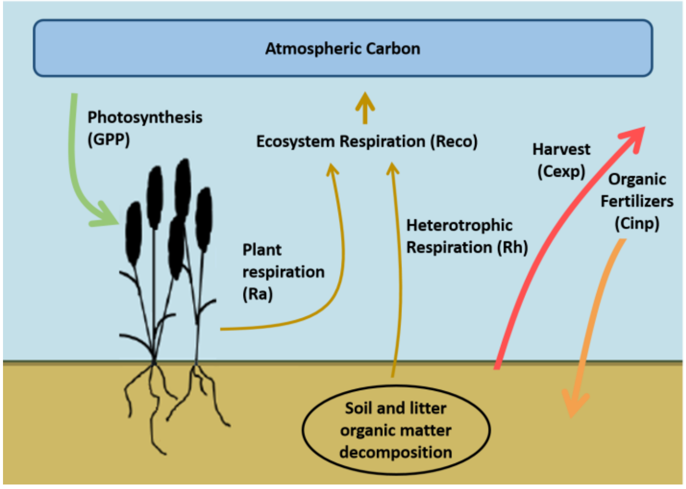


Figure 22. Components of the Net Ecosystem Carbon Balance for a cropland ecosystem.

A more recent approach consist in focusing on the fluxes, by calculating a carbon balance. If we know the carbon exported from the crop during harvest (Cexp) and the carbon imported through organic fertilization (Cimp), we can calculate a Net Ecosystem Carbon Balance (Béziat et al. (2009); Soussana et al. (2007)):

$$NECB = NEP - Cexp + Cinp = GPP - Reco - Cexp + Cinp = NPP - Rh - Cexp + Cinp \quad (6)$$

In a general way, **Cexp** is inferred from data given by farmers as *harvest×grain carbon content× (1 –grain water content)*. But some models as SAFYCO$_2$ also allow to compute Cexp (Pique et al.). **Cinp** represent carbon brought to the crop as manure, slurry, crop residues, compost, etc. It is inferred from data given by farmers.

5.3.1 Methods

To evaluate the *a priori* uncertainty that would be obtained for a soil carbon monitoring system such as the one that should be developed in IRC pillar 2, we developed a simple model computing the NECB and its associated error. We focused here on croplands but, in a later stage, the study could be extended to grasslands and forests. Other fluxes are contributing to cropland carbon budget: carbon can be lost from crops trough erosion, fire, leaching, emission of Volatile Organic Compound (VOC) or other trace gas like CH_4 and export of animal products (Soussana et al., 2019). Although it has been shown that dissolved organic carbon (DIC) can be an important component on the net ecosystem carbon balance (Kindler et al., 2010), in this study we will consider that DIC and the other fluxes mentioned above are negligible, compared photosynthesis, respiration, Cexp and Cimp.

a) Calculation of cropland carbon balance

The model that was developed takes in input the GPP, Cinp and Cexp (in gC.m^2.yr^{-1}) and C_{soil}, the stock of organic carbon in the soil (in gC.m^2), and gives in outputs the cropland NECB (hereafter noted ΔC, in gC.m^2.yr^{-1}), the absolute error on ΔC ($\sigma_{\Delta C}$, in gC.m^2.yr^{-1}) and the relative error on Δ*C*. All the value of the parameters used in this model where found in literature, they are given in table 3 with the sources. Here are the details of the calculations we used to obtain ΔC:

From equation 6, we can write:

$$\Delta C = GPP - Reco + C_{inp} - C_{exp} \qquad (7)$$

As GPP, C_{inp} and C_{exp} are input variables, we just need to compute Reco to get ΔC. Thus, we can calculate R_a and R_h (*cf.* equation 5).

Step 1: Calculation of Ra:

$$R_a = (1-k)GPP \qquad (8)$$

Where k = 0.52 (cf. table 3).

Step 2: Calculation of Rh according to the Hénin-Dupuis model (Hénin and Dupuis, 1945). We choose to work with this model simplicity and robustness although it is less complete in its representation than others are. Indeed, it considers only one compartment of organic matter in the soil while other models consider several compartment and their interactions to take into account the heterogeneity of the organic matter in the soil. RothC, for example, represents three compartment: the microbial biomass, the active humified organic matter and the inert humified organic matter (Coleman and Jenkinson, 2014). But for our study, the Hénin-Dupuis model, was completely adequate. It is a model that is still used today to simulate the storage potential of C in soils as a function of changes in cropping practices, in particular through the AMG humic balance (Bouthier et al., 2015) and it has the advantage to run with very few parameters and thus to minimize the error sources possible.

Where K1res is the fraction of organic carbon from crop residues that enrich the soil organic carbon stock, K1f ert , the fraction of organic carbon from organic fertilizer that enrich the soil organic carbon stock, and K2, the fraction of soil organic C that is mineralized each year. K2 is given by:

$$R_h = (1-K_{1_{res}}) \times C_{res} + (1-K_{1_{fert}}) \times C_{inp} + K_2 \times C_{soil} \qquad (9)$$

Where TMA is the mean annual temperature in C°, Arg the clay content of the soil in g/kg and CaCO3 the carbonate content of the soil in g/kg.

Cres , in gC.m2.yr−1, is the carbon flux via the incorporation of cropland residues:

$$K_2 = [0.03(1+0.2(TMA-10)]/[(1+0.005Arg)(1+0.0015CaCO3)] \qquad (10)$$

Where TMA is the mean annual temperature in C°, Arg the clay content of the soil in g/kg and CaCO3 the carbonate content of the soil in g/kg.

Cres , in gC.m2.yr−1, is the carbon flux via the incorporation of cropland residues:

$$C_{res} = NPP - C_{exp} \qquad (11)$$

As we choose the value of GPP, NPP can be computed through equation 4.

b) Calculation of the error on cropland carbon balance

More than obtaining the carbon balance, the aim of this model was to be able to estimate an error on ΔC. To this end, the error on the input variables, GPP, Cinp, Cexp and Csoil , were first calculated with the following formulas:

$$\sigma_{GPP} = \frac{Re \times 365}{\sqrt{Obs}} \qquad (12)$$

The error on GPP decreases when Obs, the number of usable satellite images per year, increase. Re is the Random error given by the algorithm that derive the GPP from satellite images. Here we choose 1.38 gC.m−2.yr−1 as a reference, a value obtained by Wolanin et al. (2019) using Sentinel-2 images and machine learning algorithm, because it was the lowest value found in the literature.

For Cinp, Cexp and Csoil, the errors are obtain by multiplying their values by the coefficient of variation whose values have been estimated from the literature (Beziat, 2009; Béziat et al., 2009; Pique et al.):

$$\sigma_{C_{inp}} = 0.2 \times C_{inp} \qquad (13)$$

$$\sigma_{C_{exp}} = 0.08 \times C_{exp} \qquad (14)$$

$$\sigma_{C_{soil}} = 0.1 \times C_{soil} \qquad (15)$$

Then we applied the formulas of the "Gaussian propagation of error" (cf. Box 2.) to propagate the error to the intermediate variables and the output variables.

The error on ΔC id given by:

Where σGP P −Reco is the error on the difference GP P − Reco. Those two variables have a Pearson correlation coefficient of -0.88.

Thus σGP P −Reco is given by:

$$\sigma_{\Delta C} = \sqrt{\sigma^2_{GPP-Reco} + \sigma^2_{C_{inp}} + \sigma^2_{C_{exp}}} \qquad (16)$$

Where σGP P −Reco is the error on the difference GP P − Reco. Those two variables have a Pearson correlation coefficient of -0.88. Thus σGP P −Reco is given by:

$$\sigma_{GPP-Reco} = \sqrt{\sigma^2_{GPP} + \sigma^2_{Reco} + 2 \times 0.88 \times \sigma_{GPP} \times \sigma_{Reco}} \qquad (17)$$

Where σReco is given by equation 18, that also take into account the important correlation of Ra and Rh (Pearson correlation coefficient equal to -0.9).

$$\sigma_{Reco} = \sqrt{\sigma^2_{R_a} + \sigma^2_{R_h} - 2 \times 0.9 \times \sigma_{R_a} \times \sigma_{R_a}} \qquad (18)$$

For equations 17 and 18, the Pearson coefficients were calculated with the data of the CarboEurope and GHGEurope sites. As all the variables necessary to calculate Rh are independent, σRh is given by:

$$\sigma_{R_h} = \sqrt{(1 - k_{1_{res}})^2 \times \sigma^2_{C_{res}} + (1 - k_{1_{fert}})^2 \times \sigma^2_{C_{inp}} + k_2^2 \times \sigma^2_{C_{soil}}} \qquad (24)$$

Where σCres is given by:

$$\sigma_{C_{res}} = \sqrt{\sigma^2_{NPP} + \sigma^2_{C_{exp}}} \qquad (25)$$

And σNPP by:

$$\sigma_{NPP} = NPP \times \sqrt{(\frac{k}{\sigma_k})^2 + (\frac{\sigma_{GPP}}{GPP})^2} \quad (26)$$

Finally, σRa is given by:

$$\sigma_{R_a} = R_a \times \sqrt{(\frac{k}{\sigma_k})^2 + (\frac{\sigma_{GPP}}{GPP})^2} \quad (27)$$

Once all the formulas established, we defined a reference scenario, where we attributed for each parameter or variable a default value (see table 11). Generally, the value was chosen to reflect an average case and close to the middle of the possible range for each parameter. We choose to run the sensitivity analysis with default GPP value of 1760 $gC.m^{-2}.yr^{-1}$ and Csoil value of 5000 $gC.m^{-2}$ to simulate a carbon storage of 20 $gC.m^{-2}.yr-1$, which represent an annual soil organic carbon storage of 0.4%. Based on that scenario, we tried to minimize the error and we run the sensitivity analysis . We also compared the traditional soil analysis method to the fluxes method to understand when it is more interesting to use one or the other.

Table 11: Input variable (in bold) and parameter table. The column "standard values" returns the parameter and the variable values for the reference scenario used for the sensitivity analysis. The range for each parameter was defined according to what was found in the literature.

Variable/Parameter name	Unit	Reference value	Range	Source
GPP	$gC.m^{-2}.yr^{-1}$	1760	[700-2500]	Kutsch et al. (2010)
C_{exp}	$gC.m^{-2}.yr^{-1}$	500	[300-1000]	Ciais et al. (2010); Hollinger et al. (2005); Kutsch et al. (2010)
C_{inp}	$gC.m^{-2}.yr^{-1}$	100	[0-300]	Ciais et al. (2010, 2011); Hollinger et al. (2005); Kutsch et al. (2010)
C_{soil}	$gC.m^{-2}$	5000	[3000-10000]	Constantin et al. (2020); Panagos et al. (2020)
Re	$gC.m^{-2}.yr^{-1}$	1.38	[1-2]	Wolanin et al. (2019); Pique et al.; Yuan et al. (2015)
Obs	–	21	[6-36]	Dusseux (2014)
k	–	0.53	[0.45-0.55]	Chapin et al. (2011)
σ_k	–	0.03	–	Chapin et al. (2011)
$K1_{res}$	–	0.18	[0.1-0.2]	Hénin and Dupuis (1945); Inrae (2013)
$K1_{fert}$	–	0.35	[0.35 -0.75]	Hénin and Dupuis (1945); Inrae (2013)
TMA	°C	10	[8-15]	Hénin and Dupuis (1945); Inrae (2013)
Arg	g/kg	100	[100-300]	Hénin and Dupuis (1945); Inrae (2013)
CaCO3	g/kg	50	–	Hénin and Dupuis (1945); Inrae (2013)

5.3.2. Results

Sensitivity of carbon storage uncertainty to GPP and NPP uncertainty

Figure 8 shows the influence of the NPP uncertainty controlling controlling parameters, e.g. Re, Obs and σ_k , on $\sigma_{\Delta C}$. Three different combinations of those parameters were used to draw the error bars, while the other parameters remained constant. For the "maximization scenario" indicated with the red error bars, the value for the three parameters were chosen within their possible range (table 11) to get the biggest error (Re = 2 gC.m^{-2}.yr^{-1}, Obs = 6, σ_k = 0.05). We see on figure 23.a. that for this scenario, $\sigma_{\Delta C}$ is always higher than 300 gC.m^{-2}. Thus for one year, the error is much larger than the value of ΔC. On the other hand, when we look for four years on figure 23.b. the error decreases sharply and is rather around 200 gC.m^{-2}, but this is still high compared to the value of ΔC.

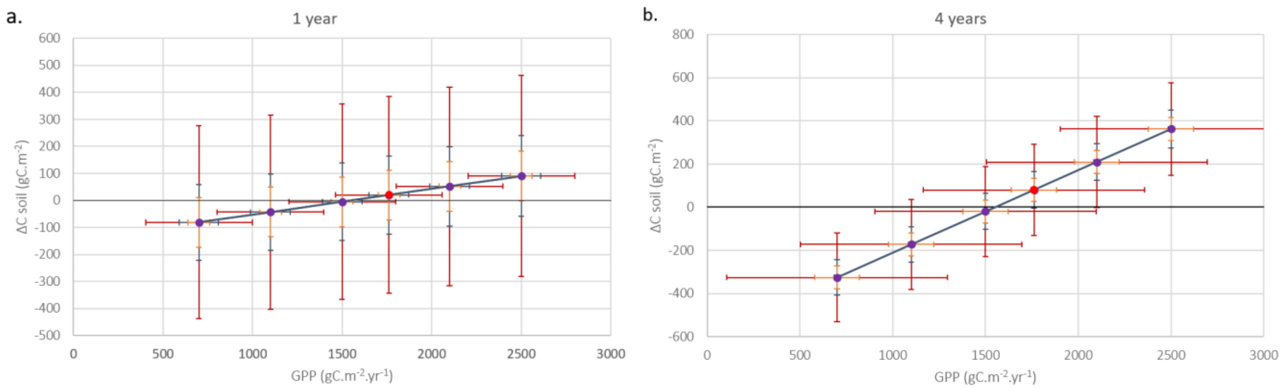


Figure 23. Soil carbon balance (ΔCsoil) as function of GPP. σΔC is represented by the error bars, in red when the parameters influencing σΔC where chosen to have the highest error, in grey for the reference scenario and in orange when the error was minimized. The red circle indicate the reference scenario, with GPP equal to 1760 gC.m−2.yr−1.

Soil analysis vs fluxes difference

Finally, we compared the flux method to the soil analysis method. To do so, figure 26 represents the Minimal Detectable Difference (MMD) of the soil carbon stock change for both method, as a function of the parameters controlling MMD. We see that, when few samples are available to do a soil analysis, the MMD is very high for that method - when the number of samples n=4, MMD=525 gC.m^{-2} but it rapidly decreases with an increase in the samples number and reach 105 gC.m^{-2} when n=100. However a sample size of 100 is very unrealistic, that is why we represented on the figure the MMD value, 332 gC.m^{-2}, with a sample of 10. MMD for the flux method does not vary as much and stays between 50 gC.m^{-2} and 144 gC.m^{-2} although we vary the value of its parameters up to 90%, which also quite unrealistic. We can also notice that the MMD of the soil analysis method becomes weaker than that of the reference scenario when the sample size is about 50.

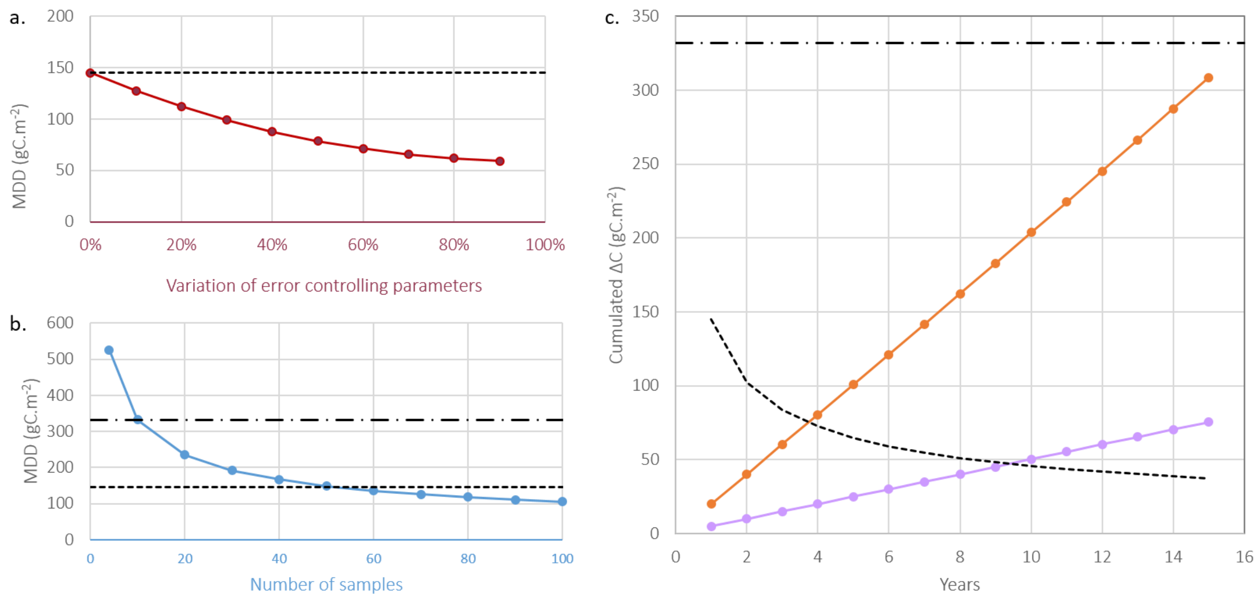


Figure 24. a) The red curve represents the MMD as a function of the percentage of change of the three parameters (Re, Obs and σk) controlling σGP P and σNP P and thus the error on ΔC for the fluxes method we developed. The value of these three parameters were changed all at once nine times, 10% in 10%, starting from the reference scenario. For Re and σk the value were diminished while it was increased for Obs. The black dashed line is the value of the MMD for the reference scenario. b) The blue curve represents the Minimable Detectable Difference (MMD) as a function of the number of samples for a soil analysis method (Schrumpf et al., 2011). The black dashed line is the value of the MMD for the reference scenario. The dashed-dotted line represents the value of the MMD for the soil analysis method with 10 samples. c) The pink curve represent the cumulated through time for a carbon storing rate of 1 ‰ with a baseline carbon stock of 5000 gC.m−2. The orange curve is for a carbon-storing rate of 4 ‰.

Figure 24.c . shows how long it takes for both method to reach the MMD with a baseline carbon stock of 5000 gC.m−2. We see that for the flux method, the MMD decreasing through $1/\sqrt{years}$. For the reference scenario of the flux method it takes about 4 years before we reach the MMD with a carbon storing rate of 4 and 10 years with a carbon storing rate of 1 ‰ . For a soil analysis the soil analysis method with a sample size of 10, the MMD is never reached.

Thus, although we have seen that by obtaining the carbon balance of a field thanks to the flux method, the error is not negligible, we can hope for improvements, especially in the field of remote sensing as a number of other avenues could be explored measured GPP with a better accuracy. For example, to minimize Re, it could be interesting to look at the accuracy of sun-induced fluorescence satellite measurements as it is strongly correlated with GPP (**Li et al.**, 2018). To increase the number of observations, we could look at what we can do in terms of satellite radar products to estimate GPP, which would solve the problem of cloud cover. Answering these questions could be part of the IRC Pillar 2 working group missions. The IRC has high hopes for this method because it is technically and economically more viable than soil analyses. Indeed, it is completely unthinkable to monitor large-scale soil carbon storage projects with soil tests despite progress made with rapid infrared measurements of soil samples (portable devices) which are however not as accurate, while a method based on remote sensing is scal- able. Once such a method is put in place, it will be possible to monitor both small plots and field crops. Farmers will just have to provide information on carbon export through harvest and carbon inputs through organic fertilizers. Even then, some models can estimate the carbon exported during harvest (**Pique et al.**).

In any case, even without significant progress on satellite GPP detection, if this method is used over long periods of time (˜10 years), it can accurately to monitor carbon stock changes. For example, it could be used to monitor carbon storage projects in agricultural soils, such as the low carbon label, currently under development in France. There are already four main families of proposed methods for measuring soil carbon for that project:

- Modelling, with model such as AMG or RothC

- Remote sensing combined with models, for example SAFYE-CO_2 (Pique et al.)

- Use of the IPCC equations (based on baseline carbon stocks multiplied by emissions factors more or less precise) with regionalized inventory change factors

- Modelling combined with the IPCC equations

All of this method are based on the prediction of carbon fate in soils. The first method, based only on IPCC equations has a precision level of Tier 2 according to the scale defined by the IPCC. Model-based methods can reach Tier 3 accuracy but often require regional calibration. The advantage of a method mainly based on remote sensing as it should be developed in the IRC Pillar 2, is that once developed it will be easily applicable and thus give a very good level of accuracy with no need for regional calibration. However, attention needs to be paid to additional sources of error that could be introduced by the introduction of new practices for storing carbon, such as cover crops. Indeed, for the moment, although the scientific community unambiguously recognizes intermediate cultures as stockpiling practices, the parameterization of models such as AMG on these crops is very uncertain and the error on ΔC could be affected (Constantin et al., 2020). But if we use basic principles as we in our study, that is GPP and soil respiration, models do not require any specific calibration for given crops. Therefore, they can be extended at global scale.

CONCLUSION and OUTLOOK

With increased obligations for reporting on GHG emissions and Nationally Determined Contributions (NDCs) under the Paris agreement, it is important that all countries are able to estimate their GHG emissions to maximise transparency, accuracy, completeness and consistency. Improving inventories requires enhanced national capability to gather relevant activity data to develop country-specific emission factors. There is a need to improve the evidence base and to better connect governments and relevant expertise to subsequently improve the quality of agricultural NDC's and the way their achievements are reflected by national GHG inventories.

Soil monitoring networks should be included in a broader cross-method validation programme to ultimately permit spatially and temporally validated comparisons both within and between countries. An open-access database, where short- or long-term soil C measurements could be uploaded and shared or an online collaborative platform as used in the CIRCASA (https://www.circasa-project.eu/Online-Collaborative-Platform-OCP) would also be of great benefit for progressing a global MRV system.

The preliminary study of uncertainty of the proposed new remote sensing and flux-based international SOC monitoring system, shows that this project is realistic. Indeed, if sufficiently long time periods are considered, carbon storage begins to be large enough to be detected with a good degree of accuracy (we would reach a relative error of about 30% at the bot of about ten years) that could allow the establishment of rewards for the farmer who stores in the form of carbon credits for example. Moreover, with the ever-increasing number of satellites being sent on Earth observation missions, it is to be hoped that the margin of error on the carbon balance will be further reduced significantly.

For developing countries, this will require international cooperation, capacity building and technology transfer , which could be facilitated within GRA, CCAFS and similar organisations, in synergy with relevant funding mechanisms, or via the recently-established "Global assessment of soil organic carbon sequestration potential (GSOCseq)" programme of the UN FAO.

The work presenting here is establishing the foundation for the knowledge system (KIS) on SOC in agriculture hosting and organizing soil and agricultural practices maps, as well as data, meta-data, handbooks and guidelines.

The CIRCASA KIS has been established to share and visualize soil data and metadata from relevant existing repositories in one unique place. With this tool, scientists and other stakeholders can access to a large range and international knowledge. The KIS provides geo-referenced meta-data and, data from experiments, data visualization, observations and surveys, as well as from models and synthesis activities and methodological guidelines developed by CIRCASA leading to an enhanced international knowledge system delivering improved scientific resources of both global and local significance (e.g. maps showing the technical potential for SOC sequestration of diverse agricultural practices.

REFERENCES

Alvarez, R., Alvarez, R., 2005. A review of nitrogen fertilizer and conservation tillage effects on soil organic carbon storage. Soil Use Manag. 21, 38–52.

Anderson, K., Peters, G., 2016. The trouble with negative emissions. Science (80-.). 354, 182–183.

Andrén, O., Kätterer, T., 2001. Basic principles for soil carbon sequestration and calculating dynamic country-level balances including future scenarios. Assess. methods soil carbon 495–511.

Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S. a., Dubayah, R., Friedl, M. a., Samanta, S., Houghton, R. a., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Chang. 2, 182–185.

Baker, J.M., Ochsner, T.E., Venterea, R.T., Griffis, T.J., 2007. Tillage and soil carbon sequestration-What do we really know? Agric. Ecosyst. Environ. 118, 1–5.

Bakker, R., Elbersen, W., Poppens, R., Jan Peter, L., 2013. Rice straw and Wheat straw. Potential feedstocks for the Biobased Economy.

Balkovič, J., van der Velde, M., Schmid, E., Skalský, R., Khabarov, N., Obersteiner, M., Stürmer, B., Xiong, W., 2013. Pan-European crop modelling with EPIC: Implementation, up-scaling and regional crop yield validation. Agric. Syst. 120, 61–75.

Balkovič, J., van der Velde, M., Skalský, R., Xiong, W., Folberth, C., Khabarov, N., Smirnov, A., Mueller, N.D., Obersteiner, M., 2014. Global wheat production potentials and management flexibility under the representative concentration pathways. Glob. Planet. Change 122, 107–121.

Bartholomé, E., Belward, A.S., 2005. GLC2000: a new approach to global land cover mapping from Earth observation data. Int. J. Remote Sens. 26, 1959–1977.

Batjes, N.H., 1996. Total carbon and nitrogen in the soils of the world.

Batjes, N.H., 2009. Harmonized soil profile data for applications at global and continental scales: Updates to the WISE database. Soil Use Manag. 25, 124–127.

Borrelli, P., Robinson, D.A., Fleischer, L.R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. Van, Montanarella, L., Panagos, P., 2017. An assessment of the global impact of 21st century land use change on soil erosion. Nat. Commun. 8.

Camino-Serrano, M., Guenet, B., Luyssaert, S., Ciais, P., Bastrikov, V., De Vos, B., Gielen, B., Gleixner, G., Jornet-Puig, A., Kaiser, K., Kothawala, D., Lauerwald, R., Peñuelas, J., Schrumpf, M., Vicca, S., Vuichard, N., Walmsley, D., Janssens, I.A., 2017. ORCHIDEE-SOM: Modeling soil organic carbon (SOC) and dissolved organic carbon (DOC) dynamics along vertical soil profiles in Europe. Geosci. Model Dev. Discuss. 1–38.

Castaldi, F., Hueni, A., Chabrillat, S., Ward, K., Buttafuoco, G., Bomans, B., Vreys, K., Brell, M., van Wesemael, B., 2019. Evaluating the capability of the Sentinel 2 data for soil organic carbon prediction in croplands. ISPRS J. Photogramm. Remote Sens. 147, 267–282.

Ceschia, E., Béziat, P., Dejoux, J.F., Aubinet, M., Bernhofer, C., Bodson, B., Buchmann, N., Carrara, A., Cellier, P., Di Tommasi, P., Elbers, J.A., Eugster, W., Grünwald, T., Jacobs, C.M.J., Jans, W.W.P., Jones, M., Kutsch, W., Lanigan, G., Magliulo, E., Marloie, O., Moors, E.J., Moureaux, C., Olioso, A., Osborne, B., Sanz, M.J., Saunders, M., Smith, P., Soegaard, H., Wattenbach, M., 2010. Management effects on net ecosystem carbon and GHG budgets at European crop sites. Agric. Ecosyst. Environ. 139, 363–383.

Chabbi, A., Lehmann, J., Ciais, P., Loescher, H.W., Cotrufo, M.F., Don, A., Sanclements, M., Schipper, L., Six, J., Smith, P., Rumpel, C., 2017. Aligning agriculture and climate policy. Nat. Clim. Chang. 7, 307–309.

Chakraborty, D., Ladha, J.K., Rana, D.S., Jat, M.L., Gathala, M.K., Yadav, S., Rao, A.N., Ramesha, M.S., Raman, A., 2017. A global analysis of alternative tillage and crop establishment practices for economically and environmentally efficient rice production. Sci. Rep. 7, 1–11.

Chang, J., Ciais, P., Viovy, N., Vuichard, N., Sultan, B., Soussana, J.F., 2015. The greenhouse gas balance of European grasslands. Glob. Chang. Biol. 21, 3748–3761.

Claverie, M., Demarez, V., Duchemin, B., Hagolle, O., Ducrot, D., Marais-Sicre, C., Dejoux, J.F., Huc, M., Keravec, P., Béziat, P., Fieuzal, R., Ceschia, E., Dedieu, G., 2012. Maize and sunflower biomass estimation in southwest France using high spatial and temporal resolution remote sensing data. Remote Sens. Environ. 124, 844–857.

Coleman, K., Jenkinson, D.S., 1987. RothC - A model for the turnover of carbon in soil. Model description and users guide, ROTHC manual. Harpenden, Herts, UK.

Coleman, K., Jenkinson, D.S., Crocker, G.J., Grace, P.R., Klír, J., Körschens, M., Poulton, P.R., Richter, D.D., 1997. Simulating trends in soil organic carbon in long-term experiments using RothC-26.3. Geoderma 81, 29–44.

Del Grosso, S., Parton, W., Mosier, A., Hartman, M., Brenner, J., Ojima, D., Schimel, D., 2001. "Simulated Interaction of Carbon Dynamics and Nitrogen Trace Gas Fluxes Using the DAYCENT Model." In: Schaffer, M., Ma, L., Hansen, S. (Eds.), Modeling Carbon and Nitrogen Dynamics for Soil Management. CRC Press, Boca Raton, Florida, pp. 301–332.

Del Grosso, S., Parton, W.J., 2011. Understanding Greenhouse Gas Emissions from Agricultural Management. In: Guo, L., Gunasekara, A., McConnell, L. (Eds.), Symposium A Quarterly Journal In Modern Foreign Literatures. American Chemical Society, Washington, D.C.

Dimassi, B., Guenet, B., Saby, N.P.A., Munoz, F., Bardy, M., Millet, F., Martin, M.P., 2018. The impacts of CENTURY model initialization scenarios on soil organic carbon dynamics simulation in French long-term experiments. Geoderma 311, 25–36.

Don, A., Schumacher, J., Freibauer, A., 2011. Impact of tropical land-use change on soil organic carbon stocks - a meta-analysis. Glob. Chang. Biol. 17, 1658–1670.

Duchemin, B., Maisongrande, P., Boulet, G., Benhadj, I., 2008. A simple algorithm for yield estimates: Evaluation for semi-arid irrigated winter wheat monitored with green leaf area index. Environ. Model. Softw. 23, 876–892.

Ehrhardt, F., Soussana, J.F., Bellocchi, G., Grace, P., McAuliffe, R., Recous, S., Sándor, R., Smith, P., Snow, V., de Antoni Migliorati, M., Basso, B., Bhatia, A., Brilli, L., Doltra, J., Dorich, C.D., Doro, L., Fitton, N., Giacomini, S.J., Grant, B., Harrison, M.T., Jones, S.K., Kirschbaum, M.U.F., Klumpp, K., Laville, P., Léonard, J., Liebig, M., Lieffering, M., Martin, R., Massad, R.S., Meier, E., Merbold, L., Moore, A.D., Myrgiotis, V., Newton, P., Pattey, E., Rolinski, S., Sharp, J., Smith, W.N., Wu, L., Zhang, Q., 2018. Assessing uncertainties in crop and pasture ensemble model simulations of productivity and N2O emissions. Glob. Chang. Biol. 24, e603–e616.

Ellis, E.C., Ramankutty, N., 2008. Putting people in the map: Anthropogenic biomes of the world. Front. Ecol. Environ. 6, 439–447.

Epplin, F., Stock, C., Kletke, D., Peeper, T., 2005. Cost of Conventional Tillage and No-till Continuous Wheat Production for Four Farm Sizes. J. ASFMRA (American Soc. Farm Manag. Rural Apprais. 8.

Erenstein, O., Laxmi, V., 2008. Zero tillage impacts in India's rice-wheat systems: A review. Soil Tillage Res. 100, 1–14.

Falloon, P., Smith, P., Coleman, K., Marshall, S., 1998. Estimating the size of the inert organic matter pool from total soil organic carbon content for use in the rothamsted carbon model. Science (80-.). 30, 1207–1211.

FAO/IIASA/ISRIC/ISSCAS/JRC, 2009. Harmonized World Soil Database (version 1.1).

FAO, IFAD, WFP., 2015. The State of Food Insecurity in the World: Meeting the 2015 international hunger targets: taking stock of uneven progress., FAO, IFAD and WFP.

Folberth, C., Elliott, J., Müller, C., Balkovič, J., Chryssanthacopoulos, J., Izaurralde, R.C., Jones, C.D., Khabarov, N., Liu, W., Reddy, A., Schmid, E., Skalský, R., Yang, H., Arneth, A., Ciais, P., Deryng, D., Lawrence, P.J., Olin, S., Pugh, T.A.M., Ruane, A.C., Wang, X., 2019. Parameterization-induced uncertainties and impacts of crop management harmonization in a global gridded crop model ensemble. PLoS One 14, 1–36.

Fuss, S., Lamb, W.F., Callaghan, M.W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., de Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G.F., Rogelj, J., Smith, P., del Mar Zamora, M., Minx, J.C., 2018a. Negative emissions - Part 2: Costs, potentials and side effects. Environ. Res. Lett. 13, 2–4.

Fuss, S., Lamb, W.F., Max, W., Nemet, G.F., Callaghan, M.W., Stechow, C. Von, Minx, J.C., Bertram, C., Nemet, G.F., Lamb, W.F., Callaghan, M.W., Minx, J.C., 2018b. Negative emissions — Part 2 : Costs , potentials and side effects. Environ. Res. Lett 13.

Gassert, F., Luck, M., Landis, M., Reig, P., Institute, T.S.-W.R., 2014, U., 2014. Aqueduct global maps 2.1: Constructing decision-relevant global water risk indicators. wri.org.

Goidts, E., Van Wesemael, B., Van Oost, K., 2009. Driving forces of soil organic carbon evolution at the landscape and regional scale using data from a stratified soil monitoring. Glob. Chang. Biol. 15, 2981–3000.

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, 3151–3171.

GRASS Development Team, 2018. Geographic Resources Analysis Support System (GRASS).

Grigss, D., 2013. Sustainable developmnet goals for people and planet. Nature 495, 305–307.

Hellwinckel, C., Larson, J., De La Torre Ugarte, D., 2003. Incentives For Switching Agricultural Land To Carbon Sequestering No-Tillage: What Duration Are Incentives Necessary? 2003 Annu. Meet. Febr. 1-5, 2003, Mobile, Alabama 35219, South. Agric. Econ. Assoc.

Himmelstein, J., Ares, A., Gallagher, D., Myers, J., 2017. A meta-analysis of intercropping in Africa: impacts on crop yield, farmer income, and integrated pest management effects. Int. J. Agric. Sustain. 15, 1–10.

Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2013. Adapting agriculture to climate change: A review. Theor. Appl. Climatol. 113, 225–245.

Hua, X., Claudia, R., 2017. Agricultural nutrient loadings to the freshwater environment: the role of climate change and socioeconomic change. Environ. Res. Lett. 12, 104008.

IFPRI, 2019. Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 1.1.

IPCC, 2019. IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Izaurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., Jakas, M.C.Q., 2006. Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecol. Modell. 192, 362–384.

Janosky, J.S., Young, D.L., Schillinger, W.F., 2002. Economics of conservation tillage in a wheat-fallow rotation. Agron. J. 94, 527–531.

Jenkinson, D.S., Harkness, D.D., Vance, E.D., Adams, D.E., Harrison, A.F., 1992. Calculating net primary production and annual input of organic matter to soil from the amount and radiocarbon content of soil organic matter. Soil Biol. Biochem. 24, 295–308.

Kahimba, F.C., Ranjan, R.S., Froese, J., Entz, M., Nason, R., 2008. Cover Crop Effects on Infiltration, Soil Temperature, and Soil Moisture Distribution in the Canadian Prairies. Am. Soc. Agric. Biol. Eng. 24, 321–334.

Kaval, P., 2004. The Profitability of Alternative Cropping Systems: A Review of the Literature. J. Sustain. Agric. 23, 47–65.

Kirkegaard, J.A., Conyers, M.K., Hunt, J.R., Kirkby, C.A., Watt, M., Rebetzke, G.J., 2014. Sense and nonsense in conservation agriculture: Principles, pragmatism and productivity in Australian mixed farming systems. Agric. Ecosyst. Environ. 187, 133–145.

Koeble, R., 2014. The Global Nitrous Oxide Calculator – GNOC – Online Tool Manual. Ispra.

Lal, R., 2003. Global Potential of Soil Carbon Sequestration to Mitigate the Greenhouse Effect. CRC. Crit. Rev. Plant Sci. 22, 151–184.

Lal, R., 2004. Soil carbon sequestration impacts on global climate change and food security. Science (80-.). 304, 1623–1627.

Lal, R., 2006. Enhancing crop yields in the developing countries through restoration of the soil organic carbon pool in agricultural lands. L. Degrad. Dev. 197–209.

Lal, R., Follett, R.F., Stewart, B.A., Kimble, J.M., 2007. SOIL CARBON SEQUESTRATION TO MITIGATE CLIMATE CHANGE AND ADVANCE FOOD SECURITY. Soil Sci. 172.

Lark, R.M., Ander, E.L., Broadley, M.R., 2019. Combining two national-scale datasets to map soil properties, the case of available magnesium in England and Wales. Eur. J. Soil Sci. 70, 361–377.

Lawrence, M.G., Schäfer, S., Muri, H., Scott, V., Oschlies, A., Vaughan, N.E., Boucher, O., Schmidt, H., Haywood, J., Scheffran, J., 2018. Evaluating climate geoengineering proposals in the context of the Paris Agreement temperature goals. Nat. Commun. 9.

Liao, Y., Wu, W.L., Meng, F.Q., Smith, P., Lal, R., 2015. Increase in soil organic carbon by agricultural intensification in northern China. Biogeosciences 12, 1403–1413.

Liski, J., Perruchoud, D., Karjalainen, T., 2002. Increasing carbon stocks in the forest soils of western Europe. For. Ecol. Manage. 169, 159–175.

Liu, C., Lu, M., Cui, J., Li, B., Fang, C., 2014. Effects of straw carbon input on carbon dynamics in agricultural soils: A meta-analysis. Glob. Chang. Biol. 20, 1366–1381.

Luo, Z., Wang, E., Baldock, J., Xing, H., 2014. Potential soil organic carbon stock and its uncertainty under various cropping systems in Australian cropland. Soil Res. 52, 463–475.

Luo, Z., Wang, E., Sun, O.J., 2010. Soil carbon change and its responses to agricultural practices in Australian agro-ecosystems: A review and synthesis. Geoderma 155, 211–223.

Mangalassery, S., Sjögersten, S., Sparkes, D.L., Mooney, S.J., 2015. Examining the potential for climate change mitigation from zero tillage. J. Agric. Sci. 153, 1151–1173.

Manley, J., Van Kooten, G.C., Moeltner, K., Johnson, D.W., 2005. Creating carbon offsets in agriculture through no-till cultivation: A meta-analysis of costs and carbon benefits. Clim. Change 68, 41–65.

Marín-Spiotta, E., Sharma, S., 2013. Carbon storage in successional and plantation forest soils: A tropical analysis. Glob. Ecol. Biogeogr. 22, 105–117.

Martin-Guay, M.-O., Paquette, A., Dupras, J., Rivest, D., 2017. The new Green Revolution: Sustainable intensification of agriculture by intercropping. Sci. Total Environ. 615, 767–772.

Martin, M.P., Cordier, S., Balesdent, J., Arrouays, D., 2007. Periodic solutions for soil carbon dynamics equilibriums with time-varying forcing variables. Ecol. Modell. 204, 523–530.

Matthews, R., Malcolm, H., Buys, G., Henshall, P., Moxely, J., Morris, A., Mackie, E., 2014. Changes to the representation of forest land and associated land-use changes in the 1990-2012 UK Greenhouse Gas Inventory. Report to Department of Energy and Climate Change, Contract GA0510,. Edinburgh.

Mattoso, M.J., Cruz, J.C., Pereira Fiiho, A.I., 2001. Custo de produção em plantio direto. In: Informe Agropecuário. pp. 109–116.

Matus, A., Derksen, D.A., Walley, F.L., Loeppky, H.A., Van Kessel, C., 1997. The influence of tillage and crop rotation on nitrogen fixation in lentil and pea. Can. J. Plant Sci. 77, 197–200.

Meersmans, J., Martin, M.P., Lacarce, E., Orton, T.G., De Baets, S., Gourrat, M., Saby, N.P.A., Wetterlind, J., Bispo, A., Quine, T.A., Arrouays, D., 2013. Estimation of Soil Carbon Input in France: An Inverse Modelling Approach. Pedosphere 23, 422–436.

Menichetti, L., Ågren, G.I., Barré, P., Moyano, F., Kätterer, T., 2019. Generic parameters of first-order kinetics accurately describe soil organic matter decay in bare fallow soils over a wide edaphic and climatic range. Sci. Rep. 9, 1–12.

Metherell, A.K., Harding, L.A., Cole, C.V., Parton, W.J., 1993. "CENTURY Soil Organic Matter Model Environment." Agroecosystem version 4.0. Technical documentation. Technical documentation, GPSR Tech. Report No. 4, USDA/ARS. FT. Collins,CO.

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., van Wesemael, B., Winowiecki, L., 2017. Soil carbon 4 per mille. Geoderma 292, 59–86.

Mittermeier, R.A., Turner, W.R., Larsen, F.W., Brooks, T.M., Gascon, C., 2011. Global Biodiversity Conservation: The Critical Role of Hotspots. In: Biodiversity Hotspots. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 3–22.

Morais, T.G., Silva, C., Jebari, A., Álvaro-Fuentes, J., Domingos, T., Teixeira, R.F.M., 2018. A proposal for using process-based soil models for land use Life cycle impact assessment: Application to Alentejo, Portugal. J. Clean. Prod. 192, 864–876.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257.

Nayak, D., Saetnan, E., Cheng, K., Wang, W., Koslowski, F., Cheng, Y.F., Zhu, W.Y., Wang, J.K., Liu, J.X., Moran, D., Yan, X., Cardenas, L., Newbold, J., Pan, G., Lu, Y., Smith, P., 2015. Management opportunities to mitigate greenhouse gas emissions from Chinese agriculture. Agric. Ecosyst. Environ. 209, 108–124.

Nelson, G.C., Rosegrant, M.W., Palazzo, A., Gray, I., Ingersoll, C., Robertson, R., Tokgoz, S., Zhu, T., Sulser, T.B., Ringler, C., Msangi, S., You, L., 2010. Food Security, Farming, and Climate Change to 2050: Scenarios, Results, Policy Options, Food Security, Farming, and Climate Change to 2050: Scenarios, Results, Policy Options.

Netzel, P., Stepinski, T., 2018. Climate Similarity Search: GeoWeb Tool for Exploring Climate Variability. Bull. Am. Meteorol. Soc. 99, 475–477.

Ogle, S.M., Breidt, F.J., Paustian, K., 2005. Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. Biogeochemistry 72, 87–121.

Ogle, S.M., Jay Breidt, F., Easter, M., Williams, S., Killian, K., Paustian, K., 2010. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Glob. Chang. Biol. 16, 810–822.

Oldfield, E.E., Bradford, M.A., Wood, S.A., 2019. Global meta-analysis of the relationship between soil organic matter and crop yields. Soil 5, 15–32.

Palosuo, T., Heikkinen, J., Regina, K., 2015. Method for estimating soil carbon stock changes in Finnish mineral cropland and grassland soils. Carbon Manag. 6, 207–220.

Pan, G., Smith, P., Pan, W., 2009. The role of soil organic matter in maintaining the productivity and yield stability of cereals in China. Agric. Ecosyst. Environ. 129, 344–348.

Pannell, D.J., Llewellyn, R.S., Corbeels, M., 2014. The farm-level economics of conservation agriculture for resource-poor farmers. Agric. Ecosyst. Environ. 187, 52–64.

Parton, W.J., Hartman, M., Ojima, D., Schimel, D., 1998. DAYCENT and its land surface submodel: description and testing. Glob. Planet. Change 35–48.

Parton, W.J., Ojima, D., Schimel, D.S., Cole, C., 1994. A general model for soil organic matter dynamics: sensitivity to litter chemistry, texture and management. Pages 147-167 in R.B. Bryant and R.W. Arnold, editors. Quantitative modeling of soil forming processes. In: Quantitative Modeling of Soil Forming Processes. Soil Science Society of America, 677 S. Segoe Rd., Madison, WI 53711, USA, pp. 147–167.

Parton, W.J., Schimel, D.S., Cole, C. V, Ojima, D.S., 1987. Analysis of Factors Controlling Soil Organic Matter Levels in Great Plains Grasslands 1. Soil Sci. Soc. Am. J. 1173–1179.

Parton, W.J., Stewart, J.W.B., Cole, C. V, 1988. Dynamics of C , N , P and S in grassland soils : a model. Biogeochemistry 131, 109–131.

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 Manag. 10, 567–587.

Peng, S., Huang, J., Sheehy, J.E., Laza, R.C., Visperas, R.M., Zhong, X., Centeno, G.S., Khush, G.S., Cassman, K.G., 2004. Rice yields decline with higher night temperature from global warming. Proc. Natl. Acad. Sci. U. S. A. 101, 9971–9975.

Perruchoud, D., Joos, F., Fischlin, A., Hajdas, I., Bonani, G., 1999. Evaluating timescales of carbon turnover in temperate forest soils with radiocarbon data. Global Biogeochem. Cycles 13, 555–573.

Pittelkow, C.M., Linquist, B.A., Lundy, M.E., Liang, X., van Groenigen, K.J., Lee, J., van Gestel, N., Six, J., Venterea, R.T., van Kessel, C., 2015. When does no-till yield more? A global meta-analysis. F. Crop. Res. 183, 156–168.

Poeplau, C., Barré, P., Cécillon, L., Baudin, F., Sigurdsson, B.D., 2019. Changes in the Rock-Eval signature of soil organic carbon upon extreme soil warming and chemical oxidation - A comparison. Geoderma 337, 181–190.

Poeplau, C., Don, A., 2015. Carbon sequestration in agricultural soils via cultivation of cover crops - A meta-analysis. Agric. Ecosyst. Environ. 200, 33–41.

Portmann, F.T., Siebert, S., Döll, P., 2010. MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochem. Cycles 24, n/a-n/a.

Powlson, D.S., Whitmore, A.P., Goulding, K.W.T., 2011. Soil carbon sequestration to mitigate climate change: A critical re-examination to identify the true and the false. Eur. J. Soil Sci. 62, 42–55.

R Core Team, 2016. R: A language and environment for statistical computing. R Foundation for Statistical Computing.

Reeves, D.W., 1997. The role of soil organic matter in maintaining soil quality in continuous cropping systems. Soil Tillage Res. 43, 131–167.

Reicosky, D.C., 2015. Conservation tillage is not conservation agriculture. J. Soil Water Conserv. 70, 103–108.

Reytar, K., Hanson, C., Henninger, N., 2014. Indicators of Sustainable Agriculture: A Scoping Study, Creating a Sustainable Food Future.

Ribera, L.A., Hons, F.M., Richardson, J.W., 2004. An economic comparison between conventional and no-tillage farming systems in Burleson County, Texas. Agron. J. 96, 415–424.

Richards, G.P., 2001. The FullCAM carbon accounting model: development, calibration and implementation for the National Carbon Accounting System, National Carbon Accounting System Technical Report No. 28. Australian Greenhouse Office, Canberra.

Richter, D. deB., Hofmockel, M., Callaham, M.A., Powlson, D.S., Smith, P., 2007. Long-Term Soil Experiments: Keys to Managing Earth's Rapidly Changing Ecosystems. Soil Sci. Soc. Am. J. 71, 266–279.

Ruane, A.C., Goldberg, R., Chryssanthacopoulos, J., 2015. Climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. Agric. For. Meteorol. 200, 233–248.

Rumpel, C., Amiraslani, F., Chenu, C., Garcia Cardenas, M., Kaonga, M., Koutika, L.-S., Ladha, J., Madari, B., Shirato, Y., Smith, P., Soudi, B., Soussana, J.-F., Whitehead, D., Wollenberg, E., 2019. The 4p1000 initiative: Opportunities, limitations and challenges for implementing soil organic carbon sequestration as a sustainable development strategy. Ambio.

Rumpel, C., Lehmann, J., Chabbi, A., 2018. Boost soil carbon for food and climate. Nature 553, 27.

Sacks, W.J., Deryng, D., Foley, J.A., Ramankutty, N., 2010. Crop planting dates: An analysis of global patterns. Glob. Ecol. Biogeogr. 19, 607–620.

Saltiel, J., Bauder, J.W., Palakovich, S., 1994. Adoption of Sustainable Agricultural Practices: Diffusion, Farm Structure, and Profitability. Rural Sociol. 59, 333–349.

Sanderman, J., Hengl, T., Fiske, G.J., 2017. Soil carbon debt of 12,000 years of human land use. Proc. Natl. Acad. Sci. U. S. A. 114, 9575–9580.

Sándor, R., Ehrhardt, F., Grace, P., Recous, S., Smith, P., Snow, V., Soussana, J., Basso, B., Bhatia, A., Brilli, L., Doltra, J., Dorich, C.D., Doro, L., Fitton, N., Grant, B., Tom, M., Kirschbaum, M.U.F., Klumpp, K., Laville, P., Léonard, J., Martin, R., Massad, R., Moore, A., Myrgiotis, V., Pattey, E., Rolinski, S., Sharp, J., Skiba, U., Smith, W., Wu, L., Zhang, Q., Bellocchi, G., 2020. Field Crops Research Ensemble modelling of carbon fluxes in grasslands and croplands. F. Crop. Res. 252, 107791.

Scharlemann, J.P., Tanner, E.V., Hiederer, R., Kapos, V., 2014. Global soil carbon: understanding and managing the largest terrestrial carbon pool. Carbon Manag. 5, 81–91.

Schillinger, W.F., Papendick, R.I., 2008. Then and now: 125 Years of dryland wheat farming in the Inland Pacific Northwest. Agron. J. 100.

Shirato, Y., Taniyama, I., 2003. Testing the suitability of the Rothamsted Carbon model for long-term experiments on Japanese non-volcanic upland soils. Soil Sci. Plant Nutr. 49, 921–925.

Skalský, R., Tarasovičová, Z., Balkovič, J., Schmid, E., Fuchs, M., Moltchanova, E., Kindermann, G., Scholtz, P., 2008. GEO-BENE global database for bio-physical modeling v. 1.0. Concepts, methodologies and data. Laxenburg.

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. Glob. Chang. Biol. 11, 2141–2152.

Smith, J, Gottschalk, P., Bellarby, J., Richards, M., Nayak, D., Coleman, K., Hillier, J., Flynn, H., Wattenbach, M., Aitkenhead, M., Yeluripurti, J., Farmer, J., Smith, P., Smith, Jo, 2010. Model to Estimate Carbon in Organic Soils – Sequestration and Emissions (ECOSSE).

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. Philos. Trans. R. Soc. B Biol. Sci. 363, 789–813.

Smith, P., Nkem, J., Calvin, K., Campbell, D., Cherubini, F., Grassi, G., Korotkov, V., Hoang, A. Le, Lwasa, S., McElwee, P., Nkonya, E., Saigusa, N., Soussana, J.-F., Taboada, M.A., Arias-Navarro, C., Cavalett, O., Cowie, A., House, J., Huppmann, D., Krishnaswamy, J., Popp, A., Roe, S., Slade, R., Stringer, L., Vizzarri, M., 2019a. IPCC SR Climate Change & Land Ch 6: Interlinkages between Desertification, Land, Food Security and GHG fluxes. In: IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems.

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, 153–225.

Smith, P., Soussana, J., Angers, D., Schipper, L., Chenu, C., Rasse, D.P., Batjes, N.H., Egmond, F., McNeill, S., Kuhnert, M., Arias-Navarro, C., Olesen, J.E., Chirinda, N., Fornara, D., Wollenberg, E., Álvaro-Fuentes, J., Sanz-Cobena, A., Klumpp, K., 2019b. How to measure, report and verify soil carbon change to realize the potential of soil carbon sequestration for atmospheric greenhouse gas removal. Glob. Chang. Biol. 1–23.

Soussana, J., Lutfalla, S., Ehrhardt, F., Rosenstock, T., Lamanna, C., Havlík, P., Richards, M., Chotte, J., Torquebiau, E., Ciais, P., Smith, P., 2019. Matching policy and science: Rationale for the ’4 per 1000-soils for food security and climate’initiative. Soil Tillage Res. 188, 3–15.

Taghizadeh-Toosi, A., Christensen, B.T., Hutchings, N.J., Vejlin, J., Kätterer, T., Glendining, M., Olesen, J.E., 2014. C-TOOL: A simple model for simulating whole-profile carbon storage in temperate agricultural soils. Ecol. Modell. 292, 11–25.

Timothy A. Wise, 2013. Can We Feed the World in 2050? A Scoping Paper to Assess the Evidence (No. 13–14), Global Development and Environment Institute.

Tuomi, M., Rasinmäki, J., Repo, A., Vanhala, P., Liski, J., 2011. Soil carbon model Yasso07 graphical user interface. Environ. Model. Softw. 26, 1358–1362.

Uekoetter, F., 2011. The Magic of One: Reflections on the Pathologies of Monoculture, RCC Perspectives.

Uri, N.D., 1999. Factors affecting the use of conservation tillage in the United States. Water. Air. Soil Pollut. 116, 621–638.

USGS, 1997. USGS 30 ARC-second Global Elevation Data, GTOPO30.

Vaudour, E., Gomez, C., Fouad, Y., Lagacherie, P., 2019. Sentinel-2 image capacities to predict common topsoil properties of temperate and Mediterranean agroecosystems. Remote Sens. Environ. 223, 21–33.

Virto, I., Barré, P., Burlot, A., Chenu, C., 2012. Carbon input differences as the main factor explaining the variability in soil organic C storage in no-tilled compared to inversion tilled agrosystems. Biogeochemistry 108, 17–26.

Wall, E., Smit, B., 2005. Climate Change Adaptation in Light of Sustainable Agriculture. J. Sustain. Agric. 27, 113–123.

Wang, G., Huang, Y., Wang, E., Yu, Y., Zhang, W., 2013. Modeling Soil Organic Carbon Change across Australian Wheat Growing Areas, 1960-2010. PLoS One 8, 1–10.

Wang, G., Li, T., Zhang, W., Yu, Y., 2014. Impacts of Agricultural Management and Climate Change on Future Soil Organic Carbon Dynamics in North China Plain. PLoS One 9, e94827.

Weersink, A., Walker, M., Swanton, C., Shaw, J., 2008. Economic Comparison of Alternative Tillage Systems under Risk. Can. J. Agric. Econ. Can. d’agroeconomie 40, 199–217.

Werner, M., 2001. Shuttle Radar Topography Mission (SRTM), Mission overview. J. Telecom. 55, 75-79.

West, T.O., Marland, G., 2002. A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United States. Agric. Ecosyst. Environ. 91, 217–232.

West, T.O., Post, W.M., 2002. Soil Organic Carbon Sequestration Rates by Tillage and Crop Rotation. Soil Sci. Soc. Am. J. 66, 1930–1946.

West, Tristram O, Post, Wilfred M, West, T O, Post, W M, 2002. Soil Organic Carbon Sequestration Rates by Tillage and Crop Rotation: A Global Data Analysis. Soil Sci. Soc. Am. J 66, 1930–1946.

Williams, J.R., 1990. The erosion-productivity impact calculator (EPIC) model: a case history. Philos. Trans. R. Soc. London. Ser. B Biol. Sci. 329, 421–428.

Williams, J.R., 1995. The EPIC model. In: Singh, V.P. (Ed.), Computer Models of Watershed Hydrology. Water Resources Publications. Water Resources Pubns, pp. 909–1000.

Woolf, D., Lehmann, J., 2019. Microbial models with minimal mineral protection can explain long-term soil organic carbon persistence. Sci. Rep. 9, 1–8.

Wüst-Galley, C., Keel, S.G., Leifeld, J., 2019. A model-based carbon inventory for National greenhouse gas reporting of mineral agricultural soils (in prep).

You, L., Wood, S., Wood-Sichra, U., Wu, W., 2014. Generating global crop distribution maps: From census to grid. Agric. Syst. 127, 53–60.

Yu, Y., Huang, Y., Zhang, W., 2012. Modeling soil organic carbon change in croplands of China, 1980-2009. Glob. Planet. Change 82–83, 115–128.

Zhang, W., Yu, Y., Li, T., Sun, W., Huang, Y., 2014. Net greenhouse gas balance in China's croplands over the last three decades and its mitigation potential. Environ. Sci. Technol. 48, 2589–2597.

Zhao, G., Bryan, B.A., King, D., Luo, Z., Wang, E., Song, X., Yu, Q., 2013. Impact of agricultural management practices on soil organic carbon: Simulation of Australian wheat systems. Glob. Chang. Biol. 19, 1585–1597.

APPENDIX

Annex A: Yield impacts for Wheat

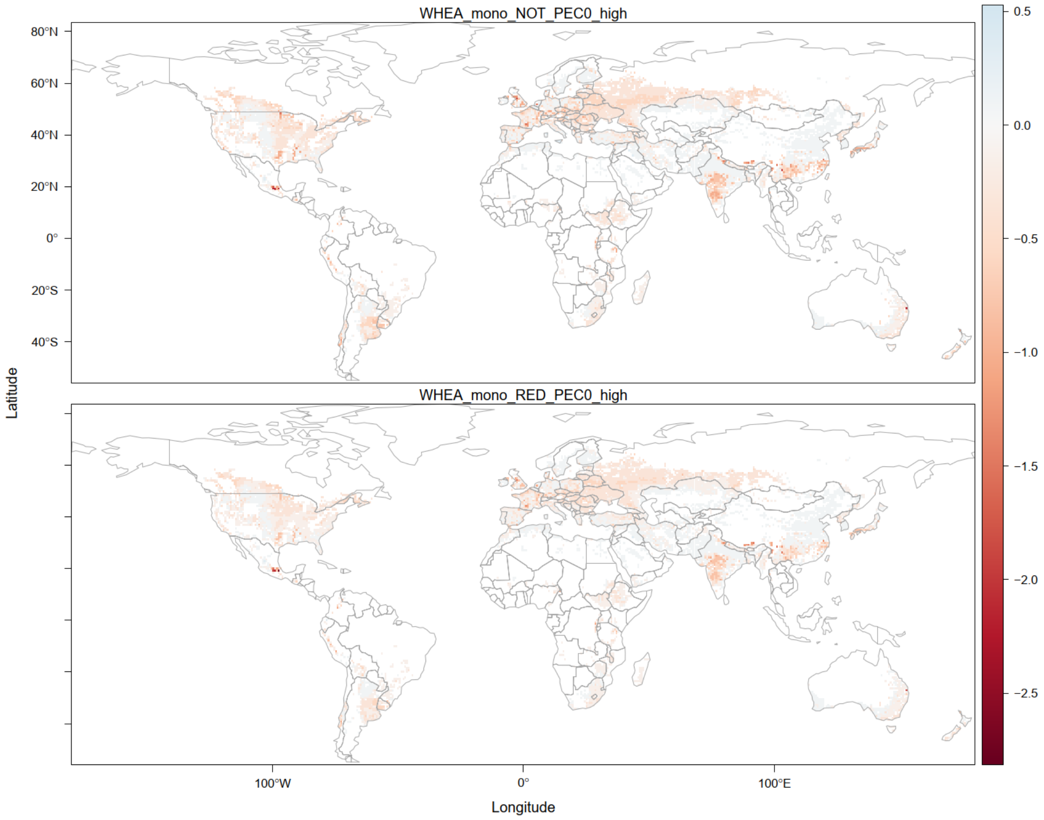
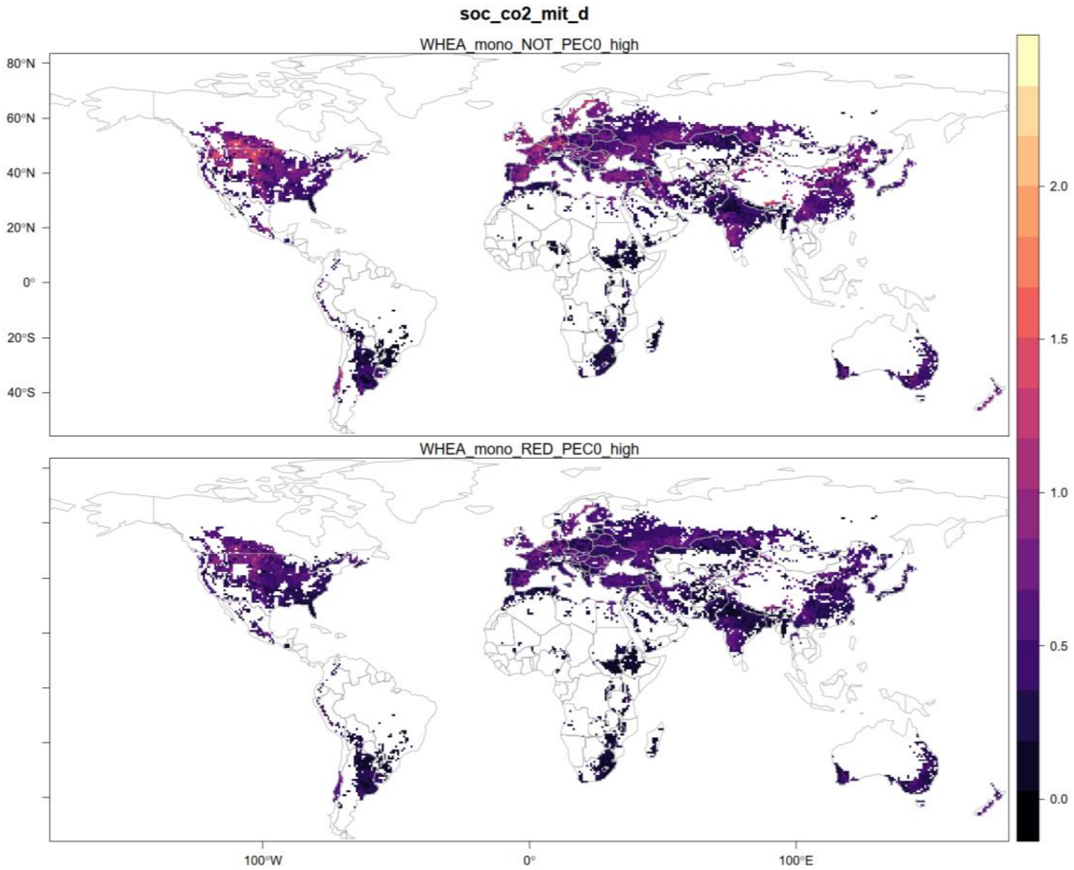


Figure A1: Wheat yield changes due to switching from conventional tillage systems to no-till (a) and reduced-till (b) systems in tons per hectare. Crop area based on (IFPRI, 2019)

Annex B: Mitigation impacts (Wheat)



2

Figure B1: Wheat mitigation effects from changing conventional tillage systems to no-till (a) and reduced-till (b) systems in tons CO_2 per hectare and year. Crop area based on (IFPRI, 2019) *. Weighted average yields for rainfed and irrigation.*

Annex C: Net-cost changes (wheat and corn)

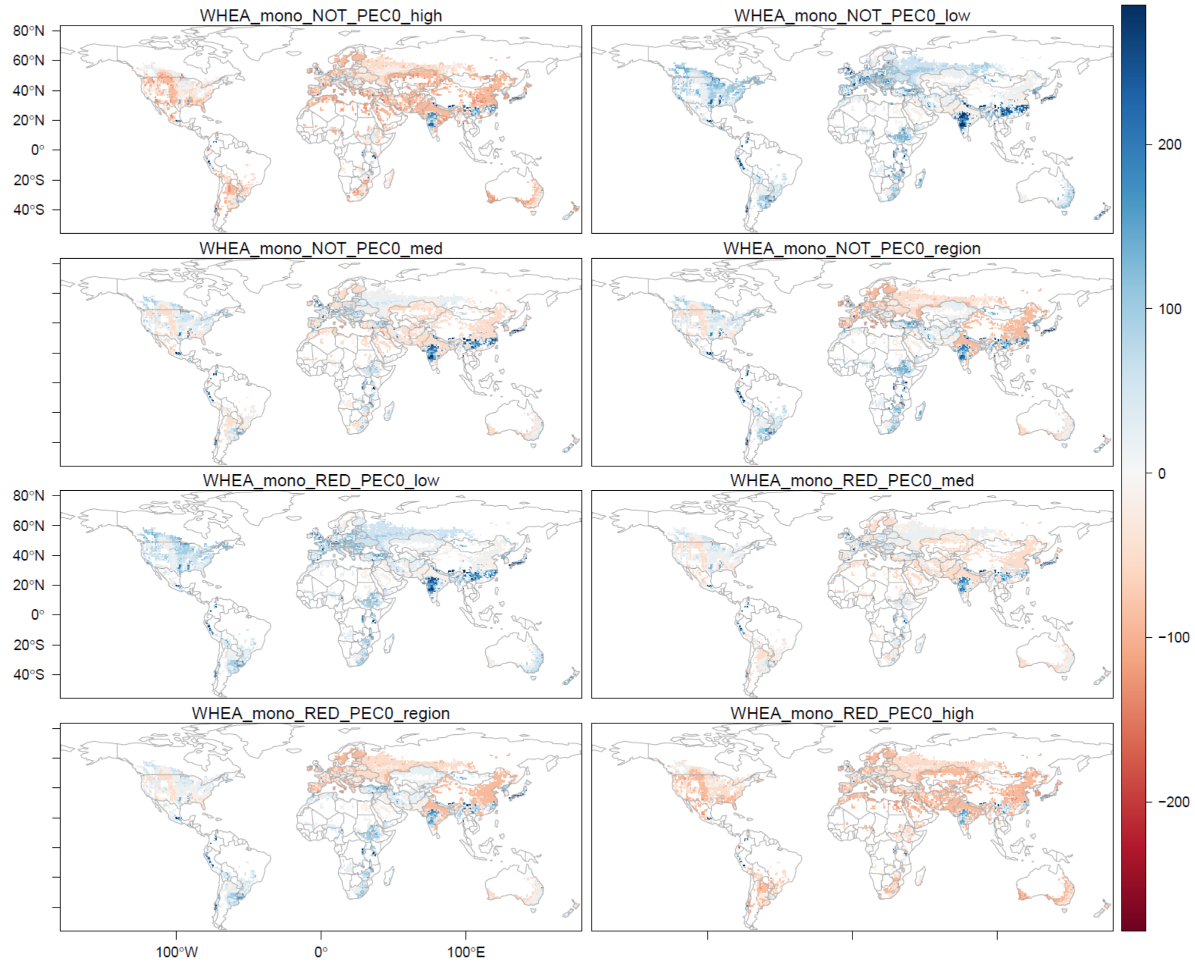


Figure C1: Changes in net-costs of wheat production [-(Δyield x price - Δproduction costs)] from changing conventional tillage systems to no-till (NOT) and reduced-till (RED) systems in $US2010 per hectare, for different assumptions on related changes of production costs (low, med, high, region; see Table 4). Crop area based on SPAM 2010 (IFPRI, 2019).

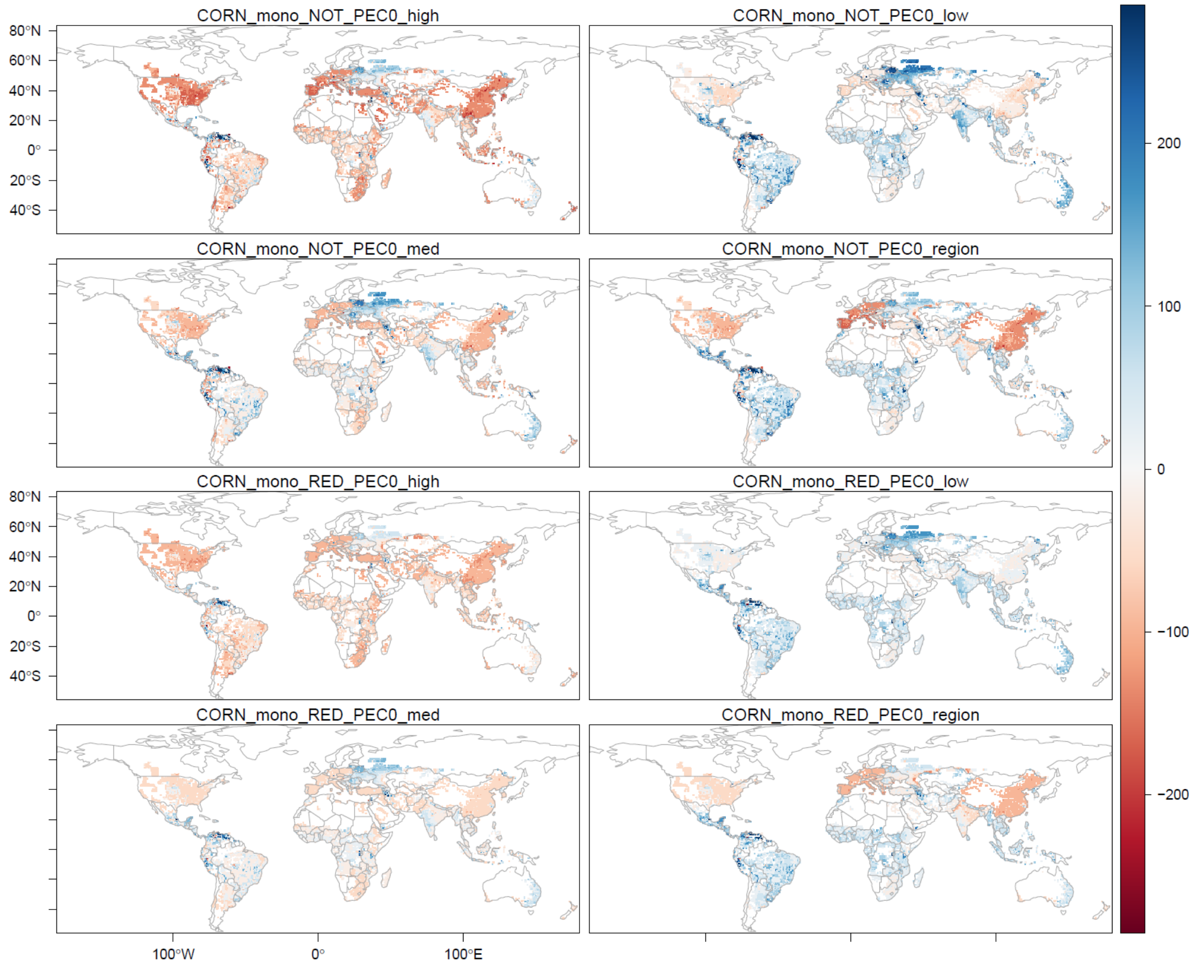


Figure C2: Changes in net-costs of corn production [-(Δyield x price - Δproduction costs)] from changing conventional tillage systems to no-till (NOT) and reduced-till (RED) systems in $US2010 per hectare, for different assumptions on related changes of production costs (low, med, high, region; see Table 5). Crop area based on SPAM 2010 (IFPRI, 2019).

Annex D: Marginal abatement cost curves

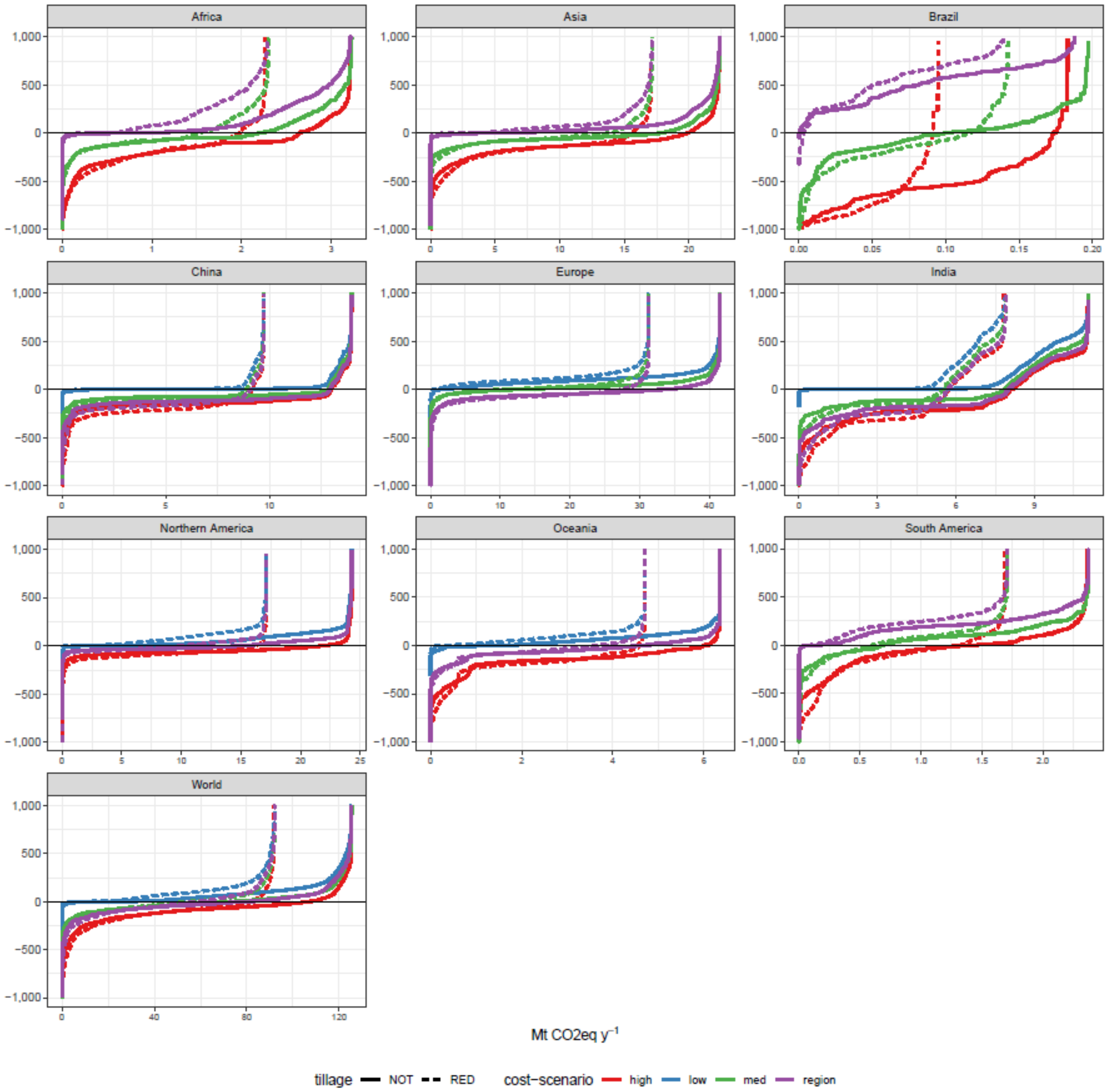


Figure D1: Regional MACCs for wheat.

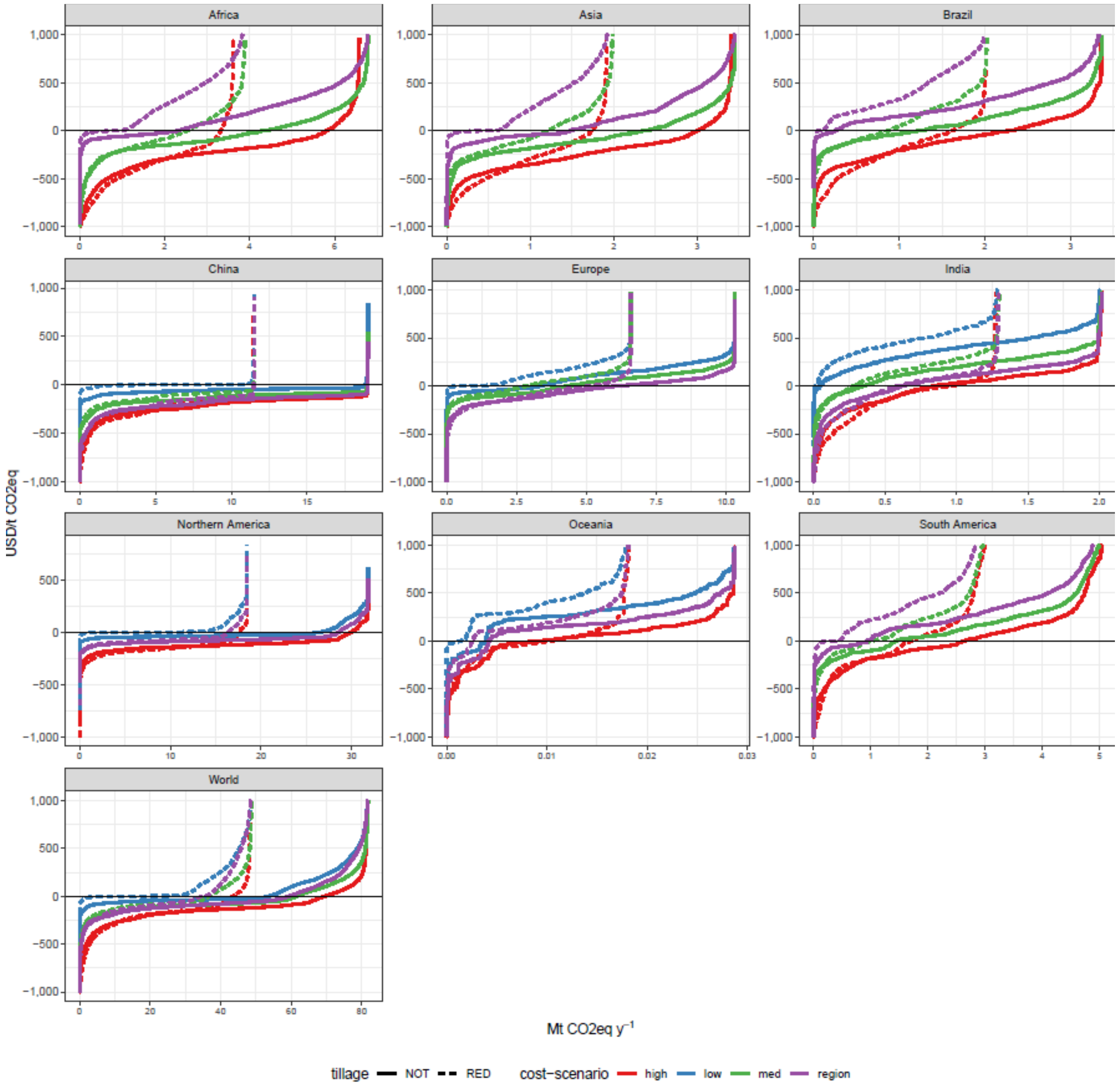


Figure D2: Regional MACCs for corn.

This project has received funding from the **European Union's Horizon 2020** research and innovation programme under grant agreement **No 774378**