Management induced changes of soil organic carbon on global croplands

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Abstract. Soil organic carbon (SOC) is one of larges carbon stocks on earth. It is three times larger than the biospheric pool and more than twice as big as the athmospheric pool, when looking into the first meter of the earth soil profile. Human cropping activties led and still lead to a depletion of SOC though, which are so far not well represented in global assessments of historic carbon emissions. While SOC models often represent well the biochemical processes that lead to the accumulation and decay of SOC, the management decisions driving these biophysical processes are still little investigated on the global scale. Here we create a spatial explicit data set for agricutural management on cropland, especially for crop residue and manure management, based on global historic production (FAOSTAT), and land-use (LUH2) data; and combine it with the IPCC Tier 2 approach to create a half degree resolution SOC stock changes on mineral soils. We estimate that due to arable farming soils have lost over 37 GtOC of which 4 GtOC have been regained within the period 1975-2010. We show that, our results on global scale based on Tier 2 IPCC methodolgy are in good agreement with Tier 1 default assumptions. We also find that SOC is very sensitive to management decision such as residue recycling indicating the nessessity to incorporated better management data in soil models.

1 Introduction

Soil Organic Carbon (SOC), the amount of organic carbon stored through the earth's soil, is the largest terrestrial carbon pool, exceeding the carbon in the atmospheric and vegetation pools multiple times (Batjes). As such, even small changes in drivers of SOC may thus lead to substantial shifts in earth carbon cycle and influence the amount of CO2 in the atmosphere (ref. permafrost melting). The specific amount of carbon stored in the soil is, however, uncertain, with estimates ranging from 1500 to 2400 GtC for the first meter of the soil profile (Batjes, 1996; more). The quality of SOC maps has markedly improved in recent decades, along with better understanding of the factors driving the global magnitude, distribution, and dynamics of SOC pools. Natural properties like climatic, biophysical, and landscape characteristics clearly play the most important roles to determine SOC variations over space and time. Human intervention, including land cover change and land management, has however added a further driver to SOC change, which alters terrestrial carbon pools in much shorter time scales and is likely one of the most dominant driver of SOC changes on managed land today (cite). Recent studies identify the anthropogenic SOC debt for the first meter of the soil profile at around 116 GtC (Sanderman et al.), compared to previous estimates between 60-130 GtC (Lal, 2006). Other studies have focused more closely on spatially disaggregation of SOC changes via advanced digital soil mapping techniques (S-World; Stoorvogel 2, 2017) or better representation of biogeochemical processes within SOC dynamics (Hararuk, 20XX). While providing a rough estimate of the order of magnitude of change, these studies lack a detailed consideration of land management, especially of agricultural activities. Field-scale models (cite Daycent, RothC, Ecosse, C-Tool) are able to capture these land management impacts by using detailed information on crop yield levels, fertilizer inputs and various other on-farm measures. However, due to the lack of comprehensive global management data as input to these models, scaling up to the global extent remains a complex challenge. Our study combines an spatially explicit estimate of agricultural management data on the global level with a 3-pool SOC model parametrized for global croplands. This allows us to estimate SOC stock change factors, as well as organic carbon flow dynamics within the agricultural system. We thereby consider change in SOC caused by historical land cover change as well as of different agricultural management practices, including residue recycling, manure amendments, irrigation, and tillage. We provide the first global, spatially explicit SOC loss maps that considers detailed agricultural management. This paper will first introduce in the methods section the basic concept of SOC dynamics as applied in this study. We continue with a detailed description of the global gridded management data used here, including crop production levels, residue recycling rates, manure amendments, and the adoption of irrigation and tillage practices. Lastly, we shortly refer to the concept of stock change factors as outlined in the Tier 1 approach of the IPCC guidelines. In our results section we focus on the SOC dynamics of global croplands by (1) analysing the spatially explicit distribution and depletion of SOC from 1975 to 2010, (2) comparing impacts of different management effects on SOC emissions and (3) quantify global agricultural carbon flows and stocks to compare the importance of various management aspects. Finally, we discuss and compare our findings – including their implications for SOC model development – and conclude with an outlook on the ability of SOC management to mitigate climate change and contribute to negative greenhouse gas emissions.

2 Method

We compile calculations as open-source R packages available at github.com/pik-piam/mrcommons (management related functions) and github.com/pik-piam/mrSOCbudget (soil dynamic related functions), which are both based on the MADRaT package (package citation?), a framework which aims to improve reproducibility and transparency in data processing. In the following chapter we outine the most important relationships and assumptions. Table @ref(append:subsection2mrfunctions) provides further information on corresponding code within the R packages.

2.1 SOC Stocks and Stock changes following the Tier 2 steady-state method

Following the tier 2 approach of the refinement of IPCC guidelines vol. 4 (IPCC (2019); short Tier 2 steady-state method) , we estimate soil organic carbon (SOC) stocks and their change over time for cropland on half-degree resolution from 1975 to 2010. We assume the current SOC state converges towards a steady state, which itself is depending on biophysical, climatic and agronomic conditions. Therefore we conduct the following three steps within each yearly timestep: (1) We calculate annual land-use (sub-)type-specific steady states and decay rates for SOC stocks, (2) we account for land conversion by transferring SOC from and to an other land-use type representad as natural vegetation, (3) we estimate SOC stocks and changes based on the stocks of the previous time period, the steady state stocks and the decay rate.

2.1.1 Steady-state SOC stocks and decay rates

In a simple first order kinetic approach the steady-state soil organic carbon stocks SOC^{eq} are given by

$$SOC^{eq} = \frac{C^{\text{in}}}{k} \qquad \forall \quad i,t(\#eq:inoutflow) \tag{1}$$

with C^{in} being carbon inputs to the soil, k denoting the soil organic carbon decay rate; as well as i representing grid cell indices and t years. We use for our calculations the Tier 2 steady-state method, which assumes three soil carbon sub-pools (active, slow and passive) and interactions between them. Annual carbon inflow to each sub-pool and annual decay rates of each sub-pool are the key components to determining steady-state SOC stocks.

Carbon Inputs to the Soil

We account for different carbon input sources depending on the two land-use types we distinguish: croplands and natural vegetated land as representative for all other land use (see table @ref(tab:datasourceinputs)). Carbon sources for cropland are recycled crop residues, below ground biomass of crops (for both see @ref(sec:residues)) and recycled manure (see @ref(sec:livstmanure)); for natural vegetation litterfall (Schaphoff et al., 2018) is the only source of carbon inflow to the soil.

Following the IPCC carbon accounting methodology, carbon inputs are disaggregated into metabolic and structural components depending on their lignin and nitrogen content (see IPCC (2019)). For each component the sum of all carbon input sources is allocated to the respective SOC sub-pools via transfer coefficients. This implies that both the amount of carbon as well as its structural composition determine the effective inflow. Data sources for all considered carbon inputs as well as for lignin and nitrogen content can be found in table @ref(tab:datasourceinputs).

Table 1. Type and data sources for carbon inputs to different land-use types

land-use types	source of carbon inputs	data source	nitrogen and lignin content
Cropland	residues	FAOSTAT, LPJmL4 [2, sec:residues]	default values given by [2]
	dead below ground biomass of crops	FAOSTAT, LPJmL4 [2, sec:residues]	default values given by [2]
	manure	FAOSTAT, Isabelle [2, sec:manure]	default values given by [2]
Natural vegetation	annual litterfall	LPJmL4 [4]	Nitrogen and lignin content of tree compartments used in CENTURY [4]

SOC decay

The sub-pool specific decay rates are influenced by climatic conditions, biophysical and biochemical soil properties as well as management factors that all vary over time (t) and space (i). Following the Tier 2 steady-state method we consider temperature (temp), water (wat), sand fraction (sf) and tillage (till) effects to account for spatial variation of decay rates. Thus k_{sub} is given by

$$
\begin{aligned}
k_{active,t,i} &= k_{active} && \cdot temp_{t,i} \cdot wat_{t,i} && \cdot till_{t,i} \cdot sf_{t,i} \\
k_{slow,t,i} &= k_{slow} && \cdot temp_{t,i} \cdot wat_{t,i} && \cdot till_{t,i} \\
k_{passive,t,i} &= k_{passive} && \cdot temp_{t,i} \cdot wat_{t,i} && (\#eq:decayrates)
\end{aligned} \tag{2}
$$

For cropland we distinguish the effect of different tillage (see @ref(sec:tillage)) and irrigation (see @ref(sec:irrigation)) practices on decay rates, whereas for natural vegetation, we assume rainfed and non-tilled conditions. Data sources as well as drivers considered for each land-use types are shown in table @ref(tab:datasourcedecay). To account for variations of decay rates within each grid cell due to different tillage and irrigation regimes, average rates based on area shares are calculated.

Table 2. Type and data sources for carbon inputs to different land-use types

land-use types	type of decay driver	parameter use to represent driver	data source
all	Soil quality	Sand fraction of the first 0-30 cm	[SoilGrids]
	Mircobial activity	air temperature	[CRUp4.0]
	Water restriction	precipitation & potential evapotranspiration	[CRUp4.0]
Cropland (additionally)	Water restriction*	irrigation	[sec:irrigation]
	Soil disturbance	tillage	[sec:tillage]

(#tab:datasourcedecay)

2.1.2 SOC transfer between land-use types

We calculate SOC stocks based on the area shares of land-use types (lut) within the half-degree grid cells (i). If land is converted from one land-use type into others (!lut), the respective share of the SOC stocks is reallocated. We account for land conversion at the beginning of each time step t by calculating a preliminary stock $SOC_{lut,t*}$ via

$$SOC_{lut,t*} = SOC_{lut,t-1} - \frac{SOC_{lut,t-1}}{A_{lut,t-1}} \cdot AR_{lut,t} + \frac{SOC_{!lut,t-1}}{A_{!lut,t-1}} \cdot AE_{lut,t} \qquad \forall \quad sub, i(\#eq:ctransfer) \tag{3}$$

with A being the area, AR the area reduction and AE the area expansion for a given land-use type lut. Note that $!lut$ denotes the sum over all other land-use types, which decreases in the specific time step t. Data sources and methodology on land-use states and changes are described in @ref(sec:landuse).

2.1.3 Total SOC stocks and stock changes

Carbon stocks SOC for each sub-pool (sub) converge towards the calculated steady-state stock SOC^{eq} for each land-use type (lut), each sub-pool (sub) and each annual time step (t) like

$$SOC_t = SOC_{t-1} + (SOC_t^{eq} - SOC_{t-1}) \cdot k_t \cdot 1\mathrm{a} \qquad \forall \qquad lut, sub, i.(\#eq:SOCstate) \tag{4}$$

Reformulating this equation, we obtain a massbalance equation as follows

$$SOC_t = SOC_{t-1} - \underbrace{SOC_{t-1} \cdot k_t \cdot 1\mathrm{a}}_{\text{outflow}} + \overbrace{SOC_t^{eq} \cdot k_t \cdot 1\mathrm{a}}^{\text{input (using equation (1))}} \qquad \forall \quad lut, sub, i.(\#eq:steadystate2budget) \tag{5}$$

The global SOC stock for each time step can than be calculated via

$$SOC_t = \sum_i \underbrace{\sum_{lut} \overbrace{\sum_{sub} SOC_{lut,sub,t,i}}^{SOC_{lut,t,i} \text{ – land-use type specific SOC stock within cell}}}_{SOC_{t,i} \text{ – total SOC stock within cell}} . \qquad (\#eq:totalstock) \tag{6}$$

According to the IPCC guidelines SOC changes can be calculates as the difference of two (aufeinander folgenden) years (see Eq. 5.0A in (IPCC, 2019)). This however will also include naturally occured changes due to climatic variance over time. For our study we will define the absolute and relative SOC changes in relation to a potential natural state SOC_{pnv} under the same climatic conditions at time t in grid cell i, that is based on the natural vegetation SOC calculations as defined above without accounting for land conversion from cropland at any time. The absolute changes ΔSOC and relative changes F^{SCF} a thus given by

$$\Delta SOC_{t,i} = SOC_{t,i} - SOC_{pnv,t,i} \quad , \qquad F^{SCF}_{t,i} = \frac{SOC_{t,i}}{SOC_{pnv,t,i}} .(\#eq:totalstock) \tag{7}$$

Note that the absolution changes ΔSOC can be also interpreted as the SOC gap due to human cropping activits; whereas relative changes F^{SCF} can be denoted as stock change factors as defined within the IPCC guidelines of 2006 (IPCC, 2006). Note that the SOC gap is to the negated cummulative SOC emission also refered to as SOC debt (cite Sanderman) of mankind.

2.1.4 Initialisation of SOC pools

To initialize all SOC sub-pools we assume that cropped land as well as natural vegetation are in a steady state for the specific configuration present within the initialization year 1961. We assume after a spin-up period of 15 years reliable results start from 1975 and improve over time, since dependency on the initial conditions will decrease.

2.2 Agricultural management data on 0.5 degree resolution

We compile country-specific FAO production and cropland statistics (FAOSTAT, 2016) to a harmonized and consistent data set. The data is prepared in 5 year time steps from 1965 to 2010, which, together with the spin up phase, restricts our analysis to time span from 1975 to 2010. For all the following data, if not declared differently, we interpolate values linearly between the time steps and hold them constant before 1965.

2.2.1 Landuse and Landuse Change

Land-use patterns are based on the Land-Use Harmonization 2 (Hurtt et al., 2020) data set, which we aggregate from quarter degree to half degree resolution. We disaggregate the five different cropland subcategories (c3ann, c3per, c4ann, c4per, c3nfx) of LUH2 into our 17 crop groups, applying the relative shares for each grid cell based on the country and year specific area harvested shares of FAOSTAT data (FAOSTAT, 2016) (see @ref(append:Tableluh2fao2mag) for more details on the crop group mapping). Land-use transitions are calculated as net area differences of the land-use data on half-degree.

2.2.2 Crop and Crop Residues Production

Crop Production

Using half-degree yield data from LPJmL (Schaphoff et al., 2018) as well as half-degree cropland patterns (see @ref(sec:landuse)) we compile crop group specific half-degree production patterns. We calibrate cellular yields with a country-level calibration factor for each crop group to meet historical FAOSTAT production (FAOSTAT, 2016). Note that by using physical cropland areas we account for multiple crop harvest events as well as for fallows.

Crop Residue Production

Crop residue production and management is based on a revised methodology of (Bodirsky et al., 2012) and key aspects are explained here given its central role for soil carbon modelling. Starting from harvested crop production (CP) estimates and their respective harvested crop area (CA), we estimate above-ground (AGR) and below-ground (BGR) residual biomass using crop group (cg) specific harvest indices (HI) and root:shoot ratios (RS) as follows

$$\begin{aligned} AGR &= CP \cdot HI_{\text{slope}} + CA \cdot HI_{\text{intercept}} && \text{and} \\ BGR &= (CP + AGR) \cdot RS && \forall \quad cg, i, t. (\#eq: resbiomass) \end{aligned} \tag{8}$$

Following the IPCC guidelines, we split the harvest index into a yield and an area dependend fraction (IPCC, 2006). Note that deviating from (Bodirsky et al., 2012) we use harvested instead of physical crop area to account for increased residue biomass due to multiple cropping and decreased amounts on fallow land. We assume that all BGR are recycled to the soil, whereas AGR can be burned or harvested for other purposes such as feeding animals (**?**), fuel or for material use.

Burned Residues

A fixed share of the AGR is assumed to be burned on field depending on the per-capita income of the country. Following (**?**)) we assume 25% burn share for low-income countries according to worldbank definitions ($< 1000 \frac{USD}{yr\,cap}$), 15% for high-income ($> 10000\,\frac{USD}{yr\,cap}$) and linearly interpolate shares for all middle-income countries depending on their per-capita income. Depending on the crop group 80–90% of the residue carbon burned on the fields are lost within the combustion process (IPCC, 2006).

Residue Usage

We compile out of our 17 crop groups, three residue groups (straw, high-lignin and low-lignin residues) with additional demand for other purposes and one residue with no double use (see @ref(append:Tablekcr2kres)). Residue feed demand for five different livestock groups is based on country- and residue-group-specific feed baskets (see (**?**)), taking available AGR biomass as well as livestock productivity into account. We estimate, for low-income countries, a material-use share for straw residues of 5% and a fuel-share of 10% for all used residues groups in low-income countries. For high-income countries, no withdrawal for material or fuel use is assumend, and middle-income countries use shares are linearly interpolated based on per-capita income. The remaining AGR as well as all BGR are assumend to be recycled to the soil. We limit high recycling shares at $10\frac{\mathrm{tC}}{\mathrm{ha}}$ to correct for outliers.

Dry Matter to Carbon Transformation

To transform dry matter estimates into carbon, we compiled crop-group and plant part specific carbon to dry matter (c:dm) ratios (see @ref(append:Tablec2dm)).

2.2.3 Livestock Distribution and Manure Excretion

We assume that manure is applied at its excretion place, leaving the livestock distribution the driving factor for the spatial pattern of manuring.

Livestock Distribution To disaggregate country level FAOSTAT livestock production values to the half-degree scale, we use the following rule-based assumptions, drawing from the approach of (Robinson et al., 2014), and uses feed basket assumptions based on a revised methodology from (**?**). We differentiate between ruminant and monogastric systems, as well as extensive and intensive systems. For ruminants, we assume that livestock is located where the production of feed occurs. We distingush between grazed pasture, which is converted into livestock products from extensive systems; and all other (crop-based) feeds, which we consider to be consumend in intensive systems. For poultry, egg and monogastric meat production we use the per-capita income of the country to divide between intensive and extensive production systems. For low-income countries, we assume extensive production systems. We locate them according to the share of built-up areas based on the idea that these animals are held in subsistence or small-holder farming systems with a high labour per animal ratio. Intensive production associated with higher income countries, is distributed within a country using again share of crop-based feed production, assuming that feed availability is the most driving factor for livestock location.

Manure Excretion, Storage and Recycling Manure production and management is based on a revised methodology of (Bodirsky et al., 2012) and is presented here due to its central role in soil carbon modelling. Based on the gridded livestock distribution we calculate excretions by estimating the nitrogen balance of the livestock system on the basis of comprehensive livestock feed baskets (**?**), assuming that all nitrogen in protein feed intake, minus the nitrogen in the slaughter mass, is excreted. Carbon in excreted manure is estimated by applying fixed C:N ratios (given by (IPCC, 2019)). Depending on the feed system we assume manure to be handled in four different ways: All manure orginated from pasture feed intake is excreted directly to pastures and rangelands (pasture grazing), deducting manure collected as fuel. Manure fuel shares are estimated using IPCC default values (**?**). Whereas for low-income countries, we adopt a share of 25% of crop residues in feed intake directly consumend and excreted on crop fields (stubble grazing), we do not consider any stubble grazing in high-income countries; middle-income countries see linearly interpolated shares depending on their per-capita income. For all other feed items we assume the manure to be stored in animal waste management systems associated with livestock housing. To estimate the carbon actually recycled to the soil, we account for carbon losses during storage and recycling shares in different animal waste management and grazing systems. Whereas we assume no losses for pasture and stubble grazing, we consider that the manure collected as fuel is not recycled. For manure stored in different animal waste management systems we compiled carbon loss rates partly depending on the nitrogen loss rates as specified in (Bodirsky et al., 2012) (see @ref(append:TableclossAWMS)). We limit high application shares at $10\frac{\mathrm{tC}}{\mathrm{ha}}$ to correct for outliers.

2.2.4 Irrigation

We use irrigation area shares to modify the water effect on decomposition by weighting the irrigated and rainfed water factors based on these shares. The LUH2v2 data set provides irrigated fractions for their cropland subcategories. We apply aggregated area shares, leading to the same impact of irrigation on all of our crop groups. Moreover we assume the irrigation effect to be present for all 12 months of a year in grid cells, that has been marked as irrigated.

2.2.5 Tillage

To account for the distribution of tillage to the three different tillage types specfied by the IPCC - full tillage, reduced tillage and no tillage -, we assume that all natural land and pastures are not tilled, whereas as default annual crops are under full and perennials under reduced tillage. Furthermore we assume no tillage in cropland cells specified as no tillage cell based on the historic global gridded tillage data set from Prowollik (Porwollik et al., 2018). Porwollik data set is extended by to the period of 1974-2010 by combining country-level data on conservation agriculture (ca) area values from AQUASTAT (FAO, 2016) and LUH2 crop areas together with the methodolgy of Porwollik to identify potential no tillage cells.

2.3 SOC Stocks and Stock changes following Tier 1

Additionally to the tier 2 approach of the refinement of IPCC guidelines vol. 4 (IPCC, 2019) and the detailed analysis of management data coming with it, SOC changes can be estimated using the IPCC tier 1 approach of IPCC guidelines vol. 4 (IPCC (2006), IPCC (2019)). Here, stocks are calculated via stock change factors (F^{SCF}) given by the IPCC for the topsoil (0-30 cm) and based on observational data. F^{SCF} are differentiated by different crop, management and input systems (here summarized under m) reflecting different dynamics under changed in- and outflows without explicitly tracking these. Moreover F^{SCF} vary for different climatic zones (c) specified by the IPCC (see @ref(append:climatemap)). The actual SOC stocks as thus calulated based on a given reference SOC stock by

$$SOC_i^{\text{target}} = \sum_{c,m} T_{c,i} \cdot SOC^{\text{ref}} \cdot F_{c,m}^{SCF} \qquad \forall \quad t, (\#eq:tier1) \tag{9}$$

with $T_{c,i}$ being the translation matrix for grid cells i into corresponding climate zones c. For this analysis we use the default F^{SCF} from the Tier 1 method of (IPCC, 2006), and (IPCC, 2019) as a comparison and constistency check for our more detailed budget approach.

3 Results

We present simulation results of our SOC budget focusing on cropland areas for the year 2010 as well as global trends of SOC stock changes for the period from 1975 to 2010.

3.1 SOC distribution and depletion

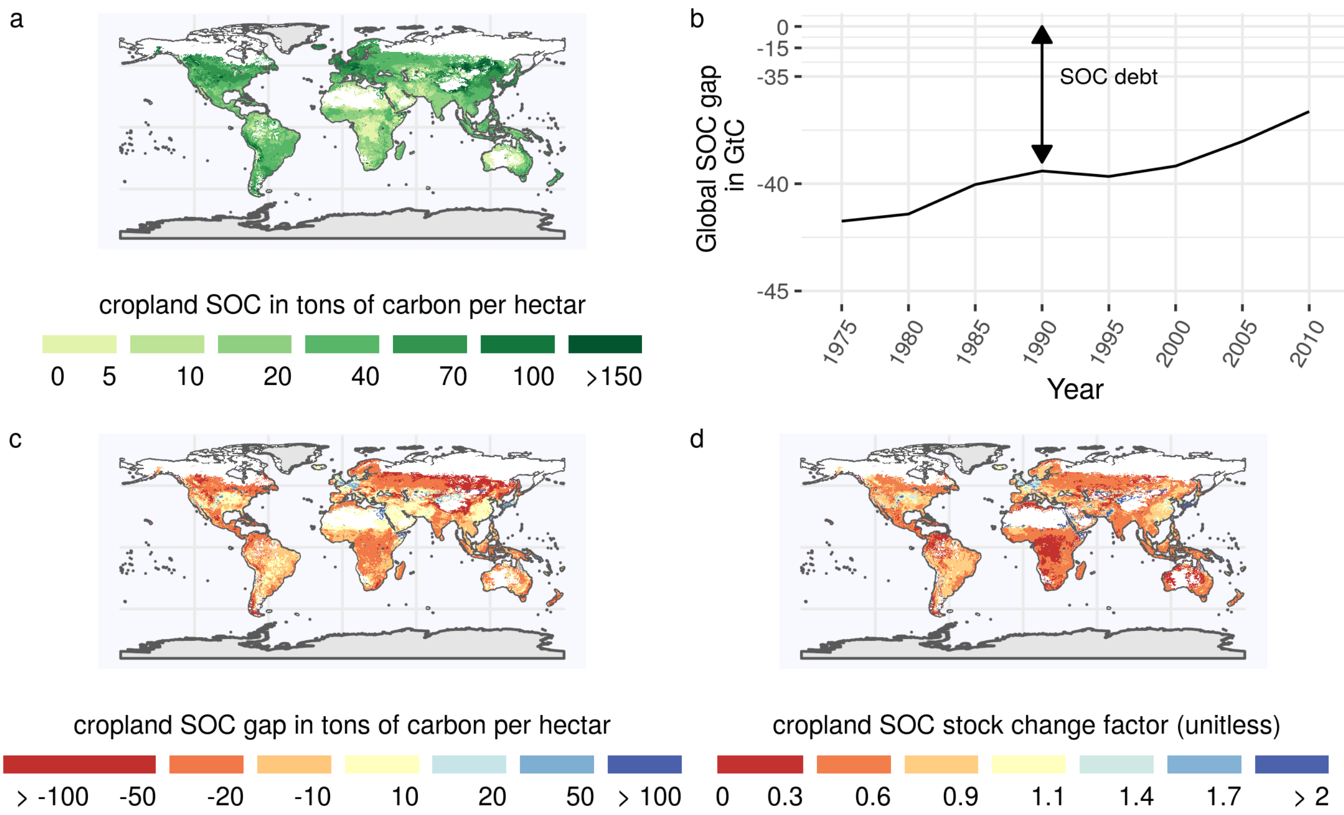

Figure 1. (a): Distribution of total global SOC stocks on cropland shows high carbon stocks in high yielding areas. (b): The SOC debt is decreasing over time, meaning net SOC gains on global croplands over the last decades. (c)+(d): Absolute (c) and relative (d) SOC stocks compared to a potential natural state showing different hot spots of SOC dynamics. Whereas the absolute losses might be in temperate dry regions, relative losses are more prominent in tropical moist areas.

In fig. 1(a) we provide the first world map of SOC on croplands considering real world management data on the global scale. Our spatially explicit results moreover show hot spots of SOC losses as well as gains in two different ways: 1. Absolute SOC changes (see fig. 1(c)) indicate areas with high importance for the global SOC emissions. The might be driven by huge relative losses or a high natural stock, from which even small deviations could lead to substantial losses. 2. To attribute SOC losses to insufficient agricultural management relative SOC changes (F^{SCF}, see fig. 1(d)) are a helpful tool. They indicate areas with huge difference in carbon inflows or SOC decay compared to natural vegetation, that might be overcome due to improved agricultural pratices.

3.2 Agricultural management effects on SOC emissions and cycling

Global cummulative SOC emissions are decreasing (see fig. 1(c)). Fig. 2 reveals the relative impact of management effects by freezing tillage areas as well as carbon inflows from residues or manure at the level of 1975. Our counterfactual scenarios show that the increasing residue carbon input had the biggest overall effect on SOC stocks. Without changes in management regimes especially in residue inflows to the soil, global cummulative SOC emissions would still grow. The strong effect of carbon residue amounts are also visible in the carbon flow diagram for agricultural production for the year 2010 (see fig. 3)

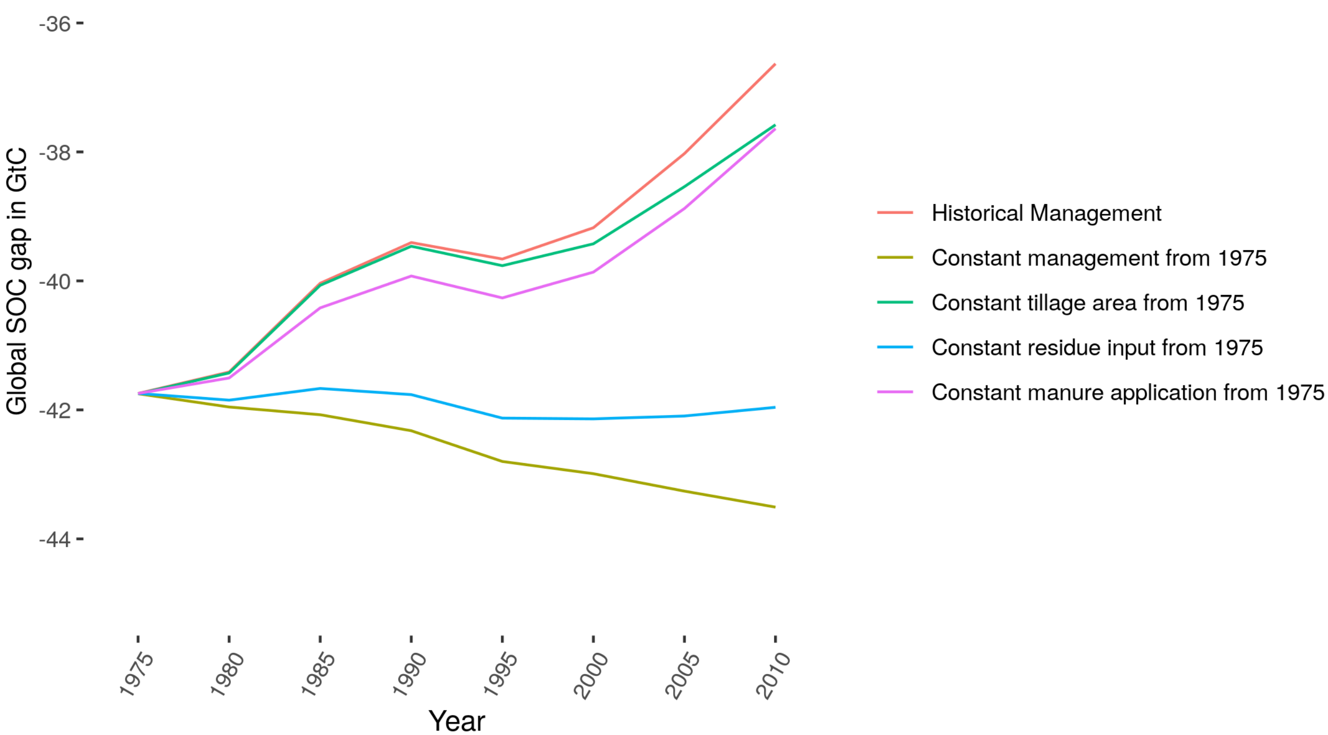

Figure 2. Global SOC gap in GtC for various stylized management counterfactual scenarios compared to the modeled historical baseline.

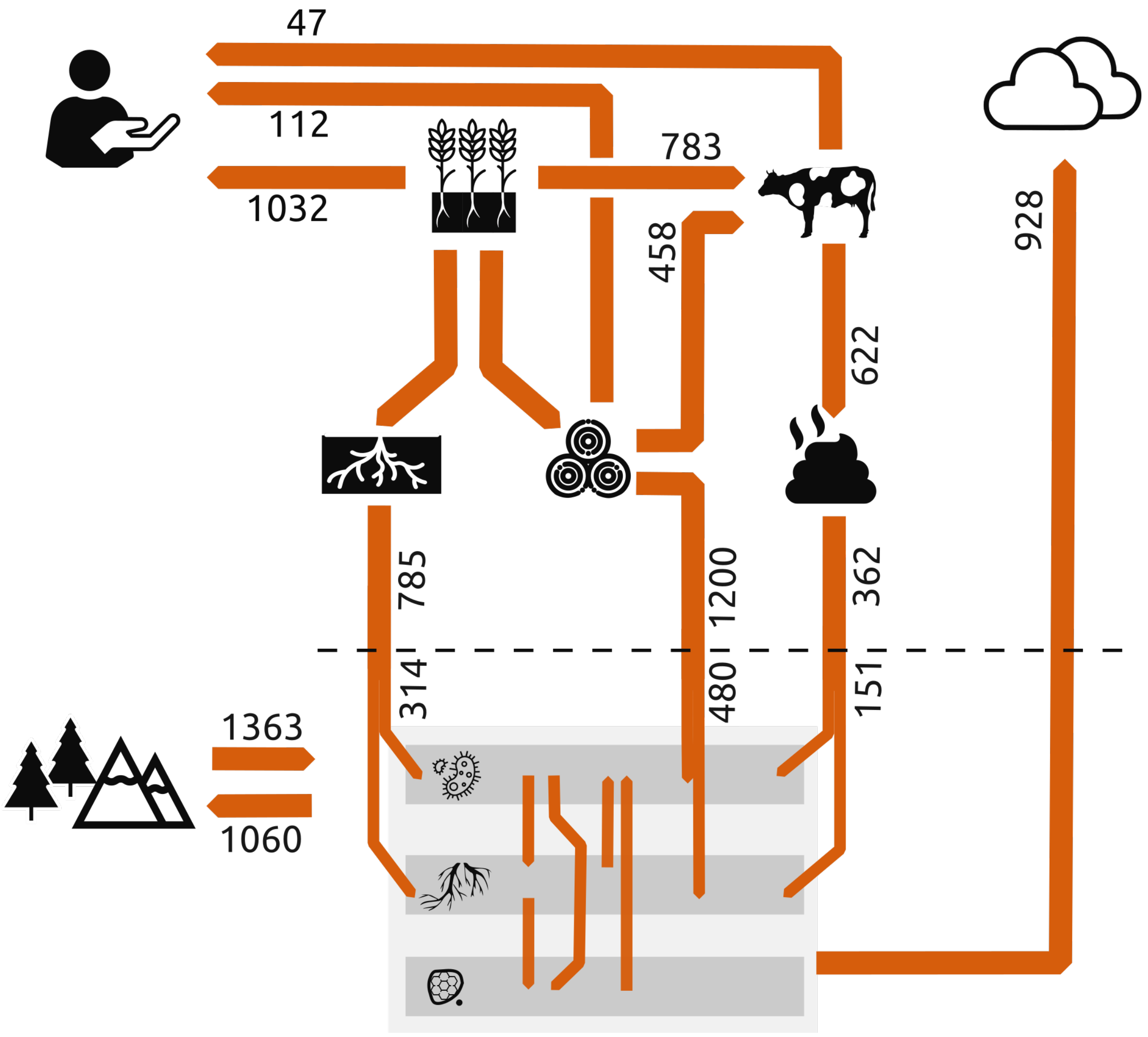

Figure 3. Global carbon flows (small numbers) and stocks (bold numbers) within the agricultural system for the year 2010 (in MtC): Most important carbon sources on cropland are crop residues. Note the two numbers on carbon inputs to soil denote carbon applied to the field and carbon entering the soil (difference is decomposted before official counting as soil).

4 Discussion

4.1 Including agricultural management data changes the sign of the trend

This study provides an analysis on historic SOC stock changes on cropland. We determine the SOC trends on cropland compared to a potential natural vegeted world under the same historic climatic conditions (SOC_{natveg}) leading to a cummulative SOC emission since dawn of mankind of around 37 GtC in 2010. Whereas recent modelling estimates on global SOC emissions indicate an on going increase of SOC emissions (Sanderman et al, Pugh et al.), our study indicates that the global SOC gap might be closing slowly.

According to Sanderman et al. cummulative SOC emissions since beginning of human cropping activities have been at around 37 GtC for the first 30 cm of the soil with half of it attributed to grazing. It was also pointed out, that this results might be conservative estimates and low compared to experimental results, leaving our estimate of 37 GtC in 2010 for cropland emissions only in alignment with Sanderman et al. estimates considering the hugh uncertainties in modelling SOC on the global scale. Furtherore the results of Sanderman et al. calculated historical trends based on agricultural land expansion without considering SOC variations due to different management systems at all. In Pugh et al. management effects like tillage and residue recycling have been considered, but neither changes over time nor alignment to oberserved historical data like yields levels or no tillage areas were taken into account. Under this assumptions this study only found marginal effect of crop productivity and other management effects on cummulative SOC emissions.

Nevertheless our results show, when purely focusing on the past decades, the moderate global cropland expansion of around 11% between 1974 and 2010, is outweighted by improved agricultural yields ad practises. Moreover our sensitivity analysis indicades that 1. yield increases and with that the increase in residue biomass might play the most important role, followed by 2. enhanced residue recycling rates, 3. improved manure recycling (e.g. due to improved animal waste management system) and 4. the adoption of no tillage practises.

Modelling management effects on the global scale comes however with huge parametic and systematic uncertainties. One aspect pointed out by Keel (2017) as well as by Smith (2019) might be that carbon input calculations are highly sensitive to the choice of allometric functions determining below and above ground residue estimates from harvested quantities. Keel et al. questioned, that below ground residues might increase with a fixed root:shot ratio rather than being independend from productivity gains. Following this argumentation SOC results shown in this study might especially in high-yielding farming system overestimate actual SOC stocks. However according to our study above ground residue biomass recycling seem to contribute even more to overall SOC stocks due to higher input rates.

4.2 Modeled management effect inline with default IPCC assumptions

To validated the effect of our modelled SOC stocks and stock changes under management, we compare our results to default IPCC stock changes factors (cite), which are based on measurement data for croplands (see @ref(tab:SCFtable)).

Source	Subsystem/Year	tropical moist	tropical dry	temperate dry	temperate moist
IPCC2006	default	0.48	0.58-0.64	0.80	0.69
IPCC2006	low input	0.44	0.55-0.61	0.74	0.66
IPCC2019	default	0.83	0.92	0.76-0.77	0.69-0.70
IPCC2019	low input	0.76	0.87	0.70-0.71	0.66-0.67
SOC budget	1990	0.37	0.41	0.62	0.55
SOC budget	2010	0.49	0.56	0.77	0.62

Figure 4. This table shows IPCC 2006 as well as 2019 default (medium input) and low input regimes stock change factors F_{SCF} without other subsystem consideration compared results of this study (SOC budget) for 1990 and 2010.

Our climate zone specific, aggregated F_{SCF} correspond very well to the tier 1 estimation of IPCC, 2006 of F_{SOC}. For the tropical regions the assumptions changed notablly from the guidelines in 2006 to the update in 2019, leaving our results too low in comparison with IPCC, 2019. Considering yield gaps in mainly developing regions in the tropics the default assumption of medium input systems, might be an overestimation of actual SOC state. The additional effect of considering low inpout regimes in tropical regions can however not explain the full mismatch to IPCC 2019 values but account for at least 5-7% of it.

4.3 SOC stocks inline with literature

The worlds SOC stock and its changes are highly uncertain (cite), which is visible by the wide range of global SOC stock estimates (see @ref(tab:SOCtable)).

Model/Database	Global SOC in GtC
SOC Budget	679.84
LPJmL4Paper	742.62
WISE	722.32
SoilGrids	1274.18
GSOC	673.39

Figure 5. Modelled as well as data based estimation for global SOC stock (for 2010) in GtC for the first 30 cm of soil.

The global esimates of SOC stock by this study are on the lower edge compared to other modelled results or more data driven estimates. Looking on regional results (fig. SX in supplement), our estimates turn out to be in good agreement for most regions with the largest deviations for boreal areas. Considering that the model was parametrized for croplands, these mismatches are not superising, since the temperature effects on decomposition is most likly fundamentally different for permaforst soils than assumend in this study. To avoid that this bias influences our results, our study focusses exclusively on cropland soils, excluding most of the boreal zone. Morover, when focussing on SOC changes, pristine natural vegetated areas without human land management under the same historic climatic conditions cancel out in the calculation of SOC emissions.

However the natural land representation that is dominating the total SOC stocks of the world and with it also the SOC initialization is lacking proper parametrization of nitrogen and lignin content of litterfall. This leaves carbon inputs and decay behaviour for natural land rather uncertained. As all results are valued against these potential natural SOC the absolute values and also the emissions over time have to be used with caution. Especially in less forested areas the natural land representation might be off, due to parameterization assumptions of the natural litterfall. Nevertheless total SOC stocks are in a reasonable range and the stock change factors F^{SCF} are in good agreement with the Tier 1 default values of 2006. In addition we preformed a sensitivity analysis for lignin and nitrogen parameterization of natural litterfall (see appendix). It shows that the general trend of decreasing SOC emissions is not altered even by rather unlikely parameter choices, that would overestimate natural SOC stocks strongly and therefor lead to high emission in the case of land conversion.

4.4 Important short commings –> move to appendix

Smaller points and shortcommings:

-This study as the IPCC guidelines suggested has limited her focus to the first 30 cm of the soil profile, leaving changes in the subsoil unnoticed. Nevertheless studies (see Don on tillage) have shown, the subsoil to be a game changer in evaluating total SOC losses or gains for no-tillage systems. It has been argued that for intensivly tilled soils, subsoil SOC is increasing due to the import of carbon rich topsoil to deeper soil layers. Following these argumentation SOC stocks in croplands might even be underestimated.

- Fertilizer interaction is not included here by accounting for additional N supply that would alter C:N ratio of the carbon inputs. Tier 2 steady-state method is neglecting fertilizer application, however we would have fertilizer ammounts at hand to include them, if proper representation of fertilizer within the method would be possible to add.

- Pasture dynamics are neglected and treated as natural vegetation, which might be – looking on pasture degradation due to overgrazing – oversimplified for some spots, but is inline with assumption on pasture SOC stocks done before (see Tier 1 IPCC). (Note that also manure excreted to pastures is neglected within these analysis, since we focus purely on cropland dynamics.)

- No tillage adaptaion is neglected on cropland due to less common adoption of no tillage and conservation agriculture. Pastures are assumed to be not tilled at all (propably only heavy managed pastures are tilled with some rotation)

- Irrigated areas are not crop specific and irrigation is not restricted to growing periods (since it is very complex to calculate average growing periods). Crop specific growing periods might be possible using LPJmL data.

- flooded rice area are not represented correctly as parameterization does not hold true for flooded conditions.

- Carbon displacement via leaching and erosion is neglected in this study.

- Non-net/Gross land use transitions are not tracked in this study.

- Within cropland we do not track croparea transitions, but rather look at statistical distributions of the crop functional types. Due to crop rotations and missing data on crop specific distributions, these transitions would be any way rather uncertain.

- The disaggregation of manure to uild-up areas (in the case of extensive monograstrics) is leeding to a lot of displaced manure (?) that is cut off

- It is known that there are mismatches between FAO statistics and LUH areas. As far as possibles there were harmonized within this study.

- “The Tier 2 method does not simulate C change but simply calculates an annual C stock change from the current C stock to the future steady-state soil C stock calculated based on current conditions.” Leading to the fact that our total stock results are highly uncertained.

5 Conclusions

Outlook including perspective on mitigation (and soc enhancement in the future).

6 Appendix

6.1 table on method subsections to functions within R packages

6.2 table on mapping LUH2FAO2MAG

6.3 kcr2kres mapping

6.4 carbon 2 dry matter

Litter is coming from LPJmL in carbon units - transformation with 0.44 is done twice reverting the effect of the transformation

6.5 closs in AWMS - Table

6.6 map on climate zone used for SCF

Code and data availability. Software code for paper and result prepartion can be found under www.github.com/k4rst3ns/. Data used for the output can be found under .

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