UNDERSTANDING THE ROLE OF AGRICULTURAL MANAGEMENT EFFECTS ON GLOBAL SOIL DEGRADATION UTILIZING BIOPHYSICAL MODELING

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"Abel was a keeper of sheep, while Cain was a tiller of the soil."

Genesis 4:2

to J and E

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Abstract

Increasing global food production to achieve food security for a growing world population while at the same time reducing the ecological footprint of agricultural production systems will remain one of the greatest challenges in the next decades. Climate change and soil degradation add additional pressure on food production systems. Different agricultural management practices are proposed as climate mitigation strategies to meet the climate targets outlined in the Paris Agreements in 2015 to limit temperature increase well below 2 °C compared to pre-industrial temperatures, yet the effects are debated among researchers. Soil degradation has negative implications on soil quality and on the capacity of soils to grow food. Previous assessments have shown that 20 to 40% of global cropland is affected by some form of degradation. This thesis aims to analyze the effects of agricultural-driven global soil degradation and advance the knowledge space in this field of research. To this end, I first review the state of knowledge on global soil degradation and give an overview of modeling assessments. I focus on soil organic carbon (SOC) decline as one of the major forms of soil degradation on cropland, which is highly affected by management practices. Further, SOC is highlighted as one of the most important attributes for healthy soils and a useful indicator of the status of soil degradation. Second, to study the effects of different pathways of agricultural management on biophysical and biogeochemical flows, I extended the global ecosystem model Lund-Potsdam-Jena managed Land (LPJmL) by a detailed representation of tillage practices and residue management. This improvement of LPJmL allows for the analysis of management-related effects on agricultural mitigation of climate change adaption and the reduction of environmental impacts. The evaluation of the modeled results shows that LPJmL is capable of reproducing observed management responses on environmental stocks and fluxes. The model can simulate the effects of conservation practices on SOC stocks and CO_2 emissions. And Third, I analyze the historical and future SOC development and the effects of different stylized management assumptions under two different climate change trajectories. This analysis reveals that approximately 215 Pg SOC was lost due to the historical conversion of natural land to cropland. Up to 38 Pg SOC could be additionally lost on already existing cropland until the end of the century if cropland is not managed sustainably. The type of tillage system has small effects on the SOC stocks, while the choice of crop residue treatment is shown to be the main driver governing SOC development. Returning residues to the soil slows the decline of SOC, and positively affects soil moisture and crop productivity, with regional differences. In total, up to 46% of todays' cropland shows the potential for SOC increase, while at least 52% of cropland today will undergo further SOC loss as a form of soil degradation.

Zusammenfassung

Eine der größten Herausforderungen in den kommenden Jahrzehnten wird sein, eine Steigerung der globalen Produktion von Nahrung zu ermöglichen um eine wachsende Weltbevölkerung zu ernähren. In der selben Zeit muss der ökologischen Fußabdruck von landwirtschaftlichen Produktionssystemen ebenfalls reduziert werden. Klimawandel und Bodendegradation üben zusätzlichen Druck auf die Produktionssysteme von Nahrung aus. Verschiedene Praktiken der landwirtschaftlichen Bewirtschaftung werden diskutiert, um das Klimaziel aus dem Pariser Klimaabkommen aus dem Jahre 2015, die atmosphärische Temperaturerhöhung weit unter 2 °C zu belassen, zu erfüllen. Jedoch ist die Wirkung dieser Praktiken in der Wissenschaft umstritten. Bodendegradation hat negative Auswirkungen auf die Bodenqualität und auf die Kapazität des Bodens, Nahrung zu erzeugen. Früheren Einschätzungen nach sind 20% bis 40% der globalen landwirtschaftlichen Fläche von einer Form von Degradation betroffen. Das Ziel dieser Arbeit ist die Analyse der Effekte von landwirtschaftlich getriebener globaler Bodendegradation und das Erweitern des Wissensraumes in diesem Wissenschaftsbereich. Um dies zu erreichen, gebe ich zuerst einen Überblick über das Thema Bodendegradation und die Entwicklungen verschiedener Modellierungsansätze, die sich diesem Thema widmen. Die Bodenbearbeitung, insbesondere das Pflügen, wurde als eine der disruptivsten landwirtschaftlichen Praktiken identifiziert, welche zum Verlust von organischem Bodenkohlenstoff (engl.: Soil Organic Carbon – SOC) und weiteren Formen der Degradation führt. Weiter wurde Bodenkohlenstoff als eine der wichtigsten Eigenschaften von gesunden Böden hervorgehoben, und dient zudem als nützlicher Indikator für den Status der Bodenqualität. Als Zweites, um die Effekte von unterschiedlichen Annahmen zu landwirtschaftlichem Management auf biogeochemische und biophysikalische Flüsse zu untersuchen, erweiterte ich das globale Ökosystemmodell Lund Potsdam Jena managed Land (LPJmL) um eine detaillierte Prozessabbildung von Pflugpraktiken und Effekten von Ernterückständen. Die Erweiterung von LPJmL ermöglicht die Analyse der Effekten von landwirtschaftlichen Managements auf die Anpassung an den Klimawandel, sowie die Analyse zur Reduktion von Umwelteinwirkungen dieser Praktiken. Die Evaluation der Modellergebnisse zeigt, dass LPJmL beobachtete Reaktionen auf Vorräte und Flüsse der Umwelt reproduzieren kann. Das Modell kann die Effekte von naturerhaltender landwirtschaftlicher Bewirtschaftung (im Englischen bekannt als Conservation Agriculture) auf Kohlenstoffvorräte im Boden und CO_2 Emissionen simulieren. Und zum dritten, analysiere ich die historische Dynamik der Entwicklung von Bodenkohlenstoff und den Effekt von stilisierten Annahmen zum zukünftigen Management unter zwei unterschiedlichen Klimaszenarien. Die Ergebnisse dieser Analyse zeigen, dass

Aufgrund der historischen Umwandlung von natürlicher Vegetation zu landwirtschaftlicher Fläche bis zu 215 Pg Kohlenstoff im Boden verloren gegangen sind. Weiterhin könnten bis zum Ende des Jahrhunderts weitere 38 Pg Bodenkohlenstoff zusätzlich verloren gehen, sollte man die heutige landwirtschaftliche Fläche nicht nachhaltig bewirtschaften. Die Ergebnisse lassen aber andeuten, dass die Bewirtschaftung mit dem Pflug geringen Einfluss auf die Kohlenstoffvorräte des gesamten Bodenprofils hat, während die Wahl der Behandlung von Ernterückständen diese erheblich kontrolliert. Die Rückführung von Ernterückständen erhöht nicht nur den Kohlenstoffanteil im Boden, sondern hat auch einen positiven Einfluss auf den Bodenwassergehalt und die Ernteproduktivität, mit regionalen Unterschieden. Die Ergebnisse zeigen, dass insgesamt sind bis zu 46% der heute bewirtschafteten Fläche das Potential zeigen, Bodenkohlenstoff zu steigern, während mindestens 52% der heutigen Agrarfläche von Kohlenstoffverlusten im Boden als eine Form der Bodendegradation betroffen sein könnten.

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Abbreviations and units

Acronym	Full name
BD	Bulk Density
C	Carbon
CAP	Common Agricultural Policy
CEC	Cation Exchange Capacity
CFT	Crop Functional Type
CH_4	Methane
CMIP5/CMIP6	Coupled Model Intercomparison Project Phase 5 & 6
CO_2	Carbon dioxide
[CO_2]	Atmospheric carbon dioxide concentration (ppm)
DGVM	Dynamic Global Vegetation Model
ESM	Earth System Model
EPIC	Environmental Policy Integrated Climate model
GHG	GreenHouse Gas
GIS	Geographical Information System
GLADA	Global Assessment of Land Degradation and Improvement
GLASOD	Global Assessment of Human-Induced Soil Degradation
LPJ	Lund-Potsdam-Jena model
LPJmL	Lund-Potsdam-Jena with managed Land model
LUC	Land-Use Change
MS	Management Setting
N	Nitrogen
N_2O	Nitrous oxide
NDVI	Normalized Difference Vegetation Index
NPP	Net Primary Production
NT_NR	No-Tillage and No Residues returned
NT_R	No-Tillage and Residues returned to the field
P	Phosphorous
PFT	Plant Functional Type
PNV	Potential Natural Vegetation
PTF	PedoTransfer Function
RCP	Representative Concentration Pathway
RD	Relative Difference
RUSLE	Revised Universal Soil Loss Equation
SDG	Sustainable Development Goal

Acronym	Full name
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
T_NR	Tillage and No Residues returned
T_R	Tillage and Residues returned to the field
PET	Potential EvapoTranspiration
USLE	Universal Soil Loss Equation
WHC	Water Holding Capacity

Units

°C	degree Celsius
Bha	Billion hectares (10^9 ha)
g	grams
ha	hectare (100x100 m)
kg	kilogram (10^3 grams)
km	kilometer (10^3 m)
m	meter
Mg	Megagram (10^6 grams)
Mha	Million hectares (10^6 ha)
Pg	Petagram (10^{15} grams)

Chapter 1

General introduction

1.1 Background and motivation

1.1.1 The impact of humans on the Earth system

Humans have shaped their surroundings for thousands of years and cultivated crops to grow food for their consumption or produce animal feed and fiber. It is argued that anthropogenic interventions have impacted Earth's climate through rising greenhouse gas (GHG) emissions already since the late Holocene thousands of years ago, which kept the climate from cooling (Ruddiman, 2007). The impact on the natural biosphere by human activities through land conversion, pollution, and resource extraction has been increasing at an alarming rate, especially since the beginning of the Industrial Revolution in the 1800s A.D. Humans have exploited natural resources and used these for their survival and flourishing of cultures, so much that it is suggested to call the current geological epoch "Anthropocene" (Crutzen, 2006), because of the large anthropogenic impact on Earth's chemical, physical and biological cycles and processes. GHG emissions, as well as the concentrations in the atmosphere, have now reached an unprecedented high level in human history. Today, we face challenges at a global scale, which need integrated assessments and solutions at global, regional, and local scales. One of the most pressing global challenges we are facing is climate change, which is mainly caused by the release of carbon dioxide (CO_2) emissions from fossil-fuel combustion, driven by an increase in human population combined with economic growth (IPCC, 2014, 2013). Economic growth goes along with dietary changes towards calorie-richer and more animal-sourced food, which increases the per-capita need for food, fiber, and energy (Bodirsky et al., 2015; Foley et al., 2011). The human population is expected to increase to 9.7 billion people by 2050 and almost 11 billion people by 2100 (United Nations et al., 2019), creating immense pressure on future food production. To meet the growing future food demand, crop production has to increase without jeopardizing the quality and health of the soil and ecosystems (United Nations et al., 2019). Land degradation and pressure on land resources stress the need for sustainable solutions for food and energy production in the future (Foley et al., 2011).

In 2015, the member states of the United Nations adopted the 2030 Agenda for Sustainable Development (United Nations, 2017) and formulated 17 Sustainable Development Goals (SDGs), which include 169 targets for a better and more sustainable future for humanity. These goals include the targets to end poverty, ensure education for all and reduce inequality. Each of the individual goals defines targets that should be achieved by the year 2030. This thesis aims to examine and answer questions related to SDG 2, "Zero hunger" with the targets to achieve food security and promote sustainable agriculture, and to SDG 15, "Life on land" with the targets to restore and promote sustainable use of terrestrial ecosystems and halt or reverse land degradation. The purpose of the targets is to lay out a framework for policymakers. However, there is an increasing need for relevant indicators to operationalize the SDGs (Hák et al., 2016), as they have been argued to be sometimes inconsistent and include conflicting relations due to the focus on consumption and economic growth as a means of development (Spaiser et al., 2017; Swain, 2018).

1.1.2 Climate change and the role of agriculture

The Earth's climate system consists of a complex interplay of various biophysical cycles, of which the carbon (C) and water cycle play a significant role. Water vapor is the most abundant GHG in our atmosphere, contributing to roughly 60% of Earth's natural greenhouse effect (Held and Soden, 2000). Without the natural greenhouse effect, the global average temperature would be considerably colder at an average of approximately -18 °C, instead of the actual average temperature of +15 °C. Atmospheric temperatures are increasing because GHG emissions in the form of CO_2, methane (CH_4), and nitrous oxide (N_2O) due to fossil fuel combustion, land use, and land-use change (LUC), are contributing to the anthropogenic greenhouse effect (IPCC, 2013). Carbon dioxide is the most abundant anthropogenic GHG contributing mainly to climate change (IPCC, 2014). In February 2021, the global average atmospheric CO_2 concentration ([CO_2]) reached 415.9 ppm (Tans and Keeling, 2021), which is the highest concentration since the middle Pliocene (~3.3-3.0 million years ago) and the highest in human history (Pagani et al., 2010). To assess the future long-term effects of GHG concentration projections on climate change, the Coupled Model Intercomparison Project

Phase 5 (CMIP5) (Collins et al., 2013) developed four different representative concentration pathways (RCPs) scenarios. These RCPs are GHG trajectories, which describe four different climate futures and represent a range of radiative forcing values in the year 2100 (IPCC, 2014).

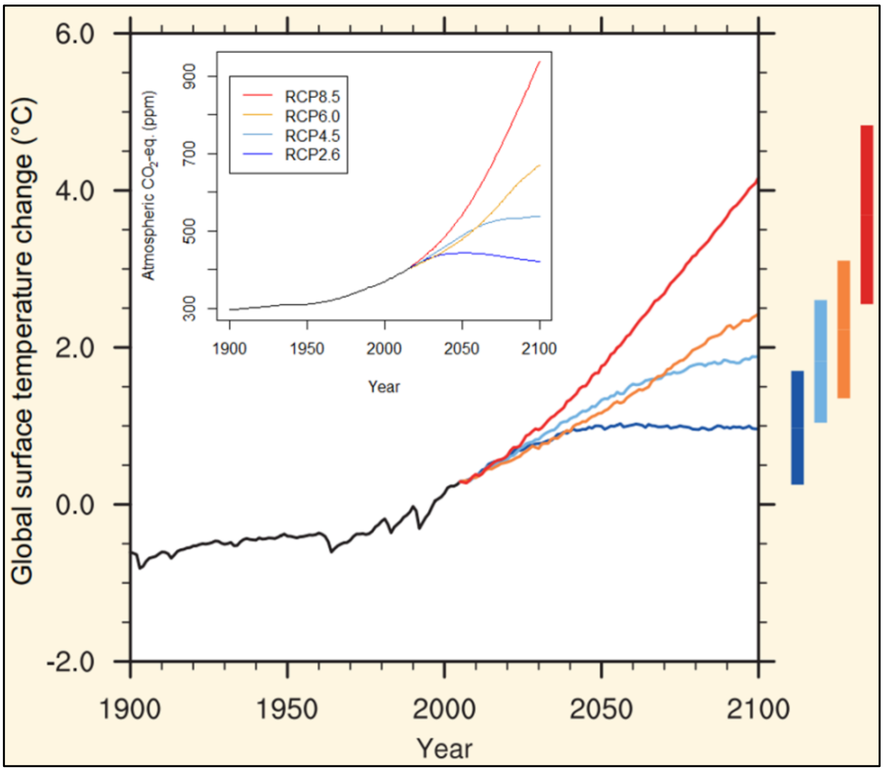

Figure 1-1: Global mean temperature change averaged across all Coupled Model Intercomparison Project Phase 5 (CMIP5) models (relative to 1986–2005) and corresponding CO_2-eq. atmospheric concentration (ppm) for the four Representative Concentration Pathway (RCP) scenarios: RCP2.6 (dark blue), RCP4.5 (light blue), RCP6.0 (orange), and RCP8.5 (red). Ranges for global temperature change by the end of the 21st century are indicated by vertical bars and explain the variability in different climate models. (adapted from Collins et al. (2013))

Each pathway can be translated into an average CO_2-equivalent atmospheric concentration, which causes the atmosphere to warm by up to +4.3 °C relative to the global mean temperature of the years 1986 to 2005 (Fig. 1-1). In Fig. 1-1, the projected global mean change in atmospheric temperatures until the end of the century of each RCP compared to the average of 1981-2005, and corresponding atmospheric CO_2-eq. in ppm, are shown. The higher the radiative forcing trajectory, the higher the average atmospheric temperature increases. In the most moderate scenario RCP2.6, the temperature increase until the end of the century (average of 2081-2100 relative to 1986-2005) could be limited to +1.0 °C (likely range +0.3 °C – +1.7 °C). Yet, in the highest radiative forcing trajectory RCP8.5, temperatures could increase by up to +4.3 °C (likely range of +2.6 °C – +4.8 °C) (IPCC, 2013). The rise in atmospheric temperatures could cause a chain of self-enforcing feedbacks that cannot be reversed, once they have trespassed a tipping point in the Earth system (Steffen et al., 2018). At the same time, higher temperatures increase the risk of droughts and extreme weather events, which reduce crop yields and add additional pressure on agricultural production (Ciais et al., 2005; Velde et al., 2011). Because of increasing atmospheric CO_2 concentrations, some types of plants could benefit through the stimulation of photosynthesis, which might offset some of the negative impacts of climate change. The detailed mechanisms of this so-called CO_2 fertilization effect are not yet fully understood, as an increase in CO_2 concentration could come at the price of micro-nutrient reductions (Müller et al., 2014). Yet, these mechanisms need to be studied and understood in more detail. For example, Köhler et al. (2019) showed that warming could lead to an increase in micro-nutrients, which might compensate for the negative effects of increasing CO_2 in the atmosphere.

Climate change can alter precipitation patterns and rainfall intensities in various regions around the globe (IPCC, 2014). For example, the number of heavy rainfall events in Europe could increase (Routschek et al., 2014) and cause severe damages to crops (Rosenzweig et al., 2002). Generally, it is expected that under climate change the occurrence of extreme weather events is likely to increase (Rahmstorf and Coumou, 2011). These changes in precipitation can have an impact on soil degradation processes, both on water erosion due to extreme rainfall events (Nearing et al., 2005) and on wind erosion due to droughts (Nordstrom and Hotta, 2004). Yet, analyzing the feedback from atmospheric water vapor on precipitation patterns and cloud formations is one of the most challenging research fields in climate science and the main source of uncertainty in climate impact assessments (Dufresne and Bony, 2008; Randall et al., 2007).

Agricultural production contributes directly to climate change through land use and LUC by releasing GHGs in the form of CH_4 from livestock and rice production, N_2O from fertilizer use (artificial fertilizer and manure), and CO_2 from microbial decay and fuel use, influencing the global C and nitrogen (N) balance (Foley et al., 2005; Houghton et al., 2012). Agriculture alone accounts for up to 60% of global anthropogenic N_2O emissions and up to 50% of CH_4 emissions (Smith et al., 2007). Additionally accounting for the emission from LUC, especially through deforestation, total agricultural emissions might be responsible for 17-32% of all anthropogenic GHG emissions (Bellarby et al., 2008).

Agriculture is the most common land use across the globe, with currently up to 1500 million hectares (Mha) of cropland and ~3500 Mha of grassland, totaling ~5000 Mha, or 5 billion hectares (Bha) (FAO, 2020). The agricultural sector alone contributes to total GHG emissions of approximately 11% (in the year 2010), which roughly increases by 1% every year (Tubiello et al., 2015). A variety of agricultural management practices for climate change mitigation have been proposed, with different results (Batjes, 1998; Lal, 2004a; Wang et al., 2016). Generally, all management practices that increase C content in the soil serve this purpose, which can have positive effects on soil quality (Bai et al., 2018), but their effectiveness especially in reducing atmospheric CO_2 is debated controversially (Stockmann et al., 2013; White et al., 2018).

1.1.3 The importance of soils as a depleting resource

Soils play an important part within the global C cycle. They constitute the third-largest reservoir of C on the globe, after the ocean and the geological C pool (Lal, 2008a). Soils store roughly 2400 Pg C in the upper 2 m (Batjes, 2014), which is roughly three times the size of the atmospheric C pool, with 760 Pg C (Lal, 2008a). Cropland soils alone are estimated to store approximately 210 Pg C in the upper 2 m of soil (Jobbágy and Jackson, 2000). The soil and vegetation pool combined store roughly 2800 Pg C and are much smaller compared to the amount of C stored in the ocean (~39000 Pg C), but are crucial for the global C balance because they are much more labile in the short term (Batjes, 2014). Soils are increasingly recognized as a non-renewable resource and play an important role in sustaining food security for the human population (Amundson et al., 2015). Soils supply us with food and fiber and additionally provide us with a variety of ecosystem services such as regulating water, filtering and storing nutrients, hosting biodiversity, controlling erosion, and storing and regulating soil organic carbon (SOC) (Adhikari and Hartemink, 2016; Baer and Birgé, 2018). Mismanagement in agricultural systems has a degrading impact on land and water and thus influences food production (Lal, 2009a). Meeting the rising global food demand in the future has to be realized under the constraints that food production has to increase while reducing the environmental footprint of agriculture at the same time (Foley et al., 2011). Soil degradation has been discussed as a reason for inadequate nutrition of humans through reducing crop yields, decreasing soil fertility, and increasing the susceptibility to drought stress (Lal, 2009b) and has been recognized as a problem at global scale (Bridges and Oldeman, 1999; Gibbs and Salmon, 2015). Soil degradation is affecting a variety of processes at different scales and can be distinguished into physical processes, such as soil compaction and erosion from water and wind; chemical processes, such as salinization, leaching, and acidification; and biological processes, such as the decline in soil biodiversity, and reductions in humus quantity and quality (Lal, 2001a). In the past, agricultural management practices have been mostly neglected in global environmental impact assessments. Yet management has an important influence on environmental processes, as agricultural practices can lead to soil erosion (Van Oost et al., 2006) and can function as a driver of LUC (Bakker et al., 2005). The relevance of degradation processes is poorly understood (Dregne, 2002). Because soil degradation consists of a complex set of processes, it is important to understand these linkages and feedbacks in the context of soil properties and plant growth, as well as on the water, C, and N cycle. Global ecosystem and crop models can provide valuable tools to assess the impact of land use and climate change on future food production, but a detailed representation of agricultural management practices and the effects on soil degradation are currently underrepresented in these models.

1.3 Research questions

The overall objective of this dissertation is to analyze the role of agricultural management practices on global soil degradation and to present a methodology to incorporate agricultural management into a global process-based model. Assessing the impact of management practices on soil degradation at the global scale allows for developing mitigation strategies for more sustainable agricultural production.

Building on the overall objective, the following research questions within this thesis are:

1. What are the most important processes related to soil degradation, and which agricultural management practices are the main drivers promoting soil degradation?
2. How can agricultural management and productivity feedbacks be adequately modeled at the global scale in a process-based modeling framework?
3. How can the impact of agricultural management practices on soil degradation be reduced considering future climate change?

Each of these questions guides the following three chapters and will be answered in the synthesis in Chapter 5.

1.4 Research approach

1.4.1 Modeling framework – Dynamic Global Vegetation Models

Dynamic Global Vegetation Models (DGVMs), as well as Earth System Models (ESMs), are mathematical models which simulate processes related to vegetation growth and incorporate water, C, and nutrient cycles at different complexity (Brovkin et al., 1999; Cox et al., 1998; Foley et al., 1996). They have been developed independently to better understand and quantify the global terrestrial ecosystem and biogeochemical cycles for about 30 years (Cramer et al., 1999; Steffen et al., 1992). DGVMs combine processes that contribute to vegetation structure dynamics and composition and changes in ecosystem geography with biochemical processes (Sitch et al., 2003). Some of these models consider interactions associated with LUC, atmospheric composition, and agricultural management (e.g. Bondeau et al., 2007; Lindeskog et al., 2013). Carbon and water cycle feedbacks, as well as N limitations, have become the main part of DGVMs and ESMs for climate change projections (Krause et al., 2018), including different models such as ORCHIDEE (Vuichard et al., 2018), LPJ (Sitch et al., 2003), Community Land Model (Thornton et al., 2007), LM3V (Gerber et al., 2010), LPJ-GUESS (Smith et al., 2014) and the Environment Policy Integrated Climate model (EPIC) (Izaurralde et al., 2006). These models are just a few examples of numerous developed model applications and models at multiple scales and complexity. Improving the C cycle has become the main focus in improving ESMs for climate change assessments (Luo et al., 2016). DGVMs and ESMs have the advantage of investigating global patterns of biophysical feedbacks and processes, enabling the identification and analysis of regions for which no field trials and ground truth data are available. For future assessments of climate change impacts, DGVMs and ESMs are valuable tools to account for changes in the terrestrial C and water cycle. They also allow for the impact assessment of changes in atmospheric temperatures on plant growth and food production.

1.4.2 The Lund-Potsdam-Jena with managed Land DGVM model

The Lund-Potsdam-Jena with managed Land (LPJmL) model is a well-established process-based dynamic global vegetation and crop model, partly developed at the Potsdam Institute for Climate Impact Research (PIK). The LPJmL model uses inputs on soil texture, climate, and land-use data and explicitly simulates process-based, global-scale representations of terrestrial vegetation, biophysical cycles, and land-atmosphere exchanges. Such cycles and feedbacks include C and water exchanges, as well as yield and productivity of crops within 0.5° grid cells (Bondeau et al., 2007; Schaphoff et al., 2018a). LPJmL extends the predecessor model LPJ (Sitch et al., 2003) that accounts for potential natural vegetation (PNV) only, by representing and simulating the productivity and yield of the most important global crops. The LPJmL model has been widely applied to answer research questions related to agricultural production (Bondeau et al., 2007; Müller and Robertson, 2014; Tilman et al., 2002), C cycle and permafrost (Schaphoff et al., 2018b, 2013), hydrology (Fader et al., 2011, 2010; Rost et al., 2008), bioenergy (Beringer et al., 2011), grassland (Rolinski et al., 2018), fire spread and behavior (Thonicke et al., 2010) and land use (Müller et al., 2007). Recently, the LPJmL model was extended by the representation of the terrestrial N cycle to account for feedbacks from N limitation (von Bloh et al., 2018).

Natural plants in LPJmL are represented as eleven plant functional types (PFTs), while Bondeau et al. (2007) introduced the representation of crops as 13 crop functional types (CFTs) that include 11 arable crops and two managed grass types to assess the impact of agriculture on the terrestrial C balance. In further developments, sugarcane (Lapola et al., 2009) and bioenergy crops (Beringer et al., 2011) were added to the list of CFTs. The model explicitly accounts for the processes of photosynthesis, soil energy and temperature exchanges, albedo effects, phenology, vegetation dynamics, fire disturbance, and mortality of plants (Schaphoff et al., 2018a). Important for the assessment of soil C dynamics are the representations of soil C and litter pools, which utilize an important part of biogeochemical processes. In LPJmL, soil types are represented as 12 different soil texture classes with specific fractions of sand, silt, and clay and classified according to the Harmonized World Soil Database (HWSD) version 1 (FAO et al., 2008). Soil layers are represented by five hydrologically active layers, each with a distinct layer thickness of 0.2, 0.3, 0.5, 1.0, and 1.0 m, respectively, followed by a 10.0 m bedrock layer. The bedrock layer serves as a heat reservoir in the computation of soil temperatures (Schaphoff et al., 2013). Soil pools consist of a slow and a fast organic matter pool, with a turnover time of 1000 and 30 years, respectively. The litter pool includes CFT- and PFT-specific pools for the wood, leaf, and root part of plants. Decomposition transfers litter C into soil C, while heterotrophic respiration accounts for C losses to the atmosphere. The terrestrial water cycle and the connection to vegetation and soils are accounted for in LPJmL and constitute a crucial element in LPJmLs functionality, as water availability and vegetation growth are closely interlinked. Soil water processes such as infiltration, percolation, and evaporation are explicitly represented in the model. Additionally, the model accounts for lateral water flow between grid cells (river routing) and can be used to assess water availability for irrigation (Jägermeyr et al., 2015). Land use and LUC are explicitly considered in LPJmL. The model simulates sowing dates based on a set of climate- and crop-specific set of rules (Waha et al., 2012) and accounts for grassland management (Rolinski et al., 2018).

Agricultural management practices and soil degradation have been underrepresented or not accounted for in the LPJmL model. The development of agricultural management in LPJmL is especially relevant to assess and quantify projections of the long-term benefits of soil conservation methods. The LPJmL model, as described in this thesis, was extended to account for tillage practices and an improved representation of residue effects. The model was also extended to account for the effect of changes in SOC content on soil moisture. In this thesis, I used and extended the LPJmL5.0 model version that accounts for N limitations (von Bloh et al., 2018).

1.5 Structure of the thesis

The motivation of this thesis is to understand the role of agricultural management-related soil degradation on a global scale and to develop the tools and methods to simulate and assess the impact of management practices on biogeochemical flows and fluxes. This dissertation is structured into five chapters, of which Chapters 2, 3, and 4 are guided by the research questions.

Chapter 2 presents an overview of the current research on regional and global soil degradation and discusses different modeling approaches at various scales. The term soil degradation is not universally defined, leading to different interpretations and approaches. This chapter identifies methods on how soil degradation can be modeled in a global process-based model framework, building the foundation for Chapter 3.

Chapter 3 provides a detailed model description and evaluation of the LPJmL5.0-tillage model and explicitly describes the new modeling framework and improvements. This chapter describes the implementation of tillage practices and residue effects and the feedbacks on soil water dynamics, productivity, and C and N fluxes. Tillage practices and residue management are evaluated against available meta-analyses. The extension of the model allows for quantifying the effects of management practices on biogeochemical cycles, crop performance, and the assessment of agricultural mitigation practices.

Chapter 4 describes a model application study and builds upon the model extension described in Chapter 3. This global assessment aims to understand the influence of agricultural management practices on historical and future SOC dynamics and to evaluate SOC sequestration potentials on current land-use patterns. The analysis includes two climate change scenarios, a high measure for climate change mitigation scenario (RCP2.6) and a high climate forcing scenario, considered as the business-as-usual case (RCP8.5). Further, the climate change mitigation potentials of the analyzed management strategies are discussed in this chapter.

Chapter 5 synthesizes the previous chapters and provides the answers to the research questions formulated in Section 1.3. This chapter discusses the limitations of the thesis, provides an outlook while discussing the options for future research, and highlights recommendations for policymakers.

1.6 Statement of author contributions

This dissertation is written as a monograph and based on one published peer-reviewed paper in Chapter 3, one paper that is accepted for publication in Chapter 4, and three additional chapters. I confirm to be the lead author for all the work presented here. The details of my co-authors and their contributions are described below.

Chapter 3 is based on the published paper: **Lutz, F.**, **Herzfeld, T.**, Heinke, J., Rolinski, S., Schaphoff, S., von Bloh, W., Stoorvogel, J. J., and Müller, C., 2019: Simulating the effect of tillage practices with the global ecosystem model LPJmL (version 5.0-tillage), Geoscientific Model Development, 12, 2419-2440, https://doi.org/10.5194/gmd-12-2419-2019, published under the Creative Commons Attribution 4.0 License. Femke Lutz and I share the lead authorship for this publication. We both had equal input in designing the study and conducting the model implementation, model runs, analysis, evaluation, and manuscript writing. Further co-authors included in this publication: Susanne Rolinski contributed to simulation analysis and manuscript preparation and evaluation, Jens Heinke contributed to the code implementation, evaluation and analysis and edited the paper, Sibyll Schaphoff contributed to the code implementation and evaluation and edited the paper. Werner von Bloh contributed to the code implementation and evaluation and edited the paper, Jetze Stoorvogel contributed to the study design and edited the paper. Christoph Müller contributed to the study design, supervised the implementation, simulations, and analyses, and edited the paper.

Chapter 4 is a follow-up analysis using the implemented tillage and residue representation in LPJmL described in Chapter 3. This chapter is based on the manuscript: **Herzfeld, T.**, Heinke, J., Rolinski, S., and Müller, C., 2021: Soil organic carbon dynamics from agricultural management practices under climate change, Earth System Dynamics, 12, 1037-1055 https://doi.org/10.5194/esd-12-1037-2021. The manuscript is published under the Creative Commons Attribution 4.0 License. I designed the study in discussion with Christoph Müller, Jens Heinke, and Susanne Roliski. I wrote the paper, conducted the model simulations and analysis, and created the graphs. Christoph Müller and Jens Heinke prepared the input data sets for manure, fertilizer, and land use. Christoph Müller, Susanne Rolinski, and Jens Heinke contributed to analyzing the results and edited the paper.

The studies presented in Chapter 3 and Chapter 4 are conducted with the contributions of others, as outlined above. Therefore these two Chapters are written in the first person plural, in contrast to the other three chapters.

Degraded soil
southern Portugal, April 2020
own photograph

Chapter 2

Approaches of modeling agricultural soil degradation for global assessments

Abstract. Soil degradation is a global phenomenon that threatens future food security. But its assessment is still subject to large uncertainties, and the term soil degradation lacks a common definition. This review identifies the most important drivers of agricultural-driven soil degradation on a global scale. Subsequently, this chapter aims to identify how soil degradation can be modeled on a global scale. Soil degradation is often studied at regional scales, and global assessments lack a process-based modeling approach or rely on proxies for degradation. The importance of SOC decline as a major type of global soil degradation is highlighted, which has the best potential to be addressed in global-scale process-based modeling. Employing the review of regional-scale model-based assessments of SOC decline, the transferability of these approaches to the global scale is discussed. The findings suggest that pedotransfer functions are a promising tool to endogenously account for changing soil properties in agricultural models to assess the effects of climate change and agricultural management on soil degradation.

2.1 Introduction

Soils provide food, feed, and fiber and are natural resources that have to be preserved and managed sustainably (FAO, 2017). Due to the intensification of agriculture from LUC, intensified mechanization, and increasing use of inputs, such as artificial fertilizer, agricultural soils have undergone degradation processes (Bindraban et al., 2012; Godfray et al., 2010; Gomiero, 2016; Tilman et al., 2002). Since the so-called “green revolution” in the 1960s, global agricultural production has, on average, more than doubled, but recent growth rates have shown signs of stagnation (Pingali, 2012; Ray et al., 2012; Wik et al., 2008). For example, in China, annual yield growth rates declined from 4% in the 1970s to 1.9% in the 1990s (Fan et al., 2011), and globally yield growth rates declined from 2% yr^{-1} to 1% yr^{-1} today (World Bank, 2007). Soil degradation and its negative effect on soil fertility and, thus, on agricultural productivity may endanger future food production (Bindraban et al., 2012).

Evaluating the global extent of degraded areas depends strongly on the methodology and the definition of land and soil degradation. Global estimates of cropland affected by some form of degradation range from 20% (Bai et al., 2008) to 40% (Bridges and Oldeman, 1999). Global degradation model assessments are scarce and mostly rely on proxies from remote sensing data (Bai et al., 2008; Helldén and Tottrup, 2008). So far, comprehensive process-based soil degradation model assessments are only available at a regional scale. Especially in global crop model assessments, degradation processes are currently underrepresented, but a few attempts to model global soil degradation exist (Cai et al., 2011; Naipal et al., 2018), and regional models are being further developed for the application at the global scale (Naipal et al., 2015). Assessments on agricultural productivity under climate change can be improved by accounting for soil degradation processes.

This review aims to provide an overview of regional and global degradation assessments and to aims to identify the most important processes that cause soil degradation from agricultural management. Additionally, it is discussed how the representation of soil degradation in global process-based models in projections of future agricultural productivity under climate change can be improved. Once implemented in agricultural models, this will help to better account for the effects of agricultural management in long-term projections of changes in agricultural productivity, for example, in climate change impact assessments.

2.2 Materials and method

This analysis was carried out using a variety of methods and sources. Specific search terms for Web of Science, Scopus online database, and Google Scholar were used. Keywords including "degrad* AND soil AND land AND management AND agriculture" resulted in a list of over 400 articles, from which approximately 100 were further selected after scanning the title and abstract. Articles were included that described a study on some form of degradation or agricultural management focusing on conservation agriculture or a study on soil treatments and their effects on soil properties. Additionally, papers were included through an additional refined search, for example, for specific aspects in soil degradation, such as on cation exchange capacity (CEC) or SOC dynamic assessments. In addition to the search in online databases, articles referenced within the identified literature have been considered, as well as cross-references. The main research for this chapter was conducted during the period from early 2015 to mid-2017. Later, literature that was released later and referenced in Chapters 3 and 4 was included, as well as cross-references and literature suggestions by colleagues.

2.3 Results and discussion

2.3.1 Definition of soil and land degradation

There is no common definition of soil and land degradation among the body of scientific literature, and both terms are used interchangeably. Generally, land degradation is defined as the long-term decline in ecosystem functions (Bai et al., 2008) and also refers to *"the reduction of the capacity and productivity of providing ecosystem services by cropland, rangeland, and woodland"* (Ceccarelli et al., 2014) and has been assessed at local, regional and global scales, while soil degradation is defined as "*the processes by which soil declines in quality and is thus made less fit for a specific purpose, such as crop production"* (OECD, 2001). The FAO puts land degradation in a broader context than soil degradation, stating that: "*Land degradation has a wider scope than soil degradation, in that it covers all negative changes in the capacity of the ecosystem in providing goods and services*", meaning land degradation includes both soil and vegetation (FAO, 2017). The term degradation is often associated with a single process, for example, wind or water erosion, or a mix of unfavorable physical and chemical changes in soil conditions, such as salinization, compaction, or loss in biodiversity. In dry regions, degradation is often referred to as desertification (Prince et al., 2009).

2.3.2 Global soil degradation assessments

Degradation assessments have been carried out at various scales, from plot size to local scale, regional, national and global scale. Several degradation assessments identified degradation at local scales, but global assessments remain scarce. The Global Assessment of Human-Induced Soil Degradation – GLASOD (Oldeman et al., 1991) was the first attempt to map degradation at the global scale and updated eight years after its first release (Bridges and Oldeman, 1999), raising awareness on the global extent of this issue. GLASOD was based on the expert judgment of soil scientists around the globe using uniform guidelines and was a source of information for policymakers and scientists at the national and global scale. Soil degradation within GLASOD is categorized in type, degree, and extent within a defined geographical area. Types of soil degradation include wind and water erosion, chemical degradation, including loss of SOC, salinization, and acidification, and physical degradation, including compaction and waterlogging, which are further categorized into severity classes: low, medium, high, and very high (Oldeman et al., 1991). Bridges and Oldeman (1999) attributed degradation to causative factors, such as deforestation, overgrazing, and agricultural activities and estimated, using this methodology, that 50% of the 2 Bha of land affected by degradation was attributed to erosion from water alone, while 40% of global cropland was affected by some form of degradation. Being aware of the shortcomings in their study, Oldeman et al. (1991) already pointed out some of the limitations and the need for a more detailed assessment. Sonneveld and Dent (2009) tested the consistency and reproducibility of GLASOD, focusing on soil erosion by water, and found that GLASOD is only moderately consistent in connecting soil degradation classes to the actual soil erosion phenomenon. This can be mainly attributed to the different degrees of conceptualization of degradation among experts, which is even more pronounced when the experts originate from different countries. These conceptual differences are also the main reason why the results cannot easily be reproduced with a parametric model approach. Given the limited consistency, GLASOD results should only be used qualitatively to raise attention to the topic of degradation as a global phenomenon, as it cannot be applied at the national scale (Sonneveld and Dent, 2009).

The Global Assessment of Land Degradation and Improvement (GLADA) by Bai et al. (2008) is an alternative assessment to identify global land degradation. GLADA used the satellite-based normalized difference vegetation index (NDVI) derived from GIMMS satellite data to estimate changes in net primary production (NPP), which served as a proxy to quantify degradation during the period 1981-2003. Their results indicated that 21% of the global land is degraded, of which one-fifth is attributed to cropland. No obvious relationship between the nature of soil and terrain and degraded land was found, which implies that the observed degradation was driven by management factors and catastrophic natural phenomena (Bai et al., 2008). This approach has also been criticized (Wessels et al., 2012). Because of the use of satellite data, areas that already have been degraded before 1981 could not be identified and accounted for. Further, fine gradients between degraded and non-degraded areas, especially for grasslands, are hard to distinguish from satellite data since no apparent threshold value of NPP that separates degraded from non-degraded area exists, and lastly, the study does not address the type, cause, and process of degradation (Gibbs and Salmon, 2015). This approach also accounted for land and soil degradation within one assessment without clearly distinguishing between these.

Helldén and Tottrup (2008) used satellite data acquired from remote sensing to identify regional desertification. They compared dryland regions prone to desertification with the results from their analysis. Satellite data from the Global Agricultural Monitoring System (GIMMS 8) to derive a global NDVI data set was included and compared with annual NDVI anomalies with corresponding rainfall data sets. With this, they found a strong relationship between NDVI and rainfall over time. Their results showed no signs of extensive land degradation and indicated a greening in dryland areas like the Mediterranean and the Sahel over the period 1982-2003. Because of the strong NDVI to rainfall relationship, they noted that their approach could not be used to verify any systematic generic degradation trend; nevertheless, the investigated regions can be compared by their intensity of desertification in a global context.

The Global Land Degradation Information System (GLADIS) combines biophysical vegetation and soil degradation conditions with land-use information systems to derive a current ecosystem-service status index and a land-degradation index at the global scale (Nachtergaele et al., 2010). They established an information system tool based on an assessment of the condition and trends of ecosystem goods and services by providing a description of the current status and the actual and potential changes of ecosystem services at low resolution. The combination of the current level and future trends indicates the overall condition of land degradation, including soil degradation. GLADIS is a recent assessment that maps global land degradation and considers several degradation aspects, such as pressure on biodiversity, salinization, water erosion, mechanization, and pollution, to derive degradation ratings with different severity statuses. To my knowledge, GLADIS has so far not undergone any revision or further update.

Cai et al. (2011) assessed the global marginal land area for biofuel production, which was considered degraded land, using a fussy logic model. The model combined data on soil type, topography, precipitation, and average air temperature with global land cover data and expert opinion. The model identified between 320 and 712 Mha of abandoned land, which is degraded cropland in their view. According to their definition, this land could be available for biofuel production. This approach was included in the analysis by Gibbs and Salmon (2015), who compared four global land and soil degradation assessments with different methodologies: satellite observation, expert opinion, biophysical modeling, and inventory of abandoned cropland. They found vast disagreements between the compared estimates on the extent of degraded land, ranging from less than 1 billion ha to more than 6 billion ha of global land area affected by degradation. These differences mainly occur due to different methodologies and definitions of degraded areas. The discrepancy highlights the uncertainty of current global degradation assessments. Assessing soil degradation, especially on a global scale, is no straightforward task. In comparison, more studies have been carried out for evaluating soil quality and long-term degradation at local and plot scales (Willekens et al. 2014; Tan et al. 2015; Wang et al. 2009).

The previously discussed examples have their methodological advantages and disadvantages but lack the explicit representation of biophysical processes related to the type of degradation, use proxies to identify degraded land, or rely on expert opinion. Cai et al. (2011) used a model approach base on environmental variables and expert opinions but lacked the integration of the biophysical process. Agricultural management as a cause for degradation is only considered in the GLASOD study. Still, it does not distinguish between different management practices and thus fails to identify the actual cause. Besides, the most significant disadvantage of all of these assessments is that they only report the current or past status of degradation. These methods are not applicable for assessments for future projections of global soil degradation.

2.3.3 Soil fertility

Soil fertility refers to the ability of the soil to provide nutrients for the growth of plants, which is well structured, allows for biotic communities to flourish, and enables natural decomposition processes (Mäder et al., 2002). Highly fertile soils can sustain intensive plant growth and crop yield output with minimal water and fertilizer input to the soil and are generally characterized by a high potential to retain water and nutrients (Bünemann et al., 2018). Nutrient retention is achieved via a high CEC, which positively correlates with a high SOC content (Chesworth, 2008). CEC is the capacity of the soil to hold and exchange cations. It is an important soil property that influences soil fertility due to its buffering effect on soil pH and nutrients and plays a vital role in controlling soil structure and nutrient availability for healthy plant growth (Hazelton and Murphy, 2007). Mueller et al. (2010) reviewed the constraints which limit soil productivity on a global scale. Their main finding suggests that soil moisture and the thermal regime are the main constraints, followed by soil structure. They also noted that crop modeling assessments at the global scale contain little soil information, limiting the ability to use these global assessments to derive soil management and sustainable strategies at the field scale. Soil fertility can be maintained and increased with additional inputs of C, N, and other nutrients (Carvalho et al., 2014). SOC stabilizes the soil, promotes soil structure, and increases the ability of the soil to retain water and nutrients, expressed as water holding capacity (WHC) and CEC (Jan-Mou et al., 2010; Ribeiro Filho et al., 2015). If soils experience a decrease in SOC content, additional C inputs have to be considered, though this otherwise can lead to a reduction in soil fertility (Pagliai et al., 2004).

There is great consensus across different studies (Alvarez 2005; Russell 1977; Potter et al. 2006; Jan-Mou et al. 2010) that SOC and nutrient availability play a crucial role in maintaining soil fertility. SOC is an essential component for soil quality because it plays a role in determining the soil's chemical, physical and biological properties (de Paul Obade and Lal, 2013; Willekens et al., 2014). Increasing the SOC content is associated with better soil structure, higher WHC, increased soil biota, stabilization of soil particles, enhanced porosity (Bronick and Lal, 2005), and better soil fertility (Russell, E. W., 1977; Sarkar et al., 2018). Increasing SOC content could have the potential to mitigate CO_2 emissions (Batjes, 1998). The loss of organic material in soils plays a vital role in the global decline in soil productivity (Amundson et al., 2015). Additional C input to the soil is needed to maintain or increase SOC stocks to compensate for SOC losses from cultivation and harvest (Lal, 2004a). For agricultural wheat systems, using a global modeling approach, Wang et al. (2016) found a globally averaged critical soil C input rate of 2.0 Mg C ha^{-1} yr^{-1}, which varies strongly across regions, is needed to reduce or reverse SOC loss in agricultural soils. They highlighted that this could be achieved by additional C input and soil management, which promotes SOC sequestration. For other agricultural systems, studies have to be conducted, but this is likely indicative of other cropping systems and demonstrates the importance of agricultural management for maintaining SOC.

2.3.4 Degradation from agricultural management practices

Soil degradation on cropland occurs from a combination of unfavorable management practices together with degradation processes, e.g., soil erosion, which can reduce soil organic matter (SOM) content and initiate a downward spiral of feedbacks resulting in reductions in yield and ultimately in human malnutrition and hunger (Magdoff and Van Es, 2009). Soil management practices can positively influence soil functional properties and can be applied to sustainably manage cropland and influence crop yields (Lal, 2000). These can play a significant role in combating soil degradation (Stavi and Lal, 2015). The physical and chemical properties of cropland soils are controlled through different management practices or influenced by natural climatic and soil-forming factors. Minimum tillage practices in combination with sustainable residue treatment, and crop rotations are some of the most promising options for managing SOC stocks, and therefore control other hydrological and chemical properties that are influenced by SOC (Alvarez and Steinbach, 2009).

Within the global C cycle, the SOC pools are the most dynamic reservoir and include twice the amount of atmosphere and biosphere C combined (Batjes, 2014), totaling roughly 2400 Pg C in the upper 2 m globally (Batjes, 2014), and 210 Pg C in global cropland soils (Jobbágy and Jackson, 2000). Due to the positive effects of enhanced SOC content on soil fertility, farmers should naturally be incentivized to choose management options that positively influence SOC content. Management methods that try to preserve the natural resource of the soil and target the accumulation or limit the reduction in declining SOC content are also known as conservation agriculture, which include the application of minimum tillage or no tillage (hereafter referred to as "no-till") practices (Ghosh et al., 2010; Hobbs, 2007; Tan et al., 2015). Reducing soil disturbance, e.g., through minimal and no-till management, is argued to enhance SOC content (Chen et al., 2009; Chi et al., 2016). Yet, it is debated if this enhancement occurs in the upper soil profile only, while at the same time decreases SOC content in the deeper soil layers (Baker et al., 2007), which would result in a limited potential for GHG mitigation (Powlson et al., 2014). Experiments investigating the effect of conventional tillage, i.e., plowing, and conservation agriculture practices mainly focus on the topsoil layer (first 30 or 40 cm of soil) and are not standardized (Derpsch et al., 2014). To estimate the GHG mitigation potentials of management practices, standardized research methods and modeling frameworks are needed, which account for the effects of deep-rooting plants on deeper soil layers (Derpsch et al., 2014).

Table 2-1: Forms of soil degradation affected by agricultural management practices. Local scale refers to point or site-specific studies, whereas regional scale refers to studies at spatial entities, including counties or regions.

Type of soil degradation	Affected by management	Affected soil property/ processes	Secondary degradation forms	Scale of study application	Exemplary references
Water erosion	Tillage, harvest, residue management	SOC, nutrients, BD	SOC loss, topsoil loss, biodiversity loss	Local, regional	Izaurralde et al., 2001; Le Roux et al., 2008; Polyakov and Lal, 2004; Renard, 1997
Wind erosion	Tillage, harvest, residue management	SOC, nutrients, BD	SOC loss, topsoil loss	Local, regional	Borrelli et al., 2014; He et al., 2018; Nordstrom and Hotta, 2004
Tillage erosion	Tillage	BD	SOC loss, topsoil loss	Local, regional	Van Oost et al., 2000, 2006
Compaction	Tractor cultivation (high mechanization), tillage	BD, WHC, infiltration	Salinization, waterlogging, biodiversity loss	Local	Batey, 2009; Bessou et al., 2010; Botta et al., 2006; Chan et al., 2006; Nawaz et al., 2013; Raghavan et al., 1990
Waterlogging	Irrigation, tractor cultivation, tillage	CEC	Salinization	Local	Chan et al., 2006; Håkansson and Reeder, 1994; Hillel et al., 2008
Salinization	Irrigation	CEC	Biodiversity loss	Local, regional	Gowing et al., 2009; Metternicht and Zinck, 2003; Utset and Borroto, 2001
Soil biodiversity loss	Tillage, species selection, pesticides	Soil structure	Nutrient loss, compaction, SOC loss	Local, regional	Jeffrey et al., 2010; Patterson et al., 2019; Spangenberg et al., 2012
Loss of SOC	Tillage, residues management	Soil structure, WHC, CEC, nutrients	Erosion	Local, regional	Chi et al., 2016; Liu et al., 2009; Nadeu et al., 2015; Ouédraogo et al., 2007; Potter, R. P. et al., 2006

*WHC: water holding capacity; CEC: cation exchange capacity; BD: bulk density

Management practices in agricultural production that affect different forms of soil degradation are summarized in Table 2-1. Specifically, three management practices stand out which are connected to promoting soil degrading: agricultural mechanization, e.g., the use of tractors which can cause soil compaction (Batey, 2009; Chan et al., 2006), intensive irrigation, which can lead to salinization (Metternicht and Zinck, 2003) and excessive conventional tillage practices, which can promote a variety of forms of degradation. Generally, soil tillage refers to the mechanical manipulation of soils to modify soil conditions, manage and control crop residues, weed, and prepare the seedbed (ASA et al., 2008). Conventional tillage practices, e.g., plowing, are argued to be highly disruptive management practices to the soil, promoting various forms of degradation, such as tillage erosion (Van Oost et al., 2006), intensifying wind and water erosion (Cerdà et al., 2009; Tan et al., 2015), promoting the loss in soil biodiversity (Patterson et al., 2019), and inducing the decline in SOC content (Alvarez and Steinbach, 2009; Chi et al., 2016; Kurothe et al., 2014; Lal, 2004b, 1993). Tillage influences the structure of the soil, which is one of the key factors determining soil quality (Bronick and Lal, 2005). SOC can be reduced from tillage through an increase in decomposition (Lal, 1993) or by losses from soil erosion (Lal, 2003a). Abdalla et al. (2016) reviewed the effects of tillage and no-till on GHG emission and found that conventional tillage practices can increase CO_2 emission from the soil by 21%.

Due to its impact on various biological, physical, and chemical properties in the soil, SOC is argued to be one of the most important indicators of soil quality (de Paul Obade and Lal, 2013; Willekens et al., 2014). High SOC content sustains plant productivity, controls the water flow, filters pollutants, stores and transforms N, phosphorous (P), and other nutrients and supports soil structure, increases bulk density (BD), and provides stable aggregates (Potter et al., 2006). Because SOC can serve as a bonding agent between macro-aggregates in the soil and stabilize against soil erosion (Degens, 1997), a decrease in SOC content could accelerate wind and water soil erosion rates. Yet, the effects of soil water and tillage erosion on the fate of SOC are the subjects for discussion among the scientific community. While erosion sedimentation of SOC is argued to be a net C sink with a sequestration potential of the magnitude of 1 Pg C yr^{-1} (Smith et al., 2001), soil erosion may at the same time be a net source of C in the same magnitude through an increase in mineralization rates (Lal, 2003). SOC is additionally lost due to LUC and can contribute to GHG emissions in the form of CO_2 (Tang et al., 2006). On a global average, LUC, mainly the conversion of forest into agricultural land is associated with 22% losses in SOC and 15% losses in soil N (Murty et al., 2002).

Unfavorable soil structure can reduce soil biodiversity due to increased soil erosion rates, decreased water infiltration, and reduced soil porosity (Bronick and Lal, 2005; Lal, 2009a; Patterson et al., 2019; Riley et al., 2008). Reduction in soil porosity in the topsoil due to tillage can be attributed to soil crusting effects (Dalla Rosa et al., 2017; Fox et al., 2004). On the other hand, reduced tillage can increase soil biodiversity (Moos et al., 2018), and positively affecting soil structure and porosity (Riley et al., 2008). Studies have shown that conventional tillage leads to a significant reduction in soil porosity (Riley et al., 2008), which can affect both the topsoil layer (0-100 cm) as well as deeper subsoil layers (400-500 cm) (Pagliai et al., 2004). A so-called "plow-pan" can cause a reduction in soil porosity in the deeper layers, i.e., a compacted layer of the soil created by the shearing by tillage implements (Gupta et al., 1991). Its significance is often underestimated because the resulting negative effects are less evident than topsoil compaction effects caused by wheel traffic (Pagliai et al., 2004). Tillage erosion, which is defined as the physical downward movement of soil caused by the tillage operation, has been identified as an important global soil degradation process on conventionally tilled cropland (Lobb, 2008). Global tillage erosion rates on cropland are estimated to be of the same magnitude as water erosion rates (Van Oost et al., 2006). Tillage erosion, water erosion and sedimentation rates depend on management factors, such as tillage depth, direction, speed, and equipment characteristics (Van Oost et al., 2006), as well as on properties of the landscape structure, i.e., field size, slope degree, aspect, and vegetation cover (Van Oost et al., 2000).

With the adoption of mechanized agriculture and tractor use, soil compaction and other forms of degradation became a global issue (Jie et al., 2002). For example, agricultural mechanization and the increasing use of tractors in Sub-Sahara Africa amplified degradation processes (Kansanga et al., 2020). This was mostly caused by unsustainable use of extensive tillage practices of untrained farmers who, for example, plow beyond the recommended tillage depth and at too high intervals (Daum and Birner, 2017). The high load of tractor wheels in mechanized farming systems can cause compaction of the soil and vary depending on tractor weight, speed, tire shape, and the number of passes (Chan et al., 2006). Controlled traffic technologies reduce the area on the field impacted by compaction (Raper, 2005; Taylor, 1983). Soil compaction can lead to waterlogging because it restricts the movement of water (Wu et al., 2018) and therefore reduces soil aeration and nutrient uptake (Hillel et al., 2008). Irrigating fields with saline water or the excessive use of irrigation can dissolve salts in the soil and cause soil salinization (Singh, 2009). The latter is promoted by the upward movement of water that transports salt to the surface through the capillary rise, where the water evaporates and allows the salt to crystallized (Chesworth, 2008). It is estimated that globally 77 Mha of land are affected by salinization due to human activity, of which roughly half is irrigated (Ghassemi et al., 1995). Future cropland expansion, especially in dryland areas, is expected to increase salinization hazards caused by irrigation (Metternicht and Zinck, 2003). The excessive and unsustainable use of fertilizer in agricultural production systems can lead to N leaching and soil acidification (Cai et al., 2015; Wallace, 1994) and negatively influence crop yields, which can be offset by lime application to the field (Holland et al., 2019; Malhi et al., 1998).

2.3.5 Modeling soil degradation driven by agricultural management

2.3.5.1 Model-based soil degradation assessments

Model assessments that identify soil degradation and quantify the extent make use of a combination of soil, climate, and topography input data in combination with remote sensing data, which are processed with a geographical information system (GIS) or a simple rule-based model (Ali and Kawy, 2012; Bai et al., 2008; Kawy, 2011). These assessments were carried out at a regional scale in countries such as China (Tang et al., 2006), Germany (Routschek et al., 2014), Italy (Confalonieri et al., 2005), Spain (Rodríguez et al., 1993), India (Bhattacharyya et al., 2015), and USA (Causarano et al., 2008; Potter et al., 2006). Remote sensing satellite data has been proven as a valuable tool to derive biophysical properties from surface vegetation, which served as a proxy for degradation (Bai et al., 2008; Helldén and Tottrup, 2008; Prince et al., 2009). The NDVI as a proxy for NPP was assessed at the global scale in GLADA (Bai et al., 2008) and regionally by Prince et al. (2009), who assessed long-term degradation in Zimbabwe, Africa. De Paul Obade and Lal (2013) reviewed remote sensing and GIS soil quality assessments and found that remote sensing and GIS technologies allow for the assessment of soil quality, but require a high density of field data. They further suggested that a hybrid approach combining field data and products from remote sensing with laboratory data could provide a solution to assess soil quality to accurately estimate soil degradation. An overview of model-based soil degradation assessments with respect to the methodological approach and the spatial domain is presented in Table 2-2.

Table 2-2: Comparison of different model approaches identifying different aspects of degradation. Abbreviations: (-) no data or not considered; (BD) bulk density; (C) census data; (CL) climate; (GIS) geographical information systems; (LU) land use; (LUC) land-use change; (MA) management; (NPP) net primary productivity; (RS) remote sensing; (SLM) sustainable land management; (TOP) topography; (ST) soil texture; (STY) soil type.

Authors	Model	Extent	Resolution	Approach	Inputs	Management	Properties / proxies	Degradation aspect
Ali and Kawy, 2012	GIS model	Regional	30 m	RS	ST, TY, TOP, CL	-	Rating: soil, TOP, CL	Degradation risk
Bai et al., 2008	GIS model	Global	8 km	RS	NDVI	-	NPP	Decline in plant productivity
Basso et al., 2006	SALUS	Regional	-	Simulation model	STY, CL, MA*	Tillage, residue MA (simulated)	Soil properties (SOC)	Change in BD, drainage, SOC content
Borrelli et al., 2017	RUSLE	Global	250 m	RS, GIS	RUSLE*, LU (MODIS), C	Conservation tillage (45% reduced erosion)	-	Erosion
Borrelli et al., 2020	RUSLE-GloSEM	Global	250 m	Empirical model	RUSLE*, LU (SSP-RCP)	Sustainable land management	-	Water erosion
Cai et al., 2011	fuzzy logic model	Global	-	Predictive model	STY, TOP, CL	-	Marginal land	Low productive land
Causarano et al., 2008	EPIC	Regional	-	Simulation model	ST,S TY, CL, MA (fertilizer, harvest)	Tillage	SOC sequestration	SOC decline
Causarano et al., 2011	EPIC	Regional	-	Simulation model	Planting, fertilizer, harvest	LUC, tillage	-	SOC decline
Doraiswamy et al., 2007	EPIC-CENTURY	Regional	-	SOC model	LU, CL, ST	Tillage (simulated)	SOC sequestration	SOC decline, erosion
Fleskens et al., 2013	PESERA-DESMICE	13 global hotspots / regional	100 m	Scenario analysis	-	-	-	Wind & water erosion, salinization
Gnanavelrajah et al., 2008	Roth C	Regional	-	Simulation model	ST, CL, MA, LU	Residues, manure	SOC sequestration	SOC decline
Greiner, 1996	SMAC	Regional	-	Optimizatio n model	TOP, GW flows, price	LU, farm structure (input)	-	Salinization
Grinblat et al., 2015	ALANDYN	Regional	-	Agent-based model	LU from RS, field data	-	Yield decline, population growth	SOC and yield decline

Author	Model	Extent	Resolution	Approach	Inputs	Management	Properties / proxies	Degradation aspect
Hoyle et al., 2014	Roth C	Regional	-	Simulation model	CL,MA	Residues	SOC sequestration	SOC decline
Izaurralde et al., 2001	EPIC	Regional, site specific	-	Simulation model	Initial SOC, SOC change rate, BD	Cultivation, fertilizer, treatments, tillage	Loss SOC	Erosion
Kawy, 2011	SLMSM	Regional	30m	RS + GIS	Soil properties, TOP, SLM indicators	-	Agriculture sustainability	Not sustainable land management
Le Roux et al., 2008	RUSLE	Regional	-	Empirical model	RUSLE*	-	Soil loss	Erosion
Mantel et al., 2014	IMAGE-USLE	Regional	-	-	ST, STY, CL, LU, topo	-	-	Erosion
Mu et al., 2014	DNDC	Regional	-	Simulation model	ST, STY, CL, tillage, fertilizer	Rotations, fertilizer (input)	SOC sequestration	SOC decline
Naipal et al., 2018	ORCHIDEE	Global	5 arcmin, 2.5°x3.75°	Simulation model	CT, MA, STY, TOP	Residues	Soil erosion	SOC erosion
Okin et al., 2001	empirical model	Regional	-	RS	-	-	Reduced plant cover	Wind erosion
Shrestha et al., 2009	CENTURY	Regional	-	Simulation model	C pools, CL, MA	Tillage, deforestation (input)	SOC sequestration	SOC loss
Smets and Borselli, 2011	EUROSEM	Local	point	Event based model	CL, soil type	Erosion control measures	Sediment discharge, runoff rate	Erosion
Tang et al., 2006	DNDC	National	-	Simulation model	Soil properties, CL, agriculture invent	Irrigation, fertilizer	SOC sequestration	SOC decline
Vågen et al., 2013	predictive model	Regional	-	RS	Soil properties (RS + laboratory)	-	Low SOC, alkaline + acid soils	Erosion, acidification

* Inputs RUSLE: rainfall-runoff erosivity factor, soil erodability factor, slope length factor, slope steepness factor, cover-management factor, support practice factor (Renard, 1997)

In simulations with EPIC (Causarano et al., 2008), DNDC (Tang et al., 2006), CENTURY (Shrestha et al., 2009), and SALUS (Basso et al., 2006), soil management practices, such as fertilizer application, harvest date, and tillage occurrences are used as input parameters. The EPIC model is a process-based model which is used for climate change impact, soil C, and degradation assessments at the regional scale (Causarano et al., 2011; Izaurralde et al., 2001; Perez-Quezada et al., 2003). It was first developed to determine the relationship between soil erosion and productivity (Williams et al., 1983) and later expanded to assess management effects on soil C dynamics (Causarano et al., 2008; Izaurralde et al., 2001). It has been applied for the regional analysis of SOC sequestration potentials (Causarano et al., 2008). Agricultural management options, such as tillage, are simulated in EPIC as three different representative tillage system options: conventional-tillage, mulch-tillage, and no-till (Potter et al., 2006). Conservation agriculture practices are represented as mulch tillage. Erosion in EPIC follows the Universal Soil Loss Equation (USLE) routine (Potter et al., 2006). Intensive wind and water erosion in EPIC reduce the soil column, but a total loss of topsoil must be accounted for and is avoided by reducing carry-over effects for each decade of the simulation period (Folberth et al., 2019). The C routines in EPIC are similar to the routines of the CENTURY model (Parton, 1996). They are coupled to soil temperature, hydrology, erosion, nutrient cycle, plant growth, and tillage system (Izaurralde et al., 2001). Five pools represent the organic material in the soil, and changes of C content are computed by daily mass balances (Potter et al., 2006). The EPIC model has been applied by Causarano et al. (2011, 2008) and Izaurralde et al. (2001) to assess SOC sequestration and SOC decline driven by management practices. Causarano et al. (2008) found an increase in SOC after the adoption of conservation tillage practices for the first 20cm of soil in Iowa, USA, but contrasting results for the entire soil profile. They highlighted the importance of soil depth consideration when assessing SOC stock and sequestration potentials, which needs further investigation. Causarano et al. (2011) modeled SOC variability and sequestration to estimate ongoing and future degradation using the EPIC model in Kazakhstan, conducting simulations for management practices such as tillage practices and fertilizer application. Their results indicated that reduced tillage practices and proper fertilizer application could increase SOC sequestration rates in the first 50 cm of soil. Doraiswamy et al. (2007) coupled the EPIC model with the soil C model CENTURY to simulate SOC sequestration in Mali. They found that most SOC in the topsoil is lost due to erosion. They highlighted that the losses can be avoided by lowering the intensity of tillage operation, e.g., ridge tillage practices.

Regional soil erosion assessments used models that incorporated soil erosion processes, such as EPIC-CENTURY (Doraiswamy et al., 2007) and EUROSEM (Morgan et al., 1998; Smets and Borselli, 2011). The Revised Universal Soil Loss Equation (RUSLE) is a well-known equation to estimate soil erosion at local and regional scales (Renard, 1997), and has been included in models such as EPIC (Williams et al., 1983). Important input parameters to drive the equation are data on climate, soil type, and topographic parameters. Compared to other soil degradation assessments, these erosion simulation assessments are event-based approaches and range from a local to regional scale. Besides, erosion modeling approaches typically operate at very high spatial resolution (Confalonieri et al., 2005; Smets and Borselli, 2011). For the application of the RUSLE equation at the global scale, Naipal et al. (2015) improved components of the function using the ORCHIDEE model, i.e., by improving the rainfall and topographical factor of the RUSLE function. By applying the new methodology they showed that soil erosion led to a total historical SOC loss of 74 ± 18 Pg C in the period 1850-2005 (Naipal et al., 2018). Levis et al. (2014) modeled CO_2 emission from land use using the Community Land Model (CLM) to account for increases in decomposition rates due to soil disturbance, e.g., tillage practices such as plowing and found a SOC loss of ~12 Pg C over 30 years. To identify highly degraded areas due to low levels of SOC for the application of conservation practices, Potter et al. (2006) developed a soil quality degradation indicator to identify the reduction of soil quality due to losses of SOC in cropland areas. This indicator highlights areas with high losses of SOC, which has a direct negative effect on soil functions and indicates the potential for the soil to support crop production sufficiently.

The overview in Table 2-2 shows that tillage, residue, and fertilizer management are the practices mostly considered in model assessments accounting for agricultural management. Different methods exist which use GIS and rely on remotely sensed data, e.g., topography and NDVI. Important input parameters for simulation models include climate data, such as air temperature and precipitation, as well as soil type and soil texture data. A disadvantage of using satellite data in remote-sensing assessments is that they can only describe and identify historical and current degradation states, but are unsuitable for modeling the effects of soil degradation under climate change and agricultural management in the future. Yet scenario assessments with process-based ecosystem models could compensate for this. Borrelli et al. (2021) extensively reviewed erosion model assessment from the last two decades. Their findings indicated that the RUSLE and the former USLE model type were mostly embedded in the methodology to assess soil degradation from erosion, and showed that empirical models have been mostly used to simulate water erosion. They also noted that process-based biophysical model assessments are far more scarce, due to the lack of necessary input data for application at a larger scale. In one of the first global erosion assessments that account for future land use and climate change impacts, Borrelli et al. (2020) modeled soil water erosion until 2070 using the RUSLE-based semi-empirical model GloSEM (Global Soil Erosion Modeling) platform. They found current global soil erosion rates of ~43 Pg of soil, which could decrease by -10% or increase by +10% depending on LUC scenario, but that climate change could drastically increase global soil water erosion rates by 30 to 66%, due to changes in rainfall patterns and intensities. Yet, they noted that because of the data-driven and semi-empirical structure of the GloSEM model, the results have to be interpreted with caution, as the model might not capture reality in detail. Jarrah et al. (2020) reviewed wind erosion models and highlighted the lack of data for model inputs and a need for long-term measurements to evaluate wind-induced soil erosion rates from environmental changes, which limits the evaluation of model performance.

This chapter highlights that global-scale assessments which account for agricultural management effects on soil degradation using process-based ecosystem modeling are still lacking, but attempts have been made to improve regional models for the application at a larger scale, which account for at least one form of soil degradation, i.e., soil water erosion.

2.3.5.2 Modeling changes in soil properties to account for soil degradation

Accounting for soil degradation effects in a process-based modeling approach is not a straightforward task, because soil degradation affects a complex set of biophysical and biogeochemical feedbacks. By accounting for changes in soil properties and conditions which are affected by agricultural management, soil degradation could be refected in global scale assessments. Management interventions such as tillage affect various forms of soil degradation, which affect soil properties such as soil water content or soil structure (see Table 2-1). It is important to understand the processes and linkages between the management system and type of soil degradation, as well as between degradation type and affected soil property. By developing useful functions which translate the type of degradation into soil properties, e.g., soil moisture or CEC, it is possible to directly account for soil degradation and evaluate subsequent effects in ecosystem model assessments. Fig. 2-1 illustrates directly and indirectly affected processes and properties that could guide the development of ecosystem model assessment. For example, intense irrigation can cause waterlogging and soil salinization, which affects CEC and therefore nutrient availability.

SOC loss is discussed in the literature as a form of soil degradation (Amundson et al., 2015; Bridges and Oldeman, 1999; Gomiero, 2016; Lal, 2009a, 2004a) and is at the same time an important soil property that determines soil quality (Lal, 1997). Relationships between management, the form of degradation, and soil properties which are known and tested from field trials and laboratory experiments provide valuable information for model assessments. The level of model complexity can be reduced by simulating indirect effects instead of directly simulation degradation processes but the choice at which complexity the processes are incorporated depends on both the detailed knowledge of processes involved and the structure of the model. Global model assessments can benefit from this, reducing computational time and, ultimately, reducing costs and resources. To highlight an example of a more simplistic approach to account for reductions in SOC and CO_2 emission from agricultural management, i.e. tillage practice, within a global model assessment, Pugh et al. (2015) increased soil decomposition rates by the factor of 2 to account for the effects of tillage. Yet, such a methodology does not account for the complexity of management effects on biophysical processes, despite being used in global scale assessments.

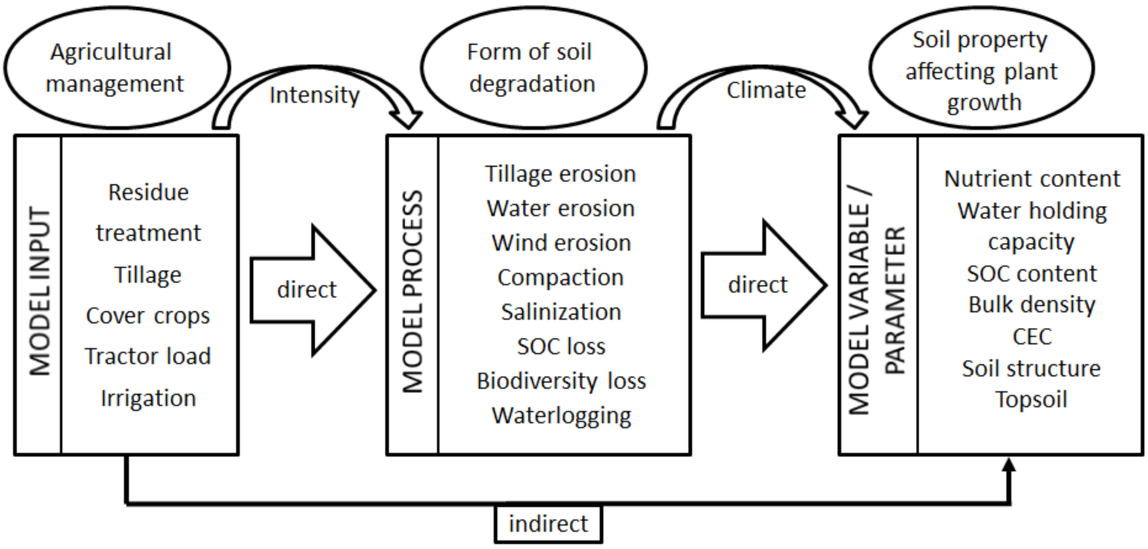

Figure 2-1: Simplified process-effect chain in model assessments of agricultural management options affecting forms of soil degradation and soil properties directly and indirectly.

To translate management effects to changes in soil water properties, pedotransfer functions (PTFs) provide a useful tool. Lal (1997) suggested the use of PTFs for model assessments of soil degradation. PTFs have been developed for various regions and vary in input properties and target variables (Van Looy et al., 2017). PTFs are defined as functions or algorithms that describe the relationship between soil properties with different levels of difficulty in measurement and availability (Pachepsky and van Genuchten, 2011) and enable the quantification of ecosystem services of soils (Vereecken et al., 2016). PTFs are being developed to calculate hydraulic properties, e.g., water content at field capacity or saturated hydraulic conductivity (Patil and Singh, 2016; Wösten et al., 2001), but some enable the estimation of chemical soil properties as well, e.g., of CEC (Krogh et al., 2000; Liao et al., 2015). PTFs are usually developed for a specific region and climate zone and cannot easily be applied to other regions, but interpolations within regions are possible (Pachepsky and van Genuchten, 2011). A basic formula for PTFs for calculating water content in soils at specific water pressures is presented in Wösten et al. (2001):

$$\Theta_h = a \cdot Sa + b \cdot Si + c \cdot Cl + d \cdot SOM + e \cdot BD + \cdots + x \cdot VarX, \tag{1}$$

with Θ_h being the water content at a specific pressure head h, Sa is the sand content, Si is the silt content, Cl is the clay content, SOM is the soil organic matter content, BD is the soil bulk density in g cm^2, *a, b, c, d, e,* and *x* are regression coefficients, and $VarX$ an additional variable that can be included in the equation. With such regression functions and models, specific points along the water retention curve can be estimated.

PTFs are developed using statistical regressions and have been proven for decades to be a reliable method to estimate soil properties that are difficult to measure (Rawls et al., 1991) and are already part of ecosystem models such as EPIC (Williams et al., 1983) or WEPP (Flanagan et al., 2007). New techniques such as artificial neural networks (Schaap et al., 1998) are also used for their development. The most common input parameters supplied for PTFs are particle size distribution, which is represented as soil texture classes, and BD (Wösten et al., 2001). Additionally, limited water retention data, mineralogical properties, organic C or organic matter content, chemical properties, and landscape position can be needed for some functions (Wösten et al., 2001). Saxton and Rawls (2006) developed a detailed functionality series to estimate a full range of soil hydraulic properties by inputs of soil texture and SOM content only. Schaap et al. (1998) developed a PTF computer program using a neural network analysis based on input parameters from soil texture classes and BD, which performed well in estimating saturated hydraulic conductivity (Alvarez-Acosta et al., 2012).

Van Looy et al. (2017) extensively reviewed PTFs for use in ESMs and argue that the potential of PTFs has not been fully exploited and integrated into these models. Using different PTFs in the same modeling framework can lead to high uncertainties due to varying input parameters and representations of relationships between soil properties (Schaap and

Leij, 1998). Like any generalizing function, PTFs exhibit uncertainties. Using a high number of sample points for PTF development can decrease the uncertainty of the PTF and improve the applicability (Pachepsky and van Genuchten, 2011; Van Looy et al., 2017). The validation of PTFs, especially for the application at larger scales, remains challenging. Contreras and Bonilla (2018) reviewed different PTFs developed from soil samples from tropical soils or samples across the USA and evaluated these with soils from Chile. They highlighted that the performance of a PTFs depends on the soils from which they are developed, but also that the PTFs showed a great potential after being calibrated to local conditions. They further noted that bulk density is a key soil variable to be able to account for changes in soil conditions through time and that the inclusion of SOM content into a PTF greatly improved the calculation of soil water retention properties. In biophysical model applications, including a PTF that accounts for SOM (and therefore SOC) changes to predict soil water properties can ensure plant-to-soil productivity feedbacks.

To summarize, PTFs enable the formulation of the relationship between measurable soil properties and less available or hard-to-measure soil parameters, which directly affect plant physiological properties (Van Looy et al., 2017). The use of PTFs to compute dynamic changes in soil water properties would allow for estimating soil degradation from agricultural management induced from SOC losses and show potential to be integrated into global ESM (Van Looy et al., 2017). Yet, the full potential, especially at the global scale, still has to be explored.

2.4 Summary and conclusion

Soil degradation is a global phenomenon and threatens future food security. Global estimates on the extent, type, and intensity of soil degradation differ widely across estimations due to the lack of a universal definition of soil degradation and a unified methodological approach. Different forms of soil degradation exist which are closely interlinked. For example, tillage can lead to subsoil compaction and cause waterlogging, while waterlogging can cause salinization, which affects CEC (Batey, 2009; Botta et al., 2006; Wu et al., 2018).

Assessments based on remote sensing data are currently the most common land degradation assessments at global and regional scales. Still, they are unsuitable for future projections due to their dependence on observations and cannot utilize a linkage to soil degradation. Dynamic simulations of degradation processes mainly focus on soil erosion processes. Soil erosion is, for example, simulated by EPIC (Williams et al., 1983) following the

RUSLE approach (Renard, 1997), but typically requires high-resolution input data on soil and terrain conditions, limiting the utilization at larger scales. But efforts are made to improve the RUSLE function for global-scale applicability (Naipal et al., 2015). Yet, soil erosion in modeling assessments considers the removal of the soil substrate and can, in the worst case, lead to total loss of the soil column (Folberth et al., 2019). The deposition of removed soil substrate is only considered in field-scale erosion models, such as EUROSEM (Morgan et al., 1998). For global-scale ESM assessments, it can be sufficient to model soil erosion at a low spatial resolution. Owing to the small-scale processes on agricultural landscapes and crop production, productivity feedbacks of SOC should be implemented in global scale assessments as a first step before including other degradation aspects, such as erosion processes at larger scales. In agricultural systems, tillage erosion plays an essential role as a soil degradation process affected by agricultural management, as well as changes in SOC (e.g., SOC loss), because of various feedbacks on soil conditions and plant productivity as well as for climate change mitigation concerns.

Process-based modeling approaches for estimating the effect of climate change (Álvaro-Fuentes et al., 2012), LUC (Müller et al. 2006), and agricultural management (DelGrosso et al. 2009) on SOC exist. To model the impact of SOC loss on soil physical and chemical properties, PTFs can serve as a useful tool to link SOC change with changes in soil physical and chemical properties. PTFs have a long history in soil modeling and have been developed for different regions worldwide. Limitations arise when using PTFs globally because PTFs are usually developed from soil samples at a specific region and show the most accurate results for these soils (Contreras and Bonilla, 2018). Nonetheless, a high number of data points in the PTF development can decrease uncertainty and improve the applicability (Pachepsky and van Genuchten, 2011; Van Looy et al., 2017). Within the same model, it is advisable to integrate one PTF to avoid high uncertainties due to regional differences from the use of various PTFs to calculate hydraulic and other soil properties. Including SOM content for the dynamic computation of soil properties can increase the soil water estimates (Contreras and Bonilla, 2018).

Current assumptions in global agricultural climate change impact assessments on static management or invariant soil properties (Rosenzweig et al. 2014) do not allow for a comprehensive assessment of climate change impacts on agricultural productivity (Folberth et al., 2019). Yet, these assessments reflect current modeling capacities. A combination of crop growth models with soil C dynamics is already possible within ecosystem-based crop models (Bondeau et al., 2007). Still, modeling protocols are typically not designed to include changes in SOC in global crop model simulations (Elliott et al. 2015). Global erosion-based degradation assessments exist (Borrelli et al., 2020, 2017; Naipal et al., 2018) but are still scarce, as water and wind erosion processes are difficult to incorporate into a global-scale simulation of agricultural productivity.

Conventional tillage, i.e., plowing, is one of the most disruptive agricultural management practices affecting many forms of soil degradation and should be included in a global modeling framework assessing soil degradation. Tillage affects a variety of complex soil processes, can increase soil decomposition, and affect soil hydrology. Soil tillage and residue management should not be treated separately, as these two management practices are closely interlinked (Guérif et al., 2001), and both should be accounted for when incorporating into a global modeling framework.

Chapter 3

Incorporating tillage practices into a dynamic global vegetation model

Abstract. The effects of tillage on soil properties, crop productivity, and global greenhouse gas emissions have been discussed in the last decades. Global ecosystem models have limited capacity to simulate the various effects of tillage. With respect to the decomposition of soil organic matter, they either assume a constant increase due to tillage, or they ignore the effects of tillage. Hence, they do not allow for analyzing the effects of tillage and cannot evaluate, for example, reduced-tillage or no-till as mitigation practices for climate change. In this chapter, we describe the implementation of tillage-related practices in the global ecosystem model LPJmL. The extended model is evaluated against reported differences between tillage and no-till management on several soil properties. To this end, simulation results are compared with published meta-analyses on tillage effects. In general, the model can reproduce observed tillage effects on global, as well as regional, patterns of C and water fluxes. However, modeled N-fluxes deviate from the literature and need further study. The addition of the tillage module to LPJmL5.0 opens opportunities to assess the impact of agricultural soil management practices under different scenarios with implications for agricultural productivity, C sequestration, greenhouse gas emissions, and other environmental indicators.

3.1 Introduction

Tillage on cropland is performed for various purposes, including the incorporation of residues and fertilizers, seedbed preparation, weed control, and water management. Tilling the soil can affect a variety of biophysical processes affecting the environment, such as soil C sequestration or greenhouse gas emissions, and can influence and promote various forms of soil degradation (e.g., erosion from water, wind, and particle movement from tillage, known as tillage erosion) (Armand et al., 2009; Govers et al., 1994; Holland, 2004). To mitigate GHG emissions in the agricultural sector, no-till or reduced tillage are being promoted as potential management strategies (Six et al., 2004; Smith et al., 2008). Yet, there are ongoing long-lasting debates about the effects of tillage and no-till on GHG emissions and SOC stock development (e.g., Lugato et al. (2018)). The consensus is that no-till and reduced tillage tend to increase SOC storage through a reduced decomposition, which results in reduced GHG emissions (Chen et al., 2009; Willekens et al., 2014). Still, discrepancies arise on the effectiveness of no-till and reduced tillage on GHG emissions. Oorts et al. (2007), for instance, found in meta-analyses that no-till systems, on average, increased CO_2 emissions by 13% compared to conventional tillage, whereas Abdalla et al. (2016) found that CO_2 emissions from no-till systems are reduced by 21% compared to conventional tillage. Aslam et al. (2000) found only minor differences in CO_2 emissions between these two management systems. As tillage affects a complex set of biophysical factors, e.g., soil moisture and soil temperature (Snyder et al. 2009), which drive several soil processes, including the C and N dynamics and crop performance, these discrepancies are not surprising. Additionally, other management practices, e.g., fertilizer application and residue management, and climatic conditions, are important driving factors (Abdalla et al., 2016; Oorts et al., 2007; van Kessel et al., 2013). Oorts et al. (2007), for instance, attributed the increase in CO_2 emissions under no-till to higher decomposition and soil moisture of crop residues left on the soil. No-till effects on CO_2 emissions are found to be most effective in dryland soils (Abdalla et al., 2016). For N_2O emissions, Van Kessel et al. (2013) found that these are smaller under no-till in dry climates, while the depth of fertilizer application plays an important role.

The effects of tillage on soil properties need to be incorporated in global ecosystem models to study and understand the role of tillage for global biogeochemical cycles, crop performance, and mitigation practices. Tillage management is already implemented in ecosystem models at different levels of complexity (Lutz et al., 2019a; Maharjan et al., 2018), yet, these practices are still underrepresented in global ecosystem models that account for biogeochemical fluxes. These models either ignore the effects of tillage or are represented by a simplified scaling factor, accounting for variations in decomposition rates. For example, global ecosystem models that ignore the effects of tillage include PROMET (Mauser and Bach, 2009), the Dynamic Land Ecosystem Model (DLEM) (Tian et al., 2010), JULES (Best et al., 2011; Clark et al., 2011), and the Community Land Model (Levis et al., 2014; Oleson et al., 2010). Tillage effects are accounted for as an increase in decomposition using a scaling factor in the models LPJ-GUESS (Olin et al., 2015; Pugh et al., 2015) and ORCHIDEE-STICS (Ciais et al., 2011). To our knowledge, crop models that have been used at the global scale, EPIC (Williams et al., 1983) and DSSAT (White et al., 2010), have similarly detailed representations of tillage practices like the one described here. Models which are used to study the global biogeochemical stocks and fluxes (Friend et al., 2014) have no or only very coarse representations of tillage effects.

Despite uncertainties in the parameterization and formalization of processes in LPJmL, the processed-based representation allows for the analysis of complex response patterns. Individual effects and feedbacks can be isolated or disabled to understand their importance.

3.2 Tillage effects on soil processes

Tillage affects different soil properties and soil processes, resulting in a complex system with various feedbacks on processes related to soil water, temperature, C, and N (Fig. 3-1). The effect of tillage has to be implemented and analyzed in conjunction with residue management as these management practices are often interrelated (Guérif et al., 2001; Strudley et al., 2008). The processes that were implemented into the model were chosen based on the importance of the process and its compatibility with the implementation of other processes within the model. Those processes are visualized in Fig. 3-1 with solid lines; processes that have been ignored in this implementation are visualized with dotted lines. To illustrate the complexity, we here describe selected processes in the model affected by tillage and residue management, using the numbered lines in Fig. 3-1.

With tillage, surface litter is incorporated into the soil [1] and increases the soil organic matter (SOM) content of the tilled soil layer [2] (Guérif et al., 2001; White et al., 2010), while tillage also decreases the BD of this layer [3] (Green et al., 2003). An increase in SOM positively affects the porosity [4] and, therefore, the WHC [5] (Minasny and McBratney, 2018). Tillage also affects the WHC by increasing porosity [6] (Glab and Kulig, 2008). A change in WHC affects several water-related processes through soil moisture [7]. For instance, changes in soil moisture influence lateral runoff [8] and leaching [9] and affect infiltration. A wet (saturated) soil, for example, decreases infiltration [10], while infiltration can be enhanced if the soil is dry (Brady and Weil, 2008). Soil moisture affects primary production as it determines the amount of water that is available for the plants [11], and changes in plant productivity again determine the amount of residues left at the soil surface or to be incorporated into the soil [1] (feedback not shown).

The presence of crop residues on top of the soil (referred to as "surface litter" hereafter) enhances water infiltration into the soil [12] (Guérif et al., 2001; Jägermeyr et al., 2016; Ranaivoson et al., 2017) and thus increases soil moisture [13]. That is because surface litter limits soil crusting, can constitute preferential pathways for water fluxes, and slows lateral water fluxes at the soil surface so that water has more time to infiltrate (Glab and Kulig, 2008). Consequently, surface litter reduces surface runoff [14] (Ranaivoson et al., 2017). Surface litter also intercepts part of the rainfall [15], reducing the amount of water reaching the soil surface, but also lowers soil evaporation [16] and thus reduces unproductive water losses to the atmosphere (Lal, 2008b; Ranaivoson et al., 2017). Surface litter also reduces the amplitude of variations in soil temperature [17] (Enrique et al., 1999; Steinbach and Alvarez, 2006). The soil temperature is strongly related to soil moisture [18] through the heat capacity of the soil, i.e., a relatively wet soil heats up much slower than a relatively dry soil (Hillel, 2004). The rate of SOM mineralization is influenced by changes in soil moisture [19] and soil temperature [20] (Brady and Weil, 2008). The rate of mineralization affects the amount of CO_2 emitted from soils [21] and the inorganic N content of the soil. Inorganic N can then be taken up by plants [22], be lost as gaseous N [23], or transformed into other forms of N. The processes of nitrate (NO_3^-) leaching, nitrification, denitrification, mineralization of SOM, and immobilization of mineral N forms are explicitly represented in the model (von Bloh et al., 2018). The degree to which soil properties and processes are affected by tillage depends mainly on the tillage intensity, which is a combination of tillage efficiency and mixing efficiency (in detail explained in Sections 3.3.2 and 3.3.5.2). Tillage has a direct effect on the BD of the tilled soil layer. The type of tillage determines the mixing efficiency, which affects the amount of incorporating residues into the soil. Over time, soil properties reconsolidate after tillage, eventually returning to pre-tillage states. The speed of reconsolidation depends on soil texture and the kinetic energy of precipitation (Horton et al., 2016).

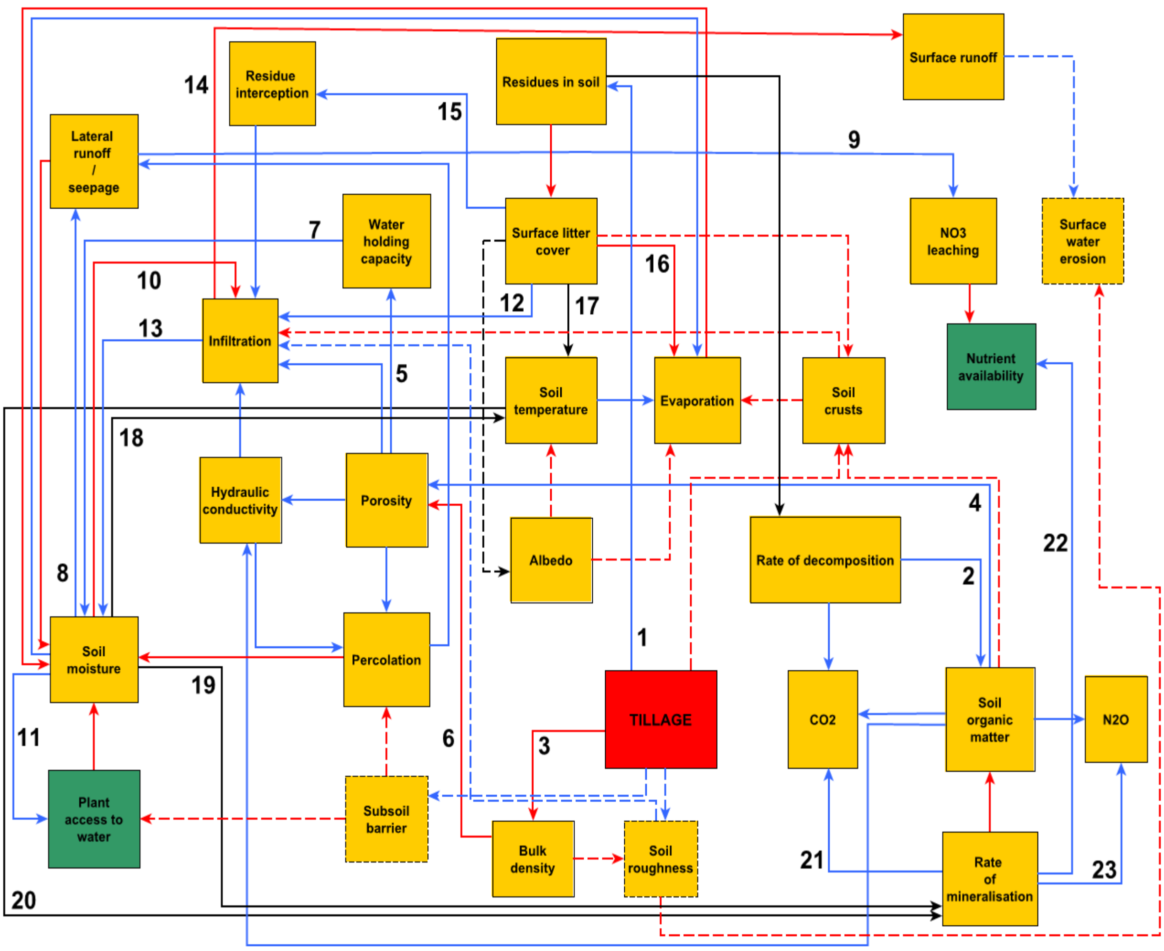

Figure 3-1: Flow chart diagram of feedback processes caused by tillage, which are considered (solid lines) and not considered (dashed lines) in this implementation in LPJmL5.0-tillage. Blue lines highlight positive feedbacks, red negative, and black are ambiguous feedbacks. The numbers in the figure indicate the processes described in Section 3.2.

This implementation mainly focuses on two processes directly affected by tillage: 1) the incorporation of surface litter associated with tillage management and the subsequent effects (Fig. 3-1, path 1 and following paths), 2) the decrease in BD and the subsequent effects of changed soil water properties (Fig. 3-1, e.g., path 3 and following paths). To limit model complexity and associated uncertainty, tillage effects that are not directly compatible with the original model structure, such as subsoil compaction, or require very high spatial resolution, are not taken into account in this initial tillage implementation, despite acknowledging that these processes can be important.

3.3 Implementation of tillage routines into LPJmL

3.3.1 The LPJmL5.0-tillage model

The tillage implementation described in this paper was introduced into the dynamic global vegetation, hydrology, and crop growth model LPJmL. This model was recently extended to also cover the terrestrial N cycle, accounting for N dynamics in soils and plants and N limitation of plant growth (LPJmL5.0; von Bloh et al., 2018). Previous comprehensive model descriptions and developments are described by Schaphoff et al. (2018a). The LPJmL model simulates the C, N, and water cycles by explicitly representing biophysical processes in plants (e.g., photosynthesis) and soils (e.g., mineralization of N and C). The water cycle is represented by the processes of rainwater interception, soil and lake evaporation, plant transpiration, soil infiltration, lateral and surface runoff, percolation, seepage, routing of discharge through rivers, storage in dams and reservoirs, and water extraction for irrigation and other consumptive uses.

In LPJmL5.0, all organic matter pools (vegetation, litter, and soil) are represented as C pools and the corresponding N pools with variable C : N ratios. Carbon, water, and N pools in vegetation and soils are updated daily as the result of computed processes (e.g., photosynthesis, autotrophic respiration, growth, transpiration, evaporation, infiltration, percolation, mineralization, nitrification, leaching; see von Bloh et al. (2018) for the full description). Litter pools are represented by the above-ground pool (e.g., crop residues, such as leaves and stubbles) and the below-ground pool (roots). The litter pools are subject to decomposition, after which the humified products are transferred to the two SOM pools that have different decomposition rates (Fig. A1A in the appendix). The fraction of litter that is harvested from the field can range between almost fully harvested or not harvested when all litter is left on the field (90%, Bondeau et al., 2007). In the soil, pools of inorganic, reactive N forms (NH_4^+, NO_3^-) are also considered. Each organic soil pool consists of C and N pools, and the resulting C : N ratios are flexible. Soil C : N ratios are considerably smaller than those of plants as immobilization by microorganisms concentrates N in SOM. In LPJmL, a soil C : N ratio of 15 is targeted by immobilization for all soil types (von Bloh et al., 2018). The SOM pools in the soil consist of a fast pool with a turnover time of 30 years and a slow pool with a 1000 year turnover time (Schaphoff et al., 2018a). Of the five active soil layers in LPJmL5.0, the first layer of 0.2 m thickness is mostly affected by tillage. LPJmL5.0 has been evaluated extensively and demonstrated good skills in reproducing C, water, and N fluxes in both agricultural and natural vegetation on various scales (Bloh et al., 2018; Schaphoff et al., 2018b).

3.3.2 Litter pools and decomposition

To account for the effects of crop residue management by different tillage practices, the original above-ground litter pool is separated into a surface litter pool ($C_{litter,surf}$) and an incorporated litter pool ($C_{litter,inc}$) for carbon, and the corresponding pools ($N_{litter,inc}$) and ($N_{litter,surf}$) for nitrogen (Fig. A1B in the appendix). Crop residues not extracted from the field are transferred to the surface litter pools. A fraction of residues from the surface litter pool is then partially or fully transferred to the incorporated litter pools, depending on the tillage practice:

$$C_{litter,inc,t+1} = C_{litter,inc,t} + C_{litter,surf,t} \cdot TL, \text{ for carbon , and} \tag{2}$$

$$N_{litter,inc,t+1} = N_{litter,inc,t} + N_{litter,surf,t} \cdot TL, \text{ for nitrogen.}$$

The $C_{litter,surf}$ and $N_{litter,surf}$ pools are reduced accordingly:

$$C_{litter,surf,t+1} = C_{litter,surf,t} \cdot (1 - TL), \tag{3}$$

$$N_{litter,surf,t+1} = N_{litter,surf,t} \cdot (1 - TL),$$

where $C_{litter,inc}$ and $N_{litter,inc}$ are the amounts of incorporated surface litter C and N, respectively, in g m^{-2} at a time step t (days). The parameter TL is the tillage efficiency, which determines the fraction of residues that are incorporated into the soil by tillage (0-1). We assume that 0.1897% of the surface litter pool is transferred to the incorporated litter pool per day (equivalent to an annual bioturbation rate of 50%). This way, we account for the vertical displacement of litter through bioturbation under natural vegetation and no-till conditions.

All litter pools are subject to decomposition, which depends on the temperature and moisture of their surroundings. The decomposition of the incorporated litter pools depends on soil moisture and temperature of the first soil layer (as described by von Bloh et al., 2018), whereas the decomposition of the surface litter pools depends on the moisture and temperature of the litter, which are approximated by the model. The decomposition rate of litter ($rdecom$ in g C m^{-2} day^{-1}) is described by first-order kinetics, and is specific for each PFT, following (Sitch et al., 2003):

$$rdecom_{(PFT)} = 1 - exp(-\frac{1}{\tau_{10(PFT)}} \cdot g(T_{surf}) \cdot F(\Theta)), \quad (4)$$

where τ_{10} is the mean residence time for litter and $g(T_{surf})$ and $F(\Theta)$ are response functions of the decay rate to litter temperature (T_{surf}) and litter moisture, respectively. The response function to litter moisture $F(\Theta)$ is defined as:

$$F(\Theta) = 0.0402 - 5.005 \cdot \Theta^3 + 4.269 \cdot \Theta^2 + 0.7189 \cdot \Theta, \quad (5)$$

where Θ is the volume fraction of litter moisture which depends on the fraction of surface covered by litter (f_{surf}), water holding capacity of the surface litter (whc_{surf}), the amount of water intercepted by the surface litter (I_{surf}) (see Section 3.3.3.1), and moisture lost through evaporation E_{surf} (see Section 3.3.3.3).

The temperature function $g(T_{surf})$ describes the temperature influence of the surface litter on decomposition (von Bloh et al., 2018):

$$g(T_{surf}) = exp(308.56 \cdot (\frac{1}{66.02} - \frac{1}{(T_{surf+56.02})})), \quad (6)$$

where T_{surf} is the temperature of surface litter (see Section 3.3.4).

A fixed fraction (70%) of the decomposed $C_{litter,surf}$ is mineralized, i.e., directly emitted as CO_2, whereas the remaining humified C is transferred to the soil C pools, where the C is subject to the soil decomposition following the description by von Bloh et al. (2018) and Schaphoff et al. (2018a). The mineralized N (also 70% of the decomposed litter) is added to the NH_4^+ pool of the first soil layer, where it is subjected to further transformations (von Bloh et al., 2018), whereas the humified organic N (30% of the decomposed litter) is allocated to the different organic soil N pools in the same shares as the humified C. Mineralized N is subject to microbial immobilization to maintain the desired C : N ratio of 15 within the soil (von Bloh et al., 2018), i.e., the transformation of mineral N to organic N directly reverting some of the N mineralization in the soil.

The surface litter influences the soil temperature and soil water fluxes (see 3.3.4 and 3.3.3). This affects the decomposition of the soil C and N pools, including the mineral N form transformations. Nitrogen fluxes, e.g., N_2O fluxes from nitrification and denitrification, are partly driven by soil moisture (von Bloh et al., 2018):

$F_{N2O,nitrification,l} = K_2 \cdot K_{max} \cdot F_1(T_l) \cdot F_1(W_{sat,l}) \cdot F(pH) \cdot NH_{4,l}^{+}$ for nitrification, and

$F_{N2O,denitrification,l} = r_{mx2} \cdot F_2(W_{sat,l}) \cdot F_2(T_l, C_{org}) \cdot NO_{3,l}^{-}$ for denitrification, (7)

where $F_{N2O,nitrification}$ and $F_{N2O,denitrification}$ are the N_2O fluxes related to nitrification and denitrification, respectively, in gN m^{-2} d^{-1} in layer l. K_{max} is the maximum nitrification rate of NH_4^+ ($K_{max} = 0.1\ d^{-1}$) and K_2 is the fraction of nitrified N lost as N_2O ($K_2 = 0.02$). $F_1(T_l)$ and $F_1(W_{sat,l})$ are response functions of soil temperature and soil water saturation, respectively, that limit the nitrification rate. $F(pH)$ is the function describing the response of nitrification rates to soil pH and $NH_{4,l}^{+}$ and $NO_{3,l}^{-}$ the soil ammonium and nitrate concentration in gN m^{-2} respectively. $F_2(T_{l,}C_{org})$, $F_2(W_{sat,l})$ are reactions for soil temperature, soil C and water saturation and r_{mx2} is the fraction of denitrified N lost as N_2O (11%, the remainder is lost as N_2). A detailed description of all the N-related processes implemented in LPJmL can be found in von Bloh et al. (2018).

3.3.3 Water fluxes

3.3.3.1 Litter interception

Applied irrigation water and precipitation in LPJmL5.0 are divided into interception, transpiration, soil evaporation, soil moisture, and runoff (Jägermeyr et al., 2015). To account for the interception and evaporation of water by the surface litter, the water can now be captured by surface litter through litter interception (I_{surf}) or lost through litter evaporation. Water subsequently infiltrates into the soil or is added to the surface runoff. Litter moisture (Θ) is calculated as the following:

$$\Theta_{t+1} = \min(WHC_{surf} - \Theta_{(t)}, I_{surf} \cdot f_{surf}). \tag{8}$$

f_{surf} is calculated by relating the amount of surface litter (in dry matter) per m^2 to the fraction of soil covered, following the equation from Gregory (1982):

$$f_{surf} = 1 - exp^{-A_m \cdot OM_{litter,surf}}, \tag{9}$$

where $OM_{litter,surf}$ is the total mass of dry matter surface litter in g m^{-2}, and A_m is the area covered per crop-specific residue amount (m^2 g^{-1}). The total mass of surface litter is calculated assuming a fixed C to organic matter ratio of 2.38 ($CF_{OM,litter}$), following Brady and Weil (2008), who suggested that 42% of the organic matter is C:

$$OM_{litter,surf} = C_{litter,surf} \cdot CF_{OM,litter}, \quad (10)$$

where $C_{litter,surf}$ is the amount of C stored in the surface litter pool in gC m^{-2}. We apply the average value of 0.006 for A_m from Gregory (1982) to all materials, not accounting for variations from different materials for surface litter. WHC_{surf} (in mm) is the water holding capacity of the surface litter, which is calculated by multiplying the litter mass with a conversion factor of 2 10^{-3} mm kg^{-1} ($OM_{litter,surf}$) adapted from Enrique et al. (1999).

3.3.3.2 Soil infiltration

The surface litter enhances precipitation or irrigation water infiltration into the soil by reducing soil crusting and affecting preferential pathways (Ranaivoson et al., 2017). Increased infiltration under the presence of surface litter is accounted for by following the approach by Jägermeyr et al. (2016). This was developed to account for in situ water harvesting in LPJmL, e.g., mulching. The soil water content of the first layer and the infiltration parameter p determine the the infiltration rate (In in mm d^{-1}):

$$In = prir \cdot \sqrt[p]{1 - \frac{W_a}{W_{sat,l=1} - W_{pwp,l=1}}}, \quad (11)$$

where $prir$ is the daily precipitation and applied irrigation water in mm, W_a the available soil water content in the first soil layer, and $W_{sat,l=1}$ and $W_{pwp,l=1}$ the soil water content at saturation and permanent wilting point of the first layer in mm. By default $p = 2$, but four different levels are distinguished ($p = 3, 4, 5, 6$) to account for increased infiltration based on the management intervention, based on Jägermeyr et al. (2016). We scale the infiltration parameter p between 2 and 6 to account for the effects of surface litter, based on the fraction of surface litter cover (f_{surf}):

$$p = 2 \cdot (1 + f_{surf} \cdot 2) \quad (12)$$

Surplus water that cannot infiltrate is added to the surface runoff and enters the river system.

3.3.3.3 Litter and soil evaporation

The surface litter cover (f_{surf}) evaporation (E_{surf} in mm) is calculated similarly to the evaporation from the first soil layer (Schaphoff et al., 2018a). Evaporation depends on the vegetation cover (f_v), the radiation energy for the vaporization of water (PET) and the water stored in the surface litter that is available to evaporate (ω_{surf}) relative to WHC_{surf}.

Here, $\mathfrak{f}_{surf}$ is considered, so that the fraction of bare soil is subject to soil evaporation as described in Schaphoff et al. (2018a):

$$E_{surf} = PET \cdot \alpha \cdot \max(1 - \mathfrak{f}_v, 0.05) \cdot \omega_{surf}^2 \cdot \mathfrak{f}_{surf}, \tag{13}$$

$$\omega_{surf} = \Theta / WHC_{surf}, \tag{14}$$

where PET is calculated based on the theory of equilibrium evapotranspiration (Jarvis and McNaughton, 1986) and α the empirically derived Priestley-Taylor coefficient ($\alpha = 1.32$) (Priestley and Taylor, 1972).

Litter at the soil surface reduces soil evaporation (E_{soil}). E_{soil} (in mm) corresponds to the soil evaporation as described in Schaphoff et al. (2018a), and is dependent on the available energy for the vaporization of water and the available water in the upper 0.3 m of the soil (ω_{evap}). With the implementation of tillage, the fraction of $\mathfrak{f}_{surf}$ now influences evaporation, i.e., less soil cover ($\mathfrak{f}_{surf}$) results in an increase in E_{soil} and vice versa:

$$E_{soil} = PET \cdot \alpha \cdot \max(1 - \mathfrak{f}_v, 0.05) \cdot \omega^2 \cdot (1 - \mathfrak{f}_{surf}) \tag{15}$$

ω is calculated as the water available for evaporation (ω_{evap}) relative to the water holding capacity in that layer (WHC_{evap}):

$$\omega = \min\left(1, \frac{\omega_{evap}}{WHC_{evap}}\right), \tag{16}$$

where ω_{evap} is all the water of the upper 0.3 m of the soil above the wilting point (Schaphoff et al., 2018a).

3.3.4 Heat flux

The surface litter temperature is calculated as the average soil temperature of the previous day (t) of the first layer ($T_{soil,l=1}$ in °C) and actual air temperature ($T_{air,t+1}$ in °C):

$$T_{litter,surf,t+1} = 0.5(T_{air,t+1} + T_{l=1,t}). \tag{17}$$

Equation (17) approximates the heat exchange described by Schaphoff et al. (2013). The upper boundary condition (T_{upper} in °C) is calculated by the average of T_{air} and T_{surf}, weighted by $\mathfrak{f}_{surf}$. As a new boundary condition, the cover of the soil with surface litter diminishes the heat exchange between atmosphere and soil:

$$T_{upper} = T_{air} \cdot (1 - \mathrm{f}_{surf}) + T_{surf} \cdot \mathrm{f}_{surf}. \tag{18}$$

The remainder of the soil temperature calculation remains unchanged from the description of Schaphoff et al. (2013).

3.3.5 Tillage effects on physical properties

3.3.5.1 Dynamic calculation of hydraulic properties

Previous versions of the LPJmL model used static soil hydraulic parameters as input parameters. Those were computed following the PTF by Cosby et al. (1984). We now introduced an approach following the PTF by Saxton and Rawls (2006), which was included in the model to dynamically simulate layer-specific hydraulic parameters that account for the amount of SOM in each layer, constituting an essential mechanism of how hydraulic parameters are affected by tillage (Strudley et al., 2008). Different methods exist to calculate soil hydraulic properties from soil texture and SOM content for various points of the water retention curve (Balland et al., 2008; Saxton and Rawls, 2006; Wösten et al., 1999) or at continuous pressure levels (Van Genuchten, 1980; Vereecken et al., 2010). Reviews that extensively describe the use of PTFs and their application in Earth system and soil modeling can be found in Van Looy et al. (2017) and Vereecken et al. (2016).

As such, Saxton and Rawls (2006) define a PTF most suitable for our needs and capable of calculating all the necessary soil water properties for our approach. Incorporating this PTF allows accounting for the dynamic effect of SOM on soil hydraulic properties and can represent changes in BD after tillage. The PTF by Saxton and Rawls (2006) was developed from a large number of data points. With this implementation, soil hydraulic properties are updated daily. Following Saxton and Rawls (2006), soil water properties are calculated as:

$$\lambda_{pwp,l} = -0.024 \cdot Sa + 0.0487 \cdot Cl + 0.006 \cdot SOM_l + 0.005 \cdot Sa \cdot SOM_l - 0.013 \cdot Cl \cdot SOM_l + 0.068 \cdot Sa \cdot Cl + 0.031, \tag{19}$$

$$W_{pwp,l} = 1.14 \cdot \lambda_{pwp,l} - 0.02, \tag{20}$$

$$\lambda_{fc,l} = -0.251 \cdot Sa + 0.195 \cdot Cl + 0.011 \cdot SOM_l + 0.006 \cdot Sa \cdot SOM_l - 0.027 \cdot Cl \cdot SOM_l + 0.452 \cdot Sa \cdot Cl + 0.299, \tag{21}$$

$$W_{fc,l} = 1.238 \cdot (\lambda_{fc,l})^2 + 0.626 \cdot \lambda_{fc,l} - 0.015, \tag{22}$$

$$\lambda_{sat,l} = 0.278 \cdot Sa + 0.034 \cdot Cl + 0.022 \cdot SOM_l - 0.018 \cdot Sa \cdot SOM_l - 0.027 \cdot Cl \cdot SOM_l - 0.584 \cdot Sa \cdot Cl + 0.078, \tag{23}$$

$$W_{sat,l} = W_{fc,l} + 1.636 \cdot \lambda_{sat,l} - 0.097 \cdot Sa - 0.064, \tag{24}$$

$$BD_{soil,l} = (1 - W_{sat,l}) \cdot MD. \tag{25}$$

SOM_l is the soil organic matter content in weight percent (%w) of layer l, $W_{pwp,l}$ is the moisture content at the permanent wilting point, $W_{fc,l}$ is the moisture content at field capacity, $W_{sat,l}$ is the moisture contents at saturation, $\lambda_{pwp,l}$, $\lambda_{fc,l}$ and $\lambda_{sat,l}$ are the moisture contents for the first solution at permanent wilting point, field capacity and saturation, Sa is the sand content in volume percent (%v), Cl is the clay content in %v, $BD_{soil,l}$ is the bulk density in kg m^{-3}, MD is the mineral density of 2700 kg m^{-3}. For SOM_l, total SOC content is translated into SOM of this layer:

$$SOM_l = \frac{CF_{OM,soil} \cdot (C_{fastSoil,l} + C_{slowSoil,l})}{BD_{soil,l} \cdot z_l} \cdot 100, \tag{26}$$

where $CF_{OM,soil}$ is the conversion factor of 2 as suggested by Pribyl (2010), assuming that SOM contains 50% SOC, $C_{fastSoil,l}$ is the fast decaying C pool in kg m^{-2}, $C_{slowSoil,l}$ is the slow decaying C pool in kg m^{-2} , $BD_{soil,l}$ is the bulk density in kg m^{-3}, and z is the thickness of layer l in m. It was suggested by Saxton and Rawls (2006) that the PTF should not be used for SOM contents above 8%, so we cap SOM_l at this maximum when computing soil hydraulic properties and thus treated soils with SOM_l content above this threshold as soils with 8% SOM content. Saturated hydraulic conductivity is also calculated following Saxton and Rawls (2006) as:

$$Ks_l = 1930 \cdot \left(W_{sat_{(l)}} - W_{fc_{(l)}}\right)^{3-\phi_l}, \tag{27}$$

$$\phi_l = \frac{\ln(W_{fc,l}) - \ln(W_{pwp,l})}{\ln(1500) - \ln(33)}, \tag{28}$$

where Ks_l is the saturated hydraulic conductivity in mm h^{-1} and ϕ_l is the slope of the logarithmic tension-moisture curve of layer l.

3.3.5.2 Bulk density effect and reconsolidation

The effects of tillage on BD are adopted from the APEX model by Williams et al. (2015), which is a follow-up development of the EPIC model (Williams et al., 1983). Tillage causes changes in BD of the tillage layer (first topsoil layer of 0.2 m) after tillage. Soil moisture content for the tillage layer is updated using the fraction of change in BD. Ks_l is also updated based on the new moisture content after tillage. A mixing efficiency parameter (mE) depending on the intensity and type of tillage (0-1), determines the fraction of change in BD after tillage. A mE of 0.90, for example, represents a full inversion tillage practice, also known as conventional tillage (White et al., 2010). The parameter mE can be used in combination with residue management assumptions to simulate different tillage types. It should be noted that Williams et al. (1983) calculate direct effects of tillage on BD, while we changed the equation accordingly to account for the fraction at which BD is changed.

The fraction of BD change after tillage is calculated the following way:

$$f_{BDtill,t+1} = f_{BDtill,t} - \left(f_{BDtill,t} - 0.667\right) \cdot mE. \tag{29}$$

Tillage density effects on saturation and field capacity follow Saxton and Rawls (2006):

$$W_{sat,till,l,t+1} = 1 - \left(1 - W_{sat,l,t}\right) \cdot f_{BDtill,t+1}, \tag{30}$$

$$W_{fc,till,l,t+1} = W_{fc,l,t} - 0.2 \cdot (W_{sat,l,t} - W_{sat,till,l,t+1}), \tag{31}$$

where $f_{BDtill,t+1}$ is the fraction of density change of the topsoil layer after tillage, $f_{BDtill,t}$ is the density effect before tillage, $W_{sat,till,l,t+1}$ and $W_{fc,till,l,t+1}$ are adjusted moisture content at saturation and field capacity after tillage and $W_{sat,l,t}$ and $W_{fc,l,t}$ are the moisture content at saturation and field capacity, respectively, before tillage.

Reconsolidation of the tilled soil layer is accounted for following the same approach by Williams et al. (2015). The rate of reconsolidation depends on the rate of infiltration and the sand content of the soil. This ensures that the porosity and BD changes caused by tillage gradually return to their initial value before tillage. Reconsolidation is calculated the following way:

$$sz = 0.2 \cdot In \cdot \frac{1+2 \cdot Sa/(Sa+e^{8.597-0.075 \cdot Sa})}{z_{till}^{0.6}}, \tag{32}$$

$$f = \frac{sz}{sz+e^{3.92-0.0226 \cdot sz}}, \tag{33}$$

$$f_{BDtill,t+1} = f_{BDtill,t} + f \cdot (1 - f_{BDtill,t}), \tag{34}$$

where sz is the scaling factor for the tillage layer and z_{till} is the depth of the tilled layer in m. This allows for faster settling of recently tilled soils with high precipitation and soils with high sand content. In dry areas with low precipitation and for soils with low sand content, the soil settles slower and might not consolidate back to its initial state. This is accounted for by taking the previous BD before tillage into account. The effect of tillage on BD can vary from year to year, but $f_{BDtill,t}$ cannot be below 0.667 or above 1.0, so that unwanted amplification is not possible. We do not yet account for fluffy soil syndrome processes (i.e., when the soil does not settle over time) and negative implications from this, which results in an unfavorable soil particle distribution that can cause a decline in productivity (Daigh and DeJong-Hughes, 2017).

3.4 Model setup

3.4.1 Model input, initialization, and spin-up

To bring vegetation patterns and SOM pools into a dynamic equilibrium stage, we make use of a 5000 years spin-up simulation of only natural vegetation, which recycles the first 30 years of climate input following the procedures of von Bloh et al. (2018). For simulations with land-use inputs and to account for agricultural management, a second spin-up of 390 years is conducted to account for historical LUC, which is introduced in the year 1700. The spatial resolution of all input data and model simulations is 0.5°. Land use data is based on crop-specific shares of MIRCA2000 (Portmann et al., 2010) and cropland and grassland time series since 1700 from HYDE3 (Klein Goldewijk et al., 2011) as described by Fader et al. (2010). Per default setting, intercrops are grown on all set-aside stands in all simulations (Bondeau et al., 2007). As we are here interested in the effects of tillage on cropland, we ignore all natural vegetation in grid cells with cropland by scaling existing cropland shares to 100%. We drive the model with daily mean temperature from the Climate Research Unit (CRU TS version 3.23, Harris et al., 2014; University of East Anglia Climatic Research Unit et al., 2015), monthly precipitation data from the Global Precipitation Climatology Centre (GPCC Full Data Reanalysis Version 7.0; Becker et al., 2013) and shortwave downward and net longwave downward radiation data from the ERA-Interim data set (Dee et al., 2011). Static soil texture classes are taken from the Harmonized World Soil Database version 1.1 (Nachtergaele et al., 2009) and aggregated to 0.5° resolution by using the dominant soil type. Twelve different soil textural classes are distinguished according to the USDA soil texture classification and one unproductive soil type, which is referred to as "rock and ice". Soil pH data are taken from the WISE data set (Batjes, 2005). The NOAA/ESRL Mauna Loa station (Tans and Keeling, 2021) provides [CO_2] concentrations. Deposition of N was taken from the ACCMIP database (Lamarque et al., 2013).

3.4.2 Simulation options and evaluation set-up

The new tillage management implementation allows for specifying different tillage and residue systems. We conducted four contrasting simulations on the current cropland area with or without the application of tillage and with or without removal of residues (Table 3-1). The default setting for conventional tillage is mE=0.9 and TL=0.95. In the tillage scenario, tillage is conducted twice a year, at sowing and after harvest. Soil water properties are updated daily, enabling the tillage effect to be effective from the subsequent day onwards until it wears off due to soil settling processes. The four different management settings (MS) for global simulations are as the following: 1) full tillage and residues left on the field (T_R), 2) full tillage and residues are removed (T_NR), 3) no-till and residues are retained on the field (NT_R), and 4) no-till and residues are removed from the field (NT_NR). The specific parameters for these four settings are listed in Table 3-1. The default MS is T_R and was introduced in the second spin-up from the year 1700 onwards, as soon as human land use is introduced in the individual grid cells (Fader et al. 2010). All of the four MS simulations were run for 109 years, starting from the year 1900. Unless specified differently, the outputs of the four different MS simulations were analyzed using the relative differences between each output variable using T_R as the baseline MS;

$$RD_X = \frac{X_{MS}}{X_{T\_R}} - 1, \qquad (35)$$

where RD_X is the relative difference between the management scenarios for variable X and X_{MS} and X_{T_R} are the values of variable X of the MS of interest and the baseline management systems: conventional tillage with residues left on the field (T_R). Spin-up simulations and relative differences for equation (35) were adjusted if a different MS was used as a reference system, e.g., if reference data are available for comparisons of different MS. The effects were analyzed for different time scales: the three-year average of year 1 to 3 for short-term effects, the average after year 9 to 11 for mid-term effects, and the average of year 19 to 21 for long-term effects. Depending on available reference data in the literature, the specific duration and default MS of the experiment were chosen. The results of the simulations are compared to literature values from selected meta-analyses. Meta-analyses allow for the comparison of globally modeled results to a set of combined results of individual studies from all around the world, assuming that the data basis presented in meta-analyses is representative. A comparison to individual site-specific studies would require detailed site-specific simulations making use of climatic records for that site and details on the specific land-use history. Results of individual site-specific experiments can differ substantially between sites, which hampers the interpretation at larger scales. We calculated the median and the 5th and 95th percentile (values within brackets) between MS to compare the model results to the meta-analyses, where averages and 95% confidence intervals (CI) are mostly reported. We chose medians rather than arithmetic averages to reduce outlier effects, which is especially important for relative changes that strongly depend on the baseline value. If region-specific values were reported in the meta-analyses, e.g., climate zones, we compared model results of these individual regions, following the same approach for each study, to the reported regional value ranges.

To analyze the effectiveness of selected individual processes (see Fig. 3-1) without confounding feedback processes, we conducted additional simulations of the four different MS on bare soil. These simulations included a constant dry matter litter input (simulation NT_NR_bs and NT_R_bs1 to NT_R_bs5) of uniform composition (C : N ratio of 20), no atmospheric N deposition, and static fertilizer input (Elliott et al., 2015). These simulations on bare soil help to isolate soil processes, as any feedbacks via vegetation performance are eliminated in this setting.

Table 3-1: LPJmL simulation settings and tillage parameters used in the stylized simulations for model evaluation.

Scenario	Simulation abbreviation	Retained residue fraction on field	Tillage efficiency (TLFrac)	Mixing efficiency of tillage (mE)	Litter cover+ (%)	Litter amount (dry matter g m^2)
Tillage + residues on 100% scaled cropland	T_R	1	0.95	0.9	variable*	variable*
Tillage + no residues on 100% scaled cropland	T_NR	0.1	0.95	0.9	variable*	variable*
No-till + residues on 100% scaled cropland	NT_R	1	0	0	variable*	variable*
No-till + no residues on 100% scaled cropland	NT_NR	0.1	0	0	variable*	variable*
No-till + no residues on bare soil	NT_NR_bs	0	0	0	0	0
No-till + residues on bare soil (1)	NT_R_bs1	1	0	0	10	17
No-till + residues on bare soil (2)	NT_R_bs2	1	0	0	30	60
No-till + residues on bare soil (3)	NT_R_bs3	1	0	0	50	117
No-till + residues on bare soil (4)	NT_R_bs4	1	0	0	70	202
No-till + residues on bare soil (5)	NT_R_bs5	1	0	0	90	383

+Litter cover is calculated following Gregory (1982).
*Litter amounts and litter cover are modeled internally.

3.5 Evaluation and discussion

3.5.1 Tillage effects on hydraulic properties

Table 3-2 presents the calculated soil hydraulic properties of tillage for each of the soil classes before and after tillage (mE of 0.9), combined with a SOM content in the tilled soil layer of 0% and 8%. In general, both tillage and a higher SOM content tend to increase WHC, $W_{sat,l}$, $W_{fc,l}$ and Ks_l. Clay soils are an exception since higher SOM content decreases WHC, $W_{sat,l}$ and $W_{fc,l}$, and increases Ks_l. The effect of increasing SOM content on WHC, $W_{sat,l}$ and $W_{fc,l}$ is greatest in the soil classes sand and loamy sand. The increasing effects of tillage on the hydraulic properties are generally weaker compared to an increase in SOM by 8% (maximum SOM content for computing soil hydraulic properties in the model). While tillage (mE of 0.9, 0% SOM) in sandy soils increases WHC by 83%, 8% of SOM can increase WHC in an untilled soil by 105% and in a tilled soil by 84%. As a comparison in silty loam soils with 0% SOM, tillage (mE of 0.9) increases WHC by 16%, while 8% SOM can increase WHC by 31% and by 26% for untilled and tilled soil, respectively.

The PTF by Saxton and Rawls (2006) uses an empirical relationship between SOM, soil texture, and hydraulic properties derived from the USDA soil database, implying that the PTF is likely to be more accurate within the United States than outside. A PTF developed for global-scale application is, to our knowledge, not yet developed. Nevertheless, PTFs are used in a variety of global applications, despite the limitations to validate at this scale (Van Looy et al., 2017).

Table 3-2: Percentage values for each soil textural class of silt, sand, and clay content used in LPJmL and correspondent hydraulic parameters before and after tillage with 0% and 8% SOM using the Saxton and Rawls (2006) PTF.

				pre-tillage, 0% SOM[b]				pre-tillage, 8% SOM				after tillage[c], 0% SOM				after tillage[c], 8% SOM			
Soil class	Silt (%)	Sand (%)	Clay (%)	WHC[d]	W_{sat}	W_{fc}	Ks	WHC	W_{sat}	W_{fc}	Ks	WHC	W_{sat}	W_{fc}	Ks	WHC	W_{sat}	W_{fc}	Ks
Sand	5	92	3	0.04	0.42	0.05	152.1	0.09	0.71	0.19	361.98	0.08	0.59	0.09	343.67	0.14	0.80	0.21	498.92
Loamy sand	12	82	6	0.06	0.40	0.09	83.23	0.12	0.70	0.23	244.20	0.10	0.58	0.13	230.13	0.17	0.79	0.25	360.89
Sandy loam	32	58	10	0.12	0.40	0.17	32.03	0.18	0.70	0.31	152.75	0.15	0.58	0.21	125.75	0.23	0.79	0.33	239.93
Loam	39	43	18	0.15	0.41	0.26	10.69	0.21	0.69	0.37	80.46	0.19	0.59	0.30	64.76	0.25	0.78	0.39	143.99
Silty loam	70	17	13	0.22	0.42	0.31	5.49	0.29	0.75	0.42	99.77	0.26	0.59	0.34	48.23	0.32	0.83	0.44	155.38
Sandy clay loam	15	58	27	0.12	0.42	0.28	6.60	0.17	0.63	0.38	36.33	0.16	0.59	0.32	48.79	0.21	0.74	0.40	87.40
Clay loam	34	32	34	0.17	0.47	0.38	2.29	0.20	0.65	0.43	24.96	0.21	0.63	0.41	26.22	0.23	0.75	0.45	63.73
Silty clay loam	56	10	34	0.21	0.50	0.42	1.93	0.23	0.69	0.45	34.54	0.24	0.65	0.45	22.45	0.25	0.78	0.47	73.85
Sandy clay	6	52	42	0.15	0.47	0.40	0.72	0.16	0.58	0.44	5.64	0.18	0.63	0.44	16.73	0.20	0.70	0.47	29.30
Silty clay loam	47	6	47	0.20	0.56	0.48	1.64	0.18	0.65	0.46	18.69	0.23	0.69	0.50	16.67	0.20	0.76	0.48	50.99
Clay	20	22	58	0.19	0.58	0.53	0.39	0.14	0.58	0.48	2.87	0.21	0.71	0.55	8.62	0.16	0.71	0.50	20.03
Rock[a]	0	99	1	0.00	0.01	0.01	0.10	0.00	0.01	0.01	0.10	0.00	0.01	0.01	0.10	0.00	0.01	0.01	0.10

[a]Soil class rock is not affected by SOM changes and tillage practices, [b]For SOM, we only consider the C part in SOM in gC m^{-2}, [c]Tillage with a mE of 0.9 for conventional tillage, [d]WHC is calculated as $WHC = W_{fc} - W_{pwp}$ in all cases.

3.5.2 Productivity

The results discussed in this and the subsequent sections refer to the simulations after ten years (average of years 9 to 11). All results are calculated as RD following Eq. (35) unless states otherwise.

Our simulations show that a slight increase in productivity, on average, can be achieved for all rain-fed crops simulated (wheat, maize, pulses, rapeseed) by adopting NT_R. Yet, across all cropland globally, increases and decreases can be observed. The increase can be observed both after three years of NT_R adoption (Fig. A2 in the appendix) and after the first ten years (Fig. 3-2A and 3-2B). The highest positive impact after NT_R adoption is found for rapeseed with a median increase of +3.5% (5^{th}, 95^{th} percentiles: -24.5%, +57.8%). For maize, the positive impact of NT_R adoption is the smallest with a median increase of +1.8% (5^{th}, 95^{th} percentiles: -24.6%, +56.2%), while for wheat, a median productivity increase of +2.5% (5^{th}, 95^{th} percentiles: -15.2%, +53.5%) can observed. These results are in contrast to the values reported by Pittelkow et al. (2015b). They report a small median increase for rapeseed and a small decrease in productivity for wheat and maize (Table 3-3).

According to Pittelkow et al. (2015b), only maize productivity is negatively affected, while productivity for wheat and rapeseed shows positive and negative effects. They also identify crop type and aridity as the most influential factors governing the productivity response after adopting no-till and retaining residues on the field. They show that no-till performed the best in dry climates (aridity index <0.65) under rain-fed conditions. This positive effect of NT_R adoption on productivity in dry regions can also be seen in our simulations. Wheat productivity, for example, increases substantially after NT_R adoption. Yet, with an increase in aridity index, this effect diminishes (see Fig. 3-2A). Maize shows similar responses of productivity after NT_R adoption (Fig. 3-2B). The positive effects on production after NT_R adoption can be connected to the presence of a litter layer which increases soil water infiltration and reduces evaporation, which leads to more soil moisture conservation. Regions in which the soil water availability is limiting crop productivity could potentially benefit from NT_R adoption (Pittelkow et al., 2015a).

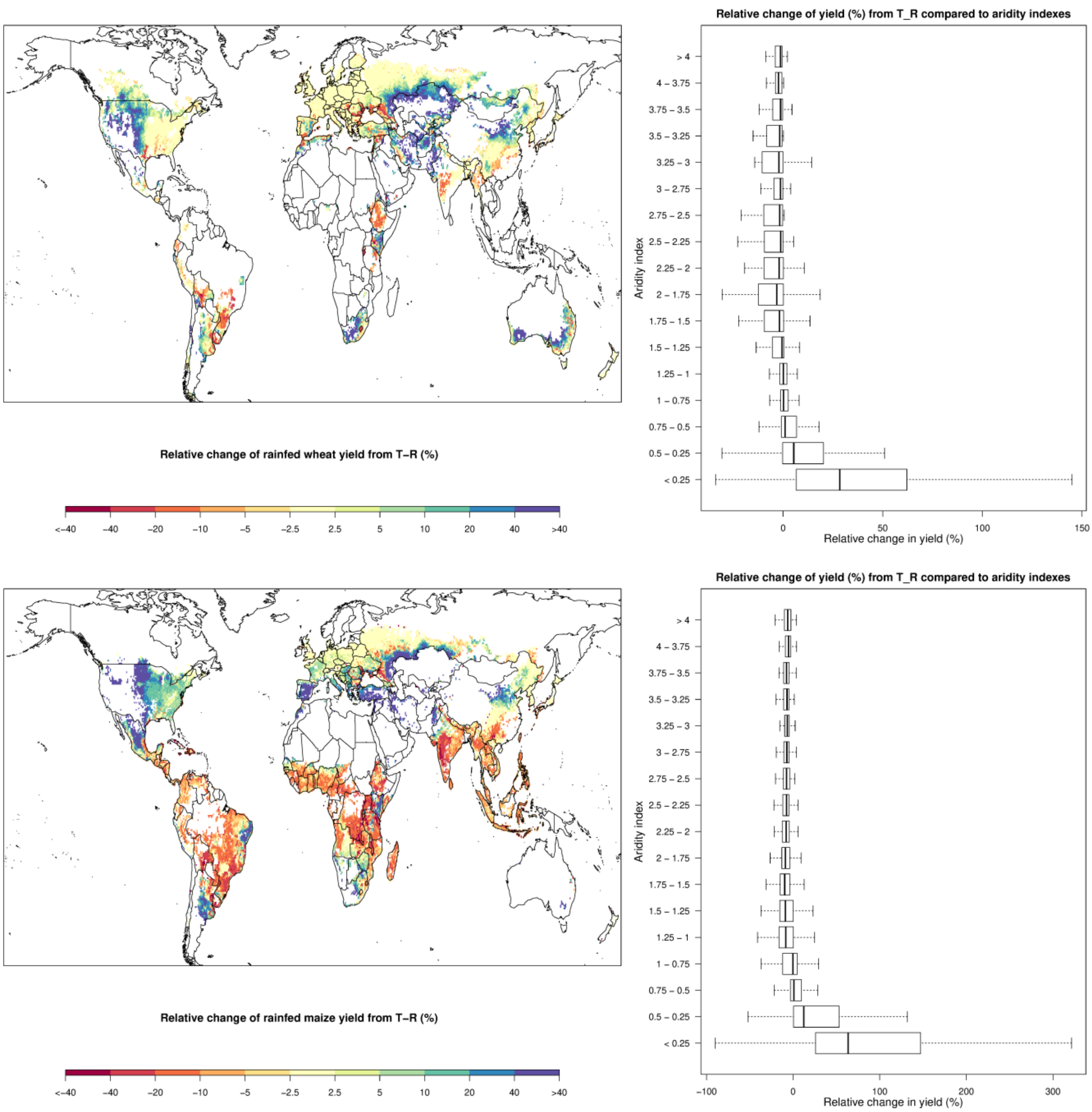

Figure 3-2: Relative yield changes for rain-fed wheat (a) and rain-fed maize (b) compared to aridity indexes after ten years NT_R vs. T_R. Low aridity index values indicate arid conditions as the index is defined as mean annual precipitation divided by potential evapotranspiration, following Pittelkow et al. (2015a). Substantial increases in crop yields only occur in arid regions, with aridity indices <0.75.

Climatic conditions can influence the effects of no-till on crop productivity, which was found in several studies, e.g., Ogle et al. (2012), Pittelkow et al. (2015a), or in van Kessel et al. (2013). Pittelkow et al. (2015a) found that productivity is reduced in dry regions. Yet, they found that if no-till is combined with crop rotation and residue retention, an increase in productivity can be observed. For humid regions with an aridity index above 0.65, this was not the case. Results indicated that the decline in productivity was independent of crop rotation or residue management for humid regions. Ogle et al. (2012) found general declines in productivity that were largest in wetter and colder climates. Declines in productivity could also be found by van Kessel et al. (2013) after no-till adoption for humid regions (-3%) and dry regions (-11%). Yet, they did not specify the residue treatment in the context of no-till or tillage management.

In our simulations, negative effects of NT_R adoption on productivity can be mostly observed in tropical regions. This can be attributed to an increase in soil moisture in those regions under NT_R management (see Fig. 3-5C), which results in a decline in soil N availability (see Fig. 3-5D). Soil moisture influences various N-related processes that can lead to a decrease in N availability to plants. An increase in soil moisture, for example, can increase denitrification, which reduces the amount of available NO_3^- (more discussed in Section 3.5.5). Additionally, high soil moisture content can also reduce the mineralization of SOM. Nonetheless, the soil moisture to N availability relationship and yield feedbacks are complex mechanisms and involve many processes.

3.5.3 Soil C stocks and fluxes

We evaluate the effects of tillage and residue management on simulated soil C dynamics and fluxes for CO_2 emissions from cropland soils, the relative change in C input, SOC turnover time as well as relative changes in SOC stocks of the topsoil (0.3 m). In our simulation, CO_2 emissions initially decrease for the average of the first three years by a median value of -11.9% (5th, 95th percentile: -24.1%, +2.0%) after introducing no-till (NT_R vs. T_R) (Fig. A3A in the appendix) and SOC stocks increase. After ten years duration (average of year 9-11), however, both CO_2 emissions and SOC stocks are higher under NT_R than under T_R (Fig. 3-3A, 3-3D). Median CO_2 emissions from NT_R compared to T_R increase by +1.7% (5th, 95th percentile: -17.4%, +32.4%) (Fig. 3-3A), while at the same time median topsoil SOC also increase by +5.3% (5th, 95th percentile: +1.4%, +12.8%) (Fig. 3-3D), i.e., the SOC stock has already increased enough to sustain higher CO_2 emissions. There are two explanations for CO_2 increase in the long term: 1) more C input from increased NPP for NT_R or 2) a higher decomposition rate over time under NT_R, due to changes in, e.g., soil moisture or temperature. Initially, CO_2 emissions decrease almost globally due to increased turnover times under T_R (Fig. A3C in the appendix), but after ten years, CO_2 emissions start to increase in drier regions, while they still decrease mostly in humid regions (Fig. 3-3A). The median of the relative differences in mean residence time of soil C for NT_R compared to T_R is small but variable (+0.0% after ten years, 5th, 95th percentile: -22.9%, +23.7%) (Fig. 3-3C), and mean residence time shows similar spatial patterns, i.e., it decreases in drier areas but increases in more humid areas. The drier regions are also the areas where we observe a positive effect of reduced evaporation and increased infiltration on plant growth, i.e., in these regions, the C-input into soils is substantially increased under NT_R compared to T_R (Fig. 3-3B) (see also 3.5.2 for productivity). As such, both mechanisms that affect CO_2 emissions are reinforcing each other in many regions. This is in agreement with the meta-analyses conducted by Pittelkow et al. (2015b), who report a positive effect on yields (and thus general productivity and thus C-input) of no-till compared to conventional tillage in dry climates. Their results show that, in general, no-till performs best relative to conventional tillage under water-limited conditions due to enhanced water-use efficiencies when residues are retained.

Abdalla et al. (2016) reviewed the effect of tillage, no-till and residues management and found that if residues are returned, no-till compared to conventional tillage increases SOC content by 5.0% (95th CI: -1.0%, +9.2%) and decreases CO_2 emissions from soils by -23.0% (95th CI: -35.0%, -13.8%) (Table 3-3). These findings of Abdalla et al. (2016) are in line with our findings for CO_2 emissions if we consider the first three years of duration for CO_2 emissions and ten years duration for topsoil SOC. Abdalla et al. (2016) do not explicitly specify a time of duration for these results. If we only analyze the tillage effect without taking residues into account (T_NR vs. NT_NR), we find in our simulation that topsoil SOC decreases by -18.0% (5th, 95th percentile: -42.5%, -0.5%) after twenty years, while CO_2 emissions increase by +21.3% (5th, 95th percentile: -1.1%, +125.2%) mostly in humid regions, whereas they start increasing in drier regions (Table 3-3). Abdalla et al. (2016) also reported SOC changes from a T_NR vs. NT_NR comparison and reported a decrease in SOC under T_NR of -12.0% (95th CI: -15.3%, -5.1%) and a CO_2 increase of +18.0% (95th CI: +9.4%, +27.3%), which is well in line with our model results.

Ogle et al. (2005) conducted a meta-analysis and reported SOC changes from NT_R compared to T_R system with medium C input, grouped for different climatic zones. They found a +23%, +17%, +16%, and +10% mean increase in SOC after converting from conventional tillage to a no-till system for more than 20 years for tropical moist, tropical dry, temperate moist, and temperate dry climates, respectively. We only find a +4.8%, +8.3%, +3.5%, and +5.8% mean increase in topsoil SOC for these regions, respectively.

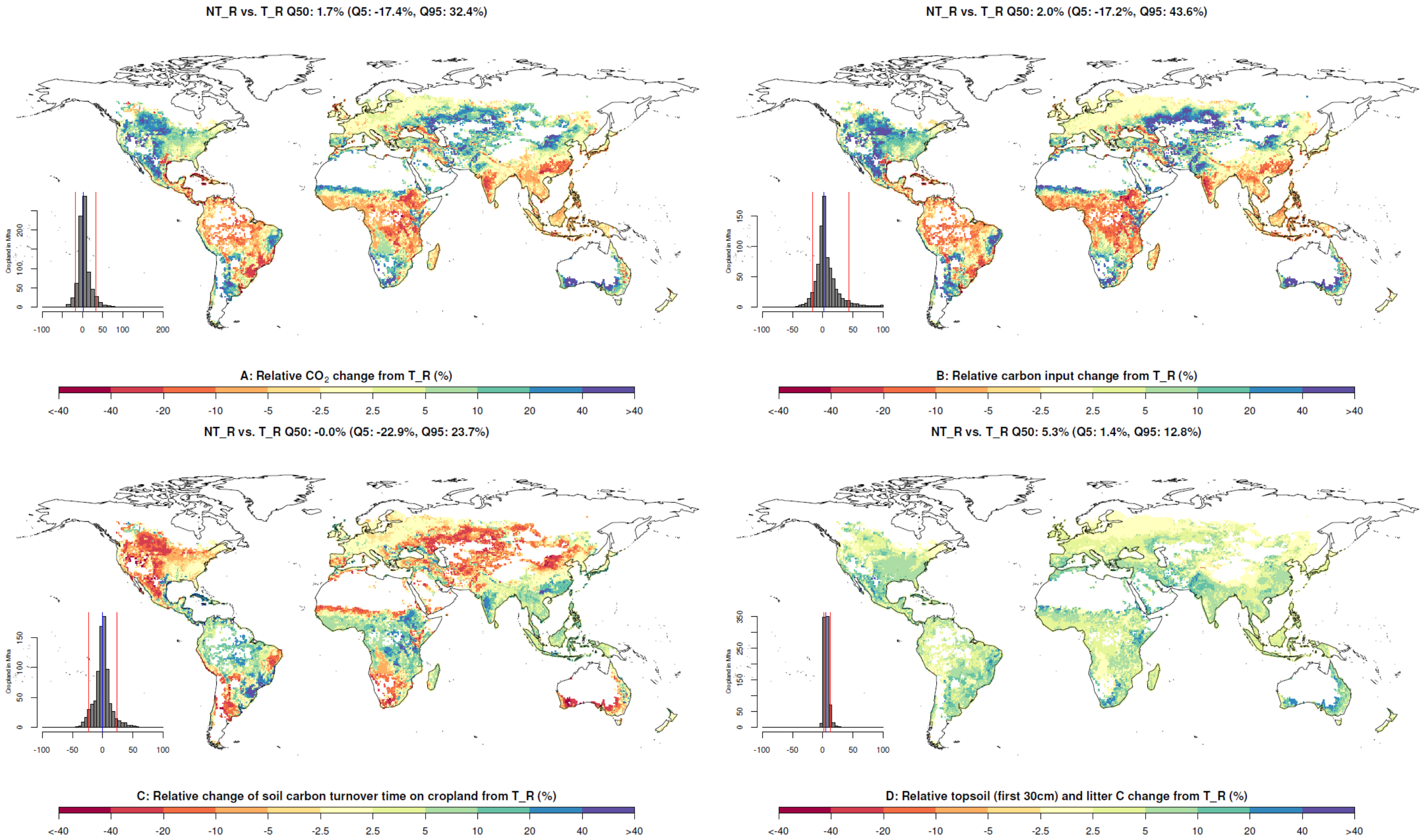

Figure 3-3: Relative C dynamics for NT_R vs. T_R comparison after ten years of simulation experiment (average of year 9–11) for relative CO2 change (a), relative C input change (b), relative change of soil C turnover time (c), and relative topsoil and litter C (SOC) change (d)

However, Ogle et al. (2005) analyzed the data by comparing a no-till system with high C inputs from rotation and residues to a conventional tillage system with medium C input from rotation and residues. We compare two similarly productive systems with each other, where residues are either left on the field or incorporated through tillage (NT_R vs. T_R), which may explain why we see smaller relative effects in the simulations. Comparing a high input system with a medium or a low input system will essentially lead to an amplification of SOC changes over time; nevertheless, we are still able to generally reproduce a SOC increase over longer periods.

Unfortunately, there are high discrepancies in the literature with regard to no-till effects on SOC since the high increases found by Ogle et al. (2005) are not supported by the findings of Abdalla et al. (2016). Ranaivoson et al. (2017) found that crop residues left on the field increase SOC content, which is in agreement with our simulation results.

3.5.4 Water fluxes

We evaluate the effects of tillage and residue management on water fluxes by analyzing soil evaporation and surface runoff. Our results show that evaporation and surface runoff under NT_R compared to T_R are generally reduced by -44.3% (5th, 95th percentiles: -64.5, -17.4%) and by -57.8% (5th, 95th percentiles: -74.6%, -26.1%), respectively (Fig. A3-4A and A3-4B in the appendix). We also analyzed soil evaporation and surface runoff for different amounts of surface litter loads and cover on bare soil without vegetation to compare our results to literature estimates from field experiments. We find that both the reduction in evaporation and surface runoff is dependent on the residue load, which translates into different rates of surface litter cover.

Water fluxes highly influence plant productivity on the process side and are affected by tillage and residue management (Fig. 3-1). Surface litter on top of the soil creates a barrier that reduces evaporation and increases the rate of infiltration into the soil. The litter which is incorporated into the soil through tillage loses this function to cover the soil. The reduction of soil evaporation and the increase of rainfall infiltration contribute to increased soil moisture and therefore plant water availability. The model accounts for both processes. Scopel et al. (2004) modeled the effect of maize residues on soil evaporation calibrated from two tropical sites. They found that a presence of 100 g m^{-2} surface litter decrease soil evaporation by -10% to -15% in the data, whereas our model shows a median decrease in evaporation of -6.6% (5th, 95th percentiles: -26.1%, +20.3%) globally (Fig. A5A in the appendix). The effect of a higher amount of surface litter is much more dominant, as Scopel et al. (2004) found that 600 g m^{-2} surface litter reduced evaporation by approx. -50%. For the same litter load, our model shows a median decrease in evaporation by -72.6% (5^{th}, 95^{th} percentiles: -81.5%, -49.1%) (Fig. A5B in the appendix), which is higher than the results found by Scopel et al. (2004). We further analyze and compare our model results to the meta-analysis from Ranaivoson et al. (2017), who reviewed the effect of surface litter on evaporation and surface runoff, and other agroecological functions. Ranaivoson et al. (2017) and the studies compiled by them do not explicitly distinguish between the different compartments of runoff (e.g., lateral-, surface-runoff). We assume that they measured surface runoff since lateral runoff is difficult to measure and must be considered in relation to the plot size. Fig. 3-4 compares modeled global results for relative evaporation and surface runoff change for 10, 30, 50, 70, and 90% soil cover on bare soil to literature values from Ranaivoson et al. (2017). Concerning the effect of soil cover on evaporation (Fig. 3-4A), we find that we are well in line with literature estimates from Ranaivoson et al. (2017) for up to 70% soil cover, especially when analyzing humid climates. For higher soil cover ≥70%, the model seems to be more in line with literature values for arid regions. Overall for a high soil cover of 90%, the model appears to overestimate evaporation reduction. We note that the estimates from Ranaivoson et al. (2017) are only taken from two field studies, which are the only representative for the local climatic and soil conditions since global data on the effect of surface litter on evaporation are not available. The model thus captures the general effect of surface litter on the reduction in soil evaporation, but the model seems to overestimate the response at high litter loads. The literature is not entirely clear if these experiments have been carried on bare soil without vegetation. Suppose crops are also grown in the experiments, water can be used for transpiration which is otherwise available for evaporation, which could explain why the model overestimates the effect of surface litter on evaporation on bare soil without any vegetation.

Ranaivoson et al. (2017) also investigated the runoff reduction under soil cover, but the results do not show a clear picture. In theory, surface litter reduces surface runoff, and literature generally supports this assumption (Kurothe et al., 2014; Wilson et al., 2008), but the magnitude of the effect varies. Fig. 3-4B compares our modeled results under different soil cover to the literature values from Ranaivoson et al. (2017). This shows that modeled results across all global cropland are on the upper end of the effect of surface runoff reduction from soil cover, but they are still well within the range reported by Ranaivoson et al. (2017). The amount of water which is infiltrated (and thus not going into surface runoff) is affected by the parameter p in Eq. (12), which is dependent on the amount of surface litter cover (f_{surf}). The parameterization of p is chosen to be at the upper end of the approach by Jägermeyr et al. (2016) at full surface litter cover, as this should substantially reduce surface runoff (Tapia-Vargas et al., 2001) and thus increase infiltration rates (Strudley et al., 2008). The parametrization of p can be adjusted if better site-specific information on the slope, soil crusting, and rainfall intensity are available.

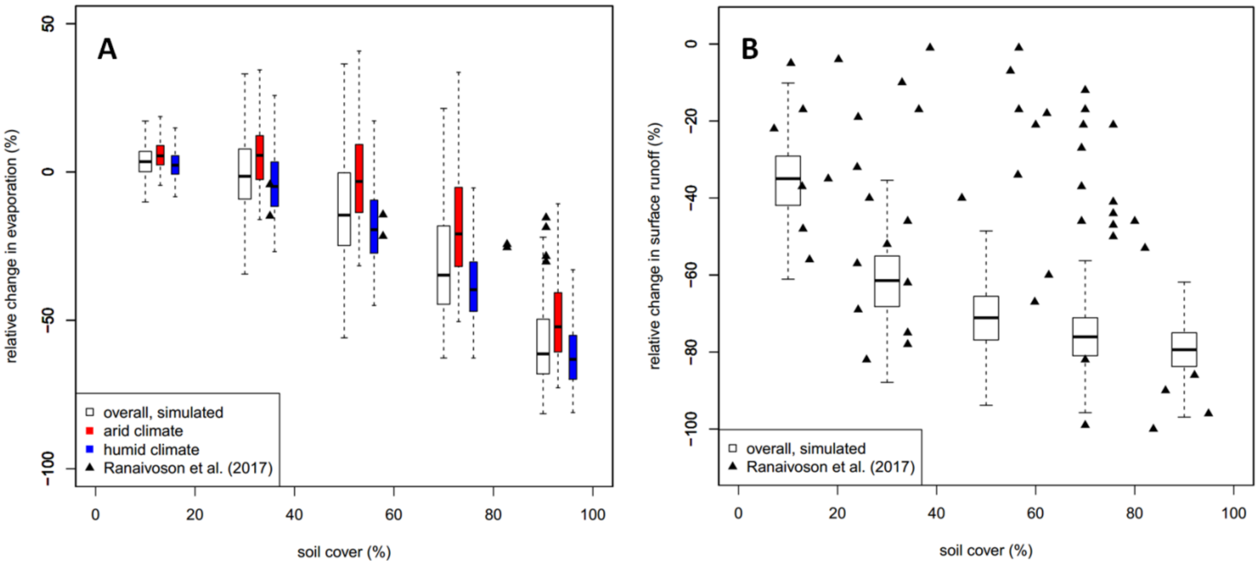

Figure 3-4: Relative change in evaporation (A) and surface runoff (B) relative to soil cover from surface residues for different soil cover values of 10 %, 30 %, 50 %, 70 %, and 90 % (simulation NT_R_bs1 to NT_R_bs5 vs. NT_NR_bs, respectively). For better visibility, the red and blue boxplots are plotted next to the overall boxplots but correspond to the soil cover value of the overall simulation (empty boxes).

3.5.5 Nitrous oxide fluxes

Simulation results show an increase in N_2O emissions by a median of +20.8% (5th, 95th percentile: -3.6%, +325.5%) (Fig. A6A in the appendix) after switching from T_R to NT_R management (see Fig. A6A in the appendix). In the cold temperate zone, this increase is the strongest. There, N_2O emissions increase by an average of +23.5% (5th, 95th percentile: -0.1%, +664.4%) (Fig. A6E in the appendix). In the tropical zone, the lowest average increase by +15.8% (5th, 95th percentile: -7.3%, +72.1%) is visible (Fig. A6C in the appendix).

After adopting no-till, N_2O emissions can increase, which in agreement with literature studies, e.g., Linn and Doran (1984), Mei et al. (2018), van Kessel et al. (2013), or Zhao et al. (2016) (see also Table 3-3). In agreement with our median estimate, Mei et al. (2018) found an overall increase in N_2O emissions of +17.3% (95th CI: +4.6%, +31.1%). The regional patterns over the different climate regions are, however, in less agreement. The LPJmL simulations highly underestimate the increase in N_2O emissions in the tropical region. Yet, this effect is overestimated for cold temperate and humid zones, which is partly also visible for warm temperate regions (see Table 3-3).

The release of N_2O to the atmosphere is generally caused by nitrification and denitrification in the soil. After adopting NT_R, the increase in N_2O emissions in our simulations is mainly driven by denitrification (+55.9%, see Fig. 3-5A), visible for most regions. N_2O emissions related to nitrification mainly decrease (median of -6.0%, see Fig. 3-5B) but show the tendency to increase in dry regions. A decrease in NO_3^- by a median of -26.4% results from a decrease in nitrification and an increase in denitrification. This effect seems to be enhanced in tropical regions (see Fig. 3-5D). Mineral N transformation to gaseous N_2O is not only affected by nitrification and denitrification but also by the availability of substrate in the form of NH_4^+ and NO_3^-. On the other hand, the availability of NH_4^+ and NO_3^- is affected by nitrification and denitrification rates and other processes, e.g., plant uptake and leaching. For example, in the Sahel zone, nitrification increases and denitrification decreases, yet NO_3^- stocks decline due to a substantial increase in leaching (see Fig. A7 in the appendix).

In LPJmL, soil moisture is mostly driving nitrification and denitrification rates. To a lesser extent, nitrification and denitrification rates are also driven by soil pH (for nitrification), SOC (for denitrification), and soil temperature. After adopting NT_R, a strong increase in average soil moisture by a median of +18.9% (see Fig. 3-5C) is observed, caused by higher soil infiltration rates and reduced soil evaporation (see Section 3.5.4). Additionally, bulk density generally increases under no-till conditions, resulting in higher relative soil moisture affecting N_2O emissions (van Kessel et al., 2013; Linn and Doran, 1984). Denitrification increases non-linearly under anoxic conditions beyond a soil moisture threshold (von Bloh et al., 2018). For nitrification and optimal soil moisture content exist and is reduced under low and high soil moisture conditions. Nitrification is reduced by no-till management in wet regions, i.e., humid and tropical areas, while it increases in dry areas.

Van Kessel et al. (2013) showed that the adoption of no-till could both increase and decrease N_2O emissions. This ambiguous response does not come by surprise, as tillage affects a complex set of biophysical factors that could positively and negatively influence N_2O emissions (van Kessel et al., 2013; Snyder et al., 2009) (see also Fig. 3-1). For example, the presence of a litter layer in a no-till system can reduce the temperature exchange between the atmosphere and soil, which could lower N_2O emissions (Enrique et al., 1999). For northern Europe and Brazil, simulation results indicate reduced N_2O emissions after no-till adoption (see Fig. A6A in the appendix).

Estimations of N_2O emissions are characterized by high spatial and temporal variability and are accompanied by high uncertainties (Butterbach-Bahl et al., 2013). This complicates the evaluation of modeled results (Chatskikh et al., 2008; Mangalassery et al., 2015). Due to the discrepancy between meta-analyses and modeled results by LPJmL, especially for specific climate regimes (i.e., tropical or cold temperate), further investigations on the effect of tillage and no-till on N_2O emissions in site-specific model comparisons are needed.

Because responses of N_2O emissions to management are highly sensitive, soil moisture effects have to be simulated correctly. Yet, soil moisture is influenced by many processes and is strongly related to vegetation performance and climate dynamics, adding uncertainty (Seneviratne et al., 2010). Further analysis is needed to understand the effects of management on N_2O emissions, preferably for different soil types, other management assumptions (e.g., fertilizer application), or different climate regions. Yet, the high variability in observed management to N_2O emission responses found in a meta-analysis (Mei et al., 2018) complicates the evaluation of model results. Anyhow, we trust the capability of LPJmL5.0-tillage to simulate biophysical feedbacks for different management responses to help understand their interactions under different environmental conditions.

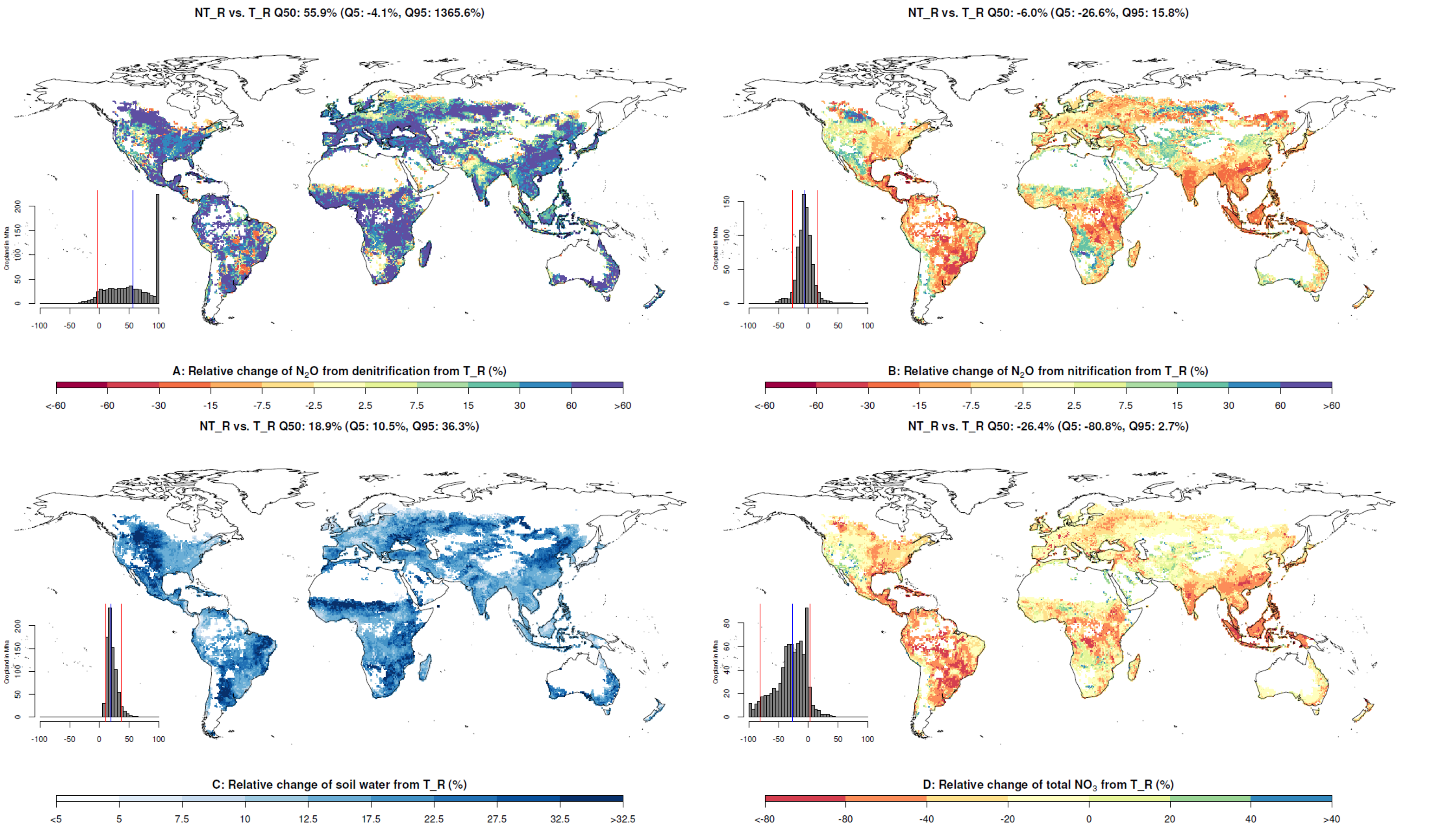

Figure 3-5: Relative changes for the average of the first three years of NT_R vs. T_R for denitrification (A), nitrification (B), soil water content (C), and NO_3^- (D).

Table 3-3: Comparison of simulated model output and literature values from meta-analyses. Values for modeled results are calculated according to Eq. (35) with adjusted default management.

Variable/Scenario	Soil depth (m)	# of paired treatments	Literature mean (95% interval)	Time horizon (years)	Modeled response (median %)	Modeled response (5% and 95% percentile)	Reference
No-till residue - till residue							
SOM (0.3m)	0 - 0.3	101	+5.0 (+1.0, +9.2)[a,d]	10[e]	+5.3	+1.4, +12.8	Abdalla et al., 2016
CO_2		113	-23.0 (-35.0, -13.8)[a]	[b]	-11.9	-24.1, +2.0	Abdalla et al., 2016
N_2O		98	+17.3 (+4.6, +31.1)[a]	[b]	+20.8	-3.6, +325.5	Mei et al., 2018
N_2O (tropical)		123	+74.1 (+34.8, +119.9)[c,d]	[b]	+15.8	-7.3, +72.1	Mei et al., 2018
N_2O (warm temperate)		62	+17.0 (+6.5, +29.9) [c,d]	[b]	+23.2	+6.0, +182.3	Mei et al., 2018
N_2O (cool temperate)		27	-1.7 (-10.5, +8.4) [c,d]	[b]	+23.5	-0.1, +664.4	Mei et al., 2018
N_2O (arid)		56	+35.0 (+7.5, +69.0)[a]	[b]	+21.1	-1.8, +496.3	Kessel et al., 2013
N_2O (humid)		183	-1.5 (-11.6, +11.1)[a]	[b]	+20.7	-9.1, +63.8	Kessel et al., 2013
Yield (wheat)		47	-2.6 (-8.2, +3.8)[a]	10[e]	+2.5	-15.2, +53.5	Pittelkow et al. 2015b
Yield (maize)		64	-7.6 (-10.1, -4.3)[a]	10[e]	+1.8	-24.6, +56.2	Pittelkow et al. 2015b
Yield (rapeseed)		10	+0.7 (-2.8, +4.1)[a]	10[e]	+3.5	-24.5, +57.8	Pittelkow et al. 2015b
Tillage noresidue – no-till noresidue							
SOM (0.3m)	0 - 0.3	46	-12.0 (-15.3, -5.1)[a]	20[e]	-18.0	-42.5, -0.5	Abdalla et al., 2016
CO_2		46	+18.0 (+9.4, +27.3)[a]	20[e]	+21.3	-1.1, +125.2	Abdalla et al., 2016
Yield (wheat) B		8	+2.7 (-6.3, +12.7)[a]	10[e]	-5.9	-15.7, +3.7	Pittelkow at al. 2015b
Yield (maize) B		12	-25.4 (-14.7, -34.1)[a]	10[e]	-5.0	-27.3, +12.0	Pittelkow et al. 2015b
Tillage noresidue - till residue							
N_2O		105	+1.3 (-5.4, +8.2)[a,d]	[b]	-9.7	-22.0, +3.6	Mei et al., 2018

[a] Estimated from a graph. [b] Time horizon of the study is unclear in the meta-analysis. The average over the first 3 years of model results is taken. [c] Includes conservation tillage. [d] Residue management for conventional tillage unsure. [e] Time horizon not explicitly mentioned by the author.

3.5.6 General discussion

The implementation of tillage into the global ecosystem model LPJmL opens opportunities to assess the effects of different tillage practices on agricultural productivity and its environmental impacts, such as nutrient cycles, water consumption, GHG emissions, and SOC sequestration and is a general model improvement to the previous version of LPJmL (von Bloh et al., 2018). The implementation involved (1) the introduction of a surface litter pool that is incorporated into the soil column at tillage events and the subsequent effects on soil evaporation and infiltration, (2) dynamically accounting for SOM content in computing soil hydraulic properties, and (3) simulating tillage effects on bulk density and the subsequent effects of changed soil water properties and all water-dependent processes (Fig. 3-1).

In general, a global model implementation on tillage practices is difficult to evaluate, as effects are often variable, depending on local soil and climatic conditions. The model results were evaluated with data compiled from meta-analyses, which implies several limitations. Due to the limited amount of available meta-analyses, not all fluxes and stocks could be evaluated within the different management scenarios. We focused on productivity, SOC stocks and fluxes, water fluxes, and N_2O dynamics for the evaluation. The sample size in some of these meta-analyses was sometimes small, which could result in biases if not a representative set of climate and soil combinations was tested. A comparison of a small sample size to simulations of the global cropland is challenging. Nevertheless, the meta-analyses gave the best overview of the overall effects of tillage practices that have been reported for various individual experiments.

We find that the model results for NT_R compared to T_R are generally in agreement with literature with regard to the magnitude and direction of the effects on C stocks and fluxes. Despite some disagreement between reported ranges in effects and model simulations, we find that the diversity in modeled responses across environmental gradients is an asset of the model. The underlying model mechanisms, as the initial decrease in CO_2 emissions after the introduction of no-till practices that can be maintained for long periods in moist regions, but is inverted in dry regions due to the feedback of higher water availability on plant productivity and reduced turnover times and generally increasing soil C stocks (Fig. 3-3), are plausible and in line with general process understanding. Certainly, the interaction of the different processes may not be captured correctly, and further research on this is needed. We trust that this model implementation representing this complexity allows for further research in this direction. Regarding the water fluxes, the model seems to overestimate the effect of surface residue cover on evaporation for high surface cover. Yet, the evaluation is constrained by the small number of suitable field studies. Effects can also change over time so that a comparison needs to consider the timing, history, and duration of management changes and specific local climatic and soil conditions. The overall effect of NT_R compared to T_R on N_2O emissions is in agreement with the literature as well. However, the regional patterns over the different climatic regimes are in less agreement. N_2O emissions are highly variable in space and time and are very sensitive to soil water dynamics (Butterbach-Bahl et al., 2013). The simulation of soil water dynamics differs per soil type as the calculation of the hydraulic parameters is texture-specific. Moreover, these parameters are now changed after a tillage event. The effects of tillage on N_2O emissions and other processes that are driven by soil water (e.g., CO_2, water dynamics) can therefore be different per soil type. The soil-specific effects of tillage on N_2O and CO_2 emissions were already studied by Abdalla et al. (2016) and Mei et al. (2018). Abdalla et al. (2016) found that differences in CO_2 emissions between tilled and untilled soils are largest in sandy soils (+29%), whereas the differences in clayey soils are much smaller (+12%). Mei et al. (2018) found that clay content <20% significantly increases N_2O emissions (+42.9%) after adapting to conservation tillage, whereas this effect for clay content >20% is smaller (+2.9%). These studies show that soil type-specific tillage effects on several processes can be of importance and should be investigated in more detail in future studies. The interaction of all relevant processes is complex, as seen in Fig. 3-1, which can also lead to high uncertainties in the model. Again, we think that this model implementation captures substantial aspects of this complexity and thus lays the foundation for further research.

It is important to note that not all processes related to tillage and no-till are taken into account in the current model implementation. For instance, NT_R can improve soil structure (e.g., aggregates) due to increased faunal activity (Martins et al., 2009), which can result in a decrease in BD. Although tillage can have several advantages for the farmer, e.g., residue incorporation and topsoil loosening, it can also have several disadvantages. For instance, tillage can cause compaction of the subsoil (Bertolino et al., 2010), which results in an increase in BD (Podder et al., 2012) and creates a barrier for percolating water, leading to ponding and an oversaturated topsoil. Strudley et al. (2008) however observed diverging effects of tillage and no-till on hydraulic properties, such as BD, Ks, and WHC for different locations. They argue that affected processes of agricultural management have complex coupled effects on soil hydraulic properties, as well as that variations in space and time often lead to higher differences than the measured differences between the management treatments. They also argue that characteristics of soil type and climate are unique for each location, which cannot simply be transferred from one field location to another. A process-based representation of tillage effects as in this extension of LPJmL allows for further studying management effects across diverse environmental conditions, but also to refine model parameters and implementations where experimental evidence suggests disagreement.

One of the primary reasons for tillage, weed control, is also not accounted for in LPJmL5.0-tillage or other ecosystem models. As such, different tillage and residue management strategies can only be assessed concerning their biogeochemical effects, but only partly with respect to their effects on productivity and not to some environmental effects (e.g., herbicide and pesticide use). Our model simulations show that crop yields increase under no-till practices in dry areas but decrease in wetter regions (Fig. 3-2). However, the median response is positive, which may be in part because the water-saving effects from increased soil cover with residues are overestimated or because detrimental effects, such as competition with weeds, are not accounted for.

The included processes now allow us to analyze long-term feedbacks of productivity on SOC stocks and N dynamics. Nevertheless, the results need to be interpreted carefully due to the capacity of the model and implemented processes. We also find that the modeled impacts of tillage are very diverse in space as a result of different framing conditions (soil, climate, management) and feedback mechanisms, such as improved productivity in dry areas if residue cover increases plant available water. The process-based representation in the LPJmL5.0-tillage of tillage and residue management and the effects on water fluxes such as evaporation and infiltration at the global scale is unique in the context of global biophysical models (e.g., Friend et al., 2014; LeQuéré et al., 2018). Future research on improved parameterization and the implementation of a more detailed representation of tillage processes and the effects on soil water processes, changes in porosity and subsoil compaction, effects on biodiversity, and soil N dynamics is needed to better assess the impacts of tillage and residue management at the global scale. The required spatial resolution to resolve processes, such as erosion, data availability, and model structure, need to be considered in further model development (Lutz et al., 2019b). Some processes, such as a detailed representation of soil crusting processes, may remain out of reach for global-scale modeling.

3.6 Conclusion

We described the implementation of tillage-related processes into the global ecosystem model LPJmL5.0-tillage. The extended model was tested under different management scenarios and evaluated by comparing to reported impact ranges from meta-analyses on C, water, and N dynamics as well as on crop yields.

We find that most arid regions benefit from no-till management with leaving residues on the field due to the water-saving effects of surface litter. We can broadly reproduce reported tillage effects on global stocks and fluxes, as well as regional patterns of these changes, with LPJmL5.0-tillage, but deviations in N-fluxes need to be further examined. Not all effects of tillage, including one of its primary reasons, weed control, could not be accounted for in this implementation. Uncertainties mainly arise because of the multiple feedback mechanisms affecting the overall response to tillage, as most processes are affected by soil moisture. The processes and feedbacks presented in this implementation are complex, and evaluation of effects is often limited in the availability of reference data.

Nonetheless, the implementation of detailed tillage-related mechanics into the global ecosystem model LPJmL improves our ability to represent different agricultural systems and understand management options for climate change adaptation, agricultural mitigation of GHG emissions, and sustainable intensification. We trust that this model implementation and the publication of the underlying source code promote research on the role of tillage for agricultural production, its environmental impact, and global biogeochemical cycles. The source code is publicly available under the GNU AGPL version 3 license. An exact version of the source code described here is archived under https://doi.org/10.5281/zenodo.2652136 (Herzfeld et al., 2019).

Chapter 4

Simulating SOC dynamics from agricultural management practices under climate change

Abstract. Sequestration of SOC on cropland has been proposed as a climate change mitigation strategy to reduce global GHG concentrations in the atmosphere, which is in particular needed to achieve the targets proposed in the Paris Agreement to limit the increase in atmospheric temperature to well below 2 °C. We here analyze the historical evolution and future development of cropland SOC using the global process-based biophysical model LPJmL, which was recently extended by a detailed representation of tillage practices and residue management (version 5.0–tillage2). We find that model results for historical global estimates for SOC stocks are at the upper end of available literature, with ~2650 Pg C of SOC stored globally in the year 2018, of which ~170 Pg C are stored in cropland soils. In future projections, assuming no further changes in current cropland patterns and under four different management assumptions with two different climate forcings, RCP2.6, and RCP8.5, results suggest that agricultural SOC stocks decline in all scenarios, as the decomposition of SOC outweighs the increase of C inputs into the soil from altered management practices. Different climate-change scenarios, as well as assumptions on tillage management, play a minor role in explaining differences in SOC stocks. The choice of tillage practice explains between 0.2% and 1.3% of total cropland SOC stock change in the year 2100. Future dynamics in cropland SOC are most strongly controlled by residue management, whether residues are left on the field or harvested. We find that on current cropland, global cropland SOC stocks decline until the end of the century by only 1.0% to 1.4% if residue-retention management systems are generally applied and by 26.7% to 27.3% in case of residue harvest. For different climatic regions, increases in cropland SOC can only be found for tropical dry, warm temperate moist, and warm temperate dry regions in management systems that retain residues.

4.1 Introduction

To meet the targets of the Paris Agreement of 2015 to keep the increase in global mean temperature well below 2 °C, and especially for the ambitious target of below 1.5°C, several negative emission technologies which remove CO_2 from the atmosphere have been proposed (Minx et al., 2018; Rogelj et al., 2018, 2016). At the same time as the climate is warming, the global human population is expected to increase to 9.7 billion people in 2050 and 10.9 billion by 2100 (United Nations et al., 2019), putting additional pressure on future food production systems. Food production alone has to increase by at least 50% (FAO, 2019) or even double by the year 2050, depending on dietary preferences, demographical trends, and climate projections, when global food demand is to be met (Bodirsky et al., 2015). Different agricultural management practices have been proposed as C sequestration strategies to mitigate climate change and increase the quality and health of the soil by increasing SOC content of cropland soils (Lal, 2004a), which also decreases the risk of soil erosion and soil degradation (Lal, 2009c).

Tillage influences many biophysical properties, such as soil temperature or soil hydraulic properties (Snyder et al., 2009b), and can increase different forms of soil degradation (Cerdà et al., 2009; Kurothe et al., 2014; Lal, 1993). The potential of SOC sequestration for agricultural management practices, e.g., the effect of no-till, is debated in the scientific community (Baker et al., 2007; Powlson et al., 2014). Because tillage management is closely interrelated with residues management (Guérif et al., 2001; Snyder et al., 2009b), these two practices should always be investigated simultaneously. Residue management can affect SOC stocks and soil water properties, as residues left on the soil surface can increase soil infiltration, reduce evaporation (Guérif et al., 2001; Ranaivoson et al., 2017), and add soil organic matter into the soil (Maharjan et al., 2018). Soil moisture and therefore plant productivity is also influenced by irrigation. While irrigated systems generally tend to have higher SOC stocks due to positive feedbacks on plant productivity, the feedbacks and mechanisms on SOC development are still not well understood (Emde et al., 2021; Humphrey et al., 2021). The effectiveness of irrigation systems on SOC development is influenced by climate and initial SOC stock and tends to be more effective in semiarid regions and less effective in humid regions (Trost et al., 2013).

Minasny et al. (2017) have proposed the '4 per 1000 Soils for Food Security and Climate' initiative, which targets to increase global SOC sequestration by 0.4% per year. They argue that under best-management practices, this target rate could be even higher. This approach would translate into a 2-3 Pg C a^{-1} SOC increase in the first 1 m of the soil, which is equivalent to about 20-35% of global greenhouse gas (GHG) emissions (Minasny et al., 2017). This proposal has been criticized as it overestimates the possible effect of SOC sequestration potential through agricultural management (de Vries, 2018; White et al., 2018). Field trials on SOC sequestration potentials show results with higher, as well as lower sequestration rates, but only represent the local soil and climatic conditions for the time of the experiment (Fuss et al., 2018; Minx et al., 2018), which reduces the likelihood for their validity on larger scales or longer time periods.

Global total SOC stocks are estimated between 1500 Pg C (excluding permafrost regions) (Hiederer and Köchy, 2011) to up to 2456 Pg C for the upper 200 cm (Batjes, 2014) and agricultural SOC stocks alone, which are subject to agricultural management, are estimated to be between 140 and 327 Pg C depending on soil depth (Jobbágy and Jackson, 2000; Zomer et al., 2017). Since the beginning of cultivation by humans approximately 12000 years ago, global SOC stocks for the top 200 cm of soil have declined by 116 Pg C because of agriculture by one estimate (Sanderman et al., 2017). Management assumptions play an important role in these estimates; e.g., Pugh et al. (2015) found that residue removal and tillage effects contribute to 6% and 8% of total LUC emissions between the years 1850 and 2012 alone, which translates into biomass and soil C losses of approx. 13.5 Pg C and 16 Pg C, respectively.

In this study, we use a modeling approach to quantify the historical development of global cropland SOC stocks using new data for agricultural management such as manure and residues management, as well as a new data set of the spatial distribution of tillage practices. In addition, we investigate the potential for SOC sequestration under different climate-change scenarios on current cropland.

4.2 Materials and methods

4.2.1 The LPJmL5.0-tillage2 model

The LPJmL5.0-tillage2 model used for the analysis in this chapter combines the dynamic phenology scheme of the natural vegetation (Forkel et al., 2014) with version 5.0-tillage, which covers the terrestrial N cycle (von Bloh et al., 2018) and the representation of tillage practices and residue management (Lutz et al., 2019a). With the term SOC we refer to the sum of all soil and litter C pools. After the harvest of crops, root C is transferred to the below-ground litter pool. The incorporation of above-ground residues into the soil is dependent on the chosen management practices. Different tillage and residue management schemes and the accounting for direct effects of SOC on soil hydraulic properties and thus on SOM decomposition and plant productivity have been introduced in the implementation of tillage practices in Chapter 3, and are thus explicitly considered here (Fig. 4-1). In LPJmL5.0-tillage2, the amount of C in biomass, which is either harvested or can be left on the field as crop residue, is dependent on productivity (plant growth). Litter pool sizes are determined by the amount of biomass that is left on the field (i.e., not harvested) and the rate at which the litter is decomposed. The model code is available at: https://doi.org/10.5281/zenodo.4625868 (Herzfeld et al., 2021).

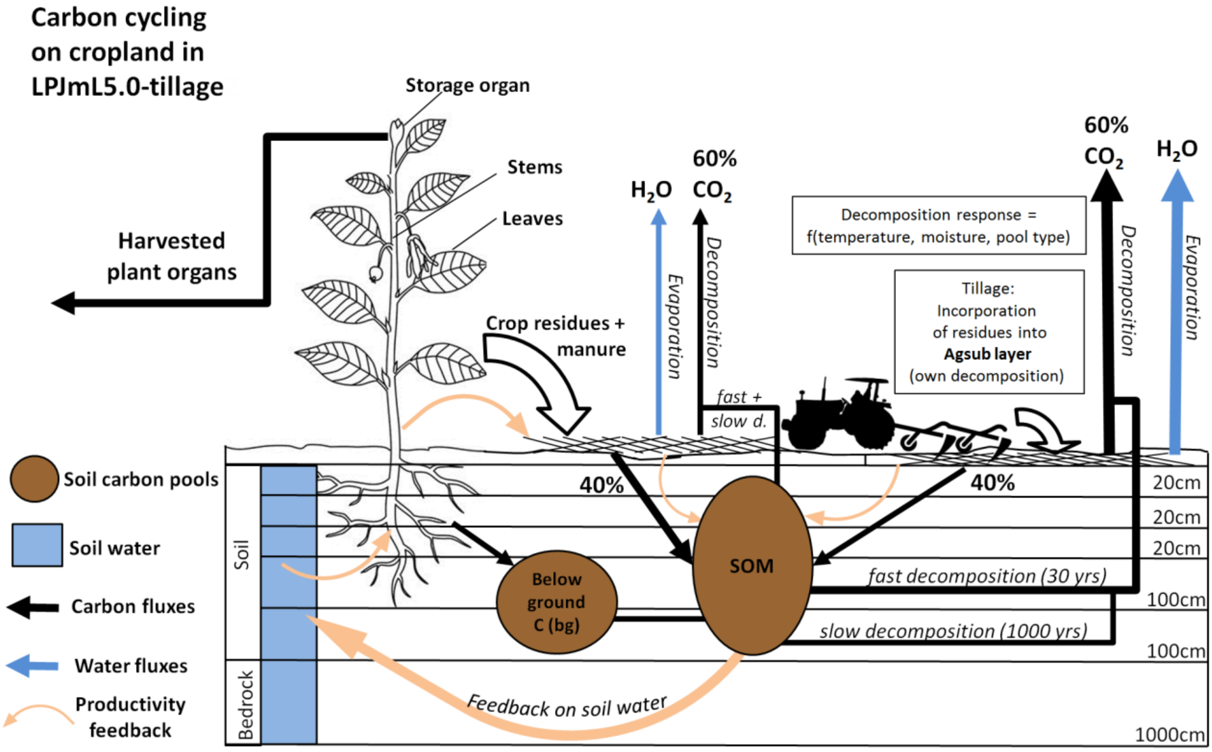

Figure 4-1: Carbon cycling on cropland and productivity feedbacks from plants to residues and soil stocks and soil water, as modeled in LPJmL5.0-tillage. Arrows indicate fluxes, boxes, and circles are stocks.

At decomposition, the model assumes a fixed amount of 40% of C that is transferred from litter to the soil C pools; the other 60% of C are emitted to the atmosphere as CO_2, as in von Bloh et al. (2018). Applied N from manure, which is now explicitly considered in contrast to the previous model version LPJmL5.0-tillage, is assumed to consist of equal shares of mineral and organic N so that 50% is added to the ammonium pool of the first soil layer and the rest is added to the above-ground leaf litter N pool. While manure composition is highly variable across animal type, feed, and treatment, a general ratio of 1:2 of ammonium to total N in manure is in principle supported by the ranges reported by Van Kessel and Reeves (2002). The organic leaf litter nitrogen is quickly decomposed and added to the ammonium pool of the soil. The C part of the organic manure is allocated to the leaf litter C pool (i.e., an easily degradable organic pool that can be left on the soil surface or incorporated into the soil column by tillage), with a fixed C : N ratio of 14.5 (IPCC, 2019). Total fertilizer amounts (i.e., mineral fertilizer and manure) are applied either completely at sowing or split into two applications per growing season. Manure is always applied at the first application event at sowing. Only when total combined fertilizer inputs (manure and mineral N) exceed 5 gN m^{-2}, half of the total fertilizer is applied in a second application as mineral fertilizer, which is applied after 40% of the necessary phenological heat sums to reach maturity have been accumulated.

4.2.2 Simulation protocol

A list of the simulations carried out for this study is summarized in Table 4-1. An initial spinup simulation per general circulation model (GCM) and Climate Research Unit gridded Time Series (CRU TS) climate data of 7000 years is conducted to bring SOC stocks into a dynamic pre-historic equilibrium (SP-GCM/SP-CRU), in which the first 30 years of weather data are cyclically recycled, mimicking stable climate conditions. A second GCM-specific spinup simulation to introduce land use dynamics starts in 1510 so that cropland older than that has reached a new dynamic equilibrium by 1901 when the actual simulations start and land-use history is accounted for otherwise. Simulations were run for three groups: a) historical runs from 1901-2018 using CRU TS Version 4.03 climate input (Harris et al., 2020) and inputs on historical management time series (which is subject to the same spinup procedures as the GCM-specific simulations), b) historical simulations from 1901-2005 with climate inputs from the four GCMs and historical management time series, c) future simulations using projections of the four GCMs for the representative concentration pathways RCP2.6 (low radiative forcing) and RCP8.5 (high radiative forcing) and four different stylized management settings: conventional tillage and residues retained (T_R), conventional tillage and residues removed (T_NR), no-till and residues retained (NT_R) and no-till and residues removed (NT_NR) and d) simulations as in c) but with [CO_2] held constant at the level of the year 2005 (379.8 ppmv) that are used to quantify the CO_2 effect. All other inputs (land-use, N-fertilizer, manure) for all future simulations were also held constant at the year 2005 values. In future simulations, we accounted for unlimited water supply from resources available for irrigation. Additionally, the rainfed to irrigated cropland pattern was held constant at the year 2005 pattern. An additional simulation per GCM was conducted where all inputs, as well as management assumptions, are static after 2005.

Table 4-1: Overview of the different simulations conducted for this study. For more details and purposes of the simulation see text. No LU – no land use, PNV – potential natural vegetation.

Name	Nr. of sim.	Years	Climate input	Tillage	Residues treatment	Fertilizer	Manure	LU data-set	Description
SP_CRU SP_GCM	5	7000	CRU TS 4.03 / HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5 Repeated 1901-1930	No LU	No LU	No LU	No LU	PNV	7000 years PNV spin-up until 1509 to compute a pre-historic dynamic SOC equilibrium
SPLU_CRU SPLU_GCM	5	390	CRU TS 4.03 / HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5 Repeated 1901-1930	First-year values of Porwollik et al. 2019	First-year values of MADRaT	First-year values of LUH2v2	First-year values of Zhang et al. (2017)	LUH2v2 (Hurtt et al., 2020)	390 years spin-up until 1900 to compute the effects of LU history, which is used as the starting point for all simulations
h_PNV	1	1901-2018	CRU TS 4.03 1901-2018	No LU	No LU	No LU	No LU	PNV	PNV run till 2018 (with 390 years spin-up for better comparability to LU runs), starting from SP_CRU
h_dLU	2	1700-2018	CRU TS 4.03 From 1700-1900 repeated 1901-1930, 1901-2018 afterward	Porwollik et al. 2019	MADRaT (Dietrich et al., 2020)	LUH2v2 (Hurtt et al., 2020)	Zhang et al. (2017)	LUH2v2 (Hurtt et al., 2020)	Historical run with dynamic LU, starting from SPLU_CRU
h_cLU	2	1700-2018	CRU TS 4.03 From 1700-1900 repeated 1901-1930, 1901-2018 afterward	Porwollik et al. 2019 Static at 2005 level	MADRaT (Dietrich et al., 2020) Static at 2005 level	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	Zhang et al. (2017) Static at 2005 level	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	Historical run with constant land use (with 390 years spin-up as in SPLU_CRU, but with the land use pattern of 2005), starting from SP_CRU
h_GCM	4	1901-2005	HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5	Porwollik et al. 2019	MADRaT (Dietrich et al., 2020)	LUH2v2 (Hurtt et al., 2020)	Zhang et al. (2017)	LUH2v2 (Hurtt et al., 2020)	CMIP5 historical scenario runs use, starting from SPLU_GCM
T_R_26/85 NT_R_26/85 T_NR_26/85 NT_NR_26/85	64	2006-2099	RCP2.6/RCP8.5 HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5	tillage / no-till	Residues retained / residues removed	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	Zhang et al. (2017) Static at 2005 level	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	CMIP5 future runs with different management options, starting from h_GCM
TRc05_26 TRc05_85	16	2006-2099	RCP2.6/RCP8.5 HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5	Porwollik et al. 2019 Static at 2005 level	MADRaT (Dietrich et al., 2020) Static at 2005 level	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	Zhang et al. (2017) Static at 2005 level	LUH2v2 (Hurtt et al., 2020) Static at 2005 level	CMIP5 future runs with tillage and residue management constant at 2005 level, starting from h_GCM

These are used to analyze the business-as-usual case under constant land use (h_cLU). To compare the results to literature values on the maximum potential of global SOC stocks without land use, an additional simulation with potential natural vegetation (PNV) was conducted, where all land is assumed to be natural vegetation with internally computed vegetation composition and dynamics.

4.2.3 Model inputs

We created input data sets for an explicit representation of land use, fertilizer, manure, and residue management, using the MADRaT tool (Dietrich et al., 2020). Historic land-use patterns of shares of physical cropland, also separated into an irrigated and rain-fed area, as well as mineral fertilizer data (application rate per crop in gN m^{-2} a^{-1}) for the period of the year 1900 to 2015, are based on the Land-Use Harmonization – LUH2v2 data (Hurtt et al., 2020), which provides fractional land-use patterns for the period of 850-2015 as part of the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Eyring et al., 2016). Manure application rates for the period 1860-2014 are based on Zhang et al. (2017) and account for organic N. With MADRaT we were also able to produce data on crop functional type (CFT) specific fractions of residue rates left on the field (recycling shares) for the period 1850-2015. We generated data on residue-recycling shares in 5-year time steps for the period 1965-2015 and interpolate linearly between time steps to get an annual time series. Between 1850 and 1965, default recycling shares for cereals of 0.25, for fibrous of 0.3, for non-fibrous of 0.3, and no-use of 0.8 were assigned to 1850 and linearly interpolated to the values of 1965. Cereals include temperate cereals, rice, maize, and tropical cereals; fibrous crops include pulses, soybean, groundnut, rapeseed, and sugarcane; non-fibrous crops include temperate roots, tropical roots, and no-use crops include sunflower, others, pastures, bioenergy grasses, and bioenergy trees. Information on conventional tillage and conservation agriculture (no-till) management was based on Porwollik et al. (2019) for the period 1974-2010. Before 1973, conventional tillage was assumed as the default management on all cropland. We assume one tillage event after initial cultivation of natural land, independent of the tillage scenario. This assumption does not affect the results of future projections as we constrain our analysis to cropland that is already cultivated in 2005.

Historical simulations were driven using the CRU TS Version 4.03 climate input (Harris et al., 2020) from 1901 to 2018. Since this data set does not provide data before 1901, the 30-year climate from 1901 to 1930 was used repeatedly for spin-up simulations covering the period before 1901. Data on [CO_2] were taken from ice-core measurements (Le Quéré et al.,

2015) and the Mauna Loa station (Tans and Keeling, 2021). Future simulations from 2006-2099 used climate scenarios from four GCMs taken from Coupled Model Intercomparison Project Phase 5 (CMIP5) in bias-adjusted as provided by the ISIMIP2b project (Frieler et al., 2017; Hempel et al., 2013): HadGEM2-ES, GFDL-ESM2M, IPSL-CM5A-LR and MIROC5 for both a weak climate forcing (Representative Concentration Pathway (RCP) 2.6) and a strong climate forcing (RCP8.5) with corresponding [CO_2] levels. The GCM data sets provide inputs for air temperature, precipitation, radiation, and [CO_2]. The historical period for these GCM-specific simulations was based on bias-adjusted data from the GCMs rather than on CRU data to avoid inconsistencies at the transition between historical and future periods. Land-use change in the future was not analyzed in this context, as the SOC potential of the current agricultural area was the focus of this investigation so that land-use patterns after 2005 were held constant. All results are presented as averages across the ensemble of climate models per RCP unless stated otherwise. Additional simulations with constant [CO_2] for both RCP2.6 and RCP8.5 allow for the isolation of CO_2 fertilization effects. Conventional tillage starts in 1700. For the period 1700-1850, the residue extraction rate of the year 1850 is assumed. The degree to which tillage affects soil properties and processes depends on the tillage intensity, which is a combination of tillage efficiency and mixing efficiency. The fraction of residues submerged (tillage efficiency) by tillage is set to 0.95. The mixing efficiency for tillage management is set to 0.90, representing a full inversion tillage practice, also known as conventional tillage (White et al., 2010). The effects of both mixing and tillage efficiency are described in detail in Sections 3.3.2 and 3.3.5.2. The fraction of residues that are harvested in case of residue extraction is 70% of all above-ground residues (with the remaining 30% of above-ground residues and all roots left on the field). In the case without residue harvest, 100% are left on the field, and only the harvested organs (e.g., grains) are removed.

4.2.4 Data analysis and metrics

Our analysis is based on simulated changes in cropland SOC stocks as well as the contributing processes, including the turnover rate, heterotrophic respiration, litterfall, and the net primary production (NPP) of cropland areas. NPP is calculated following Schaphoff et al. (2018).

The turnover rate for cropland is calculated as:

$$mtr_{SOC,agr} = \frac{rh_{agr}}{SOC_{agr}} * 100, \quad (36)$$

with $mtr_{SOC,agr}$ as the mean turnover rate for cropland SOC (% a^{-1}), SOC_{agr} is the SOC content for cropland (g) and rh_{agr} is the heterotrophic respiration for cropland (g a^{-1}).

Decomposition of organic matter pools is following the first-order kinetics described in Sitch et al. (2003). Total heterotrophic respiration (R_h) accounts for 60% of directly decomposed litter ($R_{h,litter}$) and respiration of the fast and slow soil pools (decomposition rate of 0.03 a^{-1} and 0.001 a^{-1}, respectively). From the 40% remaining litter pool, 98.5% are transferred to the fast soil C pool and 1.5% to the slow soil C pool:

$$R_{h,agr} = R_{h,litter,agr} + R_{h,fastSoil,agr} + R_{h,slowSoil,agrl}\,, \tag{37}$$

Cropland litterfall ($C_{litterfall,agr}$) in g C a^{-1} is calculated by considering root, stem, and leaf carbon in dependency of residue recycling shares:

$$C_{litterfall,agr} = (C_{root,CFT} + ((C_{leaf,CFT} + C_{stem,CFT}) \cdot f_{res,CFT})) \cdot f_{cell,agr}, \tag{38}$$

with $C_{root,CFT}$ being the C pools of crop roots per CFT, $C_{leaf,PFT}$ the C pool of crop leaves per CFT, $C_{stem,PFT}$ the stems and mobile reserves per CFT, $f_{res,CFT}$ the residue fraction which is returned to the soil per CFT and $f_{cell,agr}$ the fraction of agricultural area of the cell. The h_dLU_cropland scenario uses the results for the h_dLU simulation and accounts for the cropland SOC only, by taking the cropland area at the specific point time into account. The h_dLU_area05 scenario, on the other hand, also uses the results for the h_dLU simulation as described in Table 1 but accounts for all the area which is either already cropland or will become cropland at any point in time until 2005. To calculate the historical losses of SOC from LUC change in the h_dLU_area05 scenario, the fraction of SOC under PNV, which will become cropland is combined with the historical cropland SOC parts and calculated as:

$$SOC_{LUC,t} = d_{SOC,pnv,t} \cdot \left(area_{agr,2005} - area_{agr,t}\right) + d_{SOC,agr,t} \cdot area_{agr,t}, \tag{39}$$

where $d_{SOC,pnv,t}$ is the SOC density (g m^{-2}) for PNV area at time step t, which will become cropland in the future, calculated as:

$$d_{SOC,pnv,t} = \frac{d_{SOC,cell,t} \cdot area_{cell} - d_{SOC,agr,t} \cdot area_{agr,t}}{area_{pnv,t}}, \tag{40}$$

where $d_{SOC,pnv,t}$, $d_{SOC,cell,t}$, $d_{SOC,agr,t}$ are the SOC densities (g m^{-2}) for the PNV part within the cell, the density for the entire cell, and the agricultural part within the cell, respectively, at time step t (year), $area_{pnv,t}$ and $area_{agr,t}$ are the corresponding areas of PNV and agriculture (m^{-2}) at time step t and $area_{cell}$ is the area of the entire cell, which does not change over time. We considered different climatic regions such as tropical wet, tropical moist, topical dry, warm temperate moist, warm temperate dry, cold temperate moist, cold temperate dry, boreal moist, and boreal dry regions, following the IPCC climate zone classification (IPCC, 2006, Fig. B1 in the appendix), using averaged climate inputs for the period between the year 2000 and 2009. Polar dry, polar moist, and tropical montane regions were excluded from this analysis, as these regions do not include any cropland.

4.3 Model performance

Modeled global average SOC stocks (period 2000-2009 and year 2018) are compared with previous model versions and literature estimates (Table 4-2). Simulated SOC stocks in LPJmL5.0-tillage2 exhibit higher SOC content compared to the LPJmL5.0 (von Bloh et al., 2018) model version and LPJ-GUESS (Olin et al., 2015), with total average global SOC stocks of 2640 Pg C for simulations with land use (h_dLU) and 2940 Pg C for simulation with PNV only and no land use (h_PNV). The simulated stocks correspond well to estimates by Carvalhais et al. (2014) for global averages but are lower for cropland SOC stocks. Total SOC stocks simulated by LPJmL5.0-tillage2 are 2640 Pg for the entire soil column of 3 m, which are 300 Pg higher than estimates provided by Jobbágy and Jackson (2000). Global SOC for PNV is 2580 Pg for the upper 2 m, which compares well with estimates between 2376 Pg to 2476 Pg provided by Batjes (2014), who reported SOC stocks for the upper 2 m of soil. Global average cropland SOC stocks between the year 2000 and 2009 as well as for the year 2018 for the entire soil column are estimated to be 170 Pg C, which is higher than estimates of 148-151 Pg C by Olin et al. (2015). Zomer et al. (2017) reported cropland SOC stocks of 140 Pg C for the upper 0.3 m of soil, which are higher than the cropland SOC stocks of 75 Pg C simulated for the upper 0.3 m in LPJmL. Ren et al. (2020) reported cropland SOC stocks for the first 0.5 m of soil to be 115 Pg C for the period 2000-2010, which is higher than cropland SOC of 95 Pg C for the upper 0.5 m in LPJmL. Scharlemann et al. (2014) conducted a literature review on global SOC stock and found a wide range of estimates (504-3000 Pg C) and variability across time and space and a high dependency on soil depth, with a median global SOC stock of 1460 Pg C. Generally simulated SOC stocks by LPJmL5.0-tillage2 correspond well with literature and other model estimates.

Table 4-2: Global SOC pools (Pg C) for the LPJmL5.0-tillage2, LPJmL5.0, and LPJ-GUESS model compared to literature estimates. Values are averages for the period 2000-2009, for the year 2018, and the upper 0.3, 1, and 2 m of soil. PNV values are simulations with potential natural vegetation only (no land use), global SOC average includes PNV and land use.

	Model estimates			Literature estimates				
	LPJmL5.0-tillage2 (this study)	LPJmL5.0 (von Bloh et al., 2018)	LPJ-GUESS (Olin et al., 2015)	Carvalhais et al., 2014	Batjes, 2014	Jobbágy and Jackson, 2000	Zomer et al., 2017	Scharlemann et al., 2014
Global SOC PNV only	2940[1,a] 2960[2,a] 2580[b,1], 2185[c,1], 1555[d,1]	2344[1,a]	1671[3]	-	2376[b,4] – 2476[b,4]	-	-	-
Global SOC average	2640[1,a] 2645[2,a] 2295[b,1], 1910[c,1],	2049[1,a]	1668[3]	2397[4] (1837[x] - 3257[y])	-	1933[b], 2344[a]	-	1460 (504[d] – 3000[e])
Cropland SOC	170[1,a] 170[2,a] 145[b,1], 115[c,1], 75[d,1],	-	148[3]	327[4] (242[x] - 460[y])	-	210[b], 248[a]	140[d]	-

Values are estimates for: [a] entire soil column, [b] upper 2m of soil, [c] upper 1m of soil, [d] upper 0.3m of soil, [e] not indicated.

Year of estimate value: [1] 2000-2009, [2] 2018, [3] 1996-2005, [4] not indicated. [x] 2.5th percentile, [y] 97.5th percent

4.4 Results

4.4.1 Historical development of cropland NPP and SOC stocks

During the simulation period, cropland NPP increases in the dynamic LU simulation (h_dLU) from 0.7 Pg C a^{-1} in 1700 to 4.7 Pg C a^{-1} in 2018, while cropland SOC increases from 18 Pg C to a total of 171 Pg C (Fig. 4-2A and 4-2C) in the year 2018. The increase in cropland SOC can be explained by an increase in cropland area (Fig. B2B in the appendix). During the same time, harvested C increases from 0.1 Pg C a^{-1} to 2.0 Pg C a^{-1}. The ratio of harvested C to cropland NPP increases with time, especially after the year 1900 (Fig. 4-2B), as more material is harvested compared to cropland NPP. The aggregated SOC stock on all land that is cropland in the year 2005 declines substantially, especially after the year 1900 (red line in Fig. 4-2C), which reflects the decline in cropland SOC density (Fig. B2A in the appendix). We also find that cropland SOC density steadily increases between 1700 and 1950 and decreases since 1950 (Fig. B2A in the appendix). Simulations with a constant land use pattern of 2005 (h_cLU) for cropland NPP and cropland SOC show no substantial dynamics (Fig. 4-2A and 4-2C). These simulations are not entirely insightful because they do not account for the historical increase in inputs, e.g., fertilizer.

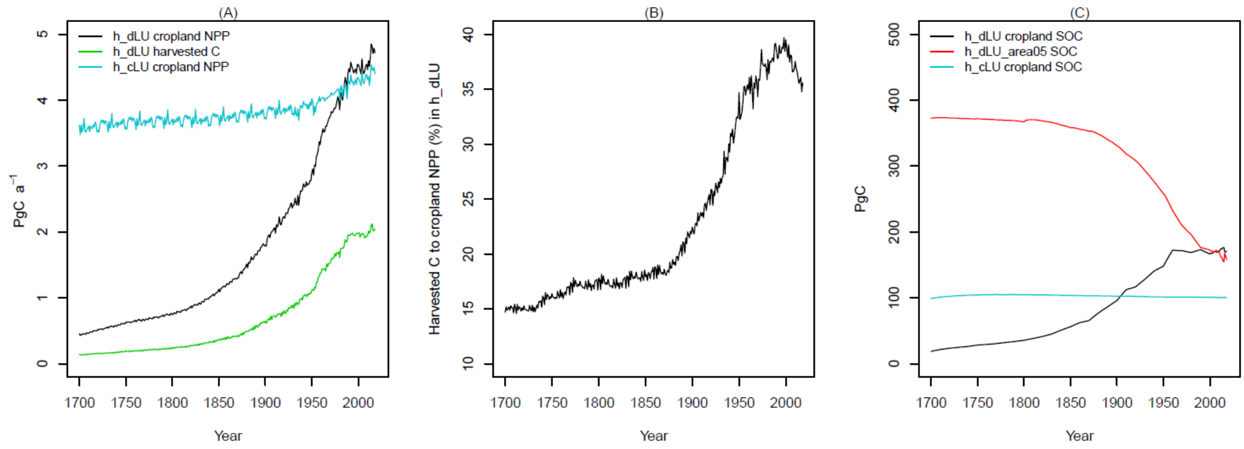

Figure 4-2: Plots for cropland NPP and harvested C (A), percentage of harvested C to cropland NPP in h_dLU (B) and SOC for cropland stocks, and historical SOC losses from LUC (C) for the years 1700-2018 for simulations with transient land use (h_dLU), constant land use of 2005 (h_cLU), transient land use and SOC development from LUC including cropland area and historical PNV area which will be converted until the year 2005 (h_dLU_area05).

In contrast to the scenario with dynamic land use and constant land use, the h_dLU_area05 scenario describes a combination of historical cropland SOC and historical SOC of natural vegetation (calculated as described in Eq. (39) and (40)), which is or has been cropland until the year 2005. This describes the SOC dynamics of all land subject to the historical LUC (Fig. 4-2C). Loss of historical SOC is calculated as the difference between the years 1700 and 2018 on the land area that was cropland at any point in time (Fig. 4-2C, red line). Through this approach, we calculate a total historical SOC loss of 215 Pg C. Cropland SOC stocks are increasing over time (Fig. 4-2C, black line), reflecting the increase of cropland area. PNV has a higher SOC density, and therefore SOC stock, before the conversion to cropland (Fig. B2A in the appendix). For the calculation of SOC loss, we here only considered the area that is converted from PNV to cropland at any point in time between 1700 and 2018 in post-processing according to Eq. (39) and (40). Because SOC density is generally lower in cropland compared to PNV (Fig. B2A in the appendix), SOC is lost after conversion (Fig. 2C, red line).

4.4.2 Future SOC development with idealized management under climate change

Future cropland SOC stock development was analyzed considering two different radiative forcing pathways (RCPs) with four different climate scenarios (GCMs) per RCP and four idealized management assumptions (Table 4-2). To estimate the SOC sequestration potential on current cropland and to exclude the influence from LUC, the cropland area was kept constant at the year 2005 pattern. Results for future SOC development show that the maximum decrease in SOC stocks on current global cropland area between the year 2005 until the end of the century occurs in the scenario with no-till applied on global cropland, no residues retained, and RCP8.5 climate (NT_NR_85). Total cropland SOC loss for this scenario is evaluated as 38.4 Pg C, or 28.1% in relative terms compared to the SOC stocks in the year 2005. All management systems, which extract residue from the field, show a substantial decrease in cropland SOC stocks, independent of the climate scenario (Fig. 4-3B). Differences for cropland SOC development between different tillage systems as well as between the two radiative forcing pathways RCP2.6 and RCP8.5 are minor. Management systems, which retain residue on the field after harvest, show the smallest reduction in cropland SOC stocks, with a maximum reduction of 5.1 Pg C (equivalent to 3.8% decline) in the T_R_26 management system. Differences between GCM-specific climate scenarios or radiative forcing pathways (RCPs) were small in comparison to differences in residue management assumptions for SOC, turnover rates, and litterfall rates (Fig. 4-3) but larger than differences in assumptions on tillage systems. Only for agricultural NPP (Fig. 4-3A), differences in radiative forcing pathways were the main determinant of NPP dynamics, followed by GCM-specific climate scenarios.

Table 4-3: Summary of absolute and relative global cropland SOC stock change between the year 2006 and 2099 for different management systems for RCP2.5 and RCP8.5 as averages across all four GCMs.

Management	Absolute cropland SOC change 2006 – 2099 (Pg C)		Relative cropland SOC change 2006 – 2099 (%)	
	RCP2.6	RCP8.5	RCP2.6	RCP8.5
Tillage and residues (T_R)	-5.1	-4.4	-3.8	-3.2
Tillage and no residues (T_NR)	-37.6	-38.1	-27.5	-27.8
No-till and residues (NT_R)	-3.6	-3.2	-2.6	-2.3
No-till and no residues (NT_NR)	-37.8	-38.4	-27.7	-28.1
Tillage and residue constant as in year 2005 (TRc05)	-24.1	-24.0	-17.6	-17.6

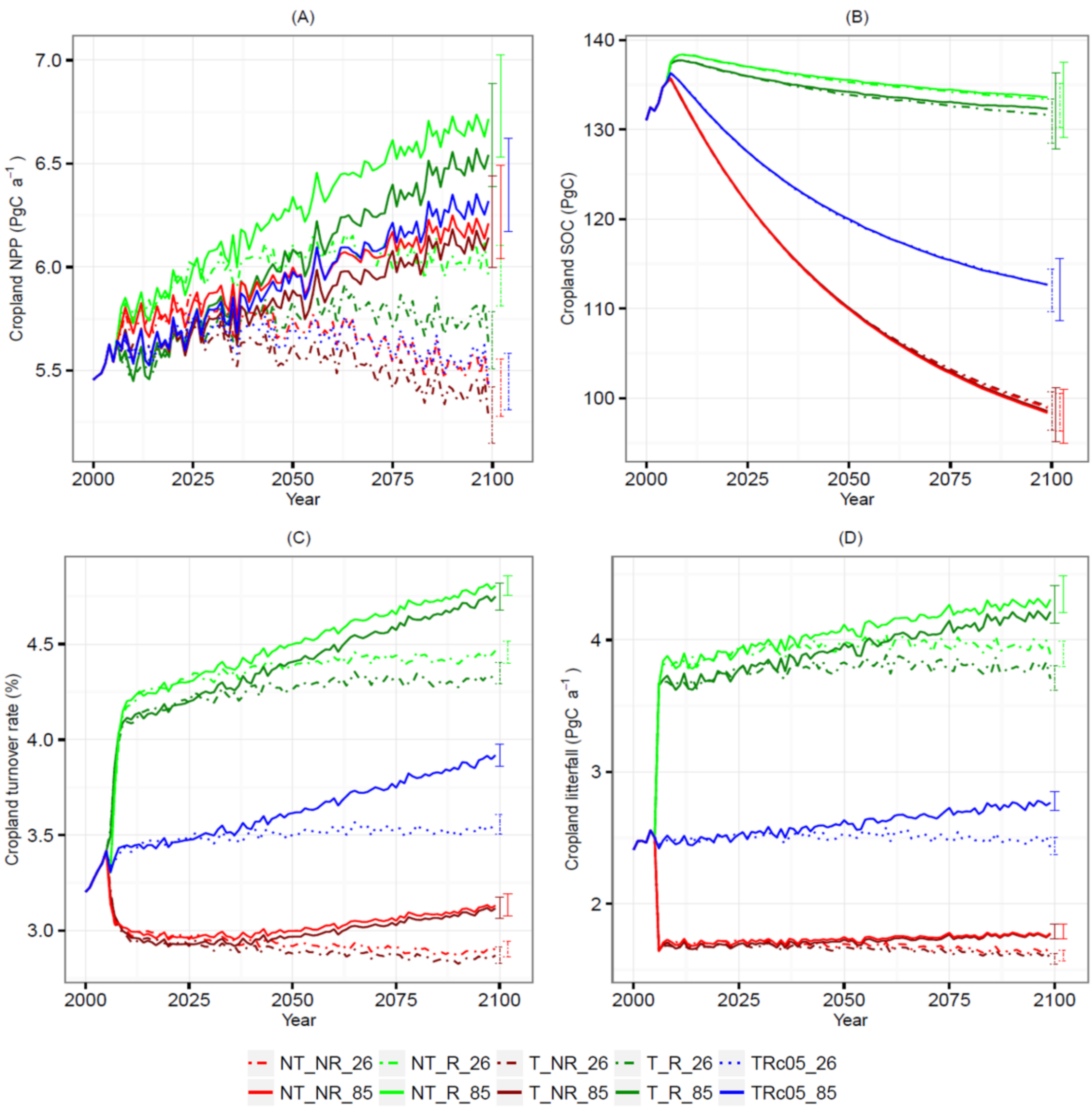

Figure 4-3: Global sums for cropland for NPP (A), SOC (B), turnover rate (C), and litterfall (D) from 2000-2005 for default management inputs and from 2006-2099 under constant cropland area of 2005 for five different management scenarios and two RCPs. Presented are the mean values across all four GCMs as lines. The spread across all GCMs is depicted as bars in the year 2100. The numbers _26 and _85 describe the climate forcing RCP2.6 (e.g., TRc05_26) and RCP8.5 (e.g., TRc05_85). Green – residues retained (R), red – residues removed (NR), dashed – RCP2.6, solid – RCP8.5, light color – no-till (NT), dark color – tillage (T). Tillage and residue management held constant at 2005 level in TRc05; tillage and residues left on the field (T_R), tillage and residues removed (T_NR), no-till plus residues left on the field (NT_R) and no-till and residues removed (NT_NR). Dynamics prior to 2005 (all scenarios equal) mostly show the expansion of cropland until 2005 so that total SOC increases because the area increases. Turnover rates between 2000 and 2005 increase because decomposition rates are high on freshly deforested land.

Stocks of cropland SOC and turnover rates (Fig. 4-3C) initially increase in systems that retain residues, such as T_R and NT_R, after the change in management after the year 2005 (Fig. 4-3B and C), as more residual C is added to the soil column in comparison to the historic residue removal rates (Fig. 4-3D).

Turnover rates are higher for the high radiative forcing pathway RCP8.5 in comparison to RCP2.6. The simulated cropland NPP (Fig. 4-3A) is sensitive to the radiative forcing, as the level of NPP is higher in the high-end RCP8.5 scenario and lower in the lower-end RCP2.6 scenario. This is because of the strong response of NPP to CO_2 fertilization, which overcompensates the climate-driven reduction in NPP (compare Fig. B3 in the appendix). NPP is less sensitive to the assumptions on tillage practices in comparison to the effects of assumptions on residue management. The no-till and residue system (NT_R) results in the highest NPP mainly due to water-saving effects, which are caused by the surface litter cover, which reduces evaporation from the soil surface and, at the same time, increases infiltration of water into the soil. NPP increases steadily until 2099 in RCP8.5 scenarios because of the CO_2 fertilization effects (compare Fig. B3 in the appendix). In RCP2.6, NPP first slightly increases and then decreases until the end of the century in all tillage and residue scenarios. However, the ranking of management effects is insensitive to the radiative forcing pathway: no-till and residue (NT_R) results in the highest NPP, tillage and no residue (T_NR) in the lowest values.

4.4.3 Regional cropland SOC analysis

Simulation results show that globally aggregated SOC stocks on current cropland decline until the end of the century for all management systems, but there are regional differences (Fig. 4-4). We find that in some regions, cropland SOC can increase until the end of the century, even though global sums indicate a total decline. For cropland SOC density, increases between the years 2006 and 2099 can be found for T_R and NT_R management systems for more than one-third of the global cropland area, most clearly in regions in Europe, India, Pakistan, Afghanistan, southern Chile, southern Mexico, eastern China, and south-eastern USA (Fig. 4-4C and 4-4D). In total, 46% of the current cropland area in NT_R shows the potential to SOC increase, while a minimum of 52% shows a decline. Historically, regions which already showed an increase in cropland SOC density since 1900 until today, such as in France or Pakistan, or a decrease, such as Canada and Argentina, tend to continue this development also in the future (see plots in Fig. 4-4 for exemplary cells). In systems where residues are not returned to the soil (T_NR and NT_NR), global cropland SOC density change is dominated by a decline.

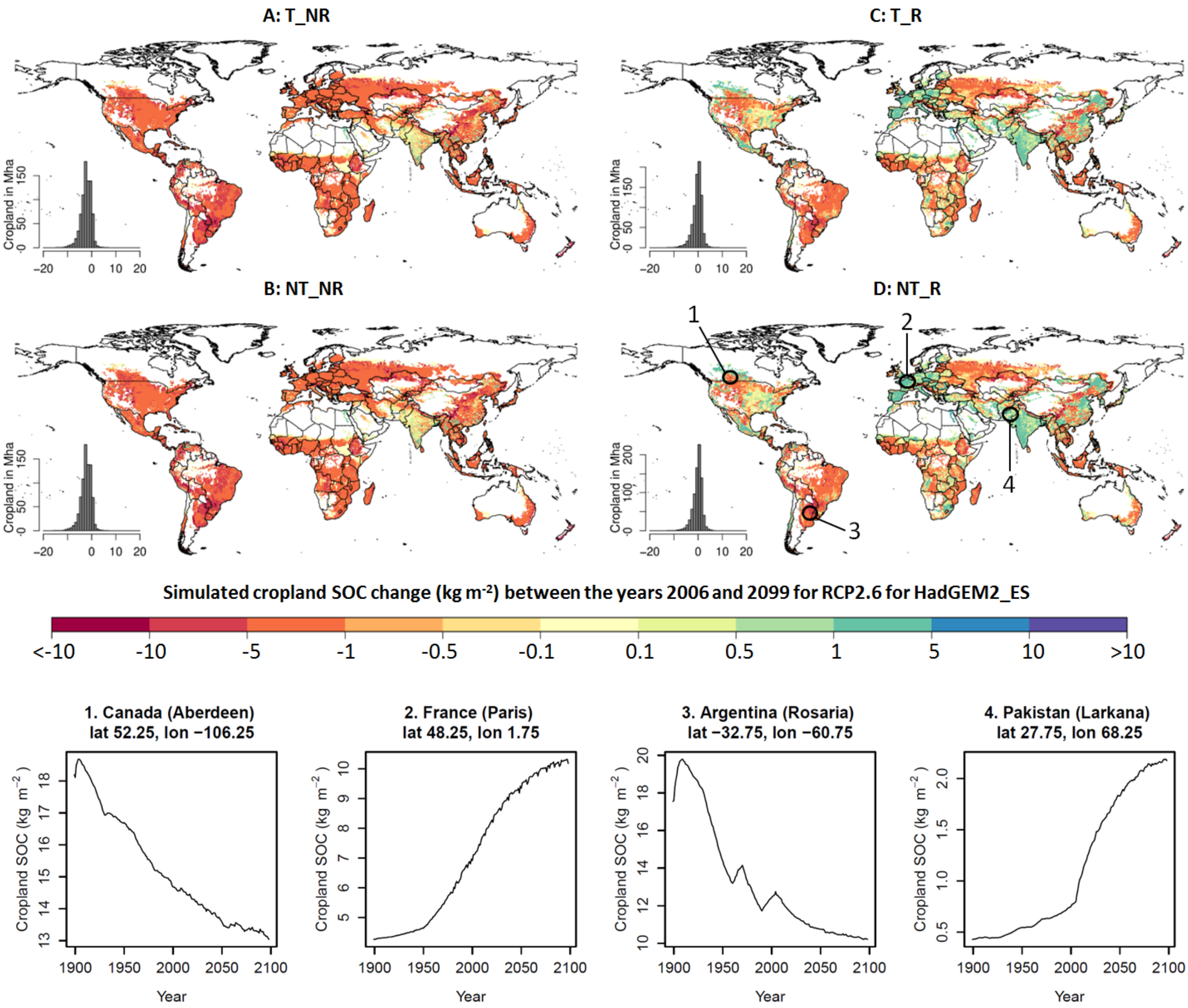

Figure 4-4: Simulated cropland SOC change (kg m-2) between the years 2006 and 2099 (kg m-2) for RCP2.6 for GCM HadGEM2-ES for the four different management options (T_R, NT_R, T_NR, and NT_NR). The plots 1.-4. show examples of SOC development (kg m-2) from the year 1900 to 2099 for different explanatory regions as shown on map D (NT_R). The difference maps of affected change categories between RCP2.6 and RCP8.5 are shown in Fig. 4-5. Maps for GFDL-ESM2M, IPSL-CM5A-LR and MIROC5, and RCP8.5 are in the appendix (Fig. B7 to B13).

Results for different climatic regions suggest that the difference between RCP2.6 and RCP8.5 radiative forcing only plays a minor role in cropland SOC stock development (Fig. 4-5). Findings indicated that a positive median increase in cropland SOC density between the years 2006 and 2099 can be found in warm temperate moist, warm temperate dry, and boreal regions for RCP2.6 (GCM average) for the tillage and residue (T_R) and the no-till and residue (NT_R) management systems (Fig. 4-5B). The total aggregated cropland SOC change for each climate region depends on the cropland extent of the region. The smallest amounts of cropland are found in boreal moist and dry regions, which results in a total cropland SOC stock change of negligible size (Fig. 4-5B and D). Total increases in cropland SOC stocks can be found for both RCP2.6 (Fig. 4-5A and B) and RCP8.5 (GCM average) (Fig. 4-5C and D) for tropical dry, warm temperate moist, and warm temperate dry regions in the tillage and residue (T_R) and the no-till and residue (NT_R) management systems. For all regions across all simulations, management systems in which residues are not returned to the soil, cropland SOC stocks decrease. The highest absolute losses of total cropland SOC stocks for these systems (T_NR and NT_NR) can be found in cold temperate dry climates, followed by tropical moist and warm temperate dry regions, which are the regions with major cropland shares.

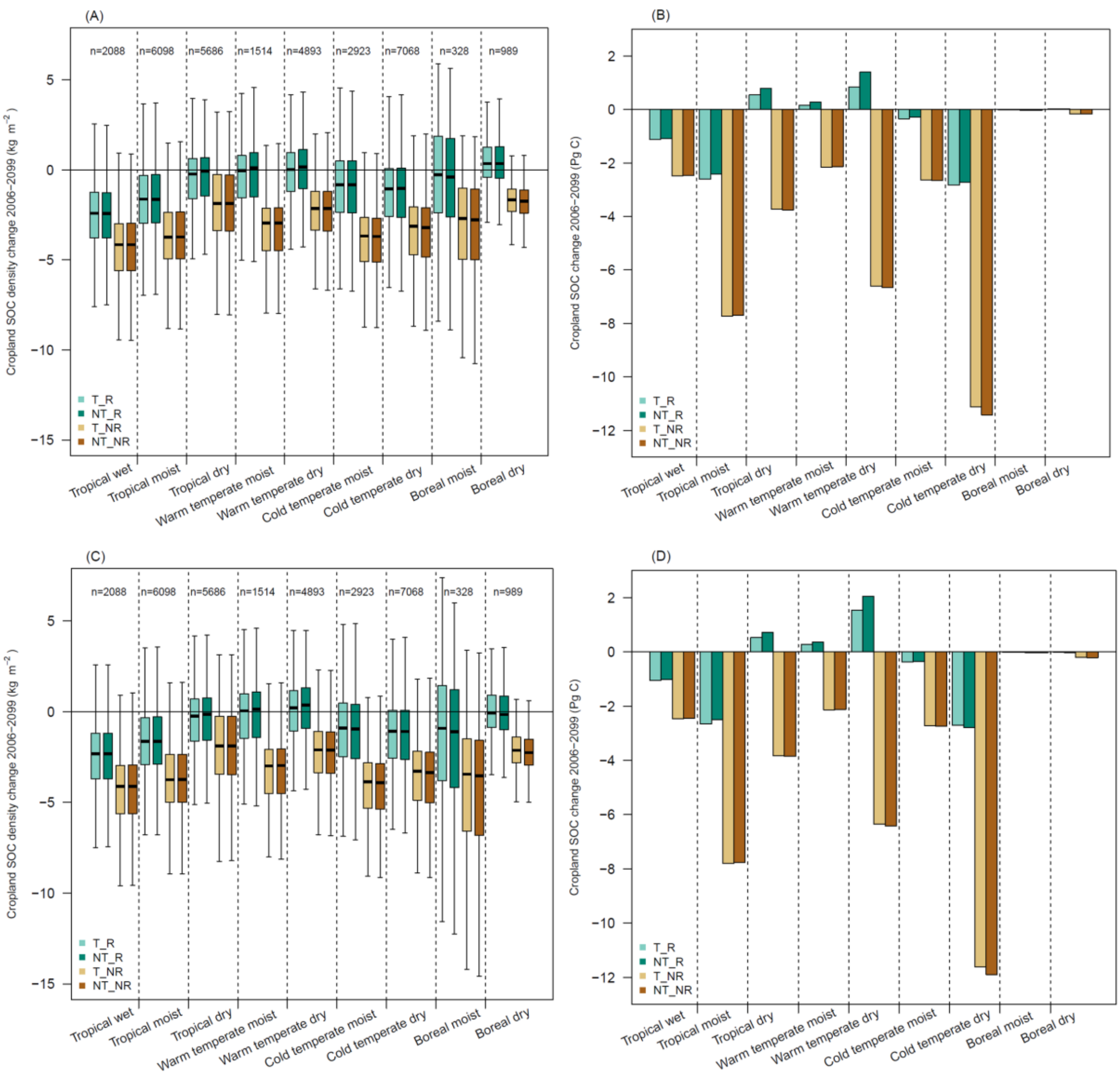

Figure 4-5: Boxplots of cropland SOC density change (kg m^{-2}) and bar plots of total cropland SOC change (Pg C) between the years 2006 and 2099, averaged across the four GCMs (HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5) in RCP2.6 (A and B) and in RCP8.5 (C and D) for the climatic regions classified by the IPCC (2006) and the four management systems T_R, NT_R, T_NR, and NT_NR. The same plots for each individual GCM can be found in Fig. B5 and B6 in the appendix; n is the number of cropland cells included in each climate region.

Regional results also indicate more significant differences between GCM-specific climate scenarios within the same radiative forcing pathway (RCP). The highest positive cropland SOC stock response can be found for GCM GFDL-ESM2M in both RCP2.6 and RCP8.5 for the tillage and residue (T_R) and the no-till and residue (NT_R) systems for warm temperate dry climates, while the positive response for tropical dry and warm temperate moist climates is lower compared to the other three GCMs (compare Fig. B5D and B6D in the appendix). Results for the IPSL-CM5A-LR climate scenarios for both RCP2.6 and RCP8.5 generally show the most negative response for cropland SOC density change and cropland SOC stock change, followed by HadGEM2_ES.

The comparison of cropland affected in RCP2.6 and RCP8.5 indicates that most regions show effects with the same direction of response in SOC density, so either it decreases or increases in both RCP2.6 and RCP8.5, which is highlighted by the blue and orange regions in Fig. 4-6. Red cells, which indicate that the effects in both RCPs go in the opposite direction, can only be found in a few regions, e.g., the United States and Turkey. In total, between 50 and 53 Mha of cropland shows the opposite directions globally for the the tillage and residue (T_R) and the no-till and residue (NT_R) systems, while this is halved (between 27 and 29 Mha) for for the tillage and no residue (T_NR) and no-till and no residue (NT_NR) management system.

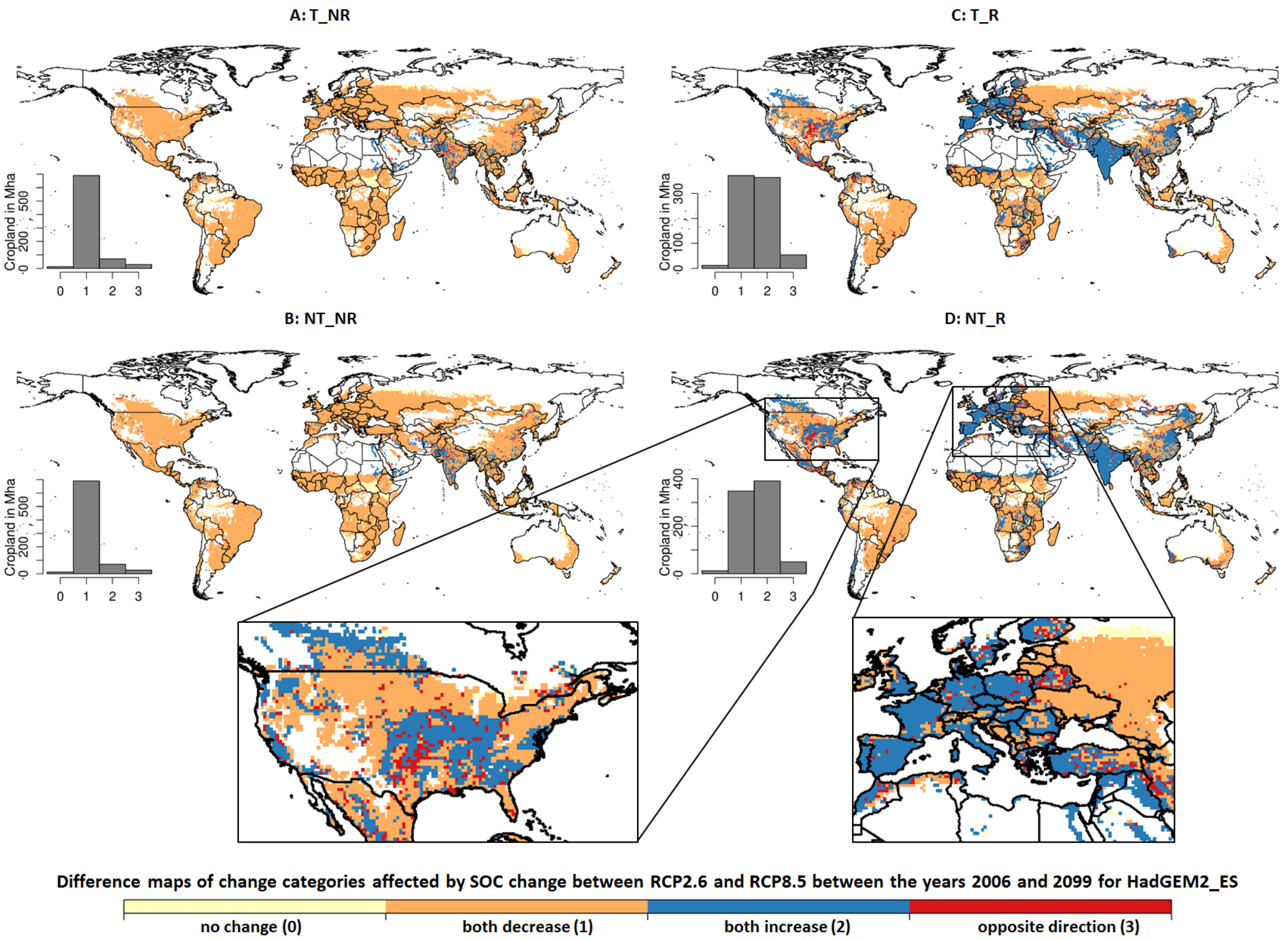

Figure 4-6: Difference maps of change categories for cropland SOC density change between both RCP2.6 and RCP8.5 from the year 2006 until 2099 for GCM HadGEM_ES in each management system. Orange areas indicate a reduction in cropland SOC density between the years 2006 and 2099 in both RCPs; blue areas show an increase in SOC density; in light yellow areas, no change occurs, and for red, SOC density change occurs in opposite directions in RCP2.6 and RCP8.5. The numbers in brackets (0) to (3) correspond to the categories in the histogram.

4.5 Discussion

4.5.1 Development of SOC in the past and C losses due to LUC

Historical simulations show that converting natural land to cropland has caused SOC losses of 215 Pg C between the year 1700 and 2018 (Fig. 4-2C). Soil C density and NPP in natural vegetation are higher compared to those found in croplands, which results in C losses after conversion of natural land to cropland. NPP in croplands is often lower compared to NPP in natural vegetation, as the cultivated period is typically shorter than the vegetative period in which natural vegetation is productive so that cultivated plants have less time to accumulate C. Further, cropland is cultivated, and crops are harvested, which results in the extraction of NPP in the form of harvested material, which leads to a further decline of SOC stocks. Cropland expansion is the main driver for increases in total cropland SOC stocks, as cropland SOC density steadily increased since the year 1700, starting at 7 kg m^{-2} and reaching its maximum in the year 1960 at 13 kg m^{-2}. Still, since then, cropland SOC density decreased, down to 11 kg m^{-2} today (Fig. B2A in the appendix). SOC density on cropland showed this trend, even though fertilizer use increased since the 1960s, which was found to be able to promote SOC sequestration, especially in temperate regions (Alvarez, 2005). Since the 1960s, cropland expansion has slowed down, but global yields have, on average, more than doubled (Pingali, 2012; Ray et al., 2012; Wik et al., 2008). Ren et al. (2020) show that historical cropland SOC increase was mainly attributed to cropland expansion, which is in agreement with the findings here. The ratio of harvested C to cropland NPP increases with time (Fig. 4-2B) so that the increase in yields does not have a positive effect on cropland SOC, as more and more C is extracted from the soil in the form of harvested material.

It was estimated that conversion of natural land to cultivated land could result in SOC loss of up to 30 to 50% (Lal, 2001b). Sanderman et al. (2017) estimated historical global SOC losses of natural land to cropland conversion by 133 Pg C, of which most of the losses occurred in the last 200 years. Pugh et al. (2015) modeled C emissions from LUC accounting for agricultural management, such as harvesting and tillage, and found maximum C losses in vegetation and SOC by 225 Pg C since the year 1850. Le Quéré et al. (2018) also estimated the C flux to the atmosphere due to LUC, including deforestation, to be 235 Pg C (± 95) since the year 1750.

4.5.2 Future cropland SOC development on current global cropland

Future SOC stocks on current cropland depend on climate and management. We find that current cropland remains to be a source of C, even though the decline of SOC on current cropland can be reduced through management. The most efficient measure to reduce SOC losses on cropland is residue management. In the model, SOC is formed by C transfer from litter to the soil through decomposition fluxes (Schaphoff et al., 2018), bioturbation, or tillage practice (Lutz et al. 2019). Residues left on the field are added to the litter C pool, where they are subject to decomposition. Root C is added to the belowground litter pool, with a specific decomposition according to soil temperature and moisture conditions. Stubbles and root biomass enter the litter pool after harvest, while the amount of residues extracted or retained depends on crop productivity. The addition of fresh material from crop residues increases the turnover rate in the soil, as this material is more easily decomposed than the remaining SOC stocks from the historical natural ecosystems. In the model, SOC decomposition is only driven by the temperature and moisture of the litter and soil layers, whereas the chemical composition of the residues is not taken into account. While the N content of the available material can strongly influence the decomposition and humification of residues and the formation of SOM (Averill and Waring, 2018; Hatton et al., 2015), this effect is not considered here and should be included in future model development.

The different management aspects show the same ranking in importance under both radiative forcing pathways, and the changes on cropland SOC only differ slightly. Cropland SOC stocks at the end of the century vary only between those two RCPs between -0.6% and +0.6% for all four management systems. This is caused by a compensating effect of higher productivity by elevated CO_2 under RCP8.5, which counteracts the increase in turnover rates at higher temperatures (see Fig. B3 in the appendix for comparison with constant [CO_2] simulations).

Even though experiments have shown that tillage can reduce SOC stocks significantly compared to no-till (Abdalla et al., 2016; Kurothe et al., 2014), tillage management only has small effects on aggregated global cropland SOC in our simulations. Tillage practices account for differences in cropland SOC stocks of 0.9% and 1.3% between T_R vs. NT_R in 2099 for RCP8.5 and RCP2.6, respectively, and less than 0.2% between T_NR vs. NT_NR for both RCPs. Differences in SOC stocks on cropland between the tillage systems decrease if residues are not retained on the field. NPP responds more strongly to the tillage system, which is likely to be driven by secondary effects (e.g., no-till increases soil moisture and nutrient availability from mineralization) but shows no long-term effect on SOC stock development.

With the given complexity in responses to tillage, the application of no-tillage has been discussed ambiguously in the literature (Chi et al., 2016; Derpsch et al., 2014, 2010; Dignac et al., 2017; Powlson et al., 2014). The LPJmL5.0-tillage model is well capable of reproducing these process interactions and diversity in results (Lutz et al., 2019a). Tillage systems thus need to be selected based on local conditions, but we find these to be less important than residue management. Given this dependency of the SOC accumulation potential on climatic and management conditions, there are great regional differences in the response of SOC to changes in management. In line with Stella et al. (2019), who investigated the contribution of crop residues to cropland SOC conservation in Germany and found a decrease in SOC stocks until 2050, if residues are not returned to the soil, we find that large parts of western Europe can indeed increase the SOC stocks under management systems in which residues are retained on the field. Zomer et al. (2017) analyzed the global sequestration potential for SOC increase in cropland soils and found the highest potentials in India, Europe, and mid-west USA, results which correspond well with our findings. Also, the duration of the historical cultivation of the cropland is an important aspect in the ability to sequester C in current cropland soils. Stella et al. (2019) find the highest SOC sequestration potentials in soils with low SOC stocks (i.e., in highly degraded soils).

4.5.3 Potential for SOC sequestration on cropland and recommendations for future analysis

For the past years, there has been an ongoing debate on how much SOC can be stored in agricultural soils through adequate management as a climate change mitigation strategy (Baker et al., 2007; Batjes, 1998; Lal, 2004a; Luo et al., 2010; Stockmann et al., 2013). For example, globally applied no-till management on cropland was estimated to have a SOC sequestration potential of 0.4-0.6 Gt CO_2 a^{-1} (Powlson et al., 2014). Additionally, the sequestration of SOC can be beneficial to soil quality and productivity and minimize soil degradation (Lal, 2004a, 2009c). An increase in cropland irrigation can effectively influence SOC development (Bondeau et al., 2007; Trost et al., 2013). In our simulations with LPJmL5.0-tillage2, we find that on current cropland, these sequestration potentials cannot be achieved by varying tillage practices and residue removal rates, even though the residue management system is important for cropland SOC dynamics. At the same time, we account for an unlimited supply of water resources available for irrigation, reducing the constrain on SOC development by limitations from irrigation water. As such, our estimates of SOC development should tend to be optimistic in all regions where irrigation is applied, but where water resources are limiting.

There is a general uncertainty in how experimental findings can be scaled up, as, e.g., demonstrated by a review conducted by Fuss et al. (2018). While process-based modeling as applied here can take environmental conditions into account and compare different management aspects, it is still subject to various uncertainties. One crucial aspect is the history of land-use systems, including the trend in land productivity. Karstens et al. (2020, under review) show that global historical cropland SOC stocks are declining even though cropland inputs are increasing at the same time. Depending on the agricultural management option, it is argued that the maximum sequestration potential is reached after the soil has a new higher equilibrium state, which can be reached after 10-100 years, depending on climate, soil type, and SOC sequestration option (Smith, 2016). The IPCC suggests a default saturation time of the soil sink of 20 years, after which the equilibrium is reached, which then has to be maintained to avoid additional release of CO_2 (IPCC, 2006). Increasing cropland SOC in a first step can be achieved by adding more C to the soil than is lost by respiration, decomposition and harvest, and soil disturbance. Maintaining SOC levels on cropland after the soil has reached a new equilibrium will require the application of management strategies that do not deplete SOC. The ‘4 per 1000’ initiative requires annual SOC sequestration on croplands of approximately 2 to 3 Pg C a^{-1} in the top 1m of cropland soils, which was criticized for being unrealistic (de Vries, 2018; White et al., 2018). In this analysis, only two management options affecting SOC, tillage treatment and residue management, are considered. High SOC sequestration potentials on cropland are argued to be only achieved by applying a variety of management options, e.g., additional restoration of degraded land (Griscom et al., 2017; Lal, 2003b), agroforestry (Lorenz and Lal, 2014; Torres et al., 2010), biochar (Smith, 2016), bio-waste compost (Mekki et al., 2019), which add forms of organic material which increase turnover times of SOC. A combination of these different practices is more likely to achieve higher SOC sequestration rates on cropland (Fuss et al., 2018). Management options that aim at increasing SOC may also affect yields, as they can maintain productivity and ensure yield stability (Pan et al., 2009), but reductions in SOC can also reduce yields substantially (Basso et al., 2018). Additionally, the productivity increase can come with an even stronger increase in harvested material, as here demonstrated, which can lead to a reduction in total cropland SOC. The conversion from natural land to cropland typically causes substantial SOC losses, which stresses the need to limit land-use expansion and thus requires an intensification of land productivity on current cropland. In our analysis, we did not account for the effects of future LUC, but projections show an increase in total cropland area in the future (Stehfest et al., 2019) so that global SOC is expected to further decline.

Further research of agricultural management practices that influence SOC development at the global scale should investigate the impact of cover crops, rotations, irrigation systems, and optimal cultivar choice per region and location (e.g., Minoli et al., 2019) and different options for cropland intensification (e.g., Gerten et al., 2020) in a more explicit manner. SOC stabilization mechanisms, such as clay mineral protection and forming of macro-aggregates in no-till managed soils (Luo et al., 2016), effects of microorganisms, such as N-fixation and P acquisition from fungi and bacteria, which also regulate plant productivity and community dynamics (Heijden et al., 2008), as well as effects of soil structure (Bronick and Lal, 2005) on SOC dynamics have not been considered here or in other global process-based assessments and should be taken into account. Plants and associated root systems can reduce surface erosion and water runoff (Gyssels et al., 2005), but losses of SOC from runoff and increased erosion (Kurothe et al., 2014; Naipal et al., 2018) are not considered here either. Residues from plants can influence labile, intermediate, and stable SOC pools through the C : N ratio. Residues with high C : N ratios (e.g., straw) decomposed relatively slow and can increase SOC but reduce N availability to the plants, while residues with low C : N decompose relatively fast and can release N to the soil through mineralization (Macdonald et al., 2018). The speed of residue decomposition can also influence the effectiveness of residues as a soil cover, with effects on soil moisture through infiltration. Impacts of biodiversity and living fauna such as microorganisms on SOC sequestration are not modeled in this analysis, even though they are recognized to have a substantial influence on the dynamics of SOC (Chevallier et al., 2001).

The implementation of such effects is desirable but needs to be assessed with respect to the process understanding, the availability of input data at the global scale, and the availability of modeling approaches (Lutz et al., 2019b). Global-scale modeling approaches, in comparison to local or regional studies, allow for the possibility to identify regional patterns related to SOC sequestration responses with the potential to foster experimental studies in areas so far not investigated but relevant for global assessments (Luo et al., 2016; Nishina et al., 2014). They are needed to upscale findings from experimental sites so that the potential of such measures for climate change mitigation can be better understood and climate protection plans are made with better estimates.

4.6 Conclusion

In conclusion, the here analyzed agricultural management systems are insufficient to increase global SOC stocks on current cropland until the end of the 21st century. The interaction of SOC sequestration and cropland productivity needs to be better disentangled. Additional C inputs from, e.g., manure, cover crops, and rotations are needed and could offset further SOC losses. Still, additional research on the potentials of these cropland management options and available amounts that could be applied is needed. We find that the potential for SOC sequestration on current global cropland is too small to fulfill expectations as a negative emission technology, which stresses the importance of reducing GHG emissions more strictly by other means to reach climate protection targets as outlined in the 2015 Paris Agreement.

Chapter 5

Synthesis

5.1 Overview

Expanding the scientific knowledge on the relationship between agricultural management and biophysical processes of soil degradation requires an in-depth process understanding. The overall objective of this research focuses on the analysis and assessment of the effects of agricultural management practices on soil degradation and on presenting a methodological approach on how management practices can be incorporated into a global ecosystem model. To this end, this thesis focuses in particular on SOC loss as a major form of agricultural-driven soil degradation from tillage and residue management and aims to contribute to the process understanding to derive climate mitigation strategies. DGVMs, such as the existing ecosystem model LPJmL that is used in this research, act as useful tools to assess the impacts of agricultural management practices on changes in soil properties, crop productivity, and greenhouse gas emissions. In this dissertation, I answer the overarching research question by first reviewing the topic within the body of scientific literature in Chapter 2 and implementing a new methodological approach into the LPJmL model described in Chapter 3. Lastly, I apply the new methodology to study the effects of management practices on past and future cropland SOC dynamics in Chapter 4.

In the following Section 5.2, I summarize the key findings of each of the previous three chapters of this thesis and answer the individual research questions. In Section 5.3, I discuss the results across the individual chapter boundaries and in the context of methodological limitations and uncertainties. In Section 5.4, I present the conclusions. In the final section, 5.5, I provide an outlook and suggest possible applications and improvements for future research approaches, which help to improve the process understanding further. At last, I discuss recommendations for policymakers.

5.2 Answers to the research questions

5.2.1 What are the most important processes related to soil degradation, and which agricultural management practices are the main drivers promoting soil degradation?

Soil degradation is a phenomenon on a global scale that is primarily driven by erosion from wind and water, salinization, compaction, loss in biodiversity, and the loss of SOC. Soil degradation can occur due to natural processes, for instance, natural soil erosion from water and wind, but soil degradation processes on cropland can be amplified by anthropogenic mismanagement (Jie et al., 2002). Cropland soils can be more susceptible to degradation due to the anthropogenic alteration of biophysical and biochemical conditions from intensive cultivation and LUC (Bindraban et al., 2012; Gomiero, 2016). Global estimates on soil degradation identified that at least 20% of global cropland has been affected by some form of degradation (Bai et al., 2008), but comprehensive global estimates are scarce, and some date many years back, e.g., Oldeman et al. (1991). Estimates on the total global land area being affected vary between 1 to 6 Bha, with high disagreements in their spatial distribution (Gibbs and Salmon, 2015).

To understand the effects of agricultural management on soil degradation, I review global and regional soil degradation assessments in Chapter 2 and investigate their applicability for global process-based model assessments. In the past, global degradation assessments relied on the collection of expert knowledge, e.g., GLASOD (Oldeman et al., 1991), or used proxy data from remote sensing such as the NDVI, e.g., GLADA (Bai et al., 2008). These assessments either neglected the processes involved in degradation and management interventions or restrained the analysis to a specific period due to limitations in data availability. Unsuitable or intensive agricultural management practices can promote soil degradation (Lal, 2013), but sustainable agronomic practices are argued to counterbalance or reverse degradation (Fowler and Rockström, 2001; Stavi and Lal, 2015). Management options on cropland include the preparation of the seedbed and control of weed through tillage, residue management, cover cropping, fallowing, crop rotations, irrigation, fertilizer application, crop cultivar choice, and the timing of sowing and harvest (Buysse et al., 2013; Enrique et al., 1999; Fowler and Rockström, 2001; Kaye and Quemada, 2017; Trost et al., 2013; Waha et al., 2012).

Conventional tillage practices (i.e., plowing) are some of the most disruptive management options (Lal, 1993) and can, if improperly used, for example, excessively in dry regions with low precipitation, accelerate agricultural-driven soil degradation (Bowman et al., 1999).

Tillage practices affect a complex set of soil properties and feedbacks, which I show in detail in Chapter 3. Excessive tillage can promote soil erosion (Cerdà et al., 2009), leading to subsoil compaction (Podder et al., 2012), which can trigger soil salinization (Ghassemi et al., 1995), reduce SOC content (Lal, 1993) and soil biodiversity (Patterson et al., 2019). Tillage practices can move soil particles down the slope, which is a degradation process known as tillage erosion (Van Oost et al., 2006) and may account for up to 5 Pg yr^{-1} soil loss (FAO and ITPS, 2015). Van Oost et al. (2006) estimated that tillage erosion rates could be of the same magnitude as water erosion rates on cropland. No-till management, if combined with residue management, is capable of slowing down or reverse negative impacts from soil degradation by reducing soil erosion by wind and water (Armand et al., 2009), preserving soil moisture, and decreasing soil temperature amplitudes (Enrique et al., 1999; Steinbach and Alvarez, 2006). Ranaivoson et al. (2017) show that a residue layer consisting of 2 to 4 t ha^{-1} dry matter can reduce surface runoff by up to 80% and thus reduce soil erosion from water. The absence of a residue layer can increase wind erosion (He et al., 2018), as the residue layer acts as a protective layer on the soil surface. Global estimates on soil loss from wind erosion are highly variable but are estimated to be in the magnitude of 2 Pg yr^{-1} (FAO and ITPS, 2015). Residues increase water infiltration into the soil (Guérif et al., 2001; Jägermeyr et al., 2016; Ranaivoson et al., 2017), as runoff from water is slowed down so that the water has more time to infiltrate (Glab and Kulig, 2008). If residues cover at least 30% of the soil and no-till management is introduced, the practice is known as conservation agriculture. Therefore, tillage management should always be considered and evaluated in conjunction with residue management, as both management practices are closely interlinked (Guérif et al., 2001; Strudley et al., 2008). Though tillage practices play a major role in promoting soil degradation, results in Chapter 4 suggest SOC loss on cropland is less sensitive to tillage practice compared to residue management. This highlights the importance of residue management on controlling and reducing soil degradation on cropland. Residues left on the field serve multiple purposes, as they add and preserve SOC in the soil and reduce soil erosion (Clay and Mishra, 2017; Leys et al., 2010).

5.2.2 How can agricultural management and productivity feedbacks be adequately modeled at the global scale in a process-based modeling framework?

The effect of cropland management on soil degradation has been underrepresented in global model assessments, as discussed in Chapter 2. Erosion from water is one of the most analyzed forms of soil degradation in regional model assessments (e.g., Le Roux et al., 2008; Morgan et al., 1998; Routschek et al., 2014). Yet, modeling soil erosion on a global scale has been a difficult challenge for a long time. The assessment requires high-resolution input data on soil and terrain conditions, which preclude the suitability at larger scales. Naipal et al. (2015) improved the applicability of the RUSLE equation for global-scale application using the ORCHIDEE model by improving the rainfall and topographical factor of this function and show that in the period between 1850-2005, soil erosion led to a total SOC loss of 74 ± 18 Pg C (Naipal et al., 2018). Borrelli et al. (2017) presented a high-resolution global erosion model by combining census data, GIS modeling, and remote sensing. Their findings showed an annual erosion rate of 36 Pg yr^{-1} of soil and indicated an increase in global soil erosion, mainly attributed to cropland expansion.

Chapter 2 highlights the importance of SOC content as one of the most crucial indicators for healthy soils and plays a significant role in agricultural soil degradation due to the feedbacks of SOC on soil water and soil nutrients, and therefore crop productivity. Further, SOC content can serve as a useful indicator in soil degradation model assessments because SOC comprises specific qualities on a biophysical and model-oriented level. These qualities include: (1) SOC affects soil processes and properties directly and indirectly, which can be translated into a process-based model using, for example, PTFs, which express the relationship between different soil properties. (2) High SOC content can be associated with healthy soil by increasing CEC and therefore positively influences the availability of nutrients, which has positive effects on crop yields. High SOC content also improves water retention, which is crucial for plant growth. (3) SOC changes within a measurable amount of time, such as days, months, or years, so that SOC changes can influence plant growth. This has been studied extensively at the field and regional scale (Angers et al., 2011; Blanco-Canqui and Lal, 2008; Bowman et al., 1999; Girmay et al., 2008; Sherrod et al., 2005), which supplies valuable insight data and process understanding on SOC development at the field and regional scale, which enables the evaluation of modeled results. For example, Bowman et al. (1999) found in a field trial that continuous cropping compared to fallow cropping can increase topsoil SOC by 20% over 5 years, while Girmay et al. (2008) found that topsoil SOC increased by 1-3% after 10 years of adopting restoration and protection measures in Ethiopia. (4) SOC effects can be included in a process-based manner into a global ecosystem model on various resolutions. And last, (5) SOC is affected by agricultural management, e.g., tillage and residue management. Lutz et al. (2019b) show that the implementation of agricultural management effects into global ecosystem models is desirable but needs to be assessed with respect to the process understanding, the availability of input data at the global scale, and the availability of modeling approaches. Lorenz et al. (2019) suggested using SOC as an indicator for soil and land degradation in the context of the UN Sustainable Development Goals. Biophysical models that consider the feedbacks between agricultural management and soil degradation should focus on the process effect-chain of various management options. It is necessary to include SOC feedback and linkages on plant productivity and associated processes in model assessments to account for soil degradation driven by SOC loss. Some global biophysical models account for agricultural management practices in an oversimplified way, e.g., by doubling soil decomposition rates to account for tillage management, as in Pugh et al. (2015).

In Chapter 3, a novel modeling approach to integrate tillage practices and residue management into a global biophysical model framework to assess the role of agricultural management on soil biophysical processes and crop productivity is described and evaluated. The processes are integrated into the well-known LPJmL model (Schaphoff et al., 2018a), which accounts for feedbacks from N limitation (von Bloh et al., 2018). Earlier versions of the LPJmL model account in some parts for the effects of agricultural management, e.g., sowing dates (Waha et al., 2012) and irrigation management (Jägermeyr et al., 2015). The effects of tillage practices on soil physical properties were adopted from the APEX model (Williams et al., 2015) by accounting for changes in BD in the tilled soil layer. Changes in BD further affect soil water properties, which are modeled by utilizing a PTF developed by Saxton and Rawls (2006). This enables the analysis of productivity feedbacks based on soil texture classes and SOC content. The effects of residues have to be accounted for to evaluate additional management effects induced by tillage practices. Therefore, the model explicitly considers the residue representation by separating the litter pool into two pools: An incorporated litter pool, as well as a surface litter pool, each with corresponded pools for C and N. The residue layer affects soil water infiltration rates as well as soil evaporation, which enables the model to account for the feedback of residue management on productivity. It is shown that the LPJmL model is capable of reproducing the ranges of biophysical effects and responses presented in different meta-analyses of tillage and residue management on C, N, and water dynamics and crop yield. The evaluation of the model on current cropland showed a median topsoil SOC increase by 5.3% and a reduction in CO_2 emission by -11.9% after switching from conventional tillage to a conservation tillage system (no-till and 30% residues retained), which is in line with the results from a meta-study by Abdalla et al. (2016). The new implementation of residue feedbacks on soil water dynamics shows that in the model, a protective residue layer can reduce soil evaporation by a median of -44.3% (5^{th}, 95^{th} percentiles: -64.5, -17.4%). The evaluation showed that the LPJmL5.0-tillage model was able to generally reproduce no-till effects in the magnitude of literature estimates, but could not reproduce responses in the literature related to N fluxes, e.g., in regional N_2O emission patterns. Lutz et al. (2020) further investigated the effects of management information and representation of soil moisture on N fluxes and found that the LPJmL model showed a general bias in overestimating soil moisture content. They further highlighted that the simulation of tillage effects on N_2O emission can be improved by adding additional information on agricultural management, e.g., the type, timing, and amount of fertilizer applied, but that this information is not always in detail available at the global scale.

Modeled results show that arid regions benefit the most from no-till management combined with a residue layer due to soil water conservation effects. Further, the model can consider a complex set of feedbacks on greenhouse gas emissions from soil respiration. The model description presented in Chapter 3 advances the LPJmL model significantly to allow for global assessments of agricultural management effects on the global biophysical flows and soil degradation, enabling climate change adaptation, mitigation of agricultural management emissions, and sustainable intensification. It presents a model approach that allows for the evaluation and analysis of management effects on biogeochemical flows such as within the C, N, and water cycle.

5.2.3 How can the impact of agricultural management practices on soil degradation be reduced considering future climate change?

To promote the global implementation of SOC sequestration to mitigate climate change and improve soil quality, Minasny et al. (2017) proposed the '4 per 1000' initiative. They proposed that a global SOC increase by 0.4% on managed land through adequate management strategies could offset all current anthropogenic CO_2 emissions. The proposal has been criticized for being overly ambitious but raised awareness on this topic and potentially initiated follow-up studies on the effectiveness of the proposed measures, such as the study in Chapter 4. To this end, my analysis in Chapter 4 builds upon the model extensions of the LPJmL5.0-tillage model described in Chapter 3, which now explicitly includes soil-to-plant productivity feedbacks.

The results in Chapter 4 show that the historical conversion of natural land to cropland has caused a total SOC reduction of 215 Pg C globally between the years 1700-2018, equivalent to 100.9 ppm of CO_2 in the atmosphere. These SOC losses can be attributed to historical LUC, which corresponds well with the magnitude found in other literature (Le Quéré et al., 2018; Pugh et al., 2015). Generally, less C is stored in cropland soils compared to natural land, as cropland is cultivated and a substantial fraction of C is lost due to harvest practices. Future simulations do not account for LUC and focus on current cropland only to exclude the effect of LUC on SOC losses. Results show that SOC stock decline in all stylized management systems and radiative climate pathways and that SOC loss is predominantly driven by the type of residue treatment. The highest cropland SOC losses are found in management systems that do not return residues, which show SOC losses of up to 38.4 Pg C (-28.1% SOC loss compared to today), which can be roughly translated into a net flux of 18 ppm CO_2 to the atmosphere. Management systems that return residues can reduce these losses substantially by limiting the losses to a maximum of 3.2 Pg C (-2.3% of SOC stock compared to today). On the other hand, results indicate minimal effects of tillage treatment (tillage compared to no-till) on SOC stocks, as tillage only explains less than 0.5% of SOC change. The results from the analysis in Chapter 4 further suggest only minor differences between the radiative forcing pathways (RCP2.6 vs. RCP8.5), with similar regional responses. SOC losses are driven by soil respiration processes, which increase when the temperatures are rising due to climate change, but the amount of residues, and therefore the return of C to soil, also plays a significant role. Simulations suggest that negative impacts of increased respiration in higher temperatures (RCP8.5) are counterbalanced by higher productivity from elevated CO_2 concentration, reducing the differences of impacts on SOC stocks between climate change trajectories.

The analysis in Chapter 4 shows that conservation tillage practices, in this case, no-till and residue return even if applied at a global scale, are not sufficient practices to support a global SOC increase on cropland, yet regional differences occur. A positive aspect is that almost half of the current global cropland area shows the potential to increase SOC content. Yet, based on these findings, further soil degradation in the form of SOC loss can be expected. Further, the analysis of additional management effects, especially at the global scale, is needed to assess the ecological footprint and mitigation measures of agricultural production systems.

5.3 Discussion

5.3.1 Soil degradation and crop productivity affected by SOC

Assessing soil degradation at a global scale is not a straightforward task, because it consists of a complex set of feedbacks and processes at various scales, as outlined and discussed in Chapter 2 and visualized in Chapter 3. The scope of this research as a global scale application adds additional complexity to the topic, as biophysical conditions and soil properties vary across time and space. Farmers are aware and sensitive to changes in climate and soil conditions and will likely choose management strategies that are easy to implement on a large scale, are the most profitable, and result in the highest yields per area with the least inputs. Scientific results can be used to inform farmers' choice to manage their land sustainably and reduce soil degradation. Soil tillage is one of the most widely applied management options to cultivate cropland. Yet, tillage can negatively influence several soil properties and affects various forms of soil degradation. Despite all these negative effects on soil properties caused by tillage, farmers still widely use it for seedbed preparation and weed control.

Managing and improving SOC content plays an essential role in combating soil degradation. Historically, a significant amount of SOC is lost due to the conversion of natural land to cropland, as shown in Chapter 4. To reverse the historical loss in SOC due to LUC, management practices that increase SOC content should be prioritized. This also helps to promote healthy soils. Simulations show that up to 46% of the cropland today shows the potential to increase SOC, depending on the management scenario. On the other hand, more than half of what is cropland today will undergo a further decline in SOC. Only less than 2% of the cropland today will show no change, as the results in Chapter 4 indicate. Yet, the applicability of model results in the real world has to be put in a broader context, as the general assumptions on management systems presented here are in some way oversimplified. For example, the scenario no-till and residues (NT_R) assumes the implementation of agricultural conservation practices applied on all available current cropland simultaneously, representing a best-case scenario but less a realistic one. Yet, Prestele and Verburg (2020) highlight that spatial variability of the effects of climate-smart agriculture and sustainable intensification needs to be considered in global-scale assessments. Because global spatially explicit datasets on future projections on the adoption of conservation agriculture practices are not yet available, I conducted a scenario assessment that provides a valuable methodology to investigate large-scale management effects.

The '4 per 1000' initiative by Minasny et al. (2017) proposed the use of management options such as organic amendments, compost and manure addition, crop residue retention, inorganic fertilization, no-till and reduced tillage, cover crops, and crop rotations. While all these practices have been shown to increase SOC content, they most likely cannot be implemented on all cropland simultaneously and for all regions at equal intensity. My results in Chapter 4 show that globally aggregated SOC sequestration through no-till and residue management is a challenging task and might not be achievable. Yet, I show that in warm temperate dry, warm temperate moist, and tropical dry regions, the potential to increase SOC exists under agricultural management practices that return residues to the soil after harvest.

Field trial studies at plot and field size and meta-analysis have shown that no-till with residue management can increase SOC (Abdalla et al., 2016; Bai et al., 2018; González-Sánchez et al., 2012; West and Post, 2002). For example, West and Post (2002) found a general SOC sequestration potential of 0.48 ± 0.13 Mg C ha^{-1} yr^{-1} by switching from conventional tillage to a no-till system. Yet, it is not advisable to upscale results to a regional or global scale, as environmental and soil conditions play a crucial role in determining the effectiveness of SOC sequestration, as also highlighted in Chapter 4.

No-till management can increase SOC stocks, but the effects on deep soil layers are debated (Luo et al., 2010). Field trials have shown that no-till tends to increase SOC in the upper soil layers (Blanco-Canqui and Lal, 2008; Cooper et al., 2021; West and Post, 2002), while the effect on lower soil layers is uncertain due to the lack of standardized research methodologies (Derpsch et al., 2014). Field trials often consider the first 30 to 40 cm of the soil with variable depth, while neglecting deeper soil layers, which highlights the need for standardized sampling methods and deeper test sampling (Derpsch et al., 2014) in addition to using standardized core sampling methods (Gross and Harrison, 2018). This circumstance limits the interpretation of field trial results and adds uncertainty to the analysis of no-till management effectiveness. For example, Causarano et al. (2008) found in their study a SOC sequestration potential of 0.5 to 0.63 Mg C ha^{-1} yr^{-1} for Iowa, USA, if the first 20 cm of topsoil is considered. On the contrary, they found losses in total SOC stocks if the entire soil column is accounted for. Because of the reported ambiguous effects of no-till management on deeper soil layer SOC, the analysis in Chapter 4 focuses on the SOC sequestration potentials and SOC stock changes of the entire soil column.

The results of Chapter 4 highlight the importance of residue treatment as the main factor determining the SOC levels in cropland soils. Still, it also reveals that tillage and residue management alone are insufficient agricultural management options, even if applied globally on all current cropland, to halt or reverse cropland SOC losses and future soil degradation. SOC is projected to decline in more than 50% of current cropland, promoting further soil degradation and reducing climate mitigation options. To put my results into a broader perspective, the maximum projected SOC loss of 38.4 Pg C until the end of the century translates into an additional 18 ppm CO_2 in the atmosphere, which is roughly three times the current global annual emission from LUC (6.6 Pg CO_2 in 2019), or half the emission from fossil-fuel combustion (36.3 Pg C in 2019) (Friedlingstein et al., 2020). Additional emitting these from the soil adds more focus on efforts to reduce CO_2 in the atmosphere, not considering the negative implication on soil biota and plant productivity. This stresses the need for the implementation of other management options that might increase SOC. These include the application of manure, which can increase SOC by 0.1 ± 0.05 Mg C ha^{-1} yr^{-1} (Buysse et al., 2013), the management of cover crops (Corsi et al., 2012), which was reported to be able to increase SOC by 0.32 Mg C ha^{-1} yr^{-1} (Poeplau and Don, 2015) and 0.54 ± 0.57 Mg C ha^{-1} yr^{-1} (reported as 1.97 ± 2.1 Mg CO_2-eq. ha^{-1} yr^{-1} in Abdalla et al. (2019)), and agroforestry (Cooper et al., 1996; Ramachandran Nair et al., 2009), which may sequester up to 2.2 Pg C globally after 50 years of agroforestry implementation (Lorenz and Lal, 2014). Majumder et al. (2008) reported a minimum return rate to the soil of 3.56 Mg C ha^{-1} yr^{-1} to maintain SOC levels and to compensate for SOC losses from cropping practices, which none of the management options mentioned above can achieve alone. Only a holistic approach that combines these practices and takes local climate and soil conditions into account will most likely achieve higher sequestration rates close to or above the required return rates. Including these practices in global biophysical crop models in future assessments allows for better analysis and evaluation of sustainable agricultural practices, especially for regions in which no field trials are currently available.

An important aspect to consider for evaluating the effectiveness of sustainable agricultural management practices as a climate mitigation measure is that once these are implemented, the measures should be maintained over a long period, or otherwise, the contributions to climate mitigation efforts can quickly diminish. For example, the accumulation of topsoil SOC can be achieved within a few years, while the transfer to deeper soil layers is much slower and can take years to decades (Balesdent et al., 2018). Therefore, if the C input into to soil is not sustained, SOC in the topsoil can be lost through decomposition and soil respiration processes, resulting in soil depletion.

5.3.2 The complexity of soil degradation and limitations to the methodological approach

Modeling the processes and effects of agricultural management on soil degradation is a complex task, and model assessments need to consider a set of various aspects to quantify the total extent, assess its severity, and estimate the impact of soil degradation on soil physical, chemical conditions, and ultimately on crop yield, yet comprehensive global soil degradation model assessments do not yet exist. As agricultural management is still underrepresented in DGVMs, the research presented here adds knowledge to fill this gap, by explicitly considering feedbacks between soil conditions and plant productivity.

Due to the complexity of soil degradation processes and the variety of affected scales, this modeling framework focuses on SOC reduction as an essential process of soil degradation. Not considered in this modeling approach are other forms of soil degradation such as soil compaction, salinization, or soil erosion from water and wind, even though they are acknowledged as important forms of soil degradation on cropland at regional and field scale (Amundson et al., 2015; Bakker et al., 2005; Batey, 2009; Lal, 2001a; Singh, 2009). Furthermore, uncertainty in the methodological approach is caused by the fact that so far, no common definition of soil and land degradation exists, as well as no universally applicable procedure on how to assess soil degradation. For this research, SOC loss is used as a proxy for soil degradation. Yet, SOC loss alone does not suffice to be used as a single indicator (Lorenz and Lal, 2016). SOC changes alone cannot reflect the complexity of soil degradation because it results from a multitude of network interactions between biophysical, socioeconomic, and political factors and occurs at various scales (Lorenz et al., 2019; Stolte et al., 2015). Yet, it is an important indicator for healthy and productive soils and should be considered in agricultural-related soil degradation model assessment.

The LPJmL5.0-tillage model can reproduce tillage effects on global stocks and fluxes reported in the literature, as well as regional patterns of these changes. The future simulations presented in Chapter 4 do not yet account for technological improvements, more efficient fertilizer use, additional use of manure and amendments, advancements in genetically optimized crops, and improvements in crop cultivar choice, as well as the use of cover crops to retain nutrients and water. These aspects are additional management choices to optimize crop productivity and other soil-related ecosystem services and enable possibilities for future assessments. The effects of LUC can substantially influence SOC stocks, as shown in the analysis of historical cropland SOC in Chapter 4 and highlighted in other studies (Olin et al., 2015; Pugh et al., 2015). While future LUC is not considered in the analysis for future SOC development in Chapter 4, cropland expansion in the decades ahead will likely lead to further SOC reductions.

Global model applications entail various levels of uncertainties related to the input data used, the detail of processes that are simulated, management assumptions, and scale. For example, in global ecosystem models, soils are currently not well represented in detail and are homogeneous within one grid cell. This can lead to uncertainty that might even outweigh the climate change signal (Folberth et al., 2016). Still, to account for the resolution of a specific global model, soil data needs to be aggregated to meet the computational requirements of the model. The here extended LPJmL model allows for the quantification of climate and LUC feedbacks on the terrestrial C and water cycles, the biosphere, and agricultural production. Information on LUC is provided from integrated assessment models. These rely on simplistic assumptions of drivers and processes related to LUC, which add uncertainty to the land-use and vegetation modeling process (Prestele et al., 2017). To quantify the feedback of LUC on C balance, climate change, and the potential reversal of the terrestrial C balance, the LPJmL model was previously coupled with the integrated assessment model IMAGE (Müller et al., 2016; Stehfest et al., 2014). Dynamic vegetation models at a global scale can follow various assumptions on the detail of the representation of biophysical processes and cycles. Analyses have shown that scale plays an important role in determining the uncertainty of model results (Ogle et al., 2010; Prestele et al., 2016). While climate change projections remain a large source of uncertainty, i.e., the assumptions on temperature increase and changes in precipitation patterns, global models suffer from high uncertainty related to the effect of CO_2 fertilization on crop growth (Rosenzweig et al., 2014).

Model intercomparison studies are valuable methods to compare and evaluate different models against each other, e.g., within the Global Gridded Crop Model Intercomparison (GGCMI) within the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013), to reduce the uncertainty from different model outcomes. Yet, due to the lack of comprehensive models incorporating degradation, there is currently no intercomparison of global model assessments related to management effects on soil degradation. Despite the shortcoming owing to the complexity of model processes and scale, one major advancement of the LPJmL model is the integration of feedbacks between soil properties and plant productivity, enabled by a dynamic calculation of soil water properties which improve the biophysical representation of crop productivity processes in the model.

5.4 Summary and conclusions

Soil degradation can be promoted by physical, chemical, and biological processes and occur at various scales. Some of the most important processes of soil degradation include the dislocation of soil particles by physical forces, e.g., wind, water, as well as changes in soil structure and bulk density, which influence the retention and transport of water in soils. In this thesis, I highlight SOC loss as one of the main forms of management-driven soil degradation, which affects soil quality and crop productivity. I was able to demonstrate the importance of SOC loss as a major form of soil degradation, show the impact of agricultural management on the global C cycle, and provide a global-scale biophysical modeling approach on tillage and residue management, which is one of the main agricultural practices that cause SOC degradation. SOC loss can serve as a useful indicator for modeling soil degradation. The model can reproduce responses of literature estimates on environmental stocks and fluxes. The modeled results show that residue management is one of the main agronomic management practices that control SOC content and can offset the negative impacts caused by tillage. In total, up to 46% of current cropland shows the potential for SOC increase under idealized management scenarios until the end of the century under climate change. In comparison, on at least 52% of current cropland, SOC is projected to decline further and could contribute to a release of up to 18 ppm CO_2 to the atmosphere, which can be slowed down by improved agricultural management practices.

In conclusion, soil degradation consists of a complex set of feedbacks and processes at various scales and can, with limitations, be included in model assessment at the global scale. Tillage practices play an important role as an agricultural management practice promoting various forms of soil degradation. But the effects of tillage on SOC loss as one form of soil degradation are outweighed by the effects of residue treatment. For assessing the effects of agricultural-related management effects, SOC loss can serve as a useful indicator for soil degradation. PTFs allow for a dynamic representation of changes in soil conditions in the context of biophysical model assessments of soil degradation. Moreover, residue management alone cannot offset SOC losses from management and climate change, yet regional differences occur in response to management. Global GHG emissions should be reduced rather sooner than later to avoid the dangerous effects of anthropogenic climate change and to avoid the transgression of tipping elements in the climate system, which can cause an unprecedented acceleration of global warming (Steffen et al., 2018).

5.5 Outlook

5.5.1 Climate change and SOC effects on crop yield on current cropland until the end of the century

To analyze and highlight possible effects on global average yield for the three main crops, wheat, rice, and maize, I followed the same simulation routines and management assumptions as described in Chapter 4. The modeled results show that the yield response of these crops is sensitive to management, with variability (Fig. 5-1). Crop yields are sensitive to environmental conditions such as temperature, water availability, nutrients, soil physical and chemical properties, including SOC content, agronomic management practices, and [CO_2]. Generally, no-till and residue management systems (NT_R) show the highest yields for RCP2.6 and RCP8.5. The lowest yields are found for management systems that do not return residues, independent of the tillage systems, as differences between tillage and no-till are small for these systems, and almost negligible if residues are harvested (NR cases).

Modeled yield for wheat, rice, and maize do not decline until the end of the century in any of the stylized management systems, even though in Chapter 4 I find substantial SOC losses on cropland until the end of the century if residues are not returned to the soil. Negative effects from changes in soil water retention or nutrient availability due to reductions in SOC could be counterbalanced by CO_2 fertilization effects under climate change. Wheat and rice, which both follow the C_3 photosynthetic pathway, benefit the most from increasing [CO_2] in RCP8.5, as yields increase by up to 35% for wheat and up to 44% for rice in the no-till and residue management system (NT_R). Yields for maize are highly variable throughout the century but increase by up to 13% for NT_R in RCP8.5 until the end of the century. Yields for maize decrease by -6% until the end of the century in the tillage and no residue management system (T_NR) for RCP2.6, which constitutes the highest yield losses of all three compared crops. Yields for the same crops for different levels of SOM content, which contains 50% SOC (see Eq. (26) in Section 3.3.5.1), are shown in Fig. 5-2. The simulation results indicate that yields are higher with increasing SOM (and therefore SOC) content, using a fixed amount of SOM across all cropland soils. This applies specifically to wheat and maize crops, but no response of SOM on yields can be found for rice (Fig. 5-2B). For wheat and maize in both RCP2.6 and RCP8.5, an increase of SOM content by 2% results in a mean yield increase of 1.5% across the century. The inter-annual variability of maize yield is stronger than the SOM effect on maize yield.

The analysis on the effects of different levels of SOM shows that rice yields are insensitive to changes in SOM, and therefore different levels of SOC. At the current state in the model, changes in SOC are translated to changes in soil water properties, but the underlying mechanisms need further investigation. While losses in SOC are argued to reduce soil productivity and, ultimately, the ability to grow crops, reductions in total SOC stocks cannot yet be directly translated into yield losses for crops. This suggests that investigation and the implementation of the effects of SOC loss on other processes, such as on the influence on CEC and nutrients, might improve the yield effects of SOC in the model. The analysis of future crop yields shows that yield for three major crop types can increase, even if SOC is projected to decrease because crop yield is controlled by various sets of biological, biophysical, and biogeochemical processes. For example, CO_2 fertilization effects can offset or counterbalance negative effects from SOC losses. This analysis opens opportunities to further look into the exact yield responses of the analyzed crops. In certain regions, crops could benefit from CO_2 fertilization effects, yet Müller et al. (2015) show that at the global scale, the overall benefits of climate mitigation to avoid damages outweigh the likely yield increase from CO_2 fertilization effects. The impacts of climate change can differ widely between regions and globally aggregated, positive and negative effects can compensate each other, leading to small median changes (Müller et al., 2015). The analysis of CO_2 fertilization effects has to be interpreted with caution, as they do not justify limiting or reversing climate mitigation efforts because of many possible feedbacks and tipping elements in the climate system. Further research to understand the underlying mechanisms controlling yield are needed, as well as to identify the possible trade-offs between negative climate change impacts and benefits at a regional and global scale.

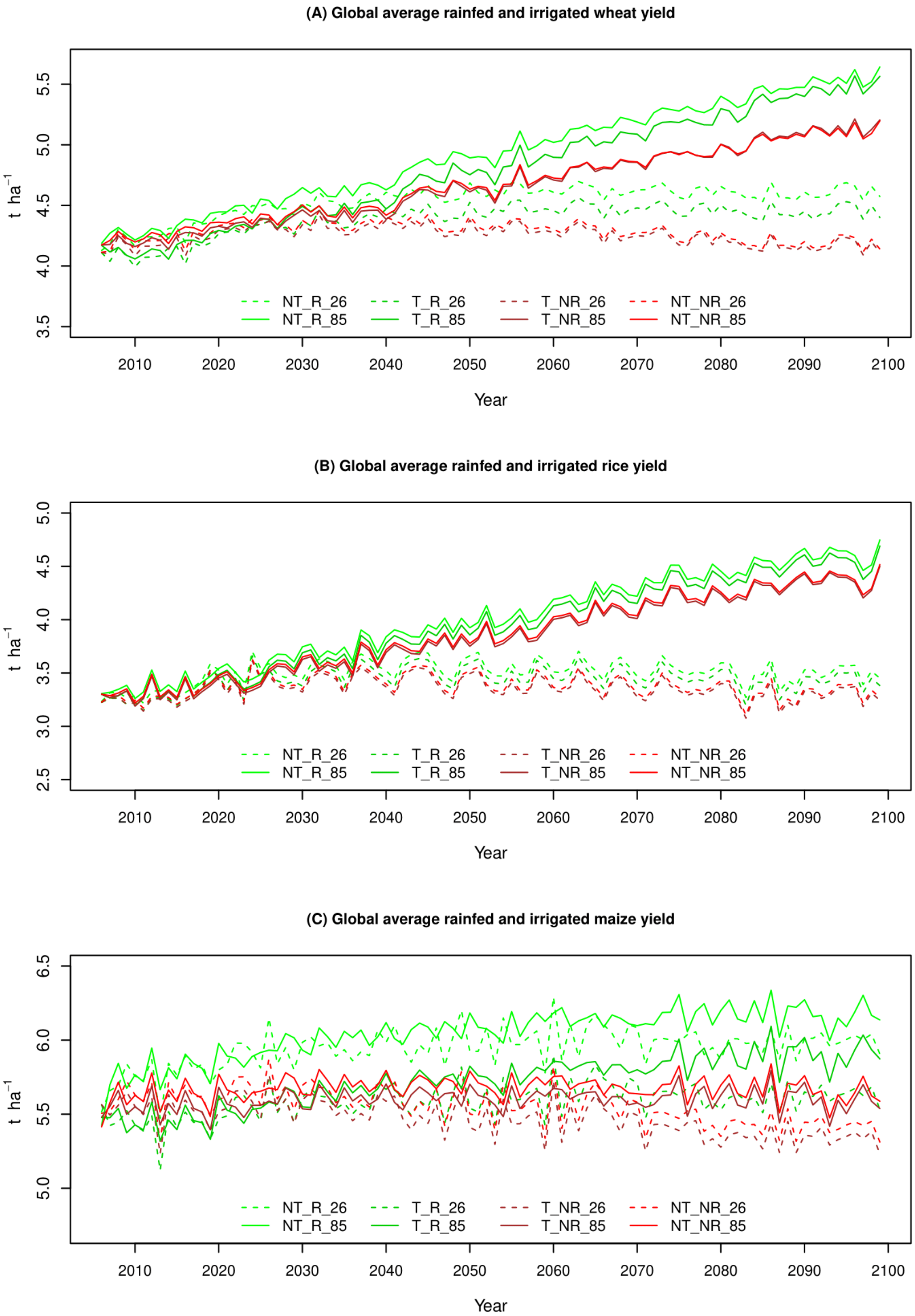

Figure 5-1: Global average yields between the year 2006 and 2100 for rainfed plus irrigated wheat (A), rice (B), and maize (C) under four globally applied stylized management systems on current cropland (no LUC): NT_R – no-till and residues returned, T_R – tillage and residues returned, T_NR – tillage and no residues returned and NT_NR – no-till and no residues returned. The numbers _26 and _85 describe the climate forcing RCP2.6 (e.g., T_R_26) and RCP8.5. Results are averaged across the four GCMs (HadGEM2_ES, GFDL-ESM2M, IPSL-CM5A-LR, MIROC5) for each RCP.

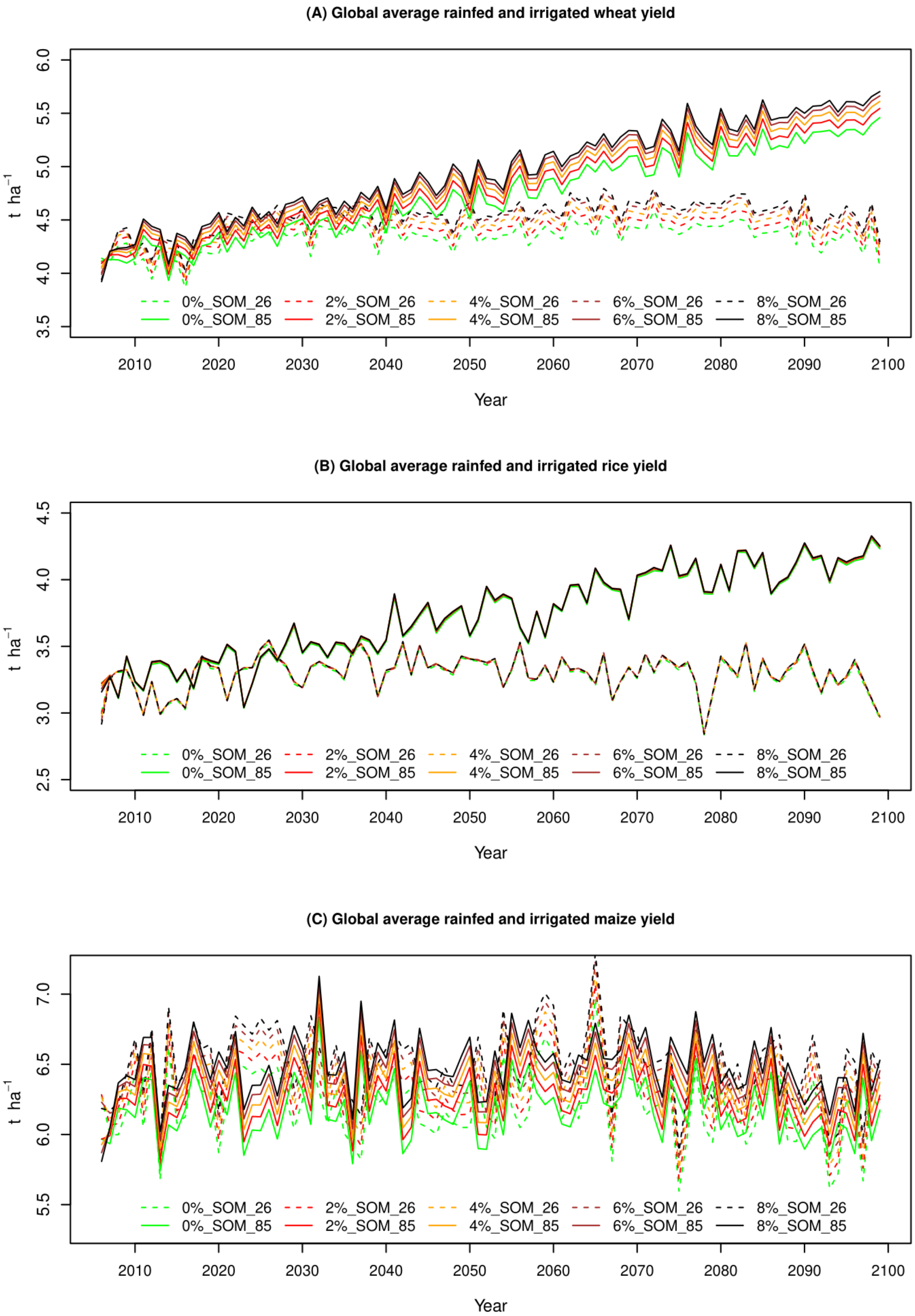

Figure 5-2: Yield response on variable SOM levels (%) of the three major crops wheat, rice, and maize between the year 2006 and 2100 under constant land use assumptions of 2005 for radiative forcing pathways RCP2.6 (e.g., 0%_SOM_26) and RCP8.5 (e.g., 0%_SOM_85). Results shown here are for the HadGEM2_ES GCM only.

5.5.2 Applications and model improvements in future research

Global vegetation and crop models enable the analysis of complex interactions of biophysical processes and feedbacks. Yet, even complex models can only represent a simplified version of ecosystem processes in the real world. Nevertheless, these models are valuable tools for a wide range of applications, e.g., modeling historical LUC impacts (Pugh et al., 2015; Ren et al., 2020), modeling terrestrial C cycle feedbacks from accelerated future climate change (Cox et al., 2000), estimating the effectiveness of C capturing and storage (Heck et al., 2018) or estimating the potential of global sustainable water management (Jägermeyr et al., 2016). Models are continuously improved and validated against ground truth and remote sensing data and exist at various scales.

The LPJmL model is a model developed for global-scale applications and utilizes a grid cell resolution of 0.5°, which is approximately 50 by 50 km at the equator. Such grid cells resolution limits the applicability of LPJmL at a local and plot scale. Still, and this is the advantage of a global model, it allows for the analysis of global and regional patterns of biophysical flows and stocks, and agricultural management effects on such. Increasing the resolution of the model would allow for a more detailed representation of soil properties, e.g., higher differentiation of soil types, as well as the analysis of local and regional soil degradation processes, e.g., information on topography for simulating water erosion. Yet, this increases the computation time of the model. For the usage of LPJmL for regional assessments, a higher resolution is desirable. Also, it has to be tested and evaluated if an increase in model and data resolution would improve model performance substantially and justify the increase in computational time.

The approach presented in this thesis allows for the investigation of global tillage effects on soil conditions and future global crop yield. In addition, tillage effects can be assessed regarding GHG emissions, such as CO_2 and N_2O. However, while the general responses of N_2O emission were in agreement with the data from meta-analyses, the regional response in different climate zones showed deviation to the reported values in the meta-analyses (see Chapter 3). For example, while van Kessel et al. (2013) reported an overall decrease of 1.5% in N_2O emission in the humid climate zone after the adoption on no-till, the LPJmL model showed a 23.5% increase in the same climate zone. A more detailed representation of soil moisture and management information in the model can improve the linkage to N_2O emissions (Lutz et al., 2020). As soil erosion from wind and water plays a crucial role in topsoil loss and influences topsoil SOC content, it is advisable to include these processes in future developments of the LPJmL to account for other forms of soil degradation. Soil compaction and subsoil compaction processes from tillage are increasingly important. Farmers are aware of the issue and minimize the tractor load by adjusting the tire pressure and size (Batey, 2009; Petersen et al., 1996) or by control traffic farming (Taylor, 1983; Tullberg et al., 2007), but these effects are not yet considered in LPJmL. Since tillage practices are now a part of the LPJmL model, future model development can build upon the processes which are now included and, for example, account for subsoil compaction from tillage.

The representation of water erosion processes could be enhanced by either increasing the resolution of LPJmL or following the methodology from Naipal et al. (2015), who improved the functionality of the RUSLE equation utilizing the ORCHIDEE model (Vuichard et al., 2018). Soil crust formation, subsoil compaction, and the impact of management on soil biodiversity loss (Moos et al., 2018; Patterson et al., 2019), which reduces the diversity of soil fauna and influences soil health, are all valuable processes, which should be considered in future model assessments. Increases in soil biodiversity can contribute substantially to the quality of the soil (Delgado-Baquerizo et al., 2017). No-till systems are associated with higher herbicide use for weed control (Alletto et al., 2010; da Silva et al., 2021; Fuglie, 1999), which can be controlled by complex crop rotations (Anderson, 2015). More research is needed to study widely applicable methods for weed control in no-till systems, as well as the effects of herbicide use on soil biodiversity and human health. So far, the impact of herbicide, as well as pesticide use has been underrepresented in DGVMs.

5.5.3 Recommendations for policymakers

Scientific results from assessments such as the one presented in this thesis can be used as a basis for discussion for recommendations for policymakers but need a discussion platform to translate the knowledge into applicable measures and to raise awareness, and gain attention. Scientific findings and recommendations need translations for policy implementations. Without them, the results from the research will have no impact on the real world. In a great effort, a global climate target to reduce GHG emissions was laid out in the Paris Agreement in 2015, but the effects of the measures are highly uncertain because they need the commitment of the signing countries to follow these targets and implement these in their national policies. So far, most signing countries are not on track with their commitments (Rogelj et al., 2016). It requires further strengthening of policy implementations at the national level to reduce GHG emissions and limit global warming to well below 2 °C (Rogelj et al., 2016). Reducing the uncertainty in future climate model projections and finding effective measures in reducing climate change and climate change impacts could improve guidance for decision-making to better account for mitigation and adaptation strategies in climate policy.

Monetary incentives to farmers who implement management strategies that sequester C and reduce GHG concentration could lead to the gradual implementation of sustainable agricultural practices. But this requires the implementation of suitable policy measures, backed by taxation, subsidies, and a C pricing scheme (Paustian et al., 2016), which could amplify these developments in the right direction to promote GHG mitigation schemes (Jensen et al., 2019). For example on the European agricultural policy level, a major revision of the Common Agricultural Policy (CAP) is still needed. The CAP subsidizes farmers and the production of food and ensures a stable supply of affordable food. Still, the CAP is criticized for favoring farmers with high shares of cropland instead of focusing on the environmental conditions of food production (Pe'er et al., 2020). The CAP has undergone a reform in 2020 but has failed to address critical targets and objectives laid out in the European Green Deal (Metta et al., 2020). The majority of the direct payments to farmers will continue to subsidize the largest landowners without environmental protection measures. From the year 2023 onwards, 20% to 30% of the direct payments are reserved for climate and environmental programs, which are called eco-schemes, and, so far, environmental protection plans are costly with a limited positive impact on the environment (Röder et al., 2021). This imbalance within the direct payments showcases the need for further reforms of the CAP, as the major part of finances through the CAP should be connected to sustainable food production and should benefit farmers who implement sustainable management practices (Röder et al., 2021). For example, it has been proposed that environmental protection measures are rewarded with a 'common good bonus' utilizing a points system, which could increase the incentive for such measures (Birkenstock and Röder, 2020).

On a global policy perspective, the OECD each year evaluates the agricultural policies of 54 countries, including the 38 OECD countries, and highlights in their recent report that the most current agricultural policies are not supporting the overall needs of food production systems (OECD, 2021). The report states that current agricultural development policies in these countries do not sufficiently support the three main challenges of food production: (1) Enable food security for a growing world population, (2) provide livelihoods and incomes for millions of people, and (3) produce food sustainably without depleting resources, while at the same time contributing to the reduction of GHG emissions through climate change mitigation efforts. Norton (2004) extensively reviewed classes of policy issues in developing countries and highlighted the importance of agricultural development policies based on common principles that guide policy actions, which include economic, social, fiscal, institutional, and environmental sustainability. He underlines that decision-making involves a diverse set of stakeholders and many parties from local organizations, businesses, local and central governments, as well as international development agencies. Diverse policies for agriculture across the many countries of the world call for a global effort to promote future agricultural policies as a global agenda (Dastagiri et al., 2014).

By fostering policies and increasing monetary incentives that support agroecological farming practices, soils can be protected from degradation by reducing the use of intensive tillage practices, reducing residue harvesting, and increasing biodiversity by reducing herbicide use. A voluntary international agreement could help to protect the world's soils from degradation, but private ownership of land hamper the implementation of binding agreements (Montanarella, 2015). Sustainable and ecological food production should focus on reducing GHG emissions by using conservation tillage systems (Cooper et al., 2021; Fowler and Rockström, 2001) and mitigating climate change through increasing SOC (Bindraban et al., 2012; Lal, 2004a). Additionally, these measures support healthy soils and increase soil biodiversity (Moos et al., 2018; Wanjiku Kamau et al., 2019) to promote a healthy ecosystem.

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Appendix A – Supplementary material to Chapter 3: Incorporating tillage practices into a dynamic global vegetation model

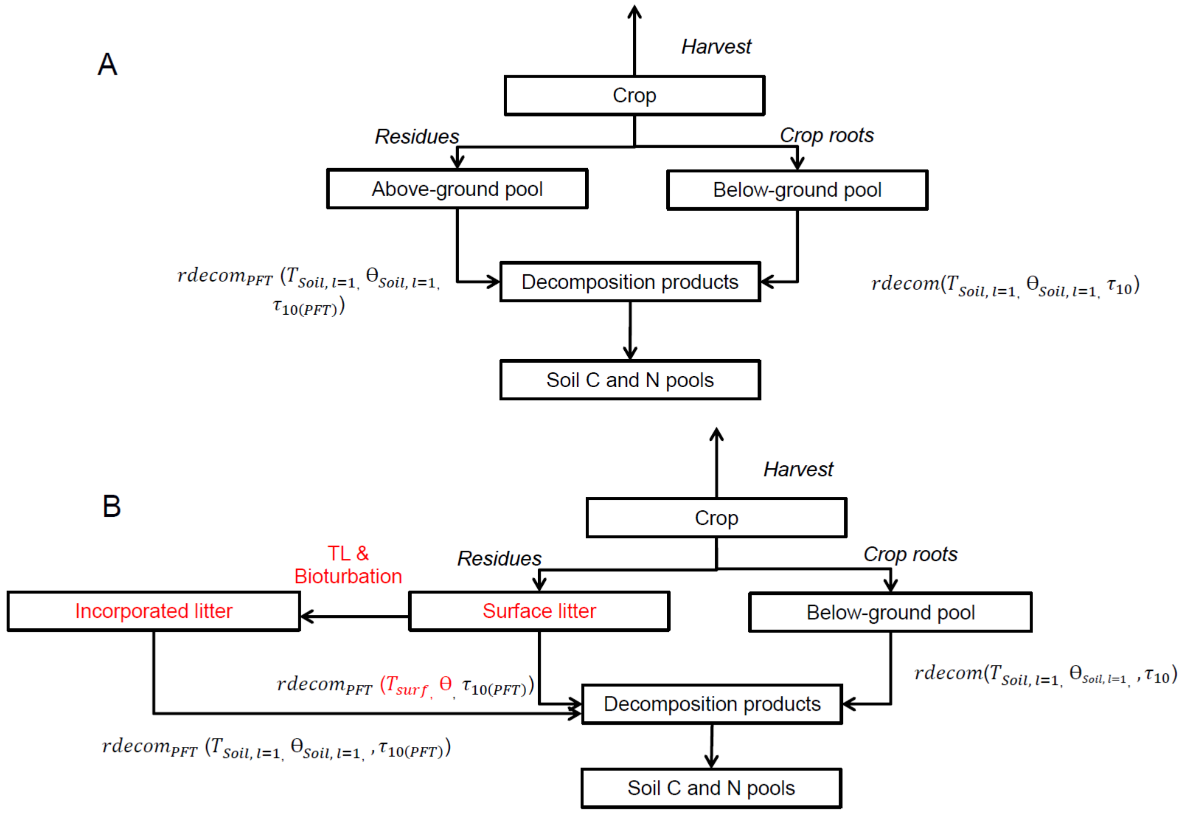


Figure A1: Description of the residue pools and corresponding C and N pools in the previous versions of LPJmL (A) and the new version LPJmL5.0-tillage (B).

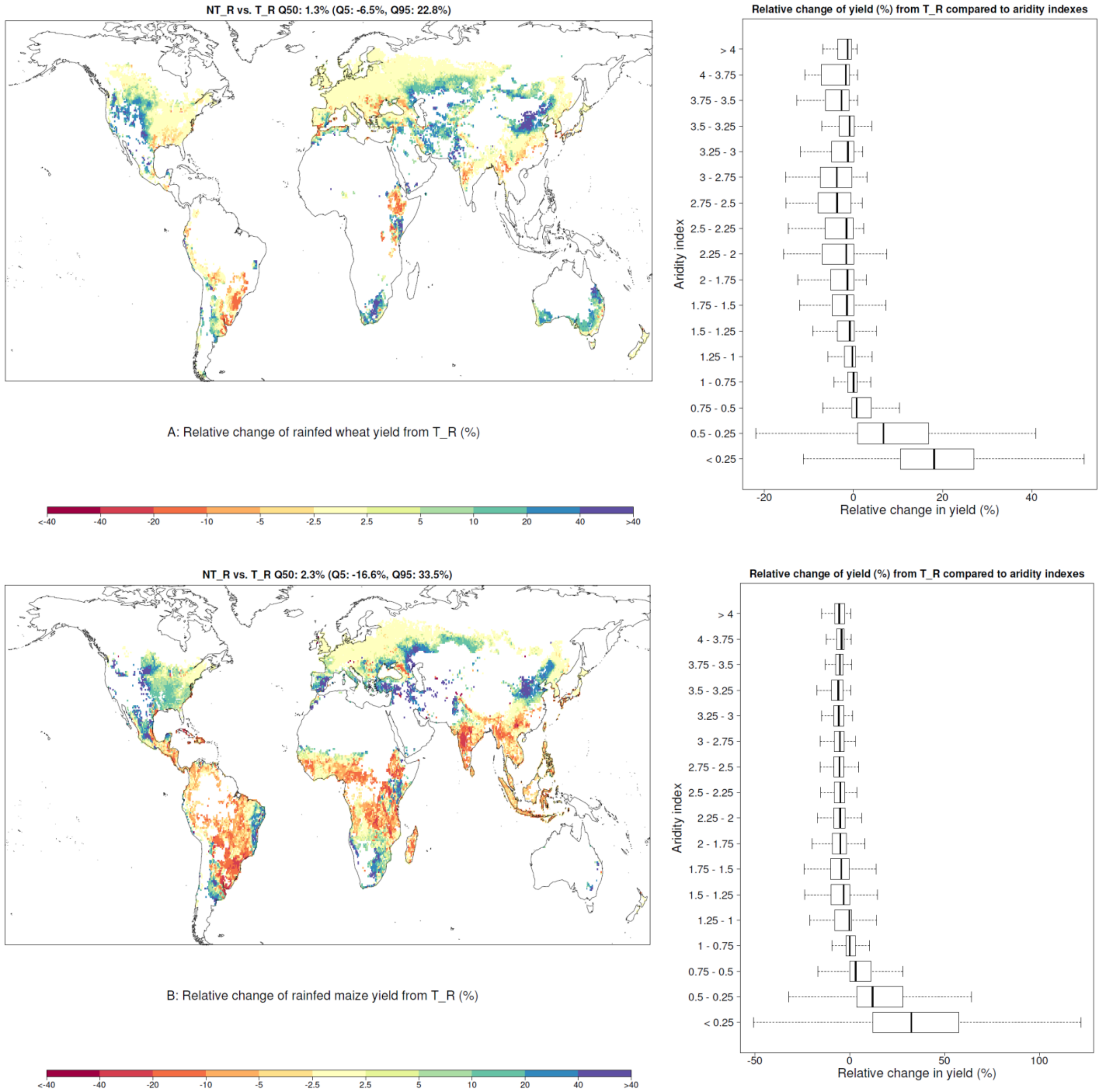


Figure A2: Relative yield changes for rain-fed wheat (A) and rain-fed maize (B) compared to aridity indexes after 3 years NT_R vs. T_R. Low aridity index values indicate arid conditions as the index is defined as mean annual precipitation divided by potential evapotranspiration, following Pittelkow et al. (2015a).

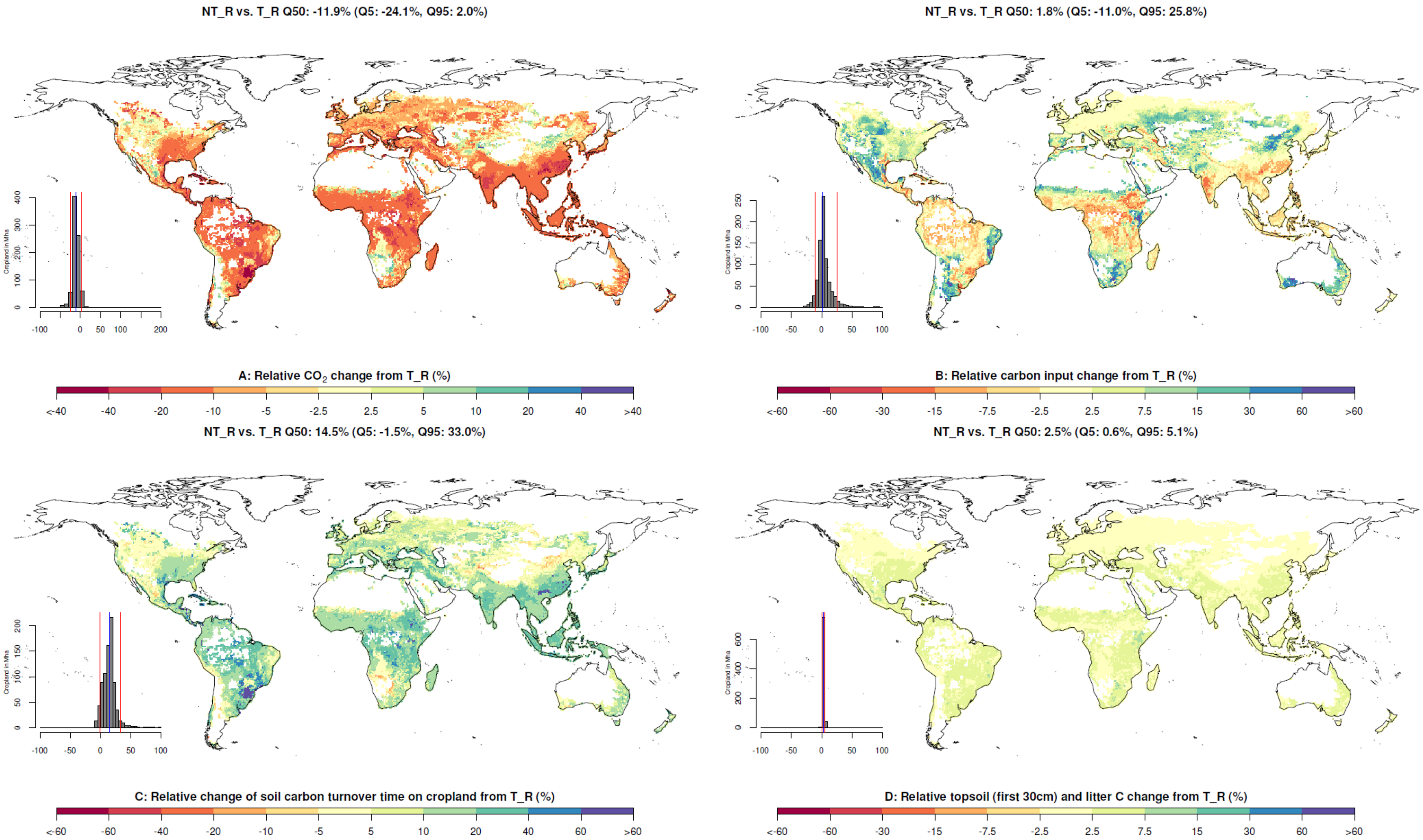


Figure A3: Relative C dynamics for NT_R vs. T_R comparison after 3 years of simulation experiment (average of year 1–3) for relative CO_2 change (A), relative C input change (B), relative change of soil C turnover time (C), and relative topsoil and litter C change (D).

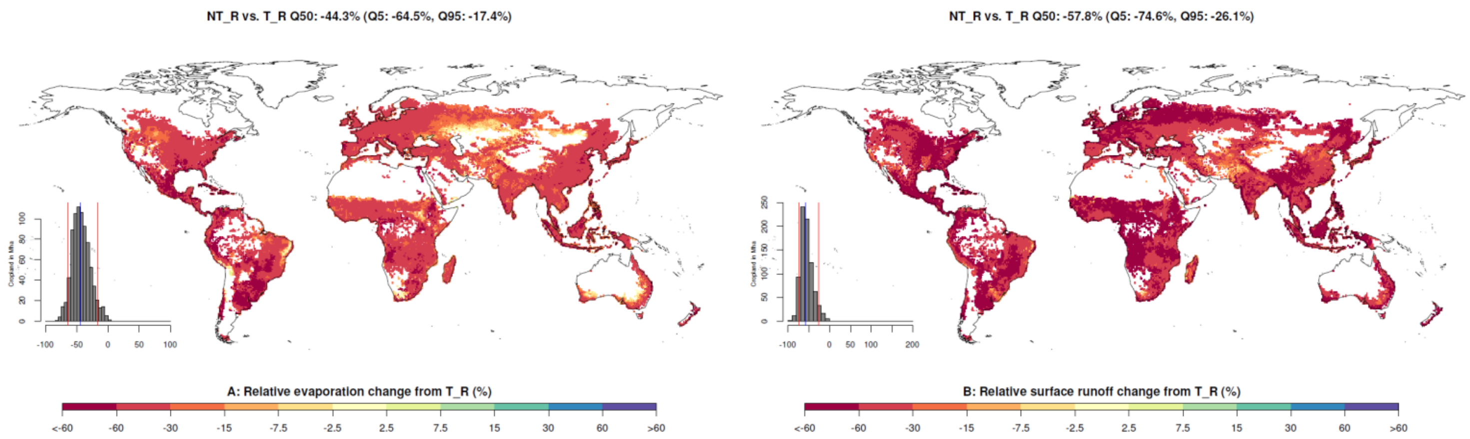


Figure A4: Relative change of soil evaporation (A) and surface runoff (B) for T_R vs. NT_R comparison after 3 years of simulation experiment (average of year 1–3).

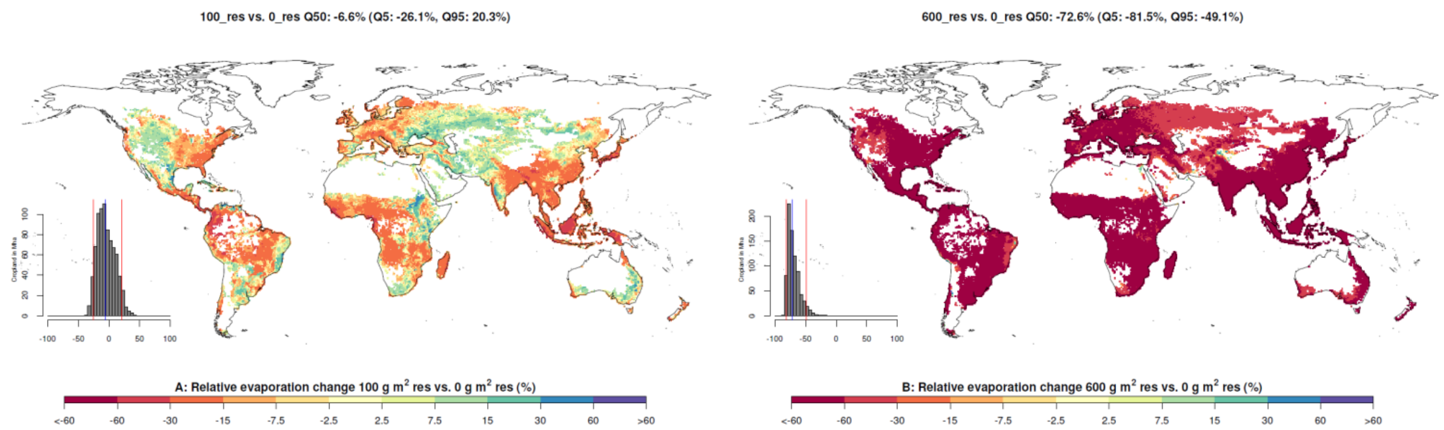


Figure A5: Relative change comparison of soil evaporation for fixed residue rates of 100g m² vs. 0 g m² (A) and 600g m² vs. 0 g m² (B) after 3 years of simulation experiment (average of year 1–3).

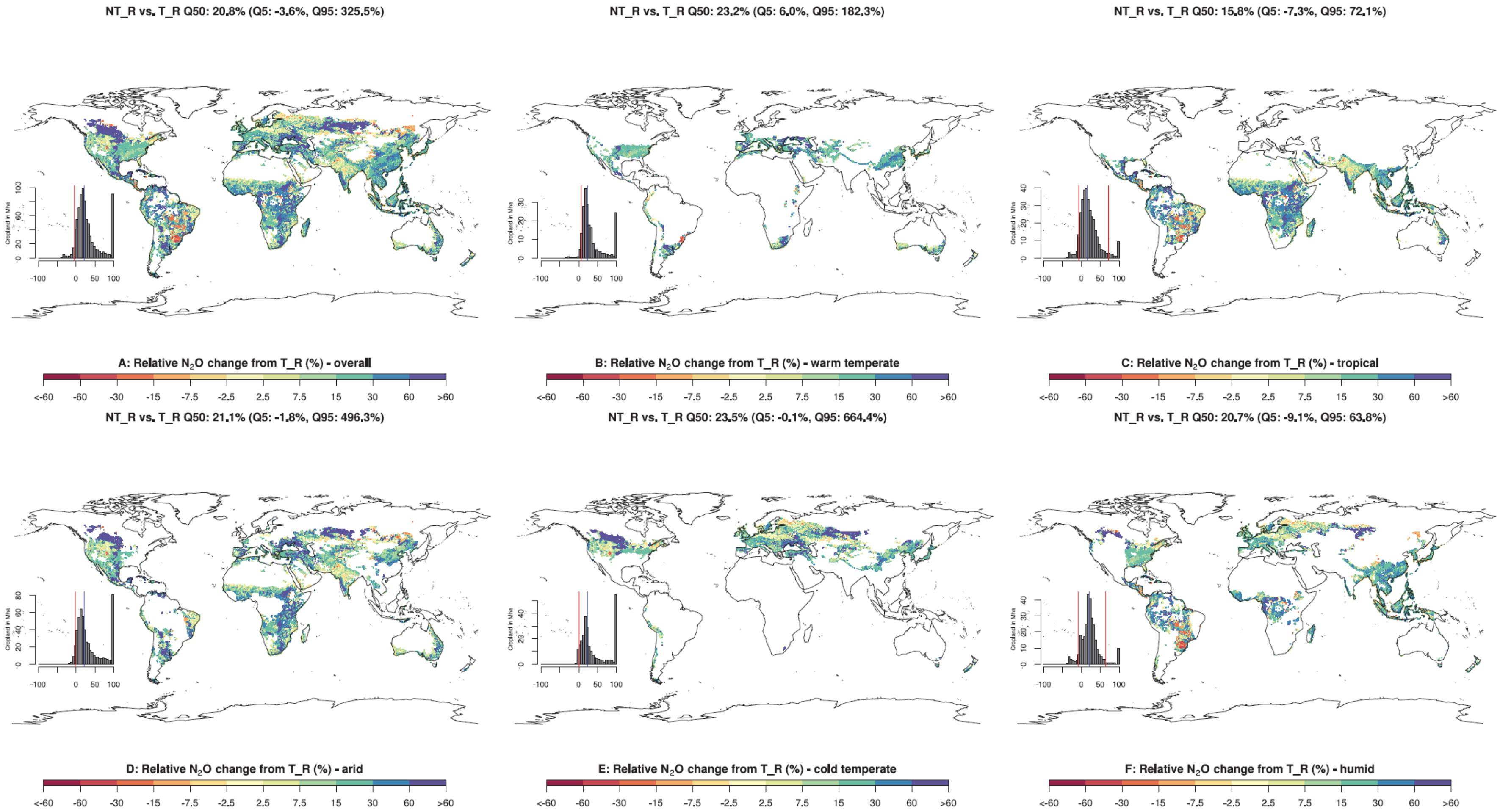


Figure A6: Relative change of N_2O emissions for NT_R vs. T_R comparison after 3 years of simulation experiment (average of year 1–3) overall (A), warm temperate (B), tropical (C), arid (D), cold temperate (E) and humid regions (F).

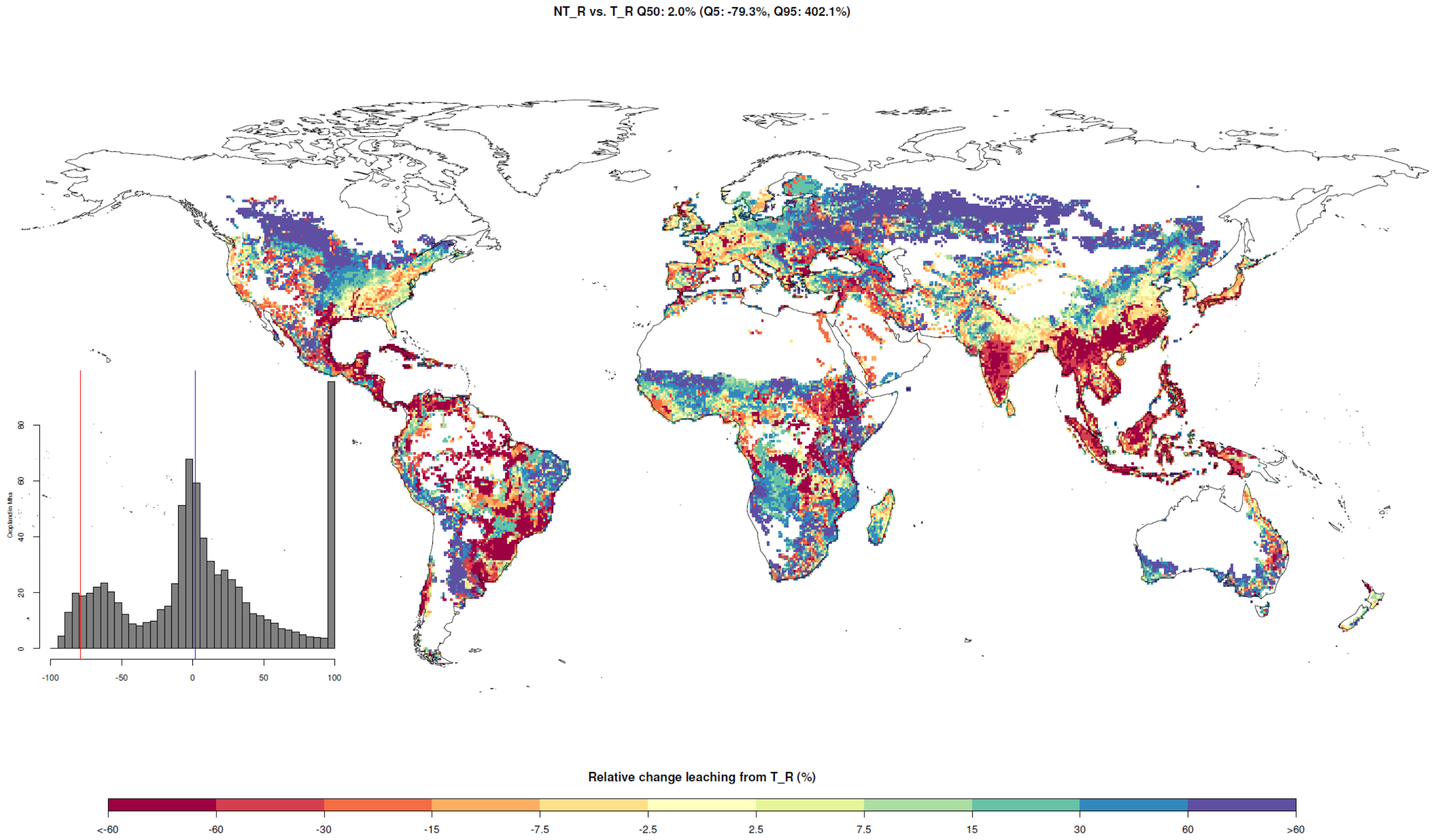


Figure A7: Relative change of N leaching for NT_R vs. T_R comparison after 3 years of simulation experiment (average of year 1–3).

Appendix B – Supplementary material to Chapter 4: Simulating SOC dynamics from agricultural management practices under climate change

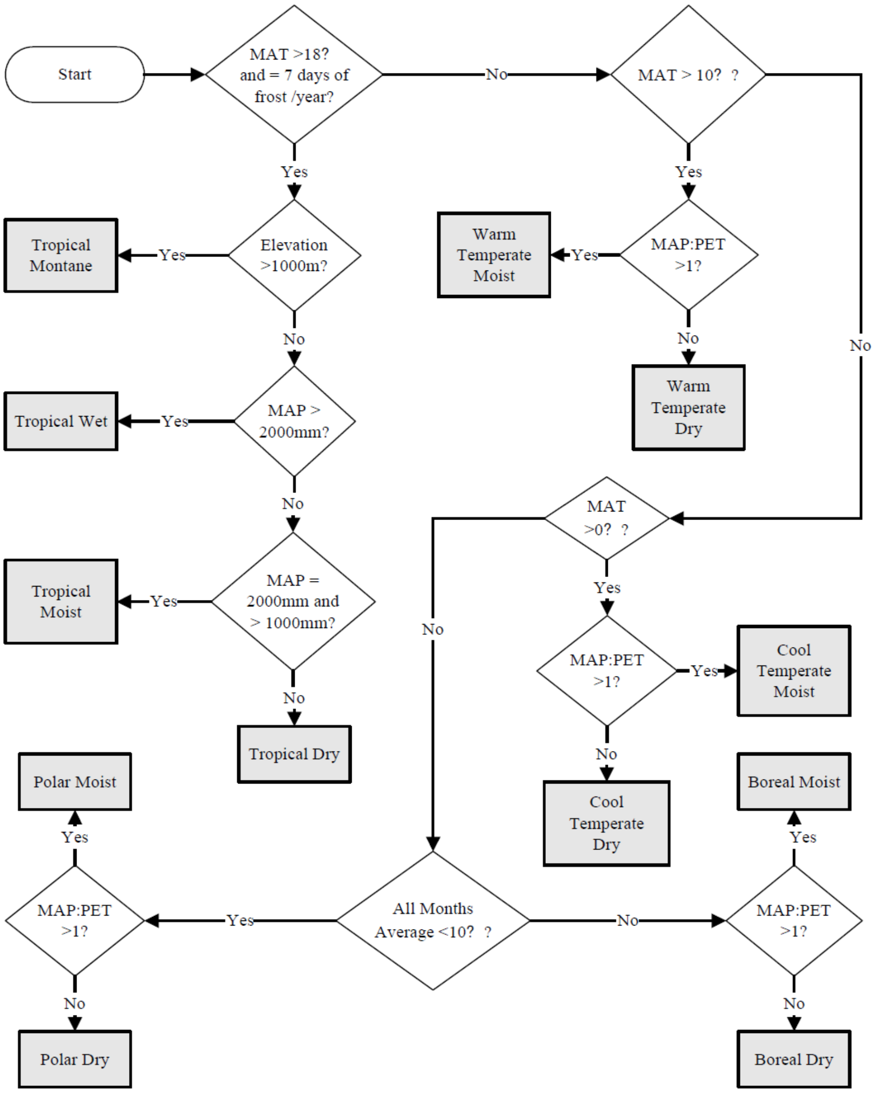


Figure B1: Climate region classification scheme according to the IPCC (2006). Polar moist, polar dry and tropical montane regions have been excluded from this analysis, as these are regions without cropland.

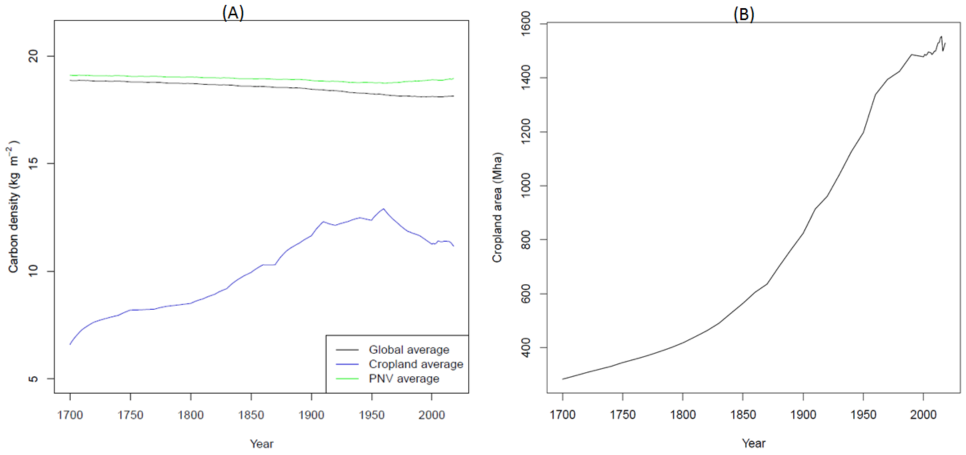


Figure B2: Time series of carbon density (kg m^{-2}) of global average, cropland average and PNV average from year 1700 to 2018 (A) and global cropland area in million hectares (Mha) from year 1700 to 2018 (B). Cropland carbon densities increase as long as the addition of new high-carbon density land through land expansion outbalances the slow decline of SOC stocks on existing cropland.

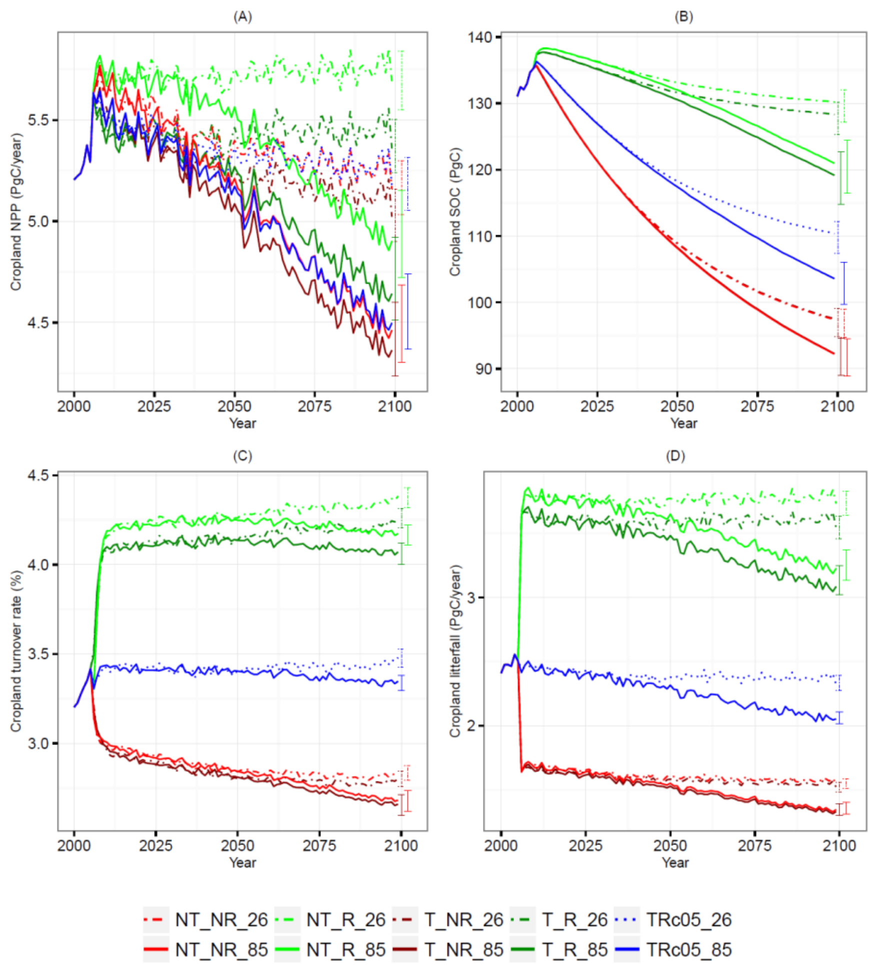


Figure B3: Global sums of cropland NPP (A), cropland SOC (B), cropland turnover time (C), and cropland litterfall (D) for cropland from 2000-2005 for default management inputs and from 2006-2099 under constant cropland area of 2005 for five different management scenarios as in Figure 3, but with constant [CO_2] level from 2005 until the end of the century (378.8 ppm). Same legend as in Figure 4-3.

An exemplary note on Figure B3:

In RCP8.5, [CO_2] is projected to increase to a level of more than 900 ppm until the end of the century, while in RCP2.6 [CO_2] it is assumed to be at 420 ppm (Fig. B3 in the appendix). Results from simulations with constant [CO_2] over the entire simulation period between the years 2006 and 2099 show that differences for cropland SOC as well as for cropland NPP between the two climate change scenarios become more prominent. Total global NPP with static [CO_2] is considerably smaller in RCP8.5 compared to RCP2.6 and decreases significantly until the end of the century in all management systems (Fig. B3A in the appendix). If production decreases in RCP8.5, inputs from residues into the soil also decrease with time and as a result, cropland SOC stocks are lower and decrease compared to RCP2.6 (Fig. B3B in the appendix), while the turnover rate is stable (Fig. B3C in the appendix). RCP2.6 with static [CO_2] shows higher SOC stocks compared to RCP8.5, as production is higher in a colder climate (compared to RCP8.5), while at the same time turnover rates are lower. This suggests that under standard RCP climate input assumptions, CO_2 fertilization effects in RCP8.5 driven by increasing [CO_2] compensate for damages from warmer climates and increases in turnover rates in order to sustain NPP. These compensating effects result in the small differences between the RCP2.6 and RCP8.5 found in the analysis in Chapter 4.4.2.

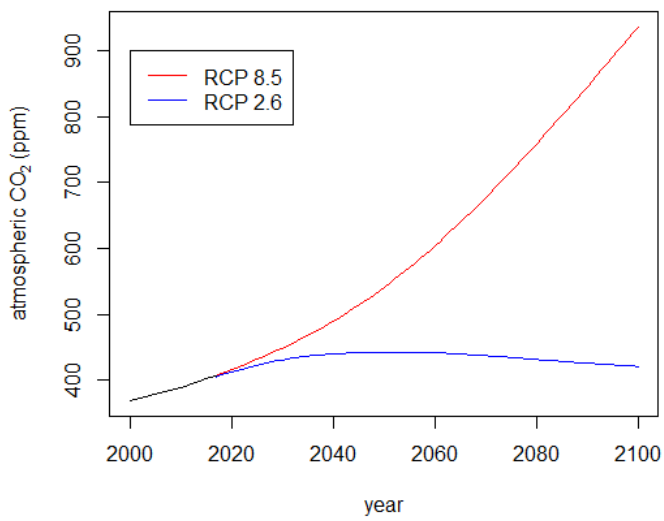


Figure B4: Atmospheric C0₂ concentration input for model runs for RCP2.6 and RCP8.5.

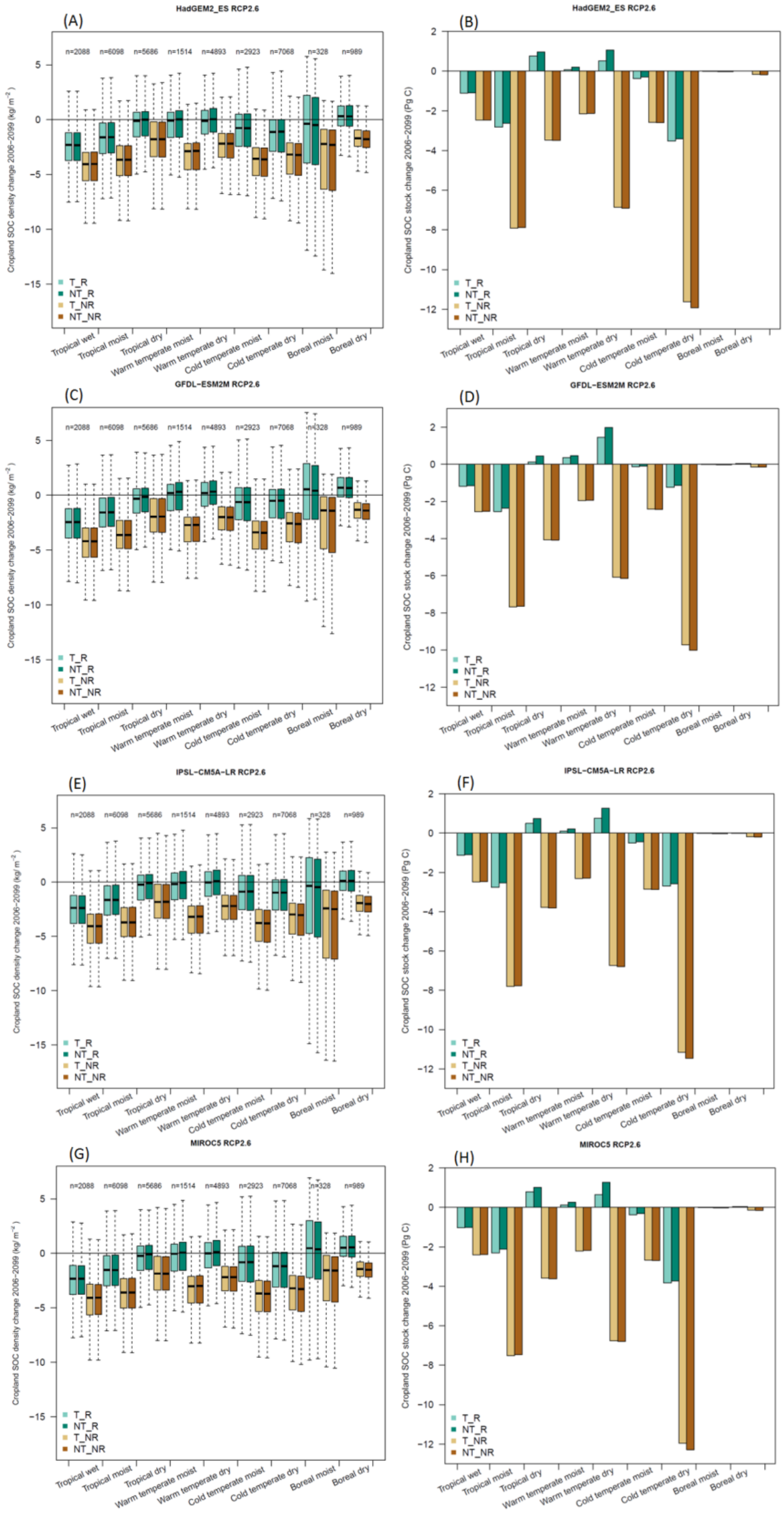


Figure B5: Boxplots of cropland SOC density change (kg/m²) and bar plots of total cropland SOC change (Pg C) between the year 2006 and 2099 for the four GCMs HadGEM2_ES (A, B), GFDL-ESM2M (C, D), IPSL-CM5A-LR (E, F), MIROC5 (G, H) in RCP2.6 for different climatic regions classified by the IPCC (2006) and the four management systems T_R, NT_R, T_NR, and NT_NR.

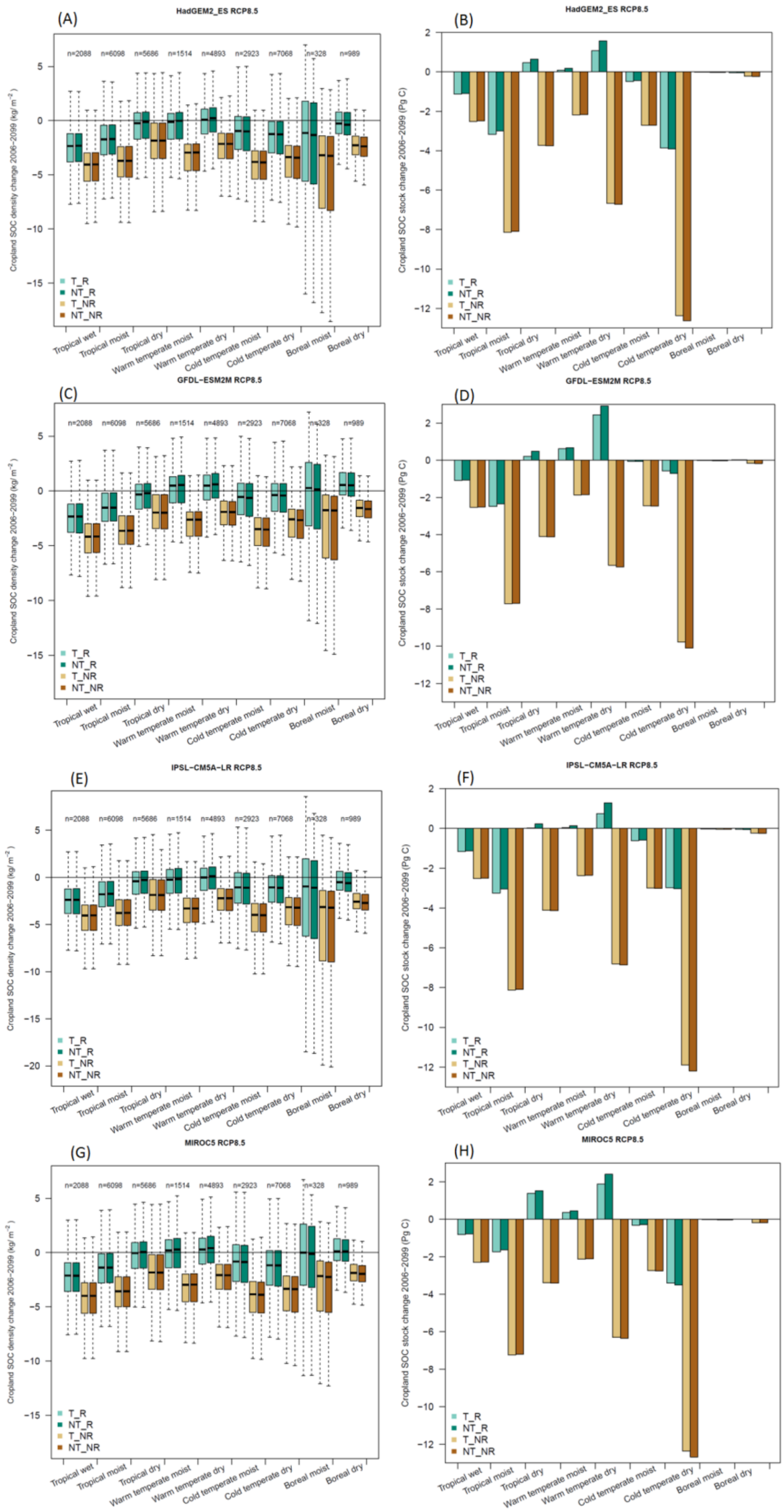


Figure B6: Boxplots of cropland SOC density change (kg/m²) and bar plots of total cropland SOC change (Pg C) between the year 2006 and 2099 for the four GCMs HadGEM2_ES (A, B), GFDL-ESM2M (C, D), IPSL-CM5A-LR (E, F), MIROC5 (G, H) in RCP8.5 for different climatic regions classified by the IPCC (2006) and the four management systems T_R, NT_R, T_NR, and NT_NR.

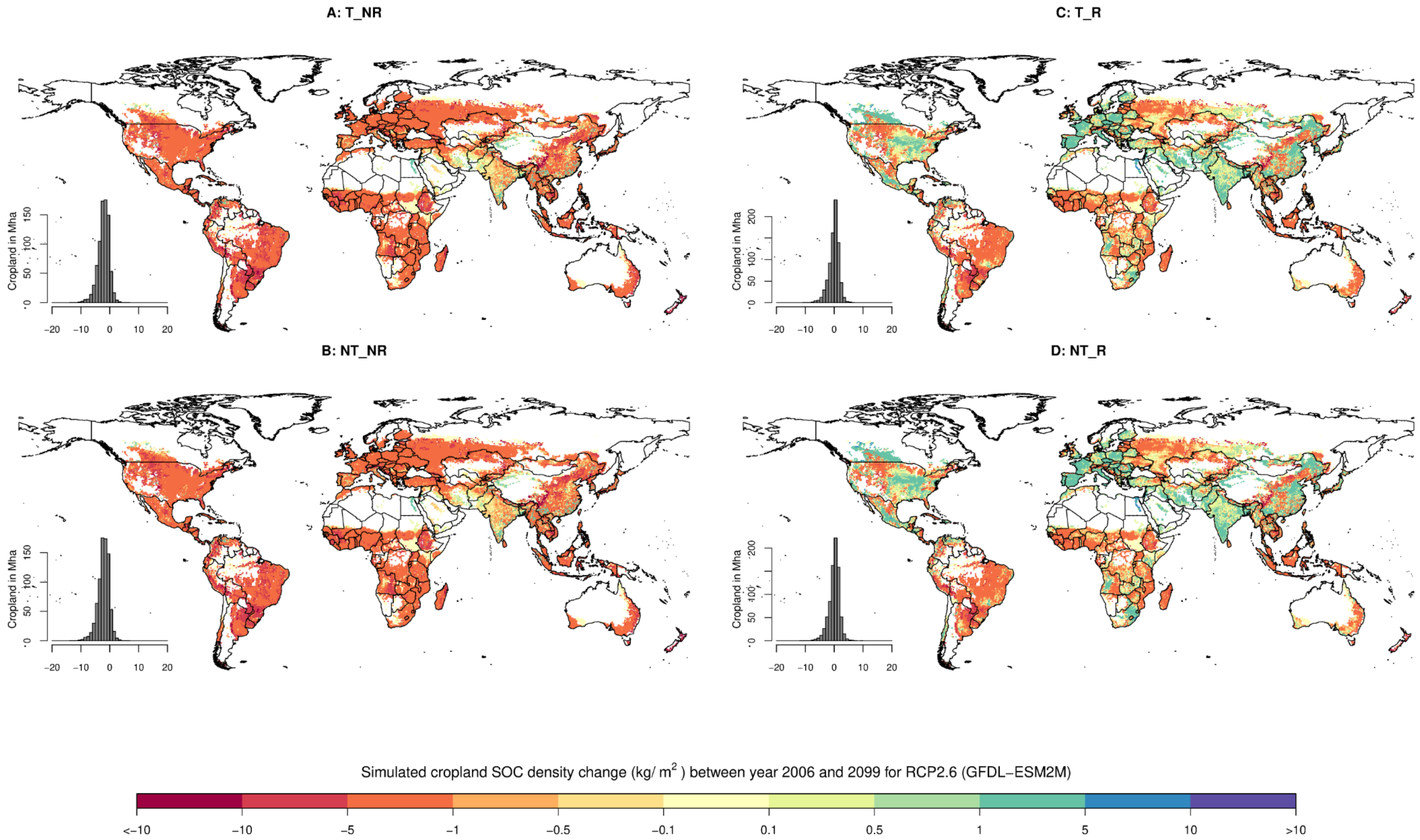


Figure B7: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP2.6 and GFDL_ESM2M.

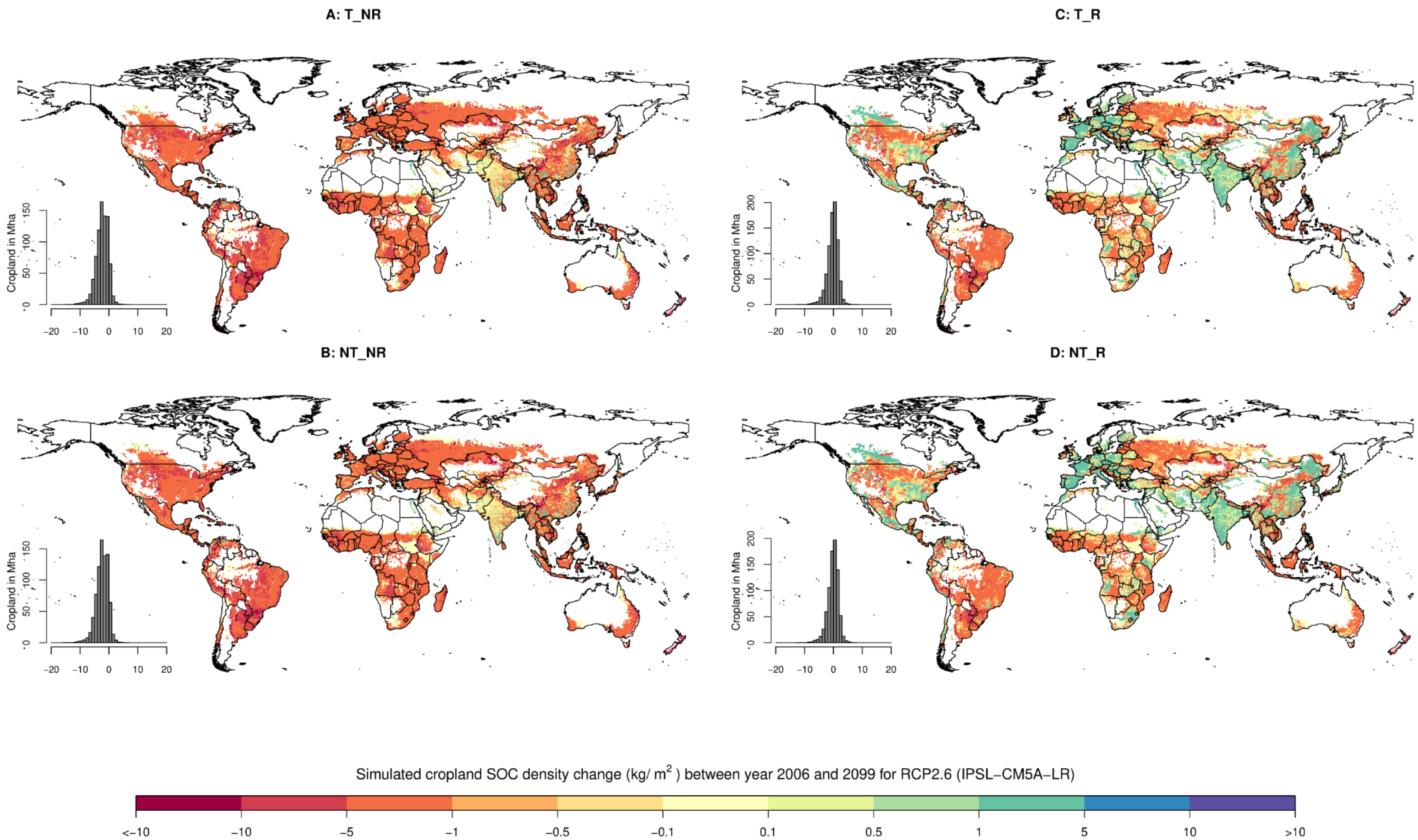


Figure B8: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP2.6 and IPSL-CM5A-LR.

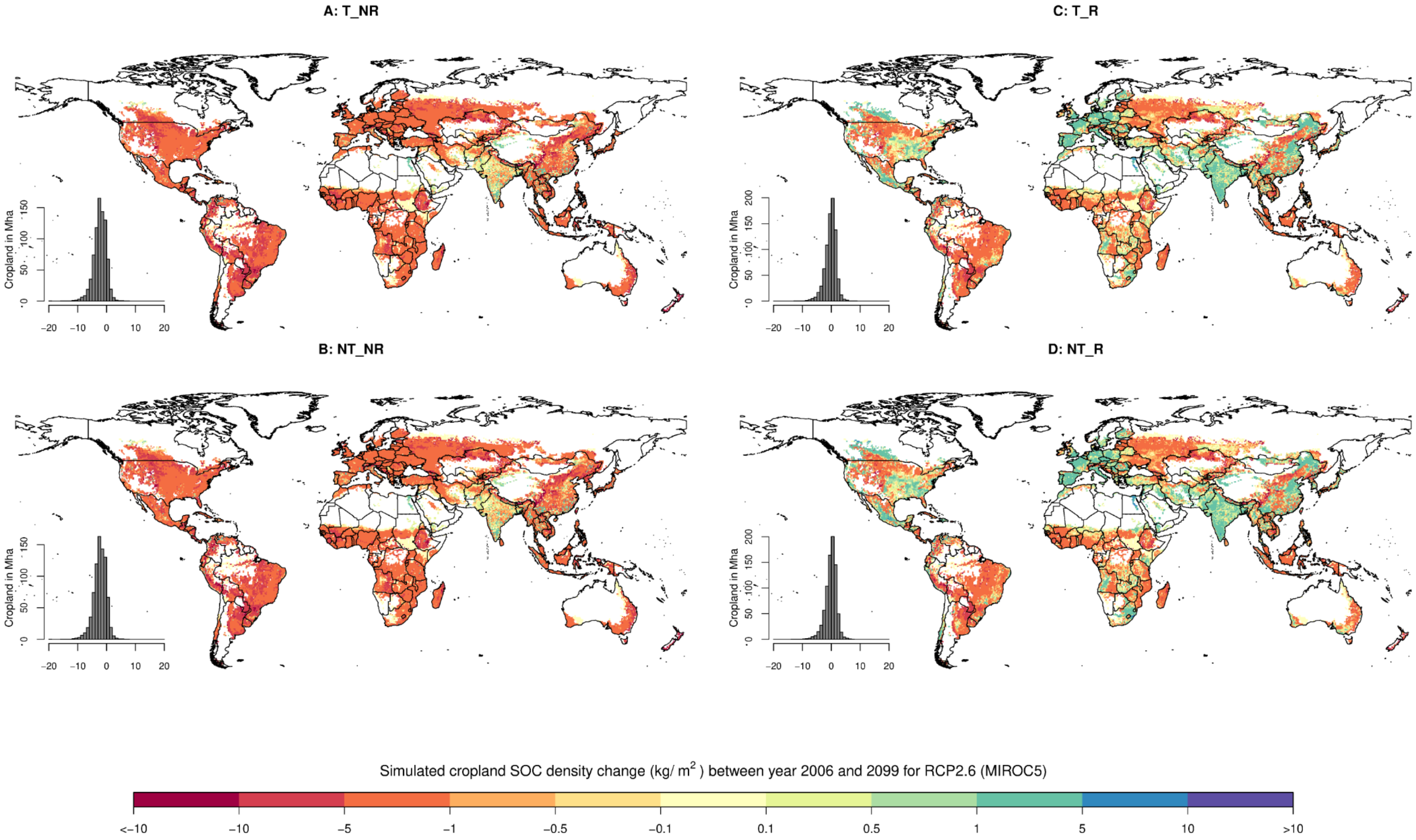


Figure B9: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP2.6 and MIROC5.

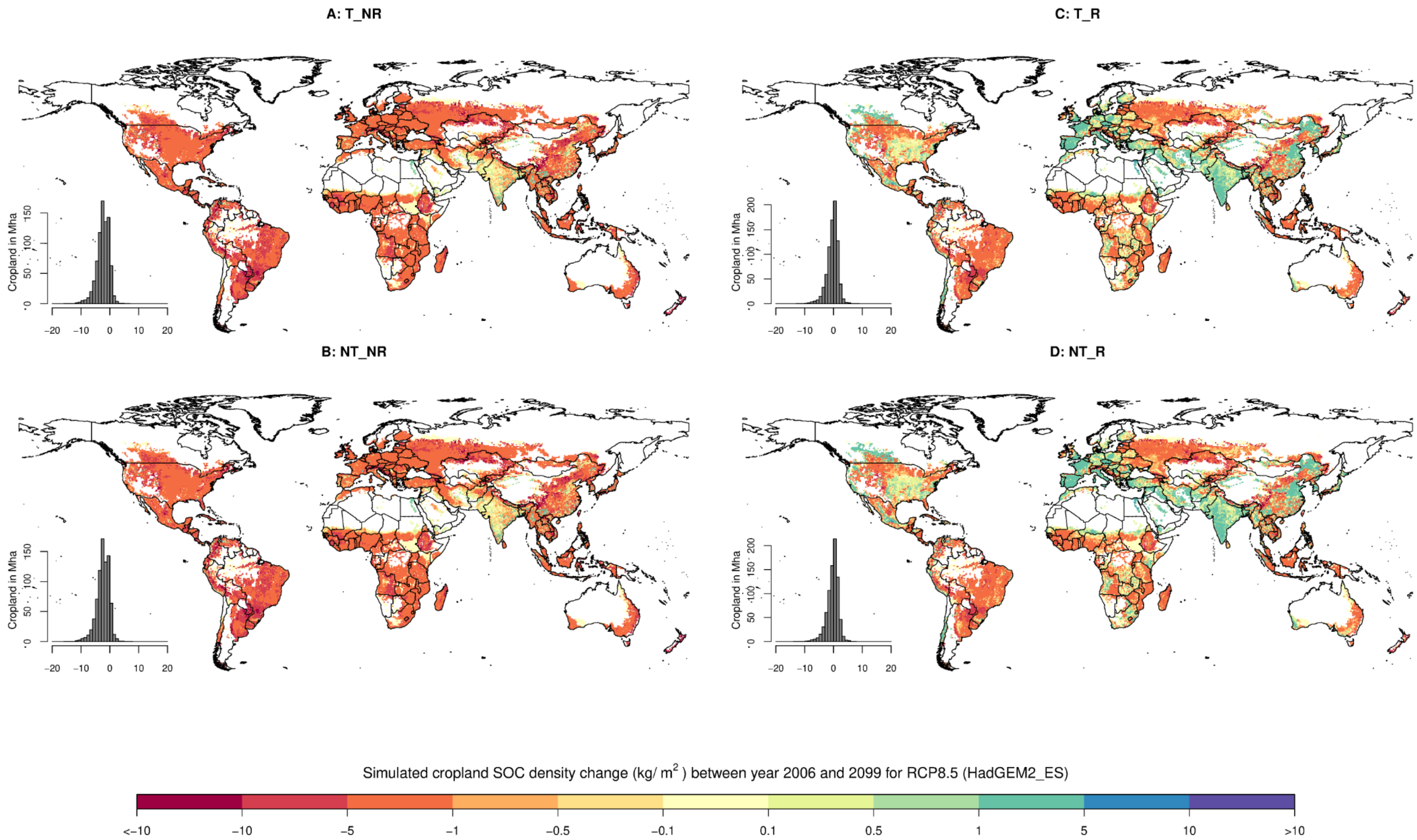


Figure B10: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP8.5 and HadGEM2_ES.

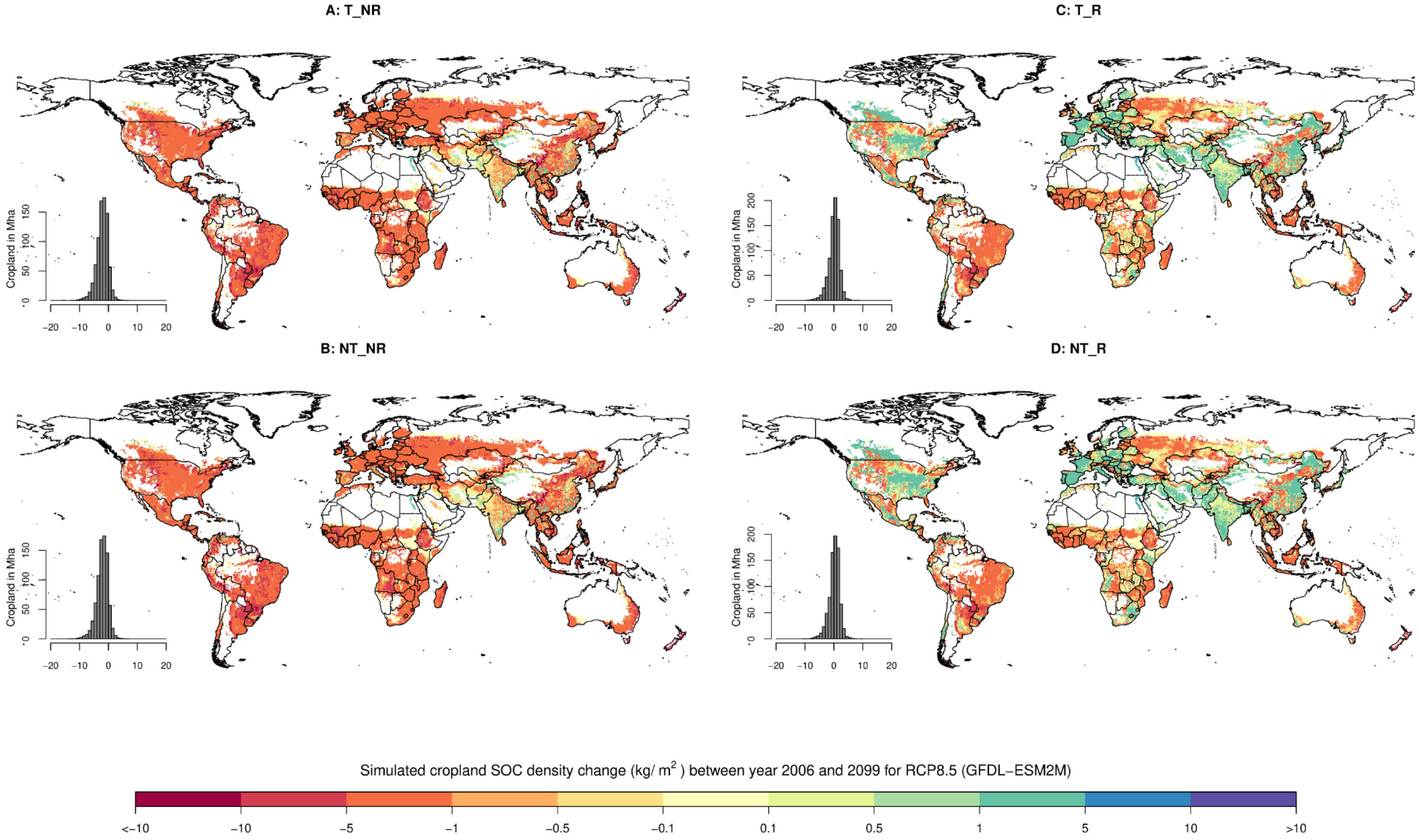


Figure B11: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP8.5 and GFDL-ESM2M.

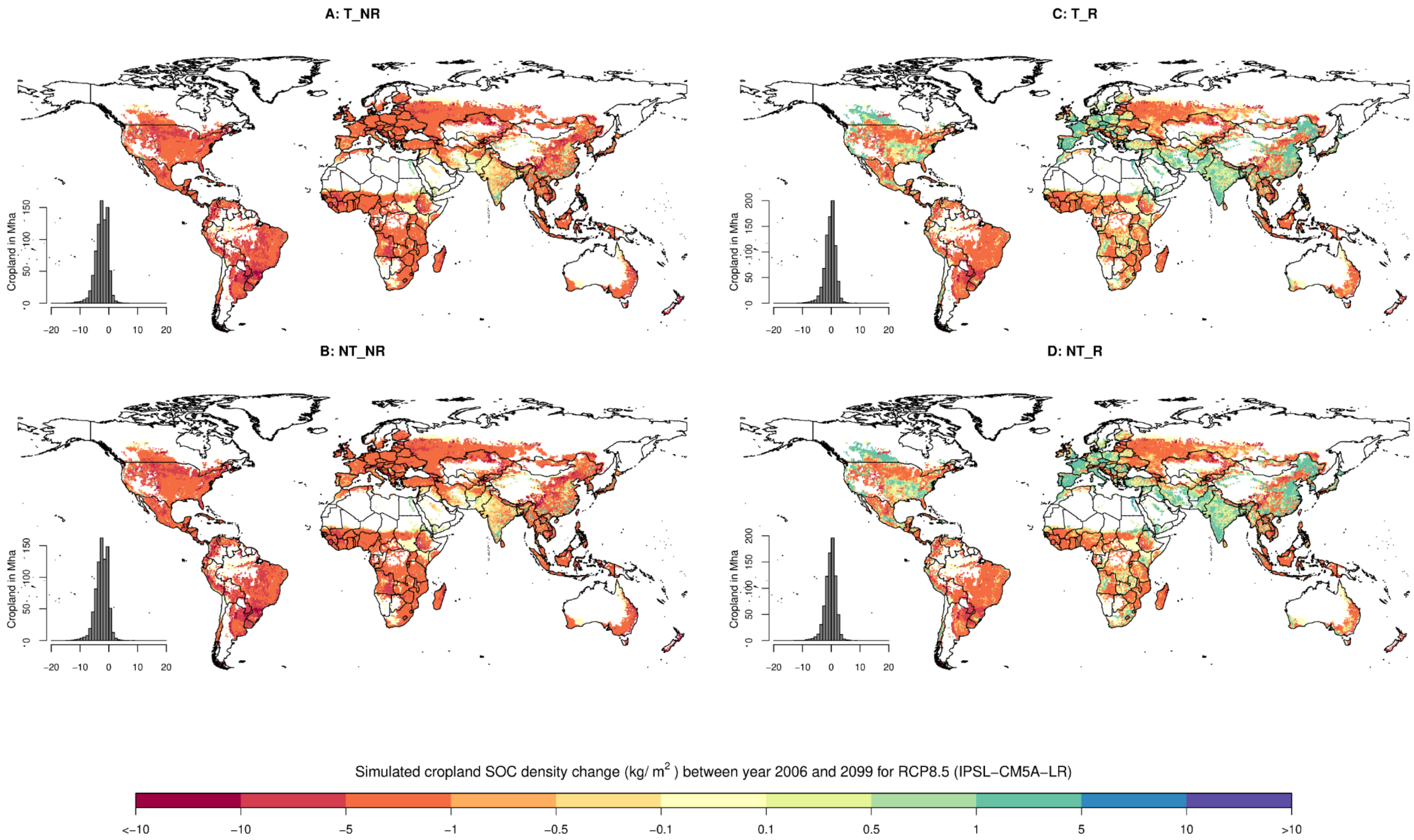


Figure B12: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP8.5 and IPSL-CM5A-LR.

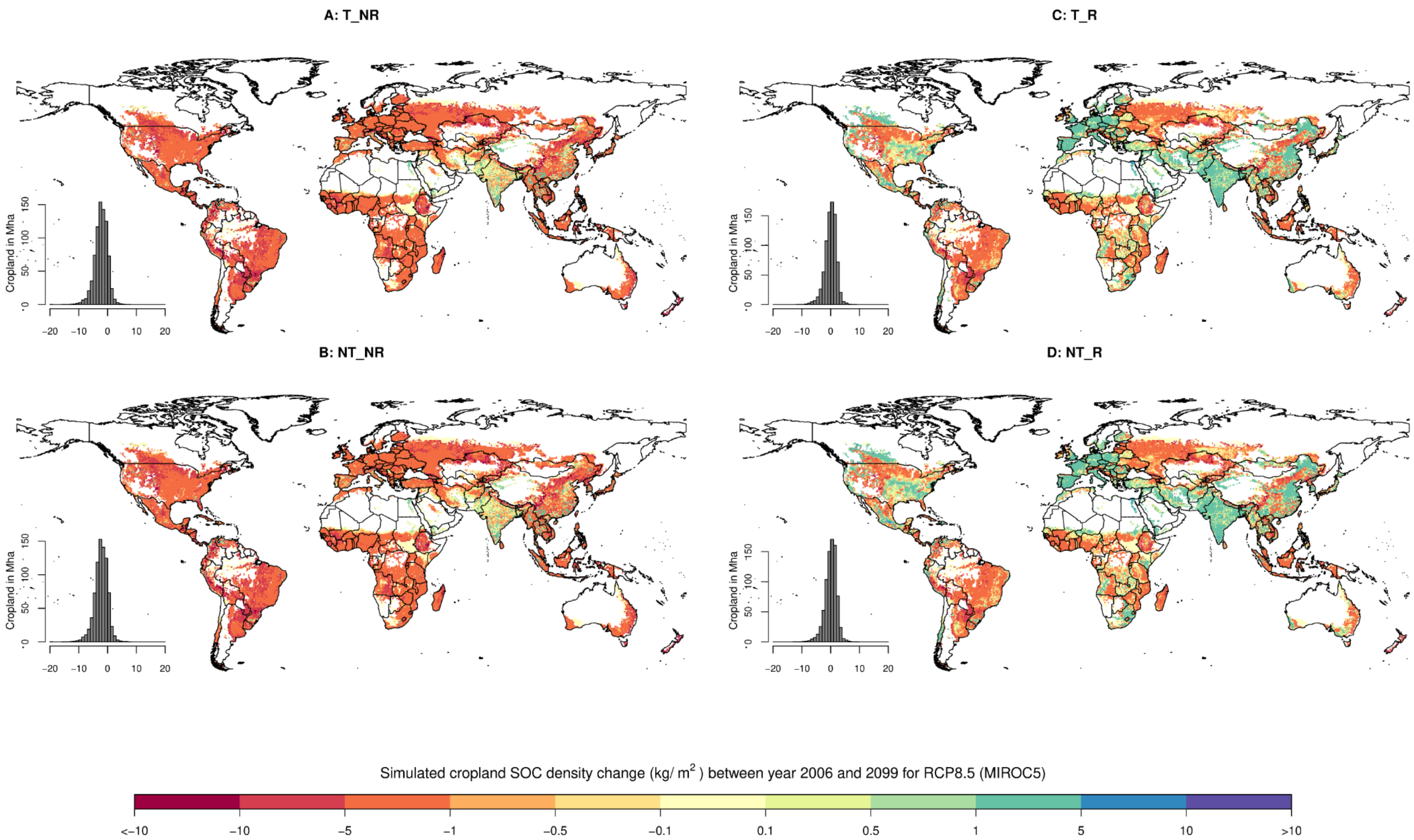
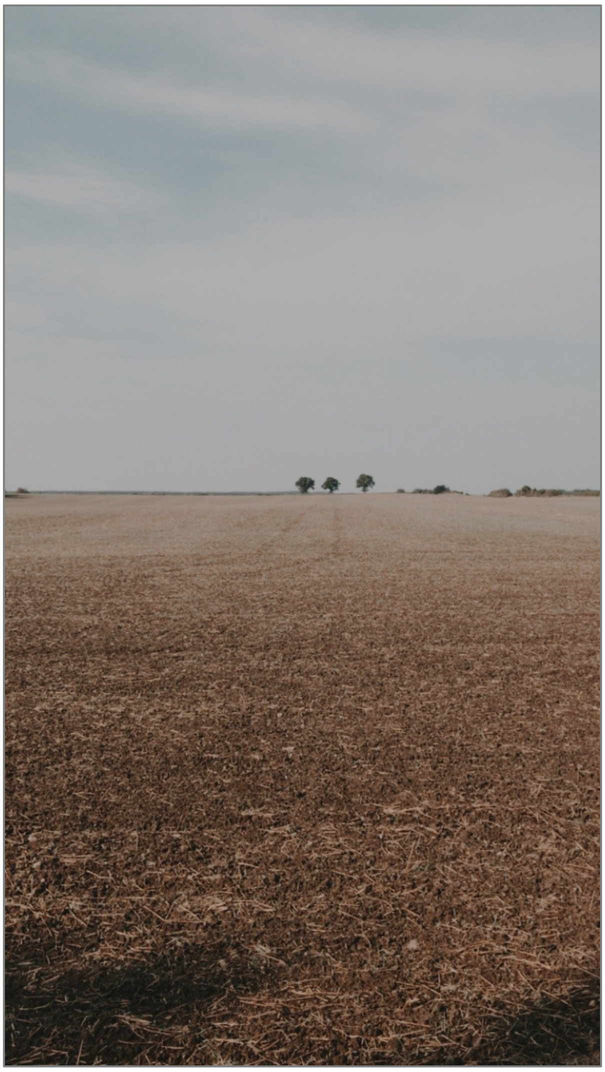


Figure B13: Simulated SOC density change between the year 2006 and 2099 (kg m^{-2}) as in Fig. 4-4, but for RCP8.5 and MIROC5.



Residues on cropland in Skåne,
southern Sweden, September 2020
own photograph

Selbständigkeitserklärung

Hiermit erkläre ich, dass ich die vorliegende Dissertation selbständig und nur unter Verwendung der von mir gemäß § 8 der Promotionsordnung der Landwirtschaftlich-Gärtnerischen Fakultät, veröffentlicht im Amtlichen Mitteilungsblatt der Humboldt-Universität zu Berlin Nr. 12/2014 am 31.03.2014 angegebenen Hilfsmittel angefertigt habe. Ich habe mich nicht anderweitig um einen Doktorgrad beworben und besitze keinen entsprechenden Doktorgrad. Ich erkläre zudem, dass keine Zusammenarbeit mit gewerblichen PromotionsbearbeiterInnen stattgefunden hat und die Grundsätze zur Sicherung guter wissenschaftlicher Praxis der Humboldt-Universität zu Berlin eingehalten wurden.

Berlin, den ______________________ ______________________

Datum Tobias Herzfeld