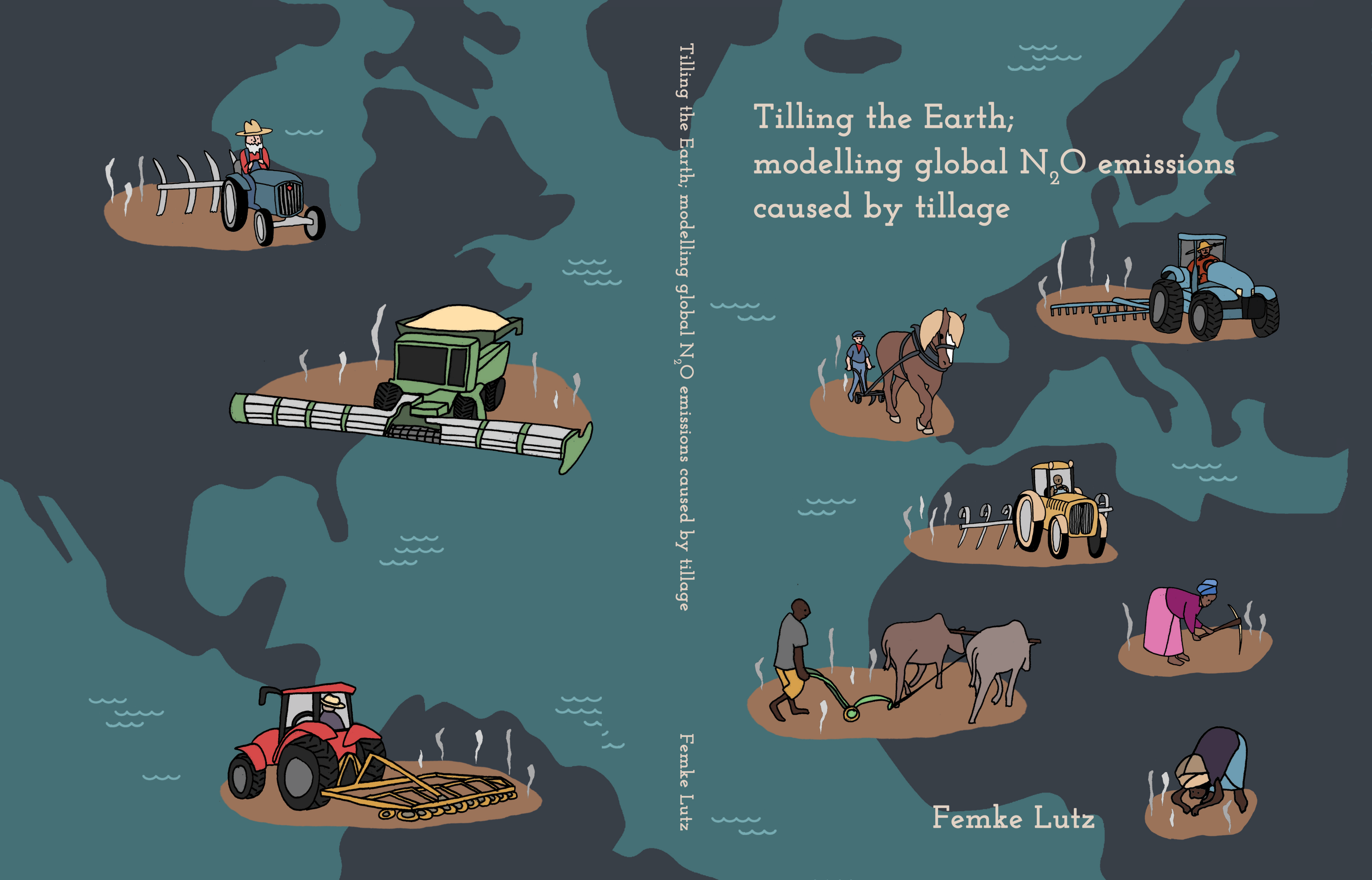

Tilling the Earth; modelling global N_2O emissions caused by tillage
Femke Lutz
Tilling the Earth;
modelling global N_2O emissions
caused by tillage
Femke Lutz

Propositions

1. Emission factors are insufficient to study the mitigation potential within agricultural production (this thesis)
2. A model evaluation at the global scale requires meta-analyses (this thesis)
3. Maximizing crop productivity while minimizing environmental harm is only possible through precision agriculture.
4. The potential of crop residues for bioenergy production is overrated.
5. Solving the so-called nitrogen crisis in the Netherlands requires pricing of nitrogen emissions.
6. Junk food is an important form of food waste.

Propositions belonging to the thesis, entitled:

"Tilling the earth; modelling global N_2O emissions caused by tillage"

Femke Lutz
Wageningen, 18 March 2020

Tilling the Earth; modelling global N_2O emissions caused by tillage

Femke Lutz

Thesis committee

Promotor
Dr J.J. Stoorvogel
Associate Professor, Soil Geography and Landscape Group
Wageningen University & Research

Co-promotor
Dr C. Müller
Leader of the Land-use Group
Potsdam Institute of Climate Impact Research, Germany

Other members:
Prof. Dr W. de Vries, Wageningen University & Research
Dr E. Stehfest, PBL Netherlands Environmental Assessment Agency, The Hague
Dr L. van Bussel, Wageningen University & Research
Dr J. Verhagen, Wageningen University & Research

This research was conducted under the auspices of the C.T. de Wit Graduate School of Production Ecology & Resource Conservation (PE&RC)

Tilling the Earth; modelling global N_2O emissions caused by tillage

Femke Lutz

Thesis
submitted in fulfilment of the requirements for the degree of doctor at
Wageningen University
by the authority of the Rector Magnificus
Prof. Dr A.P.J. Mol,
in the presence of the
Thesis Committee appointed by the Academic Board
to be defended in public
on Wednesday 18 March 2020
at 4 p.m. in the Aula.

Femke Lutz
Tilling the Earth; modelling global N_2O emissions caused by tillage
186 pages

PhD thesis, Wageningen University, Wageningen, NL (2020)
With references, with summary in English and Dutch

ISBN 978-94-6395-274-3
DOI https://doi.org/10.18174/511145

Acknowledgements

To be honest, I am quite relieved and happy to successfully finish this PhD. It has been an intense, valuable and memorable journey for me and forms an important chapter in my life. I am very thankful to all of you -colleagues, friends and family- who supported me in many ways during these years. Here, I would like to thank many people that helped me in different ways during this journey.

First of all, I would like to thank my two supervisors Christoph Müller and Jetse Stoorvogel. Without them, this thesis would have been impossible. Thank you so much for your confidence in me and guidance during this journey. Christoph, as my daily supervisor you were intensively involved during the PhD. Thank you for giving me this opportunity and your constant support during the PhD. Despite your busy schedule I could always rely on your availability to give advice, discuss ideas, insights and issues. I learnt a lot from you during these years and you always gave very helpful, constructive and precise feedback on the many drafts I sent you. I will miss our collaboration and the efficient coffee ("bakkie pleur") exchange during the day. Jetse, thank you for the laughs and your never-ending enthusiasm you had for this PhD. You always knew perfectly how and when to give my motivation a boost. I enjoyed the interesting and helpful discussions where we often managed to get a step further in the PhD.

I would also like to thank Hermann Lotze-Campen and Jakob Wallinga for giving me the opportunity to work in their research domain and chair group respectively.

Wim de Vries, Elke Stehfest, Lenny van Bussel and Jan Verhagen, thank you very much for your willingness to be a member of the thesis committee.

While doing this PhD I noticed that it was extremely helpful to share the ups and downs with colleagues and friends that were traveling their journey as well. A special thanks to Chantal, Maricke and Sara for always providing a listening ear, giving advice, encouraging words and being a great example to me. Chantal en Maricke, ik ben ontzettend dankbaar voor onze nóg hechtere vriendschap die is ontstaan de afgelopen jaren. Jullie optimisme, gevoel voor humor en openheid waren een onuitputtende bron van energie voor mij. Sara, I'm very thankful to the friendship we gained during these years. Thank you for the many interesting discussions and help (ggplot!) in which I learnt a lot and the laughs we had during and outside working hours. It made going to work a lot more fun!

A big thank you to my colleagues at the Potsdam Institute for Climate Impact Research, especially the Landuse group. I am very thankful to have worked in such a warm, passionate and inspiring group. I would especially like to thank Susanne, Kristine, Felicitas, Antoine (you count as a member because you came into the office -"goedemorgen"- so often) and Benjamin for the (spontaneous) social events events you initiated and the inspiring discussions we had. Susanne, you felt like the mother of the Landuse group who encourages collaborations, communications and social events outside working hours which is very important to me and gives another dimension to work. I also would like to thank Jens for his never-ending help on programming issues. Tobias, thank you for the nice collaboration we had on Chapter 3. Jasmin, thank you for being such a great support on this version of the thesis!

Another part of my PhD was spent at the chair group Soil Geography and Landscape in Wageningen. Although I mostly worked in Potsdam, I always felt very welcomed and home in the chair group. I would especially like to thank Selçuk, Simona, Luc, Jasper and Marijn for the laughs we had at the coffee machine, in the Spot and at Doppio, the early-morning runs, help on practical questions etc. These moments were very valuable to me. Mieke, thank you for always being stand-by and your help on practical questions.

I also want to thank the colleagues in Fort Collins where I had two fantastic and inspiring months that resulted in a very nice collaboration. Stephen DelGrosso and Inky, thank you so much for your hospitality during the time I was there and introducing me to the Colorado's IPAs. Stephen, your passion for work was really inspiring to me. Also a big thank you to Stephen Ogle, Melannie Hartman, Chris Dorich and Ernie Marx for your technical support on Daycent, insights into the model, critical questions and inspiring discussions.

I am also grateful to my Dutch and German friends for their interest, support and fun evenings during these years. Een bijzondere dank aan Chrisje Maaskant voor het maken van deze fantastische boekomslag. Jouw creativiteit is jaloersmakend!

Ik wil ook graag mijn familie bedanken: Pap, Mam, Joost, Wietske, Peter, Noortje en Joris. Bedankt voor jullie interesse die jullie hebben getoond en er altijd voor mij zijn.

Zum Schluss Matthias, ich bin so froh, dass wir einander am Anfang dieser Reise kennengelernt haben. Ich kann gar nicht in Worte fassen wie dankbar ich für deine Geduld, moralische Unterstützung und Liebe in diesen Jahren bin. Während dieser Reise, warst du immer an meiner Seite. Ich freue mich auf unsere nächste Reise zusammen in München.

Contents

		Page
Chapter 1	Introduction	1
Chapter 2	How to incorporate tillage in global ecosystem models?	9
Chapter 3	Simulating and evaluating effects of tillage at the global scale	39
Chapter 4	How to evaluate processes related to tillage?	75
Chapter 5	Representing soil heterogeneity in global modelling of N_2O emissions and soil organic matter	101
Chapter 6	Synthesis	119
References		131
Appendices		157
Summaries	Summary	173
	Samenvatting (summary in Dutch)	177
About the author		181

Chapter 1

Introduction

1.1 Greenhouse gas mitigation and agricultural management

Agriculture plays an important role in global greenhouse gas (GHG) emissions. Approximately 10-12% of the total global anthropogenic emissions originate from agriculture, around 40% of total methane (CH_4) and 60% of nitrous oxide (N_2O) emissions (IPCC, 2019; Smith et al., 2014b; Tubiello et al., 2015; FAO, 2014; Frank et al., 2019; Tubiello, 2019). Global GHG emissions from agriculture nearly doubled from 1961 to 2016 (Tubiello, 2019) and may continue to increase until 2050 (e.g. Bodirsky et al., 2014; Popp et al., 2017; Alexandratos & Bruinsma, 2012). This growth in emissions is mainly a consequence of (mineral and organic) fertilizer and enteric fermentation from livestock (Tubiello et al., 2015). Therefore, agriculture can contribute significantly to achieve global targets such as the climate change goals of the Paris Agreement (Frank et al., 2019; Wollenberg et al., 2016). Several mitigation strategies have been identified to reduce emissions from agricultural soils through improved soil management (IPCC, 2019; Burney et al., 2010; Smith et al., 2007, 2014b; Paustian et al., 2016). An extensive body of field, laboratory and modeling research over many decades demonstrates that agricultural management can reduce GHG emissions and increase soil carbon (C) stocks (Paustian et al., 2016). Examples of such management practices include: more precise application of nitrogen (N) fertilizers to minimize excess N not used by the crop, hence reducing N_2O emissions (e.g. Millar et al., 2010; Huang & Tang, 2010), residue retention to promote C sequestration (e.g. Farage et al., 2007; Smith, 2012), and alterations in drainage regimes in flooded rice to limit the effects of CH_4 production in low-oxygen environments (Smith, 2012). The potential of such practices on GHG emissions is often tested at small scales (e.g. field scales) and can give site-specific recommendations.

Knowledge about the potential of mitigation practices is especially important to address questions such as: "how much can agricultural production be adjusted to contribute to achieving global GHG mitigation targets?", or: "which regions have the greatest potential to reduce GHG emissions from agriculture through adjusted agricultural management?", or: "what is the effect of agricultural production on GHG emissions at the global scale?". Such questions are commonly addressed using global ecosystem models. Global ecosystem models are built by incorporating the process-understanding gained in field- and laboratory-studies and can thus help to upscale findings to larger scales and to experiment with altered environmental and management conditions. Moreover, global ecosystem models can guide management decisions with respect to agricultural based mitigation strategies. However, despite the many efforts that have been made to test the potentials of such management practices, the potential to reduce GHG emissions in agricultural production remains poorly understood (Del Grosso et al., 2012). Global ecosystem models are limited to find the potential of agricultural based mitigation strategies or impacts of agricultural management for three reasons (Erb et al., 2017; McDermid et al., 2017). First, the availability and quality of input data related to agricultural management typically decreases at larger scales. Knowledge gaps exists on the distribution, as well as on the timing of numerous agricultural management practices (Erb et al., 2017). For example, global spatially explicit information on fertilizer applications is limited and uncertain, especially for livestock manure (Erb et al., 2017). Second, processes related to agricultural management are currently underrepresented in global ecosystem models (McDermid et al., 2017). Third, models work at a relatively coarse resolution (e.g. 0.5 degree) whereas management and processes vary at short distances. Therefore, investments are needed in data- and model development in order to accurately estimate the potential of agricultural based mitigation (McDermid et al., 2017).

This thesis addresses the representation of processes related to agricultural management in global ecosystem models. I will focus specifically on tillage and the processes related to GHG emissions. Tillage is an important agricultural management practice that is being applied on agricultural fields (White et al., 2010). Moreover, no-tillage is discussed as one of the promising, but uncertain, options to reduce GHG emissions (Powlson et al., 2014). I will explore, extend and evaluate a global ecosystem model with tillage for simulating its effect on N_2O emissions. The analysis focuses specifically on N_2O emissions, as N_2O is a potent GHG with a global warming potential of ~300-fold that of CO_2 (Solomon et al., 2007). The aim of this thesis is to contribute to the representation of agricultural management in global ecosystem models, so that the potential of agricultural based mitigation practices can be better quantified.

1.2 Agricultural management in global models

The primary objective of agriculture is the production of food, feed and fiber, employing a range of management options (e.g. tillage, irrigation and fertilizer application). The complex interactions within soils as well as between soils, plants and the atmosphere require skilled and knowledgeable selection and combination of management options to maximize crop productivity, but also lead to unintended side effects such as GHG emissions, nutrient pollution and soil degradation. The different effects of agricultural management on both crop productivity and GHG emissions can be assessed by models at local and regional scales. Recently, additional crops, cropping cycles and agricultural management are included in the global ecosystem models (see also: McDermid et al., 2017). Yet, continuous development is needed to study the impacts of agricultural management on both soil (e.g. mineralization) and plant processes (e.g. photosynthesis) (McDermid et al., 2017; Erb et al., 2017). This first requires an understanding how agricultural management affects these processes. The level of process understanding varies between agricultural management practices. Poor process understanding exist for e.g., tillage, crop choice and residue management (Erb et al., 2017) and global-scale model representation is often in form of simple effect factors (e.g. Pugh et al., 2015). There is relative good understanding of how irrigation affects soil and plant processes (e.g. Erb et al., 2017). As a result, irrigation practices are currently represented in several ecosystem models (e.g. Jägermeyr et al., 2015; Guimberteau et al., 2012; Leng et al., 2013).

To study the effect of agricultural management on e.g. GHG emissions, soil C and agricultural production, global ecosystem models apply different procedures. For instance, the Tier 1 method of the Intergovernmental Panel on Climate Change proposes a single emissions factor for fertilizer application to agricultural soils (IPCC: Eggleston et al., 2006; Penman, 2000). Yet, a single emissions factor ignores that GHG emissions are also driven by climate, soil conditions and other management practices. Nonlinear relationships between those drivers have also been reported (Van Kessel et al., 2013; Van Groenigen et al., 2010). For example, Van Kessel et al. (2013) found that N_2O emissions from fertilizer application are also depended on climate and tillage type. Moreover, Pihlatie et al. (2004) found that N_2O emissions respond differently to soil texture and soil moisture. Other studies apply models that are originally developed for field level applications at the global scale. Del Grosso et al. (2009) for instance, studied the effects of tillage on soil C at the global scale using a field-scale model. However, applying field-scale models to scales for which they are not developed might lead to inaccuracies (Ewert et al., 2005), as other processes may play a role, and parameter calibration and input data are typically not available in similar quality at the global scale. For example, the scaling of the decomposition rate used by Del Grosso et al. (2009) to account for tillage effects might not be representative for all soil and climate conditions and may have to be calibrated to local conditions. Yet, calibration targets at the global scale are typically not available. Another option to include agricultural management in global models is to incorporate processes related to management in a global ecosystem model based on the variables and data that are available. For example, Waha et al. (2012) derived crop-specific sowing dates from climatic variables only because a global dynamic dataset of this management information is not available.

The most appropriate method to incorporate processes related to agricultural management in global ecosystem models depends on the research question. Research questions related to scientific understanding, such as mitigation effects through agricultural management on the long-term, would require a more detailed description of processes, in order to address questions about magnitude of responses, control of processes and interactions (Jones et al., 2017). However, the level of detail of agricultural management can be or should be represented to capture the most important responses, also depends on the availability of input and the model in which management is going to be incorporated.

Despite the different options to account agricultural management in global models, a methodology for structured implementation of agricultural management in global models is missing.

1.3 Aggregation in global ecosystem models

Field-scale crop models, as well as global ecosystem models, require input data on climate, soil properties and agricultural management. The input data at field scale can be very detailed, as observational data are typically available. For instance, information on soil layers may be specified as well as management information on e.g. the type, quantity and timing of fertilizer applications (e.g. Del Grosso et al., 2012). Global ecosystem models can typically only work with less detailed information for two main reasons.

First, at global scales, input data are available in less detail compared to plot- and field-scale level (Erb et al., 2017; Waha et al., 2015). For example, at the global scale there is only general information available on fertilization (e.g. Mueller et al., 2012; Potter et al., 2010), which is characterized by gaps and uncertainties (Erb et al., 2017). For instance, Mueller et al. (2012) used data from a variety of different sources (e.g. FAO/IFA/IFDC, 2003) to collect national and sub-national data on fertilizer application rates for crops. They found that not all countries reported data on their fertilizer application rates. To fill these data gaps, an income-based extrapolation technique was used, which they found to be of lower quality of information. Moreover, the data do not distinguish between different types of N and does not include information when the fertilizers are applied. As a result, general assumptions have to be made about the type, and timing of fertilizer applications.

Secondly, aggregation of input data can be necessary in order to meet the required spatial resolution of global ecosystem models. Global ecosystem models are often used for gridded simulations with a spatial resolution of 0.5° x 0.5° (which is equivalent to approximately 55 x 55 km^2 at the equator) (e.g. Schaphoff et al., 2018a; Piao et al., 2007). To date, there have been several efforts in the development of global soil databases that come in a finer resolution than the resolution typically used in global ecosystem models. For example: the Harmonized World Soil Database (HSWD; FAO & ISRIC, 2012), SoilGrids (Hengl et al., 2014) and S-World (Stoorvogel et al., 2017) come at a spatial resolution of 30 arc-sec (equivalent to approximately 1 km x 1 km at the equator). This means that, within those large grid cells, various soil texture classes or combinations of soil parameters may occur (Folberth et al., 2016). To aggregate the soil input data, the soil texture class within the grid cell is either be represented as i) using the representative soil (e.g. the dominant type) or ii) by conducting simulations with different soil representations and aggregating results in the post-processing.

Aggregation of input data may be a significant contributor to the overall uncertainty for agricultural impact assessments. In order to evaluate the effects of agricultural management on GHG emissions or soil C, these contributions in uncertainties have to be taken into account.

1.4 Thesis Overview

In order to better estimate the potential of how much agricultural based mitigation can be achieved, processes related to agricultural management have to be better represented in global ecosystem models. To represent agricultural management in global ecosystem models, I extend and evaluate in this thesis the global ecosystem model LPJmL to explicitly represent tillage for simulating its effect on N_2O emissions. LPJmL has been evaluated extensively and has demonstrated good skills to reproduce C, water and N dynamics in both agricultural and natural vegetation on different scales. However, LPJmL does not include the effects of tillage (Von Bloh et al., 2018a; Schaphoff et al., 2018a). The following research questions are addressed in this thesis. Their mutual relationship is depicted in Figure 1.1.

1. Can the global ecosystem model LPJmL be extended by a representation of tillage management to study its effects in particular on N_2O emissions?

2. Can the effects of tillage on N_2O emissions be captured at the global scale?

3. How much uncertainty is introduced by coarse representations of soil heterogeneity into global simulations of soil processes on cropland, including N_2O emissions?

1.5 Thesis Outline

These research questions are addressed in the following four chapters (Chapter 2 to 5) and the main findings of the different studies are provided in Chapter 6. The chapters have been published or have been prepared for submission to peer reviewed journals, which mean that they can be read independently. Therefore, some repetition occurs throughout this thesis.

Figure 1.1 provides an overview of the outline of the thesis and indicates the topics discussed in the chapters. In **Chapter 2** options on how to model tillage effects on N_2O emissions at the global scale are investigated. Therefore, the availability of process knowledge to model tillage effects on N_2O emissions in field-scale models is analyzed. Moreover, the data requirements to model these processes are matched to the data availability at the global scale. In **Chapter 3**, the global ecosystem model is extended with tillage related processes. The extended model is evaluated by comparing simulation results with published meta-analyses on tillage effects. In **Chapter 4**, the extended model is evaluated at four different experimental sites across Europe and the USA. Here, the focus is on the effects of tillage on N_2O emissions. Moreover, the effect of the generalization of agricultural management data on the simulated results is studied. **Chapter 5** focuses on the effects of different ways on representing soil heterogeneity on simulated soil C and N_2O emissions.

Finally, **Chapter 6** discusses the main findings of the thesis, insights obtained during the research, and directions for improvements for representations of agricultural management in global models.

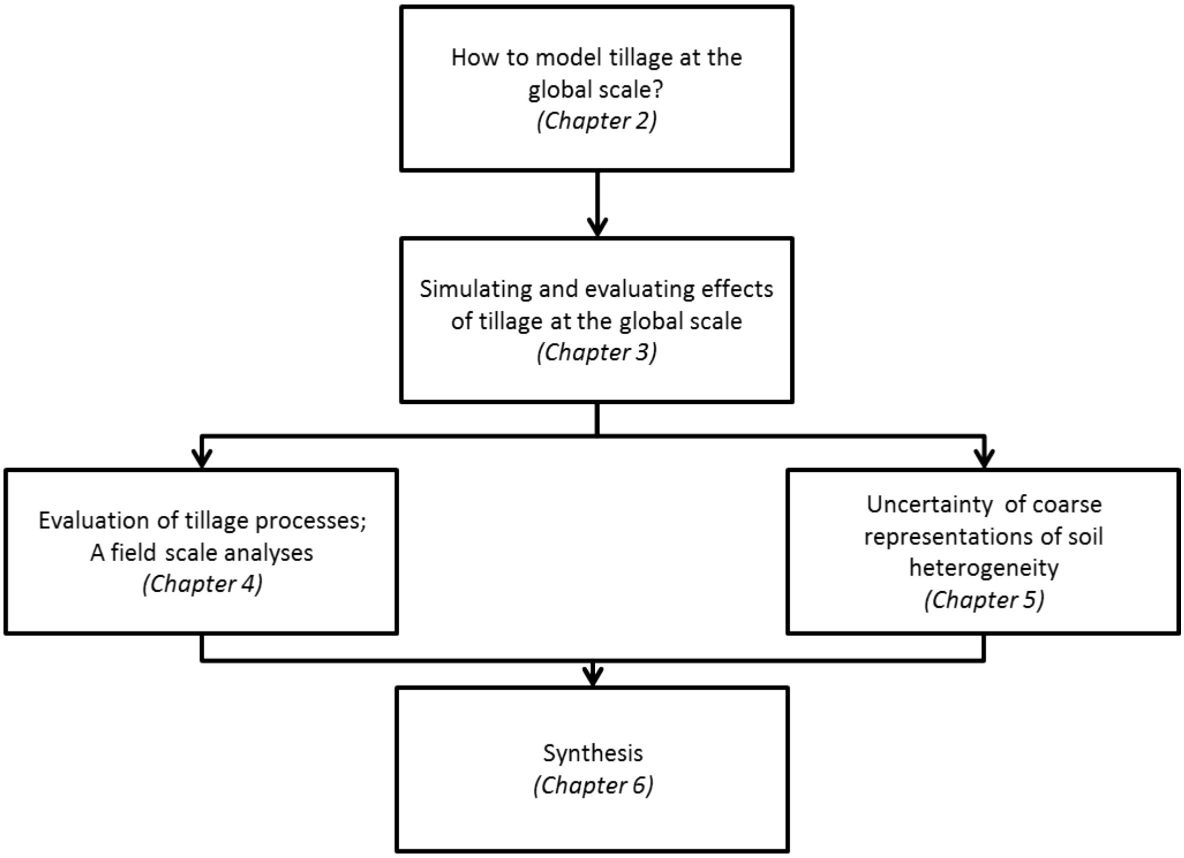


Figure 1.1: Thesis outline, indicating the logical structure of the research design and the corresponding chapters in which the different topics are studied and discussed.

Chapter 2

How to incorporate tillage in global ecosystem models?

This chapter is based on:

Lutz, F., Stoorvogel, J. J., and Müller, C., Options to model the effects of tillage on N_2O emissions at the global scale, Ecological Modelling, 392, 212–225, 2019

Abstract

Strategies on agricultural management can help to reduce global greenhouse gas (GHG) emissions. However, the potential of agricultural management to reduce GHG emissions at the global scale is unclear. Global ecosystem models often lack sufficient detail in their representation of management, such as tillage. This paper explores whether and how tillage can be incorporated in global ecosystem models for the analysis of nitrous oxide (N_2O) emissions. We identify the most important nitrogen processes in soils and their response to tillage. We review how these processes and tillage effects are described in field-scale models and evaluate whether they can be incorporated in the global-scale models while considering the data requirements for a global application. The most important processes are described in field-scale models and the basic data requirements can be met at the global scale. We therefore conclude that there is potential to incorporate tillage in global ecosystem models for the analysis of N_2O emissions. There are several options for how the relevant processes can be incorporated into global ecosystem models, so that generally there is potential to study the effects of tillage on N_2O emissions globally. Given the many interactions with other processes, modelers need to identify the modelling approaches that are consistent with their modelling framework and test these.

2.1 Introduction

Agriculture is responsible for approximately 14% of the global greenhouse gas (GHG) emissions: carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) (Carter et al., 2007; Del Grosso et al., 2009; Smith et al., 2009). Agriculture-based mitigation strategies, such as climate smart agriculture and the 4‰initiative, include soil management strategies that can substantially affect GHG emissions (Lipper et al., 2014; Minasny et al., 2017). These management strategies include the reduction of nitrogen (N) fertilizers, cover crops, rotations with legume crops, and reduced or no tillage (Paustian et al., 2016). The effect of management on GHG emissions has been investigated in many field and modelling studies (e.g. Jian-She et al., 2011; Kessavalou et al., 1998; Koga et al., 2004; Lee et al., 2009; Loubet et al., 2011). At the global scale, GHG emissions and their effects are estimated by global ecosystem models (Müller et al., 2017). However, these models typically lack the ability to evaluate the effect of management on GHG emissions in sufficient detail, implying that the models cannot evaluate the proposed mitigation strategies. A good example is that many of the global ecosystem models, which are used to simulate the terrestrial carbon and nitrogen cycles, do not deal with tillage practices, whereas zero tillage is proposed as one of the main measures to reduce N_2O emissions and increase carbon sequestration (McDermid et al., 2017).

Despite the limitations of global ecosystem models in representing the effects of agricultural management, these models are used to evaluate agricultural GHG emissions. Studies bypass these limitations through different procedures. Some assume a simple response effect of management on GHG emissions. For example, the Tier 1 method of the Intergovernmental Panel on Climate Change suggests a single emission factor across all fertilizer applications to agricultural soils (Buckingham et al., 2014; Sozanska et al., 2002). However, a single emission factor ignores that the effects of management on GHG emissions depend on e.g., soil conditions and climate (Butterbach-Bahl et al., 2013; Oertel et al., 2016). Other studies apply models, originally developed for field level applications (field-scale models), at the global scale (Del Grosso et al., 2009). This procedure has several limitations. Errors may be introduced when models are used at scales or climatic conditions for which they were not developed (Harrison et al., 2000). Moreover, detailed information for model initialization, calibration and input for field-scale models is typically not available at the global scale. As a third option, processes related to soil management are incorporated in global ecosystem models considering the variables and data available within the model. For example, Waha et al. (2012) derived crop-specific sowing dates from climatic variables only because a global dynamic dataset of this management information is not available.

Despite uncertainties, global ecosystem models are an important tool that can be used to analyze, quantify and project relevant processes to study interaction between plant-soil-atmosphere under changing practices and conditions. Tillage practices can affect these interactions as a result by altering soil properties (e.g., soil moisture). By understanding and incorporating relevant processes related to tillage and N_2O emissions into models, changes in practices and conditions could be analyzed, whereas simple response effects of management (e.g., Tier 1) cannot.

However, global ecosystem models now assume a standard increase in mineralization due to tillage (e.g. Pugh et al., 2015) or they ignore the effect of tillage (e.g. Bondeau et al., 2007). We aim to identify processes related to tillage that could be incorporated in global ecosystem models by using the existing modelling approaches and evaluating their suitability for the analysis of N_2O emissions.

This article aims to explore the options to better represent tillage impacts on N_2O emissions in global ecosystem models in 3 consecutive steps: 1) identification of relevant processes, 2) reviewing how these processes are described in field-scale models, and 3) evaluating the options to incorporate the process in global-scale models. For this, we analyze how tillage can be included in global-scale models to better estimate options to reduce agricultural N_2O emissions. If tillage were included in global-scale models, it would allow for the selection and promotion of proper tillage systems (e.g., no-tillage or reduced tillage) to decrease GHG emissions (e.g. Paustian et al., 2016). The study strongly builds on reviews that study tillage effects on soil properties, carbon sequestration and tillage models (e.g. Maharjan et al., 2018; Strudley et al., 2008; Waha et al., 2012).

2.2 Material and methods

At the global scale, the impact of tillage on N_2O emissions can only be represented with reduced complexity, because detailed information for initialization, parameterization and input as often measured for field-scale applications is not available at the global scale (e.g. Deng et al., 2016; Grant & Pattey, 2003; Molina-Herrera et al., 2016). Modelling the impact of tillage on N_2O emissions in reduced complexity can be achieved by focusing on the most important processes. The various processes that affect N_2O emissions therefore need to be analyzed for relevancy, complexity and data requirements. This analysis contains three different steps (Figure 2.1):

1. Inventory of processes with all N processes relevant to N_2O emissions.
2. Analysis of the collected processes with respect to:
    - 2.1. How important is a particular process, what are the drivers of the processes and how are they affected by tillage?
    - 2.2. How are tillage and N processes being represented?
    - 2.3. What are the data requirements?
3. Evaluation of ability to model tillage effects on N_2O emissions at the global scale.

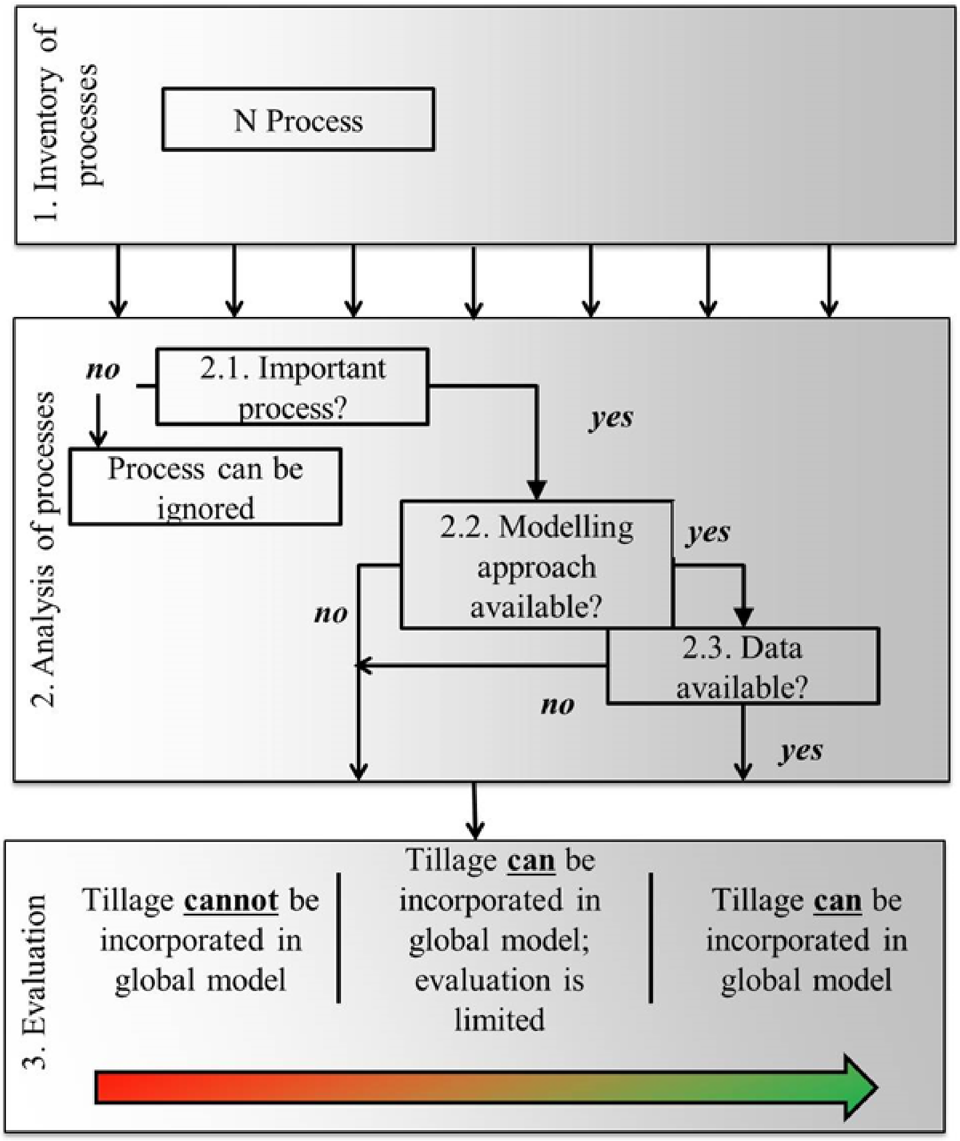


Figure 2.1: The analysis consists of three steps on how tillage can be incorporated into global ecosystem models for the analysis on N_2O emissions.

2.2.1 Inventory of processes (Step 1)

For the analysis of the N_2O producing processes, all N processes that are relevant were assembled and summarized as well as all information that is needed in the further analysis, i.e. the contribution (importance) of an N process to N_2O emissions, as well as the role of tillage for these processes, how processes are described in models as well as their data requirements.

2.2.2 Analysis of processes (Step 2)

2.2.2.1 Importance of N processes (Step 2.1)

The importance of N processes was evaluated in the context of the particular research question of interest. A true assessment to the importance requires the implementation and testing of the processes in a global ecosystem model. Here, we carried out an ex-ante assessment based on global estimates of N fluxes found in literature to assess the importance of each process. A process was considered to be important if: 1) the flux of the process was relatively large, which is -admittedly- rather a subjective choice, and 2) it was a primary process.

To determine how the effects of tillage on N_2O emissions can be modeled, we considered the processes in which N_2O is actually formed (nitrification and denitrification: primary processes) as well as the processes that affect the performance of these primary processes (secondary processes). These are, for instance, all processes that affect the availability of the primary material and the environmental conditions (drivers) that determine the dynamics of the primary processes. In order to incorporate tillage effects into a global ecosystem model, we thus ensured that the mechanisms by which tillage affects the process drivers were also included.

2.2.2.2 Processes described in models (Step 2.2)

After having identified N processes, information was collected on how models describe them. We focused on models that have been cited often, used in environmental studies and whose performance has been tested and evaluated. Moreover, preference was given to models that include all relevant soil N dynamics and tillage. In order to link the identified processes to how models describe them (modeling approaches), the models were analyzed on: 1) which processes are included and how they are represented, 2) which drivers are considered, and 3) how tillage affects these processes.

2.2.2.3 Data requirements (Step 2.3)

Any process representation in a model implies additional data and parameter requirements for the application at the global scale. The data can either be available from external sources or can be computed within the model. In this step, the data requirements to model a process were analyzed as well as management related data, such as tillage type and timing. Here, the spatial- and temporal resolution to represent a process was considered as well as of the global ecosystem model into which the processes are to be incorporated. Most global ecosystem models run at a spatial resolution of 0.5° or finer and with a daily time step. The data for the consideration of a process therefore had to be available at a minimum spatial resolution of 0.5°. The required temporal resolution of the data depends on the variability of the data to drive a process described in a model. Tillage practices, for example, do not occur on a daily basis but rather once or twice a year. Therefore, we did not necessarily require data on a daily resolution but at the appropriate time scale or with explicit timing information (Hutchings et al., 2012). Depending on the global ecosystem model, some data are calculated endogenously whereas others have to be supplied externally.

2.2.3 Evaluation (Step 3)

The structured analysis of the importance, availability of processes described in models and data requirements of processes allowed for an evaluation if and how tillage can be incorporated in global ecosystem models. It also enabled an assessment of possible caveats, where e.g., individual processes had to be combined from different models. This could yield inconsistencies in approaches and/or parameterization or where quality of available data does not match the quality requirements of the process formulation. The analysis of available options guided alternative implementation strategies and the design of sensitivity studies in the evaluation of the model implementation. The analysis of the ability to model a particular aspect of agricultural management at the global scale can help to identify the suitable scope of model application and interpretation.

2.3 Results

2.3.1 Inventory of processes (Step 1)

The addition, transformation through internal processes, and losses of N are the main elements of soil N dynamics (Fageria & Baligar, 2005). The main processes of these elements are depicted in Figure 2.2. Nitrogen is added to the soil through N-fertilization (mineral and organic), atmospheric deposition, biological N fixation and residue input. Fertilization, residue input and, in part, biological N fixation are management related processes. N-addition can be either in organic forms (residue input, organic fertilization) or in inorganic forms (mineral fertilization, atmospheric deposition and biological N fixation). After N additions, N is transformed through mineralization, immobilization and nitrification. Nitrogen can be lost from the soil to the atmosphere, through volatilization, denitrification and nitrification, to the groundwater through leaching and to surface water by erosion and surface runoff. From the soils' perspective, also the uptake by the plants is a form of N loss.

2.3.2 Analysis of processes (Step 2)

2.3.2.1 Importance of processes (Step 2.1)

In Table 2.1 and Figure 2.2, the main addition and loss fluxes of N into and from agricultural soils are shown. These numbers are based on global estimates from different literature sources. The primary processes nitrification and denitrification are regarded as important processes, since they result in the formation of N_2O. Inorganic N fertilization is the largest flux and, therefore, the most important secondary process. This is followed by biological N fixation and organic fertilizers. Plant uptake is the major loss flux of N from soils. Since these fluxes are relatively large, these processes are essential to incorporate in any simulation of N_2O emissions. The sizes of fluxes can also be influenced by tillage practices (see e.g. Minoli et al., 2015).

Tillage affects N processes and, therefore, N_2O emissions mainly indirectly, i.e., by affecting the drivers rather than the processes themselves. Table 2.2 provides an overview of the drivers of relevant processes that were identified in the steps above. Of the N addition processes, N-fertilization and residue input are both determined by management decisions. The amount of N that is added to the soil depends on the amount of N-fertilizer and/or residue and its incorporation into the soil. Biological N fixation by plant symbioses is partly driven by management decisions (crop choice), and partly by soil conditions (Brady & Weil, 2008). High levels of available N or low levels of phosphorus in the soil tend to depress biological N fixation (Brady & Weil, 2008; Smith, 1992). The atmospheric deposition of N depends on the location and on the deposition of rain, snow and dust (Brady & Weil, 2008). It is much higher in areas with high emissions, as in concentrated animal farming areas (through volatilization of mineral N).

Transformation of N through mineralization, immobilization and nitrification is controlled by microbes whose activity is driven by the amount of substrate in the soil (organic and inorganic N), soil temperature, soil moisture, soil oxygen and the soil pH (Brady & Weil, 2008). The activity of the microbes is also driven by the size and complexity of organic N, often indicated as the ratio of carbon (C) or lignin to N (lignin:N or C:N) during mineralization and immobilization. Losses from the soil occur to the atmosphere, through volatilization, nitrification and denitrification, to the groundwater through leaching, to surface water or other locations through erosion, or to the plant through plant uptake. The most important drivers that influence volatilization include the soil acidity (pH), cation exchange capacity (CEC), temperature, moisture content, weather conditions and the amount of NH_4^+ at the soil surface (Sigunga et al., 2002). Denitrification is also regulated by microbial organisms and is therefore driven by the presence of NH_3^-, soil temperature, soil moisture and additionally, the presence of dissolved C. N-leaching depends on the NH_3^- content of the soil and the percolation of water, which again depends on the water influx (from precipitation, irrigation and snowmelt), soil moisture, texture, and soil structure of the profile (Brady & Weil, 2008). The slope gradient, management (tillage type, residue management and cover crop), and the amount and intensity of precipitation are important drivers for erosion (Kinnell, 2010; Li et al., 2004). N-uptake by the plant depends on crop growth, soil moisture, root length, root length density and available N in the soil (James & Richards, 2006).

Tillage affects some of these drivers and, therefore, processes. Tillage has a direct impact on the physical properties of the soil, such as bulk density and porosity (Abdalla et al., 2007; Strudley et al., 2008) Tillage-driven changes in physical properties have pronounced effects on soil moisture and soil temperature. Soil moisture and temperature will affect several processes. The incorporation of crop residues or fertilizers through tillage changes the distribution of the different N forms in the profile. The soil moisture and soil temperature, together with the amount of N in the soil profile will therefore affect different N processes in agricultural soils and therefore N_2O emissions. As shown in Table 2.2, tillage affects almost all N processes.

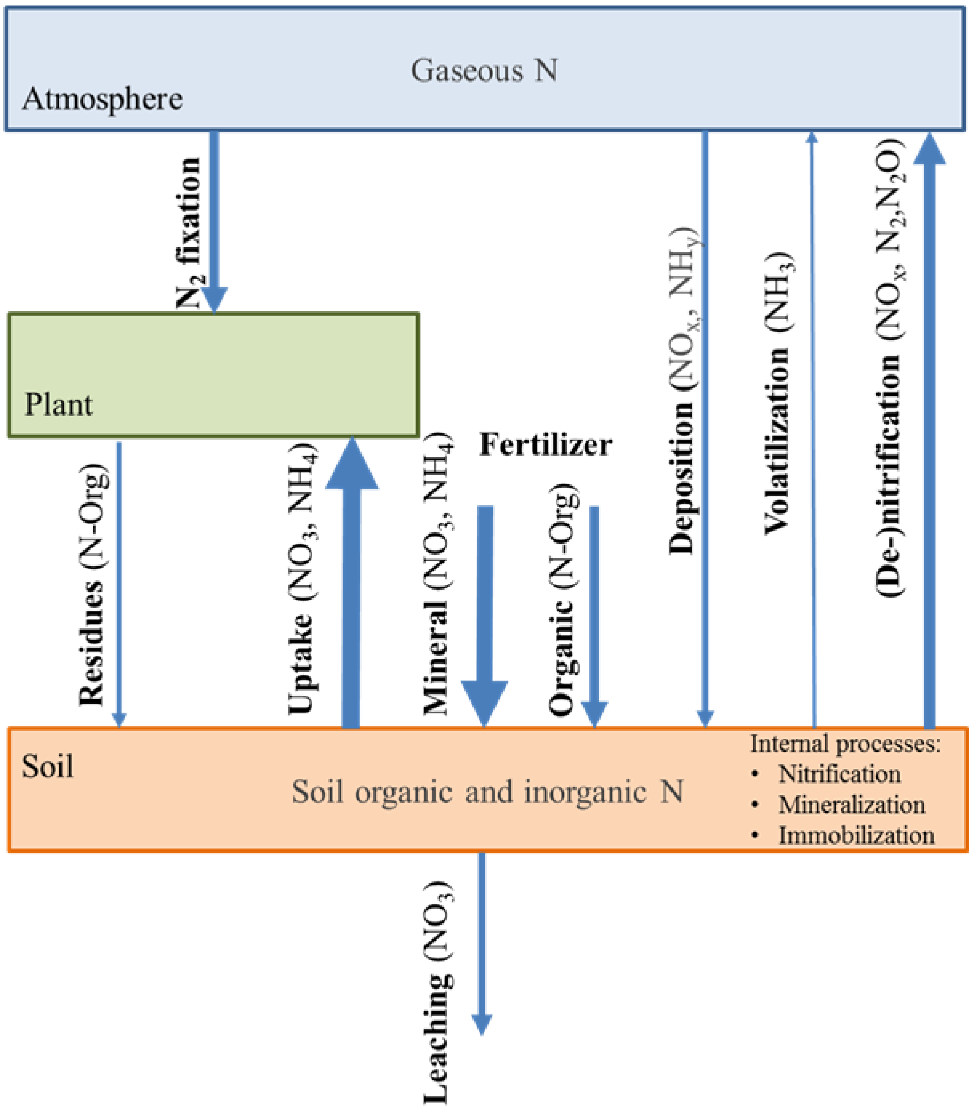


Figure 2.2: The main elements of soil N dynamics: the addition, transformation and losses of N. The thickness of the arrows represents the relative size of the fluxes.

Table 2.1: Estimates for the global fluxes of nitrogen from and to agricultural soils in $TgNYr^{-1}$ from different literature sources. No information was available on the internal processes.

Process (% of input/output)		Tg N yr^{-1}	Reference
Additions			
Fertilization: Inorganic N		78	Smil (1999)
(~ 52%)		85	Nishina et al. (2017)
		78	Bodirsky et al. (2012)
Fertilization: Organic N		17.3	Liu et al. (2010)
(~ 13%)		24	Bodirsky et al. (2012)
N_2 Fixation		22	Liu et al. (2010)
(~ 17%)		30	Billen et al. (2013)
N deposition		15	Bodirsky et al. (2012)
(~ 11%)		20	Smil (1999)
		14.5	Liu et al. (2010)
Residue input		11	Liu et al. (2010)
(~ 8%)		14	Smil (1999)
Losses			
Volatilization		11	Smil (1999)
(~ 6%)			
Denitrification	N_2	14	Smil (1999)
(~ 16%)	N_2O	4	Smil (1999)
		6	Potter et al. (1996)
	NO	4	Smil (1999)
		10	Potter et al. (1996)
Nitrification		NA	NA
Plant uptake		85	Smil (1999)
(~ 52.0)		81	Liu et al. (2010)
Leaching		23	Liu et al. (2010)
(~ 12%)		17	Smil (1999)
Erosion		20	Smil (1999)
(~ 14%)		24	Liu et al. (2010)

2.3.2.2 Processes described in models (Step 2.2)

The models selected for the literature review have often been cited, applied, and evaluated in agricultural studies. Additionally, they include both N dynamics and tillage. Table 2.3 lists the models with their main reference and validation references. Some of these models, like DSSAT and EXPERT-N, make use of other models for the simulation of certain processes. For example, the N dynamics in DSSAT can be based on the approaches

Table 2.2: Tillage affects distribution of organic material as well as mineral N in the soil profile and the soil properties that drive N processes. This table indicated which N processes are affected by tillage.

Process	Drivers	Tillage effects
Additions		
Mineral fertilization	N fertilization	Incorporation into soil. Reduces volatilization. Affects moisture, temperature, increases soil N. Ambiguous response for internal processes.
Organic fertilization	N fertilization	Incorporation into soil. Reduces volatilization. Affects moisture, temperature, increases soil N. Ambiguous response for internal processes.
N_2-Fixation	Crop choice, fertilization, Soil N content, soil moisture	Affecting moisture, temperature, soil N. Ambiguous response.
N-deposition	Deposition (rain, snow, dust)	Not affected
Residue input	Residue removal, incorporation	Incorporation into soil. Reduces volatilization. Affects moisture, temperature, increases soil N. Ambiguous response for internal processes.
Losses		
Volatilization	pH, CEC, temperature, moisture, oxygen, weather conditions, NH_4^+	Reduced by tillage if additions are incorporated.
Denitrification	temperature, moisture, oxygen, dissolved carbon, NO_3^-	Affects moisture, temperature. Ambiguous response.
Nitrification	temperature, moisture, oxygen, NO_3^-	Affects moisture, temperature. Ambiguous response.
Plant uptake	plant N demand, moisture, Soil N content	Affects moisture, temperature. Ambiguous response.
Leaching	Texture, structure, moisture, NO_3^-	Affects moisture, temperature. Ambiguous response.
Erosion	Slope length, slope steepness, management, Wind speed, rainfall amount and intensity	Increases erosion.
Internal process		
Nitrification	temperature, moisture, oxygen, NO_3^-	Affects moisture, temperature. Ambiguous response.
Mineralization	temperature, moisture, oxygen, C:N	Affects moisture, temperature. Ambiguous response.
Immobilization	C:N	Not affected

of either CERES or CENTURY. The N dynamics In EXPERT-N can be based on the approaches of LEACHN, CERES, SOILN, Daisy and Hydrus.

The models differ slightly in the number of C and N pools (Table 2.4) but can be generally distinguished into organic-and inorganic pools. The organic pools consist of the fresh organic matter $(OM)^{-}$ and soil organic matter (SOM) pools, (e.g. labile, stabil, and active pool). The pools are characterized by the C:N or lignin:N ratio and the turnover time. The inorganic matter pools represent concentrations of NH_4^+ and NO_3^-. Typically, all pools are represented in all soil layers (e.g., one NH_4^+ pool per layer), but models differ in the number and thicknesses of layers represented.

Table 2.3: Models selected for the analysis with its main reference, model version and reference to a validation study.

Model	Scale	Version	Main references	Validation
CENTURY	Plot, field, regional	5.0	Metherell et al. (1993)	Álvaro-Fuentes et al. (2012)
RZWQM2	Plot	2.0	Ahuja et al. (2000)	Cameira et al. (2007)
DNDC	Field, regional	95.0	Li (2000) Giltrap et al. (2010)	Cui et al. (2014)
Daisy	Field	5.21	Abrahamson et al. (2005)	Hansen et al. (2012)
EPIC	Field	0810	Izaurralde et al. (2006) Williams et al. (2008)	Chung et al. (1999)
CropSyst	Field	4.19.06	Stöckle et al. (2003) Stöckle et al. (2010)	Pannkuk et al. (1998)
DSSAT	Field, regional	4.5	Jones et al. (2003) Godwin & Singh (1998)	Ngwira et al. (2014)
STICS	Plot	5.0	Beaujouan et al. (2001) Brisson et al. (1998)	Coucheney et al. (2015)
DAYCENT	Field, regional, global	-	Parton et al. (1998)	Abdalla et al. (2010)
EXPERT-N	Field	3.0	Priesack (2006)	Priesack (2006)
LPJ-GUESS	Regional, global	-	Olin et al. (2015a) Smith et al. (2014a)	Olin et al. (2015b)

Fertilization

The models describe fertilization in similar ways (Table 2.4). Nitrogen is added to the soil surface and can be incorporated to deeper layers by tillage. The timing of fertilization is either predefined or can be modelled based on plant N demand. The depth to which the fertilizer is incorporated depends on the tillage type. Inorganic N is added to the actual NH_4^+ and NO_3^- pool. Organic N is added to the fresh OM pools.

Crop residue incorporation

The models describe crop residues incorporation in a similar way (Table 2.4). A fraction of the crop residues is incorporated into the soil. The size of the fraction as well as the depth of incorporation depends on the tillage type. Based on its C:N ratio, the N contained in crop residues is then allocated to one of the fresh OM pools which is then subject to mineralization.

Biological N fixation

In the various models, biological N fixation in models is 1) not described, 2) modelled as a function of plant demand, 3) as a function of evapotranspiration, or 4) modelled explicitly (Table 2.4). Biological N fixation is not described in DNDC, DSSAT and in EXPERT-N. In CENTURY, RZWQM, Daisy, and DAYCENT it is modelled as a function of plant demand. Thereby, the biological N fixation is assumed to occur only when there is insufficient mineral N to satisfy the plant N requirement and if the crop is able to fix N. In LPJ-GUESS, biological N fixation is modelled as a function of evapotranspiration (see also Cleveland et al., 1999). The process is modelled explicitly in EPIC and CropSyst by calculating the biological N fixation rate taking into account the growth stage of the plant, the soil water content and the soil N content. By considering the growth stage, biological N fixation is inhibited in young plants prior to development of functional nodules and in old plants with senescent nodules (Patterson & LaRue, 1983). When the soil water content is below a critical level and/or the soil N level above a certain level, the biological N fixation rate is also reduced. In CropSyst, the soil temperature is used to limit the biological N fixation both for too low and too high temperatures.

Mineralization

Mineralization is described according to the same principles in the studied models (Table 2.4) but the drivers differ. The mineralization rate of N depends on the mineralization rate of C and the C:N ratio of the OM. The C and N contained in the OM are split into different SOM pools. The C contained in those pools is mineralized which is described by first-order kinetics with high rate constants for the microbial pool and low rate constants for the passive pool. Although, the rate constant can be calculated based on the C:N ratio (Shaffer et al., 2001), the rate constants are predefined in the considered models. The mineralization rates of C are then reduced by non-optimal soil conditions, such as soil moisture and soil temperature. In most of the models the soil texture also influences the turnover rate. In those models (e.g., CENTURY and Daisy) an increase in clay content in the soil decreases the mineralization rate, mimicking physical protection against mineralization of OM. In CropSyst, the mineralization rate of C is reduced only by soil texture as described before. The pH and the population size of heterotrophic microbes are also included as explicit drivers of mineralization in RZWQM2. In EPIC, the bulk density is included in the mineralization rate. In EPIC the bulk density –and therefore the mineralization rate- is affected when tillage occurs. The mineralization of N occurs when the OM is respired or transferred from a donor pool to a receiving pool with a higher C:N ratio. As shown in Table 2.5, mineralization increases the soil mineral N pool, which can be both NH_4^+ and NO_3^- (e.g., CENTURY and EPIC) or NH_4^+ specifically (e.g., DNDC and Daisy).

Immobilization

The models describe N−immobilization according to the same principles (Table 2.4). As the opposite to mineralization (see also above) immobilization of N occurs when the C:N ratio of the receiving pool is lower than the C:N ratio of the donor pool. This will result in a reduction of the mineral N pool.

Nitrification

Nitrification in models is 1) not included, 2) a fixed fraction of mineralization, 3) modelled explicitly, but only simulating total gaseous losses to the atmosphere without further sub-division or 4) modelled explicitly, with explicit simulation of different gaseous loss fluxes, including N_2O (Tables 2.4 and 2.5). Nitrification is not explicitly described in CENTURY. In LPJ-GUESS a fixed fraction of mineralization (one percent) is lost towards the atmosphere, without further specifying the actual chemical compound of that N flux. In the other models reviewed here, nitrification is modelled explicitly. Nitrification is mostly modelled by a given maximum nitrification rate, which is then reduced by environmental factors. The environmental factors considered are soil moisture, soil oxygen and soil temperature in all models, and sometimes soil pH (except Daisy and CropSyst). RZWQM2 and DAYCENT also model the growth and death of nitrifying bacteria and then calculate the rate of nitrification based on this population. The CEC is included for the simulation of nitrification in EXPERT-N and its sub model (LEACHN), in order to take adsorption of NH_4^+ to clay particles into account. In STICS, nitrification is only modelled in tropical regions, whereas it assumes that NH_4^+ is directly transformed into NO_3^- in non-tropical regions. The STICS implementation assumes that this is not always the case in tropical environments because the pH of the soils combined with high temperatures and low water contents in the topsoil slow nitrification down. The DNDC model uses a more chemistry-based approach with an integrated Nernst and Michaelis-Menten equation to track microbial activities. Therefore, first a redox potential is calculated based on concentrations of the dominant oxidants (O_2) and reductants existing in the soil liquid phase. The redox potential is then integrated with the Michaelis-Menten equation in which the reaction rate is calculated by including DOC and the oxidant concentration. The integrated equation can then track the interaction between redox potential dynamics and a microbe-mediated redox reaction in the soil. In most of the models the loss of N_2O during the process is also modelled (Table 2.5). Except for RZWQM2 and some sub models of EXPERT-N (CERES and LEACHN), these losses are modelled as a fixed proportion of nitrification. The quantity of the proportion is not always the same; in DNDC the proportion is 0.24%, whereas in DAYCENT the proportion is 2% and in EXPERT-N 1%. In RZWQM2, the N lost as N_2O in the nitrification also depend on the soil moisture. In EPIC and DSSAT the loss of N_2O is not explicitly considered but included in an overall gaseous loss flux.

Volatilization

Volatilization is described in most of the models, ranging from relative simplistic to more detailed approaches (Table 2.4). In general, the simulation of volatilization can be categorized into four categories; 1) not included, 2) estimated simultaneously with nitrification, 3) estimated proportional to mineralization, and 4. modelled explicitly. Volatilization is not modelled in CENTURY, STICS, DAYCENT or LPJ-GUESS. In EPIC, the process is estimated simultaneously with nitrification. In Daisy, volatilization is modelled as a fixed proportion (20%) of the applied mineral N fertilizer that is lost to the atmosphere. In the other models, the process is modelled explicitly. The drivers of these processes are different per model. In CropSyst, DNDC and DSSAT, the soil pH and CEC are the main drivers of volatilization. In these models, the Langmuir isotherm equation is used to firstly quantify the concentration of the adsorbed NH_4^+ distributed between its free ion phase and adsorbed phase based on the isotherm equilibrium (see e.g. Li et al., 2006). The CEC is used as an indicator to the soil's potential for adsorption (see e.g. Li et al., 2006). In DNDC and DSSAT, the volatilization rate is also affected by soil temperature. In DNDC, also the moisture and clay content of the soil determine the volatilization rate. Wind speed is only considered in RZWQM2, where the volatilization flux is proportional to the wind speed.

Denitrification

Denitrification in the models is 1) not included, 2) a function of mineral N remaining after plant uptake, 3) modelled explicitly but only simulating total gaseous losses to the atmosphere without further subdivision, or 4) modelled explicitly with explicit simulation of different gaseous loss fluxes, including N_2O (Tables 2.4 and 2.5). Denitrification is not described in LPJ-GUESS. In CENTURY, the process is a function of mineral N remaining after plant uptake. In the other models, denitrification is modelled explicitly. Some of these models specify the N_2O emissions (RZWQM2, DNDC, CROPSYST, STICS, DAYCENT, EXPERT-N), whereas in other models the combined gaseous N (N_2+NO+N_2O) emissions are modelled (Daisy, EPIC, DSSAT, sub models of EXPERT-N). Most of these models simulate denitrification based on soil temperature, soil moisture and labile C. Labile C is not included in STICS and in one of the sub models of EXPERT-N (LEACHN). The soil pH and microbial activity are included as drivers of denitrification in RZWQM2 and DNDC. The DNDC model uses a more chemistry-based approach in which both the redox potential and Michaelis-Menten equation to track the microbial activity (see e.g. Li, 2007). In STICS, the soil bulk density is also taken into account. In this model, the N_2O emissions are a fixed proportion of the denitrification flux, whereas in the other models labile C and soil moisture also affect the simulation of the N2O flux. RZWQM2, CropSyst and DAYCENT use the same approach, but here the ratios of N_2 to N_2O and NO to N_2O are estimated and modified based on soil moisture, labile C and NO_3^- concentration. More details are provided by Del Grosso et al. (2000). In RZWQM2 the N_2O diffusion within the soil is also accounted for by adding the soil depth into their equation (Gillette et al., 2017). In EXPERT-N, N_2O emissions can either be distinguished as a proportion of N_2, or it can be distinguished as a function of soil moisture and so il temperature. Daisy, EPIC, DSSAT and some sub models of EXPERT-N (SOILN AND CERES) simulate denitrification explicitly in terms of the combined gaseous N (N_2+NO+N_2O) emissions based on soil moisture, soil oxygen and labile C.

Plant uptake

The uptake of N from the inorganic N pools by a plant can be divided in four categories: 1) not described, 2) modelled as a function of plant demand and the potential uptake of N, 3) modelled as a proportion of plant transpiration and as a function of plant demand and the potential uptake of N, or 4) as a function of plant demand and the potential uptake of N and the movement of N from the soil to the root surface (Table 2.4). The uptake of N by plants is not explicitly described in the documentation of CENTURY and DAYCENT. In DNDC, EPIC, DSSAT, EXPERT-N (and sub model LEACHN), and LPJ-GUESS, the uptake of N is modelled as a function of plant demand and the potential uptake of N. The plant N demand depends thereby on the growth stage and its corresponding N content of the plant. The potential uptake of N depends on the supply soil mineral N in the soil profile in all models and on the soil moisture in most of the models (except for LPJ-GUESS). Additionally, the soil temperature, the root length density, the water uptake rate and the transpiration of the plant are taken into account in some of the models (see Table 2.4). In RZWQM, the N uptake of the plant is modelled in similar matters. However, the N uptake in this model is not the minimum of, or the difference between potential uptake and plant demand, but a Michaelis-Menten equation is used, which requires information on the maximum uptake rate of mineral N (constant) and soil mineral N content in the profile (see also RZWQM Development Team et al., 1998). Additionally, a "passive" N uptake is taken into account. For this, the N uptake is calculated proportionally to the transpiration rate of the plant. In CropSyst, Daisy and STICS also the transport of N from the soil to the root surfaces is calculated through convection and diffusion as shown by (see also Hansen et al., 1990). The soil N supply in each soil layer is thereby determined by the transport of mineral N from a given soil location to the nearest root. The actual uptake of N by the plant is then calculated by a Michaelis-Menten equation, which requires a maximum uptake rate of mineral N (constants), the root density and rooting depth (CropSyst and Daisy). In STICS the minimum of potential uptake and plant demand is considered as the actual uptake.

Leaching

The models describe leaching as the movement of dissolved inorganic N with the soil water movement. The dissolved inorganic N is mostly described in the form of NO_3^-, and leaching constitutes a loss of NO_3^- from the corresponding pool to lower layers or to the aquifer. Daisy and EXPERT-N (including sub models) consider NH_4^+ explicitly (Table 2.5). The main difference between the models is how the soil water movement is computed (Table 2.4). The movement is modelled by using either the capacity soil water balance approach (CENTURY, EPIC, STICS, DAYCENT and LPJ-GUESS) or the more detailed mechanistic Richard equation (RZWQM2, EXPERT-N and sub models), or a combination of the two (DNDC, Daisy, DSSAT, EPIC and LPJ-GUESS). In the capacity approach, the water infiltrating into a soil layer fills the compartment to field capacity. When the soil water exceeds field capacity, the water percolates to the next soil layer and/or goes to runoff (EPIC and LPJ-GUESS). The leaching flux is that N that percolates out of the lowest layer or goes to runoff (Del Grosso et al., 2008). The nitrate contained in the pool is assumed to be dissolved completely in the water of the soil layer; the transport rate of N out of a soil layer is calculated by multiplying the percolation rate out of the soil layer by the concentration of nitrate in the soil layer. In DSSAT and STICS only a fraction of the NO_3^- can be leached, mimicking the adsorption of NO_3^- to the soil and the prevention of this fraction from being transported to lower soil layers (see also Van der Laan et al., 2014). In RZWQM2, CropSyst and EXPERT-N (and sub models) the Richard equation (Richards, 1931) is used for simulating the movement of water, the transport is driven by potential gradients that develop between soil layers due to gravity, water extraction by roots and water that enters or leaves the profile which causes different soil moisture suctions in the different layers. The soil moisture characteristics such as the hydraulic conductivity, soil water content-matric suction relationship and the porosity are key parameters for the calculation of the water movement. The transport of N is described by the convection-dispersion equation (see also Addiscott & Wagenet, 1985). This equation considers the solute displacement in the soil resulting from the physical process of convection or mass flow of water and the chemical process of diffusion in response to a concentration gradient. This concept and the simulation of leaching in the capacity approach are described in detail in Addiscott & Wagenet (1985). Key parameters for the equation are the volumetric water content, volumetric water flux, the solute concentration, depth and a dispersion coefficient. The main difference between models that combine the Richard equation with the convection-dispersion equation is that 1) some models differentiate between mobile and immobile water, which mimics the presence of micro- and macropores and 2) some models include adsorption of NH_4^+ and NO_3^-, which reduces the amount of N lost through leaching. A third option is a combination of the two approaches in which the capacity approach includes the hydraulic conductivity as parameter. This reduces the water movements through the soils and allows the water content to be higher than field capacity as well as water to pond on the soil surface. This option is currently used in DNDC, Daisy, EPIC, DSSAT and LPJ-GUESS.

Erosion

Erosion in models is either 1) not included, or 2) modeled as a function of weather, topography, soil and management related factors. Erosion is not included in RZWQM2, DAISY, DSSAT, STICS, EXPERT-N and LPJ-GUESS. In CENTURY, EPIC, CROPSYST and DAYCENT, it is modeled according to the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997). In DNDC the Modified Universal Soil Loss Equation (MUSLE) is used, which is also optional in EPIC (Williams, 1975).

RUSLE includes factors such as rainfall erosivity, soil erodibility, topography, land use and management. Rainfall erosivity depends on the rainfall intensity of a specific rainfall event (Risal et al., 2016). The soil erodibility factor is a function or soil texture, structure and OM content. The topographic factor is a function of slope length and slope steepness. The management related factor includes soil cover, which is influenced by tillage, and erosion reduction measures, such as grass markings (Panagos et al., 2015). MUSLE is the modified version of RUSLE, in which the rainfall erosivity factor is calculated slightly different: instead of rainfall intensity, runoff and peak discharge is taken into account; for which rainfall, the soil water content and different retention parameters are used (Deng et al., 2011; Sadeghi et al., 2013).

Tillage effects on drivers

Depending on frequency, type and depth, tillage can have major impacts on the physical properties of the soil and on the distribution of organic material as well as mineral N in the soil profile. Tillage affects the N processes either directly (availability of substrate) or indirectly via other soil properties, most prominently soil moisture and soil temperature (Table 2.2). Tillage is represented in different ways in the models which build upon each other (Table 2.6):1 tillage increases the mineralization rate temporary, 2) tillage directly affects soil properties that drive soil N processes, 3) tillage directly affects soil properties that drive soil N processes and have a temporal increase in mineralization rate, and 4) tillage affects the soil properties directly and indirectly, i.e., through the soil physical properties. The first category, in which the mineralization rate of selected pools is increased temporarily, depending on the tillage activity. The increased rate may either be predefined (LPJ-GUESS and DAYCENT) or is calculated based on soil texture and a factor of soil disturbance (CropSyst). The increase in mineralization rate is temporary in the models. In LPJ-GUESS and DAYCENT, the increase in mineralization occurs in the month of the tillage event and returns to its original rate after this month. In CropSyst, the rate decreases as a function of time and soil water content at a certain percentage per day for a soil at field capacity.

The second category, in which tillage directly affects the soil properties, can be found in the Daisy− and in the EXPERT−N models. In these models, tillage mixes or swaps the soil layers according to the tillage depth. This means that the soil properties of all soil layers within the tillage depth are averaged. Additionally, a defined fraction –which has to be specified- of the crop residues may be incorporated into the soil. Depending on the tillage type specified in the simulation, the soil layers may also be "swapped" in the Daisy model, i.e. the soil layer properties are switched with each other, mimicking the inversion of a soil profile through tillage. The mixing and swapping of soil layers is permanent and only changes its state at a new tillage event. The third category, in which the soil properties are directly affected (through mixing) and additionally a temporal increase in the mineralization rate, can be found in DNDC and CENTURY. Also in DNDC, a defined fraction of residues may be incorporated into the soil. As also described in the second category, the mixing of soil layers is permanent and only changes its state at a new tillage event. Additionally to affecting the soil properties, the mineralization rate of the different pools is increased depending on the depth of tillage practice in both models. In CENTURY, the increase in mineralization occurs in the month of the tillage event and returns to its original rate after this month. In DNDC, the tillage effect on the rate is gradually reduced depending on the rainfall event; the changes in properties caused by tillage gradually degrade due to natural reconsolidation during wetting and drying.

The direct effect on soil properties through the mixing of soil layers (with or without residues), can also be found in STICS, RZWQM2, EPIC and DSSAT. In these models, the soil moisture and soil temperature are also indirectly affected by tillage through the soil's physical properties. The primary effect of tillage on soil physical properties is on bulk density (mass to volume ratio), which can either increase (compaction) or decrease (aeriation). The extent of the effects depends on the specific tillage event. The change in bulk density affects the porosity (or saturated water content) in RZWQM2, DSSAT and STICS. A decrease in bulk density will result in an increase in porosity, which means that more water could be stored in a certain soil layer. The change in bulk density affects the mineralization rate in EPIC and the denitrification rate in STICS directly. Another property that is affected by tillage in DSSAT and RZWQM2 is the hydraulic conductivity, which describes the ease with which water can move through the soil column. The hydraulic conductivity in DSSAT is changed by a certain percentage, depending on the specific tillage event. In RZWQM2 however, the hydraulic conductivity is related to the porosity of the soil. A change in the porosity therefore leads to a change in the hydraulic conductivity (Ahuja et al., 2000). This affects the drainage- and percolation rate and thus affects all soil-water dependent N processes. The bulk density, porosity and hydraulic properties all have an effect on the soil moisture and therefore, soil temperature. In RZWQM2, the porosity is updated based on the rainfall amount and the kinetic rainfall energy. The soil porosity is then converted into soil bulk density. The rainfall energy is obtained from rainfall intensities and duration (Wischmeier & Smith,

Table 2.4: Drivers and properties to simulate different N processes in different SOM model [1]

Process	CENTURY	RZWQM2	DNDC	Daisy	EPIC	CropSyst	DSSAT	STICS	DAYCENT	EXPERT-N (sub model)	LPJ-GUESS
Addition											
Mineral fertilizer	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud Mt	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Cgs
Organic fertilizer	Ud/Cgs	Ud/Cgs	Ud Mt	Ud Mt	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Ud/Cgs	Cgs
N_2 fixation	Cnf	Cnf	–	Cnf	Cgs Sm Sn	Cgs Sm Sn St	–	Cnf	Cnf	–	We
Residue input	Mt	Mt Mtd	Mt Mtd	Mt Mtd	Mt Mtd	Mt Mtd	Mt Mtd	Mt Mtd	Mt Mtd	–	Mr
Losses											
Volatilization	-	Snh St Ww	Snh Sm Sec Sph St Stx	Mfp	Sec Sm Snh Sph St Sw	Sec Snh Sph	Sec Snh Sph St	-	-	(Snh Sm)	-
Denitrification	Mu	Slc Sm Smi Sno So Sph St	Slc Sm Smi Sno So Sph St	Slc Sm Sno So St	Slc Sm Sno So St	Slc Sm Sno So St	Slc Sm Sno So St	Sbd Sm Sno So St	Slc Sm Sno So St	Slc Sm Sno So St	-
Plant uptake	–	Cgs Cnx Crl Snh Sno We	Cgs Ct Snh Sno	Cnx Crl Snh Sno	Cgs Cur Sm Sno	Cnx Crl Crr Cur Snh Sno St	Cgs Crl Sm Snh Sno	Cac Cgs Crd Sn Snh Sno	–	Cgs Ct Cur Snh Sno	Cgs Crl Sn Snh Sno St
Leaching	Sfc Sm Sn Snh Sno Sst Stx Swp	Sk Sm Smp Sno Sp	Sec Sfc Sk Sm Sno Sst Swp	Sec Sk Sm Smp Sno Sp	Sfc Sk Sm Snh Sno Sp Sst Stx Swp	Sfc Sk Sm Sno Sp Sst/Smp Swp	Sfc Sk Sm Sno Sst Swp	Sfc Sm Sno Sst Swp Sfc Sk Sm Sno Sst/ Smp Swp	Sk Sm Smp Snh Sno Sp (Sfc Sim Sst Swp)	Sfc Sm Sn Snh Sno Sst Stxt Swp	
Erosion	Mc Mer Som Stx Str Tsl Tst Wri	–	Mc Mer Som Stx Str Tsl Tst Wra Smp	–	Mc Mer Som Stx Str Tsl Tst Wri/Wra Smp	Mc Mer Som Stx Str Tsl Tst Wri	–	–	Mc Mer Som Stx Str Tsl Tst Wri	–	–
Internal processes											
Nitrification	–	Sm Smi Snh So Sph	Sm Smi Snh So Sph St	Snh Sm So St	Sec Sm Snh So Sph St	Sm Snh So St	Sm Snh So Sph	Sm Snh So Sph	Sfm Sm Snh So Sph St	Sec Sm Snh So (Sph) T	Sfm
Mineralization	Scn Sm St Stx	Scn Sm Smi Sph St	Scn Sm St	Scn Sm St Stx	Sbd Scn Sm St Stx	Scn Stx	Scn Sm St(Stx)	Scn Sm St Stx	Scn Sm St Stx	Scn Sm St (Stx)	Scn Sm St Stx
Immobilization	Scn	Scn	–	Scn	Scn	Scn	Scn	Scn	Scn	Scn	Scn
Number of SOM pools	4	3	3	5	3	1/4	4/3	2	4	2/3/5	4

[1] Abbreviations:

Weather We: evapotranspiration; Wra: rainfall amount; Wri: rainfall intensity; Ww: wind speed.

Soil physical properties Sbd: bulk density; Sfc: field capacity; Sk: hydraulic conductivity; Smp: matrix potential; Sp: porosity; Sst: saturation; St; temperature; Str: structure; Stx: texture; Swp: wilting point.

Soil chemical properties Scn: C:N ratio; Sec: CEC; Sfm: fraction mineralization; Slc: Labile C; Sn: N in soil organic matter; Snh: NH4+; Sno: NO3; Som; soil organic matter; Sph: pH; Sr: residual N

Soil other properties Sm: moisture; Smi: microbial activity; So: oxygen.

Management: Mc: soil cover; Mer: Erosion reduction measures; Mf: fertilization; Mfp: proportion of mineral N in fertilizer; Mt: tillage; Mtd: tillage depth; Mr: fixed proportion of residue is left on the field; Mu; function of remaining mineral N after uptake.

Crop Cac: intrinsic adsorption capacity; Cgs: growth stage; Cnf: N-fixation of N stress occurs; Cnx: Maximum N concentration in the plant; Crl: root length density; Crr: root radius; Ct: transpiration; Cur: water use rate.

Topography Tsl: Slope length; Tst: Slope steepness.

Other: Ud: User defined.

1958) and is corrected for surface residues. In EPIC, the settling of the soil depends on the percolation/infiltration rate into the layer and its sand content. Near the surface, soils with high sand content will settle much faster than soils that are low in sand content, especially in low rainfall areas. In DSSAT, the soil settles depending on the amount of rainfall and the kinetic rainfall energy, which decreases per soil depth. Additionally, there is a modification factor for the soil cover and aggregate stability; the soil cover and stable aggregates will result in a relative slower settling of the soil than when there is no soil cover or instable aggregates.

Tillage effects on N_2O emissions in the models

Tillage has different effects on soil N dynamics -and therefore N_2O emissions- in the models (Table 2.6). RZWQM2 is the only model that-except for erosion- simulates all N processes explicitly -including N_2O losses during nitrification and denitrification- and the direct and indirect effects of tillage on its processes. Some other models simulate all N processes explicitly but are less detailed on tillage effects on the processes (CropSyst, EXPERT-N), or are detailed in tillage effects, but to a lesser extent in the N processes (EPIC and DSSAT). Moreover, not all models simulate N_2O emissions specifically, but simulate a combined flux with N_2 and/or NO, or do not simulate the fluxes at all.

In the models where the mineralization rate of different pools is directly increased for a certain time (LPJ-GUESS, DAYCENT and CropSyst), the inorganic N pool is increased as a consequence of tillage. The inorganic N pool is then subject to losses. In CropSyst and DAYCENT the losses as N_2O emissions are explicitly modelled. In LPJ-GUESS the gaseous losses of N are not quantified, therefore the effect of tillage on N_2O emissions cannot be quantified. In Daisy and EXPERT-N, tillage only has indirect effects on the N processes. The incorporation of residues combined with the mixing of soil layers changes the amount of organic N in the layers and the C:N ratio of different SOM pools. Additionally, averaging the soil properties within the tillage depth resulting from tillage, changes the rate of N processes due to a change in e.g., soil moisture and soil temperature, which are important drivers of N processes. In Daisy, a change in N processes will lead to a change in the combined losses of N_2O+N_2, whereas in EXPERT-N the N_2O emissions can be modelled explicitly. The mixing of soil properties and residues also affects the rate of different N processes in DNDC. In this model and in CENTURY, also a direct change in the mineralization rate of the different SOM pools is included as an effect of tillage. The direct increase of the mineralization rate will increase the inorganic N pool, which means that more N is subject to losses or further transformations, including N_2O emission by nitrification and denitrification. Since the model simulates N_2O fluxes explicitly, the change in N processes directly translates into changes in N_2O emissions. In CENTURY, the increased inorganic N pool can be subject to losses.

Table 2.5: Nitrogen products of the different processes distinguished by different SOM models. Some models distinguish products (indicated with a comma), whereas others do not (indicated with a plus).

Process	CENTURY	RZWQM2	DNDC	Daisy	EPIC	CropSyst	DSSAT	STICS	DAYCENT	EXPERT-N (sub model)	LPJ-GUESS
Losses											
Denitrification	Total N	NO,N_2O,N_2	NO,N_2O,N_2	N_2+N_2O	N_2+N_2O	NO,N_2O,N_2	$NO+N_2O+N_2$	N_2O,N_2	NO_3^-,N_2O,N_2, NO	N_2O,N_2 $(NO+N_2O+N_2)$	–
Leaching	$NH_4^++NO_3^-$, organic N	NO_3^-	NO_3^-	NO_3^-,NH_4^+	NO_3^-	NO_3^-	NO_3^-	NO_3^-	NO_3^-	NO_3^-,NH_4^+	$NH_4^++NO_3^-$, organic N
Internal processes											
Nitrification	–	NO_3^-,N_2O	NO_3^-,N_2O	NO_3^-,N_2O	NO_3^-	NO_3^-,N_2O	NO_3^-	NO_3^-,N_2O	NO_3^-,N_2O	NO_3^-,N_2O	Total N
Mineralization	$NO_3^-+NH_4^+$	$NO_3^-+NH_4^+$	NH_4^+	NH_4^+	$NO_3^-+NH_4^+$	NH_4^+	$NO_3^-+NH_4^+$	$NO_3^-+NH_4^+$	$NO_3^-+NH_4^+$	NH_4^+	$NO_3^-+NH_4^+$

Table 2.6: The directly and indirectly affected properties and processes in the models through tillage. Tillage either directly increases the mineralization rate, or has an indirect effect on N processes through direct effects on soil properties through mixing of soil layers/affecting the hydraulic properties. Crosses (X) indicate that the soil property is affected by tillage in the particular model.

Model	Mixing of soil layers	Bulk density	Hydraulic conductivity	Porosity	Water potential	Differentiation of N emissions
CENTURY	X					Total N
RZWQM2	X	X	X	X	X	N_2O
DNDC	X					N_2O
Daisy	X					N_2O+N_2
EPIC	X	X				N_2O+N_2
CropSyst						N_2O
DSSAT	X	X	X	X		$NO+N_2O+N_2$
STICS	X	X				N_2O
DAYCENT						N_2O
EXPERT-N	X					N_2O $(NO+N_2O+N_2)$[1]
LPJ GUESS						Total N

[1] The N-emissions only apply to specific sub-models

However, as in LPJ-GUESS, the gaseous losses of N are not quantified; therefore, the effect of tillage on N_2O emissions cannot be quantified. In the models where the soil properties are directly and indirectly affected resulting from tillage, a change in the soil moisture and soil temperature can be expected, as well as the N content and C:N ratios in the soil profile. In STICS and RZWQM2, these changes affect different N processes and therefore directly N_2O emissions; in these models the N_2O emissions are modelled explicitly. In EPIC and DSSAT these changes lead to a change in the combined losses of N_2O+N_2 (EPIC) and N_2O+N_2+NO (DSSAT). The tillage effects on the N processes and thus N_2O emissions decrease eventually due to soil reconsolidation.

2.3.2.3 Data requirements and availability (Step 2.3)

Tillage effects on N_2O emissions at the global scale can only be evaluated when the data required to simulate the processes are available at the global scale. In this step, we analyze which data are required to drive the simulations of different processes and an example of which data are available at the global scale is provided (Table 2.7). Data are required on environmental properties that affect the different N processes as well as management related data. Some data on properties and drivers can be supplied by endogenous computations, while others have to be supplied from external sources. The drivers and properties that are usually computed endogenously are those that are often dynamic, such as soil water content and temperature, but also other properties for which modelling capacities exist, but only sparse measurements, such as OM pools or vegetation structure and productivity. External datasets are typically needed for relatively static physical properties such as soil texture, chemical properties that cannot be modelled well, such as pH and CEC, and weather- and management related data. Most of these data can be measured in the field. However, at the global scale, we need to rely on external datasets. The management related data that are required include data on fertilizer input of organic and inorganic N forms (amount and timing), residue input, land-use, and soil management (e.g., tillage).

Most global ecosystem models work on a spatial resolution of 0.5° and a temporal resolution of one day, although finer spatial and temporal resolutions are also applied in global-scale models. Ideally, input data are available at the same spatial resolution as the model simulation, but are often aggregated or interpolated to match the model simulation's spatial and temporal resolution. Interpolation can be as simplistic as assuming static conditions, e.g., when only a single temporal snapshot is available, employ inter- and extrapolation methods or can be model assisted as e.g., in the case of weather reanalysis data. Aggregation and interpolation (or any other scaling method) is a potential source of uncertainty (Ewert et al., 2011). This is especially the case for modelling erosion. Here, information on slope steepness is needed for which static global datasets are available which would need to be aggregated to meet the spatial resolution of a 0.5°. In this case, aggregation can lead to an underestimation of slope steepness and therefore erosion.

In the absence of data, simulations can be conducted for scenario assumptions (e.g., for crop residue exports and intercrops, see Bondeau et al., 2007). Besides driving data, models need to be parametrized and evaluated. Typically, there are no good evaluation data sets available at the global scale, so that global-scale simulations need to be compared at reference sites where measurements for the comparison are available or indirectly for their effects on recorded properties, such as national yield statistics (Müller et al., 2017; Schaphoff et al., 2018a). Model parameters typically need to be taken from smaller scales for which the models have been developed, but can be calibrated if global effects do not match observational evidence.

2.3.3 Evaluation of modelling tillage and N_2O emission at the global scale (step 3)

All primary, as well as the important tillage-affected secondary processes are described in most of the models reviewed here (Table 2.4). These processes are modelled in relative simplistic (e.g., a ratio of another process) or more detailed approaches, in which different drivers of the processes are taken into account. This provides a sufficiently diverse basis for selecting the most suitable approaches needed to resolve the most important processes in a consistent manner in existing models. The most important caveat in the combination of different approaches from existing models is to avoid inconsistencies or redundancies,

Table 2.7: Example of the data requirement and availability at the global scale to describe the different processes, including the spatial and temporal resolution. The drivers and properties that are usually computed endogenously are indicated with a dash. There are many data sets for weather/climate data, for which we only list a representative example [1].

Drivers	Available data set	Spatial resolution	Temporal resolution
Physical properties (Sp, Sbd, Stx)	Batjes et al. (2017)	30 arcsec	Static
Other physical properties (St, Sfc, Swp, Sst, Sk, Smp, Sm)	–	–	–
Chemical properties (Sph, Sec)	Batjes et al. (2017)	30 arcsec	Static
Other chemical properties (Scn, Slc, Sno, Snh, Som)	Stoorvogel et al. (2017)	–	–
Microbial activity	–	–	–
Plant demand/supply (Cgs, Cnx, Cur Ct, Crr, Crl)	–	–	–
Weather/climate data			
Observational (weather stations)	Menne et al. (2012)		Daily
Observational data set	Harris et al. (2014)	0.5 degree	Monthly
Reanalysis	Berrisford et al. (2009)	0.7 degree	6-hourly
Climate scenarios	Taylor et al. (2012)	various, typically requires bias-correction to a finer-scaled reference data set, e.g., at 0.5 degree (e.g., Hempel et al. 2013)	3-hourly/coarser
Rainfall intensity	NA	NA	NA
Input/management related			
Fertilization (organic and inorganic)	Potter et al. (2010)	0.5 degree and 5 arcmin	static
Fertilization (tillage type and tillage depth)	NA	NA	NA
Residue input (tillage type and tillage depth)	NA	NA	NA
N_2 fixation	You et al. (2014)	5 arcmin	Static
Soil cover	NA	NA	NA
Erosion reduction measures	NA	NA	NA
Topography			
Slope length	NA	NA	NA
Slope steepness	WorldDEM	1 arcsec	Static

[1] Abbreviations:
Soil physical properties: Sbd : bulk density; Sfc : field capacity; Sk: hydraulic conductivity; Sm: moisture; Smp: matrix potential; Sp: porosity; Sst: saturation; St: Soil temperature; Stx: texture; Swp: wilting point.
Soil chemical properties: $^{-}$Scn: C:N ratio; Sec: CEC; Slc: Labile C; Snh: NH_4^+; Sno: NO_3; Som; soil organic matter; Sph: pH; Crop: Cgs: growth stage; Cnx: Maximum N concentration in the plant; Crl: root length density; Crr: root radius; Ct: transpiration; Cur: water use rate.

in which simpler, aggregated representations may already cover smaller processes. In such cases, a re-parameterization of already implemented processes would be necessary, if new processes would be added explicitly to the model. In all models, tillage has an effect on the N processes in which the mineralization rate is either directly affected, or indirectly through the soil properties which have an effect on the soil moisture and soil temperature of the N processes. Only few models, model the effect of tillage on N_2O emissions explicitly (Table 2.6).

The data that are required to model these processes can partly be met. Static datasets for some chemical properties (e.g., soil pH and CEC) may be acceptable, since tillage does not influence these properties in the analyzed models and these drivers are only taken into account for some of the N processes in some models. However, some of the physical properties (e.g., porosity and bulk density) may have to be endogenized by the models rather than treated as an external input, because tillage directly affects these properties. Therefore, the static values of the external databases can serve for model initialization or reference data.

The required data for modelling erosion cannot be met. Management and topography related data as well as data on rainfall intensity is lacking. Moreover, modelling erosion requires a very high spatial and temporal resolution, given that it is typically a quick and small-scale process. Naipal et al. (2015) improved the global applicability of the RUSLE model for modelling erosion by adjusting the topographical and rainfall erosivity factors. The topographical factor was adjusted by scaling the slope according to the fractal method whereas the rainfall erosivity factor was adjusted by applying a linear multiple regression method for various climate zones. Panagos et al. (2017) developed a global rainfall erosivity map at 30 arc seconds based on a Gaussian Process Regression, which can be used as the erosivity factor in the RUSLE model. However, for modelling erosion, high resolution data on slope length and the other RUSLE factors is lacking.

The required management related data (except for tillage and erosion), are also partly available (e.g., fertilizer input). These datasets are available at sufficiently fine spatial resolution but often only as static datasets with no information on sub-annual distributions. However, fertilizer inputs for example, are mostly applied more often throughout a growing season. Therefore, a dynamic dataset could give a better indication on when and how often fertilizers are being applied (Hutchings et al., 2012). For tillage and crop residue incorporation there are currently no spatial- and temporal explicit datasets available. This means that tillage can be implemented in a global ecosystem model for the analysis of how different tillage options affect agricultural N_2O emissions. However, since we lack spatial explicit datasets on tillage practices, this analysis can only be conducted in a scenario-based setting.

2.4 Discussion

The models that have been analyzed vary in the amount of processes that are taken into account and the detail in representation of processes (Table 2.4). As mentioned previously, some models include most processes explicitly, but are less detailed on the tillage effects on those processes (CropSyst, EXPERT-N), whereas some models are detailed in tillage effects, but to a lesser extent on the N-processes (EPIC and DSSAT), or cannot simulate N_2O emissions specifically. Depending on the research question, the availability of data for parameterization and model performance, some models might be more suitable to apply than others. Models that simulate certain processes more detailed are often more suitable for questions related to scientific understanding, as they can be used as tools to address research questions about control of processes, magnitude of responses and interactions (Jones et al., 2017). However, an increase in detail typically requires a larger number of parameters, which may be unknown or only known with relatively large uncertainties. As there is a tradeoff between detailed process representation and model parametrization, it is unclear what level of detail is the best for global-scale application.

A general recommendation on which model process description to choose for the implementation of individual processes cannot be provided as this depends on the current implementation of other processes in the model that is to be extended. The new implementation will have to be tested and evaluated in the model-specific and research-question specific context. Combining different processes described in models can yield inconsistencies and the individual processes of the models are typically not validated. Moreover, although the data requirements are generally met, the quality of the data is unknown or known to be poor (see e.g., Grassini et al., 2015). Model performance can only be tested against site measurements (as global measurements are lacking) and these should ideally span a broad range of environmental conditions (i.e., Jin et al., 2017; Lognoul et al., 2017; Mei et al., 2018; Van Kessel et al., 2012). This can be challenging as there is an enormous temporal and spatial variability in N_2O emissions (Butterbach-Bahl et al., 2013). Given this variability, model evaluation should be conducted at different scales, which will be a learning process that we need to engage in.

Most of the analyzed crop models have been developed for field−scale application, with processes usually simulated at daily resolution. When models (or modelling approaches) are applied at larger spatial or temporal scales, scaling to the new level of application is required. This can include modifications of input data, parameters and model simplifications (Ewert et al., 2006). The degree of how much data, parameters and models need to be modified, also depends on the research objective, the available data and what can be done regarding data and model uncertainties. Here, we are interested in tillage effects on N_2O emissions at the global spatial scale. Since we are interested in N_2O mitigation, and therefore rather a long-term research study, the temporal scale should be focused on the long-term, i.e. multiple years and decades. With respect to the modification of data and parameters, several methods can be distinguished depending on whether data manipulation refers to changes in extent, coverage or resolution (Hatfield, 2001). In Ewert et al. (2011) different scaling methods are proposed for data (input and output) and models (e.g., model parameters and model structure). In case input or output data are not matching the spatial resolution of the model simulation, aggregation (averaging) or disaggregation can be considered.

Model simplifications may be needed since large-scale model application can be resource-intensive (computational time). Model simplifications can be done by considering only those processes that matter at the global scale (as described before) and selecting an appropriate level of detail for each N process (Adam et al., 2011; Ewert et al., 2011).

Here we followed an evaluation scheme on assessing the feasibility of incorporating tillage in global ecosystem models. This method opens opportunities of incorporating and analyzing other management aspects GHG emissions at the global scale instead of working with static GHG emission factors. However, the method is limited due to several reasons. First of all, it does not provide a standard procedure for the evaluation of the performance of the processes described in models individually as well as within the global ecosystem model into which management is incorporated. Although standard evaluation procedures are not provided, evaluating the model performance can always be conducted against available data (e.g. Kelley et al., 2013; Müller et al., 2017; Schaphoff et al., 2018a).

Only a selected set of models are analyzed that should both cover N processes and tillage effects. This may have resulted in excluding models that can describe only one of the aspects well, e.g., only tillage effects on soil properties, but do not describe N processes. Additionally, the analyzed models do not always provide a full model documentation which hampers the analysis. The available documentation of individual models is mostly scattered over different articles. Full model documentations could better support information discovery and/or prevent the use of outdated information about the described processes.

The analysis on data availability does not give insight on the quality of the data. A sensitivity analysis can be conducted in order to assess the relative contribution of the inputs variables and parameters on the model outputs (see also Campolongo & Braddock, 1999; Moreau et al., 2013). Inputs that make relatively high contribution to model outputs would require relatively higher quality data, and constraints on input data quality should be considered in the interpretation of model results.

2.5 Conclusions

We studied how tillage can be implemented in global ecosystem models for the analysis of N_2O emissions from agricultural production. Existing field-scale modeling approaches on soil nitrogen dynamics and on the effects of tillage facilitate this implementation in general. However, the suitability and validity of individual processes described in models is often not evaluated and will have to be tested within the new global framework. Scaling issues for processes and data availability will have to be addressed. Data scarcity, especially on management-related data, will only allow for scenario-based analyses. We followed an evaluation scheme for assessing options for the inclusion of tillage-related processes into global ecosystem models, which could also be employed for other management aspects. We find that there are ample options to implement tillage and soil nitrogen dynamics in sufficient detail in global-scale ecosystem models. A general recommendation on what modeling approach to use is not possible, as this depends on what processes are already covered in the model that is to be extended, and tradeoffs in data availability vs. quality vs. uncertainty in model parametrization need to be considered. However, agricultural management should be better represented in global-scale ecosystem models (McDermid et al., 2017) and the formal procedure described here can help in selecting suitable options. Such better model representation can open opportunities to evaluate agricultural-based mitigation strategies, such as climate smart agriculture (Lipper et al., 2014) with global ecosystem models.

Chapter 3

Simulating and evaluating effects of tillage at the global scale

This chapter is based on:

Lutz* F, Herzfeld* T, Heinke J, Rolinski S, Schaphoff S, Bloh W von, Stoorvogel J. J., Müller C., Simulating the effect of tillage practices with the global ecosystem model LPJmL (version 5.0-tillage). Geoscientific Model Development. 12, 2419–2440, 2019

*these authors contributed equally.

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 paper, 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-analysis on tillage effects. In general, the model is able to reproduce observed tillage effects on global, as well as regional patterns of carbon and water fluxes. However, modelled N-fluxes deviate from the literature and need further study. The addition of the tillage module to LPJmL5 opens opportunities to assess the impact of agricultural soil management practices under different scenarios with implications for agricultural productivity, carbon sequestration, greenhouse gas emissions and other environmental indicators.

3.1 Introduction

Agricultural fields are tilled for various purposes, including seedbed preparation, incorporation of residues and fertilizers, water management and weed control. Tillage affects a variety of biophysical processes that affect the environment, such as greenhouse gas emissions or soil carbon sequestration and can influence various forms of soil degradation (e.g. wind-, water- and tillage-erosion Armand et al., 2009; Govers et al., 1994; Holland, 2004). Reduced-tillage or no-till is being promoted as a strategy to mitigate greenhouse gas (GHG) emissions in the agricultural sector (Six et al., 2004; Smith et al., 2008). However, there is an ongoing long-lasting debate about tillage and no-till effects on soil organic carbon (SOC) and GHG emissions (e.g. Lugato et al., 2018). In general, reduced-tillage and no-till tend to increase SOC storage through a reduced decomposition and consequently reduces GHG emissions (Chen et al., 2009; Willekens et al., 2014). However, discrepancies exist on the effectiveness of reduced tillage or no-till on GHG emissions. For instance, Abdalla et al. (2016) found in a meta-analyses that on average no-till systems reduce CO_2 emissions by 21% compared to conventional tillage, whereas Oorts et al. (2007) found that CO_2 emissions from no-till systems increased by 13% compared to conventional tillage, and Aslam et al. (2000) found only minor differences in CO_2 emissions. These discrepancies are not surprising as tillage affects a complex set of biophysical factors, such as soil moisture and soil temperature (Snyder et al., 2009), which drive several soil processes, including the carbon and nitrogen dynamics, and crop performance. Moreover, other factors such as management practices (e.g. fertilizer application and residue management) and climatic conditions have been shown to be important confounding factors (Abdalla et al., 2016; Oorts et al., 2007; Van Kessel et al., 2013). For instance Oorts et al. (2007) attributed the higher CO_2 emissions under no-till to higher soil moisture and decomposition of crop litter on top of the soil. Van Kessel et al. (2013) found that N_2O emissions were smaller under no-till in dry climates and that the depth of fertilizer application was important. Finally, Abdalla et al. (2016) found that no-till effects on CO_2 emissions are most effective in dryland soils.

In order to upscale this complexity and to study the role of tillage for global biogeochemical cycles, crop performance and mitigation practices, the effects of tillage on soil properties need to be represented in global ecosystem models. Although tillage is already implemented in other ecosystem models in different levels of complexity (Lutz et al., 2019b; Maharjan et al., 2018), tillage practices are currently underrepresented in global ecosystem models that are used for biogeochemical assessments. In these, the effects of tillage are either ignored, or represented by a simple scaling factor of decomposition rates. Global ecosystem models that ignore the effects of tillage include for example JULES (Best et al., 2011; Clark et al., 2011), the Community Land Model (Levis et al., 2014; Oleson et al., 2010) PROMET (Mauser & Bach, 2009) and the Dynamic Land Ecosystem Model (DLEM) (Tian et al., 2010). The models in which the effects of tillage are represented as an increase in decomposition include LPJ-GUESS (Olin et al., 2015a; Pugh et al., 2015) and ORCHIDEE-STICS (Ciais et al., 2011).

The objective of this paper is to 1) extend the Lund Potsdam Jena managed Land (LPJmL5) model (Von Bloh et al., 2018b), so that the effects of tillage on biophysical processes and global biogeochemistry can be represented and studied and 2) evaluate the extended model against data reported in meta-analyses by using a set of stylized management scenarios. This extended model version allows for quantifying the effects of different tillage practices on biogeochemical cycles, crop performance and for assessing questions related to agricultural mitigation practices. Despite uncertainties in the formalization and parameterization of processes, the processed-based representation allows for enhancing our understanding of the complex response patterns as individual effects and feedbacks can be isolated or disabled to understand their importance. To our knowledge, some 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, but models used to study the global biogeochemistry (Friend et al., 2014) have no or only very coarse representations of tillage effects.

3.2 Tillage effects on soil processes

Tillage affects different soil properties and soil processes, resulting in a complex system with various feedbacks on soil water, temperature, carbon (C) and nitrogen (N) related processes (Fig. 3.1). The effect of tillage has to be implemented and analyzed in conjunction with residue management as these management practices are often inter-related (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 bulk density of this layer [3] (Green et al., 2003). An increase in SOM positively affects the porosity [4] and therefore the soil water holding capacity (*whc*) [5] (Minasny & McBratney, 2018). Tillage also affects the *whc* by increasing porosity [6] (Glab & 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 & Weil, 2008). Soil moisture affects primary production as it determines the amount of water which 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 & 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, 2008; Ranaivoson et al., 2017). Surface litter also reduces the amplitude of variations in soil temperature [17] (Enrique et al., 1999; Steinbach & 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 & 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 or mineral N forms are explicitly represented in the model (Von Bloh et al., 2018b). The degree to which soil properties and processes are affected by tillage mainly depends on the tillage intensity, which is a combination of tillage efficiency and mixing efficiency (in detail explained in chapter 3.3.2 and 3.3.5.2). Tillage has a direct effect on the bulk density 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).

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, arrow 1 and following arrows), 2) the decrease in bulk density and the subsequent effects of changed soil water properties (Fig. 3.1, e.g. arrow 3 and following arrows). In order 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.

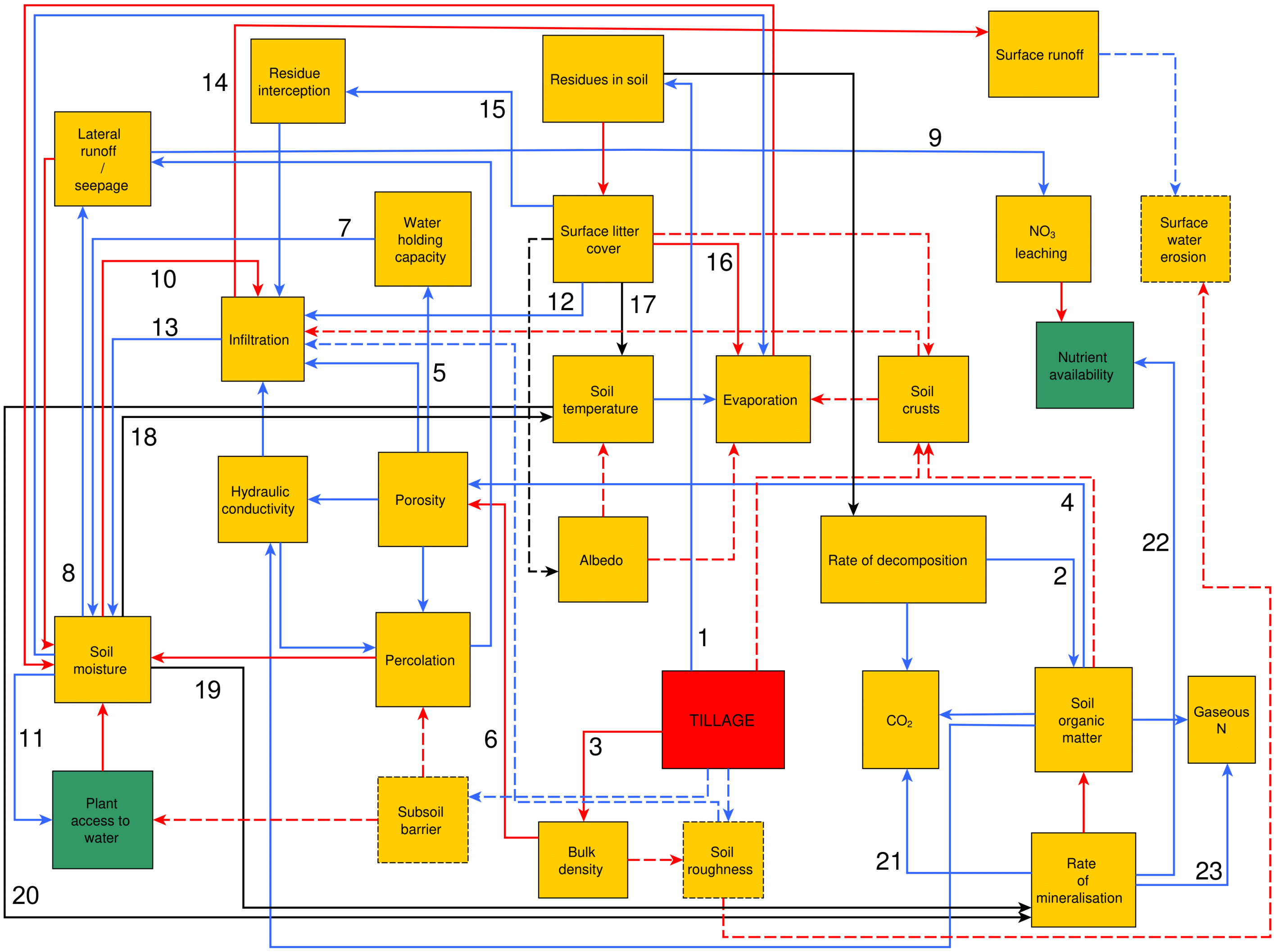


Figure 3.1: Flow chart diagram of feedback processes caused by tillage, which are considered (solid lines) and not considered (dashed lines) in this implementation in LPJmL5.0-tillage. Blue lines highlight positive feedbacks, red negative, and black are ambiguous feedbacks. The numbers in the figure indicate the processes described in Sect. 3.2.

3.3 Implementation of tillage routines into LPJmL

3.3.1 LPJmL model description

The tillage implementation described in this paper was introduced into the dynamical 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; Von Bloh et al., 2018a). 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 rain water 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, 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. (2018a) 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. A.3.1A in Appendix A). The fraction of litter which is harvested from the field can range between almost fully harvested or none, 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., 2018a). 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). Soils in LPJmL5 are represented by five hydrologically active layers, each with a distinct layer thickness. The first soil layer, which is mostly affected by tillage, is 0.2 m thick. The following soil layers are 0.3, 0.5, 1.0 and 1.0 m thick, respectively, followed by a 10.0 m bedrock layer, which serves as a heat reservoir in the computation of soil temperatures (Schaphoff et al., 2013).

LPJmL5 has been evaluated extensively and demonstrated good skills in reproducing C, water, and N fluxes in both agricultural and natural vegetation on various scales (Von Bloh et al., 2018a; Schaphoff et al., 2018a).

3.3.2 Litter pools and decomposition

In order to address the residue management effects of tillage, the original above-ground litter pool is now separated into an incorporated litter pool ($C_{litter,inc}$) and a surface litter pool ($C_{litter,surf}$) for carbon, and the corresponding pools ($N_{litter,inc}$) and ($N_{litter,surf}$) for nitrogen (Fig. A.3.1B in Appendix A). Crop residues not collected 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;

$$C_{litter,inc,t+1} = C_{litter,inc,t} + C_{litter,surf,t} * TL, \text{for carbon , and} \tag{3.1a}$$

$$N_{litter,inc,t+1} = N_{litter,inc,t} + N_{litter,surf,t} * TL, \text{for nitrogen.} \tag{3.1b}$$

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

$$C_{litter,surf,t+1} = C_{litter,surf,t} * 1 - TL, \tag{3.2a}$$

$$N_{litter,surf,t+1} = N_{litter,surf,t} * 1 - TL, \tag{3.2b}$$

where $C_{litter,inc}$ and $N_{litter,inc}$ is the amount of incorporated surface litter C and N in g m^{-2} at time step t (days). The parameter TL is the tillage efficiency, which determines the fraction of residues that is incorporated by tillage (0-1). To account for the vertical displacement of litter through bioturbation under natural vegetation and under no-till conditions, 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%).

The litter pools are subject to decomposition. The decomposition of litter depends on the temperature and moisture of its 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., 2018a), whereas the decomposition of the surface litter pools depends on the litter's moisture and temperature, 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 "plant functional type" (PFT), following Sitch et al. (2003);

$$rdecom_{(PFT)} = 1 - exp\left(\frac{-1}{\tau_{10}(PFT)} * g(T_{surf}) * F(\theta)\right), \tag{3.3}$$

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

$$F(\theta) = 0.0402 - 5.005 * \theta^3 + 4.269 * \theta^2 + 0.7189 * \theta, \tag{3.4}$$

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

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

$$g(T_{surf}) = exp\left(308.56 * \left(\frac{1}{66.02} - \frac{1}{T_{(surf+56.02)}})\right)\right), \tag{3.5}$$

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

A fixed fraction (70%) of the decomposed $C_{litter,surf}$ is mineralized, i.e., emitted as CO_2, whereas the remaining humified C is transferred to the soil C pools, where it is then subject to the soil decomposition rules as described by Von Bloh et al. (2018a) 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., 2018a), 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. In order to maintain the desired C:N ratio of 15 within the soil (Von Bloh et al., 2018a), the mineralized N is subject to microbial immobilization, i.e., the transformation of mineral N to organic N directly reverting some of the N mineralization in the soil.

The presence of surface litter influences the soil water fluxes and soil temperature of the soil (see 3.3.3 and 3.3.4), and therefore affects the decomposition of the soil carbon and nitrogen pools, including the transformations of mineral N forms. Nitrogen fluxes such as N_2O from nitrification and denitrification for instance, are partly driven by soil moisture (Von Bloh et al., 2018a):

$$F_{N_2O,nitrification,l} = K_2 * K_{max} * F_1(T_l) * F_1(W_{sat,l}) * F(pH) * NH^+_{4,l} \text{for nitrification, and} \tag{3.6a}$$

$$F_{N_2O,nitrification,l} = r_{mx2} * F_2(W_{sat,l}) * F_2(T_l, C_{org}) * NO^-_3 \text{for denitrification.} \tag{3.6b}$$

Where $F_{N_2O,nitrification,l}$ and $F_{N_2O,nitrification,l}$ are the N_2O flux related to nitrification and denitrification respectively in g N m^{-2} d^{-1} in layer l. K_2 is the fraction of nitrified N lost as N_2O (K_2=0.02),K_{max} is the maximum nitrification rate of $NH_4{}^+$ (K_{max}=0.1 d^{-1}). $F_1(T_l)$, $F_1(W_{sat,l})$, are response functions of soil temperature and 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 g N m^{-2} respectively. $F_2(T_l,C_{org})$, $F_2(W_{sat,l})$ are reaction for soil temperature, soil carbon and water saturation and r_{mx2} is the fraction of denitrified N lost as N_2O (11%, the remainder is lost as N_2). For a detailed description of the N related processes implemented in LPJmL, we refer to Von Bloh et al. (2018a).

3.3.3 Water fluxes

3.3.3.1 Litter interception

Precipitation and applied irrigation water in LPJmL5 is partitioned into interception, transpiration, soil evaporation, soil moisture and runoff (Jägermeyr et al., 2015). To account for the interception and evaporation of water by surface litter, the water can now also be captured by surface litter through litter interception (I_{surf}) and be lost through litter evaporation, subsequently infiltrates into the soil and/or forms surface runoff. Litter moisture (θ) is calculated in the following way:

$$\theta_{(t+1)} = \min(whc_{surf} - \theta_t, I_{surf} * f_{surf}). \tag{3.7}$$

f_{surf} is calculated by adapting the equation from Gregory (1982) that relates the amount of surface litter (dry matter) per m^2 to the fraction of soil covered;

$$f_{surf} = 1 - exp^{-A_m * OM_{litter,surf}}, \tag{3.8}$$

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 mass of crop specific residue (m^2 g^-1). The total mass of surface litter is calculated assuming a fixed C to organic matter ratio of 2.38 ($CF_{OM,litter}$), based on the assumption that 42% of the organic matter is C, as suggested by Brady & Weil (2008):

$$OM_{litter,surf} = C_{litter,surf} * CF_{OM,litter}, \tag{3.9}$$

where $C_{litter,surf}$ is the amount of C stored in the surface litter pool in g C m^{-2}. We apply the average value of 0.006 for A_m from Gregory (1982) to all materials, neglecting variations in surface litter for different materials. whc_{surf} (mm) is the water holding capacity of the surface litter and is calculated by multiplying the litter mass with a conversion factor of 2 10^{-3} mm kg^{-1} ($OM_{litter,surf}$) following Enrique et al. (1999).

3.3.3.2 Soil infiltration

The presence of surface litter enhances infiltration of precipitation or irrigation water into the soil, as soil crusting is reduced and preferential pathways are affected (Ranaivoson et al., 2017). In order to account for improved infiltration with the presence of surface litter, we follow the approach by Jägermeyr et al. (2016), which has been developed for implementing in situ water harvesting, e.g. by mulching in LPJmL. The infiltration rate (In in mm d^{-1}) depends on the soil water content of the first layer and the infiltration parameter p;

$$In = prir * \sqrt[p]{1 - \frac{W_a}{W_{sat,l=1} - W_{pwp,l=1}}} \tag{3.10}$$

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) by Jägermeyr et al. (2016), in order to account for increased infiltration based on the management intervention. To account for the effects of surface litter, we here scale the infiltration parameter p between 2 and 6, based on the fraction of surface litter cover (f_{surf});

$$p = 2 * (1 + f_{surf} * 2) \tag{3.11}$$

Surplus water that cannot infiltrate forms surface runoff and enters the river system.

3.3.3.3 Litter and soil evaporation

Evaporation (E_{surf},in mm) from the surface litter cover (f_{surf}), is calculated in a similar manner as evaporation from the first soil layer (Schaphoff et al., 2018a). Evaporation depends on the vegetation cover (f_v), the radiation energy for the evaporization of water (PET) and the water stored in the surface litter that is available to evaporate (ω_{evap}) relative to whc_{surf}. Here, also f_{surf} is taken into account so that the fraction of soil uncovered is subject to soil evaporation as described in Schaphoff et al. (2018a);

$$E_{surf} = PET * \alpha * \max(1 - f_v, 0.05) * \omega_{surf}^2 * f_{surf}, \tag{3.12}$$

$$\omega_{surf} = \frac{\theta}{whc_{surf}}, \tag{3.13}$$

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

The presence of litter at the soil surface reduces the evaporation from the soil (E_{soil}). E_{soil} (mm) corresponds to the soil evaporation as described in Schaphoff et al. (2018a), and depends on the available energy for vaporization of water and the available water in the upper 0.3 m of the soil (ω_{evap}). However, with the implementation of tillage, the fraction of f_{surf} now also influences evaporation, i.e., greater soil cover (f_{surf}) results in a decrease in E_{soil};

$$E_{soil} = PET * \alpha * \max(1 - f_v, 0.05) * \omega^2 * (1 - f_{surf}) \tag{3.14}$$

ω is calculated as the evaporation-available water (ω_{evap}) relative to the water holding capacity in that layer (whc_{evap});

$$\omega = \min(1, \frac{\omega_{evap}}{whc_{evap}}), \tag{3.15}$$

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

3.3.4 Heat flux

The temperature of the surface litter is calculated as the average of 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), in the following way:

$$T_{litter,surf,t+1} = 0.5(T_{air,t+1} + T_{l=1,t}). \tag{3.16}$$

Equation (3.16) is an approximate solution for the heat exchange described by Schaphoff et al. (2013). The new upper boundary condition (T_{upper} in °C) is now calculated by the average of T_{air} and $T_{surfweighted}$ by f_{surf}. With the new boundary condition, the cover of the soil with surface litter diminishes the heat exchange between soil and atmosphere;

$$T_{upper} = T_{air} * (1 - f_{surf}) + T_{surf} * f_{surf}. \tag{3.17}$$

The remainder of the soil temperature computation 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 inputs, computed following the pedotransfer function (PTF) by Cosby et al. (1984). Different methods exist to calculate soil hydraulic properties from soil texture and SOM content for different points of the water retention curve (Balland et al., 2008; Saxton & Rawls, 2006; Wösten et al., 1995) or at continuous pressure levels (Van Genuchten, 1980; Vereecken et al., 2010). Extensive reviews 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). We now introduced an approach following the PTF by Saxton & Rawls (2006), which was included in the model in order to dynamically simulate layer-specific hydraulic parameters that account for the amount of SOM in each layer, constituting an important mechanism of how hydraulic parameters are affected by tillage (Strudley et al., 2008).

As such, Saxton & Rawls (2006) define a PTF most suitable for our needs and capable of calculating all the necessary soil water properties for our approach: it allows for a dynamic effect of SOM on soil hydraulic properties, and is also capable of representing changes in bulk density after tillage and was developed from a large number of data points. With this implementation, soil hydraulic properties are now all updated daily. Following Saxton & Rawls (2006), soil water properties are calculated as:

$$\begin{aligned}\lambda_{(pwp,l)} = {} & -0.024 * Sa + 0.0487 * Cl + 0.006 * SOM_l \\ & + 0.005 * Sa * SOM_l - 0.013 * Cl * SOM_l + 0.068 * Sa * Cl + 0.031, \end{aligned} \tag{3.18}$$

$$W_{pwp,l} = 1.14 * \lambda_{pwp,l} - 0.02, \tag{3.19}$$

$$\begin{aligned}\lambda_{fc,l} = {} & -0.251 * Sa + 0.195 * Cl + 0.011 * SOM_l \\ & + 0.006 * Sa * SOM_l - 0.027 * Cl * SOM_l + 0.452 * Sa * Cl + 0.299, \end{aligned} \tag{3.20}$$

$$W_{fc,l} = 1.238 * (\lambda_{fc,l})^2 \mp 0.626 * \lambda_{fc,l} - 0.015, \tag{3.21}$$

$$\begin{aligned}\lambda_{sat,l} = {} & 0.278 * Sa + 0.034 * Cl + 0.022 * SOM_l \\ & - 0.018 * Sa * SOM_l - 0.027 * Cl * SOM_l - 0.584 * Sa * Cl + 0.078, \end{aligned} \tag{3.22}$$

$$W_{sat,l} = W_{fc,l} + 1.636 * \lambda_{sat,l} - 0.097 * Sa - 0.064, \tag{3.23}$$

$$BD_{soil,l} = (1 - W_{sat,l}) * MD. \tag{3.24}$$

SOM_l is the soil organic matter content in weight percent (%w) of layer l, $\mathrm{W}_{pwp,l}$ is the moisture content at the permanent wilting point, $\mathrm{W}_{fc,l}$ moisture contents at field capacity, $\mathrm{W}_{sat,l}$ 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, following:

$$SOM_l = \frac{CF_{OM,soil} * (C_{fastSoil,l} + C_{slowSoil,l})}{BD_{soil,l} * z_l} * 100, \tag{3.25}$$

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 & Rawls (2006) that the PTF should not be used for SOM content 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 & Rawls (2006) as:

$$K_{S_l} = 1930 * (W_{sat_l} - W_{fc_l})^{3-\phi_l}, \tag{3.26}$$

$$\phi_l = \frac{\ln(W_{fc,l}) - \ln(W_{pwp,l})}{\ln(1500) - \ln(33)}, \tag{3.27}$$

where K_{S_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. K_{S_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:

$$f_{BDtill,t+1} = f_{BDtill,t} - (f_{BDtill,t} - 0.667) * mE. \tag{3.28}$$

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

$$W_{sat,till,l,t+1} = 1 - (1 - W_{sat,l,t}) * f_{BDtill,t+1}, \tag{3.29}$$

$$W_{fc,till,l,t+1} = W_{fc,l,t} - 0.2 * (W_{sat,l,t} - W_{sat,till,l,t+1}), \tag{3.30}$$

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, $\mathrm{W}_{sat,till,l,t+1}$ and $\mathrm{W}_{fc,till,l,t+1}$ are adjusted moisture content at saturation and field capacity after tillage and $\mathrm{W}_{sat,l,t}$ and $\mathrm{W}_{fc,l,t}$ are the moisture content at saturation and field capacity 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:

$$sz = 0.2 * In * \frac{\left(\frac{1+2*Sa}{Sa+\mathrm{e}^{(8.597-0.075*Sa)}}\right)}{z_{till}^{0.6}}, \tag{3.31}$$

$$f = \frac{sz}{sz + \mathrm{e}^{3.92-0.0226*sz}}, \tag{3.32}$$

$$f_{BDtill,t+1} = f_{BDtill,t} + f * (1 - f_{BDtill,t}), \tag{3.33}$$

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 a faster settling of recently tilled soils with high precipitation and for soils with a 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 bulk density 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 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 implication from this, which results in an unfavorable soil particle distribution that can cause a decline in productivity (Daigh & DeJong-Hughes, 2017).

3.4 Model set-up

3.4.1 Model input, initialization, and spin-up

In order to bring vegetation patterns and SOM pools into a dynamic equilibrium stage, we make use of a 5000-year spin-up simulation of only natural vegetation, which recycles the first 30 years of climate input following the procedures of Von Bloh et al. (2018a). 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 land-use change, which is introduced in the year 1700. The spatial resolution of all input data and model simulations is 0.5°. Land-use data are 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., 2010) as described by Fader et al. (2010). As 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;University of East Anglia Climate Research Unit, 2015; Harris et al., 2014), monthly precipitation data from the Global Precipitation Climatology Centre (GPCC Full Data Reanalysis version 7.0; Becker et al., 2013), and shortwave down-ward and net long wave 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(HWSD) 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 & Keeling, 2015) provides atmospheric 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 current cropland area with or without the application of tillage and with or without removal of residues Table3.1. 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 on a daily basis, 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 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;

$$RD_X = \frac{X_{MS}}{X_{(T\_R)}} - 1, \tag{3.34}$$

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 (34) were adjusted, if a different MS was used as 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 5^{th} and 95^{th} percentile (values within brackets) between MS in order 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 with uniform 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). This helps isolating soil processes, as any feedbacks via vegetation performance is 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 m2)
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 prior to 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 K_{S_l}. Clay soils are an exception, since higher SOM content decreases whc, $W_{sat,l}$ and $W_{fc,l}$, and increases K_{S_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 increase whc by 83%, 8% of SOM can increase whc in an untilled soil by 105% and in a tilled soil by 84%. As 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 & 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 US 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).

3.5.1.1 Productivity

In our simulations adopting NT_R slightly increases productivity for all rain-fed crops simulated (wheat, maize, pulses, rapeseed) on average, but ranges from increases to decreases across all cropland globally. This increase can be observed for the first three years (Fig. A.3.2a in Appendix A), and for the first ten years (Fig. 3.2A and 3.2B). All the results shown here and in the subsequent sections are calculated as RD following Eq. 3.34, unless otherwise stated. The numbers discussed in this section refer to the productivity after 10 years (average of year 9-11). The largest positive impact can be found for rapeseed, where NT_R results in a median increase of +3.5% (5^{th}, 95^{th} percentiles: -24.5%, +57.8% The positive impact is lowest for maize, with median increases by +1.8% (5^{th}, 95^{th} percentiles: -24.6%, +56.2%). The median productivity of wheat increases slightly by +2.5% (5^{th}, 95^{th} percentiles: -15.2%, +53.5%) under NT_R. The slight increases in median productivity under NT_R are contrasting to the values reported by Pittelkow et al. (2015a), who reports slight decreases in productivity for wheat and maize and small median increases for rapeseed (Table 3.3).

They report both positive and negative effects for wheat and rapeseed, but only negative effects for maize. Pittelkow et al. (2015a) identify aridity and crop type as the most important factors influencing the responses of productivity to the introduction of no-till systems with residues left on the field. The aridity index was determined by dividing the mean annual precipitation by potential evaporation. No-till performed best under rain-fed conditions in dry climates (aridity index <0.65), by which the overall response was equal or positive compared to T_R.

The positive effects on productivity under NT_R in dry regions can also be found in our simulations. For instance, wheat productivity increases substantially under NT_R whereas this effect diminishes with increases in aridity indexes (Fig. 3.2A). Similar results are found for maize productivity (Fig. 3.2B). This positive effect can be attributed to the presence of surface litter, which leads to higher soil moisture conservation through increased water infiltration into the soil and decreases in evaporation. Areas where crop productivity is limited by soil water could therefore potentially benefit from NT_R (Pittelkow et al., 2015b). The influence of climatic condition of no-till effects on productivity was already found by several other studies (e.g. Ogle et al., 2012; Pittelkow et al., 2015b; Van Kessel et al., 2013). Ogle et al. (2012) found declines in productivity, but that these declines were larger in the cooler and wetter climates. Pittelkow et al. (2015b) found only small declines in productivity in dry areas, but emphasized that increases in yield can be found when no-till is combined with residues and crop rotation. This was not the case for humid areas (aridity index >0.65), there declines in productivity were larger under no-till regardless if residues and crop rotations were applied. Finally, Van Kessel et al. (2013) found declines in productivity after adapting to no-till in dry areas (-11%) and humid areas (-3%). However, in their analysis it is not clear how crop residues are treated in no-till and tillage (i.e. removed or retained).

Negative effects of NT_R on productivity can be observed in mainly the tropical areas. As soil moisture increases in the tropical areas under NT_R as well (Fig. 3.5C), the decline is resulting from a decrease in N availability is the soil (Fig. 3.5D). Soil moisture drives many N-related processes that can cause a decline of N. For instance, the increase in soil moisture can lead to an increase in denitrification, which decreases the amount of NO_3^- (which will be more discussed in chapter 3.5.3). On the other hand, mineralization can also be reduced if soil moisture is too high. However, the soil moisture-N availability and yield feedback is complex as many processes are involved.

3.5.2 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, relative change in C input, SOC turnover time as well as relative changes in soil and litter C 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

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) pedotransfer function.

				pre-tillage, 0% SOM**				pre-tillage, 8% SOM				after tillage+ 0% SOM				after tillage+ 8% SOM			
Soil class	Silt (%)	Sand (%)	Clay (%)	whc++	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	152.05	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*	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

* Soil class rock is not affected by SOM changes and tillage practices

** For SOM we only consider the C part in SOM in gC/m^2

+ Tillage with a mE of 0.9 for conventional tillage

++ whc is calculated as: whc = W_{fc}- W_{pwp} in all cases

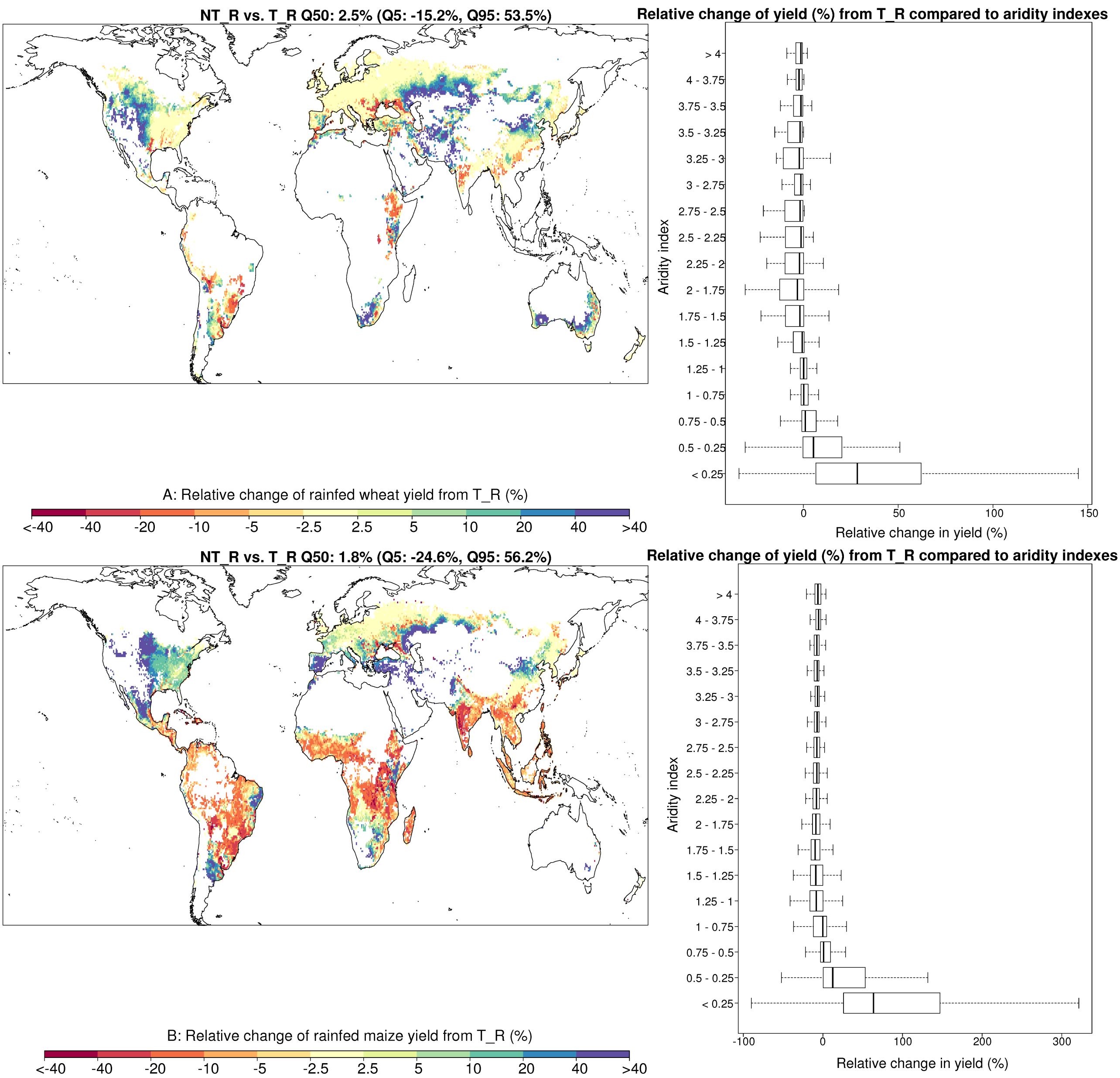


Figure 3.2: Relative yield changes for rain-fed wheat (A) and rain-fed maize (B) compared to aridity indexes after 10 years NT_R vs. T_R. Low aridity index values indicate arid conditions as the index is defined as mean annual precipitation divided by potential evapotranspiration, following Pittelkow et al. (2015a). Substantial increases in crop yields only occur in arid regions, with aridity indices < 0.75.

median value of -11.9% (5^{th}, 95^{th} percentile: -24.1%, +2.0%) after introducing no-till (NT_R vs. T_R) (Fig. A.3.3A in Appendix A) and soil and litter C stocks increase. After ten years duration (average of year 9-11) however, both CO_2 emissions and soil and litter C 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% (5^{th}, 95^{th} percentile: -17.4%, +32.4%) (Fig. 3.3A), while at the same time median topsoil and litter C also increase by +5.3% (5^{th}, 95^{th} percentile: +1.4%, +12.8%) (Fig. 3.3D), i.e. the soil and litter C 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 net primary production (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. A.3.3B in Appendix A), but after ten years, CO_2 emissions start to increase in drier regions, while they still decrease in most humid regions (Fig. 3.3A). The median of the relative differences in mean residence time of soil carbon for NT_R compared to T_R is small, but variable (+0.0% after ten years, 5^{th}, 95^{th} 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 Sect. 3.5.1.1 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. (2015a), 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 soil and litter C content by 5.0% (95^{th} CI: -1.0%, +9.2%) and decreases CO_2 emissions from soils by -23.0% (95^{th} CI: -35.0%, -13.8%) (Table 3.3). These findings of Abdalla et al. (2016) are in line to 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 and litter C. 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 and litter C decreases by -18.0% (5^{th}, 95^{th} percentile: -42.5%, -0.5%) after twenty years, while CO_2 emissions increase by +21.3% (5^{th}, 95^{th} 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 soil and litter C changes from a T_NR vs. NT_NR comparison and reported a decrease in soil and litter C under T_NR of -12.0%

(95^{th} CI: -15.3%, -5.1%) and a CO_2 increase of +18.0% (95^{th} 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 a 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 and litter C for these regions, respectively. 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 soil and litter C 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 soil and litter C, 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 increases soil and litter C content, which is in agreement with our simulation results.

3.5.2.1 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% (5^{th}, 95^{th} percentiles: -64.5%, -17.4%) and by -57.8% (5^{th}, 95^{th} percentiles: -74.6%, -26.1%), respectively (Fig. A.3.4A and A.3.4B in Appendix A). We also analyzed soil evaporation and surface runoff for different amounts of surface litter loads and cover on bare soil without vegetation in order to compare our results to literature estimates from field experiments. We find that both the reduction in evaporation and surface runoff are dependent on the residue load, which translates into different rates of surface litter cover.

On the process side, water fluxes highly influence plant productivity and are affected by tillage and residue management (Fig. 3.1). Surface litter, which is left on the surface of the soil, creates a barrier that reduces evaporation and also increases the rate of infiltration into the soil. Litter which is incorporated into the soil through tillage loses this function to cover the soil. Both, the reduction of soil evaporation and the increase of rainfall infiltration contribute to increased soil moisture and hence 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 and 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% (5^{th}, 95^{th} percentiles: -26.1%, +20.3%) globally (Fig. A.3.5A in Appendix A). The effect of a higher amount of surface litter is much more dominate, 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. A.3.5B in Appendix A), 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 agro-ecological functions. Ranaivoson et al. (2017) and the studies compiled by them 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 has to be considered in relation to plot size. In Fig. 3.4, modeled global results for relative evaporation and surface runoff change for 10, 30, 50, 70 and 90% soil cover on bare soil are compared 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 $\geq$70%, the model seems to be more in line with literature values for arid regions. Overall for high soil cover of 90%, the model seems to overestimate the reduction of evaporation. It should be noted that the estimates from Ranaivoson et al. (2017) are only taken from two field studies, which are only representative for the local climatic and soil conditions, since global data on the effect of surface litter on evaporation are not available. The general effect of surface litter on the reduction in soil evaporation is thus captured by the model, but the model seems to overestimate the response at high litter loads. It is not entirely clear from the literature if these experiments have been carried on bare soil without vegetation. If 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. 3.11, 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 slope, soils crusting and rainfall intensity is available.

3.5.3 N_2O fluxes

Switching from tillage to no-till management with leaving residues on the fields (NT_R vs. T_R) increases N_2O emissions by a median of +20.8% (5^{th}, 95^{th} percentile: -3.6%, +325.5%) (Fig. A.3.6A in Appendix A). The strongest increase is found in the cool temperate zone where the average increase is +23.5% (5^{th}, 95^{th} percentile: -0.1%, +664.4%) (Fig. A.3.6E in Appendix A). The lowest increase is found in the tropical zone +15.8% (5^{th}, 95^{th} percentile: -7.3%, +72.1%) (Fig. A.3.6C in Appendix A).

The increase in N_2O emissions after switching to no-till is in agreement with several literature studies (Linn & Doran, 1984; Mei et al., 2018; Van Kessel et al., 2013; Zhao et al., 2016) (Table 3.3). Mei et al. (2018) reports an overall increase of +17.3% (95^{th} CI: +4.6%, +31.1%), which is in agreement with our median estimate. However, the regional patterns over the different climatic regimes are in less agreement. LPJmL simulations strongly underestimate the increase in N_2O emissions in the tropical zone, whereas simulations overestimate the response in cool temperate and humid zones and to some extent in the warm temperate zone (Table 3.3).

In general, N_2O emissions are formed in two separate processes: nitrification and denitrification. The increase in N_2O emissions after adapting to NT_R is mainly resulting from denitrification in our simulations (+55.9%, Fig. 3.5A). This increase is visible in most of the regions. The N_2O emissions resulting from nitrification decrease mostly (median of -6.0%, Fig. 3.5B) but tends to increase in dry areas. The increase in denitrification and decrease in nitrification, results in a decrease in NO_3^- (median of -26.4%), which appears to be stronger in the tropical areas as well (Fig. 3.5D). The transformation of mineral N to N_2O is not only affected by the nitrification and denitrification rates, but also by substrate availability (NH_4^+ and NO_3^-). These in turn are affected by nitrification and

Table 3.3: Comparison of simulated model output and literature values from meta-analysis. Values for modeled results are calculated according to Eq. 3.34 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
notill residue - till residue							
SOM (0.3m)	0 - 0.3	101	+5.0(+1.0, +9.2)*‡	10§	+5.3	+1.4, +12.8	Abdalla et al. (2016)
CO_2		113	-23.0(-35.0, -13.8)*	**	-11.9	-24.1, +2.0	Abdalla et al. (2016)
N_2O		98	+17.3(+4.6, +31.1)*	**	+20.8	-3.6, +325.5	Mei et al. (2018)
N_2O (tropical)		123	+74.1(+34.8, +119.9)†‡	**	+15.8	-7.3, +72.1	Mei et al. (2018)
N_2O (warm temperate)		62	+17.0(+6.5, +29.9)†‡	**	+23.2	+6.0, +182.3	Mei et al. (2018)
N_2O (cool temperate)		27	-1.7(-10.5, +8.4)†‡	**	+23.5	-0.1, +664.4	Mei et al. (2018)
N_2O (arid)		56	+35.0(+7.5, +69.0)*	**	+21.1	-1.8, +496.3	Van Kessel et al. (2013)
N_2O (humid)		183	-1.5(-11.6, +11.1)*	**	+20.7	-9.1, +63.8	Van Kessel et al. (2013)
Yield (wheat)		47	-2.6(-8.2, +3.8)*	10§	+2.5	-15.2, +53.5	Pittelkow et al. (2015b)
Yield (maize)		64	-7.6(-10.1, -4.3)*	10§	+1.8	-24.6, +56.2	Pittelkow et al. (2015b)
Yield (rapeseed)		10	+0.7(-2.8, +4.1)*	10§	+3.5	-24.5, +57.8	Pittelkow et al. (2015b)
till noresidue - notill noresidue							
SOM (0.3m)	0 - 0.3	46	-12.0(-15.3, -5.1)*	20§	-18.0	-42.5, -0.5	(Abdalla et al., 2016)
CO_2		46	+18.0(+9.4, +27.3)*	20§	+21.3	-1.1, +125.2	(Abdalla et al., 2016)
Yield (wheat) B		8	+2.7 (-6.3, +12.7)*	10§	-5.9	-15.7, +3.7	(Pittelkow et al., 2015b)
Yield (maize) B		12	-25.4(-14.7, -34.1)*	10§	-5.0	-27.3, +12.0	(Pittelkow et al., 2015b)
till noresidues - till residue							
N_2O		105	+1.3(-5.4, +8.2)**‡	**	-9.7	-22.0, +3.6	(Mei et al., 2018)

* estimated from graph
** Time horizon of the study is unclear in the meta-analysis. The average over the first three years of model results is taken.
† includes conservation till
†† at least 30% on soil
‡ Residue management for conventional till unsure
§ Time horizon not explicitly mentioned by author

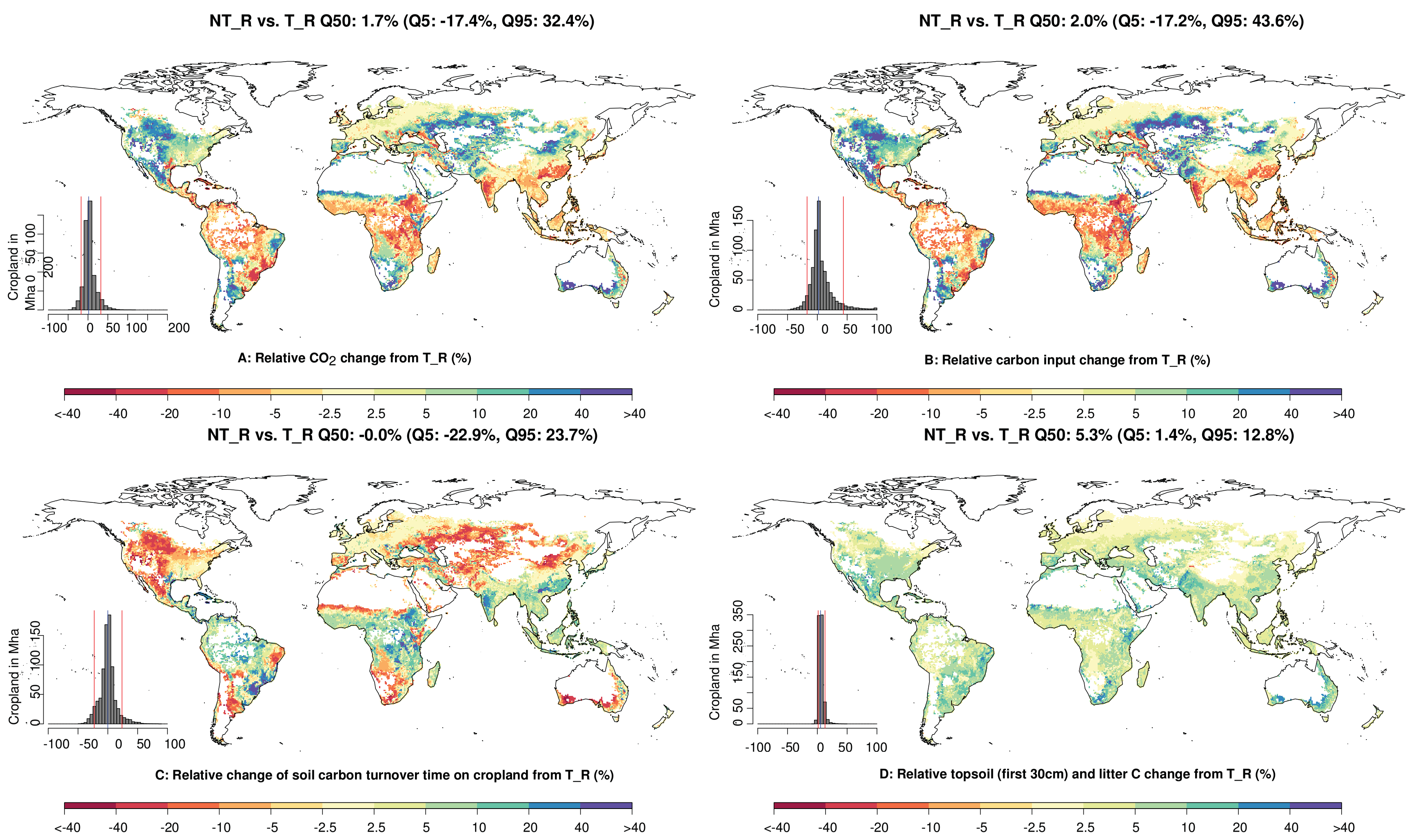
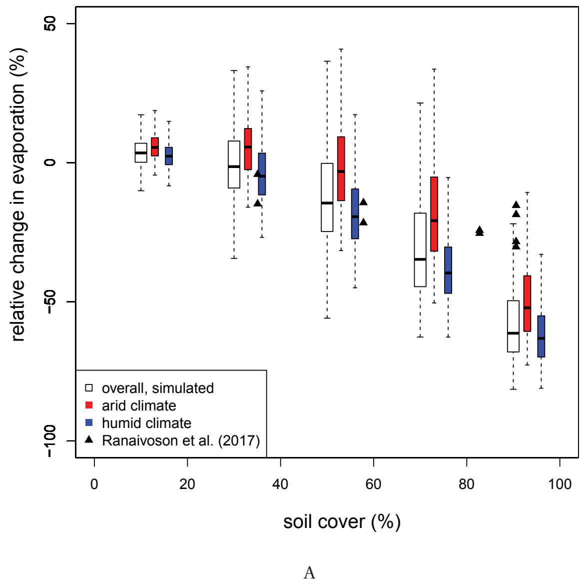


Figure 3.3: Relative C dynamics for NT_R vs. T_R comparison after 10 years of simulation experiment (average of year 9–11) for relative CO_2 change (a), relative C input change (b), relative change of soil C turnover time (c), and relative topsoil and litter C change (d).



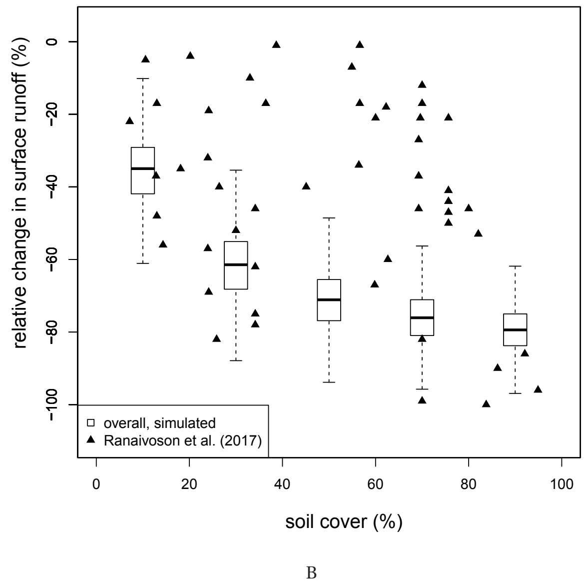


Figure 3.4: Relative change in evaporation (a) and surface runoff (b) relative to soil cover from surface residues for different soil cover values of 10 %, 30 %, 50 %, 70 %, and 90% (simulation NT_R_bs1 to NT_R_bs5 vs. NT_NR_bs, respectively). For better visibility, the red and blue boxplots are plotted next to the overall boxplots, but correspond to the soil cover value of the overall simulation (empty boxes).

denitrification rates, but also by other processes, such as plant uptake and leaching. In the Sahel zone for example, denitrification decreases and nitrification increases, but NO_3^- stocks decline, because leaching increase more strongly (Fig. A.3.7 in Appendix A).

In LPJmL, denitrification and nitrification rates are mainly driven by soil moisture and to a lesser extent by soil temperature, soil C (denitrification) and soil pH (nitrification). A strong increase in annually averaged soil moisture can be observed after adapting NT_R (median of +18.9%, Fig. 3.5C). Denitrification, as an anoxic process, increases non-linearly beyond a soil moisture threshold (Von Bloh et al., 2018a), whereas there is an optimum soil moisture for nitrification, which is reduced at low and high soil moisture content. In wet regions, as in the tropical and humid areas, nitrification is thus reduced by no-till practices whereas it increases in dryer regions. The increase in soil moisture under NT_R is caused by higher water infiltration rates and reduced soil evaporation (see section 5.4). Also, no-till practices tend to increase bulk density and thus higher relative soil moisture contents (Fig. 3.1) also affecting nitrification and denitrification rates and therefore N_2O emissions (Van Kessel et al., 2013; Linn & Doran, 1984).

Empirical evidence shows that the introduction of no-till practices on N_2O emissions can cause both increases and decreases in N_2O emissions (Van Kessel et al., 2013). This variation in response is not surprising, as tillage affects several biophysical factors that influence N_2O emissions (Fig. 3.1) in possibly contrasting manners (Van Kessel et al., 2012; Snyder et al., 2009). For instance no-till can lower soil temperature exchange between soil and atmosphere, through the presence of litter residues, which can reduce N_2O emissions (Enrique et al., 1999). Reduced N_2O emissions under no-till compared to tillage MS can also be observed in the model results, for instance in Northern Europe and areas in Brazil (Fig. A.3.6A in Appendix A).

As several biophysical factors are affected, N_2O emissions are characterized by significant spatial and temporal variability. As a result, the estimation of N_2O emissions are accompanied with high uncertainties (Butterbach-Bahl et al., 2013), which hampers the evaluation of the model results (Chatskikh et al., 2008; Mangalassery et al., 2015).

The deviations from the model results compared to the meta-analyses especially for specific climatic regimes (i.e. tropical- and cool temperate) require further investigations and verification, including model simulations for specific sites at which experiments have been conducted. The sensitivity of N_2O emissions highlights the importance of correctly simulating soil moisture. However, simulating soil moisture is subject to strong feedback with vegetation performance and comes with uncertainties, as addressed by e.g. Seneviratne et al. (2010). The effects of different management settings (as conducted here), on N_2O emissions and soil moisture requires therefore further analyses, ideally in different climate regimes, soil types and in combination with other management settings (e.g. N-fertilizers). We expect that further studies using this tillage implementation in LPJmL will increase the understanding of management effects on soil nitrogen dynamics. The great diversity in observed responses in N_2O emissions to management options (Mei et al., 2018) renders modeling these effects as challenging, but we trust that the ability of LPJmL5.0-tillage to represent the different components can also help to better understand their interaction under different environmental conditions.

3.5.4 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 C sequestration and is a general model improvement to the previous version of LPJmL (Von Bloh et al., 2018a). 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 reported often to be quite variable, depending on local soil and climatic con-

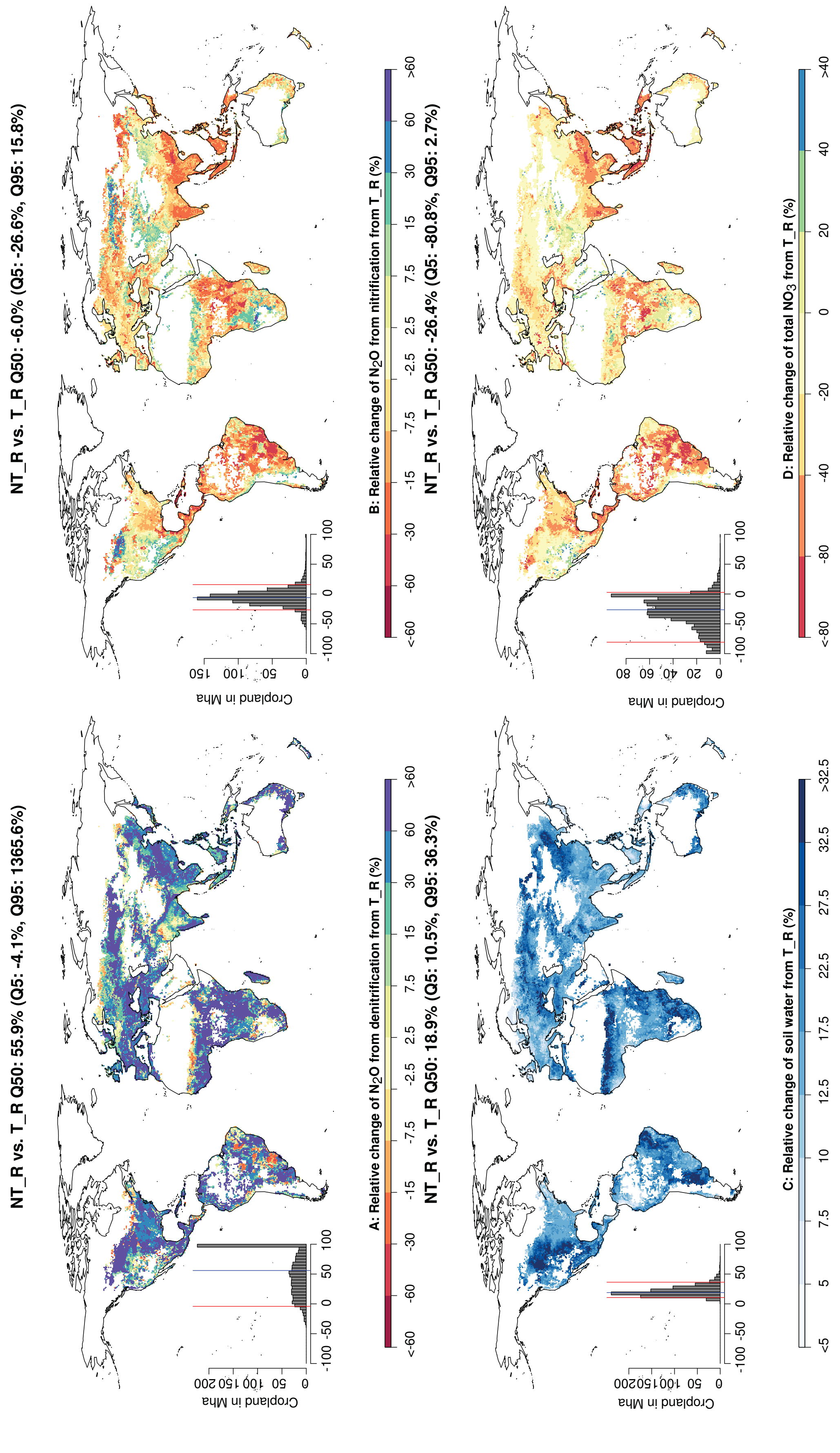


Figure 3.5: Relative changes for the average of the first 3 years of NT_R vs. T_R for denitrification (a), nitrification (b), soil water content (c), and NO_3^- (d).

ditions. 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. For the evaluation we focused on productivity, soil and litter C stocks and fluxes, water fluxes and N_2O dynamics. The sample size in some of these meta-analyses was sometimes low, which may result in biases if not a representative set of climate and soil combinations was tested. Clearly 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 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 introduction of no-till practices that can be maintained for longer time 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 carbon 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. For water fluxes, the model seems to overestimate the effect of surface residue cover on evaporation for high surface cover, but the evaluation is also 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 are in agreement with 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, as well as 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 was 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 result 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, K_S 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 in other ecosystem models. As such, different tillage and residue management strategies can only be assessed with respect to their biogeochemical effects, but only partly with respect to their effects on productivity and not with respect to some environmental effects (e.g. pesticide use). Our model simulations show that crop yields increase under no-till practices in dry areas but decrease in wetter regions (Fig. 3.2A and 3.2B). 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 soil and litter C 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 more detailed representation of tillage processes and the effects on soil water processes, changes in porosity and subsoil compaction, effects on biodiversity and on soil N dynamics is needed in order to better assess the impacts of tillage and residue management at the global scale. The spatial resolution needed to resolve processes, such as erosion, data availability, and model structure need to be considered in further model development (Lutz et al., 2019b). As such, some processes, such as a detailed representation of soil crusting processes, may remain out of reach for global-scale modeling.

3.6 Conclusions

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 mostly arid regions benefit from a no-till management with leaving residues on the field, due to the water saving effects of surface litter. We are able to 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, especially 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 more detailed tillage-related mechanics into global ecosystem model LPJmL improves our ability to represent different agricultural systems and to 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.

Code and data availability. 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.

Author contributions. F.L and T.H. both share the lead authorship for this manuscript. They had equal input in designing and conducting the model implementation, model runs, analysis and writing of the manuscript. S.R. contributed to simulation analysis and manuscript preparation/evaluation. J.H. contributed to the code implementation, evaluation and analysis and edited the paper. S.S. contributed to the code implementation and evaluation and edited the paper. W.v.B. contributed to the code implementation and evaluation and edited the paper. J.S. contributed to the study design and edited the paper. C.M. contributed to the study design, supervised implementation, simulations and analyses and edited the paper.

Competing interests. All authors declare no competing interests.

Acknowledgements F.L., T.H. and S.R. gratefully acknowledge the German Ministry for Education and Research (BMBF) for funding this work, which is part of the MACMIT project (01LN1317A). J.H. acknowledges BMBF funding through the SUSTAg project (031B0170A). We thank the two anonymous reviewers for their helpful comments on earlier versions of the paper.

Chapter 4

How to evaluate processes related to tillage?

This chapter is based on:

Lutz F, Del Grosso S, Ogle S, Williams S, Minoli S, Rolinski S, Heinke J, Stoorvogel J. J., Müller C., The importance of management information and soil moisture representation for simulating tillage effects on N_2O emissions in LPJmL5.0-tillage. Geoscientific Model Development (in review).

Abstract

No-tillage is often suggested as a strategy to reduce greenhouse gas emissions. Modeling tillage effects on nitrous oxide (N_2O) emissions is challenging and subject to large uncertainties, as the processes producing the emissions are complex and strongly non-linear. Previous findings have shown deviations between LPJmL5.0-tillage model and the results from meta-analysis on global estimates of tillage effects on N_2O emissions. Here we tested LPJmL5.0-tillage at four different experimental sites across Europe and the USA, to verify whether deviations in N_2O emissions under different tillage regimes result from a lack of detailed information on agricultural management and/or the representation of soil water dynamics. Model results were compared to observational data and outputs from field-scale Daycent simulations. Daycent has been successfully applied for the simulation of N_2O emissions and provides a richer data base for comparison than non-continuous measurements at the experimental sites. We found that adding information on agricultural management improved the simulation of tillage effects on N_2O emissions in LPJmL. We also found that LPJmL overestimated N_2O emissions as well as the effects of no-tillage on N_2O emissions, whereas Daycent tended to underestimate the emissions of no-tillage treatments. LPJmL showed a general bias to over-estimate soil moisture content. Modifications of hydraulic properties in LPJmL in order to match properties assumed in Daycent, as well as of the parameters related to residue cover, improved the overall simulation of soil water as well as the N_2O emissions simulated under tillage and no-tillage separately. However, the effects of no-tillage (shifting from tillage to no-tillage) did not improve. Advancing the current state of information on agricultural management as well as improvements in soil moisture highlight the potential to improve LPJmL5.0-tillage and global estimates of tillage effects on N_2O emissions.

4.1 Introduction

Agricultural fields are often tilled to suppress weeds, incorporate crop residues, aerate the soil, prepare the seedbed and improve infiltration. The resulting changes in physical and chemical properties of the soil affect several biochemical processes, including the formation of greenhouse gases (GHG). Many field-scale models and experiments evaluated the effects of tillage and no-tillage on GHG and soil organic carbon (SOC) (Álvaro-Fuentes et al., 2012; Del Grosso et al., 2009; Jin et al., 2017; Oorts et al., 2007) . Nitrous oxide (N_2O) is a very strong GHG and predominantly emitted in agricultural production (Ciais et al., 2014; Smith, 2017). However, studies reported mixed results for the impacts of adapting no-tillage on N_2O emissions from croplands (Deng et al., 2016; Venterea et al., 2011). For instance, no-tillage was found to increase N_2O emissions (Mei et al., 2018; Van Kessel et al., 2013), decrease N_2O emissions (Deng et al., 2016; Plaza-Bonilla et al., 2018; Yoo et al., 2016) or having no significant effects (Alvarez et al., 2012; Boeckx et al., 2011) in comparison to conventional tillage systems.

Soils emit N_2O through a series of processes involving denitrification and nitrification. These processes are driven by microbial activity and strongly respond to soil properties such as moisture, temperature, oxygen, mineral N, and organic carbon (Mosquera et al., 2005; Snyder et al., 2009; Van Kessel et al., 2013). These soil properties are affected by tillage (Lutz et al., 2019a,b) and other management practices (e.g., fertilizer application and residue treatment) (Van Kessel et al., 2013). Due to the complexity of the system, the simulation of tillage effects on N_2O emissions is challenging and subject to large uncertainties.

Lutz et al. (2019a) extended a dynamic global vegetation, hydrology and crop model to explicitly account for the effects of tillage in the simulations of biogeochemical cycles, hydrology and crop yields. This enables simulations of the effects of tillage on crop productivity, the water, carbon and nitrogen cycles, including N_2O emissions at the global scale. However, they found that simulated N_2O emissions from no-tillage exceeded values in most of the climate zones reported in meta-analyses. These deviations between observations and simulations of tillage effects on N_2O emissions can have several different causes, including missing processes and lack of process understanding. Also the parameterization of implemented processes as well as detailed information on management aspects that are explicitly addressed in the model can lead to model deficiencies that could cause the mismatch between observations and simulations.

For example, as detailed information about agricultural management practices is lacking for global-scale applications, assumptions on agricultural management are necessary in these global simulations about e.g., the type, amount and timing of fertilizer applications. Detailed information on fertilization can typically be dealt with in field-scale modeling experiments, whereas at the global scale, there is only general information on fertilization (e.g. Mueller et al., 2012; Potter et al., 2010) which is characterized by gaps and uncertainties (Erb et al., 2017). These generalizations may be a significant contributor to the overall uncertainty for agricultural impact assessments. For instance, Folberth et al. (2019) found that differences in management assumptions (about e.g., growing season, and fertilization) resulted in substantial differences in modeled crop yields using the same crop model.

Second, the formation of N_2O in soils is very sensitive to soil moisture (Butterbach-Bahl et al., 2013). How the effect of tillage on soil moisture is simulated is thus another source of uncertainty that could explain the inaccuracy in modeling tillage effects on N_2O emissions.

In this study, we test the importance of management information as well as the representation of soil water dynamics for the ability to simulate N_2O emissions under different tillage regimes with LPJmL5.0-tillage (Lutz et al., 2019a), for four different experimental sites across Europe and the USA. Simulation results are compared to measurements of N_2O emissions from experimental studies under tillage and no-tillage in different simulation experiments, varying from using observed site-specific information to using the default assumptions usually applied in the global-scale simulations. Because of the importance of soil moisture for N_2O emissions, we test the accuracy of the simulated soil moisture dynamics and its effects on N_2O emissions against observations. As simulating tillage effects on N_2O emissions is generally challenging, we use the site-specific model Daycent (Del Grosso et al., 2009; Parton et al., 1996), which has previously been applied at the study sites as a benchmark and to provide more detailed information on soil hydrology than the sparse observations. Daycent is a well-established model that has been used for questions related to agricultural impact assessments at various scales (e.g. Begum et al., 2019; Del Grosso et al., 2009; Del Grosso et al., 2002; Gryze et al., 2010). Daycent can be used as a benchmark for which the underlying mechanisms can be analyzed and used for improvements of LPJmL5.0-tillage, even though the performance of Daycent has to be compared to observations first.

4.2 Material and methods

4.2.1 Overview

In Lutz et al. (2019a), model results deviated from meta-analyses when comparing simulated tillage effects on N_2O emissions. First, we tested whether the deviations are due to a lack of detailed management information. Four experimental sites for which detailed information on management are available were identified. On those sites, LPJmL5.0-tillage was run using management assumptions usually used in a global simulation experiment (LPJmL.G.Orig). To find out if LPJmL5.0-tillage performed better with detailed information on management, we also applied LPJmL5.0-tillage using detailed site-specific management information to derive inputs (LPJmL.D.Orig). In order to analyze the importance of individual management information (e.g. on irrigation and fertilization), we conducted a set of simulations as in the LPJmL.D.Orig, but kept one of the site-specific management practice as in the LPJmL.G.Orig setup (Table 4.1).

The site-specific Daycent model was used as benchmark to analyze the underlying mechanisms of the N_2O producing processes. For all the simulations of Daycent, detailed information of management was used. Except for the experimental site in Boigneville, Daycent has been used and calibrated for field-scale assessments at the chosen sites (i.e. Campbell et al., 2014; Del Grosso et al., 2009; Yang et al., 2017). Therefore, we expect it to perform better on simulating the effects of tillage on N_2O emissions than LPJmL. We also expect to learn from the underlying mechanisms simulated by Daycent and to use this information for improving process representation and parameterization in LPJmL. All model versions considered here require similar inputs (soil properties, vegetation type, land management information, latitude, daily precipitation, and daily air temperature (minimum and maximum).

4.2.2 LPJmL5.0-tillage

LPJmL5.0-tillage is a dynamic global vegetation, hydrology and crop model that simulates nitrogen (N), carbon (C) and water dynamics in natural and agricultural ecosystems. Soils are represented by five hydrologically active layers, with different layer thicknesses.

LPJmL5.0-tillage (in the following referred to as LPJmL) uses three litter pools; representing surface litter, incorporated litter and below-ground litter as well as two soil organic matter (SOM) pools per soil layer, which are characterized by fast and slow decomposition rates, respectively, and by separate C and N components for each pool. The surface litter pool consists of crop residues which are not removed at harvest or incorporated into the first soil layer through tillage. Residue cover is calculated from the surface litter following Gregory (1982). This residue cover intercepts some rainfall, promotes infiltration into the soil, and limits soil evaporation. Moreover, the presence of a residue cover insulates the soil from air temperature fluctuations. The effects of residue cover on soil water dynamics and soil temperature fluctuations are thoroughly described in Lutz et al. (2019a).

Surface litter decomposes and is incorporated through bioturbation and tillage, forming the incorporated litter pool in the first layer. The below ground litter pool includes crop roots that remain in the soil after harvest. All pools are subjected to decomposition, which is driven by the moisture content and temperature of the soil (for the incorporated litter and below-ground litter pool), or of the moisture content and temperature of the surface litter (surface litter pool). A fixed fraction of the decomposed litter is mineralized and emitted as CO_2, whereas the humified C is transferred to the SOM pool, where it is then subject to soil C decomposition (see also Von Bloh et al., 2018a). The mineralized

Table 4.1: Overview of management data used in LPJmL.D.Orig, LPJmL.G.Orig, Daycent and experimental runs.

			Experimental runs					
Management information	**LPJmL.D. Orig**	**LPJmL.G. Orig**	**LPJmL.D.Orig**					**Daycent**
			-F*	**-I***	**-GS***	**-PS***	**-T***	
Fertilizer (amount, type, timing)	Observed data	LPJmL Data	LPJmL data	Observed data	Observed data	Observed data	Observed data	Observed data
Irrigation (amount, timing)	Observed data	LPJmL data	Observed data	LPJmL data	Observed data	Observed data	Observed data	Observed data
Growing season	Observed data	LPJmL data	Observed data	Observed data	LPJmL data	Observed data	Observed data	Observed data
Tillage	Observed data	LPJmL data	Observed data	Observed data	Observed data	Observed data	LPJmL data	Observed data
Soil C and N pool	Observed data	LPJmL data	Observed data	Observed data	Observed data	LPJmL data	Observed data	Observed data

* Experimental runs; all management information is as in the Detail setting, except for one scenario. For example, LPJmL.D-F* excludes fertilization information. The other settings exclude information on irrigation (LPJmL.D-I*), growing season (LPJmL.D-GS*), Pool N and C sizes (LPJmL.D-PS*), and tillage (LPJmL.D-T*)

N is added to the NH_4^+ pool which is subject to further transformations into other forms of nitrogen (Von Bloh et al., 2018a).

Nitrification and denitrification are simulated throughout the entire soil profile and are dependent on the water-filled pore space (WFPS), soil temperature, NH_4^+, pH, SOC (denitrification) and NO_3^-. The N_2O emissions from denitrification increases exponentially when the WFPS reaches a threshold value of $\geq 90\%$, as denitrification occurs only in oxygen deficit conditions (see also Krysanova & Wechsung, 2000).

In addition to tillage effects on residues (i.e. incorporating residues into the soil), tillage affects the hydraulic properties of the soil by decreasing the bulk density. Soil hydraulic parameters are calculated through a pedotransfer function (PTF) from Saxton & Rawls (2006) which uses soil texture, SOM, and bulk density changes to calculate field capacity (FC), wilting point (WP), saturation (WSAT) and the saturated hydraulic conductivity (Ksat). The hydraulic parameters determine the water holding capacity- and the water dynamics of the soil. For instance, soil water above WSAT runs off as lateral runoff, while remaining soil water above FC percolates to the next soil layer and generates lateral subsurface runoff or vertical seepage from the soil column.

A full overview of the tillage implementation into LPJmL5.0 as well as affected soil properties and processes can be found in Lutz et al. (2019a), the nitrogen implementation is described by Von Bloh et al. (2018a) and a comprehensive description of the LPJmL model is provided by Schaphoff et al. (2018a) and Schlüter et al. (2018).

4.2.3 Daycent

The Daycent ecosystem model simulates crop growth, soil water, C and nutrient dynamics (N, P) in natural and agricultural ecosystems (Del Grosso et al., 2009; Parton et al., 1998). The soil is represented by user-specified layers which are hydrologically active. Daycent has two litter pools, representing surface-litter and below-ground litter and three SOM pools (active, slow and passive) characterized by different decomposition rates.

The active and the slow organic matter pools have surface as well as soil components while the passive pool has only a soil component. The litter pools are partitioned into structural and metabolic pools as a function of the lignin to N ratio in the residue, which are subject to decomposition. Decomposition products of litter supply the SOM pools (surface active, soil active, surface slow and soil slow) and are partitioned among pools based on lignin content. Decomposition of litter and soil organic matter and nutrient mineralization are a function of substrate availability, substrate quality (lignin content, C:N ratio), soil moisture, soil temperature and tillage intensity. N-mineralization, N-fertilization and N-fixation supply the N-pools. NO_3^- is distributed throughout the soil profile, whereas NH_4^+ is confined to the top 10 cm. NO_3^- and NH_4^+ can then be taken up by plants, leached to lower layers (NO_3^-) or transformed to N gas emissions (e.g.

N_2O) through nitrification or denitrification (Del Grosso et al., 2000; Parton et al., 2001). N_2O emissions from nitrification are calculated as a function of soil NH_4^+ concentration, temperature, pH, texture and soil moisture. N_2O from denitrification is calculated as a function of soil NO_3^- concentration, soil moisture, texture and heterotrophic CO_2 respiration rate. N_2O emissions from denitrification increases exponentially when the WFPS exceeds the texture related threshold value and levels off as the soil approaches saturation. The model can simulate different types of tillage (i.e. plowing, tandem disk and field cultivator). Depending on the type of tillage, the decomposition of litter and SOM (active and slow) pools are increased by a specific factor for one month, and a fraction of aboveground residues is transferred to surface litter and top soil layer. Tillage also impacts soil temperature and water dynamics indirectly because the model assumes that precipitation intercepted by surface litter and living biomass evaporates before entering soil. On the other hand, the presence of surface litter insulates the soil from air temperature fluctuations.

If site level measurements of soil hydraulic properties required for Daycent are not available, they are calculated through the PTF from Saxton et al. (1986) and are static throughout the simulations. The PTF uses soil texture to calculate FC, WP, bulk density and Ksat. The soil water model simulates unsaturated water flow using Darcy's equation, runoff, snow dynamics, and the effect of soil freezing on saturated water flow (Pannkuk et al., 1998). Daycent has been shown to reliably model soil water content, N mineralization and N_2O emission rates from different soil types and management practices (Kelly et al., 2000; Parton et al., 2001). For an extensive overview of validation results of Daycent, we refer to Del Grosso et al. (2002).

4.2.4 Experimental sites

Four experimental sites were selected in which the effects of tillage and no-tillage on N_2O emissions were studied (Table 4.2 and Table 4.3). The sites were selected based on the availability of observational data and treatment combination of tillage and no-tillage.

The first study site is located at the Agricultural Research Development and Education Center (ARDEC) near Fort Collins, CO (40° 39'6" N, 104° 59'57" W; 1555 m asl). It was initiated in 1999 on a clay loam soil (fine-loamy, mixed, mesic Aridic Haplustalfs), that was continuously cropped with maize (Zea mays L.) for six years. Shortly before sowing, fertilizers (67 kg N ha^{-1}) were applied. The fields were sprinkler irrigated during the growing season. In the tillage treatment, fields were tilled shortly before sowing, and with harvest, followed by tandem disking and then moldboard plowing to a depth of 25 to 30 cm. N_2O emissions were measured three times per week during the growing season (2002-2006) with closed chambers. Soil moisture was measured two to three times per month during the growing season from 2003 to 2006. Soil organic carbon (SOC) was measured once in October 2005. A detailed description of the experimental site can be found in Halvorson et al. (2006).

The second study site is located at the University of Nebraska-Lincoln Agricultural Research and development Center, Ithaca, NE (41° 9'43.3"N, 96° 24'41.4" W; 349 m asl). The experiment was established in 2002 on a silt loam soil that was previously cropped with rain fed maize, soybean (Glycine max (L.) Merr.), oat (Avena sativa L.) and alfalfa (Medicago sativa L.). From 2000 on, maize was grown continuously. During the experiment, N fertilizers were injected to a depth of 10-15 cm, once during the growing season at various rates and compositions (Table 4.2). The soil in tillage treatments was tilled, before sowing and at harvest, to a depth of 15-20 cm. The field was irrigated with varying irrigation amounts. N_2O emissions were measured from April 2011 through May 2016 monthly during the growing season using closed chambers. Soil moisture was measured at varying intervals from one to five times per month between 2011 and 2015. SOC was measured in May 2001, November 2010, and November 2014 for different depths (0-0.15, 0.15-0.30, 0.30-0.60, 0.60-0.90, 0.90-1.20 and 1.20-1.50 m). More information regarding the experimental study site is provided by Jin et al. (2017).

The third study site is the W.K. Kellogg Biological Station Long-Term Ecological Research (KBS LTER) experiment located in Southwest Michigan (42° 24' N, 85° 24' W, 288 m asl) on loam soils (Typic Hapludalfs). The experiment was established in 1988 on an agricultural field that had been tilled for at least 100 years before the experiment. The crop rotation before 1995 consisted of maize followed by soybean. In 1995, wheat (Triticum aestivum L.) was planted after soybean, which resulted in a maize-soybean-wheat rotation. After the harvest of wheat, the fields stayed bare until the fields were cropped with maize again. This sequence was followed during the time span analyzed here (1989-2010). Different quantities of N-fertilizers were applied at sowing and/or during the growing season for maize, during the growing season for wheat, and soybean did not receive fertilizers (Table 4.2). The tillage treatment was tilled each year with sowing, then during the growing season and at harvest, to a depth of 20 cm. The fields were not irrigated during the experiment. N_2O emissions were measured once or twice a month from June 1991 to October 2016 using closed chambers. Soil moisture was measured once per month during the growing season from 1989 until 2017. SOC was measured annually since 1989 at multiple sampling depths. More information regarding the experimental study site is provided by Grandy et al. (2006) and on the KBS LTER website (http://lter.kbs.msu.edu, *accessed November 2018*).

The last study site is located in Boigneville, France (48° 33'N, 2° 33'E, altitude unknown) on a silt loam soil (Haplic Luvisoil) (FAO, 1998). The experiment started in 1970 that had been tilled to 30 cm depth annually. During the experiment, the site was cropped with a maize-wheat rotation, with maize being sown in April, harvested in October and directly followed by tillage (20 cm for tillage treatments) and sowing of wheat. After harvest of wheat in April, the soil was left bare and was tilled (20 cm) in November, until the fields were cropped with maize again. This sequence was followed during the time span analyzed here (2003-2004). During the experiment, the maize received N-fertilizers in May and wheat in February and April (Table 4.2). The fields were irrigated between the end of June and July. N_2O emissions were measured on average every three weeks using closed chambers. Soil moisture was not measured. Soil organic carbon was measured twice in 2003 and once in 2004 on various depths. More information regarding the study site can be found in (Oorts et al., 2007).

4.2.5 Management information

4.2.5.1 LPJmL standard setup using global input data

In the LPJmL.G.Orig scenario, all management information as well as soil C and N-pools were used as within the default global simulation of LPJmL (Table 4.1). The amount of mineral and organic fertilizers was provided by the global gridded crop model intercomparison (Elliott et al., 2015) of the Agricultural Model Intercomparison and Improvement Project (AgMIP, Rosenzweig et al., 2013). It is based on global, gridded data sets for each crop (Mueller et al., 2012; Potter et al., 2010). Fertilizer is assumed to consist of 50% NO_3^- and 50% NH_4^+. If fertilizer input is low ($\leq$ 5.0 gN m^{-2}), all is applied at sowing. Otherwise, only half of the fertilizer is applied at sowing and the remainder is applied when the phenological stage fraction (unitless) of the crop reaches 0.4 (Von Bloh et al., 2018a).

Irrigation events occur when the fractional soil moisture of the water holding capacity (unitless) is below an irrigation threshold value of 0.7 for maize (Jägermeyr et al., 2015).

In the experiments with tillage, tillage occurs twice a year; once at sowing and once at the day of harvest. Sowing dates are calculated internally following Waha et al. (2012). Thereby, the sowing dates are calculated based on a set of rules depending on crop specific thresholds and climate. Here, the sowing date depends on a crop-specific temperature threshold (i.e. 14 °C for maize; Waha et al., 2012).

The size of the C and N pools are calculated internally during the spinup (5000 years) of the natural vegetation and land-use history. The land-use history is simulated as with Daycent, in order to establish a comparable starting point when the simulations for the experiments are conducted. Thereby, the spin-up is followed by a simulation of historical land-use change to account for effects on the pools based on the best available information of land management.

Table 4.2: Overview of experimental sites selected for the study.

Location	Years of Experiment	Soil texture	Land use	Observations Timespan (average freq. in growing season)	Reference
Boigneville, France	1971–2004	Silt loam	Maize-Wheat	N_2O: 2003-2004 (three weeks)	Oorts et al. (2007)
Fort Collins, Colorado	1999–2006	Clay loam	Maize	N_2O: 2003-2006 (three days)	Halvorson et al. (2006)
Hickory Corners, Michigan	1989–2010	Loam	Maize-Wheat-Soybean	N_2O: 1991-2016 (2 weeks)	Grandy et al. (2006)
Mead, Nebraska	2001–2015	Silt loam	Maize	N_2O: April 2011-May 2016 (2 weeks)	Jin et al. (2017)

Table 4.3: Overview of observed input data and LPJmL input data

	Observed data							LPJmL data						
Site	Fertilization		Tillage	Growing Season		Soil Pools		Fertilization		Tillage	Growing Season		Soil Pools	
	Amount ($g\ N\ m^{-2}$)	Day of year	Day of year	Sowing Day of year	Harvest Day of year	Soil C g C **	Soil N g N **	Amount ($g\ N\ m^{-2}$)	Day of year	Day of year	Sowing Day of year	Harvest Day of year	Soil C g C**	Soil N g N **
France	15.8	131	301	107	282	4553.3	450.3	10.4	122	122	122	297	3827.8	297.0
								10.4	191	303				
Colorado	6.7	118	30	118	288	6092.0	460.4	8	123	123	123	249	6267.7	335.7
			109					8	188	270				
			119											
			330											
Michigan	3.3	135	136	128	293	9834.2	1148.2	7.155	125	125	125	238	6188.4	760.4
	12.3	179	139					7.155	175	251				
Nebraska	20.2	165	114	123	270	1762.2	1529.14	8.4	124	124	124	234	6267.7	335.7
								8.4	177	131				

- The data are for the years where maize is grown, and vary between years.

** Size of pools are given for soil depth: France, Colorado, Michigan and Nebraska are from 0 to 0.2, 0.2, 1.0 and 1.5 respectively.

4.2.5.2 LPJmL detailed setup using observed input data

Site-specific observed information for all management inputs as well as soil C and N pools were prescribed for simulation LPJmL.D.Orig (Table 4.1). For practical reasons, irrigation water was added to precipitation to enable the specification of the amount and the timing of irrigation events. This mimics a sprinkler irrigation technique as part of the irrigation water is intercepted by the canopy. As the current implementation of soil layers and tillage in LPJmL does not allow for distinguishing more detailed tillage types other than conventional tillage and no tillage, we ignored tillage activities that were less intensive (e.g. "shredding"). In order to specify the growing season, phenological heat unit requirements and base temperatures were parameterized so that the simulated harvest dates were matching the reported harvest dates.

The soil C and organic N pools from the simulations were scaled to the observed values. This was done twice, once at the introduction of land-use during spin-up and once at the start of the treatment of the experimental site. If observations were not available for the start of the experiment, the first available observation was taken, assuming that pool sizes remained stable over that time period. The pools (P) at each site were scaled as in equation 4.1:

$$P_{(cor,l)} = P_{(sim,l)} * \frac{Total_{(obs)}}{Total_{(sim)}} \tag{4.1}$$

Where $P_{(cor)}$ are the scaled carbon or nitrogen content of the soil pools (g C or N m^{-2}) in layer l of the experimental site and $P_{(sim)}$, the simulated amounts of C or N contained in the soil and litter pools of the different layers l of the experimental site. $Total_{(obs)}$ and $Total_{(sim)}$, are the total of C or N contained in the soil and litter pools summed over the different layers (l) for which observational data of soil organic C and N were available (in g C or g N m^{-2}, respectively) of the experimental site.

The differences between simulated and observed input data are depicted in Table 4.1.

4.2.6 LPJmL experimental simulations

Agricultural management consists of several practices. To analyze the importance of individual management aspects, we conducted a set of simulations as in LPJmL.D.Orig but ignored one site-specific management practice and replace it with the global assumption as in LPJmL.G.Orig (Table 4.1). As an example: LPJmL.D.Orig-F, refers to the simulation where all management information are as in the LPJmL.D.Orig, except for the fertilizer information. Instead, the amount, timing and type of fertilizers were used as in LPJmL.G.Orig. Other experimental simulations refer to: LPJmL.D.Orig-I, LPJmL.D.Orig-GS, LPJmL.D.Orig-PS and LPJmL.D.Orig-T, that use the management information as in LPJmL.D.Orig, except for irrigation (I; timing and amount), growing season (GS; sowing- and harvest days), C and N pool sizes (PS) and the timing of tillage (T) respectively. The naming of the simulation consists of three parts: 1) model used (LPJmL), 2) the experiment conducted (e.g. I, GS or PS) and 3) whether it includes modifications ("Mod"; see 4.2.7) or not ("Orig").

4.2.7 Model modifications

Lutz et al. (2019a) found that LPJml overestimates N_2O emissions. Because of the importance of soil moisture for N_2O emissions, we tested if modifying the simulation of soil moisture can contribute to improving the simulation of N_2O emission. We modified the model with respect to the treatment of the residue cover of the soil in no-tillage systems and with respect to changing the soil parameterization.

As the soil covered by residues under no-tillage practices in LPJmL simulations is very high and thus leads to high soil moisture levels throughout the year (as soil evaporation is reduced and infiltration is enhanced), we tested modifications of the relevant functions for this aspect. To this end, we tested modifications of the parameters that translate litter amounts into soil cover (Gregory, 1982) and those that determine how long the soil is covered with residues. Rather than changing well-established functions on litter decomposition (Schlüter et al., 2018), we modified the parameter on bioturbation that was introduced by Lutz et al. (2019a) and tested its effects on the reduction of the residue cover of the soil.

Lutz et al. (2019a) used an average value of 0.006 (m^2 g^{-1}) to translate litter biomass into a fraction of soil being covered with residues, which was applied to all litter, neglecting variations in surface litter for different materials. The bioturbation rate was increased from 0.19% day^{-1} to 0.63% day^{-1} to account for the surface litter being transferred to the incorporated litter pool per day (equivalent to an annual bioturbation rate of 90%, versus 50% as assumed previously).

High N_2O emissions can also result from biases in the parameterization of hydraulic properties. For example, small differences between FC and WSAT lead to frequent triggering of denitrification. To study the role of soil moisture for causing deviations in tillage effects on N_2O emissions, we analyzed if the parameterization of the hydraulic properties causes the overestimation in soil moisture. As observational data on the hydraulic properties are lacking, we here compared the hydraulic properties in relation to soil moisture from Daycent.

4.2.8 Analyses

4.2.8.1 N_2O emissions

As N_2O emissions are characterized by a high temporal variability, we analyzed two different aggregation levels: annual averages of N_2O emissions and emissions of individual days within the year. We analyzed each tillage type (*tt*, i.e. conventional tillage and no-tillage) separately (N_2O_{tt}, equation 4.2) and differences between the two for both aggregation levels ($N_2O_{diff,year}$; equation 4.3 and $N_2O_{diff,day}$; equation 4.4).

$$N_2O_{tt} = \frac{\sum_{day=1}^{n} N_2O_{day,tt}}{n_{tt}} \tag{4.2}$$

N_2O_{tt} is the annual average of simulated and observed N_2O emissions (in g N ha^{-1} d^{-1}) of *tt* (tillage type: conventional tillage (*till*) or no-tillage (*notill*)), and n_{tt} is the number of days with N_2O emissions simulated or observed in the year of *tt*. Thereby, n_{tt} equals all 365 days in the simulations and for the observations $n_{tt} < 365$ as observations are not available for every day in the year. We thus assumed that the scarcer observations still represent the full year's dynamics.

The differences in N_2O emissions on annual average ($N_2O_{diff,year}$) were calculated as in equation 4.3:

$$N_2O_{diff,year} = \frac{\sum_{day=1}^{n} N_2O_{day,notill}}{n_{notill}} - \frac{\sum_{day=1}^{n} N_2O_{day,till}}{n_{till}} \tag{4.3}$$

Where $N_2O_{day,notill}$ and $N_2O_{day,till}$ are daily N_2O emissions in g N ha^{-1} d^{-1} for all the days in the year and n_{notill} and n_{till} the number of days with N_2O emissions simulated or observed in the year for no-tillage and tillage, respectively.

The differences in N_2O emissions for individual days were calculated as in equation 4.4:

$$N_2O_{diff,day} = N_2O_{notill} - N_2O_{till} \tag{4.4}$$

Where N_2O_{notill} and N_2O_{notill} are daily emissions in all years.

The relative difference (RD in %) of no-tillage to conventional tillage was calculated as in equation 4.5:

$$RD = \left(\frac{\sum_{day=1}^{n} N_2O_{notill}}{\sum_{day=1}^{n} N_2O_{till}} \right) * 100(\%) \tag{4.5}$$

Where N_2O_{notill} and N_2O_{till} are daily N_2O emissions in g N ha^{-1} d^{-1} for all the days in the year and n is the number of days with N_2O emissions simulated or observed.

4.2.8.2 Soil moisture

For the analyses of soil moisture, we focused on the first 0.2 m of the soil, which is the tillage-affected layer. We analyzed the experimental site in Nebraska as this site had the most observations of soil moisture compared to the other experimental sites. As N_2O emissions are regulated by the WFPS in both LPJmL and Daycent, we normalized the soil moisture content and hydraulic properties to porosity (W_{SAT} in mm). The WFPS (fraction) is calculated as in equation 4.6:

$$WFPS = \frac{W}{W_{SAT}} \tag{4.6}$$

where W is the volumetric soil water content (mm). The $WFPC_{FC}$ (fraction) and $WFPC_{WP}$ (fraction) are the field capacity and wilting point values normalized to WFPS as in equations 4.7 and 4.8:

$$WFPC_{FC} = \frac{W_{FC}}{W_{SAT}} \tag{4.7}$$

$$WFPC_{WP} = \frac{W_{WP}}{W_{SAT}} \tag{4.8}$$

The W_{FC} and W_{WP} are the water content at field capacity and wilting point, respectively.

4.2.8.3 Evaluation metrics

To quantify the performance of simulated N_2O emissions, we conducted an analyses of coincidence (equation 4.9) and an analysis of association (equation 4.10), following Smith & Smith (2007). Therefore, we calculated the deviation between simulated and observed values were by the root mean squared deviation (RMSD in g N ha^{-1} d^{-1}) for the different sites as in equation 4.9:

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{n}} \tag{4.9}$$

O_i is the average observed N_2O emission (in g N ha^{-1} d^{-1}) of year i and S_i the average simulated value of N_2O emission (in g N ha^{-1} d^{-1}) of year i and n the total number of valid value pairs for comparison.

To describe how well the dynamics in the observations were captured in the simulations, we calculated the degree of association (r) as in equation 4.10:

$$r = \frac{\sum_{i=1}^{n}(O_i - \overline{O})(S_i - \overline{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2 \sum_{i=1}^{n}(S_i - \overline{S})^2}} \tag{4.10}$$

Where $\overline{O}$ and $\overline{S}$ are the average observed and average simulated value respectively over all years (in g N ha^{-1} d^{-1}). The significance of r corresponds to the tests, null hypothesis: r=0.

The mean bias (MB in fraction) was calculated as in equation 4.11:

$$MB = \frac{\overline{O}}{\overline{S}} \tag{4.11}$$

For soil moisture, the $RMSD$ and r were calculated as well. However, there we focused on one site and calculated the average $RMSD$ and r over all the years, as not much variation in soil moisture is expected between the years.

4.3 Results and discussion

4.3.1 Importance of management information

4.3.1.1 Tillage effects on N_2O emissions

Annual averages

The N_2O emissions were overestimated in the LPJmL.G.Orig experiment when analyzing yearly averages of the different sites (Fig. 4.1 A). This effect was stronger for simulated emissions under no-tillage (RMSD=36.2 g N ha^{-1} d^{-1}, r=-0.07) than under tillage (RMSD= 23.6 g N ha^{-1} d^{-1}, r=-0.31). Daycent was closer to the observed values for both tillage (RMSD=7.60 g N ha^{-1} d^{-1}, r=0.67) and no-tillage (RMSD=4.61 g N ha^{-1} d^{-1}, r=0.66). For the full statistical analyses, we refer to Table B.4.1 in the Appendix B.

Using detailed site-specific management information in LPJmL (LPJmL.D.Orig) improved the correlation between the observed and simulated values (Fig. 4.1 B). The simulated N_2O emissions under no-tillage deviated more from the observed values (RMSD= 38.9 g N ha^{-1} d^{-1}, r=0.36), as the N_2O emissions were still overestimated. This held for the simulated N_2O emissions resulting under conventional tillage as well (RSMD=31.7 g N ha^{-1} d^{-1}, r=0.34).

When analyzing the effect of tillage (difference between no-tillage and tillage), LPJmL.G.Orig showed an increase in emissions with no-tillage (Fig. 4.2 A), and LPJmL.D.Orig showed both an increase and decrease with no-tillage (Fig. 4.2 B). On average, no-tillage increased N_2O emissions by 59.5% in LPJmL.G.Orig, and 22.4% in

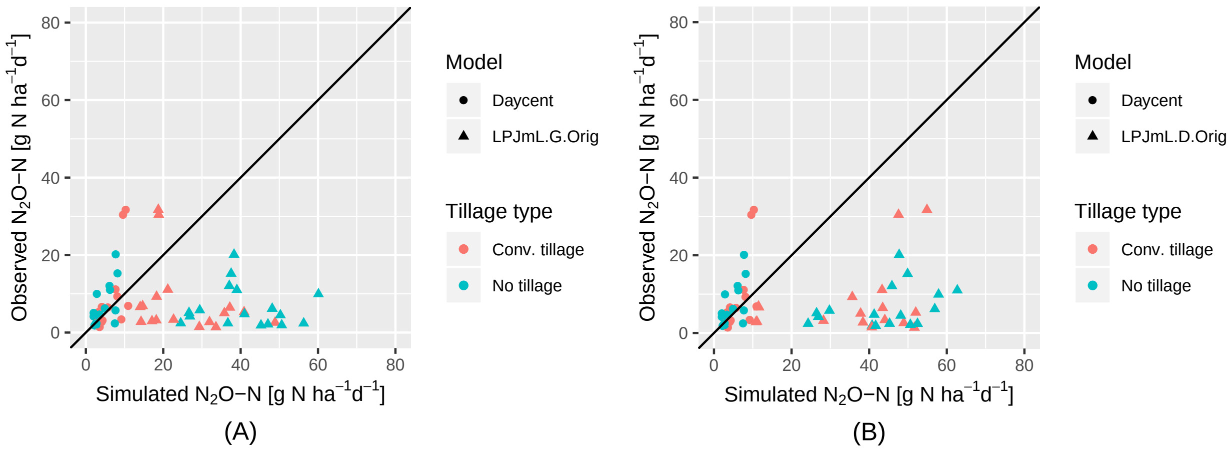


Figure 4.1: Comparison of observed and simulated yearly averages of N_2O emissions by tillage type and models LPJmL.G.Orig (A), LPJmL.D.Orig (B) and DayCent. Data refer to all four sites and years of the experiments. Each point represents the average of all measured daily values within one year and tillage treatment. Tillage types are indicated by different colors.

LPJmL.D.Orig across all sites and years.In observations, no-tillage decreased N_2O emissions on average by 16.0% and Daycent shows a reduction of 24.3%. However, observations across the different sites showed, that no-tillage can have very different effects on N_2O emissions. In Boigneville and Michigan, N_2O emissions increased under no-tillage (49.3% and 15.7% respectively), whereas it decreased in Colorado (by 9.01%) and Nebraska (by 29.2%). LPJmL.D.Orig reproduced the observed differences in tillage better (RSMD=12.0 g N ha^{-1} d^{-1}, r=0.48) than LPJmL.G.Orig (RSMD=18.0 g N ha^{-1} d^{-1}, r=-0.16), see also Fig. 4.2. Yet, both versions mainly projected an increase in N_2O emissions from no-tillage practices. Daycent results were closer to the observed values, but slightly underestimated the effects of no-tillage on N_2O emissions (RMSD= 4.96 g N ha^{-1} d^{-1}, r=0.34).

Daily emissions

The simulations with different management information showed that these are relevant for the simulated tillage effects on N_2O emissions on individual days (Fig. 4.3). On average, more accurate information on management improved the simulations of differences between conventional and no-tillage systems in LPJmL except for the site in Colorado. However, there was no clear pattern between the different experimental runs of LPJmL (Fig. B.4.1 in Appendix B). None of the simulations with partial usage of detailed management information (Table 4.1) performed clearly better or worse between the LPJmL simulations. There were only small differences in the distribution of no-tillage effects on N_2O emissions as well as between the averages. The observations showed that no-tillage both increased (Boigneville, Michigan) and decreased N_2O emissions (Colorado, Nebraska) on average, as well as on the individual days. The negative effects were reproduced by Daycent in Colorado and Nebraska. The positive and negative effects were reproduced by LPJmL.D.Orig as well, except in Michigan. LPJmL.G.Orig however, only

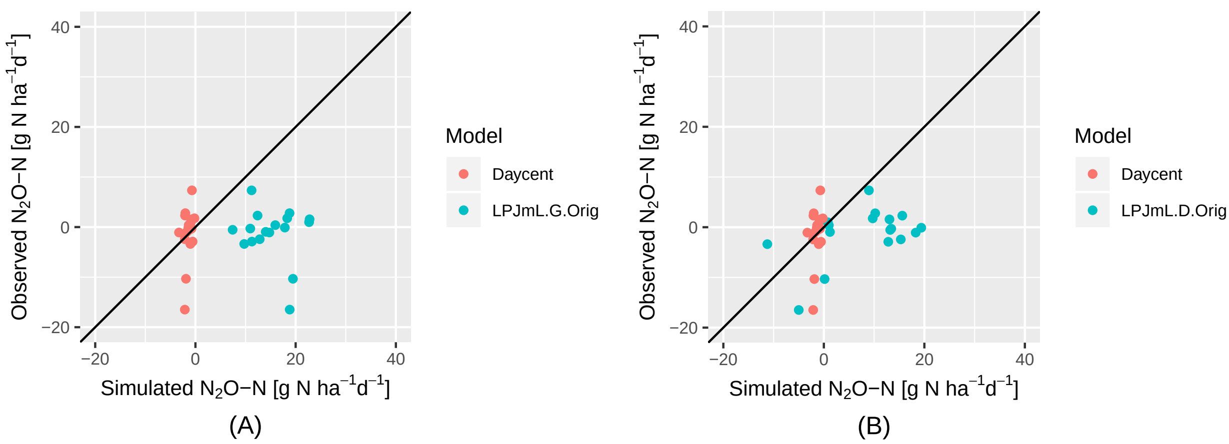


Figure 4.2: Comparison of observed and simulated effects after converting to no-tillage. The data refer to yearly averages of N_2O emissions and models LPJmL.G.Orig (A), LPJmL.D.Orig (B) and DayCent, of all four sites and years of the experiments.

reproduced the increase in N_2O emissions in Michigan (Fig. 4.3).

In Colorado, observations showed a decrease in N_2O emissions under no-tillage compared to conventional tillage. In contrast, LPJmL.D.Orig and LPJmL.G.Orig showed an increase in emissions with no-tillage, whereas the observed decrease was well captured by Daycent. In Boigneville, the increase in N_2O emissions under no-tillage was well captured by LPJmL.D.Orig. Daycent and LPJmL.G.Orig did not capture the increase in N_2O emissions with no-tillage. In Nebraska, LPJmL.D.Orig and Daycent agreed with observations that no-tillage decreases N_2O emission. In Michigan, no-tillage resulted mainly in an increase in emissions in LPJmL, which can also be found in the observations but not in Daycent simulations.

For all sites, LPJmL showed a high variability in N_2O emissions between days (Fig. 4.3 and Table B.4.1 in Appendix B). The interquartile ranges from LPJmL simulations were often much wider compared to observations and Daycent simulations. Hence, the variability of no-tillage effects on daily N_2O emissions was overestimated. Daycent on the other hand, tended to underestimate the variability of N_2O emissions between days (Table B.4.1).

In LPJmL, the N_2O emissions from no-tillage were entirely caused by changes in denitrification, whereas no-tillage mainly caused decreases on N_2O emissions from nitrification (Fig. B.4.2 in Appendix B). This can be explained by higher soil moisture levels with no-tillage in LPJmL. In general, higher soil moisture levels trigger N_2O emissions from denitrification (anaerobic process), whereas nitrification is decreased (aerobic process). In Daycent, no-tillage mainly decreased N_2O emissions emitted from nitrification and had little effects on denitrification.

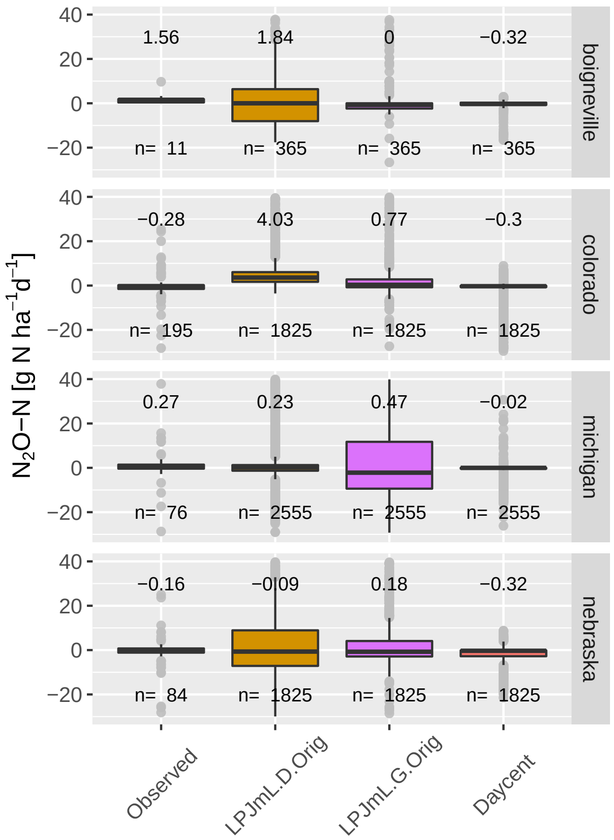


Figure 4.3: Effects of no-tillage on N_2O emissions on individual days (and on average), including the original LPJmL settings, the observations and simulated values by DayCent.

4.3.2 Soil hydrology and model modifications

4.3.2.1 Soil hydrology

The soil moisture (WFPS) simulated by LPJmL.D.Orig for no-tillage in Nebraska, is high compared to the observed values (RMSD= 0.24 (unitless), r= 0.28) (Fig. 4.4). Daycent was closer to the observed values for no-tillage (RMSD= 0.10 (unitless), r=0.50) and tillage (RMSD= 0.11 (unitless), r=0.49). After modifying the parameters for surface litter and the hydraulic properties, the simulated soil moisture in the experiment LPJmL.D.Mod was closer to the observed values and simulation results from Daycent (Fig. 4.4). These combined effects showed the best performance for both tillage (RSMD=0.12 (unitless), r=0.33) and no-tillage (RSMD=0.14 (unitless), r=0.48), compared to implementing the modifications separately (Table 4.4). The dynamics in soil moisture simulated in the experiment LPJmL.D.Mod better reflected the dynamics simulated by Daycent. For instance, after October, a decrease in soil moisture was simulated by Daycent (and measured) which was previously not captured by LPJmL.D.Orig. In LPJmL.D.Orig, soil moisture was mostly stationary around FC, which in LPJmL.D.Mod was only the case from April to June.

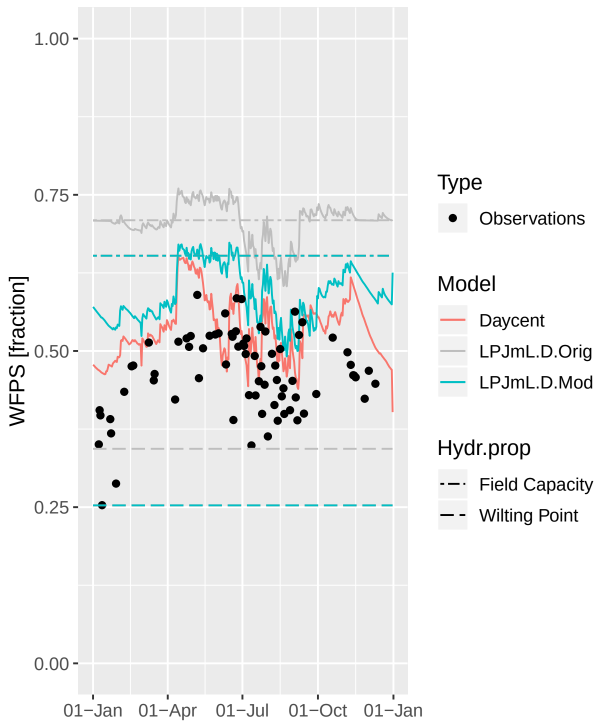


Figure 4.4: Observed and simulated soil moisture of no-tillage in the top soil (0-20 cm) in Nebraska.

Although the simulation of soil moisture was improved with the modified settings, LPJmL simulations still overestimated soil moisture in comparison to observations.

Table 4.4: Performance of Daycent, and LPJmL compared to soil water observations in Nebraska. The results are shown for both conventional tillage and no-tillage

	RMSE		*r*	
	Conv. tillage	**No tillage**	**Conv. tillage**	**No tillage**
LPJmL.D.Orig	0.21	0.24	0.10	0.28
Bioturbation	0.20	0.22	0.19	0.40
Parameter residue cover	0.19	0.24	0.20	0.32
Hydraulic properties Daycent	0.15	0.18	0.07	0.23
LPJmL.D.Mod	0.12	0.14	0.33	0.48
Daycent	0.11	0.10	0.49	0.50

4.3.2.2 Tillage effects on N_2O emissions after modifications

Yearly averages

The modifications of the parameters for surface litter and the hydraulic properties improved the yearly tillage and no-tillage effects on N_2O emissions across all the different sites (Fig. 4.5). The emissions under no-tillage (RSMD=18.1 g N ha^{-1} d^{-1}, r=0.60) and under tillage (RSMD=16.3 g N ha^{-1} d^{-1}, r=0.38) were much closer to the observed values than with the original hydrologic parameterization. Although the modifications improved the simulation of tillage and no-tillage, LPJmL.D.Mod still overestimated the changes in emissions when switching from conventional tillage to no-tillage systems (Fig. 4.5, Table B.4.1). The modifications did not improve the simulation of N_2O emissions after shifting to no-tillage (Fig. 4.6). Although the deviations of the absolute differences between tillage systems decreased, the correlation with observations was less well captured (RMSD=7.35 g N ha^{-1} d^{-1}, r=-0.04), negating the improvements achieved through the consideration of detailed management information (LPJmL.G.Orig vs. LPJmL.D.Orig). The conversion to no-tillage systems increased N_2O emissions by 13.0% in LPJmL.D.Mod. The increase in N_2O emissions after shifting to no-tillage in the modified simulations was found across all sites in LPJmL.D.Mod, whereas Daycent showed decreases in N_2O emissions across all sites at the yearly aggregation (Fig. 4.6). However, the observations showed both increases and decreases in N_2O emissions after shifting to no-tillage for all sites at the yearly aggregation.

Daily emissions

The modified hydrology (LPJmL.D.Mod and LPJmL.G.Mod), decreased the variability of no-tillage effects on N_2O emissions of individual days in most LPJmL simulations (Fig. B.4.3 in Appendix B). The interquartile ranges from daily N_2O emissions simulated by LPJmL were more in agreement compared to the observations and Daycent, as the variability of no-tillage effects on N_2O emissions is declined between days.

In the LPJmL.D.Mod experiment, simulated N_2O emissions from no-tillage are now produced by both denitrification and nitrification (Fig. B.4.2 in Appendix B). The increases in emissions from denitrification were smaller than in the LPJmL.D.Orig experiment and closer to the simulated values by Daycent in Boigneville and Nebraska. The emissions from nitrification increased by switching from conventional tillage to no-tillage systems, whereas they decreased in the LPJmL.D.Orig experiment. However, changes in nitrification remain small, compared to changes in denitrification.

4.4 General discussion

Detailed information on agricultural management improved the LPJmL simulation of N_2O emissions produced by tillage and no-tillage, as well as of the effect of switching from conventional tillage to no-tillage systems. However, also with detailed information, LPJmL overestimated the N_2O emissions. The overestimation is caused by too high simulated soil moisture, resulting in high fluxes from denitrification. After correcting for the overestimation in soil moisture, by modifying 1) the parameter that translate litter amounts into soil cover, 2) the parameter that determines the duration of the surface litter layer and 3) hydraulic properties, the yearly averages of N_2O emissions were closer to the observed values for tillage and no-tillage separately, but not for shifting from conventional tillage

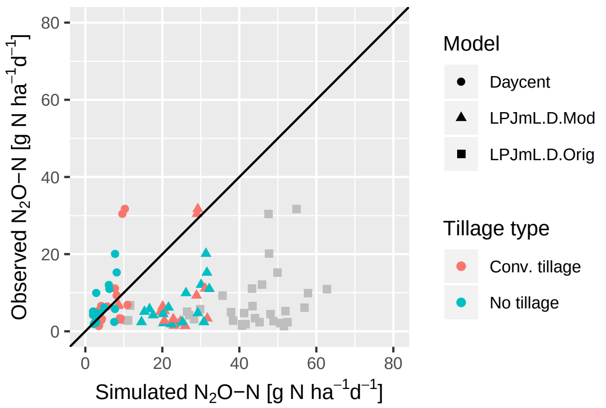


Figure 4.5: Comparison of observed and simulated yearly averages of N_2O emissions by tillage type and models DayCent, LPJmL.D.Mod and LPJmL.D.Orig (in grey). Data refer to all four sites and years of the experiments. Each point represents the average of all measured daily values within one year and tillage treatment. Tillage types are indicated by different colors.

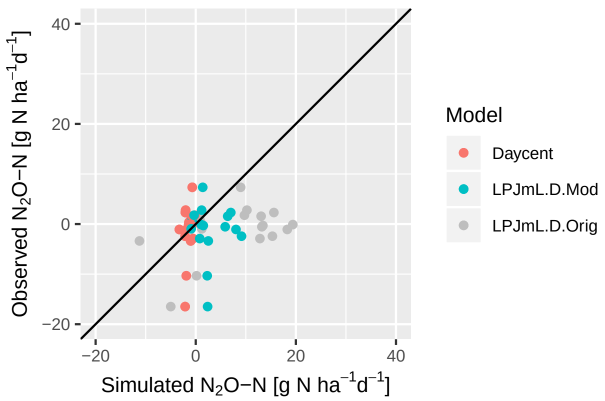


Figure 4.6: Comparison of observed and simulated effects after converting to no-tillage. The data refer to yearly averages of N_2O emissions and models DayCent, LPJmL.D.Mod and LPJmL.D.Orig (in grey). Data refer to all four sites and years of the experiments.

to no-tillage. However, the variability of no-tillage effects on N_2O emissions between the days is now reduced in most of the LPJmL simulations and the interquartile ranges from LPJmL simulations are now in better agreement with observations and Daycent.

Daycent performed better in simulating tillage and no-tillage effects on N_2O emissions on the yearly averages. However, Daycent tended to underestimate the overall effects and the inter annual variability of no-tillage on the emissions. Daycent mostly simulated a decrease in N_2O emissions upon shifting to no-tillage. A major reason for this is that in Daycent conversion to no-tillage leads to increasing soil organic matter which is associated with decreased availability of mineral N. However, observations showed that no-tillage can also increase N_2O emissions. For example, no-tillage can result in increased soil moisture content which can promote N_2O emissions from denitrification. Daycent simulations showed basically no response in N_2O emissions from denitrification. On the other hand, conventional tillage can increase the decomposition rate of (soil) organic matter, through improved aeration of the soil. Increased decomposition leads to an increase of available N that can be transformed to N_2O through nitrification and denitrification. The higher N_2O emissions with conventional tillage in Daycent, indicates that the increase in decomposition rate of (soil) organic matter due to tillage, is dominant in comparison to the effect of increased soil moisture-driven denitrification rate.

The overall better performance by Daycent likely reflects the years of model development and testing at this scale and previous application at these sites (except the site in Boigneville) (Campbell et al., 2014; Del Grosso et al., 2008; Yang et al., 2017), which enabled more accurate reproduction of observed N_2O emissions. The testing of the model performance as well as improvements to reproduce observed N_2O emissions has been conducted in several studies (Necpálová et al., 2015; Fitton et al., 2014; Del Grosso et al., 2010). For example, model calibration has been conducted to test the model performance based on contributing parameters and key processes that affect N_2O emissions. For instance, the maximum amount of N_2O emissions produced during nitrification as well as the proportion of nitrified N that is lost as N_2O can be specified. LPJmL on the other hand, is developed for global-scale applications and is therefore usually not calibrated, as suitable calibration targets are typically not available at that scale.

The application of LPJmL at the experimental sites provided much insight in the deviations of the tillage effects on N_2O emissions from observations. It enabled to use site-specific information on agricultural management, whereas missing information at global scale has to be supplemented with assumptions. As detailed information improved the simulation of tillage effects on N_2O emissions, advancing the current state of information on agricultural management at the global scale could improve global estimates of tillage effects on N_2O emissions. The study also highlighted the potential of improving the simulation of N_2O emission by improving soil moisture dynamics. Any modification to improve LPJmL5.0-tillage needs to be evaluated at the global scale, as LPJmL is typically applied at that scale (e.g. Heinke et al., 2019; Rolinski et al., 2018; Schaphoff et al., 2018a). A first recommendation is to revisit the PTF used in LPJmL5.0-tillage. We saw in this exercise that LPJmL overestimated soil moisture independent of the tillage system. Although the modifications in residue cover improved the results on soil moisture, the most important modification was in the hydraulic properties resulting from the PTF. The modifications still resulted in relatively high soil moisture contents, and therefore possibly still overestimations in N_2O emissions. A reason for this could be the relatively inefficient percolation of soil moisture to lower soil layers as soon as soil moisture is higher than FC.

N_2O emissions from denitrification increase exponentially when the WFPS exceeds a certain threshold value in LPJmL. This threshold value (which is around 0.8 of WFPS) is a proxy for assuming anaerobic conditions, and is static for all soil texture types. However, finer-textured soils have lower gas diffusivity at a given WFPS than coarser textured soils (e.g. Del Grosso et al., 2000). In soils with lower gas diffusivity, denitrification is assumed to occur at lower levels of WFPS, because atmospheric O_2 may not diffuse into the soil fast enough to fully satisfy microbial demand (Parton et al., 1996). Threshold values for anoxic conditions that are soil texture type specific are currently not accounted for in LPJmL. In Daycent, the effect of gas diffusivity of different soil texture types is taken into account. An index of gas diffusivity is calculated based on the WFPS, bulk density and FC, which is a proxy for pore size distribution and air filled pore space. This index influences the denitrification rate (i.e. lower diffusivity increases denitrification), N_2 to N_2O and NO_x to N_2O ratios. Including such processes in LPJmL might improve simulated N_2O emissions. However, this would require suitable reference data in order to parameterize these processes well.

4.5 Conclusions

Previous findings have shown deviations between simulations with the LPJmL5.0-tillage model and the results from meta-analyses on global estimates of tillage effects on N_2O emissions. In this study, we tested LPJmL5.0-tillage at different experimental sites to study whether deviations in N_2O emissions result from a lack of detailed information on agricultural management and/or the representation of soil water dynamics. The results were compared to observed values of the experimental sites as well as to results of the field-scale model Daycent.

Adding site-specific information on agricultural management improved the simulation of N_2O emissions under conventional tillage and no-tillage practices, as well as changes in emissions from shifting from conventional tillage to no-tillage in LPJmL5.0-tillage. Although adding information on agricultural management improved the performance of LPJmL5.0-tillage, simulated N_2O emissions remained too high, due to a general bias in over-estimations of soil moisture. By modifying the parameters related to residue cover and the hydraulic properties as used in Daycent, the simulation of soil moisture and N_2O emissions by LPJmL5.0-tillage improved substantially.

Generally, there is substantial uncertainty in simulating the effects of different tillage systems on N_2O emissions. Daycent performed better in simulating N_2O emissions under conventional tillage and no-tillage, but generally showed little response in N_2O emissions on changes in tillage practices. LPJmL5.0-tillage simulations reproduced a broader range of tillage effects on N_2O emissions, but tended to overestimate N_2O emissions in general. Modifications to the detail of management information considered and soil hydrology could always only improve in one deficiency (bias or dynamics) but not in both.

This study confirmed that the deviations in N_2O emissions can be explained by both lacking detailed information on management and relative high soil moisture levels simulated by LPJmL5.0-tillage. Advancing the current state of information on agricultural management can thus improve global estimates of tillage effects on N_2O emissions. Furthermore, the representation of soil water dynamics and N_2O dynamics highlights the potential to improve LPJmL5.0-tillage. However, given the limited skill to reproduce observed patterns in simulations with LPJmL5.0-tillage, the model currently does not lend itself to evaluating the impacts of different tillage systems on N_2O emissions but requires further research on better representation of soil hydrology and its effects on N_2O emissions.

Acknowledgements F.L., S.M and S.R. gratefully acknowledge the German Ministry for Education and Research (BMBF) for funding this work, which is part of the MACMIT project (01LN1317A). F.L also acknowledges the Huub and Julienne Spiertz Fund that enabled to visit the Colorado State University and USDA to collaborate on this research. Support for this research was also provided by the NSF Long-term Ecological Research Program (DEB 1832042) at the Kellogg Biological Station and by Michigan State University AgBioResearch.

Chapter 5

Representing soil heterogeneity in global modelling of N_2O emissions and soil organic matter

This chapter is based on:

Lutz, F., Stoorvogel, J. J., and Müller, C., Representing soil heterogeneity in global modelling of soil carbon and N_2O emissions, to be submitted to Global Change Biology.

Abstract

Global Ecosystem Models (GEMs) are used to evaluate climate change impacts on the global biogeochemistry. Increasingly, they also cover the effects of agriculture on the environment. The fine-scale variability of soils is often ignored by GEMs as they are often run at a relatively coarse spatial resolution and typically work with the dominant soil texture class (STC_{dom}) in each grid cell. Conceptually, high resolution soil maps can be represented in different ways in these simulations. In this study, we analyzed the effect of different representation methods of soil texture classes on simulated nitrous oxide (N_2O) emissions and soil organic carbon (SOC) content on cropland. To this end, we used the dynamic global vegetation, hydrology and crop model LPJmL5.0-tillage and the high resolution soil database S-World. We first identified the areas that are at high, low or intermediate risk for erroneous model results when using STC_{dom} in the grid cell for analyses of N_2O emissions and SOC content. Then we analyzed the effect of the different soil representation methods on N_2O emissions and SOC, at the global scale as well as within the risk areas. Our findings highlight that choosing STC_{dom} in studies on N_2O emissions and SOC content is a feasible method for global analyses. The global averages on simulated N_2O emissions and SOC content, only showed small differences between the different representation methods. However, considerable differences were found when analyzing local and regional differences. For local or regional assessments on N_2O emissions and SOC content, using STC_{dom} can therefore lead to distortions, especially in the high risk areas. In these areas, soil variability should be more explicitly accounted for. The similarity in spatial patterns of high-risk areas for N_2O and SOC suggests that a non-regular grid can be defined for all output variables from GEMs, hence increasing regional model fidelity without substantially increasing computation demands.

5.1 Introduction

There is an increasing demand for global studies providing insights into phenomena of global relevance, such as climate change and the sustainable development goals (Griggs et al., 2013). These studies often rely on the use of global models. Computational reasons often require global models to operate at a relatively coarse resolution of e.g., 0.5° (e.g. Liu et al., 2013; Schaphoff et al., 2018a). However, the coarse resolution also poses a number of challenges in dealing with high spatial variability of input data and using datasets at higher resolutions. A good example are the Global Ecosystem Models (GEMs) that are used to evaluate climate-change impacts, adaptation and the effects of agricultural production on the environment (Müller et al., 2017; Pugh et al., 2015). Amongst the wide range of input data describing land use and environmental variation, they make use of soil data. With a wide range of different, more detailed global soil maps available at, for example, 30 arc-second resolution e.g., HWSD (FAO & ISRIC, 2012), S-World (Stoorvogel et al., 2017) and SoilGrids (Hengl et al., 2014),, the question remains how to represent the soil heterogeneity at the coarser resolution of the GEM simulation. Within those large-scale grid cells, various soil types, or combinations of soil types may occur (Folberth et al., 2016). GEMs typically use the dominant soil type within a grid cell (Folberth et al., 2016; Schaphoff et al., 2018a). As a result, soil heterogeneity within the larger grid cells is ignored and the response on the dominant soil type is not necessarily the average response across all soil types present in the grid cell. In addition, cropland may not be located on the dominant soil type but on specific (e.g., highly fertile) soil types that may be present in only smaller parts of the grid cell. In some areas with limited soil variability like the vast Chernozem areas in Russia and Romania, the use of a dominant soil type can be expected to be unproblematic. However, the inland valleys in West Africa are a good example where intensive agriculture is located in (and at the fringes of) narrow valleys with relatively high water availability and soil fertility compared to the vast majority of the area. Therefore, the representation of soil by the dominant soil type may lead to an overall uncertainty and biases in model-based assessments, although this depends on the model sensitivity for soil differences. For instance, Folberth et al. (2016) found that impacts of climate change on yield can be negative or positive across different climate regions, depending on the chosen soil type.

This study aims to obtain better insights in the effect of the representation of high resolution soil data in global models and to explore whether it is possible to give a priori prediction where these aggregation effects are likely to play a major role. We evaluated the simulation of N_2O emissions and soil organic carbon (SOC) using the dynamic global vegetation, hydrology and crop model LPJmL5.0-tillage (Lutz et al., 2019a, 2020). As this study requires a finer resolution of soil data that is per default used by LPJmL5.0-tillage, we here use the S-World ("Soils of the World") soil property database which comes at a spatial resolution of 30 arc-seconds (Stoorvogel et al., 2017). LPJmL5.0-tillage uses the 12 soil texture classes (STC; Staff, 2003) for the characterization of soils. In order to determine which soils are present in the cropland area, we use the high-resolution cropland mask of GlobCover (Bontemps et al., 2011).

We first identify the areas at risk for simulation errors when using the dominant STC (STC_{dom}) within each 0.5° grid cell. Problems can occur where the area share that is covered by the dominant STC is relatively small and where high variability in model results across STCs is found. To evaluate the overall effects of different representation methods, as well as its effects in the risk areas we analyze the N_2O emissions and SOC content. We focus at the global-scale aggregation level as well as on the spatial distribution of and relevancy of the representation of the soil heterogeneity within these risk categories.

5.2 Material and methods

5.2.1 Model and data

5.2.1.1 LPJmL

The GEM used for this study is the dynamic global vegetation, hydrology and crop model LPJmL5.0-tillage (from now on referred to as LPJmL). LPJmL simulates both natural and agricultural ecosystems, typically at a spatial resolution of 0.5° (Schaphoff et al., 2018a). The model simulates carbon (C), nitrogen (N) and water cycles by representing biophysical processes in plants (e.g. photosynthesis) and soils (e.g. mineralization of organic matter). The model divides the soil column into five hydrologically active layers of 0.2, 0.3, 0.5 and 1 m thickness (Schaphoff et al., 2013). In LPJmL, the organic matter pools consist of vegetation, litter and soil compartments and are represented as C pools and the corresponding N pools with variable C:N ratios (Von Bloh et al., 2018a). The litter pools are subject to decomposition, after which the humified products are transferred to the two soil organic matter (SOM) pools that have different decomposition rates (Von Bloh et al., 2018a). The N contained in those pools can be mineralized after which it is added to the ${NH_4}^+$ pool of the respective soil layer and is subject to further transformations (e.g. nitrification and denitrification). Recently, LPJmL was extended by a tillage module to account for the effects of tillage practices on hydraulic properties and residue management (Lutz et al., 2019a). With tillage, crop residues are incorporated into the first soil layer whereas in no-tillage systems, the residues cover the soil. The residue cover hampers soil evaporation and promotes soil water infiltration into the first soil layer. Over time, the residue cover diminishes due to decomposition and bioturbation until the next harvest event. Next to the effects on residues, tillage also affects the hydraulic properties of the soil, by increasing the soil's water-holding capacity. For a full overview of tillage practices and effects implemented in LPJmL, see Lutz et al. (2019a). While soil carbon and nitrogen pools are modeled in LPJmL, data on soil texture classes (STCs) are required as model input.

5.2.1.2 S-World

Several global soil property databases are available. S-World is a high resolution (30 arc-seconds), spatially exhaustive soil property data base (Stoorvogel et al., 2017) that is developed for global environmental modelling studies. The database is based on a disaggregation of the Harmonized World Soil Database (HWSD; Batjes, 2009). The HWSD describes global soil variability based on discrete soil map units. These map units are described by 1 to 10 different soil types. In a first step, S-World disaggregated the complex map units (described by multiple soil types) into simple soil map units (described by a single soil type) using a global digital elevation model and through the development of logical sequences of soil types according to their topographic position in the landscapes. Ranges in soil properties per soil type were determined using the WISE3.1 soil profile database (Batjes, 2009). Then, through a model based on a meta-analyses, soil properties are estimated at each location using the soil type and landscape properties (climate, topography, land use). A full description of the procedure underlying the disaggregation is described in (Stoorvogel et al., 2017). S-World includes average clay and sand fractions for the soil profile. For this study, the sand and clay fractions in S-World are classified as STCs (according to the USDA classification: Staff (2003)) resulting in a global 30 arc-seconds soil texture class map.

5.2.1.3 GlobCover

The information of cropland cover was derived from GlobCover (Bontemps et al., 2011). GlobCover is a global land cover database at a 10 arc-seconds resolution. It was created from satellite imagery, and represents 22 land-cover classes following the UN Land Cover Classification System (LCCS). The land-cover classes may represent predominantly cropland or a certain fraction of cropland. GlobCover was first aggregated to a map of cropland shares at 30 arc-seconds by adding up all cropland areas (m^2) of the finer-resolution GlobCover that belong to the coarser 30 arc-seconds grid cells and dividing it by the total area of the 30 arc-seconds grid cell (m^2). This yields a 30 arc-seconds map of cropland where each value represents the % of the grid cell covered by cropland.

5.2.2 Simulation and analysis

5.2.2.1 LPJmL simulations

N_2O emissions and SOC were simulated with LPJmL for each STC. This was done by creating input data for LPJmL where the entire world was covered by a single STC. To bring vegetation patterns and SOM pools into a dynamic equilibrium stage, we follow a standard procedure for LPJmL simulations (Schaphoff et al., 2018a) using a 5000 year spin-up simulation for potential natural vegetation, followed by a second spin-up simulation of 390 years to account for historical land use change that accounts for agricultural management (including tillage) that starts changing dynamically in 1700 (Fader et al.,

2010) and ended in 1998 accounting for the historical land-use change during that period. After the second spin-up simulation, the experimental simulations were conducted that started in 1998 and ended in 2017.

Land-use data for the simulation runs are based on the crop-specific shares of MIRCA2000 (Portmann et al., 2010) and grassland and cropland time series since 1700 from HYDE3 (Klein Goldewijk et al., 2010) as described by Fader et al. (2010). For this study, we focus on the rain-fed areas only and do not consider any land-use change after 1998 so that results refer to the cropland extent in 1998. The model is driven by monthly temperatures, precipitation, cloudiness and wet days per months from the Climate Research Unit (Harris & Jones, 2019), version TS4.02 (Harris et al., 2014) that are internally interpolated to daily weather variables using a weather generator (Schaphoff et al., 2018a). The hydraulic properties are derived dynamically during the simulation for each grid cell by using the pedotransfer function from Saxton & Rawls (2006) that derives hydraulic properties from SOC and soil texture classes.

5.2.2.2 SOC and N_2O emissions based on representations of dominant soil texture classes

The 30 arc-second STC map is represented as dominant soil texture classes in two ways at the 0.5° resolution. The first procedure, the standard in LPJmL, takes the STC with the largest coverage in the grid cell defined as the STC_{dom}. For analyses purposes, a corresponding 0.5° resolution map is created representing the % coverage of STC_{dom} in each grid cell. A second procedure also takes the dominant STC but now only considering the cropland within each grid cell, using the information of aggregated 30 arc-seconds GlobCover map. So within each 0.5° grid cell the dominant STC is determined by its spatial overlap with cropland at 30 arc-seconds resolution ($STC_{dom,cropland}$). These two representations of soils could now be linked to the simulation results, selecting the STC-specific simulation results for each grid cell, according to its STC_{dom} and $STC_{dom,cropland}$.

5.2.2.3 SOC and N_2O emissions based on a weighted average of simulated results

An alternative procedure is to aggregate the modelling results rather than the soil map. This is done by first assigning the 0.5° resolution modelling results (i.e., the twelve maps for SOC and N_2O emissions for each of the STCs) to the 30 arc-seconds STC map ($STC_{S-world}$) resulting in a 30 arc-seconds resolution map of SOC and N_2O emissions. These results can then be aggregated in two different ways: i) an area weighted average for all the 30 arc-second resolution grid cells in each 0.5° grid cell ($SOM_{weightedaverage}$ and $N_2O_{weightedaverage}$) and ii) an area weighted average for all the 30 arc-second resolution grid cells under cropland in each 0.5° grid cell.

The weighted average of model outputs on N_2O emissions and SOC on bases of high resolution soil texture masks are computed as in equation 5.1

$$X_{agg,c} = \sum_{i=1}^{12} w_{i,c} * X_{i,c} \tag{5.1}$$

Where $X_{agg,c}$ is a weighted average of the simulation result X (N_2O emissions or SOC content (in g N m^{-2} or g C m^{-2} respectively)) for each aggregation scheme agg in each 0.5° grid cell c. The individual weights for each STC i ($w_{i,c}$) add up to exactly 1 in each grid cell c, i.e. $\sum_{i=1}^{n} w_{i,c} = 1$; with n being the number of STC present in grid cell c. Simulation results per STC and grid cell c are depicted as $X_{i,c}$ where X is either the output for SOC or for N_2O of STC i. The weights w are different per aggregation scheme agg.

5.2.3 Analyses

5.2.3.1 Indication of risk areas

As GEM studies typically use the dominant soil within a grid cell (Folberth et al., 2016), we study in which areas this type of soil representation can constitute a risk for introducing simulation errors ($Risk$ in fraction). Problems can occur where for instance the area covered by STC_{dom} is relatively low as a high variability in STCs is found in the grid cell. On the other hand, if the sensitivity of simulated N_2O emissions or SOC content between the STCs is low, the method of aggregation is relatively unimportant. Here we relate the coverage of STC_{dom} (Cov_{dom} in %) and the model sensitivity for N_2O emissions and SOC content in terms of the coefficient of variation (CV_X), for each STC within the grid cell (i) as in equation 5.2

$$Risk_i = (1 - Cov_{dom,i}) * CV_{X,i} \tag{5.2}$$

The coverage of the dominant STC (Cov_{dom}) is calculated following equation 5.3, where $Coverage_{STC_{dom}}$ is the area covered by the STC_{dom} and $Coverage_{tot}$ the total reference area (either of the entire grid cell c in the case of STC_{dom} or the total cropland area in the case of $STC_{dom,cropland}$); quantifying all area measures in m^2.

$$Cov_{dom,i} = \frac{Coverage_{STC_{dom,i}}}{Coverage_{STC_{tot,i}} * 100(\%)} \tag{5.3}$$

The $Risk$ is ranked in three different classes: 1) high risk, 2) moderate risk and 3) low risk. The highest third of the $Risk$ values are thereby classified as high risk, the middle third is classified as moderate risk and the lowest third is classified as lowest risk.

The CV of STCs relating to SOC content and N_2O emissions is calculated following equation 5.4;

$$CV_{X,c} = \frac{SD_{X,c}}{mean_{X,c} * 100(\%)} \tag{5.4}$$

Where SD_X is the standard deviation of SOC content (in g C m^{-2}) or N_2O emissions (in g N m^{-2}) and $mean_X$ is the mean value of the output variable X over the different STCs present in the grid cell c.

To assess where the sensitivity of global-scale results of different aggregation schemes for N_2O emissions and SOC content is highest, we additionally calculated a variant of the coefficient of variation $CVglobal$ on basis of the global mean ($\mathrm{mean}_{global,X}$) as in equation 5.5:

$$CVglobal_{X,c} = \frac{SD_{X,c}}{mean_{global,X} * 100(\%)} \tag{5.5}$$

5.2.3.2 Effects of soil representation on simulated SOC and N_2O emissions

To analyze the effects of representation of soils on simulated SOC content and N_2O emissions (X), we calculated the representation effect $f_{X,rep}$ as the differences between the representation schemes using the results of the standard representation scheme STC_{dom} (X_{dom}) as the reference case (see equation 5.6).

$$f_{(X,rep)} = X_{dom} - X_{rep} \tag{5.6}$$

5.3 Results

5.3.1 S-World

5.3.1.1 Soil textural classes of S-world (30 arc-seconds)

The transformation of soil properties from S-World to STCs according to the USDA classification results in a detailed global map of STCs (Fig. 5.1a) that is the basis for further aggregation to 0.5° (Fig. 5.1b). A high spatial variation in STCs on cropland areas can be observed in many regions of the world, including e.g. Central Europe, the mountainous regions of North America, Australia and China. The spatial variation in STCs is relatively low in central South America, Central Africa and Southeast Asia. In those regions, the STC is mainly dominated by clay, whereas a mixture of clay- silt- and sandy loam are found in large parts of the remainder of the world. The diversity of soils is also reflected by the dominance of the dominant soil type, i.e. how much of the 0.5° pixel is covered by the dominant soil type, as shown in Fig. 5.1c. The regions with smaller shares of the dominant STC (STC_{dom}) mostly overlap with the regions with high STC diversity. In those regions, choosing STC_{dom} ignores the variability of the STCs (e.g. Central Europe, East Africa and East Asia).

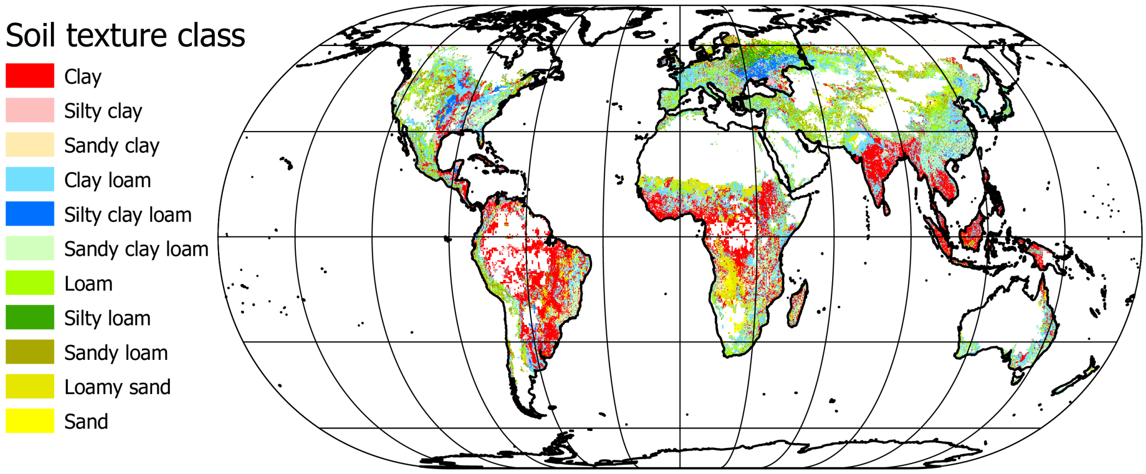


Figure 5.1a: Soil texture classes provided by S-world (30 arc-seconds, for technical reasons, the high resolution cannot be adequately reproduced in print). White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010).

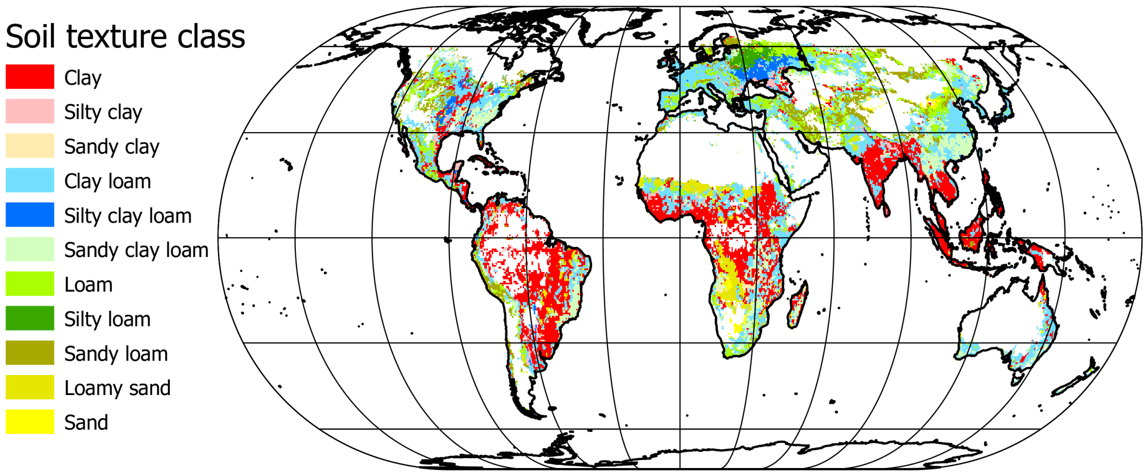


Figure 5.1b: Dominant soil texture classes (0.5 degree). White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010).

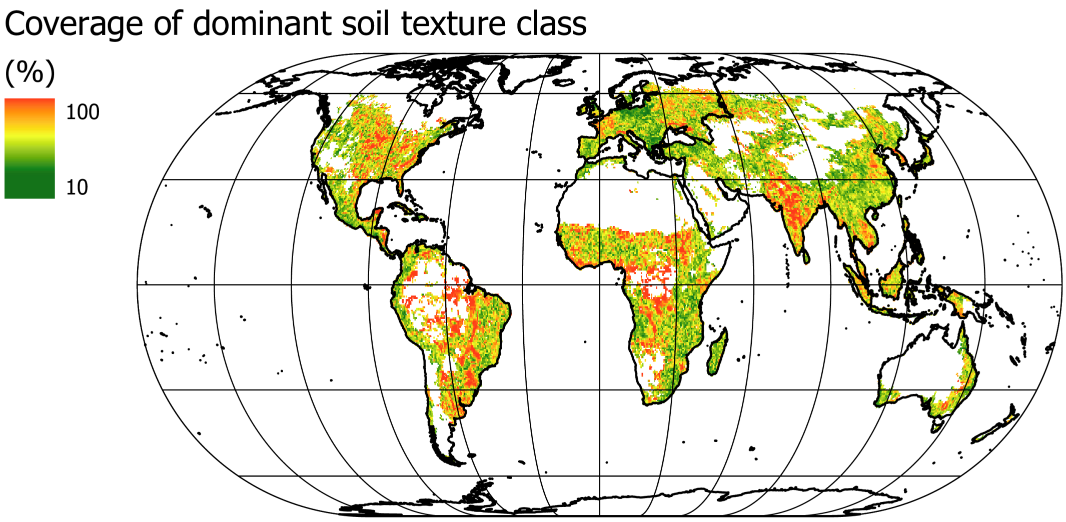


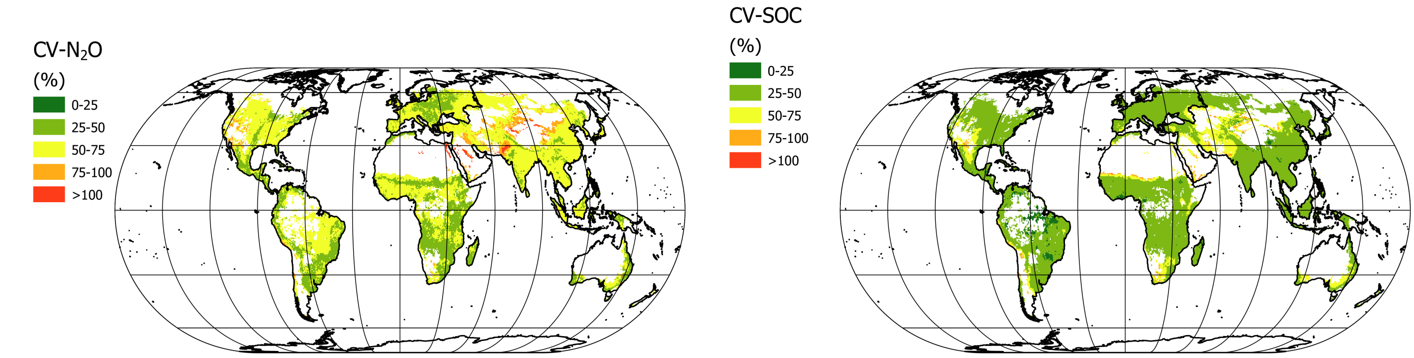
Figure 5.1c: Area share (%) covered by dominant soil texture class within each 0.5 degree grid cell. White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010).

5.3.2 Identification of risk areas

5.3.2.1 Model sensitivity of N_2O emissions and SOC content to variations in STCs

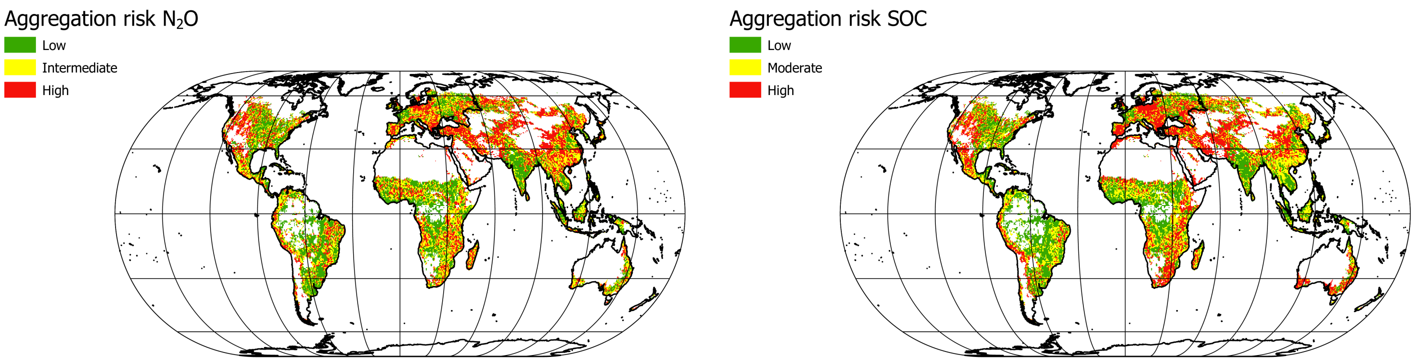
The simulation of N_2O emissions by LPJmL is sensitive to the different STCs. Simulation results for N_2O emissions are typically more sensitive in dry regions such as central Asia and the western North America, even though exceptions exist (e.g. parts of Australia) and it can also be moderately high in regions with relatively high precipitation as in the Amazon region (Fig. 5.2a). The simulated SOC content is overall less sensitive compared to the sensitivity of simulated N_2O emissions to the different STCs (Fig. 5.2b). Also here, the simulations of SOC content are more sensitive to STCs in the arid regions compared to the rest of the world.

The relative high sensitivity to the STCs in the arid regions can be explained by the relative low N_2O emissions and SOC content across the different STCs. In these regions, small variations between the STCs can therefore already result in a high sensitivity values if this is expressed as the CV. However, when assessing where the sensitivity is most important for global assessments, these regions become unimportant. We demonstrate this by computing the sensitivity of simulated N_2O emissions with the modified *CV global* (see equation 5.5) using the global average of simulated N_2O emissions rather than the grid-cell average. In this metric, the arid areas are relatively insensitive to the STCs (Fig. C.5.1a in Appendix C). The areas with relative high N_2O emissions become now more important as the variation between STCs in relation to the global average becomes larger (Fig. C.5.1b in Appendix C). This also holds true for the simulation of SOC content, where a similar pattern can be found (Fig. C.5.1a in Appendix C).



(a) **(b)**

Figure 5.2: The sensitivity of N_2O emissions (a) and SOC content (b) in terms of the CV of the simulated results for different soil texture classes. White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010)



(a) **(b)**

Figure 5.3: The spatial distribution of areas at low, high and intermediate risk of introducing modeling errors by generalizing STC variability using STC_{dom} for N_2O emissions (a) and SOC content (b). White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010)

5.3.2.2 Risk areas for the analyses of N_2O emissions and SOC content

The areas at high risk of introducing errors into simulation results by using STC_{dom} for the analyses on N_2O emissions are in many of the arid- (e.g. Central Asia and western United States) and temperate regions (e.g. Europe and eastern China) (Fig 5.3a). The areas at low risk are mainly located in the tropical regions (e.g. Central Africa and South America). The areas with a moderate risk are more evenly spread across the globe.

The areas at high, low and intermediate risk when using STC_{dom} for the analyses of SOC content under tillage are similar to the regions found to be sensitive in the simulation of N_2O emissions (Fig 5.3b). Also here, the areas at risk of introducing modeling errors by using STC_{dom} are found in the arid regions as well as parts of the cold- and temperate zones. Additionally, some areas at risk are also found in the tropical regions (e.g. eastern Africa), but a high spatial variation in risk classes can be observed.

The share of the dominant STC (STC_{dom}) within 0.5° grid cells (Fig. 5.1c is often small in regions where simulation results are also sensitive to STCs (e.g. Central Europe) so that the areas at high risk of introducing modeling errors by using STC_{dom} is often an amplification of the two factors. However, there are also regions where a low STC_{dom} share is sufficient to result in high risk classes (e.g. parts of Madagascar). However, only high sensitivity of model results to different STCs is insufficient to constitute high risk of introducing modeling errors by using STC_{dom} if there is little diversity in STCs, as e.g. in parts of Pakistan.

5.3.3 Effect of representing soil heterogeneity

Between the different methods of soil representation, there are only small differences to the estimates with STC_{dom} at the global average for both the N_2O emissions and SOC content (Table 5.1). However, locally there are considerable differences and the standard deviations of the differences between aggregation methods are high. These local differences increase considerably with an increase in risk.

On average, the representation using $STC_{dom,cropland}$ shows the largest differences with the representation using STC_{dom}, for both the N_2O emissions and SOC content at the global aggregation (Table 5.1). The smallest difference is found when using $STC_{frac,cropland}$ for N_2O emissions and STC_{frac} for SOC.

Although the representation of soil heterogeneity using dominant STC on cropland $STC_{dom,cropland}$ shows largest differences with the representation using STC_{dom} for both the N_2O emissions and SOC content at the global aggregation (Table 5.1), there are no clear visible differences in the map (Fig. 5.4c for N_2O and 5.5c for SOC). Presumably, the large differences on average are strongly influenced by outliers, as also suggested by the larger standard deviation of differences in space (Table 5.1). There are also no clear differences found between $STC_{frac,cropland}$ and STC_{frac} for both the N_2O emissions and SOC content, indicating that the representation of soil heterogeneity by the dominant STCs (STC_{dom} and $STC_{dom,cropland}$) and the weighted averages of the simulated results ($STC_{frac,cropland}$ and STC_{frac}) are very similar to each other at the global aggregation. However, there are stronger regional differences detectable, as shown in Fig. 5.4 b and d for N_2O emissions and in Fig. 5.5 b and d for SOC. Here, regional positive and negative differences compensate each other at the global aggregation level.

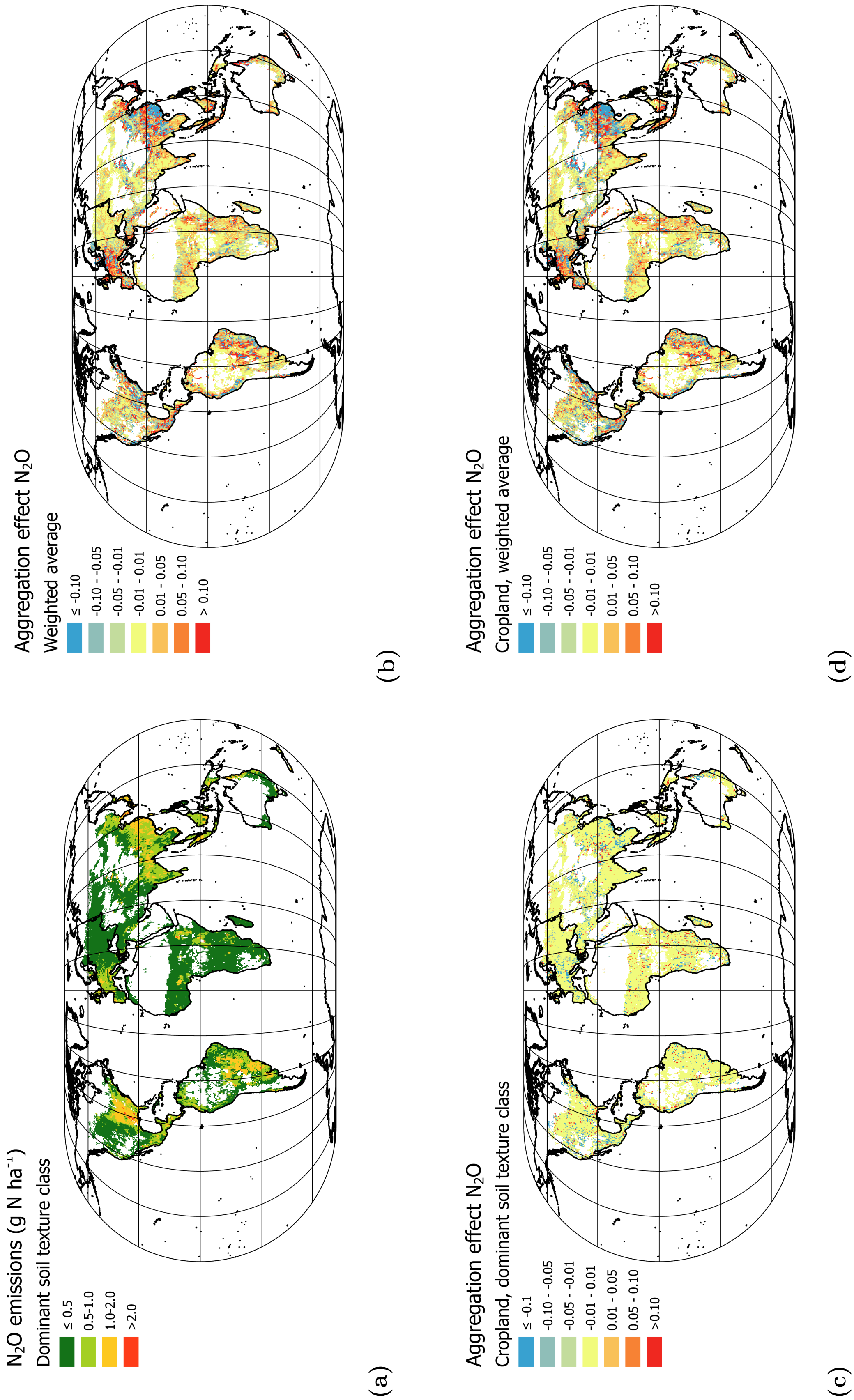


Figure 5.4: The N_2O emissions simulated under STC_{dom} (a), and its differences with the soil representation method STC_{frac} (b), $STC_{dom,cropland}$ (c) and $STC_{frac,cropland}$ (d). White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010)

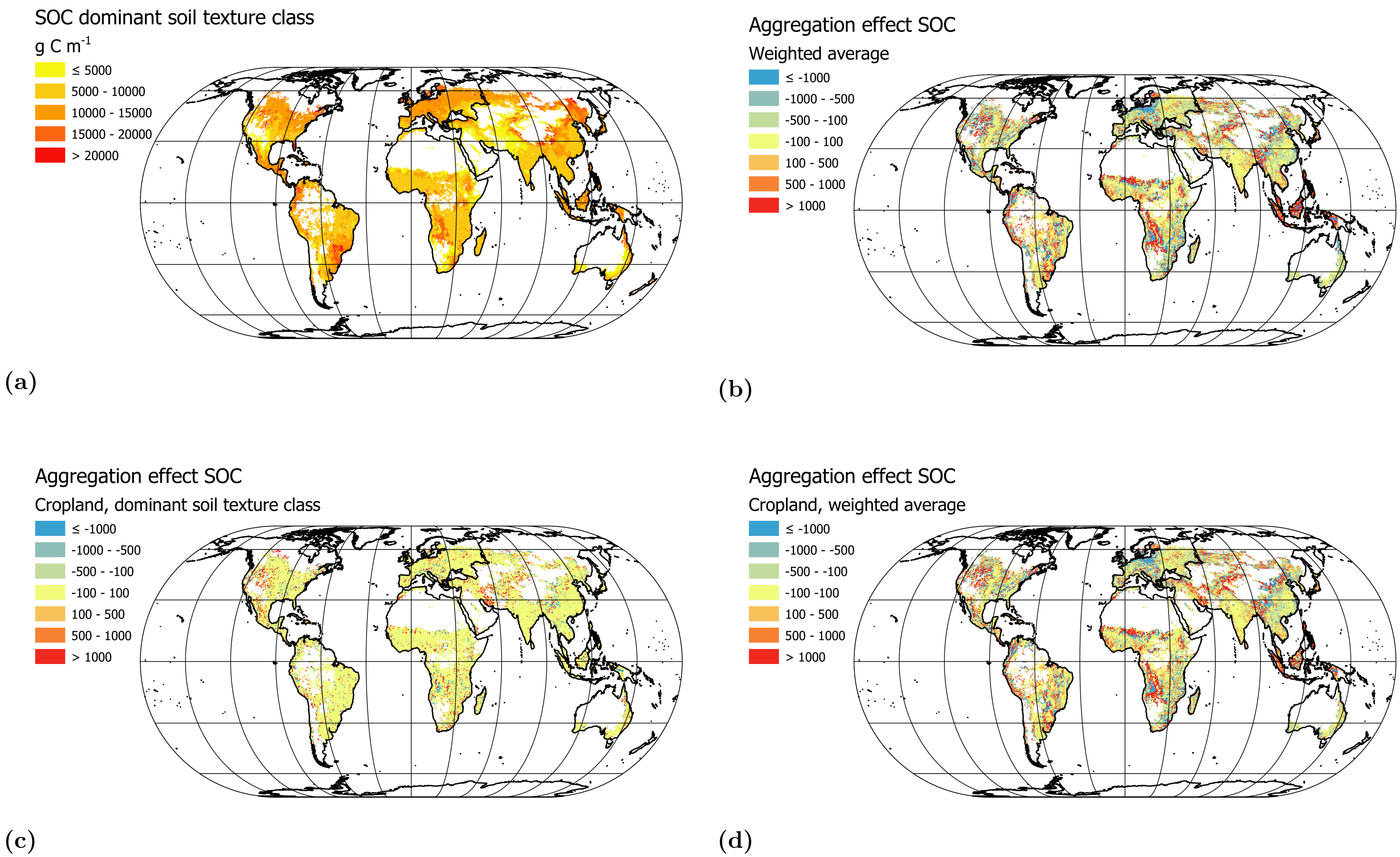


Figure 5.5: The SOC content simulated under STC_{dom} (a), and its differences with the soil representation method STC_{frac} (b), $STC_{dom,cropland}$ (c) and $STC_{frac,cropland}$ (d). White areas indicate regions without cropland, according to MIRCA2000 (Portmann et al., 2010)

Table 5.1: This table represents the average of differences between the generalization and the estimates with STC_{dom}. The standard deviation is also shown (between parentheses).

	Overall	Low risk	Moderate risk	High risk
N_2O emissions (in g N m^{-1})				
STC_{frac}	0.007 (0.093)	0.001 (0.009)	0.008 (0.062)	0.006 (0.129)
$STC_{dom,cropland}$	-0.013 (0.123)	0.001 (0.018)	0.002 (0.076)	-0.011 (0.145)
$STC_{frac,cropland}$	-0.004 (0.107)	-0.003 (0.051)	-0.006 (0.077)	-0.025 (0.171)
SOC (in g C m^{-1})				
STC_{frac}	21 (1197)	37 (145)	90 (925)	-59 (1558)
$STC_{dom,cropland}$	72 (1546)	17 (408)	6 (1151)	160 (2033)
$STC_{frac,cropland}$	57 (1379)	40 (249)	77 (1093)	39 (1761)

5.4 Discussion

To our knowledge, this is the first global study where the different effects of representation methods of soil heterogeneity on simulations of SOC and N_2O emissions are analyzed. In this study, we first identified the areas at risk of introducing modeling errors by using STC_{dom}, which is the most often-used representation method for soil heterogeneity in GEM studies. To evaluate the overall effects of different aggregation methods, as well as its effects in the risk areas, we analyzed the simulated N_2O emissions and SOC, at the global scale as well as in these risk areas under different soil representation methods.

Our findings highlight that choosing STC_{dom} for a global analyses on N_2O emissions and SOC content is a feasible approach to keep computational requirements manageable as errors are both positive and negative and largely compensate at the global aggregation. The global averages on simulated N_2O emissions and SOC content, showed only small differences between the different methods for representing soil heterogeneity. However, considerable differences were found in the local and regional patterns. For local or regional assessments on N_2O emissions and SOC content, using STC_{dom} within 0.5° grid cells can therefore lead to modeling errors.

The high risk areas for introducing modeling errors by using STC_{dom} show very similar spatial patterns for both the simulation of N_2O emissions and of SOC. These high risk areas were mainly found in the regions where the coverage of STC_{dom} was low, and in the arid regions where the N_2O emissions and SOC content were very sensitive to the different STCs. This sensitivity is often a result of very low mean values, especially in the case of SOC simulations, so that variations in their low values do not affect the global average much. However, assessments within these regions, should therefore more explicitly account for soil variability in order to improve the overall assessments related to N_2O emissions and SOC content. Presumably, the aggregation in which the relative share of STCs is calculated under cropland gives the most accurate result. This requires a high resolution (e.g. 30 arc-seconds) STC soil map and cropland cover as well as substantial computational resources. A global simulation at 30 arc-seconds is about 3600 times more expensive than a simulation at 0.5°.

The variability in STCs might be underrepresented in many regions in the S-World dataset as the availability and spatial coverage of soil data are very variable across different world regions. Regions identified as low risk areas for introducing modeling errors by using STC_{dom} may thus be falsely classified, merely reflecting the poor data availability in these regions and the homogeneous gap-filling methods applied (Stoorvogel et al., 2017).

Similarly, we here present results only for one GEM, LPJmL. This is a widely used dynamic global vegetation, hydrology and crop model (Schaphoff et al., 2018a) and has been evaluated comprehensively (Schaphoff et al., 2018b; Müller et al., 2017). However, given the diversity in model implementations across crop (Müller et al., 2017) and biome models (Friend et al., 2014), the sensitivity of simulation results to STCs will likely be quite different across GEMs.

This is also true for the indicators considered here. Model responses are also likely different across modeled outputs. Folberth et al. (2016) found strong effects of yield simulations with the gridded global crop model GEPIC to STC selection in 0.5° grid cells. Because of the sensitivity of their results, they emphasized that global model studies should more explicitly account for soil variability by using high soil resolution data.

Although various soil data sources are available at a high spatial resolution (e.g. Hengl et al., 2014; Batjes et al., 2017), aggregating soil data is often needed as the computational capacity to run a global model is too low to conduct global simulations at high resolution. An option to cope with high resolution soil data and cropland cover, is through following the same procedure conducted in this study: i.e. conduct individual simulations for each STC and link the outputs to the high resolution soil map. This would open opportunities to conduct the aggregation of outputs based on fractions of STCs under cropland. However, this implies that conversions between cropland, managed grassland and natural vegetation cannot be adequately represented in such analyses, in which results are aggregated in the post-processing only. The temporal dynamics in land-use have strong effects on the biogeochemical cycles (e.g. Bondeau et al., 2007; Pugh et al., 2015) and an accounting for the diversity in STCs in the post-processing is thus limited to static analyses as here. Irregular grids with higher spatial resolution only in regions with high STC diversity and larger effects on the simulation results, which we have identified as high risk areas, could be a way forward to combine spatial diversity and temporal dynamics. This will have to be tested, especially with its implications for lateral interaction such as river routing schemes (Rost et al., 2008).

5.5 Conclusions

GEMs are increasingly applied to evaluate climate change impacts, the role of agricultural adaptation and the effects of agriculture on the environment. For global-scale analyses, such models are often applied at a relatively coarse spatial resolution, which in many regions implies that the variability of soils is underrepresented as the most dominant soil texture class is typically used to represent the entire grid cell. As there are different methods to represent soil heterogeneity, we here tested the effect of different representation methods on simulated N_2O emissions and SOC content under tillage, using the LPJmL model.

Our findings highlight that choosing STC_{dom} for global analyses on N_2O emissions and SOC content with LPJmL is a feasible compromise between computational constraints and relevant spatial detail. The global averages on simulated N_2O emissions and SOC content, showed only small differences between the methods of representing soil heterogeneity. For research questions related to global assessments on N_2O emissions and SOC content, using the dominant soil texture type within the grid cell is therefore feasible. However, locally and regionally there are considerable differences. In this study we could identify the areas that are at high risk of introducing modeling errors when analyzing N_2O emissions and SOC content by using the dominant soil texture class. In these areas, soil variability should be more explicitly accounted for, especially in regional to local studies. We hypothesize that the representation in which the relative share of STCs is calculated under cropland gives the most accurate result. An aggregation of results with high-resolution soil texture class data in the post-processing as done here, conflicts with accounting for land-use change dynamics in time. As such, this does not represent an adequate approach to resolve the conflict between high computational demand for such high-resolution simulations and the necessary spatial detail in all regions. However, the identification of high-risk areas could help to define non-regular grid sizes as a compromise. Even though we only looked at two different output variables (N_2O emissions and SOC), the similarity in spatial patterns of high-risk areas for N_2O emissions and SOC suggests that an non-regular grid can be defined for all output variables from GEMs.

Chapter 6

Synthesis

6.1 Challenges of agricultural management representations in global ecosystem models

Agriculture is responsible for 10-12% of the global GHG emissions, mainly in form of carbon dioxide, (CO_2), methane (CH_4) and nitrous oxides (N_2O) (IPCC, 2019; Smith et al., 2014b; Tubiello et al., 2015; FAO, 2014; Frank et al., 2019; Tubiello, 2019). Several agricultural-based mitigation strategies have been identified to reduce emissions from agricultural soils, through improved soil management (Smith et al., 2014b; Paustian et al., 2016). The efficacy of improved soil management on reducing GHG emission from agricultural soils has been demonstrated in many field and field-scale modeling studies (e.g. Amado et al., 2006; Chen et al., 2009; Jiang et al., 2019; Pezzuolo et al., 2017). However, the potential of reducing GHG emissions from agriculture through improved management at the global scale remains poorly understood. Global ecosystem models often lack the capacity to assess the potential of agricultural-based mitigation strategies or agricultural management impacts in general. The global models work with a simplified representation of the agricultural systems that simply excludes or strongly simplifies certain management practices such as tillage. This has three underlying causes: i) processes related to agricultural management are currently underrepresented in global ecosystem models (Erb et al., 2017; McDermid et al., 2017), ii) knowledge gaps exist on the distribution and timing of numerous agricultural management practices (Erb et al., 2017; McDermid et al., 2017), and iii) the models work at a relatively coarse resolution (e.g., 0.5°) whereas agricultural management may vary greatly between farming systems in close proximity.

Field-scale crop models typically include detailed descriptions of processes related to agricultural management. Field-scale models that have a broad range of agricultural management options incorporated are for example DSSAT (Jones et al., 2010), EPIC (Williams et al., 2008) and Daycent (Parton et al., 1998). These models can simulate residue management and include different types of tillage which are typically ignored or underrepresented in global ecosystem models. Sometimes, field-scale models have been applied at global scales to enable studying effects of agricultural management, such as tillage, at the global scale (Del Grosso et al., 2009). However, field-scale models cannot simply be applied at scales for which they are not developed as other processes or conditions may play a role that were not relevant or considered in the field-scale model applications. Moreover, field-scale models typically include many descriptive variables and parameters for which at the global scale data are lacking. Therefore, for global-scale analyses, global ecosystem models are preferred. This requires, however, the incorporation of processes related to agricultural management in these global models in an adequate level of detail.

Although the application of field-scale models at the global scale is problematic, the implementation of agricultural management into global ecosystem models can benefit from the description of processes in field-scale models. The detailed process descriptions from the field-scale models can be used to extend the global models. In the selection of suitable approaches, the importance of processes has to be considered, as well as the input data requirements and availability at the global scale. Yet, a guiding principle on where to start and how to make these decisions on model extension was not available.

Next to data and knowledge gaps on processes related to agricultural management and its environmental impacts, uncertainties in inputs may impact simulated effects of agricultural management on GHG emissions. For example, current global ecosystem models neglect soil heterogeneity within grid cells, which has been shown to seriously affect simulated yields (Folberth et al., 2016). Folberth et al. (2016) therefore emphasized the importance of considering high resolution soil data in global crop simulations. Although soil data are available at high spatial resolution (e.g. Hengl et al., 2014; Stoorvogel et al., 2017, for soil data), it is necessary to upscale the data to meet the required spatial resolution of global ecosystem models. Often, the computational capacity to run global ecosystem models is too low to cope with input data that comes at a fine resolution (Grosz et al., 2017). Representing soil heterogeneity can be conducted in different ways, for example, by averaging the underlying detail. The decision on how soil heterogeneity is represented can have implications when assessing agricultural management effects on GHG emissions. Yet, how to decide on the method of representing soil heterogeneity and what kind of implications this may have, remains poorly understood.

This thesis aimed to improve the representation of agricultural management in global ecosystem models, so that the potential of agricultural-based mitigation practices can be better quantified. Therefore, this thesis first addressed if and how processes related to agricultural management can be described in global ecosystem models. The research focused on processes related to tillage and N_2O emissions. Tillage is a common agricultural practice and changes in tillage management are a promising option to reduce GHG emissions (Paustian et al., 2016). N_2O emissions are particularly important as N_2O is a potent GHG with a global warming potential of ~300-fold that of CO_2 (Solomon et al., 2007). After indicating how processes related to tillage can be described, they were implemented into the global ecosystem model LPJmL. Subsequently, the extended LPJmL model was evaluated on its performance at the global scale and for a number of experimental sites. Finally, the effect of representing of soil heterogeneity on global modelling of SOC and N_2O emissions was tested.

This final chapter discusses and synthesizes the main findings of the thesis. Insights obtained during conducting the research for this thesis are addressed as well as directions for improvements in the representation of agricultural management in global models.

6.2 Can an existing global ecosystem model be extended by tillage management to study its effects in particular on N_2O emissions?

Several field-scale models simulate the effects of tillage on N_2O emissions (Chapter 2). However, not all tillage related processes described in field-scale models are suitable for incorporation into global ecosystem models. In order to make an informed decision on which approach to choose, or whether it is actually possible to incorporate tillage in that level of detail into global ecosystem models that allows for analyses on tillage effects on N_2O emissions, a standardized framework is proposed in Chapter 2. The framework consists of three different steps (Figure 2.1). First, the most important nitrogen (N) processes in soils were identified including their response to tillage. Second, the description of these processes and tillage effects in field-scale models are reviewed. The third step included an evaluation whether they can be incorporated in global ecosystem models, while considering the data requirements for a global application. As the most important processes of tillage, its effects on soil conditions and subsequently the formation of N_2O were described in field-scale models and the basic data requirements can be met at the global scale, I concluded that we can incorporate tillage into global ecosystem models for the analyses on N_2O emissions. However, a spatial explicit dataset on tillage was missing, which only allows for scenario-based analyses.

Chapter 2 identified several options to represent tillage in field-scale models. The option where tillage directly affected the physical soil properties through changes to bulk density was found to be most appropriate to extend a global ecosystem model, as it affects the main drivers (soil moisture and soil temperature) of N_2O emissions. Some of the field-scale models also simulated the effects of tillage in relation with residue management where, for example, a fraction of crop residues was incorporated into the first soil layer. As tillage practices and residue management are indeed often inter-related (Strudley et al., 2008), the two effects of tillage (physical soil properties and residue incorporation) were considered to be necessary for incorporation into a global ecosystem model. The effects of tillage on physical soil properties and residues is also supported by several studies (e.g. Schlüter et al., 2018; Strudley et al., 2008; Kurothe et al., 2014; Alvarez & Steinbach, 2009).

6.3 Can the effects of tillage on N_2O emissions be captured at the global scale?

As I found that tillage can be incorporated into global ecosystem models, the global ecosystem model LPJmL was extended with tillage management (Chapter 3). LPJmL is a dynamic global vegetation, hydrology and crop model that simulates N (including the most important N processes that are relevant for N_2O emissions), C and water dynamics in natural and agricultural ecosystems (Von Bloh et al., 2018a; Schaphoff et al., 2018a). The model has been evaluated extensively and reproduced C, water and N dynamics in both agricultural and natural ecosystems in a proper way Schaphoff et al. (2018b). The resulting model extension led to a global ecosystem model with a more detailed representation of tillage than typically found in other global-scale models, in combination with detailed nitrogen dynamics while keeping input data requirements manageable (Lutz et al., 2019a).

The first step after extending a model with a new module is to evaluate its performance. Ideally, the evaluation is done at the same scale for which the model was developed. The most common approach of model evaluation is through comparison against observations (Oreskes, 2003). However, it is unrealistic to expect observational data of tillage effects on soil processes, GHG emissions and crop yields with global coverage. Moreover, a comparison to individual site-specific studies would require detailed site-specific simulations, in which land-use history, weather data and other agricultural management practices are specified. Therefore, the results of the simulations were compared to literature values from selected meta-analyses. Meta-analyses allow for comparing the simulated results to a set of combined results of world-wide individual studies. Using meta-analyses therefore enables evaluating the magnitude and variability of an effect.

In Chapter 3, the extended model was evaluated by using four contrasting simulations: with and without the application of tillage in combination with two contrasting assumptions on residues: with and without the removal of residues. The simulated results of soil organic carbon (SOC), CO_2 and N_2O emissions and water-fluxes across the global cropland were then compared to reported effect sizes and distributions from meta-analyses. In general, the model was able to reproduce observed effects of no-tillage on global, as well as regional patterns of agricultural productivity, water- and carbon (C) fluxes. For N_2O emissions, I found that the overall effect of no-tillage compared to tillage on N_2O emissions was in overall agreement with data reported in meta-analyses as well. However, the regional patterns over the different climate regimes were strongly deviating from the meta-analyses. For example, Mei et al. (2018) found that no-tillage decreases N_2O emissions in the cool temperate climate zones by 1.7% on average, whereas the simulations from LPJmL resulted in an increase by 23.5% on average with no-tillage. Furthermore, Van Kessel et al. (2012) found that no-tillage decreases N_2O emissions by 1.5% on average in the humid climate zone, whereas the simulations from LPJmL resulted in an increase by 23.5% on average with no-tillage in the humid climate zone.

Meta-analyses can be very useful in order to get an indication of model responses to agricultural management, such as tillage. Yet, using meta-analyses for evaluating the model performance can be limited for two main reasons. First, meta-analysed are typically biased from uneven or sparse samples of experiments covered. For instance, Mei et al. (2018) reported in their meta-analyses that no-tillage increases N_2O emissions by 17.8% on average over all data analysed, with significant differences among climate regimes. However, in their analyses the amount of paired observations between climate regimes differed, with having many more paired observations in the tropical regime than in the warm- and cool temperate regime together. The overall average reported by Mei et al. (2018) might therefore be biased, resulting to an over-representation of the tropical climate regime.

Second, meta-analyses can only give a first indication of overall model performance. Mismatches between reported effect ranges and simulated results cannot provide any insights on the underlying mechanisms or model deficiencies that lead to this mismatch. Modelled tillage effects on N_2O emissions can deviate from reported values in meta-analyses for different reasons. The deviations can be a result of model parameter uncertainties, the quality of the input data, and uncertainties in the processes related to tillage effects on N_2O emissions. For instance, at the global scale assumptions have to be made on agricultural management, as detailed information about management is typically lacking (such as fertilizer application, sowing dates, irrigation and residue management) (Erb et al., 2017). Moreover, as mentioned previously, the spatial variability of soil conditions within grid cells is ignored, which can have implications when assessing tillage effects on N_2O emissions.

The deviations in tillage effects on N_2O emissions can also result from uncertainties in the process representation of tillage. To test if the deviations result from a lack of detailed input on management practices or the representation of processes related to tillage, the extended model LPJmL was applied at different experimental sites in Chapter 4. Four experimental sites were selected in which the effects of tillage and no-tillage on N_2O emissions were studied, and site-specific information on management, weather and soil was available. This enabled using site-specific information on agricultural management, soil and weather information and thus, understanding if model input or process representation causes the observed mismatch between global simulations and reported values in meta-analyses.

Chapter 4 showed that adding site-specific information on management improved the simulated N_2O emissions produced by tillage and no-tillage, as well as the effect of switching from conventional tillage to no-tillage. However, also with detailed information, the N_2O emissions were strongly deviating from the observations across all the experimental sites. LPJmL was strongly overestimating N_2O emissions in general and did not reproduce the effects of tillage and no-tillage on N_2O emissions. The observations showed that shifting to no-tillage could both increase and decrease N_2O emissions (e.g. Halvorson et al., 2006; Oorts et al., 2007; Jin et al., 2017). However, LPJmL was not able to reproduce decreases in N_2O emissions at the annual aggregation at any of the four sites.

The application of LPJmL at the experimental sites provided much insight in why the effects of tillage on N_2O emissions were deviating from observations. It enabled to use site-specific information on agricultural management, whereas at global scale we have to work with assumptions. As detailed information improved the simulation of tillage effects on N_2O emissions, advancing the current state of information on agricultural management at the global scale could improve global estimates of tillage effects on N_2O emissions. The study also highlighted the potential of improving the simulation of N_2O emission by improving soil moisture dynamics. Chapter 4 showed that the high emissions were a result of high soil moisture levels. Soil moisture is a major driver of N_2O emissions as it regulates the oxygen availability to soil microbes. In many models, including LPJmL, soil moisture is used as a proxy for anaerobic conditions. As denitrification is an anaerobic process, high soil moisture levels trigger N_2O emission from denitrification. In LPJmL, N_2O emission from denitrification increases exponentially when the soil moisture exceeds a certain threshold value. As denitrification is therefore very sensitive to soil moisture levels in LPJmL, it is very important to more accurately simulate soil moisture in LPJmL. However, as high soil moisture levels can result from various reasons (e.g. parameterization of hydraulic properties), further research is needed to improve the representation of soil hydrology in LPJmL. However, an adjusted parameterization of soil hydraulic properties could substantially reduce the general overestimation of N_2O emissions in LPJmL simulations, indicating that this is indeed a promising way forward.

6.4 How much uncertainty is introduced by coarse representations of soil heterogeneity into global simulations of soil processes on cropland, including N_2O emissions

A possible cause of uncertainty to accurately estimate the potential of agricultural-based mitigation is the relatively coarse resolution at which global models are typically applied. Global ecosystem models often work at a spatial resolution of 0.5° (equivalent to approximately 55 km at the equator) (Clark et al., 2011; Olin et al., 2015a; Oleson et al., 2010, e.g.) and typically work with the most dominant soil type within the grid cell. As a result, soil heterogeneity within the large grid cells is ignored. Moreover, croplands may not be located on the dominant soil type within the grid cell but on specific (e.g. high fertile) areas that only cover specific parts of that grid cell.

As this can contribute to the uncertainty in simulating N_2O emissions, four different ways of representing heterogeneity in soil conditions and their effects on simulated N_2O emissions and SOC were tested in Chapter 5. To this end, I combined simulations from the global ecosystem LPJmL and the high resolution (30 arc-seconds) global soil property data base S-World Stoorvogel et al. (2017) as well as the high-resolution cropland map of Globcover (Bontemps et al., 2011). The four different ways of representing soil heterogeneity on simulated N_2O emissions and SOC included: i) using the dominant soil type in the grid cell (the method that is typically used), ii) using the dominant soil type under cropland in the grid cell iii) using the high resolution soil map and aggregate the outputs of N_2O emissions and SOC, which were generated in individual simulations for each soil texture classes (STC), using the shares of STCs within the entire grid cell as aggregation weights and iv) following the same procedure as in iii) but using only STC shares under cropland within the grid cell. We also identified areas that are at low, high or intermediate risk for modeling errors when using the dominant soil texture class within the grid cell. Areas at high risks for modeling errors can occur where for instance the area covered by the dominant STC is relatively low as a high heterogeneity in STCs are found in the grid cell. On the other hand, if the sensitivity of N_2O emissions between the STCs is low, the method of representing soil heterogeneity is relatively unimportant.

Chapter 5 indicated that for global assessments using LPJmL, the dominant soil type can be used for simulating N_2O emissions and SOC content, as the errors across regions tend to compensate each other, so that only small differences were found between the methods of representing soil heterogeneity. However, considerable differences were found when analyzing local and regional differences. For local or regional assessments on N_2O emissions and SOC content, using the dominant soil texture within the grid cell can therefore lead to distortions, especially in the high risk areas.

The results of this study confirmed that ignoring the heterogeneity in soil conditions can indeed be a source of uncertainty when simulating N_2O emissions and SOC content, especially for local and regional assessments. As mentioned previously, in Chapter 3 I found that the regional patterns over the different climate regimes were strongly deviating from the meta-analyses. Accounting more explicitly for soil heterogeneity, especially in the indicated high-risk areas (Chapter 5) can potentially improve the simulation of tillage effects on N_2O emissions by LPJmL.

As the spatial patterns of the indicated high risk areas for N_2O emissions and SOC content were similar, I hypothesized that a non-regular grid could be defined for soil inputs/output variables from global ecosystem models as a compromise between computational constraints and required spatial detail. The irregular grids can have a higher spatial resolution only in those regions (e.g. high-risk areas) where one should account for the higher heterogeneity in soil properties. However, further research efforts are required to determine if that indeed can improve the simulation of tillage effects on N_2O at the regional scale, and hence at the global scale.

6.5 General discussion

An evaluation of the effects of agricultural management on GHG emissions requires the closure of knowledge gaps on processes related to agricultural management and its effects on the environment as well as data gaps on the spatial distribution and timing of agricultural practices. Moreover, the effects of representing of soil heterogeneity on global modelling of SOC and N_2O emissions has to be addressed. This thesis focused on the representation of processes related to tillage management in the global ecosystem model LPJmL. Besides developing an extended LPJmL model for such large-scale assessments, the effects of preparing input data, such as the representation of heterogeneous soil properties for assessing N_2O emissions were studied. The process representation in field-scale models can be used for such an extension by following a standardized framework (Chapter 2). The standardized framework enabled to make informed decisions on how to implement tillage into the global ecosystem model for the analyses of N_2O emissions (Chapter 3). However, the evaluation of the model performance on simulating tillage effects on N_2O emissions showed substantial deviations compared to the data reported in meta-analyses (Chapter 3), and observations from field experiments (Chapter 4). LPJmL showed a general bias to overestimate soil moisture content (Chapter 4) and therefore N_2O emissions, especially from denitrification. Next to uncertainties in the processes related to the simulation of N_2O emissions, I also found that the method of representing soil heterogeneity can contribute to the uncertainties of simulating tillage effects on N_2O emissions (Chapter 5).

Agricultural management affects both crop productivity and the associated GHG emissions. An analysis based on simple Tier 1 emission factors is insufficient to study the mitigation potential in agricultural production, as these do not account for the multiple options in which emissions and productivity can be modified by management and diverse environmental conditions. Further development of global ecosystem models is thus needed to study the impacts of agricultural management on soil and plant processes, which first requires an understanding of how agricultural management affects these processes. For the implementation in global ecosystem models, one can make use of existing process knowledge from field-scale models. To make an informed decision on how to do that, the standardized framework from Chapter 2 can be followed. Although the framework is focused on tillage effects on N_2O emissions in Chapter 2, the framework could also be employed for other management aspects. The framework provides guidance on where to start management implementation in global ecosystem models, but cannot substitute careful model development, testing and eventually model refinement. The suitability and validity of processes that are described in the field-scale models are often not evaluated and will have to be tested within the global ecosystem model, along with an adequate parameterization.

Yet, the process representation of agricultural management in global ecosystem models is not the only gap that has to be filled. Data-scarcity on the spatial distribution and timing of agricultural management will have to be addressed. However, in the absence of management-related data, scenario-based analyses can allow for evaluating the effects of agricultural management. In Chapter 3 for example, the extended global ecosystem model LPJmL is evaluated by using four scenarios: with and without the application of tillage and with and without the removal of residues. As processes related to agricultural management can be incorporated by following the standardized framework, and data-scarcity on agricultural management not necessarily limits the evaluation of the extended model, I therefore argue that there is no barrier to extend global ecosystem models to better represent agricultural management. The exclusion of explicit management options in models also implicitly represents some form of management, so that it is not possible to avoid making assumptions on management in response to the large uncertainties connected with these.

The incorporation of agricultural management practices into a global ecosystem model should be followed by an evaluation of its performance. However, this can be a challenging task as the simulated effects can be very variable, depending on climatic and soil conditions. Because of the high data collection and preparation requirements, it would be unrealistic to conduct simulations at so many sites where data are available so that a site-specific evaluation is possible. The use of meta-analyses can be very helpful, as they can give the magnitude and variability of model responses to agricultural management. Therefore, using meta-analyses for model evaluations can be suggested as a good strategy for model evaluation at the global scale. However, the evaluation of an extended ecosystem model should additionally be evaluated at the field scale when deviations with meta-analyses are observed. First, using meta-analyses might under-represent certain climate and soil combinations which can result in biases, especially when the sample size is low. Using observational data of single field experiments — rather than results of combined experiments — can give a better indication of the model responses. Ideally, the single studies span a broad range of environmental- and climatic conditions. Second, site-specific information of the field experiments can be used as inputs for the model. Generalized inputs on management information and soil data affect model results, which can be a cause of model deviations with observed values (Chapter 4 and 5). By specifying site-specific inputs and using site-specific observations with higher temporal resolution, more insights can be obtained in processes related to management, and can give directions for model improvements.

To better assess the impacts of tillage at the global scale, different tillage types (e.g. reduced tillage) need to be incorporated into LPJmL. In this initial implementation, conventional tillage and no-tillage can be distinguished. In reality, there are various different types of tillage (Porwollik et al., 2019), such as reduced tillage. Differences in tillage types vary in the objective (e.g. seedbed preparation, weeding or cultivation) and the intensity of tillage management (e.g. tillage affected soil depth, amount of residues incorporated). These differences in tillage types can affect GHG emissions (Abdalla et al., 2013) which can currently not be captured by LPJmL. Porwollik et al. (2019) provide a globally spatial explicit dataset on different types of tillage. In order to use this dataset, these tillage types need to be represented by LPJmL. This can be done through a parameterization of the already incorporated processes (e.g. hydraulic properties and residue incorporation).

The extended global ecosystem LPJmL was not capable of accurately simulating tillage effects on N_2O emissions. Hence, the potential of mitigating N_2O emissions through tillage management cannot be well assessed. Therefore, the question how strongly other mitigation efforts are needed to meet the targets from e.g. the Paris Agreement remains equally unclear, as the overall contribution of tillage effects to mitigation efforts cannot be evaluated. Yet, we have now a much better understanding of processes related to tillage and its interaction with N_2O emissions. For example, tillage affects N_2O emissions by altering soil properties that drive N_2O emissions (Chapter 2). By understanding and incorporating such processes into models, changes in practices and conditions can be analyzed, whereas a simple response effect of management cannot (e.g. Tier 1 and Del Grosso et al., 2009). For example, the IPCC Tier 1 methodology estimates N_2O emissions based on N inputs only and does not account for soil conditions and weather which hampers the evaluation of mitigation options, except for those that involve reducing N fertilizers (IPCC: Eggleston et al., 2006; Penman, 2000).

Although LPJmL was not capable of accurately simulating tillage effects on N_2O emissions, the model is able to reproduce observed effects of tillage on the other dimensions such as agricultural production, SOC and CO_2 emissions at various scales. The implementation of the more detailed tillage-related mechanisms into LPJmL improves the ability to represent different agricultural systems and understand agricultural management options for the mitigation of agricultural GHG emissions, climate change adaptation and reducing environmental impacts. For example, in Chapter 3 I could identify the regions where no-tillage can be beneficial for agricultural productivity. Moreover, regions where an increase in CO_2 emissions were found after shifting to no-tillage were identified, indicating that no-tillage is not necessarily a mitigation practice in those regions. Such findings can guide management decisions at various scales with respect to agriculture-based mitigation strategies. Decisions, such as when and where no-tillage should be adapted to mitigate GHG emissions, can inform policymakers in order to define a realistic portfolio of different mitigation options that include reliable estimates of the potentials and spatial patterns of agricultural mitigation options. This could support the achievement of regional and global mitigation goals, such as the Paris Agreement (Frank et al., 2019; Wollenberg et al., 2016) and its interactions (i.e. synergies and trade-offs) with the Sustainable Developments Goals (Griggs et al., 2013; Steffen et al., 2015).

6.6 General conclusions

To improve the representation of agricultural management in global ecosystem models, this thesis addressed how tillage effects on N_2O emissions at the global scale can be evaluated. This works shows that:

1. Process knowledge and model implementation schemes related to agricultural management can be obtained by analyzing existing field-scale modeling approaches. In order to make an informed decision on how to use existing approaches and if they are suitable for incorporation into global ecosystem models, a standardized frame-work can be followed.

2. In the absence of management-related data with suitable detail and spatial coverage, a scenario-based analyses can be used to evaluate the effects of agricultural management.

3. As processes related to agricultural management can be incorporated into global ecosystem models by following the standardized framework, and data-scarcity on agricultural management does not necessarily limit the evaluation of the extended model, there is no general barrier to extend global ecosystem models by modules for the representation of agricultural management.

4. The performance of the extended ecosystem model should be evaluated both at the global scale, as well at the field-scale. The evaluation of the model at field-scale enables using site-specific input information and therefore provides understanding whether model input or process representation causes possible mismatches simulations and reported values.

5. LPJmL was not capable of accurately simulating tillage effects on N_2O emissions. Hence, the potential of mitigating N_2O emissions through tillage management cannot be assessed here. However, options for further improving the model could already be identified.

6. Accounting more explicitly for soil heterogeneity in areas at risk of aggregation errors can potentially improve the simulation of tillage effects on N_2O emissions and SOC content by LPJmL.

7. The implementation of the more detailed tillage-related mechanism into the global ecosystem model LPJmL improves the ability to represent different agricultural systems and understand agricultural management options for agricultural mitigation of CO_2 emissions, climate change adaptation and reducing environmental impacts.

References

Abdalla, K., Chivenge, P., Ciais, P., & Chaplot, V. (2016). No-tillage lessens soil CO_2 emissions the most under arid and sandy soil conditions: results from a meta-analysis. *Biogeosciences*, *13*, 3619–3633. doi:10.5194/bg-13-3619-2016.

Abdalla, M., Jones, M., Yeluripati, J., Smith, P., Burke, J., & Williams, M. (2010). Testing DayCent and DNDC model simulations of N_2O fluxes and assessing the impacts of climate change on the gas flux and biomass production from a humid pasture. *Atmospheric Environment*, *44*, 2961–2970. doi:10.1016/j.atmosenv.2010.05.018.

Abdalla, M., Osborne, B., Lanigan, G., Forristal, D., Williams, M., Smith, P., & Jones, M. (2013). Conservation tillage systems: a review of its consequences for greenhouse gas emissions. *Soil use and management*, *29*, 199–209.

Abdalla, M. A., Mohamed, A. E., & Makki, E. K. (2007). The response of two-sorghum cultivars to conventional and conservation tillage systems in central sudan. *Ama, Agricultural Mechanization in Asia, Africa & Latin America*, *38*, 67.

Abrahamson, D., Radcliffe, D., Steiner, J., Cabrera, M., Hanson, J., Rojas, K., Schomberg, H., Fisher, D., Schwartz, L., & Hoogenboom, G. (2005). Calibration of the Root Zone Water Quality Model for simulating tile drainage and leached nitrate in the georgia piedmont. *Agronomy journal*, *97*, 1584–1602. doi:10.2134/agronj2004.0160.

Adam, M., Van Bussel, L., Leffelaar, P., Van Keulen, H., & Ewert, F. (2011). Effects of modelling detail on simulated potential crop yields under a wide range of climatic conditions. *Ecological Modelling*, *222*, 131–143. doi:10.1016/j.ecolmodel.2010.09.001.

Addiscott, T., & Wagenet, R. (1985). Concepts of solute leaching in soils: a review of modelling approaches. *Journal of Soil Science*, *36*, 411–424. doi:10.1111/j.1365-2389.1985.tb00347.x.

Ahuja, L., Rojas, K., & Hanson, J. (2000). *Root zone water quality model: modelling management effects on water quality and crop production*. CO, USA: Water Resources Publication.

Alexandratos, N., & Bruinsma, J. (2012). World agriculture towards 2030/2050: the 2012 revision. *FAO Agricultural Development Economics Division*, .

Alvarez, C., Costantini, A., Alvarez, C. R., Alves, B. J., Jantalia, C. P., Martellotto,

E. E., & Urquiaga, S. (2012). Soil nitrous oxide emissions under different management practices in the semiarid region of the Argentinian pampas. *Nutrient cycling in agroecosystems*, *94*, 209–220.

Alvarez, R., & Steinbach, H. S. (2009). A review of the effects of tillage systems on some soil physical properties, water content, nitrate availability and crops yield in the Argentine Pampas. *Soil and Tillage Research*, *104*, 1–15. doi:10.1016/j.still.2009.02.005.

Álvaro-Fuentes, J., Morell, F. J., Plaza-Bonilla, D., Arrúe, J. L., & Cantero-Martínez, C. (2012). Modelling tillage and nitrogen fertilization effects on soil organic carbon dynamics. *Soil and Tillage Research*, *120*, 32–39.

Amado, T. J. C., Bayer, C., Conceicao, P. C., Spagnollo, E., De Campos, B.-H. C., & Da Veiga, M. (2006). Potential of carbon accumulation in no-till soils with intensive use and cover crops in southern Brazil. *Journal of environmental quality*, *35*, 1599–1607.

Armand, R., Bockstaller, C., Auzet, A.-V., & Van Dijk, P. (2009). Runoff generation related to intra-field soil surface characteristics variability: Application to conservation tillage context. *Soil and Tillage Research*, *102*, 27–37. doi:https://doi.org/10.1016/j.still.2008.07.009.

Aslam, T., Choudhary, M., & Saggar, S. (2000). Influence of land-use management on CO_2 emissions from a silt loam soil in New Zealand. *Agriculture, Ecosystems & Environment*, *77*, 257–262. doi:10.1016/S0167-8809(99)00102-4.

Balland, V., Pollacco, J. A., & Arp, P. A. (2008). Modeling soil hydraulic properties for a wide range of soil conditions. *Ecological Modelling*, *219*, 300–316. doi:10.1016/j.ecolmodel.2008.07.009.

Batjes, N. (2005). *ISRIC-WISE global data set of derived soil properties on a 0.5 by 0.5 degree grid (version 3.0)*. Technical Report Report 2005/08, ISRIC – World Soil Information Wageningen.

Batjes, N. (2009). Harmonized soil profile data for applications at global and continental scales: updates to the wise database. *Soil Use and Management*, *25*, 124–127.

Batjes, N. H., Ribeiro, E., Oostrum, A. v., Leenaars, J., Hengl, T., & Mendes de Jesus, J. (2017). WoSIS: providing standardised soil profile data for the world. *Earth System Science Data*, *9*, 1–14. doi:10.5194/essd-9-1-2017.

Beaujouan, V., Durand, P., & Ruiz, L. (2001). Modelling the effect of the spatial distribution of agricultural practices on nitrogen fluxes in rural catchments. *Ecological modelling*, *137*, 93–105. doi:10.1016/S0304-3800(00)00435-X.

Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., Schamm, K., Schneider, U., & Ziese, M. (2013). A description of the global land-surface precipitation data products of the Global Precipitation Climatology Centre with sample applications including centennial (trend) analysis from 1901–present. *Earth System Science Data*, *5*, 71–99.

doi:https://doi.org/10.5194/essd-5-71-2013.

Begum, K., Kuhnert, M., Yeluripati, J. B., Ogle, S. M., Parton, W. J., Williams, S. A., Pan, G., Cheng, K., Ali, M. A., & Smith, P. (2019). Modelling greenhouse gas emissions and mitigation potentials in fertilized paddy rice fields in Bangladesh. *Geoderma*, *341*, 206–215.

Berrisford, P., Dee, D., Fielding, K., Fuentes, M., Kallberg, P., Kobayashi, S. et al. (2009). The ERA-INTERIM archive. ERA report series. No. 1. technical (ERA) report. european centre for medium-range weather forecasting, shinfield park. *Reading, UK*, .

Bertolino, A. V. F. A., Fernandes, N. F., Miranda, J. P. L., Souza, A. P., Lopes, M. R. S., & Palmieri, F. (2010). Effects of plough pan development on surface hydrology and on soil physical properties in Southeastern Brazilian plateau. *Journal of Hydrology*, *393*, 94–104. doi:10.1016/j.jhydrol.2010.07.038.

Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R., Ménard, C. B., Edwards, J. M., Hendry, M. A., Porson, A., & Gedney, N. (2011). The Joint UK Land Environment Simulator (JULES), model description–Part 1: energy and water fluxes. *Geoscientific Model Development*, *4*, 677–699.

Billen, G., Garnier, J., & Lassaletta, L. (2013). The nitrogen cascade from agricultural soils to the sea: modelling nitrogen transfers at regional watershed and global scales. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *368*, 20130123. doi:10.1098/rstb.2013.0123.

Bodirsky, B. L., Popp, A., Lotze-Campen, H., Dietrich, J. P., Rolinski, S., Weindl, I., Schmitz, C., Müller, C., Bonsch, M., Humpenöder, F. et al. (2014). Reactive nitrogen requirements to feed the world in 2050 and potential to mitigate nitrogen pollution. *Nature communications*, *5*, 3858.

Bodirsky, B. L., Popp, A., Weindl, I., Dietrich, J. P., Rolinski, S., Scheiffele, L., Schmitz, C., & Lotze-Campen, H. (2012). N_2O emissions from the global agricultural nitrogen cycle–current state and future scenarios. *Biogeosciences*, *9*, 4169–4197. doi:10.5194/bg-9-4169-2012.

Boeckx, P., Van Nieuland, K., & Van Cleemput, O. (2011). Short-term effect of tillage intensity on N_2O and CO_2 emissions. *Agronomy for Sustainable Development*, *31*, 453–461. doi:10.1007/s13593-011-0001-9.

Bondeau, A., Smith, P. C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-Campen, H., MüLler, C., Reichstein, M., & Smith, B. (2007). Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Global Change Biology*, *13*, 679–706. doi:10.1111/j.1365-2486.2006.01305.x.

Bontemps, S., Defourny, P., Van Bogaert, E., Arino, O., Kalogirou, V., & Perez, J. R. (2011). *GLOBCOVER 2009, Products description and validation report* volume 2. ESA and Université Catholique de Louvain. doi:http://doi.org/10.1594/PANGAEA.787668.

Brady, N. C., & Weil, R. R. (2008). *The nature and properties of soils* volume 360. Pearson Prentice Hall Upper Saddle River.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M. H., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C. et al. (1998). STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. *Agronomie*, *18*, 311–346.

Buckingham, S., Anthony, S., Bellamy, P., Cardenas, L., Higgins, S., McGeough, K., & Topp, C. (2014). Review and analysis of global agricultural N_2O emissions relevant to the uk. *Science of the Total Environment*, *487*, 164–172. doi:10.1016/j.scitotenv.2014.02.122.

Burney, J. A., Davis, S. J., & Lobell, D. B. (2010). Greenhouse gas mitigation by agricultural intensification. *Proceedings of the national Academy of Sciences*, *107*, 12052–12057.

Butterbach-Bahl, K., Baggs, E. M., Dannenmann, M., Kiese, R., & Zechmeister-Boltenstern, S. (2013). Nitrous oxide emissions from soils: how well do we understand the processes and their controls? *Philosophical Transactions of the Royal Society B: Biological Sciences*, *368*, 20130122.

Cameira, M. R., Fernando, R. M., Ahuja, L. R., & Ma, L. (2007). Using RZWQM to simulate the fate of nitrogen in field soil–crop environment in the mediterranean region. *Agricultural water management*, *90*, 121–136. doi:10.1016/j.agwat.2007.03.002.

Campbell, E. E., Johnson, J. M., Jin, V. L., Lehman, R. M., Osborne, S. L., Varvel, G. E., & Paustian, K. (2014). Assessing the soil carbon, biomass production, and nitrous oxide emission impact of corn stover management for bioenergy feedstock production using DAYCENT. *Bioenergy research*, *7*, 491–502.

Campolongo, F., & Braddock, R. (1999). Sensitivity analysis of the IMAGE greenhouse model. *Environmental Modelling & Software*, *14*, 275–282. doi:10.1016/s1364-8152(98)00079-6.

Carter, T., Jones, R., Lu, X., Bhadwal, S., Conde, C., Mearns, L., O'Neill, B., Rounsevell, M., & Zurek, M. (2007). *New assessment methods and the characterisation of future conditions*.

Chatskikh, D., Olesen, J. E., Hansen, E. M., Elsgaard, L., & Petersen, B. M. (2008). Effects of reduced tillage on net greenhouse gas fluxes from loamy sand soil under winter crops in Denmark. *Agriculture Ecosystems & Environment*, *128*, 117–126. doi:10.1016/j.agee.2008.05.010. WOS:000258247600014.

Chen, H., Hou, R., Gong, Y., Li, H., Fan, M., & Kuzyakov, Y. (2009). Effects of 11 years of conservation tillage on soil organic matter fractions in wheat monoculture in Loess Plateau of China. *Soil and Tillage Research*, *106*, 85–94. doi:10.1016/j.still.2009.09.009.

Chung, S. W., Gassman, P. W., Kramer, L. A., Williams, J. R., & Gu, R. (1999). Validation of EPIC for Two Watersheds in Southwest Iowa. *Journal of Environment Quality*, *28*, 971. doi:10.2134/jeq1999.00472425002800030030x.

Ciais, P., Gervois, S., Vuichard, N., Piao, S. L., & Viovy, N. (2011). Effects of land use change and management on the European cropland carbon balance. *Global Change Biology*, *17*, 320–338. doi:10.1111/j.1365-2486.2010.02341.x.

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., Chhabra, A., DeFries, R., Galloway, J., & Heimann, M. (2014). Carbon and other biogeochemical cycles. In *Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 465–570). Cambridge University Press.

Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., & Blyth, E. (2011). The Joint UK Land Environment Simulator (JULES), model description–Part 2: carbon fluxes and vegetation dynamics. *Geoscientific Model Development*, *4*, 701–722.

Cleveland, C. C., Townsend, A. R., Schimel, D. S., Fisher, H., Howarth, R. W., Hedin, L. O., Perakis, S. S., Latty, E. F., Fischer, J. C. V., Elseroad, A., & Wasson, M. F. (1999). Global patterns of terrestrial biological nitrogen (N_2O) fixation in natural ecosystems. *Global Biogeochemical Cycles*, *13*, 623–645. doi:10.1029/1999gb900014.

Cosby, B. J., Hornberger, G. M., Clapp, R. B., & Ginn, T. R. (1984). A Statistical Exploration of the Relationships of Soil Moisture Characteristics to the Physical Properties of Soils. *Water Resources Research*, *20*, 682–690. doi:10.1029/WR020i006p00682.

Coucheney, E. et al. (2015). Accuracy, robustness and behavior of the STICS soil–crop model for plant, water and nitrogen outputs: Evaluation over a wide range of agro-environmental conditions in France. *Environmental Modelling & Software*, *64*, 177–190. doi:10.1016/j.envsoft.2014.11.024.

Cui, F., Zheng, X., Liu, C., Wang, K., Zhou, Z., & Deng, J. (2014). Assessing biogeochemical effects and best management practice for a wheat–maize cropping system using the DNDC model. *Biogeosciences*, *11*, 91–107. doi:10.5194/bg-11-91-2014.

Daigh, A. L. M., & DeJong-Hughes, J. (2017). Fluffy soil syndrome: When tilled soil does not settle. *Journal of Soil and Water Conservation*, *72*, 10A–14A. doi:10.2489/jswc.72.1.10A.

Dee, D. P. et al. (2011). The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, *137*, 553–597. doi:10.1002/qj.828.

Del Grosso, S., Ogle, S., Parton, W., & Breidt, F. (2010). Estimating uncertainty in n2o emissions from us cropland soils. *Global Biogeochemical Cycles*, *24*.

Del Grosso, S., Ojima, D., Parton, W., Mosier, A., Peterson, G., & Schimel, D. (2002). Simulated effects of dryland cropping intensification on soil organic matter and greenhouse gas exchanges using the DAYCENT ecosystem model. *Environmental pollution*, *116*, S75–S83.

Del Grosso, S., Parton, W., Mosier, A., Ojima, D., Kulmala, A., & Phongpan, S. (2000). General model for N_2O and N_2 gas emissions from soils. *Global Biogeochemical Cycles*, *14*, 1045–1060.

Del Grosso, S., Parton, W., Ojima, D., Keough, C., Riley, T., & Mosier, A. (2008). Chapter 18. daycent simulated effects of land use and climate on county level n loss vectors in the usa. In J. L. Hatfield, & R. Follett (Eds.), *Nitrogen in the Environment: Sources, Problems, and Management* (pp. 1–28). Amsterdam, Boston: Academic Press/Elsevier.

Del Grosso, S. J., Ojima, D. S., Parton, W. J., Stehfest, E., Heistemann, M., DeAngelo, B., & Rose, S. (2009). Global scale daycent model analysis of greenhouse gas emissions and mitigation strategies for cropped soils. *Global and Planetary Change*, *67*, 44–50.

Del Grosso, S. J., Ojima, D. S., Parton, W. J., Stehfest, E., Heistemann, M., DeAngelo, B., & Rose, S. (2009). Global scale DAYCENT model analysis of greenhouse gas emissions and mitigation strategies for cropped soils. *Global and Planetary Change*, *67*, 44–50. doi:10.1016/j.gloplacha.2008.12.006.

Del Grosso, S. J., Parton, W. J., Adler, P. R., Davis, S. C., Keough, C., & Marx, E. (2012). Daycent model simulations for estimating soil carbon dynamics and greenhouse gas fluxes from agricultural production systems. *Managing agricultural greenhouse gases: coordinated agricultural research through GRACEnet to address our changing climate*, (pp. 241–250).

Del Grosso, S. J., Parton, W. J., Mosier, A. R., Ojima, D. S., Kulmala, A. E., & Phongpan, S. (2000). General model for N_2O and N_2 gas emissions from soils due to dentrification. *Global Biogeochemical Cycles*, *14*, 1045–1060. doi:10.1029/1999gb001225.

Deng, J., Zhu, B., Zhou, Z., Zheng, X., Li, C., Wang, T., & Tang, J. (2011). Modeling nitrogen loadings from agricultural soils in southwest China with modified DNDC. *Journal of Geophysical Research*, *116*. doi:10.1029/2010jg001609.

Deng, Q., Hui, D., Wang, J., Yu, C.-L., Li, C., Reddy, K. C., & Dennis, S. (2016). Assessing the impacts of tillage and fertilization management on nitrous oxide emissions in a cornfield using the DNDC model. *Journal of Geophysical Research: Biogeosciences*, *121*, 337–349. doi:10.1002/2015jg003239.

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K. (2006). *2006 IPCC guidelines for national greenhouse gas inventories* volume 5. Institute for Global Environmental Strategies Hayama, Japan.

Elliott, J. et al. (2015). The Global Gridded Crop Model Intercomparison: data and modeling protocols for Phase 1 (v1.0). *Geoscientific Model Development*, *8*, 261–277.

doi:10.5194/gmd-8-261-2015.

Enrique, G. S., Braud, I., Jean-Louis, T., Michel, V., Pierre, B., & Jean-Christophe, C. (1999). Modelling heat and water exchanges of fallow land covered with plant-residue mulch. *Agricultural and Forest Meteorology*, *97*, 151–169. doi:10.1016/S0168-1923(99)00081-7. WOS:000083648600002.

Erb, K.-H., Luyssaert, S., Meyfroidt, P., Pongratz, J., Don, A., Kloster, S., Kuemmerle, T., Fetzel, T., Fuchs, R., Herold, M. et al. (2017). Land management: data availability and process understanding for global change studies. *Global change biology*, *23*, 512–533.

Ewert, F., Rounsevell, M., Reginster, I., Metzger, M., & Leemans, R. (2005). Future scenarios of european agricultural land use: I. estimating changes in crop productivity. *Agriculture, Ecosystems & Environment*, *107*, 101–116.

Ewert, F., Van Ittersum, M. K., Heckelei, T., Therond, O., Bezlepkina, I., & Andersen, E. (2011). Scale changes and model linking methods for integrated assessment of agri-environmental systems. *Agriculture, Ecosystems & Environment*, *142*, 6–17. doi:10.1016/j.agee.2011.05.016.

Ewert, F., Van Keulen, H., Van Ittersum, M., Giller, K., Leffelaar, P., & Roetter, R. (2006). Multi-scale analysis and modelling of natural resource management options. In *3rd Biennial Meeting of the International Environmental Modelling and Software Society*.

Fader, M., Rost, S., Müller, C., Bondeau, A., & Gerten, D. (2010). Virtual water content of temperate cereals and maize: Present and potential future patterns. *Journal of Hydrology*, *384*, 218–231. doi:10.1016/j.jhydrol.2009.12.011.

Fageria, N., & Baligar, V. (2005). Enhancing Nitrogen Use Efficiency in Crop Plants. In *Advances in Agronomy* (pp. 97–185). Elsevier. doi:10.1016/s0065-2113(05)88004-6.

FAO (1998). *World reference base for soil resources* volume 3. Food & Agriculture Org.

FAO (2014). Agriculture, forestry and other land use emissions by sources and removals by sinks: 1990-2011 analysis. *FAO, Rome, Italy*, .

FAO, I., & ISRIC, I. (2012). Jrc: Harmonized world soil database (version 1.2). *FAO, Rome, Italy and IIASA, Laxenburg, Austria*, .

FAO/IFA/IFDC (2003). *Fertilizer use by crop. Fifth edition.*. Food and Agriculture Organization of the United Nations/International Fertilizer Industry Association/International Fertilizer Development Center.

Farage, P., Ardö, J., Olsson, L., Rienzi, E., Ball, A., & Pretty, J. (2007). The potential for soil carbon sequestration in three tropical dryland farming systems of africa and latin america: A modelling approach. *Soil and Tillage research*, *94*, 457–472.

Fitton, N., Datta, A., Hastings, A., Kuhnert, M., Topp, C., Cloy, J., Rees, R., Cardenas, L., Williams, J., Smith, K. et al. (2014). The challenge of modelling nitrogen management at the field scale: simulation and sensitivity analysis of n2o fluxes across nine experimental sites using dailydaycent. *Environmental Research Letters*, *9*, 095003.

Folberth, C., Elliott, J., Müller, C., Balkovič, J., Chryssanthacopoulos, J., Izaurralde, R. C., Jones, C. D., Khabarov, N., Liu, W., Reddy, A. et al. (2019). Parameterization-induced uncertainties and impacts of crop management harmonization in a global gridded crop model ensemble. *PloS one*, *14*, e0221862.

Folberth, C., Skalskỳ, R., Moltchanova, E., Balkovič, J., Azevedo, L. B., Obersteiner, M., & Van Der Velde, M. (2016). Uncertainty in soil data can outweigh climate impact signals in global crop yield simulations. *Nature communications*, *7*, 11872.

Frank, S., Havlík, P., Stehfest, E., van Meijl, H., Witzke, P., Pérez-Domínguez, I., van Dijk, M., Doelman, J. C., Fellmann, T., Koopman, J. F. et al. (2019). Agricultural non-CO_2 emission reduction potential in the context of the 1.5° c target. *Nature Climate Change*, *9*, 66.

Friend, A. D. et al. (2014). Carbon residence time dominates uncertainty in terrestrial vegetation responses to future climate and atmospheric CO_2. *Proceedings of the National Academy of Sciences*, *111*, 3280–3285. doi:10.1073/pnas.1222477110.

Gillette, K., Ma, L., Malone, R. W., Fang, Q., Halvorson, A. D., Hatfield, J. L., & Ahuja, L. (2017). Simulating N_2O emissions under different tillage systems of irrigated corn using RZ-SHAW model. *Soil and Tillage Research*, *165*, 268–278. doi:10.1016/j.still.2016.08.023.

Giltrap, D. L., Li, C., & Saggar, S. (2010). DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. *Agriculture, Ecosystems & Environment*, *136*, 292–300. doi:10.1016/j.agee.2009.06.014.

Glab, T., & Kulig, B. (2008). Effect of mulch and tillage system on soil porosity under wheat (Triticum aestivum). *Soil and Tillage Research*, *99*, 169–178. doi:https://doi.org/10.1016/j.still.2008.02.004.

Godwin, D. C., & Singh, U. (1998). Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In *Understanding Options for Agricultural Production* (pp. 55–77). Springer Netherlands. doi:10.1007/978-94-017-3624-4_4.

Govers, G., Vandaele, K., Desmet, P., Poesen, J., & Bunte, K. (1994). The role of tillage in soil redistribution on hillslopes. *European Journal of Soil Science*, *45*, 469–478.

Grandy, A. S., Loecke, T. D., Parr, S., & Robertson, G. P. (2006). Long-term trends in nitrous oxide emissions, soil nitrogen, and crop yields of till and no-till cropping systems. *Journal of Environmental Quality*, *35*, 1487–1495.

Grant, R., & Pattey, E. (2003). Modelling variability in N_2O emissions from fertilized agricultural fields. *Soil Biology and Biochemistry*, *35*, 225–243. doi:10.1016/s0038-

0717(02)00256-0.

Grassini, P., Van Bussel, L. G., Van Wart, J., Wolf, J., Claessens, L., Yang, H., Boogaard, H., de Groot, H., Van Ittersum, M. K., & Cassman, K. G. (2015). How good is good enough? data requirements for reliable crop yield simulations and yield-gap analysis. *Field Crops Research*, *177*, 49–63. doi:10.1016/j.fcr.2015.03.004.

Green, T. R., Ahuja, L. R., & Benjamin, J. G. (2003). Advances and challenges in predicting agricultural management effects on soil hydraulic properties. *Geoderma*, *116*, 3–27. doi:10.1016/S0016-7061(03)00091-0.

Gregory, J. M. (1982). Soil cover prediction with various amounts and types of crop residue. *Transactions of the ASAE*, *25*, 1333–1337. doi:10.13031/2013.33723.

Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M. C., Shyamsundar, P., Steffen, W., Glaser, G., Kanie, N., & Noble, I. (2013). Policy: Sustainable development goals for people and planet. *Nature*, *495*, 305.

Grosz, B., Dechow, R., Gebbert, S., Hoffmann, H., Zhao, G., Constantin, J., Raynal, H., Wallach, D., Coucheney, E., Lewan, E. et al. (2017). The implication of input data aggregation on up-scaling soil organic carbon changes. *Environmental modelling & software*, *96*, 361–377.

Gryze, S. D., Wolf, A., Kaffka, S. R., Mitchell, J., Rolston, D. E., Temple, S. R., Lee, J., & Six, J. (2010). Simulating greenhouse gas budgets of four California cropping systems under conventional and alternative management. *Ecological applications*, *20*, 1805–1819.

Guimberteau, M., Laval, K., Perrier, A., & Polcher, J. (2012). Global effect of irrigation and its impact on the onset of the indian summer monsoon. *Climate dynamics*, *39*, 1329–1348.

Guérif, J., Richard, G., Dürr, C., Machet, J. M., Recous, S., & Roger-Estrade, J. (2001). A review of tillage effects on crop residue management, seedbed conditions and seedling establishment. *Soil and Tillage Research*, *61*, 13–32.

Halvorson, A. D., Mosier, A. R., Reule, C. A., & Bausch, W. C. (2006). Nitrogen and tillage effects on irrigated continuous corn yields. *Agronomy Journal*, *98*, 63–71.

Hansen, S., Abrahamsen, P., Petersen, C. T., & Styczen, M. (2012). Daisy: Model Use, Calibration, and Validation. *Transactions of the ASABE*, *55*, 1317–1335. doi:10.13031/2013.42244.

Hansen, S., Jensen, H., Nielsen, N., & Svendsen, H. (1990). Daisy − a soil plant atmosphere system model. In *NPO−research from the National Agency of Environmental Protection No. A10* (pp. 1–272).

Harris, I., & Jones, P. (2019). Cru ts4.02: Climatic research unit (cru) time-series (ts) version 4.02 of high-resolution gridded data of month-by-month variation in climate (jan. 1901- dec. 2017). *University of East Anglia Climatic Research Unit Centre for Environmental Data Analysis*, . doi:10.5285/b2f81914257c4188b181a4d8b0a46bff.

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology*, *34*, 623–642. doi:10.1002/joc.3711.

Harrison, P. A., Porter, J. R., & Downing, T. E. (2000). Scaling-up the AFRCWHEAT2 model to assess phenological development for wheat in Europe. *Agricultural and Forest Meteorology*, *101*, 167–186. doi:10.1016/s0168-1923(99)00164-1.

Heinke, J., Müller, C., Lannerstad, M., Gerten, D., & Lucht, W. (2019). Freshwater resources under success and failure of the Paris climate agreement. *Earth System Dynamics*, *10*, 205–217.

Hengl, T., de Jesus, J. M., MacMillan, R. A., Batjes, N. H., Heuvelink, G. B., Ribeiro, E., Samuel-Rosa, A., Kempen, B., Leenaars, J. G., Walsh, M. G. et al. (2014). Soilgrids 1km global soil information based on automated mapping. *PloS one*, *9*, e105992.

Hillel, D. (2004). Chapter 12 Soil temperature and heat flow. In *Introduction to Envrionmental Soil Physics* (pp. 215–234). Amsterdam: Elsevier Academic Press Inc.

Holland, J. M. (2004). The environmental consequences of adopting conservation tillage in Europe: reviewing the evidence. *Agriculture, ecosystems & environment*, *103*, 1–25.

Horton, R., Horn, R., Bachmann, J., & Peth, S. (2016). *Essential Soil Physics - An introduction to soil processes, functions, structure and mechanic*. E. Schweizerbart'sche Verlagsbuchhandlung.

Huang, Y., & Tang, Y. (2010). An estimate of greenhouse gas (N_2O and CO_2) mitigation potential under various scenarios of nitrogen use efficiency in chinese croplands. *Global change biology*, *16*, 2958–2970.

Hutchings, N. J., Reinds, G. J., Leip, A., Wattenbach, M., Bienkowski, J. F., Dalgaard, T., Dragosits, U., Drouet, J. L., Durand, P., Maury, O., & De Vries, W. (2012). A model for simulating the timelines of field operations at a European scale for use in complex dynamic models. *Biogeosciences*, *9*, 4487–4496. doi:10.5194/bg-9-4487-2012.

IPCC (2019). Summary for policymakers. In M. J. S. S. Edvin Aldrian, Bruce McCarl (Ed.), *Climate Change and Land: An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems* book section SPM. (pp. 1–1542).

Izaurralde, R., Williams, J., McGill, W., Rosenberg, N., & Jakas, M. Q. (2006). Simulating soil C dynamics with EPIC: Model description and testing against long-term data. *Ecological Modelling*, *192*, 362–384. doi:10.1016/j.ecolmodel.2005.07.010.

James, J. J., & Richards, J. H. (2006). Plant nitrogen capture in pulse-driven systems: interactions between root responses and soil processes. *Journal of Ecology*, *94*, 765–777.

doi:10.1111/j.1365-2745.2006.01137.x.

Jarvis, P. G., & McNaughton, K. G. (1986). Stomatal control of transpiration: scaling up from leaf to region. *Advances in Ecological Research*, *15*, 1–49. doi:10.1016/S0065-2504(08)60119-1.

Jian-She, Z., Fu-Ping, Z., Jin-Hua, Y., Jin-Ping, W., Ming-Li, C., Li, C.-F., & Cao, C.-G. (2011). Emissions of N_2O and NH_3, and nitrogen leaching from direct seeded rice under different tillage practices in central china. *Agriculture, Ecosystems & Environment*, *140*, 164–173. doi:10.1016/j.agee.2010.11.023.

Jiang, Q., Qi, Z., Madramootoo, C. A., & Crézé, C. (2019). Mitigating greenhouse gas emissions in subsurface-drained field using RZWQM2. *Science of The Total Environment*, *646*, 377–389.

Jin, V. L., Schmer, M. R., Stewart, C. E., Sindelar, A. J., Varvel, G. E., & Wienhold, B. J. (2017). Long-term no-till and stover retention each decrease the global warming potential of irrigated continuous corn. *Global Change Biology*, *23*, 2848–2862. doi:10.1111/gcb.13637.

Jones, J., Hoogenboom, G., Porter, C., Boote, K., Batchelor, W., Hunt, L., Wilkens, P., Singh, U., Gijsman, A., & Ritchie, J. (2003). The DSSAT cropping system model. *European Journal of Agronomy*, *18*, 235–265. doi:10.1016/s1161-0301(02)00107-7.

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S. et al. (2017). Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agricultural systems*, *155*, 269–288.

Jones, J. W., Hoogenboom, G., Boote, K. J., & Porter, C. H. (2010). DSSAT v4.5 Cropping System Model Documentation, . *4*, 450.

Jägermeyr, J., Gerten, D., Heinke, J., Schaphoff, S., Kummu, M., & Lucht, W. (2015). Water savings potentials of irrigation systems: global simulation of processes and linkages. *Hydrology and Earth System Sciences*, *19*, 3073–3091. doi:https://doi.org/10.5194/hess-19-3073-2015.

Jägermeyr, J., Gerten, D., Schaphoff, S., Heinke, J., Lucht, W., & Rockström, J. (2016). Integrated crop water management might sustainably halve the global food gap. *Environmental Research Letters*, *11*, 025002. doi:10.1088/1748-9326/11/2/025002.

Kelley, D. I., Prentice, I. C., Harrison, S. P., Wang, H., Simard, M., Fisher, J. B., & Willis, K. O. (2013). A comprehensive benchmarking system for evaluating global vegetation models. *Biogeosciences*, *10*, 3313–3340. doi:10.5194/bg-10-3313-2013.

Kelly, R., Parton, W., Hartman, M., Stretch, L., Ojima, D., & Schimel, D. (2000). Intra-annual and interannual variability of ecosystem processes in shortgrass steppe. *Journal of Geophysical Research: Atmospheres*, *105*, 20093–20100.

Kessavalou, A., Mosier, A. R., Doran, J. W., Drijber, R. A., Lyon, D. J., & Heinemeyer, O. (1998). Fluxes of Carbon Dioxide, Nitrous Oxide, and Methane in Grass Sod and Winter Wheat-Fallow Tillage Management. *Journal of Environment Quality*, *27*, 1094. doi:10.2134/jeq1998.00472425002700050015x.

Kinnell, P. I. A. (2010). Event soil loss, runoff and the Universal Soil Loss Equation family of models: A review. *Journal of Hydrology*, *385*, 384–397. doi:10.1016/j.jhydrol.2010.01.024.

Klein Goldewijk, K., Beusen, A., Van Drecht, G., & De Vos, M. (2010). The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years: HYDE 3.1 Holocene land use. *Global Ecology and Biogeography*, *20*, 73–86. doi:10.1111/j.1466-8238.2010.00587.x.

Koga, N., Tsuruta, H., Sawamoto, T., Nishimura, S., & Yagi, K. (2004). N_2O emission and CH_4 uptake in arable fields managed under conventional and reduced tillage cropping systems in northern Japan. *Global Biogeochemical Cycles*, *18*, n/a–n/a. doi:10.1029/2004gb002260.

Krysanova, V., & Wechsung, F. (2000). SWIM (soil and water integrated model) user manual.

Kurothe, R. S., Kumar, G., Singh, R., Singh, H. B., Tiwari, S. P., Vishwakarma, A. K., Sena, D. R., & Pande, V. C. (2014). Effect of tillage and cropping systems on runoff, soil loss and crop yields under semiarid rainfed agriculture in India. *Soil and Tillage Research*, *140*, 126–134. doi:10.1016/j.still.2014.03.005.

Lal, R. (2008). Managing soil water to improve rainfed agriculture in India. *Journal of Sustainable Agriculture*, *32*, 51–75.

Lamarque, J.-F. et al. (2013). Multi-model mean nitrogen and sulfur deposition from the Atmospheric Chemistry and Climate Model Intercomparison Project (ACCMIP): evaluation of historical and projected future changes. *Atmospheric Chemistry and Physics*, *13*, 7997–8018. doi:https://doi.org/10.5194/acp-13-7997-2013.

Lee, J., Hopmans, J. W., Van Kessel, C., King, A. P., Evatt, K. J., Louie, D., Rolston, D. E., & Six, J. (2009). Tillage and seasonal emissions of CO_2, N_2O and no across a seed bed and at the field scale in a Mediterranean climate. *Agriculture, Ecosystems & Environment*, *129*, 378–390. doi:10.1016/j.agee.2008.10.012.

Leng, G., Huang, M., Tang, Q., Sacks, W. J., Lei, H., & Leung, L. R. (2013). Modeling the effects of irrigation on land surface fluxes and states over the conterminous united states: Sensitivity to input data and model parameters. *Journal of Geophysical Research: Atmospheres*, *118*, 9789–9803.

LeQuéré, C. et al. (2018). Global Carbon Budget 2017. *Earth System Science Data*, *10*, 405–448. doi:https://doi.org/10.5194/essd-10-405-2018.

Levis, S., Hartman, M. D., & Bonan, G. B. (2014). The Community Land Model underestimates land-use CO_2 emissions by neglecting soil disturbance from cultivation. *Geoscientific Model Development*, *7*, 613–620.

Li, C. (2000). Modeling Trace Gas Emissions from Agricultural Ecosystems. *Nutrient Cycling in Agroecosystems*, *58*, 259–276. doi:10.1023/a:1009859006242.

Li, C. (2007). Quantifying greenhouse gas emissions from soils: Scientific basis and modeling approach. *Soil Science and Plant Nutrition*, *53*, 344–352. doi:10.1111/j.1747-0765.2007.00133.x.

Li, C., Farahbakhshazad, N., Jaynes, D. B., Dinnes, D. L., Salas, W., & McLaughlin, D. (2006). Modeling nitrate leaching with a biogeochemical model modified based on observations in a row-crop field in Iowa. *Ecological Modelling*, *196*, 116–130. doi:10.1016/j.ecolmodel.2006.02.007.

Li, F., Zhao, L.-Y., Zhang, H., Zhang, T.-H., & Shirato, Y. (2004). Wind erosion and airborne dust deposition in farmland during spring in the Horqin Sandy Land of eastern Inner Mongolia, China. *Soil and Tillage Research*, *75*, 121–130. doi:10.1016/j.still.2003.08.001.

Linn, D. M., & Doran, J. W. (1984). Effect of water-filled pore space on carbon dioxide and nitrous oxide production in tilled and nontilled soils 1. *Soil Science Society of America Journal*, *48*, 1267–1272.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., Henry, K. et al. (2014). Climate-smart agriculture for food security. *Nature Climate Change*, *4*, 1068.

Liu, J., Folberth, C., Yang, H., Röckström, J., Abbaspour, K., & Zehnder, A. J. (2013). A global and spatially explicit assessment of climate change impacts on crop production and consumptive water use. *PLoS One*, *8*, e57750.

Liu, J., You, L., Amini, M., Obersteiner, M., Herrero, M., Zehnder, A. J. B., & Yang, H. (2010). A high-resolution assessment on global nitrogen flows in cropland. *Proceedings of the National Academy of Sciences*, *107*, 8035–8040. doi:10.1073/pnas.0913658107.

Lognoul, M., Theodorakopoulos, N., Hiel, M.-P., Regaert, D., Broux, F., Heinesch, B., Bodson, B., Vandenbol, M., & Aubinet, M. (2017). Impact of tillage on greenhouse gas emissions by an agricultural crop and dynamics of n_2o fluxes: Insights from automated closed chamber measurements. *Soil and Tillage Research*, *167*, 80–89. doi:10.1016/j.still.2016.11.008.

Loubet, B. et al. (2011). Carbon, nitrogen and Greenhouse gases budgets over a four years crop rotation in northern France. *Plant and Soil*, *343*, 109–137. doi:10.1007/s11104-011-0751-9.

Lugato, E., Leip, A., & Jones, A. (2018). Mitigation Potential of Soil Carbon Management

Overestimated by Neglecting n_2o Emissions. *Nature Climate Change*, *8*, 219.

Lutz, F., DelGrosso, S., Ogle, S., Williams, S., Minoli, S., Rolinski, S., Heinke, J., Stoorvogel, J. J., & Müller, C. (2020). The importance of management information and soil moisture representation for simulating tillage effects on n_2o emissions in lpjml5.0-tillage. *Geoscientific Model Development Discussions*, *2020*, 1–32. doi:10.5194/gmd-2019-364.

Lutz, F., Herzfeld, T., Heinke, J., Rolinski, S., Schaphoff, S., von Bloh, W., Stoorvogel, J. J., & Müller, C. (2019a). Simulating the effect of tillage practices with the global ecosystem model LPJmL (version 5.0-tillage). *Geoscientific Model Development*, *12*, 2419–2440. doi:10.5194/gmd-12-2419-2019.

Lutz, F., Stoorvogel, J. J., & Müller, C. (2019b). Options to model the effects of tillage on N_2O emissions at the global scale. *Ecological Modelling*, *392*, 212–225. doi:10.1016/j.ecolmodel.2018.11.015.

Maharjan, G. R., Prescher, A.-K., Nendel, C., Ewert, F., Mboh, C. M., Gaiser, T., & Seidel, S. J. (2018). Approaches to model the impact of tillage implements on soil physical and nutrient properties in different agro-ecosystem models. *Soil and Tillage Research*, *180*, 210–221. doi:10.1016/j.still.2018.03.009.

Mangalassery, S., Sjoegersten, S., Sparkes, D. L., & Mooney, S. J. (2015). Examining the potential for climate change mitigation from zero tillage. *Journal of Agricultural Science*, *153*, 1151–1173. doi:10.1017/S0021859614001002. WOS:000359288500002.

Martins, I. C. F., Cividanes, F. J., Barbosa, J. C., Araújo, E. d. S., & Haddad, G. Q. (2009). Faunal analysis and population fluctuation of Carabidae and Staphylinidae (Coleoptera) in no-tillage and conventional tillage systems. *Revista Brasileira de Entomologia*, *53*, 432–443.

Mauser, W., & Bach, H. (2009). PROMET–Large scale distributed hydrological modelling to study the impact of climate change on the water flows of mountain watersheds. *Journal of Hydrology*, *376*, 362–377.

McDermid, S., Mearns, L., & Ruane, A. (2017). Representing agriculture in e arth s ystem m odels: Approaches and priorities for development. *Journal of advances in modeling earth systems*, *9*, 2230–2265.

Mei, K., Wang, Z., Huang, H., Zhang, C., Shang, X., Dahlgren, R. A., Zhang, M., & Xia, F. (2018). Stimulation of N_2O emission by conservation tillage management in agricultural lands: A meta-analysis. *Soil and Tillage Research*, *182*, 86–93. doi:10.1016/j.still.2018.05.006.

Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E., & Houston, T. G. (2012). An Overview of the Global Historical Climatology Network-Daily Database. *Journal of Atmospheric and Oceanic Technology*, *29*, 897–910. doi:10.1175/jtech-d-11-00103.1.

Metherell, A. K., Harding, L. A., Cole, C. V., & Parton, W. J. (1993). CENTURY

Soil Organic Matter Model Environment - Technical Documentation Agroecosystem Version 4.0. *Great Plains System Research Unit USDA-ARS Technical Report No. 4*, .

Millar, N., Robertson, G. P., Grace, P. R., Gehl, R. J., & Hoben, J. P. (2010). Nitrogen fertilizer management for nitrous oxide N_2O mitigation in intensive corn (maize) production: an emissions reduction protocol for us midwest agriculture. *Mitigation and adaptation strategies for global change*, *15*, 185–204.

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., Chaplot, V., Chen, Z.-S., Cheng, K., Das, B. S. et al. (2017). Soil carbon 4 per mille. *Geoderma*, *292*, 59–86.

Minasny, B., & McBratney, A. B. (2018). Limited effect of organic matter on soil available water capacity. *European Journal of Soil Science*, *69*, 39–47. doi:10.1111/ejss.12475.

Minoli, S., Acutis, M., & Carozzi, M. (2015). NH_3 emissions from land application of manures and N-fertilisers: a review of the Italian literature. *Italian Journal of Agrometeorology*, *20*, 5–24.

Molina-Herrera, S. et al. (2016). A modeling study on mitigation of N_2O emissions and NO_3 leaching at different agricultural sites across europe using landscape DNDC. *Science of The Total Environment*, *553*, 128–140. doi:10.1016/j.scitotenv.2015.12.099.

Moreau, P., Viaud, V., Parnaudeau, V., Salmon-Monviola, J., & Durand, P. (2013). An approach for global sensitivity analysis of a complex environmental model to spatial inputs and parameters: A case study of an agro-hydrological model. *Environmental Modelling & Software*, *47*, 74–87. doi:10.1016/j.envsoft.2013.04.006.

Mosquera, J., ter Beek, C., & Hol, J. (2005). *Precise soil management as a tool to reduce CH_4 and N_2O emissions from agricultural soil. II. Field measurements at arable soils in the Netherlands*. Report 9067549851, Agrotechnology & Food Innovations.

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

Müller, C. et al. (2017). Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications. *Geoscientific Model Development*, *10*, 1403–1422. doi:10.5194/gmd-10-1403-2017.

Nachtergaele, F., Van Velthuizen, H., Verelst, L., Batjes, N., Dijkshoorn, K., van Engelen, V., Fischer, G., Jones, A., Montanarella, L., & Petri, M. (2009). Harmonized World Soil Database (version 1.1). Food and Agriculture Organization of the United Nations. Rome, Italy and IIASA, Laxenburg, Austria.

Naipal, V., Reick, C., Pongratz, J., & Oost, K. V. (2015). Improving the global applicability of the RUSLE model – adjustment of the topographical and rainfall erosivity factors. *Geoscientific Model Development*, *8*, 2893–2913. doi:10.5194/gmd-8-2893-2015.

Necpálová, M., Anex, R. P., Fienen, M. N., Del Grosso, S. J., Castellano, M. J., Sawyer,

J. E., Iqbal, J., Pantoja, J. L., & Barker, D. W. (2015). Understanding the daycent model: Calibration, sensitivity, and identifiability through inverse modeling. *Environmental Modelling & Software*, *66*, 110–130.

Ngwira, A., Aune, J. B., & Thierfelder, C. (2014). DSSAT modelling of conservation agriculture maize response to climate change in Malawi. *Soil and Tillage Research*, *143*, 85–94. doi:10.1016/j.still.2014.05.003.

Nishina, K., Ito, A., Hanasaki, N., & Hayashi, S. (2017). Reconstruction of spatially detailed global map of NH_4^+ and NO_3^+ application in synthetic nitrogen fertilizer. *Earth System Science Data*, *9*, 149–162. doi:10.5194/essd-9-149-2017.

Oertel, C., Matschullat, J., Zurba, K., Zimmermann, F., & Erasmi, S. (2016). Greenhouse gas emissions from soils—a review. *Geochemistry*, *76*, 327–352. doi:10.1016/j.chemer.2016.04.002.

Ogle, S. M., Breidt, F. J., & Paustian, K. (2005). Agricultural management impacts on soil organic carbon storage under moist and dry climatic conditions of temperate and tropical regions. *Biogeochemistry*, *72*, 87–121. doi:10.1007/s10533-004-0360-2.

Ogle, S. M., Swan, A., & Paustian, K. (2012). No-till management impacts on crop productivity, carbon input and soil carbon sequestration. *Agriculture, Ecosystems & Environment*, *149*, 37–49. doi:10.1016/j.agee.2011.12.010.

Oleson, K. W., Lawrence, D. M., Gordon, B., Flanner, M. G., Kluzek, E., Peter, J., Levis, S., Swenson, S. C., Thornton, E., & Feddema, J. (2010). *Technical description of version 4.0 of the Community Land Model (CLM)*. National Center For Atmospheric Research.

Olin, S., Lindeskog, M., Pugh, T. A. M., Schurgers, G., Wårlind, D., Mishurov, M., Zaehle, S., Stocker, B. D., Smith, B., & Arneth, A. (2015a). Soil carbon management in large-scale Earth system modelling: implications for crop yields and nitrogen leaching. *Earth System Dynamics*, *6*, 745–768. doi:10.5194/esd-6-745-2015.

Olin, S., Schurgers, G., Lindeskog, M., Wårlind, D., Smith, B., Bodin, P., Holmér, J., & Arneth, A. (2015b). Modelling the response of yields and tissue C : N to changes in atmospheric CO_2 and N management in the main wheat regions of Western Europe. *Biogeosciences*, *12*, 2489–2515. doi:10.5194/bg-12-2489-2015.

Oorts, K., Merckx, R., Gréhan, E., Labreuche, J., & Nicolardot, B. (2007). Determinants of annual fluxes of CO_2 and N_2O in long-term no-tillage and conventional tillage systems in northern France. *Soil and Tillage Research*, *95*, 133–148. doi:10.1016/j.still.2006.12.002.

Oreskes, N. (2003). The role of quantitative models in science naomi oreskes. *Models in ecosystem science, edited by: Canham, CD, Cole, JJ, and Lauenroth, WK*, (pp. 13–31).

Panagos, P., Borrelli, P., Meusburger, K., Van der Zanden, E. H., Poesen, J., & Alewell,

C. (2015). Modelling the effect of support practices (p-factor) on the reduction of soil erosion by water at European scale. *Environmental Science & Policy*, *51*, 23–34. doi:10.1016/j.envsci.2015.03.012.

Panagos, P. et al. (2017). Global rainfall erosivity assessment based on high-temporal resolution rainfall records. *Scientific Reports*, *7*. doi:10.1038/s41598-017-04282-8.

Pannkuk, C., Stockle, C., & Papendick, R. (1998). Evaluating CropSyst simulations of wheat management in a wheat-fallow region of the US pacific northwest. *Agricultural Systems*, *57*, 121–134. doi:10.1016/s0308-521x(97)00076-0.

Parton, W., Holland, E., Del Grosso, S., Hartman, M., Martin, R., Mosier, A., Ojima, D., & Schimel, D. (2001). Generalized model for NO_x and N_2O emissions from soils. *Journal of Geophysical Research: Atmospheres*, *106*, 17403–17419.

Parton, W., Mosier, A., Ojima, D., Valentine, D., Schimel, D., Weier, K., & Kulmala, A. E. (1996). Generalized model for N_2 and N_2O production from nitrification and denitrification. *Global biogeochemical cycles*, *10*, 401–412.

Parton, W. J., Hartman, M., Ojima, D., & Schimel, D. (1998). DAYCENT and its land surface submodel: description and testing. *Global and Planetary Change*, *19*, 35–48. doi:10.1016/s0921-8181(98)00040-x.

Patterson, T. G., & LaRue, T. A. (1983). Nitrogen Fixation by Soybeans: Seasonal and Cultivar Effects, and Comparison of Estimates1. *Crop Science*, *23*, 488. doi:10.2135/cropsci1983.0011183x002300030012x.

Paustian, K., Lehmann, J., Ogle, S., Reay, D., Robertson, G. P., & Smith, P. (2016). Climate-smart soils. *Nature*, *532*, 49.

Penman, J. (2000). *Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventries, IPCC National Greenhouse Gas Inventries Programme Published for the IPCC by the Institute for Global Environmental Strategies, Japan*. Technical Report, Institute for Global Environmental Strategies, Japan. URL: `http://www.ipccnggip.iges.or.jp/public/gp/english/`.

Pezzuolo, A., Dumont, B., Sartori, L., Marinello, F., Migliorati, M. D. A., & Basso, B. (2017). Evaluating the impact of soil conservation measures on soil organic carbon at the farm scale. *Computers and Electronics in Agriculture*, *135*, 175–182.

Piao, S., Friedlingstein, P., Ciais, P., Viovy, N., & Demarty, J. (2007). Growing season extension and its impact on terrestrial carbon cycle in the northern hemisphere over the past 2 decades. *Global Biogeochemical Cycles*, *21*.

Pihlatie, M., Syväsalo, E., Simojoki, A., Esala, M., & Regina, K. (2004). Contribution of nitrification and denitrification to N_2O production in peat, clay and loamy sand soils under different soil moisture conditions. *Nutrient Cycling in Agroecosystems*, *70*, 135–141.

Pittelkow, C. M., Liang, X., Linquist, B. A., van Groenigen, K. J., Lee, J., Lundy, M. E., van Gestel, N., Six, J., Venterea, R. T., & van Kessel, C. (2015a). Productivity limits and potentials of the principles of conservation agriculture. *Nature*, *517*, 365–368. doi:10.1038/nature13809.

Pittelkow, C. M., Linquist, B. A., Lundy, M. E., Liang, X., van Groenigen, K. J., Lee, J., van Gestel, N., Six, J., Venterea, R. T., & van Kessel, C. (2015b). When does no-till yield more? A global meta-analysis. *Field Crops Research*, *183*, 156–168. doi:10.1016/j.fcr.2015.07.020.

Plaza-Bonilla, D., Álvaro Fuentes, J., Bareche, J., Pareja-Sánchez, E., Justes, É., & Cantero-Martínez, C. (2018). No-tillage reduces long-term yield-scaled soil nitrous oxide emissions in rainfed mediterranean agroecosystems: A field and modelling approach. *Agriculture, Ecosystems & Environment*, *262*, 36–47.

Podder, M., Akter, M., Saifullah, A. S. M., & Roy, S. (2012). Impacts of plough pan on physical and chemical properties of soil. *Journal of Environmental Science and Natural Resources*, *5*, 289–294. doi:10.3329/jesnr.v5i1.11594.

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M. et al. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, *42*, 331–345.

Portmann, F. T., Siebert, S., & Döll, P. (2010). MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. *Global Biogeochemical Cycles*, *24*, GB1011. doi:10.1029/2008GB003435.

Porwollik, V., Rolinski, S., Heinke, J., & Müller, C. (2019). Generating a rule-based global gridded tillage dataset. *Earth System Science Data*, *11*, 823–843.

Potter, C. S., Matson, P. A., Vitousek, P. M., & Davidson, E. A. (1996). Process modeling of controls on nitrogen trace gas emissions from soils worldwide. *Journal of Geophysical Research: Atmospheres*, *101*, 1361–1377. doi:10.1029/95jd02028.

Potter, P., Ramankutty, N., Bennett, E. M., & Donner, S. D. (2010). Characterizing the spatial patterns of global fertilizer application and manure production. *Earth Interactions*, *14*, 1–22.

Powlson, D. S., Stirling, C. M., Jat, M. L., Gerard, B. G., Palm, C. A., Sanchez, P. A., & Cassman, K. G. (2014). Limited potential of no-till agriculture for climate change mitigation. *Nature Climate Change*, *4*, 678.

Pribyl, D. W. (2010). A critical review of the conventional SOC to SOM conversion factor. *Geoderma*, *156*, 75–83. doi:10.1016/j.geoderma.2010.02.003.

Priesack, E. (2006). *Expert-N Dokumentation der Modellbibliothek*. Habilitation Technische Universität München München.

Priestley, C. H. B., & Taylor, R. J. (1972). On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. *Monthly Weather Review*, *100*, 81–92. doi:10.1175/1520-0493(1972)100<0081:OTAOSH>2.3.CO;2.

Pugh, T. A. M., Arneth, A., Olin, S., Ahlström, A., Bayer, A. D., Klein Goldewijk, K., Lindeskog, M., & Schurgers, G. (2015). Simulated carbon emissions from land-use change are substantially enhanced by accounting for agricultural management. *Environmental Research Letters*, *10*, 124008. doi:10.1088/1748-9326/10/12/124008.

Ranaivoson, L., Naudin, K., Ripoche, A., Affholder, F., Rabeharisoa, L., & Corbeels, M. (2017). Agro-ecological functions of crop residues under conservation agriculture. A review. *Agronomy for Sustainable Development*, *37*, 1–17. doi:10.1007/s13593-017-0432-z.

Renard, K., Foster, G., Weesies, G., Mccool, D., & Yoder, D. (1997). *Predicting soil erosion by water: a guide to conservation planning with the revised universal soil loss equation (RUSLE)* volume 703. United States Department of Agriculture.

Richards, L. A. (1931). Capillary Conduction of liquids through porous mediums. *Physics*, *1*, 318–333. doi:10.1063/1.1745010.

Risal, A., Bhattarai, R., Kum, D., Park, Y. S., Yang, J. E., & Lim, K. J. (2016). Application of Web ERosivity Module (WERM) for estimation of annual and monthly R factor in Korea. *CATENA*, *147*, 225–237. doi:10.1016/j.catena.2016.07.017.

Rolinski, S., Müller, C., Heinke, J., Weindl, I., Biewald, A., Bodirsky, B. L., Bondeau, A., Boons-Prins, E., Bouwman, A., & Leffelaar, P. (2018). Modeling vegetation and carbon dynamics of managed grasslands at the global scale with LPJmL 3.6. *Geoscientific Model Development*, .

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S. et al. (2013). The agricultural model intercomparison and improvement project (agmip): protocols and pilot studies. *Agricultural and Forest Meteorology*, *170*, 166–182.

Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., & Schaphoff, S. (2008). Agricultural green and blue water consumption and its influence on the global water system. *Water Resources Research*, *44*. doi:10.1029/2007WR006331. `arXiv:https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2007WR006331`.

RZWQM Development Team, Hanson, J., Ahuja, L., Shaffer, M., Rojas, K., DeCoursey, D., Farahani, H., & Johnson, K. (1998). RZWQM: Simulating the effects of management on water quality and crop production. *Agricultural Systems*, *57*, 161–195. doi:10.1016/s0308-521x(98)00002-x.

Sadeghi, S., Gholami, L., Darvishan, A. K., & Saeidi, P. (2013). A review of the application of the MUSLE model worldwide. *Hydrological Sciences Journal*, *59*, 365–375. doi:10.1080/02626667.2013.866239.

Saxton, K., Rawls, W., Romberger, J., & Papendick, R. (1986). Estimating generalized soil-water characteristics from texture 1. *Soil Science Society of America Journal*, *50*, 1031–1036.

Saxton, K. E., & Rawls, W. J. (2006). Soil Water Characteristic Estimates by Texture and Organic Matter for Hydrologic Solutions. *Soil Science Society of America Journal*, *70*, 1569–1577. doi:10.2136/sssaj2005.0117.

Schaphoff, S. et al. (2018a). LPJmL4 – a dynamic global vegetation model with managed land – Part 1: Model description. *Geoscientific Model Development*, *11*, 1343–1375. doi:https://doi.org/10.5194/gmd-11-1343-2018.

Schaphoff, S., Forkel, M., Müller, C., Knauer, J., von Bloh, W., Gerten, D., Jägermeyr, J., Lucht, W., Rammig, A., Thonicke, K., & Waha, K. (2018b). LPJmL4 – a dynamic global vegetation model with managed land – Part 2: Model evaluation. *Geoscientific Model Development*, *11*, 1377–1403. doi:10.5194/gmd-11-1377-2018.

Schaphoff, S., Heyder, U., Ostberg, S., Gerten, D., Heinke, J., & Lucht, W. (2013). Contribution of permafrost soils to the global carbon budget. *Environmental Research Letters*, *8*, 014026. doi:10.1088/1748-9326/8/1/014026.

Schlüter, S., Großmann, C., Diel, J., Wu, G.-M., Tischer, S., Deubel, A., & Rücknagel, J. (2018). Long-term effects of conventional and reduced tillage on soil structure, soil ecological and soil hydraulic properties. *Geoderma*, *332*, 10–19.

Scopel, E., Da Silva, F. A., Corbeels, M., Affholder, F., & Maraux, F. (2004). Modelling crop residue mulching effects on water use and production of maize under semi-arid and humid tropical conditions. *Agronomie*, *24*, 383–395. doi:10.1051/agro:2004029.

Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., & Teuling, A. J. (2010). Investigating soil moisture–climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*, 125–161.

Shaffer, M., Ma, L., & Hansen, S. (Eds.) (2001). *Modeling Carbon and Nitrogen Dynamics for Soil Management*. CRC Press. doi:10.1201/9781420032635.

Sigunga, D. O., Janssen, B. H., & Oenema, O. (2002). Ammonia volatilization from Vertisols. *European Journal of Soil Science*, *53*, 195–202. doi:10.1046/j.1351-0754.2002.00454.x.

Sitch, S., Smith, B., Prentice, I. C., Arneth, A., Bondeau, A., Cramer, W., Kaplan, J. O., Levis, S., Lucht, W., Sykes, M. T., & others (2003). Evaluation of ecosystem dynamics, plant geography and terrestrial carbon cycling in the LPJ dynamic global vegetation model. *Global Change Biology*, *9*, 161–185. doi:10.1046/j.1365-2486.2003.00569.x.

Six, J., Ogle, S. M., Jay breidt, F., Conant, R. T., Mosier, A. R., & Paustian, K. (2004). The potential to mitigate global warming with no-tillage management is only realized when practised in the long term. *Global Change Biology*, *10*, 155–160.

doi:10.1111/j.1529-8817.2003.00730.x.

Smil, V. (1999). Nitrogen in crop production: An account of global flows. *Global Biogeochemical Cycles*, *13*, 647–662. doi:10.1029/1999gb900015.

Smith, B., Wårlind, D., Arneth, A., Hickler, T., Leadley, P., Siltberg, J., & Zaehle, S. (2014a). Implications of incorporating N cycling and N limitations on primary production in an individual-based dynamic vegetation model. *Biogeosciences*, *11*, 2027–2054. doi:10.5194/bg-11-2027-2014.

Smith, J., & Smith, P. (2007). *Environmental modelling: an introduction*. Oxford University Press.

Smith, K. (2017). Changing views of nitrous oxide emissions from agricultural soil: key controlling processes and assessment at different spatial scales. *European Journal of Soil Science*, *68*, 137–155.

Smith, P. (2012). Agricultural greenhouse gas mitigation potential globally, in europe and in the UK: what have we learnt in the last 20 years? *Global Change Biology*, *18*, 35–43.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Haberl, H., Harper, R., House, J., Jafari, M. et al. (2014b). Agriculture, forestry and other land use (afolu). In *Climate change 2014: mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Smith, P. et al. (2008). Greenhouse gas mitigation in agriculture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*, 789–813. doi:10.1098/rstb.2007.2184.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C. et al. (2007). Greenhouse gas mitigation in agriculture. *Philosophical transactions of the royal Society B: Biological Sciences*, *363*, 789–813.

Smith, V. H. (1992). Effects of nitrogen: phosphorus supply ratios on nitrogen fixation in agricultural and pastoral ecosystems. *Biogeochemistry*, *18*, 19–35. doi:10.1007/bf00000424.

Smith, W., Grant, B., & Desjardins, R. (2009). Some perspectives on agricultural GHG mitigation and adaptation strategies with respect to the impact of climate change/variability in vulnerable areas. *Quarterly Journal of the Hungarian Meteorological Service*, *113*, 103–115.

Snyder, C. S., Bruulsema, T. W., Jensen, T. L., & Fixen, P. E. (2009). Review of greenhouse gas emissions from crop production systems and fertilizer management effects. *Agriculture Ecosystems & Environment*, *133*, 247–266. doi:10.1016/j.agee.2009.04.021.

Solomon, S., Qin, D., Manning, M., Averyt, K., Marquis, M., & Tignor, M. M. (2007).

Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC volume 4. Cambridge university press.

Sozanska, M., Skiba, U., & Metcalfe, S. (2002). Developing an inventory of N_2O emissions from British soils. *Atmospheric Environment*, *36*, 987–998. doi:10.1016/s1352-2310(01)00441-1.

Staff, S. S. (2003). *Keys to soil taxonomy*. Department of Agriculture: Natural Resources Conservation Service.

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W., De Wit, C. A. et al. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*, 1259855.

Steinbach, H. S., & Alvarez, R. (2006). Changes in soil organic carbon contents and nitrous oxide emissions after introduction of no-till in Pampean agroecosystems. *Journal of Environmental Quality*, *35*, 3–13. doi:10.2134/jeq2005.0050.

Stöckle, C., Higgins, S., Kemanian, A., Nelson, R., Huggins, D., Marcos, J., & Collins, H. (2010). Carbon storage and nitrous oxide emissions of cropping systems in eastern washington: A simulation study. *Journal of Soil and Water Conservation*, *67*, 365–377. doi:10.2489/jswc.67.5.365.

Stoorvogel, J. J., Bakkenes, M., Temme, A. J., Batjes, N. H., & ten Brink, B. J. (2017). S-world: A global soil map for environmental modelling. *Land degradation & development*, *28*, 22–33.

Strudley, M. W., Green, T. R., & Ascough, J. C. (2008). Tillage effects on soil hydraulic properties in space and time: State of the science. *Soil and Tillage Research*, *99*, 4–48. doi:10.1016/j.still.2008.01.007.

Stöckle, C. O., Donatelli, M., & Nelson, R. (2003). CropSyst, a cropping systems simulation model. *European Journal of Agronomy*, *18*, 289–307. doi:10.1016/s1161-0301(02)00109-0.

Tans, P., & Keeling, R. (2015). Trends in Atmospheric Carbon Dioxide, National Oceanic & Atmospheric Administration, Earth System Research Laboratory (NOAA/ESRL), available at: https://www.esrl.noaa.gov/gmd/ccgg/trends/.

Tapia-Vargas, M., Tiscareño-López, M., Stone, J. J., Oropeza-Mota, J. L., & Velázquez-Valle, M. (2001). Tillage system effects on runoff and sediment yield in hillslope agriculture. *Field Crops Research*, *69*, 173–182. doi:10.1016/S0378-4290(00)00139-8.

Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the Experiment Design. *Bulletin of the American Meteorological Society*, *93*, 485–498. doi:10.1175/bams-d-11-00094.1.

Tian, H., Chen, G., Liu, M., Zhang, C., Sun, G., Lu, C., Xu, X., Ren, W., Pan, S., & Chappelka, A. (2010). Model estimates of net primary productivity, evapotranspiration, and water use efficiency in the terrestrial ecosystems of the southern United States during 1895–2007. *Forest ecology and management*, *259*, 1311–1327.

Tubiello, F. (2019). Greenhouse gas emissions due to agriculture. In P. Ferranti, E. M. Berry, & J. R. Anderson (Eds.), *Encyclopedia of Food Security and Sustainability*. doi:10.1016/B978-0-08-100596-5.21996-3.

Tubiello, F. N., Salvatore, M., Ferrara, A. F., House, J., Federici, S., Rossi, S., Biancalani, R., Condor Golec, R. D., Jacobs, H., Flammini, A. et al. (2015). The contribution of agriculture, forestry and other land use activities to global warming, 1990–2012. *Global Change Biology*, *21*, 2655–2660.

Van der Laan, M., Annandale, J., Bristow, K., Stirzaker, R., du Preez, C., & Thorburn, P. (2014). Modelling nitrogen leaching: Are we getting the right answer for the right reason? *Agricultural Water Management*, *133*, 74–80. doi:10.1016/j.agwat.2013.10.017.

Van Genuchten, M. (1980). A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils1. *Soil Science Society of America Journal*, *44*. doi:10.2136/sssaj1980.03615995004400050002x.

Van Groenigen, J., Velthof, G., Oenema, O., Van Groenigen, K., & Van Kessel, C. (2010). Towards an agronomic assessment of N_2O emissions: a case study for arable crops. *European Journal of Soil Science*, *61*, 903–913.

Van Kessel, C., Venterea, R., Six, J., Adviento-Borbe, M. A., Linquist, B., & van Groenigen, K. J. (2013). Climate, duration, and n placement determine N_2O emissions in reduced tillage systems: a meta-analysis. *Global Change Biology*, *19*, 33–44.

Van Kessel, C., Venterea, R., Six, J., Adviento-Borbe, M. A., Linquist, B., & Van Groenigen, K. J. (2012). Climate, duration, and N placement determine N_2O emissions in reduced tillage systems: a meta-analysis. *Global Change Biology*, *19*, 33–44. doi:10.1111/j.1365-2486.2012.02779.x.

Van Looy, K. et al. (2017). Pedotransfer Functions in Earth System Science: Challenges and Perspectives: PTFs in Earth system science perspective. *Reviews of Geophysics*, *55*, 1199–1256. doi:10.1002/2017RG000581.

Venterea, R. T., Maharjan, B., & Dolan, M. S. (2011). Fertilizer source and tillage effects on yield-scaled nitrous oxide emissions in a corn cropping system. *Journal of Environmental Quality*, *40*, 1521–1531.

Vereecken, H. et al. (2016). Modeling Soil Processes: Review, Key Challenges, and New Perspectives. *Vadose Zone Journal*, *15*. doi:10.2136/vzj2015.09.0131.

Vereecken, H., Weynants, M., Javaux, M., Pachepsky, Y., Schaap, M. G., & Genuchten, M. v. (2010). Using Pedotransfer Functions to Estimate the van Genuchten–Mualem Soil Hydraulic Properties: A Review. *Vadose Zone Journal*, *9*, 795. doi:10.2136/vzj2010.0045.

Von Bloh, W., Schaphoff, S., Müller, C., Rolinski, S., Waha, K., & Zaehle, S. (2018a). Implementing the nitrogen cycle into the dynamic global vegetation, hydrology, and crop growth model LPJmL (version 5.0). *Geoscientific Model Development*, *11*, 2789–2812. doi:https://doi.org/10.5194/gmd-11-2789-2018.

Von Bloh, W., Schaphoff, S., Müller, C., Rolinski, S., Waha, K., & Zaehle, S. (2018b). LPJmL5 Model Code. doi:10.5880/pik.2018.011.

Waha, K., Huth, N., Carberry, P., & Wang, E. (2015). How model and input uncertainty impact maize yield simulations in West Africa. *Environmental Research Letters*, *10*, 024017.

Waha, K., Van Bussel, L., Müller, C., & Bondeau, A. (2012). Climate-driven simulation of global crop sowing dates. *Global Ecology and Biogeography*, *21*, 247–259.

White, J. W., Jones, J. W., Porter, C., McMaster, G. S., & Sommer, R. (2010). Issues of spatial and temporal scale in modeling the effects of field operations on soil properties. *Operational Research*, *10*, 279–299. doi:10.1007/s12351-009-0067-1.

Willekens, K., Vandecasteele, B., Buchan, D., & De Neve, S. (2014). Soil quality is positively affected by reduced tillage and compost in an intensive vegetable cropping system. *Applied Soil Ecology*, *82*, 61–71. doi:10.1016/j.apsoil.2014.05.009.

Williams, J. (1975). Sediment-Yield Prediction with Universal Equation Using Runoff Energy Factor. *Present and Prospective Technology for Predicting Sediment Yield and Sources, USDA, ARS-S-40, Washington DC*, (pp. 244–252).

Williams, J., Izaurralde, R., & Steglich, E. (2008). Agricultural policy/environmental Extender Model Theoretical Documentation. *Blackland Research and Extension Center Temple, Texas*, .

Williams, J., Izaurralde, R. C., Williams, C., & Steglich, E. (2015). Agricultural Policy / Environmental eXtender Model. Theoretical Documentation. Version 0806. AgriLIFE Research. Texas A&M System.

Williams, J. R., Renard, K. G., & Dyke, P. T. (1983). EPIC: A new method for assessing erosion's effect on soil productivity. *Journal of Soil and Water Conservation*, *38*, 381–383.

Wilson, G. V., McGregor, K. C., & Boykin, D. (2008). Residue impacts on runoff and soil erosion for different corn plant populations. *Soil and Tillage Research*, *99*, 300–307. doi:10.1016/j.still.2008.04.001.

Wischmeier, W. H., & Smith, D. D. (1958). Rainfall energy and its relationship to soil loss. *Transactions, American Geophysical Union*, *39*, 285. doi:10.1029/tr039i002p00285.

Wollenberg, E., Richards, M., Smith, P., Havlík, P., Obersteiner, M., Tubiello, F. N., Herold, M., Gerber, P., Carter, S., Reisinger, A. et al. (2016). Reducing emissions from agriculture to meet the 2 c target. *Global change biology*, *22*, 3859–3864.

Wösten, J., Finke, P., & Jansen, M. (1995). Comparison of class and continuous pedotransfer functions to generate soil hydraulic characteristics. *Geoderma*, *66*, 227–237. doi:10.1016/0016-7061(94)00079-P.

Yang, Q., Zhang, X., Abraha, M., Del Grosso, S., Robertson, G., & Chen, J. (2017). Enhancing the soil and water assessment tool model for simulating N_2O emissions of three agricultural systems. *Ecosystem Health and Sustainability*, *3*, e01259.

Yoo, J., Woo, S.-H., Park, K.-D., & Chung, K.-Y. (2016). Effect of no-tillage and conventional tillage practices on the nitrous oxide (N_2O) emissions in an upland soil: soil N_2O emission as affected by the fertilizer applications. *Applied Biological Chemistry*, *59*, 787–797.

You, L., Wood, S., Wood-Sichra, U., & Wu, W. (2014). Generating global crop distribution maps: From census to grid. *Agricultural Systems*, *127*, 53–60. doi:10.1016/j.agsy.2014.01.002.

Zhao, X., Liu, S.-L., Pu, C., Zhang, X.-Q., Xue, J.-F., Zhang, R., Wang, Y.-Q., Lal, R., Zhang, H.-L., & Chen, F. (2016). Methane and nitrous oxide emissions under no-till farming in China: a meta-analysis. *Global change biology*, *22*, 1372–1384.

Appendices

Appendix A

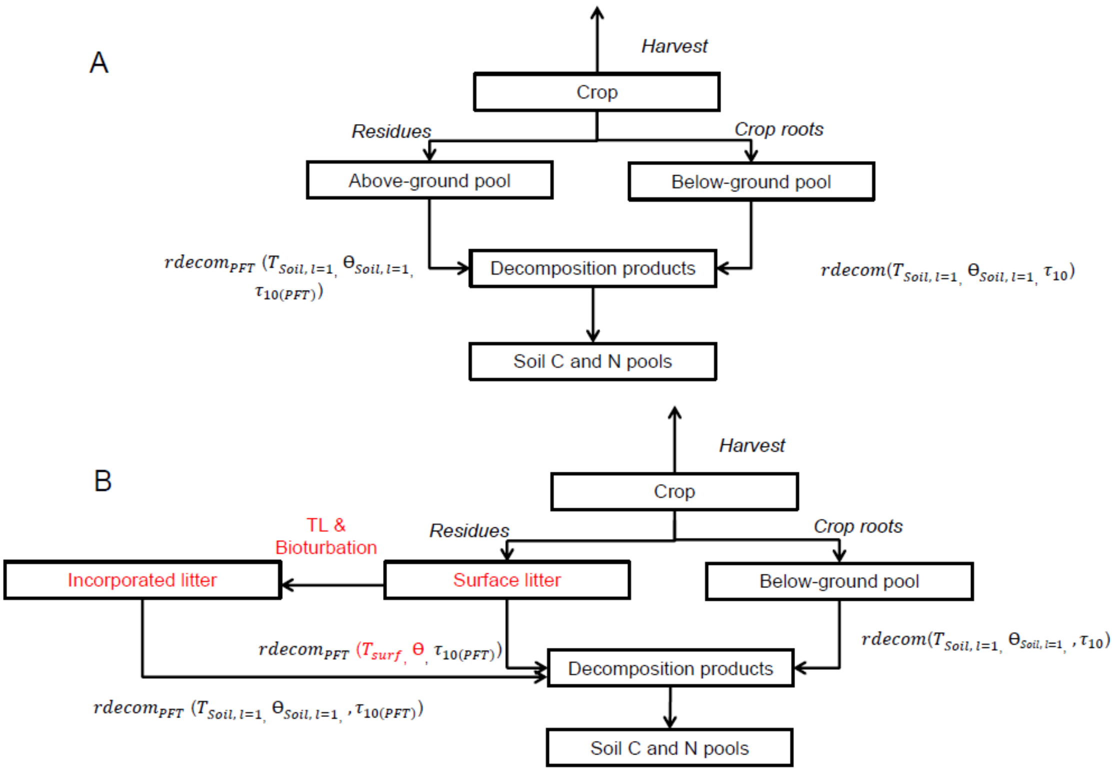


Figure A.3.1: The litter- and soil organic matter pools in LPJmL5.0 (A) and in LPJmL5.0-tillage (B)

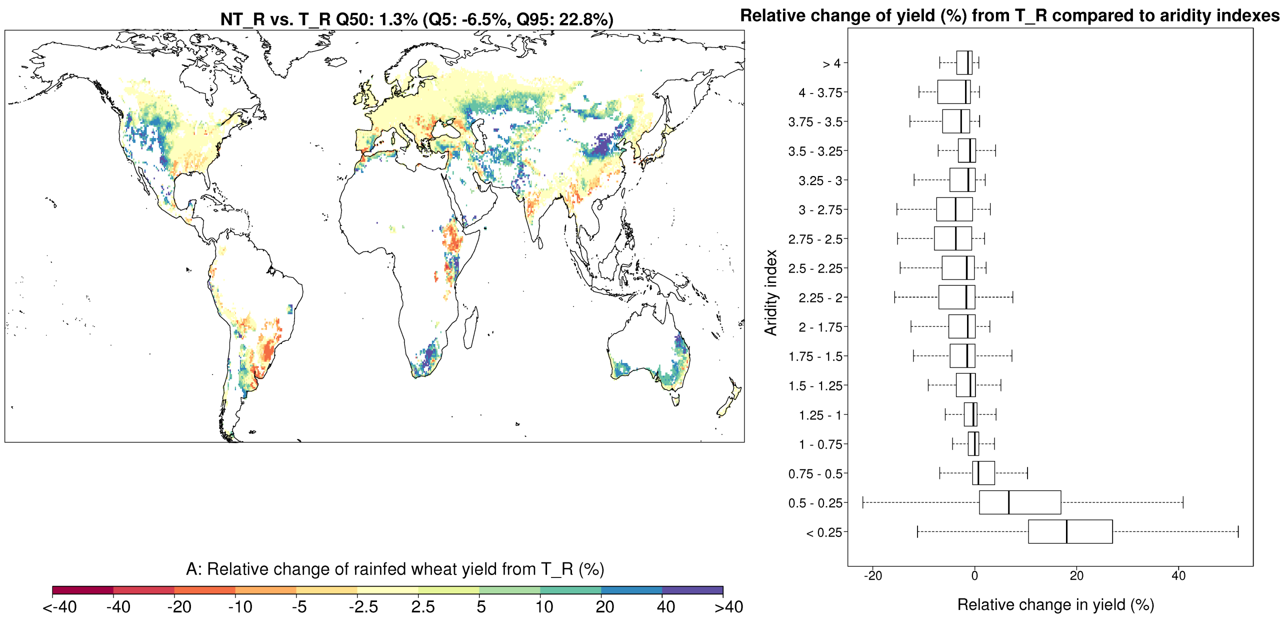


Figure A.3.2a: Relative yield changes for NT_R vs. T_R of rain-fed wheat compared to aridity indexes after three years.

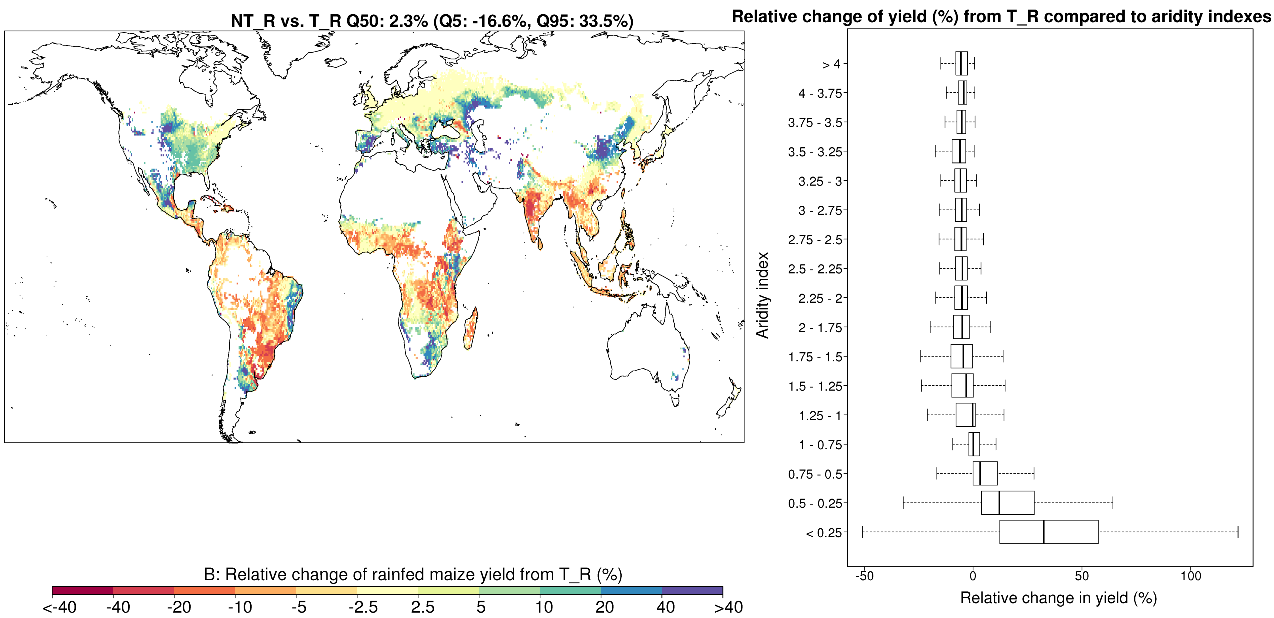


Figure A.3.2b: Relative yield changes for NT_R vs. T_R of rain-fed maize compared to aridity indexes after three years.

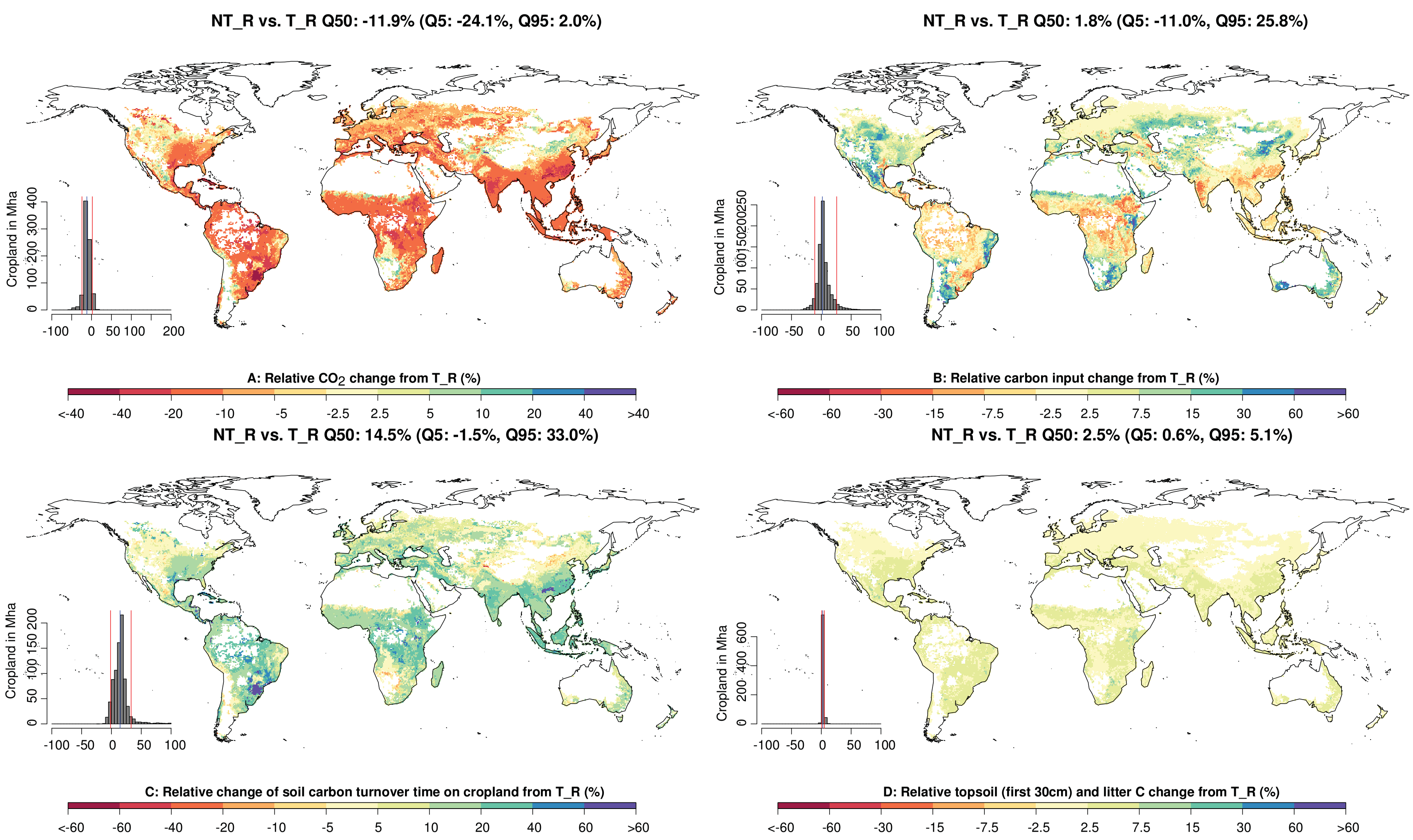


Figure A.3.3: Relative C dynamics for NT_R vs. T_R comparison after three years of simulation experiment for relative CO_2 change (A), relative C input change (B), relative change of soil C turnover time (C), and relative topsoil and litter C change (D).

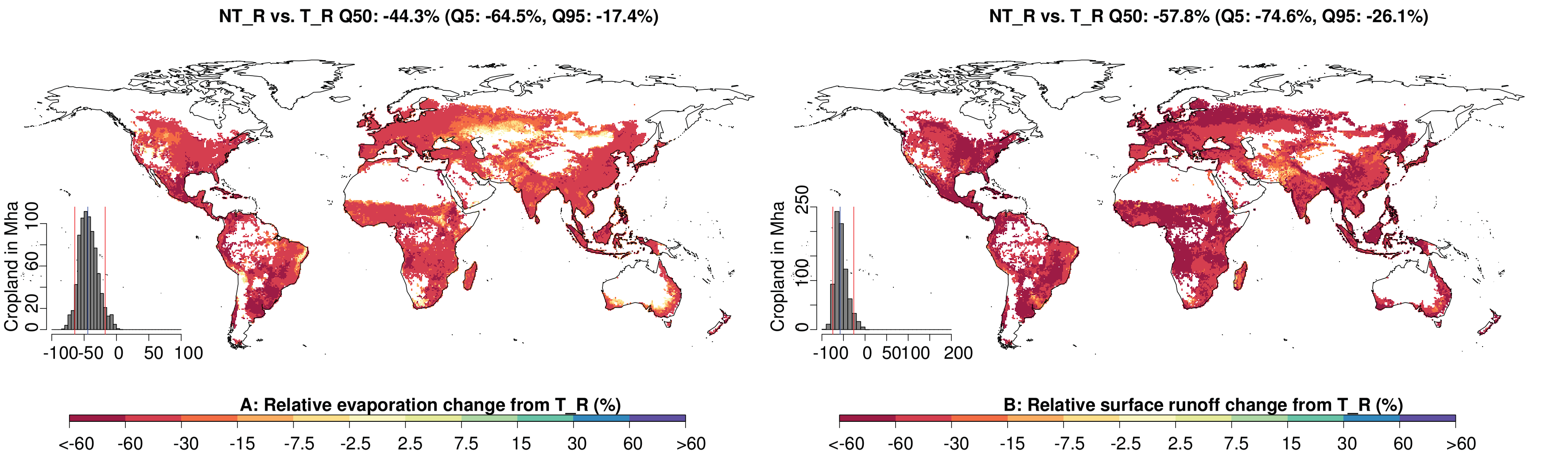


Figure A.3.4: Relative change for NT_R vs. T_R in evaporation (A) and surface runoff (B) after two years of the simulation experiment.

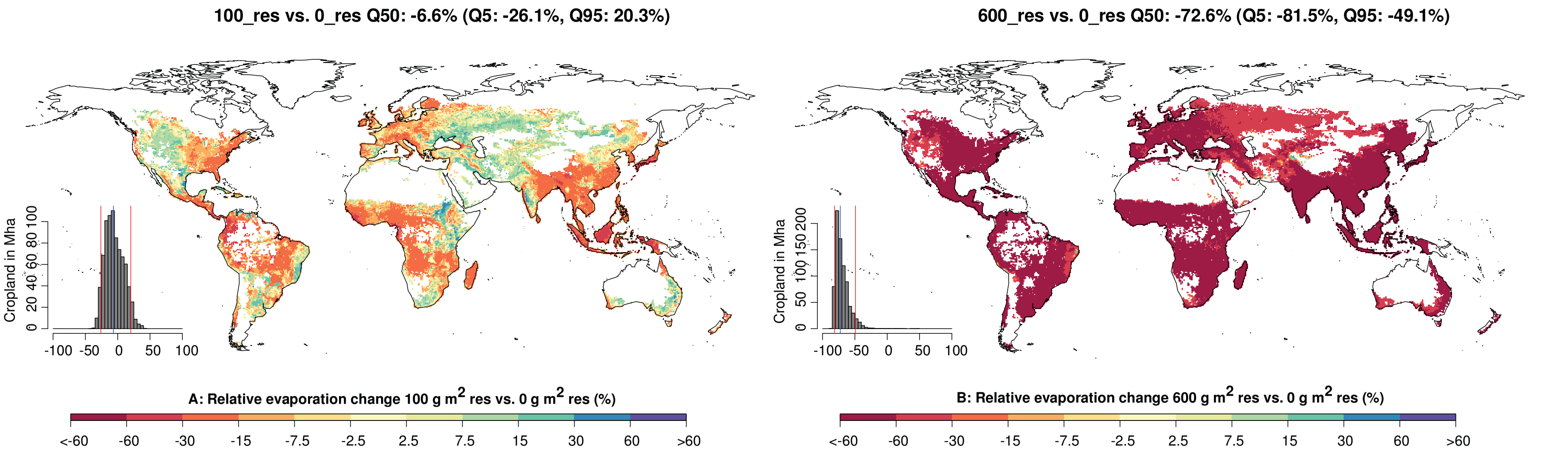


Figure A.3.5: Relative changes in evaporation for NT_R vs. T_R after two years from for the bare soil experiments with fixed dry matter loads of 100 g m^2 (A) and 600 g m^2 (B) compared to bare soil with no residues.

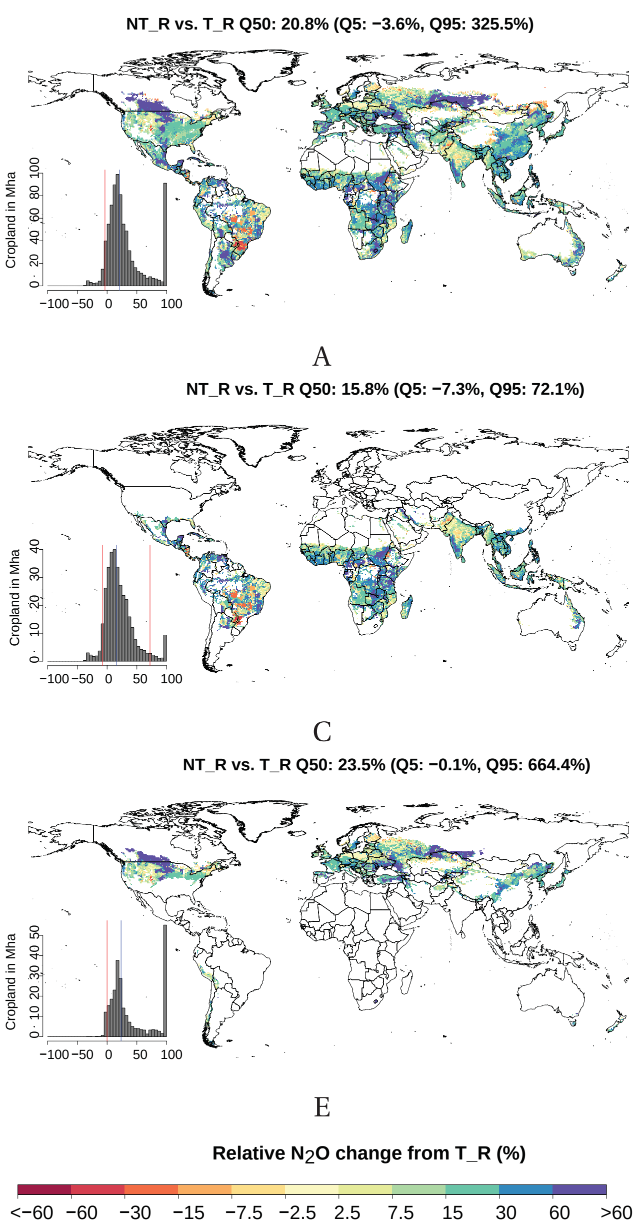


Figure A.3.6: Relative changes for N_2O dynamics for the average of the first three years of NT_R vs. T_R of the simulation experiment for different climates – overall (A), warm-temperate (B), tropical (C), arid (D), cold-temperate (E) and humid (F).

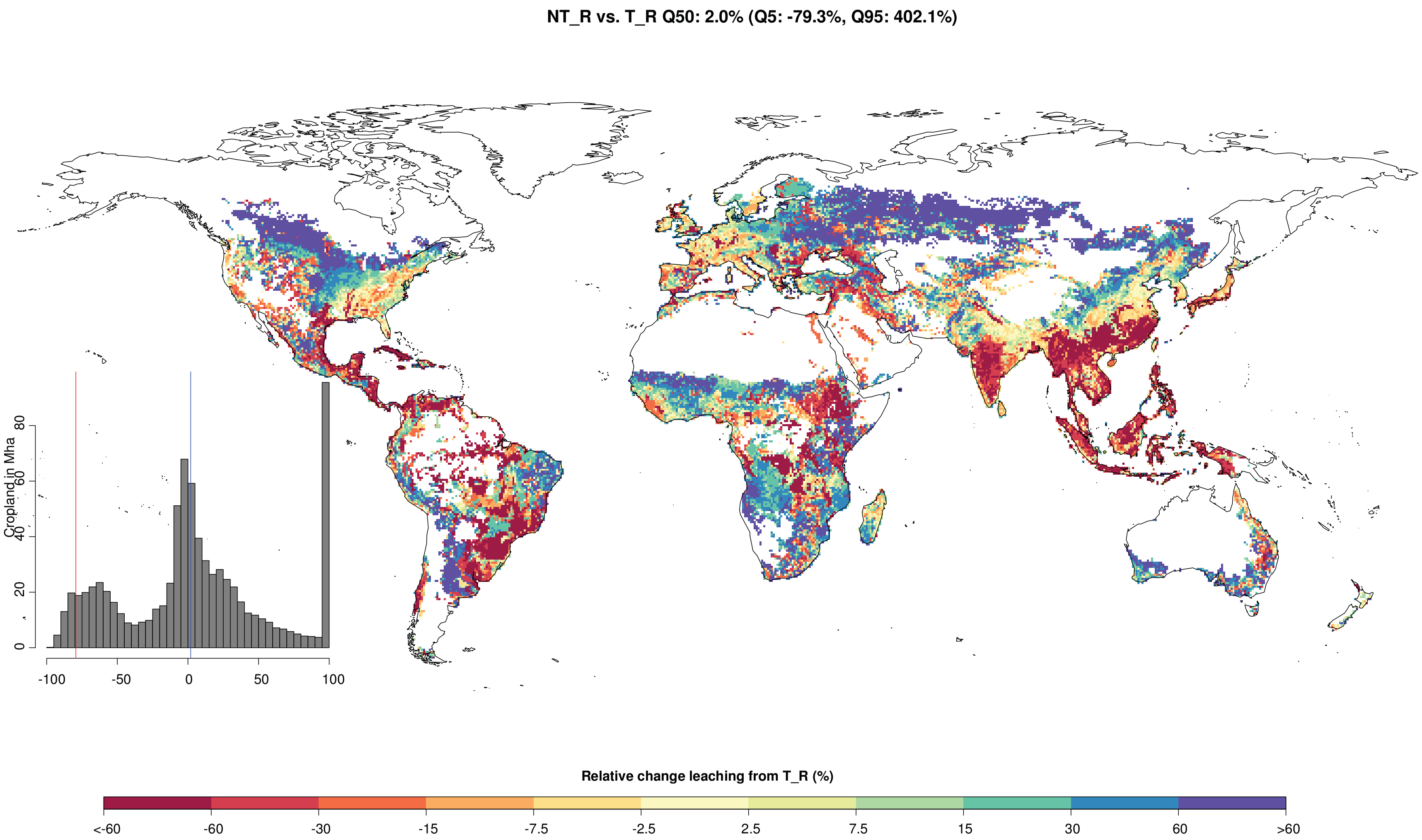


Figure A.3.7: Relative changes for NO_3 leaching dynamics after two years for NT_R vs. T_R simulation experiment.

Appendix B

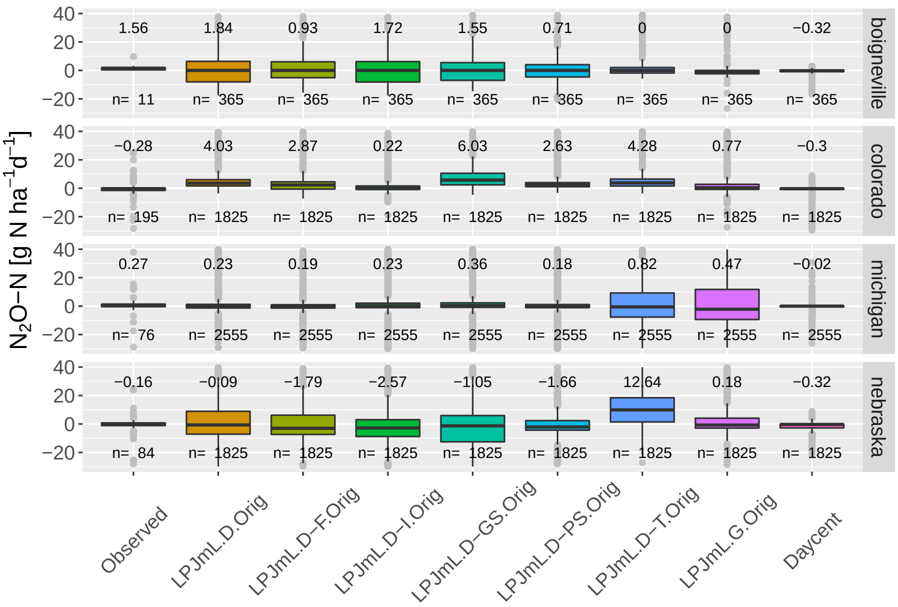


Figure B.4.1: Effects of no-tillage on N_2O emissions on individual days by the different experimental simulations, including the original runs of LPJmL, the observations and simulated values by DayCent.

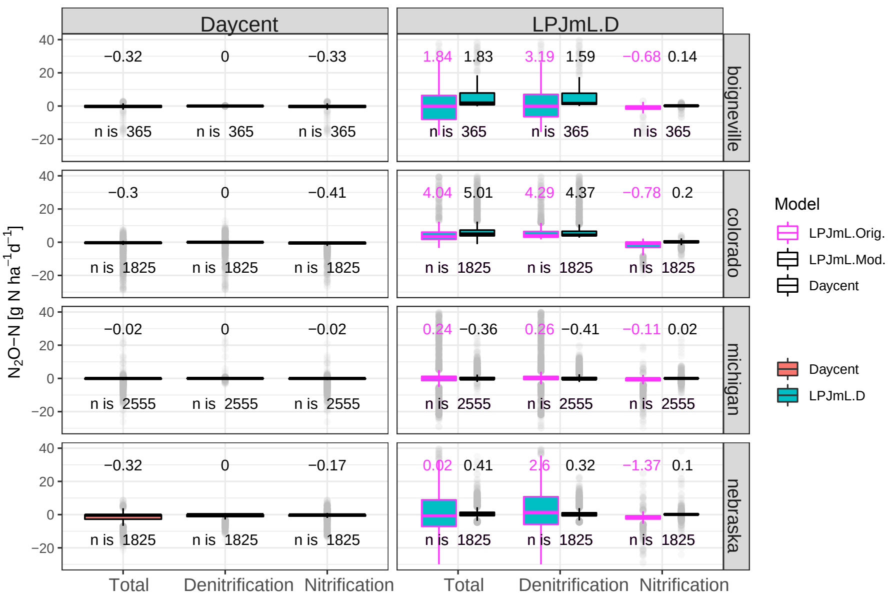


Figure B.4.2: The relative share of N_2O emissions from nitrification and denitrification on individual days with no-tillage. The simulated values include the original (purple lines) and the modified (black lines) LPJmL settings. The simulated values by DayCent are also shown. Observed values are not available.

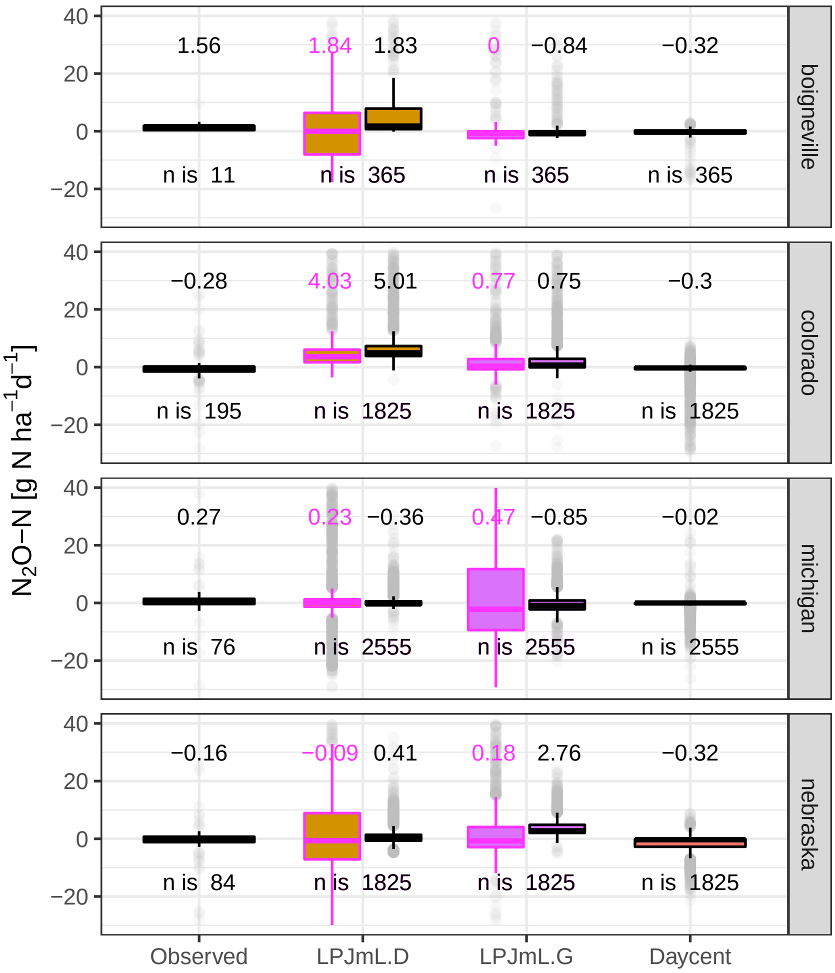


Figure B.4.3: Effects of no-tillage on N_2O emissions on individual days by the different experimental simulations, including the original- (purple lines) and the modified (black lines) simulations from LPJmL, the observations and simulated values by DayCent.

Table B.4.1: Performance Daycent and LPJmL over all sites and years

Models	Tillage type	RMSD	r	Sign. (H_0: $r = 0$)	Mean Bias	Standard Deviation
Daycent	Conv. tillage	7.60	0.67	0.00	1.35	3.24
Daycent	No tillage	4.61	0.66	0.00	1.50	2.29
LPJmL.G.Orig	Conv. tillage	23.60	-0.31	0.23	0.31	0.86
LPJmL.G.Orig	No tillage	36.20	-0.07	0.80	0.16	0.51
LPJmL.D.Orig	Conv. tillage	31.70	0.34	0.18	0.22	0.59
LPJmL.D.Orig	No tillage	38.90	0.36	0.16	0.15	0.46
LPJmL.G.Mod	Conv. tillage	14.25	-0.47	0.06	0.46	2.68
LPJmL.G.Mod	No tillage	13.86	-0.07	0.79	0.34	2.41
LPJmL.D.Mod	Conv. tillage	16.30	0.38	0.13	0.37	1.11
LPJmL.D.Mod	No tillage	18.10	0.60	0.01	0.27	0.88
Daycent	No tillage- Conv.tillage	4.96	0.34	0.02	0.88	6.85
LPJmL.G.Orig	No tillage- Conv.tillage	18.00	-0.16	0.55	-0.08	1.17
LPJmL.D.Orig	No tillage- Conv.tillage	12.00	0.48	0.05	-0.16	0.61
LPJmL.G.Mod	No tillage- Conv.tillage	7.17	-0.33	0.19	-0.60	2.21
LPJmL.D.Mod	No tillage- Conv.tillage	7.35	-0.04	0.89	-0.45	1.64

Appendix C

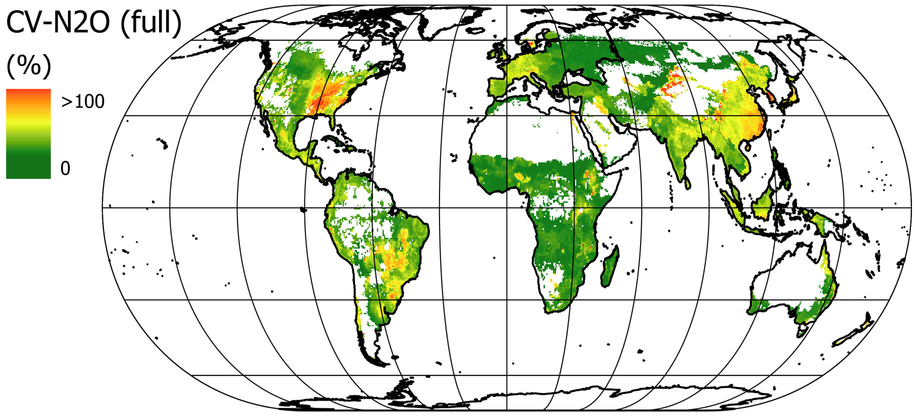


Figure C.5.1a: As Fig. 5.2 but the sensitivity of simulated N_2O expressed as *CV global* to indicate the relevance for analyses at the global aggregation.

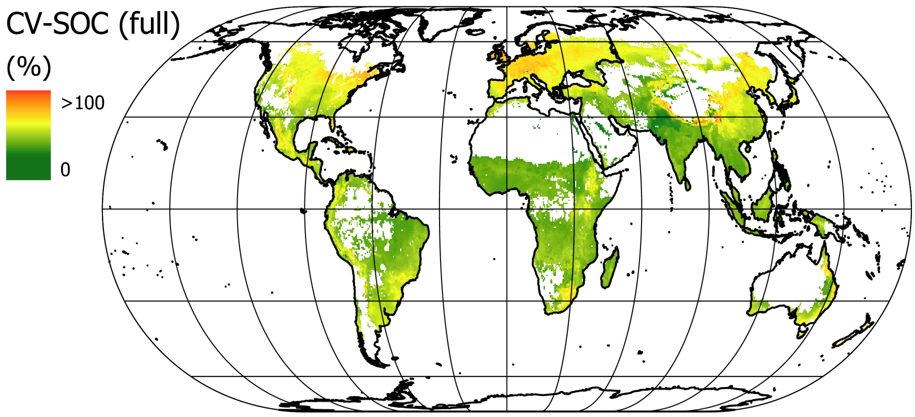


Figure C.5.1b: As Fig. 5.2 but the sensitivity of simulated SOC expressed as *CV global* to indicate the relevance for analyses at the global aggregation.

Summary

Agriculture is the largest contributor of non- CO_2 anthropogenic greenhouse gas emissions (GHG). Several agricultural based mitigation strategies (e.g. no-tillage and reducing fertilizers) have been identified to reduce emissions from agricultural soils through improved management. Yet, the potential of reducing GHG emissions from agricultural production through agricultural-based mitigation strategies remains poorly understood. Global ecosystem models often lack the capacity to assess the potential of agricultural-based mitigation strategies or even the impacts of agricultural management in general for three reasons. First, processes related to agricultural management are currently underrepresented in global ecosystem models. Second, knowledge gaps exist on the application and timing of numerous agricultural management practices. Third, models work at a relatively coarse resolution (e.g. 0.5°) whereas agricultural management may vary greatly between farming systems in close proximity.

The aim of this thesis was to contribute to the representation of agricultural management in global ecosystem models, so that the potential of agricultural based mitigation practices can be better quantified. The research was focused on processes related to tillage and N_2O emissions. The first study of this thesis first addressed if and how processes related to tillage can be described in global ecosystem models. After indicating how processes related to tillage can be described, they were implemented into the global ecosystem model LPJmL. The performance of the extended model was then evaluated at the global scale and for a number of experimental sites. Finally, the effect of representing of soil heterogeneity on global modelling of SOC and N_2O emissions was assessed.

Approaches to represent new processes related to agricultural management in global ecosystem model, such as tillage, can be obtained by making use of process knowledge from field-scale models. However, not all processes described in field-scale models are suitable for incorporation into global ecosystem models. Thereby, the importance of processes has to be considered, as well as the input requirements and input data availability at the global scale. Yet, a guiding principle on where to start and how make decisions was previously still missing. This thesis, therefore firstly provided a standardized framework that can be followed to decide if and how processes related to agricultural management can be incorporated into global ecosystem models. The general framework was applied to

the implementation of tillage-induced processes for the analyses of N_2O emissions. The standardized framework consists of three steps. First, the most important nitrogen (N) processes in soils are identified, and their response to environmental conditions and how these are affected by tillage. Then the description of how these processes and tillage effects are described in field-scale models, followed by an evaluation whether they can be incorporated in global ecosystem models, while considering the data requirements for a global scale application. As the most important processes were described in field-scale models and the basic requirements can be met, I concluded that tillage can be incorporated into global ecosystem models for the analyses on N_2O emissions. However, a spatial explicit dataset on tillage management was missing, which only allowed for scenario-based analyses.

The global ecosystem model LPJmL was then extended with new processes and modules for the representation of tillage management. More specifically, the tillage effects on physical properties (bulk density) and residue incorporation into the soil including feedbacks on soil water and N dynamics were considered to be the most relevant aspects with approaches suitable for implementation into a global model. After extending the model with an explicit representation of tillage practices, the model was evaluated by using four contracting simulations: with and without the application of tillage and with and without the removal of residues. This scenario-based analysis enabled to evaluate the performance of the model, as a spatial explicit dataset on tillage was not available. The performance of the model was tested by comparing modeling results of carbon and water-fluxes, crop productivity and N_2O emissions with reported data from meta-analyses. In general, the model was able to reproduce observed effects of no-tillage on global, as well as regional patterns of agricultural productivity, water- and carbon fluxes. The overall effect of no-tillage on N_2O emissions were in overall agreement with reported data ranges as well. However, the regional patterns over the different climate regimes were strongly deviating from the meta-analyses.

Deviations of tillage effects on N_2O emissions compared to reported values in meta-analyses can have different causes, such as a lack of detailed input data on management practices or the representation of processes related to tillage. To gain insight if the deviations resulted from a lack of detailed input data on management practices or from distortions in the representation of processes related to tillage, the extended model was applied at different experimental sites. This enabled using site-specific information on agricultural management, soil and weather information and thus understanding if model input or process representation caused mismatches between the reported values in the meta-analyses and model simulations. A comparison with the field-scale model Daycent that was previously calibrated for and applied at these sites helped to fill gaps in measurements and gain further insights into the model behavior.

Evaluating the global ecosystem model LPJmL at field-scale, gave much insight in finding why the effects of tillage on N_2O emissions were deviating from observations. It showed that specifying site-specific information on management improved the performance of the model. However, also with detailed information, the N_2O emissions were strongly deviating from the observations due to a general overestimation of N_2O emissions simulated by LPJmL. The high emissions were a result of high soil moisture levels simulated by the model. As N_2O emissions are very sensitive to soil moisture, it is very important to more accurately simulate soil moisture with LPJmL. As high soil moisture levels can result from various reasons, further research is needed to improve the representation of soil hydrology in LPJmL. However, the study could already indicate the potential of improving soil hydrology through adjusted parameterization of soil hydraulic properties, and therefore reduce the general overestimation of N_2O emissions.

Next to uncertainties in the soil hydrology, another source of uncertainty can be the relatively coarse resolution at which global models are typically applied. Global ecosystem models often work at a spatial resolution of 0.5° (equivalent to approximately 55 km at the equator) and typically work with the most dominant soil texture class within the grid cell. As a result, the soil heterogeneity is ignored. In Chapter 5, we tested four different ways of representing heterogeneity in soil conditions and their effects on simulated N_2O emissions and SOC using LPJmL. Moreover, we identified the areas at risk for modeling errors when using the dominant soil texture within the grid cell, which is the common practice. The results of the study indicated that for global assessments the method typically used by global ecosystem models (i.e. using dominant soil texture class) is feasible for simulating N_2O emissions and SOC content, as the errors across regions tend to compensate each other, so that only small differences were found between the methods of representing soil heterogeneity. However, considerable differences were found when analyzing local and regional differences. For local or regional assessments on N_2O emissions and SOC content, using the dominant soil texture class within the grid cell can therefore lead to distortions, especially in high-risk areas. In these areas, the soil heterogeneity should be more explicitly accounted for. As the spatial patterns of the indicated high risk areas for N_2O emissions and SOC content were similar, I hypothesized that a non-regular grid could be defined for soil inputs/output variables from global ecosystem models as a compromise between computational constraints and required spatial detail. This could potentially also improve the simulation of tillage effects on N_2O emissions and SOC content, but requires further research.

The extended global ecosystem model LPJmL was not capable of accurately simulating tillage effects on N_2O emissions. The global potential of mitigating N_2O emissions through tillage management cannot be well assessed. Yet, there is a better understanding of processes related to tillage and interactions with N_2O emissions. Moreover, the model was able to reproduce observed effects of tillage on other dimensions, such as agricultural production, soil C and CO_2 emissions at various scales. The implementation of the more detailed tillage related mechanism into LPJmL therefore improves the ability to represent different agricultural systems and understand agricultural management options for agricultural adaptation and for mitigation options of agricultural GHG emissions. Such findings can guide management decisions at various scales with respect to agricultural-based mitigation strategies in order to support regional and global mitigation goals, such as the Paris Agreement.

Samenvatting

Landbouw levert de grootste bijdrage aan antropogene broeikasgasemissies anders dan CO_2. Verschillende mitigatiestrategieën voor de landbouw zijn geïdentificeerd om de uitstoot van landbouwgronden te verminderen door middel van beter bodembeheer (bijv. het verminderen van grondbewerking en mest). Toch is het potentieel om de uitstoot van broeikasgassen door de landbouwproductie wereldwijd te verminderen via deze mitigatiestrategieën nog onduidelijk. Globale ecosysteemmodellen missen vaak het vermogen om het potentieel van de op landbouw gebaseerde mitigatiestrategieën of zelfs de algemene effecten van landbouwbeheer te beoordelen om drie redenen. Ten eerste zijn de processen die verband houden met landbouwbeheer momenteel ondervertegenwoordigd in globale ecosysteemmodellen. Ten tweede bestaat er een hiaat in kennis over het toepassen van landbouwbeheer praktijken in relatie tot broeikasgasemissies. Ten derde werken deze modellen met een relatief grove resolutie (bijv. 0.5 °), terwijl landbouwbeheer sterk kan verschillen tussen landbouwsystemen in de directe nabijheid.

Het doel van dit proefschrift was landbouwbeheer beter te beschrijven in de globale ecosysteemmodellen, zodat het potentieel van de mitigatiepraktijken voor de landbouw beter kan worden gekwantificeerd. Het onderzoek was gericht op processen met betrekking tot grondbewerking en N_2O emissies. In de eerste studie van dit proefschrift werd onderzocht of en hoe processen gerelateerd aan grondbewerking kunnen worden beschreven in globale ecosysteemmodellen. Vervolgens werden deze processen geïmplementeerd in het globale ecosysteemmodel LPJmL. De prestaties van het vernieuwde model werden vervolgens op wereldwijde schaal en voor een aantal experimentele sites geëvalueerd. Tot slot werd het effect van bodemheterogeniteit op de modellering van bodem-organische stof en N_2O emissies beoordeeld op de globale schaal.

Om processen met betrekking tot landbouwbeheer, zoals grondbewerking, in een globaal ecosysteemmodel te beschrijven kan proceskennis vanuit veldmodellen worden gebruikt. Niet alle processen die worden beschreven in veldmodellen zijn echter geschikt om geïmplementeerd te worden in globale ecosysteemmodellen. Daarbij moet rekening worden gehouden met het belang van de processen en met beschikbaarheid van de benodigde data op globale schaal. Een leidraad om te beoordelen of processen die worden beschreven in veldmodellen ook gebruikt kunnen worden in een globaal ecosysteem model ontbrak. Dit

proefschrift leverde daarom in de eerste plaats een gestandaardiseerd raamwerk dat kan worden gevolgd om te beoordelen of en hoe processen met betrekking tot landbouwbeheer kunnen worden opgenomen in globale ecosysteemmodellen. Het raamwerk werd toegepast op de implementatie van processen die gerelateerd zijn aan grondbewerking en de interactie met N_2O emissies. Het raamwerk bestaat uit drie stappen. Eerst worden de belangrijkste stikstof processen in de bodem, hun reactie op omgevingsfactoren en hun relatie tot grondbewerking geïdentificeerd. Vervolgens wordt geanalyseerd hoe deze processen en grondbewerking beschreven worden in veldschaalmodellen, gevolgd door een evaluatie of ze kunnen worden opgenomen in globale ecosysteemmodellen, rekening houdend met de inputvereisten voor de toepassing op wereldschaal. Aangezien de belangrijkste processen in veldmodellen werden beschreven en aan de basisvereisten kan worden voldaan, concludeerde ik dat grondbewerking kan worden opgenomen in globale ecosysteemmodellen voor de analyse van N_2O emissies. Een expliciete ruimtelijke dataset over grondbewerking ontbrak echter, waardoor de analyse beperkt is tot scenario's.

Het globale ecosysteemmodel LPJmL werd vervolgens uitgebreid met nieuwe processen en modules voor grondbewerking. In het bijzonder werden de grondbewerkingseffecten op fysische eigenschappen (bulkdichtheid) en de opname van gewasresten in de bodem, inclusief terugkoppelingen van bodemwater en N-dynamiek, beschouwd als de meest relevante aspecten die geschikt zijn voor implementatie in een globaal model. Na de implementatie met een expliciete weergave van grondbewerkingsmethoden, werd het model geëvalueerd met behulp van vier verschillende simulaties: met en zonder het toepassen van grondbewerking en met en zonder het verwijderen van gewasresten. Deze op scenario gebaseerde analyse maakte het mogelijk om de prestaties van het model te evalueren. De prestaties van het model werden getest door de model resultaten van koolstof- en waterfluxen, gewasproductiviteit en N_2O emissies te vergelijken met gerapporteerde gegevens uit meta-analyses. Over het algemeen kon het model de waargenomen effecten van niet-grondbewerking op de globale, evenals regionale patronen van gewasproductiviteit, water- en koolstoffluxen reproduceren. Het algemene effect van niet-grondbewerking op N_2O emissies was ook in overeenstemming met de gerapporteerde gegevens uit meta-analyses. De regionale patronen over de verschillende klimaatregimes weken echter sterk af.

Afwijkingen van grondbewerkingseffecten op N_2O emissies ten opzichte van gerapporteerde gegevens in meta-analyses kunnen verschillende oorzaken hebben, zoals een gebrek aan gedetailleerde gegevens over landbouwbeheer of de weergave van processen die gerelateerd zijn aan grondbewerking. Om inzicht te krijgen of de afwijkingen het gevolg waren van een gebrek aan gedetailleerde inputgegevens van landbouwbeheer of in de weergave van processen met betrekking tot grondbewerking, werd het model toegepast op verschillende veldexperimenten. Ruimtelijke specifieke informatie van landbouwbeheer, bodem en weerscondities vanuit de experimenten kon gebruikt worden om te begrijpen of modelinput of procesrepresentatie afwijkingen veroorzaakte tussen de gerapporteerde gegevens van de meta-analyses en model resultaten. Een vergelijking met het veldmodel

Daycent, dat eerder op deze locaties was toegepast en gekalibreerd, hielp om gaten in de metingen te vullen en meer inzicht te krijgen in het gedrag van het model.

Evaluatie van het globale ecosysteemmodel LPJmL op veldschaal gaf veel inzicht in het achterhalen waarom de effecten van grondbewerking op N_2O emissies afweken van waarnemingen. Hieruit bleek dat het gebruiken van locatie-specifieke informatie over landbouwbeheer de prestaties van het model verbeterde. Echter, ook met gedetailleerde informatie, weken de N_2O emissies sterk af van de waarnemingen vanwege een algemene overschatting van N_2O emissies die werden gesimuleerd door LPJmL. De hoge emissies waren een resultaat van hoge bodemvochtgehaltes gesimuleerd door het model. Aangezien N_2O emissies zeer gevoelig zijn voor bodemvocht, is het erg belangrijk om bodemvocht nauwkeuriger te simuleren met LPJmL. Omdat een hoge bodemvochtigheid verschillende oorzaken kan hebben, is verder onderzoek nodig om de weergave van de bodemhydrologie in LPJmL te verbeteren. De studie kon echter al wijzen op een potentiële verbetering van de bodemhydrologie door middel van het aanpassen van hydraulische parameters van de bodem, en daarmee de algemene overschatting van N_2O emissies te verminderen.

Naast onzekerheden in de bodemhydrologie, kan een andere bron van onzekerheid de relatief grove resolutie zijn waarop globale modellen doorgaans worden toegepast. Globale ecosysteemmodellen werken vaak met een ruimtelijke resolutie van 0,5 ° (gelijk aan ongeveer 55 km bij de evenaar) en werken meestal met de meest dominante bodemtextuurklasse in de rastercel. De heterogeniteit van de bodem binnen de rastercel wordt hierdoor genegeerd. In Hoofdstuk 5 hebben we vier verschillende manieren getest om heterogeniteit in de bodemcondities en hun effecten op gesimuleerde N_2O emissies en bodem-organische stof met LPJmL weer te geven. Bovendien hebben we de gebieden geïdentificeerd die risico lopen op fouten bij het gebruik van de dominante bodemtextuur in de rastercel. De resultaten van de studie gaven aan dat voor globale studies, de methode die doorgaans wordt gebruikt door globale ecosysteemmodellen (dat wil zeggen met behulp van de dominante bodemtextuurklasse) haalbaar is voor het simuleren van N_2O emissies en bodem-organische stof gehalte, aangezien de fouten in regio's de neiging hebben elkaar te compenseren, zodat slechts kleine verschillen werden gevonden tussen de methoden om bodemheterogeniteit weer te geven. Er werden echter aanzienlijke verschillen gevonden bij het analyseren van lokale en regionale verschillen. Voor lokale of regionale beoordelingen van N_2O emissies en bodem-organische stof gehalte kan daarom het gebruik van de dominante bodemtextuurklasse in de rastercel leiden tot onzekerheden, vooral in risicovolle gebieden. In deze gebieden moet expliciet meer rekening worden gehouden met de bodemheterogeniteit. Omdat de ruimtelijke patronen van de gebieden met een hoog risico voor N_2O emissies en bodem-organische stof gehalte vergelijkbaar waren, veronderstelde ik dat een niet-regelmatig raster zou kunnen worden gedefinieerd voor bodeminput/outputvariabelen van globale ecosysteemmodellen als een compromis tussen beperkingen in de rekencapaciteit van een model en vereisten in ruimtelijk detail. Dit kan potentieel ook de simulatie van grondbewerkingseffecten op N_2O emissies en bodem-organische stof gehalte verbeteren, maar vereist verder onderzoek.

Het uitgebreide wereldwijde ecosysteemmodel LPJmL was niet in staat om grondbewerkingseffecten op N_2O emissies nauwkeurig te simuleren. Het potentieel voor het verminderen van N_2O emissies door grondbewerking op globale schaal, kan daardoor niet goed worden beoordeeld. Toch is er een beter inzicht verkregen in processen gerelateerd aan grondbewerking en hun interacties met N_2O emissies. Bovendien kon het model de waargenomen effecten van grondbewerking op andere dimensies reproduceren, zoals landbouwproductie, bodemkoolstof en CO_2 uitstoot op verschillende schalen. De implementatie van het meer gedetailleerde grondbewerkingsmechanisme in LPJmL verbetert daarom het vermogen om verschillende landbouwsystemen weer te geven en inzicht te krijgen in landbouwbeheeropties voor landbouwaanpassing en voor mitigatie opties voor broeikasgasemissies in de landbouw. Dergelijke bevindingen kunnen beslissingen over landbouwbeheer op verschillende schalen helpen met betrekking tot op landbouw gebaseerde mitigatiestrategieën ter ondersteuning van regionale en wereldwijde mitigatiedoelstellingen, zoals de Paris Agreement.

About the author

Femke Lutz was born on May 24th 1988 in Barendrecht, the Netherlands. After finishing secondary school in 2006, she was involved in a student exchange program for which she attended one year of high school in Minnesota in the United States. When she came back, she started her bachelor study Environmental Science at the University of applied sciences at INholland in 2007. In 2010 she attended Utrecht University for a semester course on Physical Geography. After finishing her bachelor study she continued with her master Earth and Environment at the Wageningen University in 2011. During her studies, she did an internship at the Corporación Bananera Nacional where she studied the impact of banana pseudostem removal on soil fertility in Costa Rican banana plantations. After her internship, she did her master thesis where she explored the potential of soil and water conservation as adaptation strategy towards climate change, which involved field-work in Kenya.

After finishing her studies, Femke continued with a PhD at the Potsdam Institute for Climate Impact Research in Germany (2014-2019) where she was part of the junior research group (MACMIT), supervised by Christoph Müller. During her PhD, she studied the effects of tillage on N_2O emissions at the global scale. During that time, she published papers in peer-reviewed journals, presented her work at international conferences and acquired a travel fund to visit and collaborate with the DayCent modelling team at the Colorado State University.

Since February 2020, she works at Vista GmbH in Munich, where she is working on optimizing nitrogen management on farming systems through the combined use of a crop growth model and satellite data.

PE&RC Training and Education Statement

With the training and education activities listed below the PhD candidate has complied with the requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

The C.T. De Wit Graduate School PE&RC
PRODUCTION ECOLOGY & RESOURCE CONSERVATION

Review of literature (6 ECTS)

- Comprehensive understanding of the agricultural nitrogen dynamics, options to affect these by agricultural management and suitable approaches for global-scale modelling

Writing of project proposal (4.5 ECTS)

- Evaluating the impact of agricultural management strategies on soil nutrient dynamics at the global scale

Post-graduate courses (5.5 ECTS)

- Climate smart agriculture; PE&RC (2016)
- International school on global greenhouse gases; School of GeoSciences, the University of Edinburgh (2015)
- Hands on global soil information facilities; ISRIC (2015)

Laboratory training and working visits (4.5 ECTS)

- LPJmL-Daycent comparison study; Colorado State University (2018)

Deficiency, refresh, brush-up courses (1.5 ECTS)

- Programming language course; Humboldt University (2016)

Competence strengthening / skills courses (3.9 ECTS)

- Communicating with general public and media; WGS (2018)
- Career orientation; WGS (2018)
- Competence assessment; WGS (2017)
- On doing sound and ethical science; Humboldt Graduate school (2016)
- How to write a review; Humboldt Graduate school (2015)

PE&RC Annual meetings, seminars and the PE&RC weekend (1.2 ECTS)

- PE&RC PhD Day: the social network nature (2018)
- PE&RC First years weekend (2015)

Discussion groups / local seminars / other scientific meetings (10 ECTS)

- PhD Discussion group where the potential reductions and costs of greenhouse gas emissions from agriculture at different scales were presented and debated in a multidisciplinary setting; Graduate School LandPakt (2019)
- Local seminars for climate impact research; Potsdam Institute (2015-2019)

International symposia, workshops and conferences (6.9 ECTS)

- European Geosciences Union conference; poster presentation; Vienna, Austria (2019)
- The International Soil Modelling consortium; poster presentation; Wageningen (2019)
- European Geosciences Union conference; poster presentation; Vienna, Austria (2018)

This research has received funding from i) the German Federal Ministry of Education and Research (grant no. 01LN1317A), ii) the Soil Geography and Landscape group of Wageningen University, and iii) the Huub and Julienne Spiertz Fund. They are all gratefully acknowledged.

Cover design by Chrisje Maaskant